Shakeouts

Firm Survival and Technological Change in New Manufacturing Industries

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Shakeouts: Technological Change and Firm Survival in New Manufacturing Industries

Abstract

New manufactured products commonly experience a rise in number of producers followed by a "shakeout" in which the number of firms drops off. Several recent theories have depicted shakeouts as a consequence of technological change. Hence, the theories posit relationships between technology and the determinants of market structure. To examine these relationships, longitudinal empirical tests related to technology, entry, survival, and profits are carried out based on the theories in four products with severe shakeouts: automobiles, tires, televisions, and penicillin. The statistical survival analyses used involve methodological innovations.

Individual technological events, such as refinement inventions or dominant designs, apparently did not trigger the shakeouts. Rather, some gradual process continually increased competitive pressure, eventually making entry untenable. Meanwhile, exit continued at a roughly constant aggregate rate. The combination of decreased entry and continued exit caused the number of firms to fall. Survivors from the earliest entrants came to dominate in the long run, driving out most other firms. The sources of early-mover advantage are difficult to disentangle, but available evidence concurs that some technology-related source contributed at least part of the advantage in these four products. Indeed, the four product industries turn out to have been some of the most technology-intensive industries of their times.

To help confirm the findings in a broad sample, novel longitudinal survival data on forty-nine products are used. Entry and survival patterns concur with the four-product findings, indicating that shakeouts tend to involve cessation of entry and an early-mover advantage.

Contents

Preface

As an undergraduate at MIT, I grew fascinated with the dynamic behavior of social systems. I began studying many different approaches to examining change in social systems, seeking to identify methods that could help discern their inner workings. Among the groups and people with whom I associated are the System Dynamics Group and Professor John Sterman, who led me to realize the enormous benefit that the US and the world might realize from improvements in business and industry that could result from academic research.

At Carnegie Mellon I found a home for such research, working with Professor Steven Klepper, who pioneered attempts to document and understand "shakeouts" in industries. In a great many manufacturing industries, the number of companies making a product rises after the product's introduction, reaches a peak, and then drops off. The dropoff, or "shakeout," typically happens even while industry output grows. As I arrived at Carnegie Mellon, Steven was beginning a project to gather new and detailed data on shakeouts. I became fascinated with shakeouts, and so this project began. Steven has been involved as an equal partner throughout the project. In addition to papers and research each of us is doing independently, we have written and plan to write a series of joint papers on shakeouts. I learned an immense amount from him, and I gained an appreciation of his careful and thoughtful work habits and high quality standards.

Many others have contributed their ideas, feedback, and assistance to this project. Professor John Miller drew on his knowledge of demography and paleobiology to suggest several methods of analysis which have turned out to be valuable tools for understanding shakeouts. He and many others contributed ideas which helped in continual refocusing, revision, and rewriting. Professors Ashish Arora, Wes Cohen, David Hounshell, and

Mark Kamlet all contributed valuable comments, and Tom Åstebro, Stephanie Byram, and Sally Sleeper provided timely assistance and ideas.

Invaluable assistance for this project was also provided by a large number of research assistants. Chris Mega (especially), Stepan Babayan, Eric Bryner, Laura Demensik, Jon Didier, Carl Dockhorn, Kristina Keenan, Sun Kim, Albert Kurland, Julia LaSalle, Nick Lee, Linda Schmidt, Ken Sharp, Chris Struble, Earl Wagoner, Joan Yang, and Sunny Yang helped to gather information and assisted with analyses. Another team that grew to over a dozen undergraduates, including Lauren Sroczynski who helped to direct the team, worked with Steven Klepper for four years compiling data from annual volumes of *Thomas' Register of American Manufacturers*. Ruth Silverman also provided invaluable assistance throughout the project. She learned to appreciate the colorful history of industries such as automobiles and TV picture tubes. Michele Colón and Carole Deauanovich handled essential tasks related to financing and employment records. Thanks also to David Maltz, John Miller, and Sasha Wood for offering the use of their workstation computers.

The Interlibrary Loan office of Carnegie Mellon deserves special thanks and praise. In and out through their door flowed a constant stream of books, articles, reports, government documents, and dissertations. Through their heroic efforts we obtained whole library shelves full of annual trade publications, allowing me to compile the time series data that appear in the following pages. In many cases it turned out to be impossible to obtain books except by taking a trip, and I have gained a firsthand appreciation especially for libraries that save outdated trade registers. These libraries, including Baker Library at Harvard University, the Boston Public Library, New York Public Library, and the Library of Congress, deserve commendation because it is distressingly common for old trade registers to wind up in dumpsters, the last home for many valuable sources of economic data.

Outside of Carnegie Mellon, economists, historians, industry experts, and tradespeople have given me ideas and tolerated my requests for information. Thanks to Bill Barnett, Theodore Daykin, Rebecca Henderson, Will Mitchell, Dick Nelson, Dan Raff, David Simons, John Sterman, Marc Surchat, Jim Utterback, and Sid Winter. Valuable comments also came from seminar participants at the MIT Sloan School, the Census Bureau's Center for Economic Studies, the Austrian Institute of Economic Research, the University of London, and the ASSA 1994 meetings.

This research relies continually upon past industry studies and data collection projects. For each of the four primary industries studied here, I have pored over volume after volume, continually using bibliographies to lead me to more literature. A majority of the available studies, including many of the most valuable works, have been doctoral theses. My heartfelt thanks goes to the people who completed these studies. Only by standing on the shoulders of people who are rarely called giants.... My research also draws upon continually evolving thought about the role of technology in industries. Without the theorizing of various students of technology and industry, it would have been difficult (perhaps impossible) to develop the perspective used here to analyze the role of technology in industry shakeouts. Other people have provided non-technological explanations for industry shakeouts, and their ideas are also considered here, to the extent it has been possible to do so given limitations on evidence and time. Specific contributions will be apparent from citations in the text.

This material is based upon work supported under a National Science Foundation Graduate Fellowship. Any opinions, findings, conclusions or recommendations expressed in this publication are those of the author and do not necessarily reflect the views of the National Science Foundation. Without the support of the National Science Foundation my work as a graduate student would have been continually handicapped. I am grateful for the Foundation's assistance, and I hope the benefits of this research can repay my country's contribution.

Shakeout Theories & The Determination of Industry Structure

1

Introduction

Throughout the world, today's automobile industry is a concentrated oligopoly. You might expect, given the enormous production scales required today, that the industry was always the domain of a few giant producers. But this is not so. In the early 1900s, in the US, hundreds of firms created novel designs and competed for a share of the (then relatively small) market. According to one source, shown in Figure 1.1, the number of manufacturers rose from four in 1895 to a peak of 274 in 1909. The number then dropped rapidly, reaching 30 firms by 1929, to an eventual low of seven around 1960. Given the small number of firms remaining, it is no surprise that the industry is a concentrated oligopoly.

Such an increase in firm numbers and then "shakeout" is common among new manufacturing industries. A shakeout, as I define it, is the period from the peak in the number of firms (in automobiles, 1909) until the number levels off or starts to increase (1956). Its severity is the percentage decrease in number of firms between these two times (in automobiles, 97%).[1] Empirical studies by Gort and Klepper (1982) and Klepper and Graddy (1990) suggest that some degree of shakeout occurs in most products once they have been manufactured for at least several decades. While the shakeout in automobiles was unusually severe, it is surprisingly easy to find other industries, also of great economic importance, that experienced shakeouts nearly as dramatic. Figures 1.2 through 1.4 show

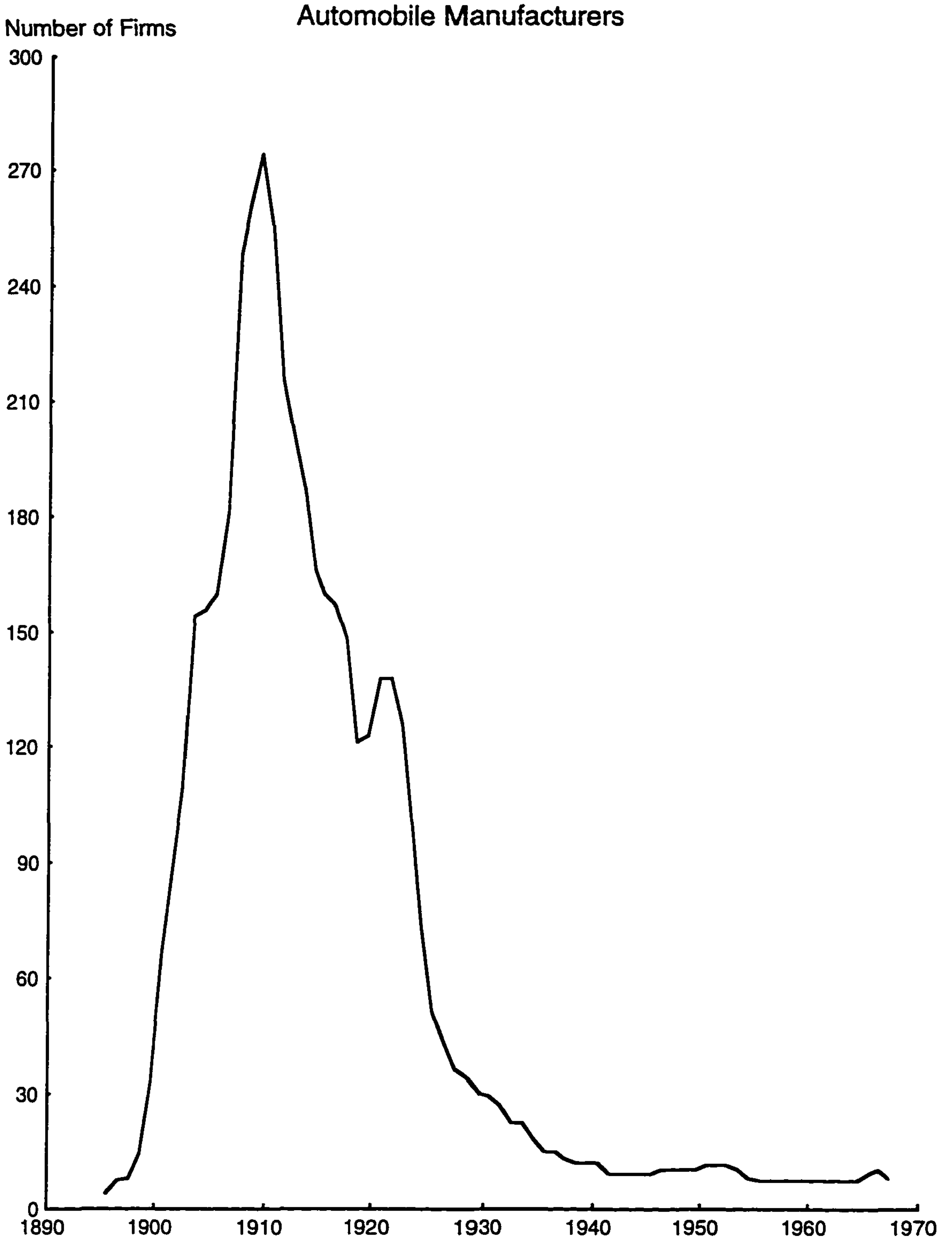


Figure 1.1. Number of automobile manufacturers in the US, 1895-1966. Source: Based on a list published by Smith (1966), but converted to a number of firms rather than a number of makes (brands).

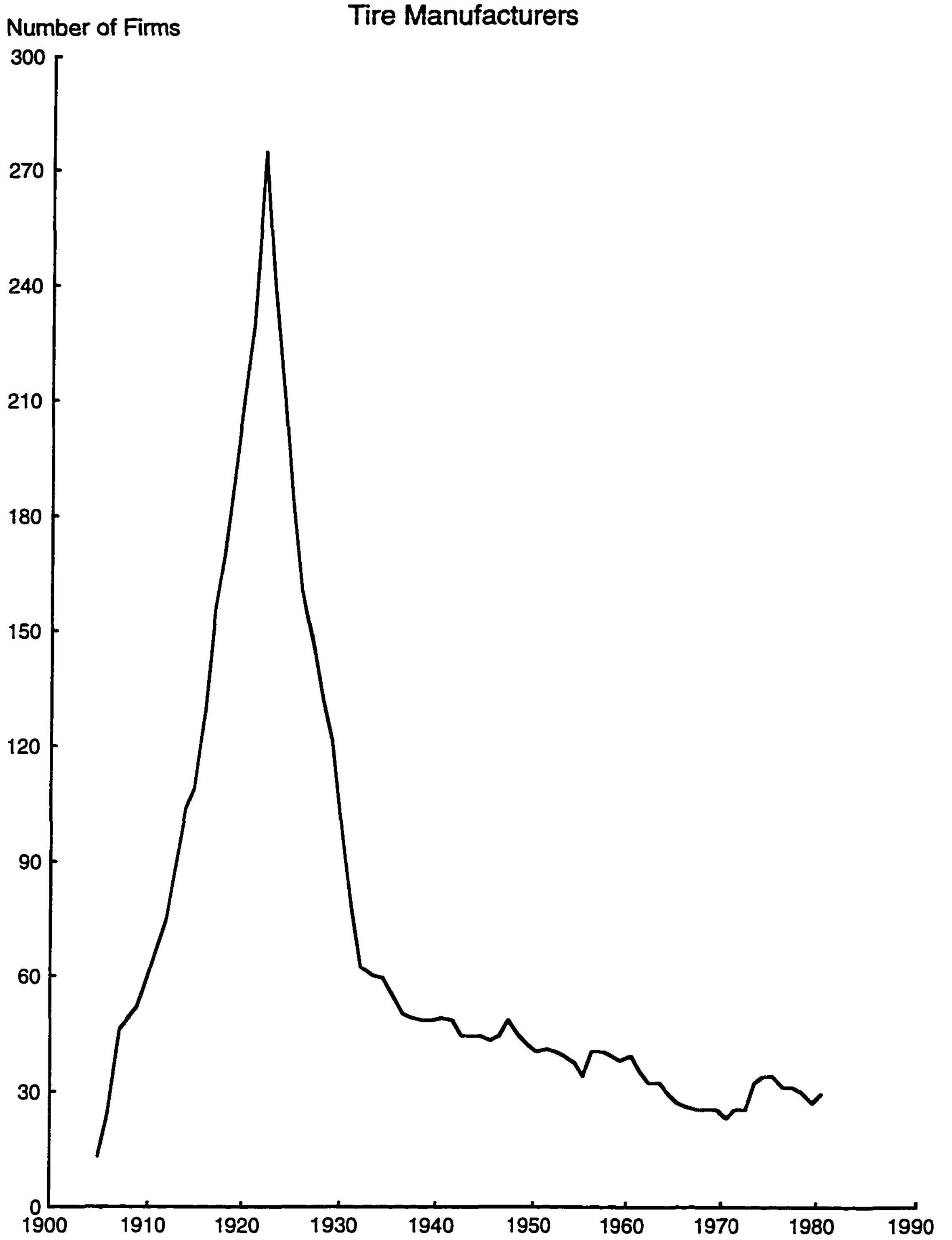


Figure 1.2. Number of tire manufacturers in the US, including pneumatic and cushion rubber tires for automobiles and trucks, 1905-1980. Source: Based on *Thomas' Register* 1905-1981.

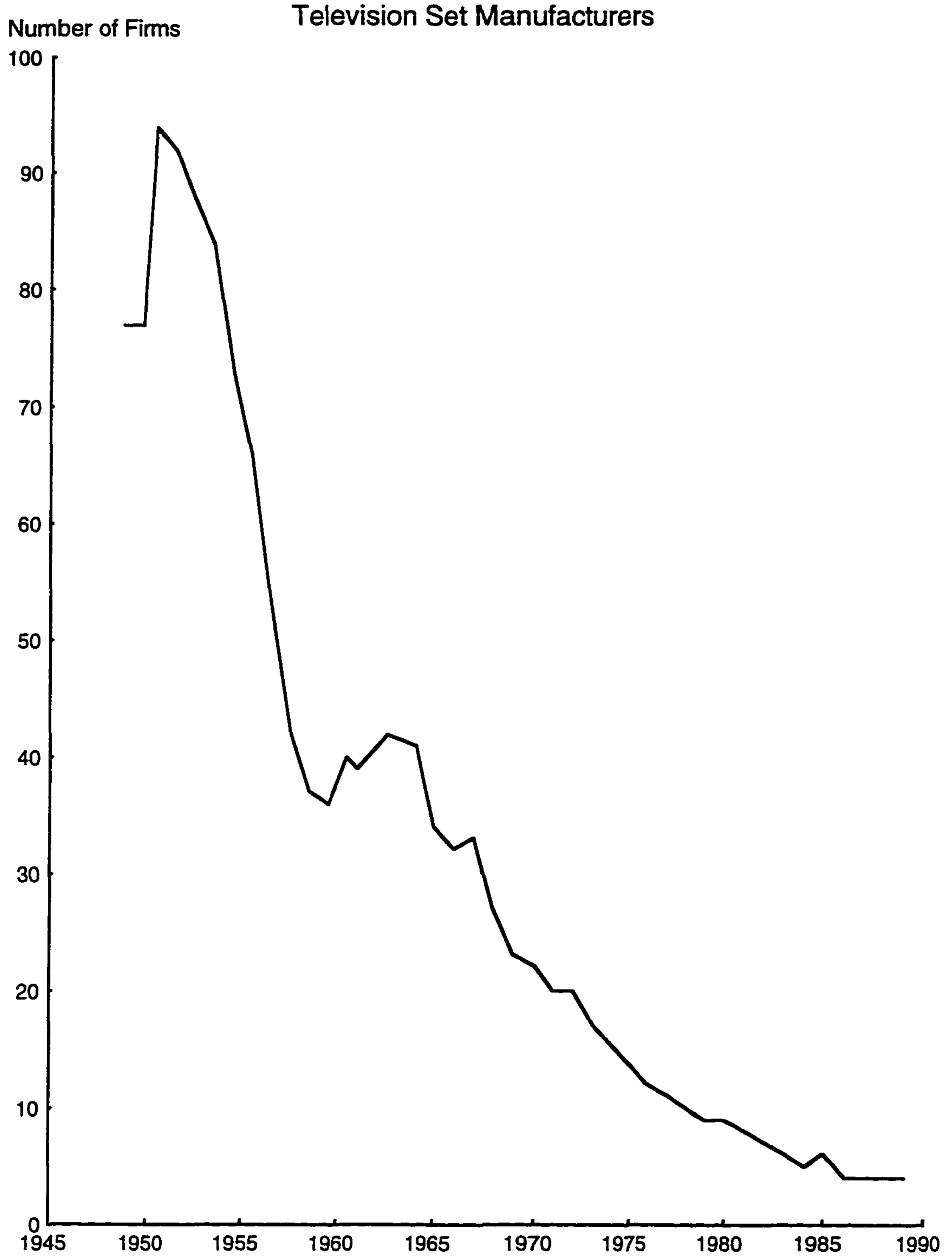


Figure 1.3. Number of television set manufacturers in the US, 1947-1989. Source: Based on *Television Factbook* (1948-1990). Foreign entrants into US production are excluded.

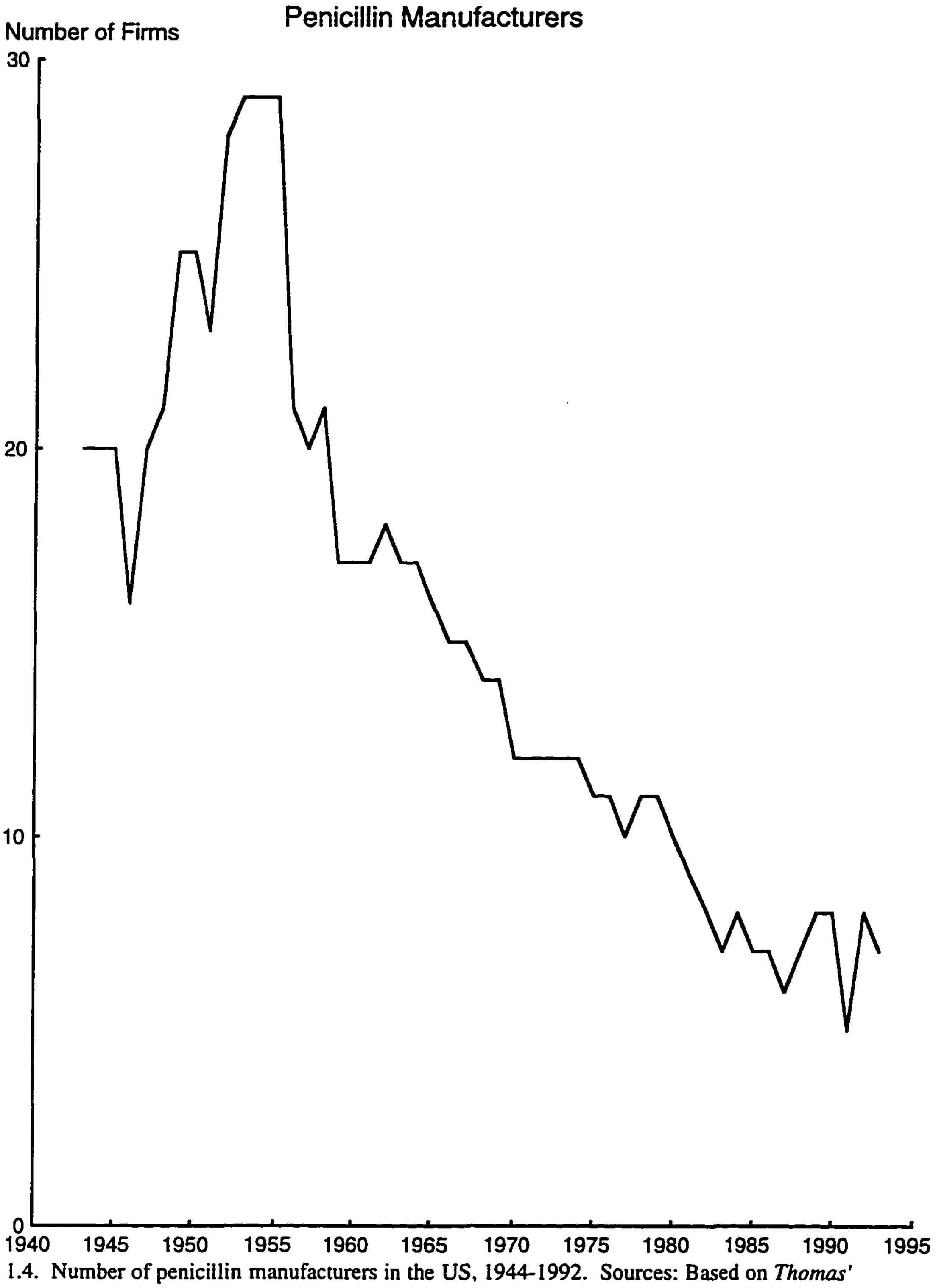


Figure 1.4. Number of penicillin manufacturers in the US, 1944-1992. Sources: Based on *Thomas' Register of American Manufacturers* (1945-1993), US Tariff Commission (1945-1991), Federal Trade Commission (1958), and Elder (1970a).

the rise and fall in number of manufacturers in tires, television sets, and penicillin. This dissertation focuses on these four industries as a means to explore the causes of shakeouts, on the assumption that in cases with severe shakeouts, the causes are likely to be most apparent.

You might expect shakeouts to be just a result of rising economies of production scale, or of declining demand. But it is not so. As will become apparent over the pages of this dissertation, some other process is involved. Plant sizes are generally too large to be explained by economies of production scale, given the much smaller efficient scale of production machinery (e.g., Bain, 1956). And shakeouts usually happen when output is growing rapidly. In automobiles, the shakeout began just when growth in industry output reached substantial amounts; the other three industries experienced a range of output patterns and eventually all reached much higher quantities of output. Some different process is at work, not simply the growth of scale economies or the decline of demand.

Close study of automobiles, tires, television sets, and penicillin reveals that all four industries experienced extremely rapid technological change, suggesting that technology may be involved in the shakeouts. These products were among the most technologically progressive of their times. And indeed, several theories have been developed recently to explain shakeouts as a result of technological change.

The theories join a long line of research that has explored how market structure may determine technological change and *vice versa*. At least since Schumpeter (1934, 1942), economists have investigated whether technological "creative destruction" (Schumpeter, 1942) may cause a concentration in the number of producers, or whether larger firms or firms in more concentrated markets are more innovative than smaller firms. As will be discussed in chapter two, the web of relationships between technology and market structure has been difficult to disentangle. Indeed, it has been difficult to determine even whether causality flows from market structure to technological change or in the reverse direction. In part, these difficulties have resulted from the nature of most empirical data, which allow cross-sectional analyses at a point in time. By analyzing the non-equilibrium processes that operate over time to determine eventual market structure, this research has new opportunities to discern the temporal ordering of causality in relationships between technology and market structure.

To analyze how technology may be involved in shakeouts, it will help to have a theoretical framework. Several relevant theories have been proposed in the past few years, showing how technological change may result in a dropoff in the number of producers.[2] The theories are of two types. First, given the abrupt dropoff in number of firms, it is tempting to suggest that a dramatic technological event triggers a shakeout. In the first type of theories, a technological event annihilates firms that cannot adapt to the new technology, like a meteor from outer space may have annihilated the dinosaurs.[3] The technological event may be a single invention (Jovanovic and MacDonald, 1994b) or a dominant product design (Utterback and Suárez, 1993). If an invention triggers the shakeout, firms must adapt to the invention and succeed at a stream of related technological innovations. Firms that do not succeed are annihilated by the forces of competition. If a dominant design triggers the shakeout, competition shifts at the time of the design from building a better product to building the standardized product at lowest possible cost. Competition annihilates firms that cannot successfully produce the standard design at low cost.

In contrast, the second type of theory has nothing sudden about it. Gradually intensifying competition annihilates firms, like gradual cooling might have annihilated the dinosaurs. The competitive process may be affected by R&D. According to a model by Klepper (1994), firms have R&D-related advantages that take the form of size and skill. As process innovation and expansion of industry output gradually drive down the price, profitable entry requires increasingly skillful managers and R&D personnel. When the skill requirement for entry becomes overwhelming, entry ceases altogether. Size advantage results because, for a given R&D budget, larger firms have a lower per-unit cost of R&D,

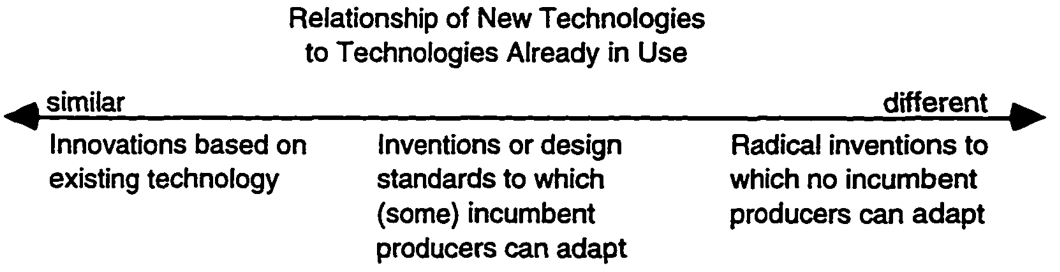


Figure 1.5. A continuum of innovations, from less radical to more radical.

and hence achieve greater profit margins than smaller firms. Larger firms benefit from R&D projects more marginal than those pursued by smaller firms, and hence choose to do more R&D and achieve still lower unit cost and greater profit margins. When entry ceases, exit continues, causing a shakeout, because some firms always have less size and skill than others.

This dissertation uses the theories to guide empirical tests of the causes of industry shakeouts. The data analyzed intentionally exclude cases in which a new technology causes a near-complete replacement of old producers with new firms. Figure 1.5 illustrates the continuum from competence-enhancing to competence-destroying technological changes. At the left side of the figure, great numbers of technological changes may occur, but each change is relatively small. The new technology is similar enough to the current state of the art that up-to-date firms need do relatively little work to adopt any given technological change. These fairly similar innovations match with the process proposed by Klepper (1994) in which many small innovations together yield a substantial cost-spreading advantage to larger firms.

At the center of Figure 1.5, technological changes are different enough from current technology that many firms are unable to adapt to the new conditions. A single radical invention may make it necessary for firms to innovate much more than was previously necessary in order to remain competitive, as proposed by Jovanovic and MacDonald (1994b), so that only the best or luckiest innovators succeed. Or a standardization of the product may necessitate a shift to low-cost production of the standard design, as proposed by Utterback and Suárez (1993), so that firms less competent at low-cost manufacturing are forced out of the industry.

In contrast, at the right side of Figure 1.5, the new technology is so different from current technology used in the industry that virtually all producers are wiped out as the new technology replaces the old. For example, such technology-related annihilation of producers occurred when transistors replaced vacuum tubes (Tilton, 1971) and when electronic calculators replaced mechanical calculators (Majumdar, 1982). In such cases, I define the new and old technologies as separate industries, and focus on the forces that determine concentration within each industry, ignoring the annihilation of producers that occurs at the time of the new technology. Such an annihilation of an industry happens to be rare in the sample used here, occurring in only a few of the forty-nine products analyzed in chapter eleven of this thesis, and in none of the four primary products. The issue of radical creative destruction that replaces virtually all existing producers with new firms is left for others to research.[4]

The empirical tests combine case-study and cross-sectional research approaches, using theory to guide deduction of hypotheses. It is useful to compare this approach with past approaches. Case study research on industries, common earlier in this century, seems largely to have been abandoned by IO economists because it was not leading to generalizeable conclusions. This was followed by research waves of cross-sectional statistical analysis and then of theoretical modeling. Cross-sectional statistical work has the advantage of generalizeability, and theoretical work has the advantage of yielding clear predictions. However, people have often been dissatisfied with solely cross-sectional work because it lacked the rich depth of understanding that comes from case studies, and with theoretical work because it yielded conflicting conclusions and did not necessarily match with reality. This study integrates these three traditional approaches, case study, cross-sectional statistical analysis, and theory, allowing each to contribute its strength.

The dissertation gathers new evidence about shakeouts, technological change, and firm survival in industries evolving from inception. It develops distinctive predictions of the shakeout theories, then tests the theories. After an introduction and literature review, the dissertation outlines predictions implied by the theories and methods of testing the predictions. The tests are carried out in two empirical sections.

The first empirical section focuses on four industries that experienced severe shakeouts. It provides an in-depth study of survival patterns, technological change, and the causes of shakeouts under situations of extreme change, when non-equilibrium behavior is as likely as ever to be easily discerned. The focus on four industries allows the choice of narrowly-defined products that cover a range of product technologies and historical eras, and for which a considerable array of information can be gathered. Quantitative data and qualitative evidence for this section come from an extensive review of economic, historical, and trade literatures.

The second empirical section uses a much broader sample of industries. The industries represent a range from no shakeout to severe shakeout, and span a range of product types and historical eras. Only a few kinds of data can be collected across so many industries, given limited time and money, but the evidence that is available—evidence on survival and shakeouts—allows tests of the theories across many types of industries. A novel longitudinal data set shows the dates of participation of firms in forty-nine product manufacturing industries, from near the inception of each product until at least 1980. Using this broad sample, it will be possible to check for inter-industry differences in the applicability of shakeout theories, and to try to understand why industries experience shakeouts of widely differing severity.

Once the theories have been tested in the two samples, the thesis sums up the implications of the findings and discusses promising directions for future research. Implications apply to industry economics, organizational ecology, labor economics, technology policy, antitrust law, and business strategy.

2

Literature Review: Technology, Market Structure, and Shakeouts

In this section, I review previous research on the relationship between technology and market structure. Since the changes in industrial market structure investigated in this dissertation involve shakeouts, I describe empirical findings about industry shakeouts. Then I introduce the technology-related theories of shakeouts. The next chapter will discuss these theories in more detail, drawing out and contrasting their predictions. Finally, I describe several non-technological theories of shakeouts. While technology-related theories are the focus of the thesis, to the extent relevant evidence is available I discuss how the non-technological theories compare to the evidence.

Technology and Market Structure

Schumpeter's *Theory of Economic Development* (1934) and *Capitalism, Socialism, and Democracy* (1942) generated considerable controversy among economic researchers and led to considerable research on the relationship between technology and market structure. In *Capitalism, Socialism, and Democracy*, Schumpeter asserted that larger firms and firms in more concentrated markets were more innovative. Thus, he argued that the classical economic conception that many small firms competing yields an efficient market was misplaced. Large firms and monopoly might result in technological progress whose benefits would quickly outpace the benefits of an efficient competitive market composed of small firms. In reaction, numerous economists began to investigate how firm size and market concentration affect R&D and innovation by firms. I review these investigations drawing especially upon Cohen (1995) and Phillips (1971), which can be consulted for a more detailed treatment.[5]

Firm Size

Researchers focused primarily on R&D intensity, and to a lesser extent on innovative intensity, as dependent variables. Thus, they divided a measure of the amount of R&D pursued by a firm, or a measure of successful innovation resulting from R&D, by a measure of firm size. These intensity measures were regressed on measures of firm size, market concentration, and other industry (and rarely, firm) characteristics, using cross-sectional firm data. Some initial studies suggested that R&D intensity might increase with firm size (e.g., Comanor, 1967; Meisel and Lin, 1983), or increase with firm size up to a threshold (Scherer, 1965a), or fall slightly with size among the smallest firms and rise somewhat among the largest firms (Bound, Cummins, Griliches, Hall, and Jaffe, 1984). But after controlling for firm and industry characteristics, whatever relationships had been observed seem to disappear to insignificance (Cohen, Levin, and Mowery, 1987). Similarly, industry-level analyses, not subject to biases resulting from an assumed identical firm size-R&D relationship across all industries, indicated in most industries only insignificant relationships between firm size and R&D intensity (e.g., Mansfield, 1964) and between firm size and patent intensity (Scherer, 1965b, 1984), with no consistent pattern among the few industries with significant coefficients. In short, while methodological concerns complicate the conclusions, R&D intensity and innovative intensity appear to remain roughly constant with firm size after controlling for firm effects and industry characteristics.

Many economists interpreted the rough proportionality of R&D and firm size to mean that larger firms emphasized innovation about as much as smaller firms. Furthermore, larger firms were found in most situations to achieve fewer innovations or patents per dollar spent on R&D (e.g., Scherer, 1965a; Pavitt, Robson, and Townsend, 1987; Acs and Audretsch, 1990). Perhaps, many researchers thought, larger firms are less efficient innovators than small firms, or perhaps the results come from a bias in the available data for small firms (Bound, Cummins, Griliches, Hall, and Jaffe, 1984; Griliches, 1990). Cohen and Klepper (1993) recently proposed an alternative viewpoint. While the R&D intensity of large firms appears to be nearly the same as that of small firms, that does not mean that the achievements of larger and smaller firms are equivalent. Since total firm R&D spending increases roughly in proportion to firm size, large firms may be duplicating the R&D of small firms and in addition may be pursuing R&D of more marginal benefit. Thus larger firms may achieve greater net gains in productivity or quality but at the same time have lower average returns to R&D. This situation gives larger firms an advantage, because they obtain greater improvements in manufacturing cost and product quality while retaining a similar per-unit R&D cost compared to smaller firms. If the expansion rate of firms is limited and innovations are not easily copied by other firms, the spreading of R&D expenses over a firm's output—known as R&D cost-spreading—gives a competitive advantage to larger firms.

R&D cost-spreading is one of several sources that could give an advantage to larger or older firms. As Phillips (1966) argued and later illustrated in the aircraft production industry (Phillips, 1971), a technology-related "success breeds success" dynamic can result in growing barriers to entry that eventually allow a few increasingly successful firms to dominate an industry. Thus, he argued that a growing advantage to successful firms could result in a lasting concentration of industry structure. While Schumpeter had argued that technological changes would cause industrial concentration, as well as vice versa, the concentration resulting from firms' innovation was expected to be a temporary phenomenon. In contrast, Phillips argued that a permanent concentration of the market occurred. Nelson and Winter (1978) argued a similar theme, portraying the source of advantage giving rise to the success-breeds-success dynamic as the greater R&D spending of larger, and hence more profitable, firms. Sutton (1991) illustrates that an advantage resulting in the success-breeds-success dynamic can stem from non-technological sources as well, such as the cost-spreading of national advertising costs.[6]

Industry Concentration

Schumpeter argued that firms in concentrated industries, by virtue of their greater profits, may be more able to come up with internal R&D funds. Furthermore, the greater stability that may occur in concentrated industries could serve as a more conducive environment for innovation. And also, the ability to capture control over prices and sales in the long term, which may be correlated with present market concentration, is likely to encourage innovation. These arguments have been attacked and defended through theoretical models, as well as examined through usually indirect empirical tests.

Theoretical models addressing these issues have used a range of contrasting assumptions that yield differing predictions about relationships of market structure to technology. Arrow (1962), for example, pointed out that if the returns to invention are perfectly appropriable, a monopolist with no competition from other potential innovators has less incentive to make an improvement innovation than a competitive firm. In contrast, other models forgo both the assumptions of perfect appropriability and of lack of innovative competition. Some models, such as those by Phillips (1966), Nelson and Winter (1978), and others, either depict effects of technology on market structure rather than the more commonly portrayed reverse causality, or depict technology and market structure as components of an endogenous feedback process.

Empirically, the effects of industry concentration on R&D have primarily been examined through cross-sectional studies. Research on concentration and R&D mostly suggested that more R&D occurs in more concentrated industries (e.g., Horowitz, 1962; Hamberg, 1964; Scherer, 1967; Mansfield, 1968), though a few studies found the opposite pattern (e.g., Williamson, 1965). Scherer (1967) first observed a weak inverted-U relationship in which somewhat more intensive R&D seems to occur among firms in moderately concentrated industries (four-firm concentration ratio of 50-55%) than in industries with lower or higher concentration ratios. In all these studies, however, market concentration explained only a few percent of the variance in R&D intensity across business units (Scott, 1984; Cohen and Levin, 1989). Far greater ability to explain the statistical variation came from industry characteristics such as technological opportunity, measures of ability to appropriate the returns to innovation, and demand (Scott, 1984; Levin, Cohen, and Mowery, 1985). Indeed, the variations in R&D and innovation attributed to concentration may in fact be either a consequence of or mediated by these other variables (e.g., Scherer, 1967).

Related empirical research has begun to shed light on the evolutionary processes underlying relationships between market structure and innovation. Mueller and Tilton (1969) and Geroski (1991a) show evidence that the effects of market structure change over the life cycle of a product. Entry, often concentrated in the earlier years of the product life cycle, is one force involved in such shifting processes, and as Geroski (1991a, 1991b) reports, the entry of new firms appears to be a stimulus to innovation. Geroski (1991a) argues that technological opportunities initially attract firms to enter, but that entry later falls since the maturing product corresponds to increasing concentration and rising entry barriers, and simultaneously innovation becomes more incremental and more oriented toward improving manufacturing processes. These findings match with the impressions gained from studies of the product life cycle, such as Abernathy (1978) and Abernathy and Utterback (1978).

Empirical Pattern of Shakeouts

Gort and Klepper (1982) and Klepper and Graddy (1990) find that, of 46 products manufactured in the US, most experienced some sort of shakeout. Several products experienced 80% decreases in number of manufacturers over periods of about two decades. Not all products exhibited a shakeout, and some had only small decreases in number of manufacturers, but in about a third of their sample the dropoff exceeded 50%. The dropoffs would be more severe if the sample could be observed for more decades. Other sources have documented especially severe cases in particular industries, with 80-90% decreases in firm numbers over fifteen-year periods.[7] Shakeouts occur in many historical eras and are not simply the result of national economic fluctuations. Nor are they the consequence of declining industry output, for in most of the industries studied by Gort and Klepper, output was increasing, often dramatically, at the times of shakeouts.

While evidence is limited outside the US, shakeouts appear to have occurred in other nations as well. Shakeouts apparently occurred in European countries that were producing automobiles in the early 1900s (Hannan et al., 1995; Carroll and Hannan, 1995), and the British television set industry experienced a shakeout in the 1950s to 1980s (Arnold, 1985, pp. 59-60). To avoid bias from foreign competition, for the four products studied in greatest detail, this thesis focuses on industries for which US firms dominated foreign competitors during the shakeout eras. This does not mean that international competition is irrelevant to shakeouts! Nor does it mean that shakeouts are irrelevant to international competition. Global markets are common in present decades, and matters of international competition will be taken up in the conclusion of the thesis and studied in future research.

Technological Event Theories

Two kinds of technological events have been considered as causes of shakeouts. First, a single invention may change the technological landscape, making possible a stream of improvements to the product or manufacturing process. Since firms can gamble to make money by trying to innovate based on the invention, I label this theory the "innovative gamble." Second, a dominant product design, which is a set of product standards, may become locked in, so that consumers prefer to buy (or companies benefit by selling) products that match the standardized design. I label this theory the "dominant design."

Innovative Gamble

The first theory can be traced back at least to Schumpeter (1911). Many models embodying Schumpeter's ideas about industry evolution have been proposed (cf. Nelson and Winter, 1978; Futia, 1980; Metcalfe and Gibbons, 1988), and Jovanovic and MacDonald (1994b) formalize Schumpeter's ideas in a model to explain industry shakeouts. They modify a model of diffusion of many ongoing technological changes (Jovanovic and MacDonald, 1994a) so that a single technological change stands out above the others. This technological change triggers the shakeout.

Two inventions occur, a basic invention and a refinement invention. The basic invention creates a new product. Entry of producers drives expected returns to entry to normal levels. Thereafter no entry or exit occurs until the time of the refinement. The refinement creates an opportunity for an innovative gamble. New firms may choose to enter and undertake the gamble. Entry of producers again drives expected returns to normal levels, and no further entry occurs. Firms that fail at the gamble exit the industry. Incumbents have a higher chance to win the gamble than entrants, because incumbents have more innovative experience.[8] Since entry has ceased, the exit of failing gamblers yields the shakeout.

Dominant Design

The second theory comes from observations about how new technologies develop over time, notably the product life cycle theories of Abernathy and Utterback.[9] A version of this theory has been used by Utterback and Suárez (1993) to explain shakeouts. In the early stages of a new industry, according to their view, many competing versions of a product are sold, and competition is a matter of who can create a better product. Entry can occur fairly easily because there are opportunities to break into the industry using a novel product idea. Entry is common.

As producers and consumers experiment with the product, certain of its features may develop *de facto* (or formal) standards. The new, standardized form of the product, labeled the "dominant design," becomes locked in. The lock-in may occur for reasons of technological superiority or simply because a given technology happens to be better-researched at a given moment (Arthur, 1989), because it develops a strong base of users or owners (David, 1985; Katz and Shapiro, 1985; Langlois, 1992), or for other reasons.

Emphasis then shifts from making a more desirable product to making the standardized product at the lowest possible cost. Firms can no longer easily enter just by having novel product ideas, so entry slows or stops. Simultaneously, the probability of exit increases because some firms have little competence at low-cost production. Low-cost production becomes more practical once the dominant design appears because, the theory argues, the dominant design allows firms to refine their production processes without fear that production improvements will be made obsolete by new products requiring new production techniques. Consequently, innovation shifts its focus from product innovation to process innovation. Since entry slows and the probability of exit rises at the time of the dominant design, the number of firms decreases, yielding a shakeout.

A related model by Hopenhayn (1993) offers a slightly different explanation of shakeouts. In Hopenhayn's model, once the dominant technology becomes locked in,

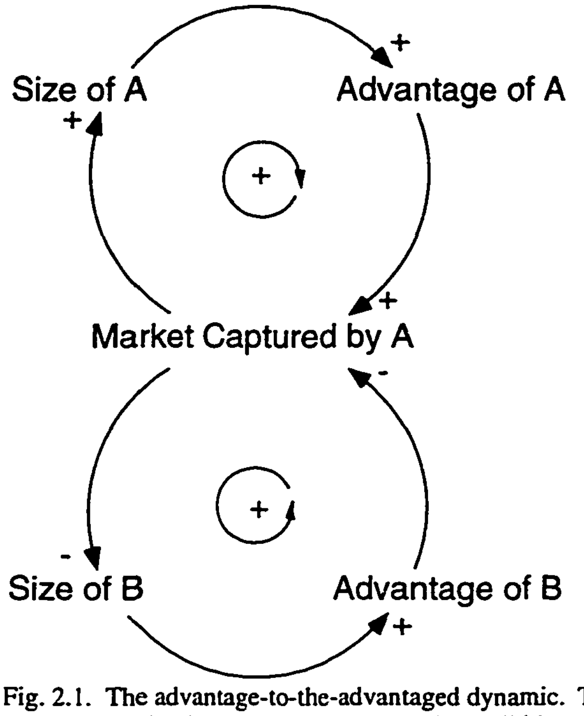


Fig. 2.1. The advantage-to-the-advantaged dynamic. The bigger is firm A, the more advantage it has, and the more market it captures, hence growing still bigger, and gaining more advantage.... The smaller is firm B, the less advantage it has, allowing firm A to capture its market share, making B still smaller, leaving it with still less advantage.... These two feedback spirals cause a snowballing effect in which firm A's advantage is locked in and firm B's market share is forced eventually to zero.

incumbent firms innovate and expand. Their expansion leaves less room for profitable entry, so entry decreases. The probability of exit need not change at all; in fact, in Hopenhayn's model the exit rate goes down because the probability of exit decreases with firm size, and the average firm size is larger once the dominant technology emerges. The shakeout results from decreased entry.[10]

Technological Advantage-to-Advantaged Theories

Various success-breeds-success theories suggest that leading firms can gain some kind of locked-in advantage over other firms. In the theories, firms at an advantage tend to keep their advantage or to gain even further advantage (fig. 2.1). The advantage may be related to size, cumulative production, or age. For example, Sutton (1991) shows that twenty food product industries can be divided into two groups where advertising does or does not provide a locked-in advantage to dominant firms. An advantage can come from spreading the costs of national advertising over a firm's total output, because for the same amount of advertising, larger firms have a lower advertising cost per unit sold. In some industries and industry segments (e.g. high-quantity institutional buyers), advertising seems to have relatively little impact on purchasing decisions, and advertising does not provide an advantage; in other industries and industry segments, advertising has a strong impact on consumer purchasing decisions. Researchers of progressive cost reduction have sometimes recommended that firms enter early and hurry to lower prices and increase output so that they achieve the lowest costs and capture the market (Spence, 1981; Dasgupta and Stiglitz, 1988; Boston Consulting Group, 1968). Nelson and Winter (1978) develop a model in which advantage takes the form of technological leadership, with leaders more likely to generate follow-on innovations. Other reasons for dominant firm advantage have been suggested, including economies of scale in production, R&D, or distribution; the ability of larger firms to hire better management; and political connections. Historian Alfred Chandler (1977, 1990), in two monumental works on American industrial development, argues that reasons such as these give firms their leadership, so that a few leading firms come to dominate in the many industries where these sources of advantage are relevant. Yet the sources of advantage have remained difficult to disentangle, and few of the reasons for dominant firm advantage have received strong empirical support.

Size and Skill

Cohen and Klepper (1992; 1993), among others, have suggested an advantage to leading firms that comes from R&D cost-spreading. They have found that the theory fits fairly well with empirical evidence. Consider a firm that spends r dollars on R&D. The expected return to its spending is to make production-cost-per-unit-of-quality equal to $c(r)$, where $c'(r) < 0$, and $c''(r) > 0$. If the firm produces q_{t+1} units at this cost, its optimal behavior is to maximize $q_{t+1}(p - c(r_t)) - r_t$. It is assumed that q_{t+1} is closely related to q_t, perhaps because of convex costs of rapid expansion. For a simple demonstration, let $q_{t+1} = kq_t$. Then $\pi_{t+1} = kq_t (p - c(r_t)) - r_t$, and optimal firm behavior is given by $-c'(r_t^*) = 1 / kq_t$. Thus, among firms that optimize, $-c'(r_t^*)$ is smaller for larger firms, which means (since $c''(r) > 0$) that larger firms do more R&D (and more marginal R&D) and achieve lower production costs. Cohen and Klepper expect their theory to hold better for process R&D than for product R&D, since the condition that q_{t+1} is related to q_t is more likely to be violated when new products could open up entirely new markets.

Klepper (1994) has used R&D cost-spreading as the focus of a model to explain industry shakeouts. His theory accords with Mueller and Tilton's (1969) description of how new industries evolve, and is also consistent with a model developed by Dasgupta and Stiglitz (1980) to explain the relationship between industry structure and technological change.[11] Similar theories could be constructed using other reasons for an advantage of well-established firms, but his model deliberately focuses on an R&D cost-spreading advantage.

In this deterministic model and a probabilistic variant (Klepper, 1995), firms enter and expand in a new industry, causing the product's price to fall over time. The falling price continually causes some firms to become unprofitable and exit the industry. Size and skill result in higher profits and hence reduce the chance of exit. Size conveys an advantage because firms spread the cost of process R&D over their total output. Skill conveys an advantage because it affects expected returns from product innovation. Firms enter only if their skill is sufficient to allow a profit despite their small entry size. Since the price falls over time, over time the minimum skill of entrants increases. At some point, no potential entrant is competent enough to expect a profit, and entry ceases. Once entry ceases, and maybe earlier depending on exit patterns, the number of firms drops off, yielding the shakeout.

Non-Technological Theories

A full study of possible explanations of shakeouts would require a detailed review of the literatures on entry and exit, since a shakeout results when exit surpasses entry. Whole books have been written to review these literatures. Instead, I undertake a modest task and review only theories that have been created intentionally to explain shakeouts.

Paich and Sterman (1994) develop a model of a single firm in which the firm reaches a situation of overcapacity and goes from boom to bust. Sterman has pointed out instances where an entire industry may go through such a boom and bust. This is particularly likely to occur given one or both of two conditions. First, market demand may be temporary, perhaps based on a fad, as with a popular toy that eventually goes out of style (e.g., Trivial Pursuit or Laser Tag). When demand dries up, firms are shouldered with excess production capacity that is no longer useful, and consequently have severe financial losses. Second, if firms receive many more orders than they can fill, a long backlog of orders may be created. Firms may expand rapidly to deplete the backlog, but once they finally fill all backlogged orders, they may be left with production capacities that far exceed their incoming order rate. This problem can occur because firms must expand in excess of the incoming order rate in order to deplete the backlog. If projections about sales growth are wrong, or if the difference between sales and capacity is ignored, it is easy to develop overcapacity. In fact, most of a large sample of MBA students who took part in a simulation of this situation developed dramatic overcapacity which resulted in a boom and bust, even though much better strategies exist. While the reasons for a boom and bust are quite plausible, they do not seem to explain the shakeouts studied here. First, the shakeouts occurred in high-growth industries, so that output was expanding rapidly even while the shakeout occurred. Second, where information is available, large backlogs do not seem to have been common in these industries. High growth and low backlogs suggest that the boom-and-bust dynamic is not at work in most industry shakeouts.

Sidney Winter has suggested a reason why shakeouts may sometimes occur. Price in a new industry may be forced to remain flat at the price p_0 of a competing product. Output increases over time in the new industry, driving price down the demand curve until eventually price falls below p_0. When price suddenly starts to fall, large numbers of firms—those with higher costs—may be forced out of the industry, causing a sudden rise in exit rate. For two reasons, this explanation seems to hold rarely if at all. First, available price series almost never agree with this pattern. Second, as will be seen in the empirical analyses, neither do the data on exit rate as a function of time.

The ecological Lotka-Volterra model can generate a shakeout in numbers of one of two populations, if two populations compete with each other. One might suggest that the different "species" of firms are manufacturers of two competing products. But the products studied in this thesis did not lose sales to competing products at the time of the shakeouts, and hence do not fit this variant of the Lotka-Volterra model. As an alternative, one might suggest that the two competing species are more-skilled and less-skilled firms. This alternative is more plausible, and indeed is related to the technological theories. However, observed entry and exit patterns do not match with a pure Lotka-Volterra model, so a more elaborate variant (such as the technological theories) would have to be developed before the model could explain most manufacturing industry shakeouts.

Hopenhayn (1993) identifies another possible reason for a shakeout. Even when demand continues to grow, a shakeout may result when growth slows. The shakeout occurs because once growth slows, the percentage of firms that are large increases, leaving fewer firms and a lower number of firms that can enter profitably each year. The theory is intended to explain situations where entry and exit continue indefinitely, as seen for example in the highly-aggregated industry data of Dunne, Roberts, and Samuelson (1989) and Geroski (1991b). But in fact the aggregate data on entry and exit exhibit much different patterns than the data on narrowly-defined shakeout industries, for which—as will be seen later in this thesis—entry and net exit (as opposed to annual percent exit) eventually come to an almost complete stop. Nevertheless, Hopenhayn's point that a slowdown in demand growth may be related to a shakeout is duly noted.[12]

3

Predictions of the Theories

Industry shakeouts, a key phenomenon of industry evolution, have been predicted in the three technology-related theories. The assumptions and predictions of these theories conflict. This dissertation tests the assumptions and predictions to see which theories, or which aspects of the theories, agree with empirical evidence. In this section, I contrast the theories' assumptions and predictions with regard to four kinds of evidence: technological change, entry, survival (exit), and profits. I also point out how the predictions differ between shakeout and non-shakeout industries. Table 3.1 catalogues the predictions described below.

Innovative Gamble

Jovanovic and MacDonald's (1994b) theory predicts that a refinement invention occurs not long before the shakeout begins. This invention creates a technological gamble that leads to entry and exit of firms. The survivors are the firms that manage to adopt or create innovations based on the refinement invention. Obviously, there should not have been earlier inventions with the same effects as the refinement, or according to the theory they would have caused a shakeout to occur earlier.

Table 3.1. Predictions of the Theories.

	Technological Event		Advantage to Advantaged
	Innovative Gamble	Dominant Design	Size and Skill
Technological Change	A "refinement" invention occurs not long before the shakeout begins, and this invention is responsible for the ensuing entry and adoption of related innovations.	A dominant product design crystallizes just before the shakeout begins. Thereafter, most process-upsetting technological change ceases. When the shakeout begins, the share of R&D that is process innovation increases abruptly.	Substantial innovation occurs continually, especially cost-reducing process innovation. Larger firms do more R&D, especially process R&D. The share of total R&D that is process R&D increases over time, at least once entry stops.
Entry	Entry when product appears, then again just before the shakeout, but "zero" entry at other times.	Entry decreases at the time of the shakeout.	Eventually entry declines to zero, at (or after) the peak in number of firms.
Exit (Survival)	Hazard rate rises when the shakeout occurs. "No" exit before the shakeout.	Hazard rate rises when the shakeout occurs. (Hopenhayn: Hazard rate falls.)	No prediction.
Exit (Survival) by Firm Entry Year	Entrants just before the shakeout (just after the refinement) have a higher hazard rate than incumbents.	Especially in their first year of existence, pre-dominant design entrants have lower hazard rates than post-dominant design entrants. (Hopenhayn: No difference.)	At old ages, earlier entrants have lower hazard rates than later entrants. At young ages, this difference is less pronounced or possibly reversed.
Profits	Return on investment drops to the free-entry level until the shakeout begins. Return on investment rises for successful innovators at the time of the shakeout, then falls toward normal levels. For unsuccessful innovators, return on investment falls to below-normal levels when the shakeout begins, then rises toward normal levels.	No prediction.	Return on investment for the largest firms may rise initially, but at least eventually it falls over time. Return on investment for smaller firms begins to fall immediately.

The model assumes a free-entry equilibrium. Firms enter when a "basic" invention makes it possible to create the product. Entry drives expected returns to entry to normal levels, then stops. Given the assumed constant demand, and the assumption that no exit occurs, no entry occurs since further entry would be unprofitable. In practice, Jovanovic and MacDonald expect random deviations from the predicted zero entry and exit. When the refinement invention occurs, additional firms may enter because of a profit opportunity from the innovative gamble. Again, entry equals the amount that causes expected returns to reach a normal level. Entry occurs immediately, since the quickest possible entry gives firms the maximum time to innovate before the gamble is won or lost. The maximum time for innovation yields the highest expected return, and so gamblers all enter as soon as the refinement occurs. Additional entry would yield below-normal expected returns, so no firms enter later.

If a shakeout occurs, it is because firms are driven out of the industry after the refinement. Firms that succeed at innovation based on the refinement expand and drive out some firms that have not yet innovated. The number of unsuccessful firms that exit equals the number that leaves a normal expected return to their remaining in the industry. Exit decreases total industry output, and hence raises the price, so that the expected return is normal. The exact amount of exit depends on parameters of the model, but exit is certainly higher during the shakeout than before the shakeout began. Specifically, the percentage of firms that exit per year is higher during the shakeout than before.

Incumbents, who begin attempts to innovate based on the refinement before late entrants, develop a technological leadership in the industry. As a result of this leadership, a larger proportion of incumbents than late entrants succeed at innovation based on the refinement. However, if and when late entrants successfully innovate, there is no longer a distinction between early and late entrants. Successful innovators have all attained the state of the art in technology. During the shakeout, entrants at or after the time of the refinement (i.e., entrants just before the shakeout) have higher hazard rates than earlier entrants, but the difference between the two groups eventually returns to normal, after the exit of the unsuccessful firms.[13]

Prices and profits stabilize immediately, because of the model's stylized depiction of a free-entry equilibrium. Just enough entry occurs so that further entry would yield only a normal expected return. All entry occurs at the outset of the industry, and profits remain steady until the refinement is invented. An additional proof can be added to the ones in Jovanovic and MacDonald's paper to show the post-refinement profit pattern implied by the model.[14] Once the refinement occurs, profits rise among successful innovators, but eventually fall toward normal levels. Among unsuccessful innovators, profits fall to below-normal levels by the time exit begins, then rise toward normal levels. The predictions will be tested primarily with return on investment data.

Dominant Design

Utterback and Suárez's (1993) dominant design theory focuses on a standardization of the product. Key product standards crystallize to form a dominant product design. Before the dominant design occurs, firms are reluctant to pursue process innovation, because changes in the product might require a redesign of the production process, making prior process innovations worthless. With a dominant design, firms need not fear product changes upsetting their production processes, so they do more process innovation. Hence, the fraction of R&D that is process, rather than product, R&D increases abruptly when the dominant design appears. With the dominant design comes the shakeout, because firms unable to achieve low-cost production are forced out of the industry, and because entry decreases.

The theory makes only one prediction about entry. Once the dominant design appears, possibilities are much reduced to break into the market by creating novel product designs. Therefore, fewer firms use this entry strategy, and entry slows. The slowdown in entry occurs at the time of the shakeout, since the shakeout begins when the dominant design appears.

At this time, incumbent firms must adapt to new competitive conditions, in which low-cost producers win the competitive battle. Since firms that were competent product innovators are not necessarily competent low-cost manufacturers, Utterback and Suárez argue that many firms will be forced to exit. They write, "The wave of entry [before the dominant design] will be followed by a corresponding wave of exits...." (p. 5). While they do no more to specify how the amount of exit should compare before and after the dominant design, they imply that, when the shakeout begins, the hazard rate rises. In Hopenhayn's (1993) variant, however, the hazard rates for firms that have and have not adopted improved production methods remain constant over time. Successful adopters have a lower hazard rate than non-adopters. Since the fraction of firms that are successful adopters rises during the shakeout, Hopenhayn predicts that the average hazard rate falls.

Suárez and Utterback (1991) predict that post-dominant design entrants have higher hazard rates than earlier entrants. They write (p. 11), "The development by incumbents of collateral assets and economies of scale (due to increased production after a dominant design) will represent significant barriers to entry for firms that adventure to enter the industry after a dominant design. Moreover, strong patent positions may have been established by earlier entering firms that are difficult for later entrants to completely circumvent." Presumably later entrants that do successfully compete narrow their competitive deficiency, so that as they grow older the surviving firms become equally competitive compared to earlier entrants. They predict that the hazard function of post-dominant design entrants is higher than that of pre-dominant design entrants, especially during the first year of firms' existence.

Size and Skill

Klepper's (1994) model assumes that all firms choose to spend the same amount on product R&D, because the expected returns to product R&D are proportional to the size of the market created by those product innovations. In contrast, the model emphasizes differences in process R&D. Process R&D does not garner new sales by creating new, desirable varieties of the product, but merely lowers the production cost of varieties already being manufactured. Larger firms choose to spend more money than smaller firms on process R&D, as a result of their larger outputs. They are willing to do R&D that yields a relatively small savings per unit produced, whereas small firms are only willing to do R&D that yields a relatively large savings. For example, a firm that manufactures 100,000 automobiles per year might choose to create a process improvement that costs $10,000 but saves ten cents per car per year, whereas for a company that manufactures only 1,000 cars per year, the savings from the process improvement would not justify the expense. The model relies on the assumption that considerable process innovation occurs in the industry, causing substantial reductions in manufacturing cost.

In the model, potential entrants differ in their skill at carrying out and managing R&D. In order to enter, potential entrants must have sufficient skill to expect a profit despite their relatively small initial size. Since the model assumes there is a maximum possible skill, as the price falls continually there comes a point when all potential entrants are unable to expect a profit. At this time, entry ceases. This will occur at or after the peak in the number of firms, since of course the number of firms cannot increase if there is no entry.

At young ages, the model does not predict how entry cohort affects the hazard rate. Each firm's profitability depends on two traits, size (age) and skill. At any given time, later entry cohorts have higher minimum values of skill. As the price falls, the minimum skill required for incumbents to remain profitable rises in at least the later entry cohorts, causing some firms to become unprofitable and exit. Assuming the distribution of skill among potential entrants remains constant over time, the fraction of firms forced to exit from a cohort in each period may be either higher or lower for earlier entry cohorts. At one extreme, a stylized model by Klepper (1995) points out that later entrants, at young ages, could even have unambiguously higher survival rates than early entrants, exactly opposite the pattern the theory predicts at old ages.[15] At old ages, according to both of Klepper's models, later entry cohorts become extinct before earlier entry cohorts, because with their smaller size the later entrants would eventually need more than the maximum possible skill to remain profitable. At young ages the relative hazard rates do not disadvantage later entrants, but at old ages later entrants have higher hazard rates.

Prices decline over time, according to the model, because entry and expansion increase the total industry output. In every period the decline in price causes some firms to become unprofitable and hence to exit. Within a cohort profits need not fall initially, because expansion and falling price have opposing effects on profits.[16] But eventually, once exit begins within a cohort, profits must fall continually for all firms in the cohort. Since expansion may require investment over time, return on investment, used for most of the empirical tests of profitability, may begin to fall all the sooner.

Differences in Predictions

The first two theories, innovative gamble and dominant design, describe a technological event that occurs at a point in time, causing a wave of exit and a decrease in entry and hence triggering a shakeout. The third theory, size and skill, describes a gradual process in which competition heightens over time (prices decline and quality standards improve), firms enter until entry is no longer profitable, and continually some firms are forced out of the industry. If a single technological event wiped out 80-90% of the firms in an industry (and more, since some of the survivors entered late), the event is likely to be dramatically apparent in many of the writings about the technological and economic literatures for each product. If these literatures are voluminous yet show no evidence of a single outstanding event, the very paucity of evidence would cast doubt on the technological event theories.

If there is evidence of a technological event, how can one distinguish a radical refinement innovation from a dominant design? A dominant design is likely to involve multiple standards all coalescing as part of the same design, whereas a refinement invention is one single invention followed by any related innovations. The dominant design involves standardization of some aspects of the product, whereas a refinement invention could even lead to the opposite, a diversity of approaches all exploiting the basic idea of the invention. A dominant design pertains to the product, not the manufacturing process, whereas a refinement invention may be product or process, in some cases affecting the manufacturing process without affecting the product. In some cases the two definitions overlap, but the theories can still be tested according to ramifications that are supposed to result from a given technological change.

Further differences in innovation patterns have to do with the amount of industry-wide product and process innovation over time. Critical to the dominant design theory is that at the time of a dominant design, manufacturers focus attention on low-cost production, rather than the development of new product features. Before the dominant design, firms avoid doing R&D related to production processes because changes in the product could necessitate changes in the production line, making previous process R&D obsolete. When the product design stabilizes, firms no longer need to fear that changes in the product will require a redesign of production processes. Thus, at the time of the shakeout, process innovation increases abruptly, and product innovation decreases. In contrast, the size-and-skill theory predicts, as a side-effect of entry and exit patterns, a more gradual shift in R&D patterns. In the size-and-skill theory, when new producers cease to enter and the number of firms falls, the diversity of product innovation decreases, and when producers grow larger they gain incentive to pursue more process innovation, causing process innovation to rise over time.

Entry predictions are similar across all three theories. The innovative gamble and size-and-skill theories predict "zero" entry at certain times, but in both cases this is a simplification.[17] Leaving convenient simplifications aside, all the models predict that entry declines sometime around the time of the shakeout. If the empirical evidence does not show this decline, then there is something wrong with all the models.

Exit predictions fall into two groups: aggregate exit rate, and exit rate as a function of time of entry. For aggregate exit rate, the technological event theories predict a rise in exit rate (percentage of firms exiting per year) during the shakeout. The technological event puts some firms at a disadvantage, causing them to exit the industry. In the innovative gamble theory, firms that fail at the stream of improvements resulting from the refinement innovation lose the gamble and exit. In the dominant design theory, firms that fail to convert to low-cost production cease to be profitable and exit. Hopenhayn's (1993) theory points out that the dominant design theory need not assume increased exit. His variant of the dominant design theory assumes that incumbents expand when they adopt the stabilized technology. Since he assumes that larger firms have lower exit rates (but otherwise exit rates never vary), and since entry slows as incumbents occupy more market share, the overall exit rate *falls* at the time of the shakeout. While the nature of the innovative gamble requires that the exit rate increase at the time of the shakeout, a dominant design apparently does not have to increase the exit rate in order to cause a shakeout. The size-and-skill theory makes no prediction about the aggregate exit rate, except to say that some exit continues indefinitely.

For exit rate as a function of entry date, all the theories predict that pre-shakeout entrants have higher survival rates than later entrants. However, the specifics of the prediction vary markedly between theories. The innovative gamble theory assumes that early entrants have more time than later entrants to adapt to the industry's technology.

Therefore, pre-refinement entrants have a higher survival rate than entrants at the time of the refinement. The advantage to early entrants should be substantial at young ages, but should diminish with firm age, as the later entrants that survive gain the same skill with the technology as is held by surviving early entrants. Suárez and Utterback also predict, for the dominant design theory, that earlier entrants have a higher survival rate at young ages. They point to a difference between entrants before and during the shakeout. In contrast, the size-and-skill theory predicts an old-age advantage, an advantage that accrues to any earlier entry cohort relative to any later cohort. In that theory, some of the earliest entrants eventually dominate the industry. Later-entering firms are forced out of the industry in reverse order of entry. These differences are apparent only at old ages. At young ages, because later entrants include only those firms with enough skill advantage to counteract their small entry size disadvantage, exit rates are comparable for early and late entrants. But as firms grow old, only the more-skilled early entrants remain, because they have time to grow and capture both size and skill advantages, and the exit of all later entrants ensures a higher survival rate for early entrants at old ages. Thus, the technological event theories predict a strong relationship between early entry and high survival only at young ages, whereas the size-and-skill theory predicts a strong relationship only at old ages.

Profit patterns allow one further check on the innovative gamble and size and skill theories. The innovative gamble theory distinguishes between successful and unsuccessful innovators at the time of the shakeout. As proved above in a footnote, for successful innovators, it predicts a temporary increase in return on investment, followed by a return toward normal levels as competitors also succeed at the innovation, whereas for unsuccessful innovators it predicts a low return that rises over time. The size and skill theory, in contrast, predicts that profits fall continually over time, though for large firms the dropoff in profits may not begin for some time.

Empirical Tests: Four Products with Severe Shakeouts

4

Four Products with Severe Shakeouts

The first set of empirical tests analyzes four products: automobiles, tires, television sets, and penicillin. These products experienced severe shakeouts, with eventual 83-97% decreases in firm numbers. They cover a range of historical eras and span mechanical, electronic, and biochemical technologies, so that findings common to the four products are likely to apply to other products with severe shakeouts. Also, the papers that develop the technological gamble and dominant design theories cite three of these products as examples, giving an opportunity to understand and test those theories where they are most likely to hold.

Product Definitions

Product industries are defined, for the purposes of this study, according to three criteria. First, it is often necessary to define an industry at the level of aggregation for which data are available. For example, while data are available on the tire industry, I have not found comparable data for the much broader rubber industry. Second, the product definition must be narrow enough that consumers could generally use the products of almost any company in the industry for the purposes for which they apply the product, and broad enough that the category could not be expanded and meet the same criterion. For example, even if data were available for the entire rubber industry, the rubber tire industry by itself would be a preferable definition.[18] While a choice of breadth sometimes involves some arbitrariness, this is of little importance as long as one recognizes that larger product categories are built up of smaller categories, each of which may experience a shakeout, so that in particularly broad categories the apparent lack of a shakeout may be simply a consequence of aggregation.[19] Third, in the few cases in the second half of this dissertation where a technologically quite different product supersedes an older product and causes the original producers to be overthrown, the two technologies will be treated as different products. This separation focuses on the empirical goal of studying shakeouts, rather than technological overthrow, by identifying both time periods and groups of producers for which a shakeout might have occurred, and by avoiding clouding the patterns through an intermingling of data. For example, mechanical and electronic calculators are treated as distinct products, because each involved a separate set of producers and each experienced a distinct shakeout (see Majumdar, 1982, for a description of the shift from mechanical to electronic calculators). Taken together, these criteria give a workable means to study shakeouts.

Shakeout Patterns

The shakeout patterns in the four products have been shown in the introduction, but for convenience they are reproduced as figure 4.1. In automobiles, according to data based on Smith (1968), there were four firms in 1895. The number of firms rose to a peak of 273 in 1909, then fell off to 30 firms by 1929 and 7 firms by 1955. In tires, according to data based on *Thomas' Register of American Manufacturers*, the number of firms was at least about thirteen by 1905. The number rose to 275 in 1922, then fell to 44 firms by 1942 and 23 by 1970. In television sets, according to data based on *Television Factbook*, there were seventy firms by late 1948, when the *Factbook* was first published. After reaching a

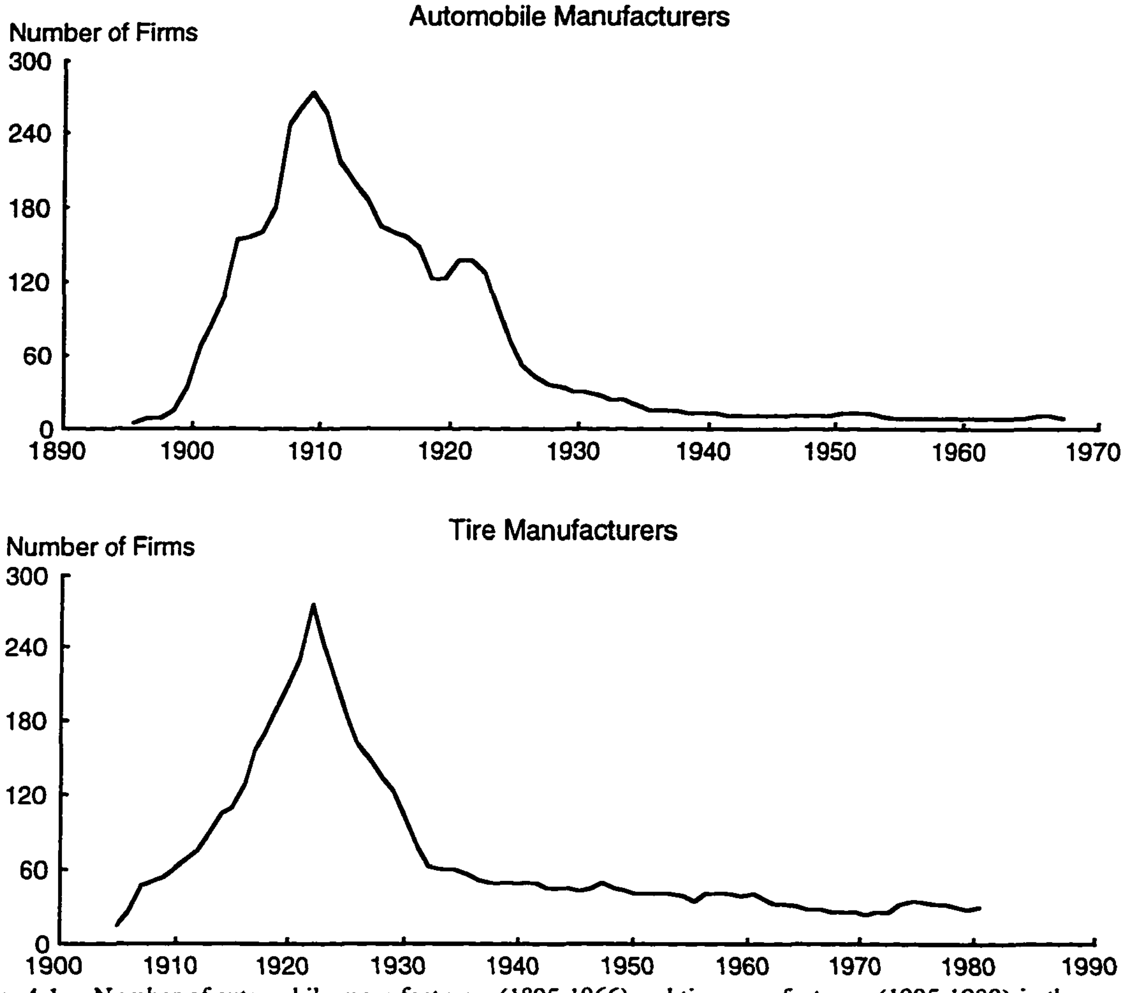


Figure 4.1a. Number of automobile manufacturers (1895-1966) and tire manufacturers (1905-1980) in the US. Tires includes pneumatic and cushion rubber tires for automobiles and trucks. Sources: Automobiles based on a list published by Smith (1966), tires based on Thomas' Register 1905-1981.

peak of 89 firms in 1951, the number of US-based firms fell to 18 by 1971 and 4 by 1986. In penicillin, according to data based on *Thomas' Register* and augmented with other sources (see below), there were twenty firms in 1943. The number rose to 29 in 1953-1955, then fell to 11 by 1975 and 5 by 1991. Thus, the four shakeouts are dated as beginning just after 1909, 1922, 1950, and 1955, respectively, according to the times of their peak numbers of firms.

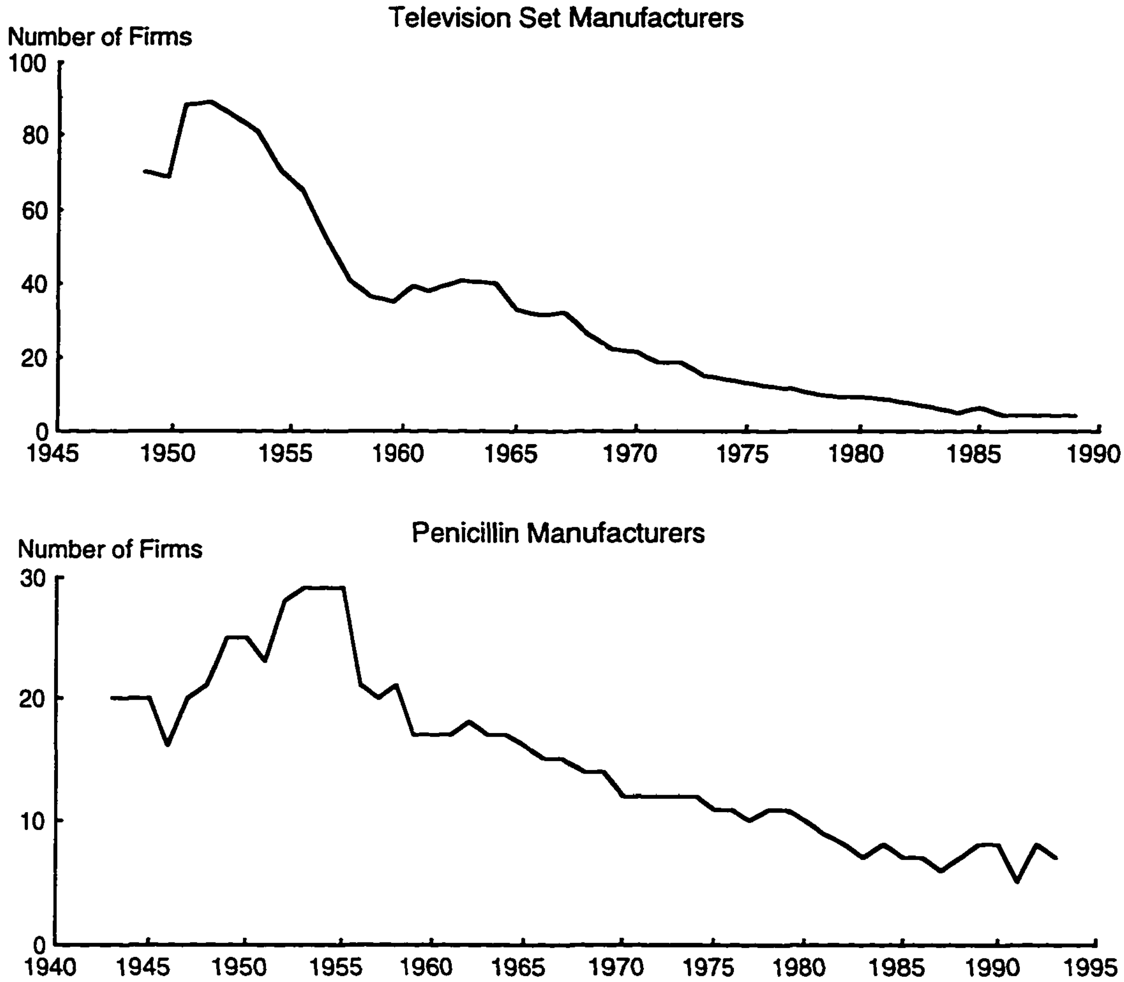


Figure 4.1b. Number of television set manufacturers (1947-1989) and penicillin manufacturers (1944-1992) in the US. In televisions, foreign entrants into US production are excluded. Sources: Televisions based on *Television Factbook* (1948-1990) and penicillin based on *Thomas' Register of American Manufacturers* (1945-1993), US Tariff Commission (1945-1991), Federal Trade Commission (1958), and Elder (1970a).

Every attempt was made to ensure the validity of the rosters of firms used to construct the time series of numbers of firms and the entry and exit patterns discussed in future chapters. Each series was chosen to include only manufacturers of the final product. Dealers and component manufacturers are excluded. For automobiles, the data are based on one of the most extensive lists compiled by a historian. Alternative lists are discussed below. For the other three products, the data come from annual trade registers. Since trade registers served as information sources for buyers and dealers, firms had an incentive to inform the registers' publishers of omissions. The publishers did not charge a listing fee, and *Thomas' Register* urged users of the registers to point out any errors. The publishers attempted to include all manufacturers making a product, even the tiniest companies. Thus, the compilers of the rosters of companies intended to create well-defined, inclusive lists, and (with the exception of Smith's automobile list) any companies inadvertently left off the list had an incentive to fix the error.

Nevertheless, no data source is perfect, and it is instructive to compare alternative sources where possible. For automobiles, I identified six possible sources, compared in figure 4.2. These sources varied in their definitions of a manufacturer. One list, by Epstein (1928), purports to include "only such firms as seem actually to have produced and sold cars in a commercial way, firms which sold cars to customers other than their few principal stockholders or promoters, and which operated plants for more than merely two or three weeks or a month." In practice, Epstein's list tends to leave out small yet still legitimate producers that show up in other lists, and that can be verified to have produced cars for well over a month. The list seems to have a disproportionate number of large producers compared to other sources. Epstein's list shows 32 firms in 1903, rising to a peak of 93 firms in 1922 (after a temporary peak of 79 firms in 1910), then falling to 49 firms in 1927, when his series ends.

Thomas (1965, p. 324) shows data on the number of firms, entry, and exit for all firms he could trace through automotive journals. He includes two lists. The first considers even very tiny firms, perhaps even firms that never went into production. The second is restricted to what he calls "type one" firms, firms that seemed larger and more legitimate. The "type one" data agree favorably with Epstein's series, with the number of firms going from one in 1905 to a peak of 88 in 1921, then dropping off to 20 firms by 1929, when the series ends. However, according to Thomas' more comprehensive list, the number of firms rises from five in 1895 to a peak of 250 in 1908, then falls to 23 by 1929, when the series ends.

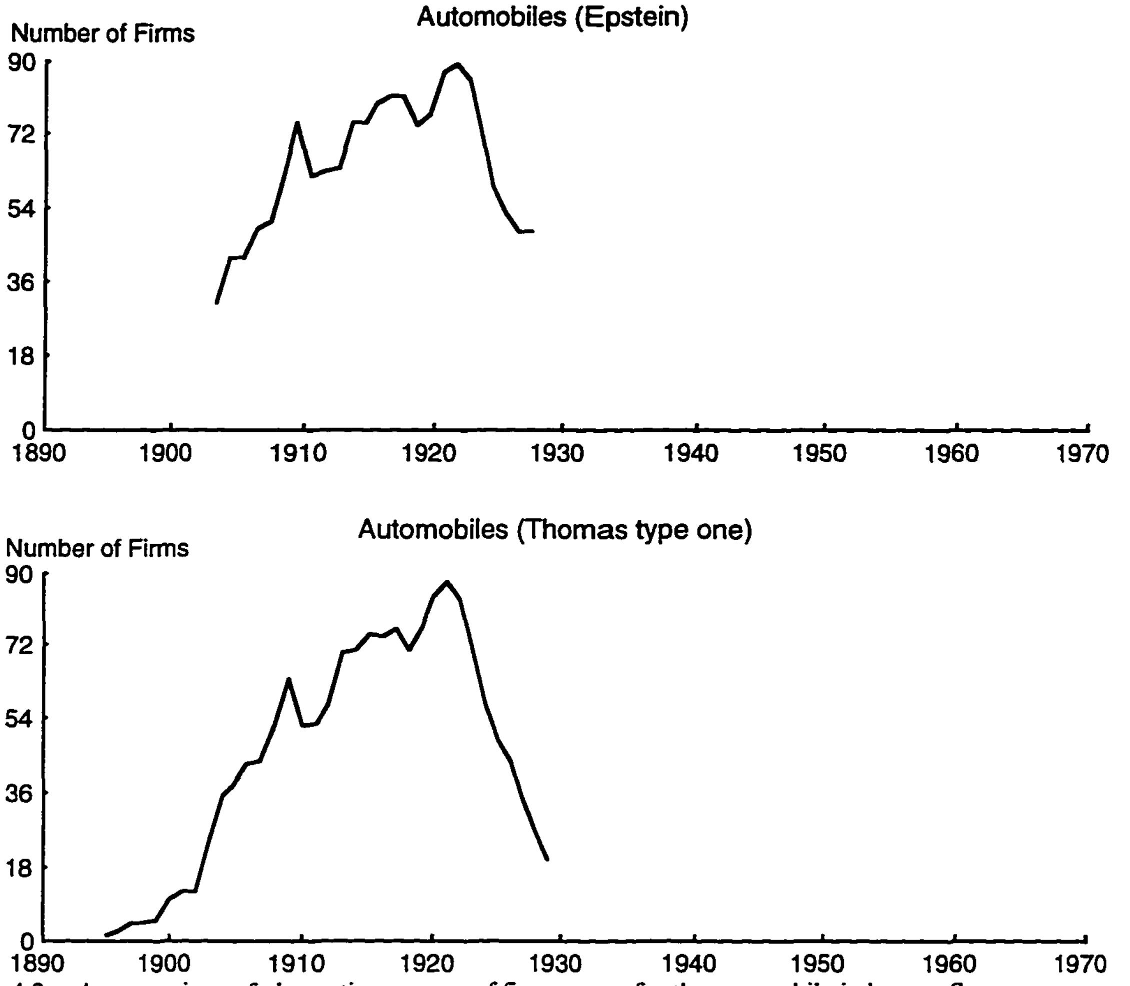


Figure 4.2a. A comparison of alternative sources of firm counts for the automobile industry. Sources: Based on Epstein (1928) and Thomas (1965, p. 324).

Thomas' Register of American Manufacturers includes annual rosters of automobile manufacturers, which I used to construct counts of the number of firms. The *Register* intends to include even the smallest firms that manufacture automobiles, with agents sent around the country to survey local communities and identify all manufacturers. The *Register* shows a peak in the number of firms in 1912, a date close to that of Thomas' comprehensive list, particularly given that the *Register* sometimes shows a lag of one or a few years before noting the appearance or disappearance of a firm. The number of firms

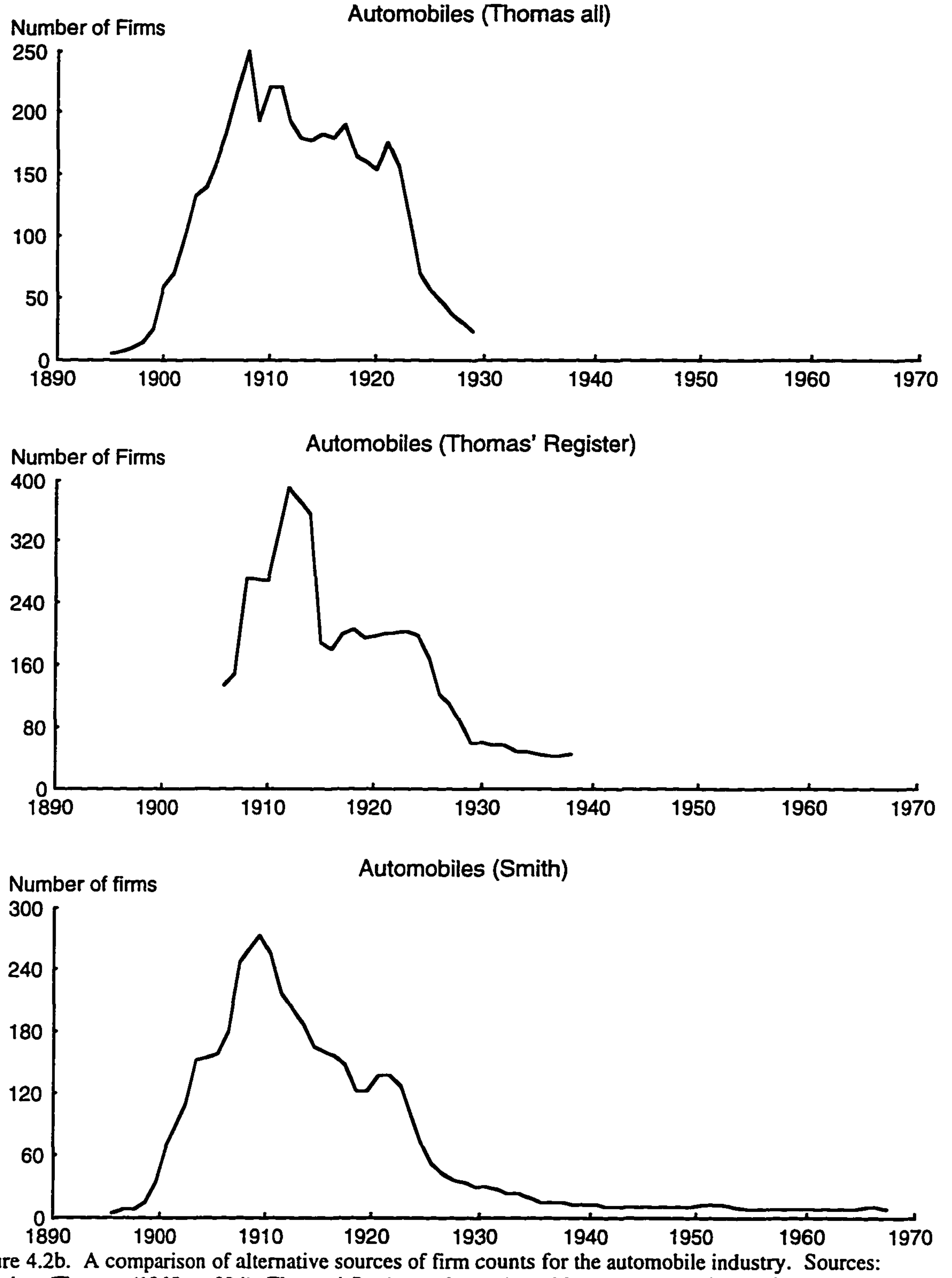


Figure 4.2b. A comparison of alternative sources of firm counts for the automobile industry. Sources: Based on Thomas (1965, p. 324), *Thomas' Register of American Manufacturers* (1905-1938), and Smith (1966).

rises from 133 just before 1905, the first year of publication, to a peak of 389 in 1912, falls off abruptly to 181 firms in 1916, and then falls again in the mid-1920s, reaching 47 firms by 1932.

Perhaps the most comprehensive and authoritative list that has been compiled by Glenn Carroll (Carroll and Hannan, 1995). The list is based on the extensive three-volume *Standard Catalog of American Cars*, the most detailed and comprehensive source for historical information on American cars, compiled by a huge number of historians, collectors, enthusiasts, archivists, and museums (Kimes and Clark, 1988; Gunnell, 1992; Flammang, 1989). The *Standard Catalog* includes many tiny firms that never manufactured automobiles for sale.[20] Carroll's list shows about 20 firms by 1895, rising to around 320 by 1902, then dropping to around 240 in 1906 before rising to a peak of about 350 firms in 1910. After the peak, the number of firms drops off, with some increases around 1914 and 1921, falling to just below 40 by 1930 and continuing to fall until World War II.

Thus, all the comprehensive lists, including the one based on Smith (1966), roughly agree that the number of firms peaked around 1908-1912, and then dropped off, with an especially rapid dropoff in the 1920s. Apparently the number of better-established firms dropped off later than the number of tiny producers, so that sources examining only these better-established firms show a shakeout beginning in 1921 or 1922. This dissertation uses the list based on Smith (1966) for its primary source, but verifies the conclusions where possible using Epstein (1928) and Thomas (1965).[21]

In tires, the *Thomas' Register* series can be compared with data compiled by French (1986, p. 33; 1991, p. 48) for 1919 to the mid-1930s (fig. 4.3). Unfortunately, his data are admittedly sparse, and perhaps as a consequence his data on the number of firms are not consistent with his data on entry and exit. Depending on whether one believes the number of firms or entry-exit data, either the number of firms decreased

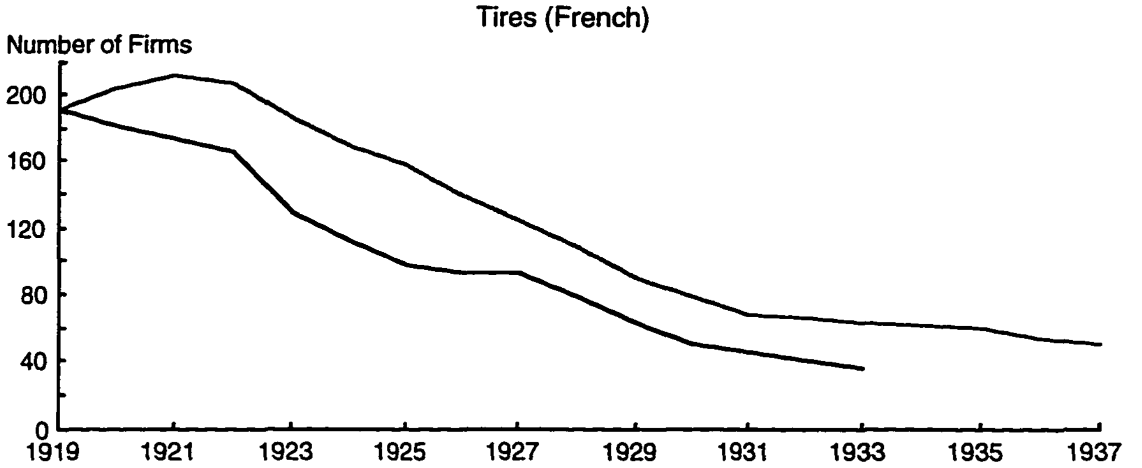


Figure 4.3. Number of firms in the US tire manufacturing industry, 1919-1937. The black line shows figures for the number of firms. The gray line shows figures computed for the number of firms using entry and exit data, assuming the number of firms in 1919 to be correct. Source: French (1986, p. 33; 1991, p. 48).

between 1919 and 1922 (black line, based on number of firms) or peaked in 1921 (gray line, based on entry and exit figures). Thus, the data show a shakeout as in the *Thomas' Register* data, although they suggest that the shakeout may have begun one or a few years before the 1922 date of the *Register.*

In televisions, Utterback and Suárez (1993) show a peak in the number of firms in 1952, based on *Television Factbook.* Using the same source, I reached essentially the same conclusion.[22] A broader list in *Thomas' Register of American Manufacturers* includes many of the same firms as in *Television Factbook.* The *Thomas' Register* dates are in a few cases slightly different, but correcting for the difference would merely put the peak in number of firms in 1950 rather than 1951.

In penicillin, data are available from three different sources. According to data from *Thomas' Register of American Manufacturers* (1945-1993), six firms manufactured penicillin by 1944 (Figure 4.4). The number rose to 26 in 1952, then fell to 8 by 1972 and 4 by 1981. A US government publication, *Synthetic Organic Chemicals* (US Tariff Commission, 1945-1991) includes a much smaller sample of firms, perhaps restricted to companies involved in international trade, but nevertheless it has some basis for comparison. In 1945, the first year when *Synthetic Organic Chemicals* included penicillin in its lists, the document named 16 manufacturers of penicillin. The number declined unevenly thereafter, reaching a low of 7 by 1960. A report by the Federal Trade Commission (1958), also with a limited sample of firms, shows a dropoff in the number of manufacturers beginning by 1948. Thus, the sources show a decrease in number of firms beginning sometime between 1945 and 1953.

Each of these sources appears to have substantial disadvantages. *Synthetic Organic Chemicals* and the Federal Trade Commission report miss many small producers. *Thomas' Register* is late in listing many manufacturers (perhaps because of delays in shifting from military to civilian production), and it ceases listing many firms long before they ceased to manufacture penicillin, as can be verified by noting that *Synthetic Organic Chemicals* continues to update information about the particular kinds of penicillin produced by many firms for, in a few cases, decades after *Thomas' Register* stopped listing the firms. To create a comprehensive and less problematic roster of penicillin manufacturers, I combined the *Thomas' Register* and *Synthetic Organic Chemicals* lists, treating firms as producers at any times when they appeared in either list. In addition, I added data describing which firms produced penicillin during World War II, using information from Elder (1970a) and the Federal Trade Commission (1958) report. This combined roster is the primary dataset used here for analyses of penicillin.

The shakeout in penicillin might have been much more dramatic than it was, if the US government had allowed more firms to participate in the wartime penicillin program. Many more firms wished to produce penicillin than were allowed to do so. Elder (1970b, p. 10), in a 1944 letter, writes,

> Over a hundred companies desiring to produce penicillin have been discouraged from submitting projects because it appeared probable that the plants [coming on line] should be completed before further expansion should be contemplated.

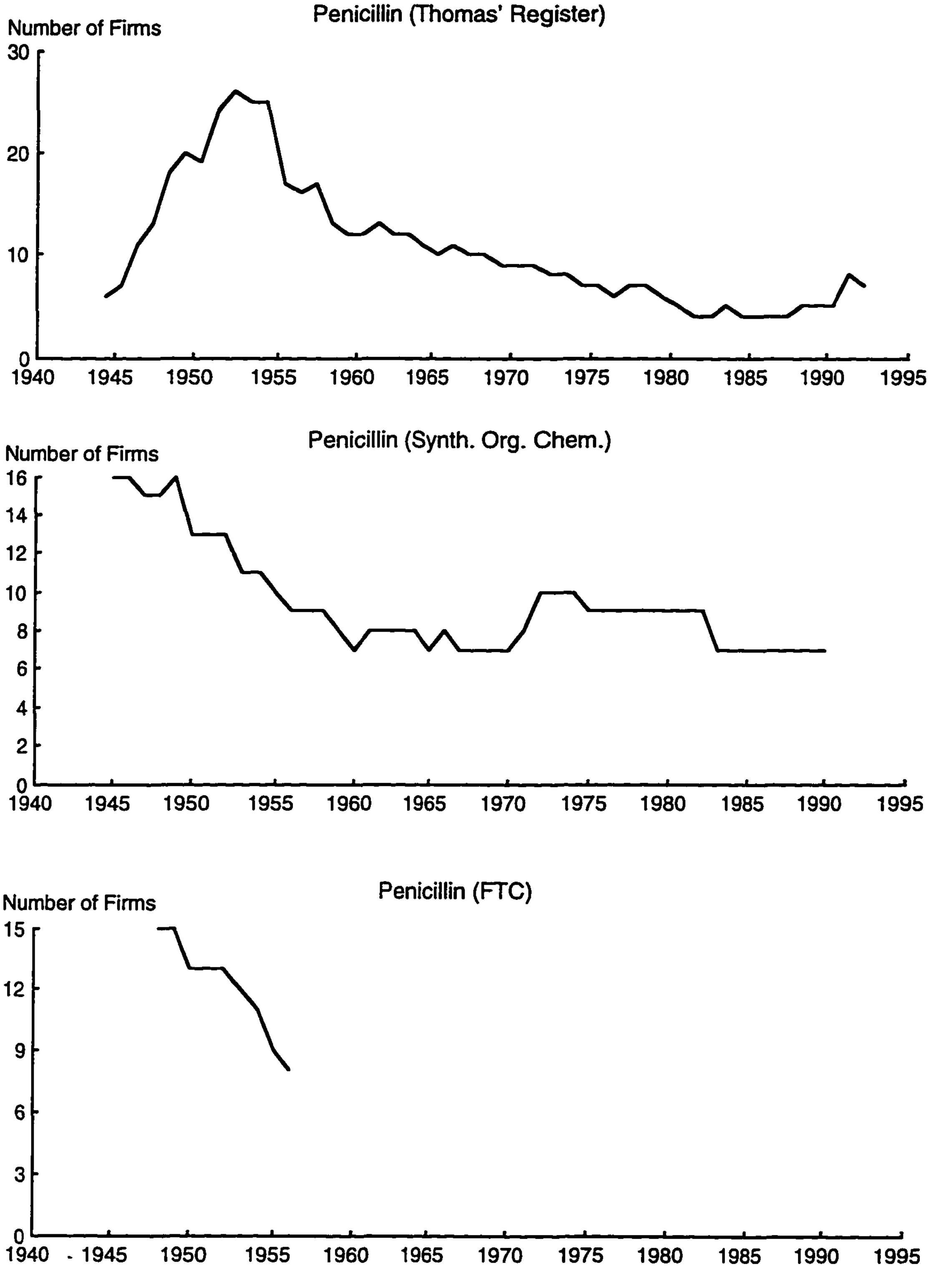


Figure 4.4. A comparison of alternative sources of firm counts in the US penicillin manufacturing industry, 1945-1990. Sources: *Thomas' Register of American Manufacturers* (1945-1993), US Tariff Commission (1945-1991), and Federal Trade Commission (1958, pp. 74-75).

Had these companies been encouraged to produce penicillin instead of discouraged, and had the industry ended up with the same long-run number of producers, the shakeout might have been five times more severe.

Dates for all the data series based on trade registers have assumed that a list of firms was current not at the date stamped on the cover of a trade register, but at approximately the time when the list was compiled or updated. To obtain a date for when a list of firms was compiled or updated, I averaged the date of publication of the register with the list of firms and the date of publication of the previous edition of the register (if no previous edition was published, I used the date six months prior to publication of the register). In later chapters in which graphs of entry and exit are shown, the dates chosen for entry and exit are half-way between the dates when firms are known to have existed; for example if a firm was known to be in production at the time 1922.5 but to have exited by 1923.5, then for purposes of graphs, its exit was dated as occurring at the time 1923.0.

Mergers

Mergers of firms were accounted for by studying historical sources about each industry. In automobiles, Smith (1966) catalogued mergers and transfers of ownership. His notes and diagrams were combined, where necessary, with a detailed study of company histories using the *Standard Catalog of American Cars* (Kimes and Clark, 1988). Wherever one automobile manufacturer was bought by another, or both were bought by a single owner, or two companies merged, the smaller of the companies was counted as exiting the industry by merger, rather than by cessation of production, and the larger was counted as a continuing firm. For tires and televisions, mergers are defined similarly, using information from industry studies including Gettell (1940), Epstein (1949), Federal Trade Commission (1966), Dick (1980, p. 45), French (1991), Levy (1981), Willard (1982), and Teitelman (1994, pp. 52-76).[23]

Imports

Imports are important for a study of shakeouts because they could explain the demise of domestic manufacturers. However, for the four products studied here, imports into the US were inconsequential well into each shakeout. The US automobile industry quickly outgrew the automobile industries of the European countries where automobiles were invented. By 1902, exports of automobiles and automobile parts exceeded imports, and by 1908 US production exceeded the production of all Europe (US Bureau of the Census, 1907, p. 16; Laux, 1992, pp. 8 and 17). Non-US auto manufacturers had little impact on the US industry from about 1905 through at least 1940, except perhaps by restraining US firms in foreign markets.

In tires, foreign producers had little impact on the US industry through World War II. In 1924, the year with the greatest volume of imports, imports were less than 0.4% of US sales. Exports from the US were also small (Gaffey, 1940, pp. 53-54). Some US manufacturers built overseas factories to avoid tariffs (West, 1984, pp. 18-19; French, 1991, pp. 126-130).

In televisions, Japanese producers did not have a major impact on the US industry until around 1970 (e.g. *Consumer Electronics 1969*, pp. 11-12; *Consumer Electronics Annual Review 1977*, pp. 11-13 and 27). Despite that Japanese firms pioneered techniques for improved quality and lower production costs, the dollar share of the US market taken up by imports was only about one ten-thousandth by 1960 rising to about one seventh by 1970 and under a fifth in 1976, when foreign firms began to manufacture in the US.[24]

In penicillin, after World War II, U.S. exports far exceeded imports, and the U.S. helped many countries establish their own penicillin production for humanitarian reasons (Woodbridge, 1950, p. 439; Yagisawa, 1980). Even by the 1980s exports far outweighed imports (Scholz, 1992). Thus, in none of the four products could imports have caused the shakeouts.

Demand

Nor did the shakeouts result from a drying up of demand. Figure 4.5 shows the industry sales or production from early in the history of each of the four products well into its shakeout. Arrows indicate when shakeouts began. In automobiles, the shakeout began just when production began to take off. In tires, production was rising rapidly when the shakeout began. In televisions, the time of the shakeout coincides with the leveling off of demand for black-and-white televisions, but the shakeout continued in earnest even while production increased with the rapid growth of the color television market after 1962. In penicillin, the shakeout began while output was rising, although output dropped somewhat two years later before resuming its rapid rise.[25] Thus, only in televisions and penicillin was there any decrease in demand around the time the shakeout began, and in both cases dramatic shakeout continued even as demand subsequently took off.

Patents

Finally, none of the shakeouts resulted from patents used to capture the market. In automobiles, a cross-licensing agreement allowed almost all firms to license patents freely (Epstein, 1928, pp. 235-239).[26] A notable exception only further proves how ineffective patents were as a way to capture the market. Hudson Motor Company engineer Stephen I. Fekete developed a counterbalanced engine crankshaft to reduce vibration and allow increased engine speeds (Renner, 1973, pp. 99-108). Hudson executives tried to keep the crankshaft outside of the patent pool using an escape clause for revolutionary inventions,

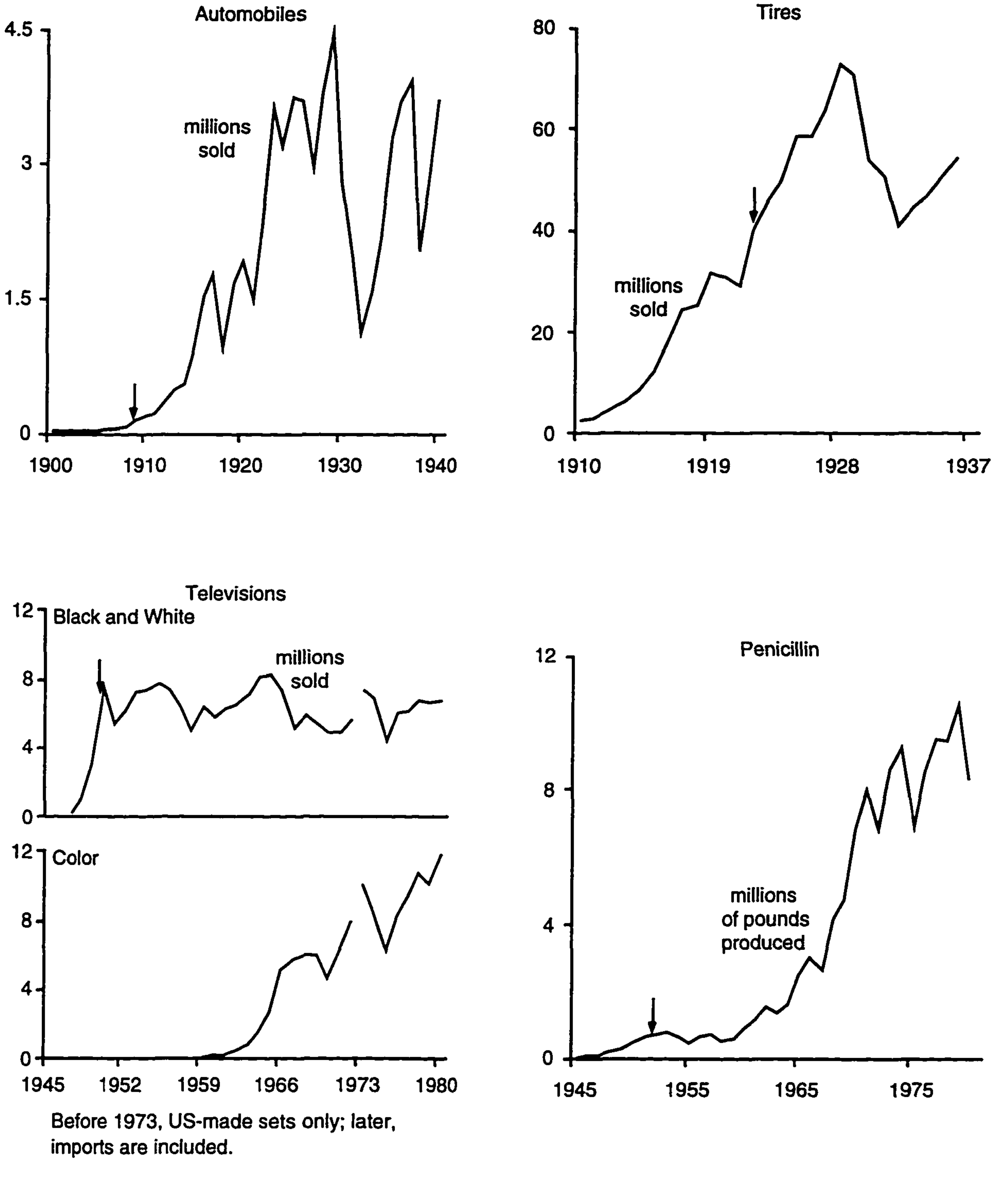


Figure 4.5. Industry sales or production in the US for the four products. Sources: For automobiles, Thomas (1965, pp. 321-322); for tires, Gaffey (1940, p. 54); for televisions, *Television Factbook* (1991, pp. C-329 and C-332-333); for penicillin, *Synthetic Organic Chemicals* (1945-1955) and Salaices (1989).

but other firms immediately challenged Hudson's classification of the invention. After five years of argument, the Arbitration Board of the National Automobile Chamber of Commerce (NACC) determined that the invention was not revolutionary, but just one step in an ongoing effort to deal with crankshaft vibrations. In the interim, firms invented alternative approaches to deal with high-speed engine vibration, many of which were used in preference to Fekete's approach long after the NACC's decision. The revolutionary production techniques used by Ford not only were not patented, but were readily viewed by the public and by engineers from around the world.[27]

In tires, pneumatic tires were first patented in England in 1845, then rediscovered in 1887, after the original patent was defunct. Product and process innovations were usually quickly imitated by other producers. The only notable exception, the clincher tire patent, was ruled inapplicable in 1907.[28]

In televisions, patents were freely licensed, with RCA and Hazeltine owning essential patents (Levy, 1981, pp. 154-163). The patents could not have disadvantaged small firms, because royalties were based on a percentage of sales rather than a fixed fee.[29] In fact, RCA encouraged development of the television industry by sharing its technology and by making its manufacturing know-how available to competitors (Levy, 1981, p. 165; Graham, 1986, p. 60). In 1958, following a series of lawsuits, RCA agreed to license most of its existing patents without royalties and to set up a royalty-free pool with its color TV patents.[30]

In penicillin, basic forms of the drug were not patented, nor were critical production techniques. During World War II, the strains of Penicillium mold needed to produce penicillin were made widely available to manufacturers, and the US Department of Agriculture allowed royalty-free licensing of patents on essential production methods that it developed (Federal Trade Commission, 1958, pp. 228-229). The first major variant of penicillin, procaine penicillin, was patented in 1950 by Lilly, which widely licensed the

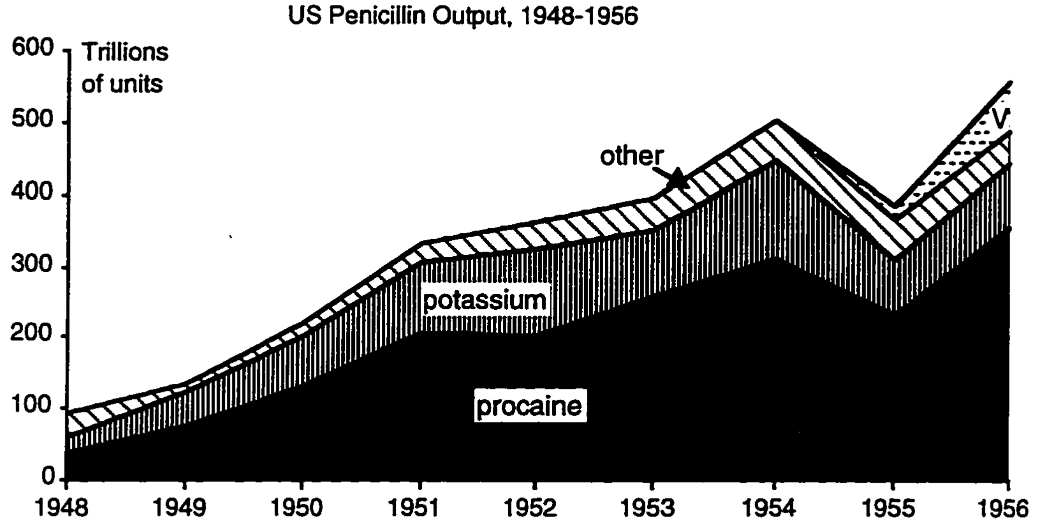


Fig. 4.6. US penicillin output by type of penicillin, 1948-1956. Source: Federal Trade Commission (1958, pp. 71 and 73).

drug after a series of lawsuits over interference (Federal Trade Commission, 1958, pp. 242-245).[31] Later varieties of penicillin, most notably the "semisynthetic" penicillins developed after 1958 (Sheehan, 1982),[32] were patented and held under tight control. However, a substantial market continued to exist for the older forms of penicillin that could be manufactured by any firm. Figure 4.6 shows penicillin production by type from 1950 to 1956. Of the different types, only penicillin V (phenoxymethylpenicillin), which made up a tiny fraction of unit output, was kept under tight control. Early forms of penicillin continue to be high-volume products even today. Thus, in all four products patenting was relatively unimportant except for the creation of new varieties of penicillin, and in no case can patents explain the shakeout.

Imports, demand shifts, and patents apparently do not explain the shakeouts in automobiles, tires, television sets, and penicillin. Having ruled out these obvious possible causes of shakeouts, I turn next to the technological theories. The obvious starting point is a detailed look at technology and innovation in each product.

5

Technological Change

In this chapter, I use the theories' predictions and assumptions about technology to guide a study of technological change in the four products. What can the concepts embodied in the theories contribute to an understanding of industry shakeouts? Based on a detailed review of the historical, trade, and economic literature about each product, I use the available evidence to examine each theory's conception of technological change in industries with shakeouts. Technological event-triggered shakeouts are hypothesized to result from a refinement invention or dominant design, either of which might be identified. Further, the shift from product to process innovation said to result from a dominant design and to cause the shakeout can be tested for using time-series data on innovation. And finally, the size-and-skill theory's R&D cost-spreading hypothesis can be tested with evidence on size-innovation and size-productivity relationships.

Refinement Invention

According to Jovanovic and MacDonald's (1994b) innovative gamble theory, a refinement invention makes possible a stream of improvements to a product or its manufacturing process. Firms that successfully innovate based on the invention survive, but other firms are forced to cease production, gradually or simultaneously, in a competitive game of survival of the fittest. If as the theory says a single invention caused the elimination of 85-97% of the firms in an industry (even more, since some of the original firms are replaced by new ones), this particularly important invention should be relatively easy to uncover in a study of the industry's inventions. For an invention to have triggered the shakeout, three criteria must be met: 1. The invention must have been adopted by most surviving firms around the time of the shakeout. 2. The invention itself or follow-on innovations must have had an unusually large effect on product quality or cost. 3. Only some of the industry's firms (the survivors) could have adopted the innovation or carried out successful follow-on innovation. I start with evidence that has been used to support the theory, the Banbury mixer in the tire industry. Then I move on to consider other possible refinement inventions in the four products.

The Banbury Mixer

Jovanovic and MacDonald (1994b) identify the Banbury mixer, invented in 1916, as the likely cause of the tire industry's shakeout. Mixers (or rubber "milling" machines) combined chemical compounds with rubber, giving the rubber strength, resistance to oxidation, color, and accelerated curing time. Compared to older mixing machines that ran the rubber and chemical compounds between rollers, the Banbury mixer's vat with blades could process larger quantities of rubber faster with fewer workers. The Banbury mixer could in 2 minutes mix 750 pounds of rubber, compared to 25 minutes for 1000 pounds of rubber in the largest old milling machines (Allen, 1949, pp. 44-45), although using Banbury mixers required that an extra step, sheeting, be added.

The Banbury mixer was patented in 1916, and the manufacturer of the mixers, the Birmingham Iron Foundry, sold them to any interested buyers in a wide range of sizes (Killeffer, 1962). Yet the innovation was not so important that major firms felt they had to adopt it quickly. It was not widely adopted until the 1920s (French, 1991, p. 51), and major plants were still replacing older equipment with Banbury mixers as late as 1928-1931. As of 1933 there were "still a number of plants which either have no Banbury mixers at all or use both mixing mills and Banbury mixers," yet which were still quite viable, competitive producers (Stern 1933, pp. 40-44, quote on p. 41). The slow adoption of this readily-available product suggests that Banbury mixers were not thought to be important for firms' survival, but a careful reckoning of their importance requires evidence about their effects on manufacturing costs.

Data on productivity gains caused by the mixer are available from Stern (1933) for six tire plants that were still operating as of 1928-1931. While the data pertain to labor productivity gains, this is approximately comparable to total productivity gains, since the quantities of materials involved were independent of the machinery.[33] The data cover the department of tire plants that dealt with washing, milling, compounding, and calendering of rubber. Productivity improvements also occurred in other departments. In fact, among the plants Stern studied in 1928-1931, the two subdepartments dealing with bead-making and with the making of chafers, cushions, breakers, and other rubberized strips inserted into tires (both in the stock preparation and carcass building department) contributed the greatest labor productivity savings (Stern, 1933, p. 48). As Figure 5.1 shows, the subdepartments with the greatest productivity improvements were quite distinct from the department that used Banbury mixers. Despite that at least two of the six plants were replacing older mixers with Banbury mixers during 1928-1931 (and three others might have been; the information is simply not available), greater productivity improvements resulted from the continual redesign of manufacturing processes in other departments.

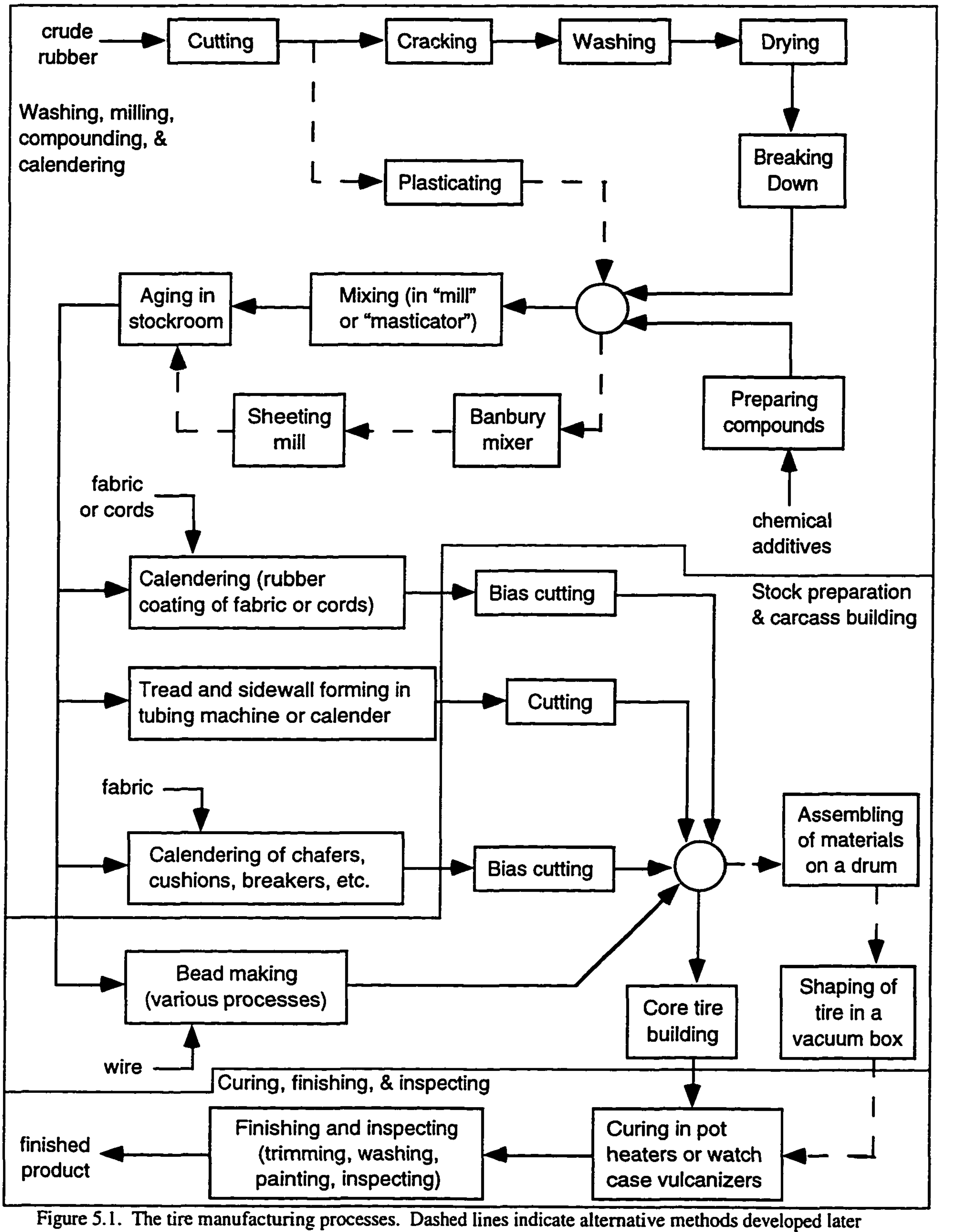


Figure 5.1. The tire manufacturing processes. Dashed lines indicate alternative methods developed later than methods shown with solid lines.

Table 5.1. Output per Hour of Labor as Affected by the Adoption of Banbury Mixers (washing, milling, compounding, and calendering department)

	Plant A				Plant B			
Year	tires	%Δ	pounds	%Δ	tires	%Δ	pounds	%Δ
1919	2.49	1.2	51.71	-2.9	6.66	19.8	75.69	16.4
1920	2.52	0.0	50.19	9.2	7.98	44.5	88.07	55.8
1921	2.52	21.8	54.79	20.2	11.53	-2.6	137.22	-5.5
1922	3.07	4.2	65.86	5.8	11.23	5.1	129.68	5.1
1923	3.20	30.0	69.69	12.6	11.80	19.3	136.33	20.0
1924	4.16	3.4	78.50	14.4	14.08	-11.4	163.62	-6.3
1925	4.30	5.8	89.84	16.2	12.47	9.0	153.37	14.3
1926	4.55	-11.6	104.36	-5.6	13.59	-28.4	175.31	-26.0
1927	4.02	-1.7	98.54	2.8	9.73	0.2	129.79	7.2
1928	3.95	6.8	101.30	13.4	9.75	21.4	139.12	26.0
1929	4.22	-3.8	114.84	8.4	11.84	6.5	175.35	11.2
1930	4.06	13.5	124.45	13.5	12.61	-7.5	195.07	-3.6
1931	4.61		141.26		11.67		187.97	

The dotted lines indicate times of adoption of Banbury mixers. Output is given in tires per hour and pounds per hour, and the annual percentage changes in these figures are listed in the "%Δ" columns. Source: Stern (1933, pp. 45-47).

Stern includes time series productivity data starting in 1919 for two plants with known installation dates for Banbury mixers. Table 5.1 shows productivity trends in the relevant department of these plants. The installation dates for the mixers are indicated by gray lines. As a reading of the table shows, in terms of both number of tires per labor hour and number of pounds per labor hour, the productivity gains at the times of installation were not inordinately high. The gains in terms of tires per labor hour were perhaps as high as 5.8% in plant A and 19.3% in plant B, substantial gains, but not atypical compared to other years. That other years showed even greater improvements is not surprising when one realizes that the tire industry thrived on constant process innovation and manufacturing improvement of every variety, giving it for a long period the fastest labor productivity improvement of any US manufacturing industry.[34] These productivity improvements stemmed from the cumulative effect of vast numbers of innovations. While Banbury mixers may have been one of the industry's most important advances, they nevertheless appear to be only one part in an ongoing flood of technological improvement.

When one checks for related improvements that might have yielded a competitive advantage over the course of several years after the adoption of Banbury mixer, a similar negative conclusion results. Some follow-on innovations did occur, as shown by table 5.2's data on the sources of labor savings in the relevant department in 1928-1931. For example, plant D modified its production line by adding an electric elevator and conveyor that compounded (mixed) ingredients and fed them directly into the Banbury mixers. However, a glance back at table 5.1 will show that these follow-on innovations did not yield unusual cost reductions. In fact, the average annual change in labor productivity actually decreased after adoption. In the washing, milling, compounding, and calendering department, plant A went from a 12.1% (12.3%) annual increase in tires (pounds) per labor hour in 1919-1925 to a 0.3% (7.1%) annual increase in 1926-1931. Plant B went from 19.3% (5.5%) in 1919-1923 to -2.5% (1.7%) in 1924-1931.

Thus, all the telltale signs suggest that Banbury mixers did not trigger the shakeout in the tire industry. The labor savings resulting from the installation of the mixers, while substantial, were relatively small compared to the net effect of other ongoing innovations and manufacturing line improvements. The savings is relatively small even within the single department in which the mixers were installed, whereas at least as of 1928-1931 the greater productivity improvements came from another department. The same conclusion is reached regardless of whether one considers the immediate effect of installation or a stream of related improvements that take place over several years. Banbury mixers were easy for plants to adopt, since Birmingham Iron Foundry helped firms to adapt their production lines for the mixers and since it sold mixers of many different sizes to accommodate plants with varying production scales. The late adoption of the mixers might seem surprising given that productivity improvements resulted from their use, but, as historians of the industry often suggest, the high capital cost of replacing older mixers with Banbury mixers

Table 5.2. Technological Changes and their Effects on Labor Requirements in the Washing, Milling, Compounding, and Calendering (WMCC) Department

Process change: Worker-hours per day saved	Process change: Worker-hours per day saved
Plant C, 1928-31, WMCC Dept. *1,536 worker-hours per day saved* *63-94% of savings related to Banbury mixers*	*Plant E, 1930-31, WMCC Dept.* *728 worker-hours per day saved* *15-22% of savings related to Banbury mixers*
New cutter for crude-rubber bales installed: 16	3 crude-rubber plasticators installed: 328
2 Banbury mixers installed with necessary conveyers and other equipment: 960	A power-driven belt conveyor and a cooling conveyor installed for handling and cooling of plasticated rubber: 88
Additional spray-cooled Banbury mixer and 3 spray sheeting mills installed, together with all accessory equipment: 480	4 additional mixing mills installed: 48
2 tread calenders with automatic feed devices: 48	Automatic system installed to deliver compounding ingredients to mill room and Banbury mixers: 40
Tandem calenders equipped with push-button controls: 32	Liquid soapstoning devices installed for Banbury mixers: 24
	Compounding unit installed for servicing all Banbury mixers: 48
Plant D, 1929-31, WMCC Dept. *856 worker-hours per day saved* *54% of savings related to Banbury mixers*	Automatic ribbon feeder installed, delivering rubber from warming-up mill to calender: 48
Sliding chute erected leading from crude-rubber cutter to the plasticators: 32	Tandem and other calenders equipped with automatic operating control: 32
2 rubber plasticators installed: 208	Large calenders equipped with electric hoist: 24
Electric elevator and conveyor installed for the direct compounding of ingredients for 5 Banbury mixers: 260	Tread calender equipped with mechanical feed conveyor: 48
Banbury mixers installed for 2 tandem calenders: 128	
Additional conveyor installed for Banbury mixers: 72	
Tandem calenders equipped with automatic feeding device: 120	
Automatic feed installed for tread calender: 36	

Whether plants listed here are the same as A and B in table 4.1 was kept confidential.
Source: Stern (1933, pp. 43-44). Descriptions of technological changes are quoted verbatim.

may explain the late adoption. In the industry used as an illustration in the paper that develops the innovative gamble theory, the innovation cited as the probable cause of the shakeout apparently did not cause the shakeout.

Possible Refinement Inventions in All Four Products

To uncover other possible refinement innovations that might have caused the shakeouts in the four products, I searched the historical, trade, and economic literatures in each product. A technological change with such a dramatic impact on industry structure would, presumably, be a subject of some attention in the writings of the economists, historians, and trade journalists who focused much of their life's work on the products. To the extent that evidence of a dramatic technological effect on an industry was not recorded, the refinement invention theory of shakeouts is not testable directly. Indirect tests will be considered in later chapters. The point of this chapter is to uncover what evidence does exist, for or against the theories, of the technological changes they predict.

Pre-existing lists of inventions and innovations, where available, helped make the study more objective. The lists allowed me to uncover innovations that might otherwise have gone unnoticed, and to objectively identify what others thought were the most important innovations in each product. In automobiles, Abernathy, Clark, and Kantrow (1983) catalogue 631 innovations. Each innovation is labeled as having to do with either manufacturing process or one of three product categories, dated, and ranked on a 7-point scale according to the importance of its impact on the industry. Innovations ranked 6 or 7 on the 7-point scale, from the start of the industry to 1930, are shown here. In tires, a list constructed by Dick (1981a, 1981b) is augmented with several process innovations discussed in other sources. I include tire innovations through 1940. In televisions, I use a list due to Levy (1981, pp. 48-52 and 71). In penicillin, Achilladelis (1993) catalogues the major product innovations, and I constructed my own list of process innovations using all available sources.[35] The four lists appear in table 5.3. From the literature search and the lists of innovations, I identified innovations that seem to have had the greatest impacts, beginning in automobiles.

Table 5.3a. Major product and process innovations in automobiles, tires, TVs, and penicillin.

Automobiles

Year	Product Innovation	Originating Firm
1908	Magneto integrated into flywheel	Ford
1908	Detachable cylinder heads	Ford
1912	All-steel open car body	Budd Design on Hupmobile; Oakland (GM)
1914	First large-scale production V-8 engine	Cadillac (GM)
1922	Inexpensive closed car built of wood and steel	Hudson
	Process Innovation	
1896	First multiple production of one-car design (13 vehicles)	Duryea
1901	World's first mass-produced automobile	Oldsmobile
1910	Industry's first branch assembly plant	Ford
1914	Elevated, moving chassis assembly line	Ford
1917	Baked enamel finishes	Ford
1924	Lacquer paint finish (DUCO-Pyroxolin)	Oakland

Tires

Year	Product Innovation	Originating Firm
1845	Pneumatic tire	R.W. Thompson
1888	Commercial pneumatic bicycle tire	J.B. Dunlop
1896	Automobile tire	
1900	Tire cord first used instead of square-woven fabric	
1905	Flat-tread, straight-sided tire developed	Goodyear
1910s	Plantation rubber used	
1912	Carbon black for reinforcement	Diamond Rubber
1913	First patent on a radial tire	
1924	Low-pressure balloon tires developed	
1924	Aldehyde/amine antioxidants discovered	
1925	Cord ply "completely" replaced square woven fabric	
1928	First patent on a tubeless tire	E.P. Killen
1929	White sidewalls	
1931	First synthetic commercial rubber (neoprene) developed	DuPont
1935	Modern tire dimensions evolved	
1938	Rayon sometimes used instead of cotton cord	Goodyear & DuPont
1939	Resorcinol-Formaldehyde latex for rubber-to-cord adhesion	DuPont
1940	Butyl rubber developed	
	Process Innovation	
1839	Vulcanization discovered	Charles Goodyear
1906	Analine derivatives used to accelerate rubber curing	Diamond Rubber
1916	Banbury mixer	Birmingham Iron Foundry
1919-1930s	Drum tire-building machines	
circa 1920s	Chutes, slides, conveyors, and rearrangement of layouts	
1921	2-Mercaptobenzothiazole accelerator discovered	C.W. Bedford, L.B. Sebrell
1930s	Assembly lines	

Table 5.3b. Major product and process innovations in automobiles, tires, TVs, and penicillin.

Televisions

Year	Product Innovation: Display	Originating Firm
1950	Shadow mask picture tube	RCA
1953	Curved shadow mask	CBS
mid-1950s	Wide-angle tubes	many firms
pre-1960s	Projection television	
1961	Light sensor for automatic brightness adjustment	Magnavox
1963	Rectangular color picture tube	Motorola and National Video
early 1960s	Bonded safety glass and barefaced picture tubes for implosion protection	various glass companies
1964	Automatic degaussing	RCA
1964	Rare earth phosphors	Sylvania
1965	In-line picture tube, small screen	General Electric
1968	Trinitron picture tube	Sony
1969	Black Surround, or black matrix, picture tube	Zenith
beginning in early 50s	Very large size tubes	
	Tuning	
before 1965	Automatic fine tuning	
1950s to 70s	Remote control	Zenith was a leader
late 1960s to 70s	Electronic tuning	European firms
	Chassis	
late 1940s	Intercarrier sound system	GE
late 1940s	Electromagnetic deflection	
1950s	Portable receivers	
early to mid-1960s	Solid state	
1967	Modular construction	Motorola
	Circuitry	
continual	gradual improvements by components suppliers	
continual	cumulative engineering improvements	
1966	integrated circuits on a chip	
	Process Innovation	
mid-1950s	Printed circuits	several firms
mid-1950s	Dip soldering	several firms
late 1950s	Solid state components (introduced in stages for different functions)	
early 1950s	Automatic component insertion	

Table 5.3c. Major product and process innovations in automobiles, tires, TVs, and penicillin.

Penicillin

Year	Product Innovation	Originating Firm
1942	Penicillin	Merck, Pfizer
1955	Phenoxymethylpenicillin ("V")	Glaxo (UK), Lilly
1959	Phenethicillin	Beecham (UK), Bristol
1963	Ampicillin	Beecham (UK)
1969	Carbenicillin	Pfizer, Beecham (UK)
1978	Azlocillin	Bayer (Germany)
1984	Amdinocillin	Roche (Switzerland)
1986	Sulbactam	Pfizer
	Process Innovation	
early 1940s	Assay methods	
early 1940s	High-volume production of extremely pure air	
1940s	Freeze-drying techniques for penicillin	
beginning circa 1941	Deep vat fermentation methods and experimentation with growth media	Northern Regional Research Laboratory, other laboratories, many firms
beginning circa 1942	Mutation & breeding of Penicillium mold, to increase production yields & to produce forms of penicillin with new properties	government & university laboratories, many firms
1940s-50s	Continual redesign of fermentation equipment, to achieve higher stirring ("agitation") power, higher capacity, and continuous processing	many firms
1940s-60s	Recovery methods improved & largely standardized	
1950s-60s	pH control using autoclavable electrodes and metering pumps	
1950s -60s	Pumps for aseptic addition of nutrients and precursors	
1950s-60s	More efficient antifoams & other methods of control foams in fermentors, including electronic systems to add antifoam	
circa 1950s-60s	Automated data collection & control consoles (measuring variables such as pH, CO_2 content of effluent gases, dissolved oxygen, dissolved sugar, nutrient inflow, and antifoam inflow)	
1950s & 60s	Semiautomated batching facilities	

Automobiles

Perhaps the best known technological change in automobiles is the moving assembly line used by Ford and other firms starting in the 1910s and 1920s. In 1913, Ford engineers tried out the industry's first moving assembly line to make flywheel magnetos at the company's Highland Park plant, and in 1914 they installed a moving assembly line for automobile chassis. Other companies adopted assembly line techniques in the late 1910s and early 1920s. Could the moving assembly line be the refinement invention central to the innovative gamble theory?

The moving assembly line departs from Jovanovic and MacDonald's innovative gamble story in two ways. First, since Ford began using assembly lines four or five years after the shakeout began, another cause would be required to explain the first five years of the shakeout. Second, while the theory suggests that a radical invention creates the opportunity for follow-on innovations, allowing successful innovators to reduce their costs, an inspection of Abernathy, Clark, and Kantrow's (1983) list of innovations shows that virtually all of them are unrelated to assembly lines and hence could have taken place without the development of assembly lines.[36]

It becomes all the more apparent that huge numbers of technological advances swamped the effects of any single innovation when one examines the other automobile product and process innovations in table 5.3. The four innovations listed as occurring around the time of the shakeout are the magneto integrated into the flywheel, detachable cylinder heads, the first branch assembly plant, and the all-steel open car body. None of them are mentioned as particularly important in the literature, and precise evidence about their effects on firms' costs and on continuing R&D is not available.[37] Rather than relying solely upon a subjective impression of the literature, I use an alternative approach exploiting Abernathy, Clark, and Kantrow's data.

I searched their data for any follow-on innovations related to table 5.3's major innovations. I used all major automobile innovations occurring after 1901 and by 1930.[38]

I considered all subsequent innovations of any rank that were technologically related to the major automobile innovations and that had occurred by 1930. Cases where a relationship is questionable were included, to give the innovative gamble theory the benefit of the doubt. The results appear in table 5.4. Only two of the major (rank 6 or 7) innovations had more than two related innovations (of any rank) in the following ten years. These major innovations were the V-8 engine, introduced in 1914, and Hudson's closed steel body of 1922. As for the V-8 engine, not only did it not appear until five years after the shakeout began, but V-8 engines were not mass-produced until 1932 (Committee on the Judiciary, 1958, p. 23) and through the 1920s made up at most a few percent of annual sales (Figure 5.2). As for Hudson's closed steel body, it appeared over a decade after the shakeout began, too late to have caused the shakeout (more will be said later about how it may have affected competition in the 1920s). Thus, a search for follow-on innovations related to the major innovations in Abernathy, Clark, and Kantrow's list again fails to find any candidates for the refinement invention.

Table 5.4. Innovations judged to be possibly related to, and that occurred after, the automobile product innovations and the 1910-1924 automobile process innovations of Table 5.3.

Year	Producer(s)	Innovation
Related to the Magneto integrated into flywheel (Ford, 1908):		
1913	Ford	Moving flywheel assembly line
Related to the All-steel open car body (Budd Design on Hupmobile, Oakland, 1912):		
1912	Budd	Electric spot welding (on all-steel car)
1914	Dodge	Mass production of all-steel open car body
1923	Dodge	All-steel, closed sedan car body
1923	Oldsmobile (GM)	Sectionalized body production
1925	Studebaker	Duplex body type (steel accessory top)
1928	Ford	Seam welding method
1929	Auburn; Cord	X-shaped crossmember frame
Related to the First large-scale production V-8 engine (Cadillac, 1914):		
1916	Hudson	Counter-balancing of crankshaft in multi-cylinder (6) engine
1916	Packard	Aluminum alloy pistons
1916	Packard	First production model V-12 engine
1921	Duesenberg; Kenworthy	Straight-eight (or in-line) engine (first major American use)
1922	Nash	Rubber engine mounts
1924	Cadillac (GM)	Balanced V-type 8-cylinder engine (counterweighted crankshaft)
1924	Packard	Mass-produced straight-8 L-head engine
1926	Chrysler	Engine isolated from frame
1926	Oakland (GM)	L-6 engine (begins low stroke-to-bore ratio trend)
Related to Baked enamel finishes (Ford, 1917):		
1924	Oakland (GM)	Lacquer paint finish (DUCO-Pyroxolin)
1925	Ford	Pyroxolin paints in multicolors[39]
Related to Inexpensive closed car built of wood and steel (Hudson, 1922):		
1923	Oldsmobile (GM)	Sectionalized body production
1925	Studebaker	Duplex body type (steel accessory top)
1928	Ford	Seam welding method
1929	Auburn; Cord	X-shaped crossmember frame
Related to Lacquer paint finish (Oakland, 1924):		
1925	Ford	Pyroxolin paints in multicolors

If innovations from Table 5.3 are not mentioned here, no related innovations were listed by 1930.
Source: Compiled using Abernathy, Clark, and Kantrow (1987, pp. 155-179).

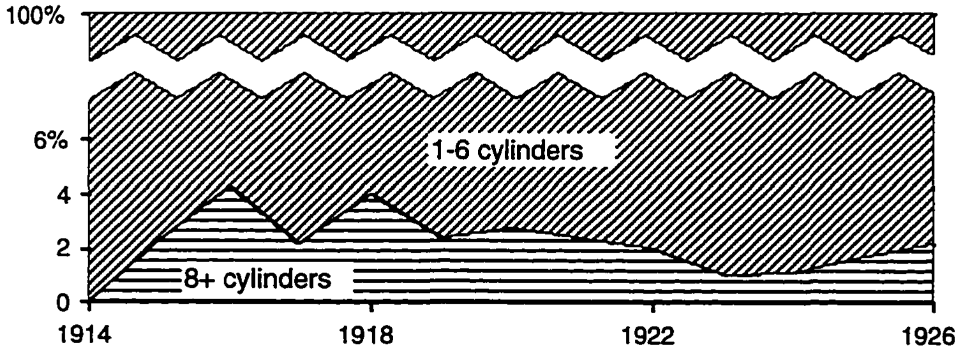


Figure 5.2. Number of cylinders in automobile engines, as percentages of industry-wide factory sales.
Source: Epstein (1928, pp. 90-91, 122-125).

Tires

In addition to the Banbury mixer, Jovanovic and MacDonald mention two other innovations in the tire industry, straightside[40] and cord[41] tires. They rule out these innovations as incompatible with scale-increasing requirements of their theory. Indeed, the two innovations are also incompatible for another reason. For years before the shakeout began, a substantial percentage of the industry's production was straightside and cord tires. Furthermore, the shakeout continued well after the switch to these designs. Figure 5.3 shows the adoption of straightside and cord designs as a percentage of industry production from 1910 to 1935. Also shown in Figure 5.3 is the adoption of another tire design innovation, the balloon tire.[42] Again, the time of adoption, with few balloon tire sales until 1925, does not coincide with the time of the shakeout. Among the other major innovations listed in table 5.3, only one other appears to be a possible candidate for a radical innovation: the drum tire building machine.[43]

Gaffey (1940, p. 90) writes that in the tire industry from 1915 to 1940, "only one innovation can be considered revolutionary. This was the shift from the core process of tire building to the flat drum process,[44] which was introduced in some plants as early as 1919 and was in use in nearly all tire factories by 1927." Most of the adoption occurred between 1923 and 1926 (French, 1991, p. 51). Productivity data are available from Stern (1933) for the relevant department of one plant that is known to have adopted drum tire machines in 1928. As table 5.5 shows, this department's labor productivity improved most in the year in which drum tire machines were adopted. Above-average productivity improvements continued for the next three years, consistent with the innovative gamble theory's concept that an invention may make possible a stream of follow-on innovations. Among all six tire plants studied by Stern, Figure 5.4 shows the estimated percentage of employees in the six plants that would be laid off annually because of technological change,

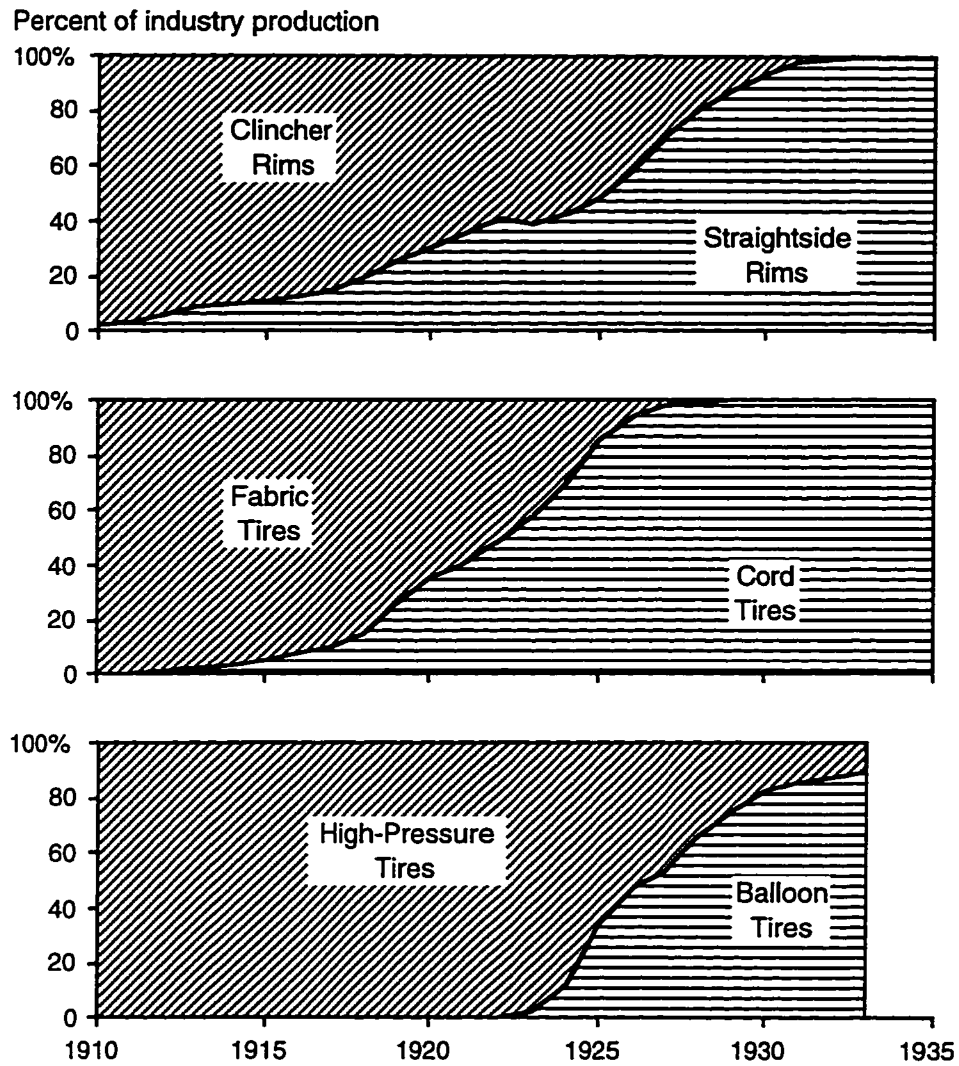


Figure 5.3. Adoption of straightside, cord, and balloon tires, as estimated percentages of industry production. Source: Holt (1933, p. 16), cited in Gaffey (1940, p. 43).

assuming a constant production volume. The source of the displacement is broken down by departments: washing, milling, compounding, and calendering; stock preparation and carcass building (where drum tire machines were used); and curing, finishing, and inspecting. Labor displacement increased in all departments, but particularly in stock preparation and carcass building, during the year 1925, around when most firms adopted drum tire machines.[45] Thus, the evidence is consistent with the idea that drum tire machines reduced firms' costs at the time of adoption and perhaps also during the

Table 5.5. Output per Hour of Labor as Affected by the Adoption of Drum Tire Equipment (stock preparation and tire building department)

	Plant F			
Year	tires	%Δ	pounds	%Δ
1922	2.70	2.6	33.25	2.5
1923	2.77	0.0	34.07	-0.2
1924	2.77	-9.4	34.00	3.3
1925	2.51	-2.0	35.11	-3.8
1926	2.46	2.0	33.79	6.5
1927	2.51	15.1	35.97	23.1
1928	2.89	9.0	44.27	21.0
1929	3.15	7.6	53.55	19.6
1930	3.39	9.7	64.07	6.9
1931	3.72		68.46	

The dotted line indicates the time of adoption of drum tire equipment. Output is given in tires per hour and pounds per hour, and the annual percentage changes in these figures are listed in the "%D" columns. Plant F may be the same as A-E, but it is impossible to know since this was kept confidential. Source: Stern (1933, pp. 55-56).

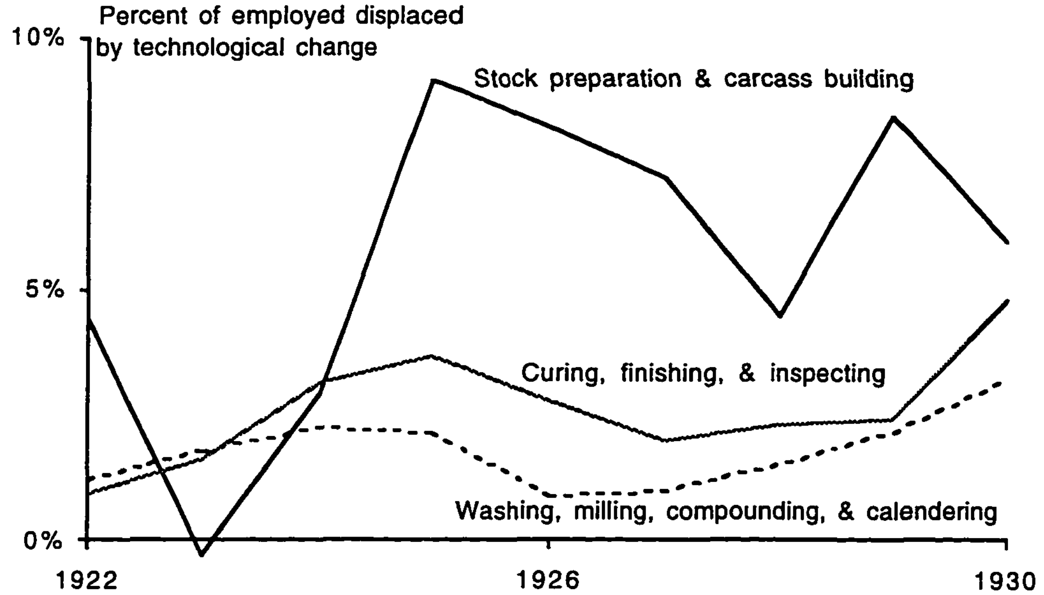


Figure 5.4. Estimated annual percentage of all employees in the entire plant displaced because of technological change in individual departments, for aggregate data on six tire plants. Source: Based on Stern (1933).

following several years. No evidence is available to resolve whether these changes gave a competitive edge to some firms, or whether all firms could adopt the machines, and use them as a basis for further innovation, with equal ease. While the lack of critical evidence about adoption and follow-on innovation makes the drum tire machine's role uncertain, apparently the machine might have caused or contributed to the shakeout starting sometime around 1923.

Televisions

Based on interviews with television engineers and executives, Levy (1981, p. 36) identifies two television inventions as outstanding breakthroughs: black-and-white and color. Otherwise, the engineers and executives uniformly indicated, technical progress on televisions was "evolutionary rather than... revolutionary." Therefore I focus first and foremost on the development of color television as a possible cause of the shakeout. While production of color televisions began as early as 1950, they could not have caused the shakeout. Color television sales remained minuscule until around 1962, nine years after the shakeout began.[46] While most manufacturers originally planned to produce color television sets after the 1953 acceptance of RCA's color broadcast standard, all but two suspended color set production by 1958 because the expected sales failed to materialize (Willard, 1982, p. 173).[47] Color set sales remained less than 5% of dollar sales of TVs through 1959 (Consumer Electronics, 1969, p. 12). Black-and-white television, not color, was the focus of competition during the 1950s when the shakeout began.

Among the evolutionary, not revolutionary, innovations of table 5.3, the individual product innovations were not particularly important determinants of competitive prowess because they were sold as components.[48] Manufacturers bought these and other components and assembled them into finished sets. Perceived product quality was as much or more a function of advertising as of carefully crafted products. As for process

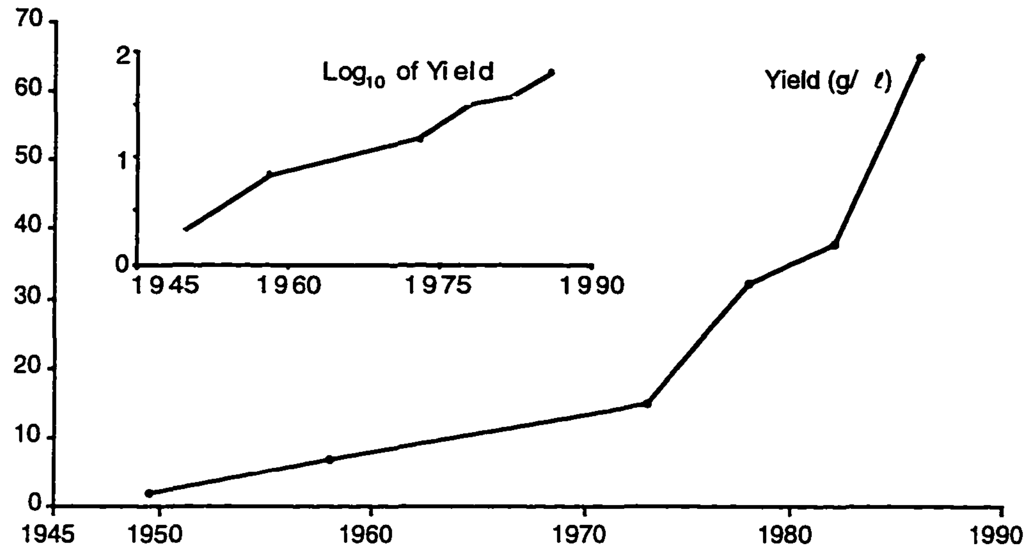


Figure 5.5. Yields of penicillin in grams per liter of fermentation broth. Source: Calam (1987, p. 120).

innovations, little information is available to confirm the view that progress was evolutionary rather than revolutionary.[49] Thus, while the prevailing view is that no radical invention existed that could have caused the shakeout in televisions, the available evidence is quite limited.

Penicillin

In penicillin, product innovations can explain the success of technological leaders such as Beecham, a key developer of the new "semisynthetic" penicillins, but product innovations were not responsible for the shakeout. When new varieties of penicillin became available in the 1950s and later, they became separate markets, tightly held through patents, with production by the patent holder and rarely by a few licensees. The original varieties retained strong sales, but developed highly competitive commodity markets. To explain the shakeout of commodity penicillin producers, one must explain the processes of competition within those markets.

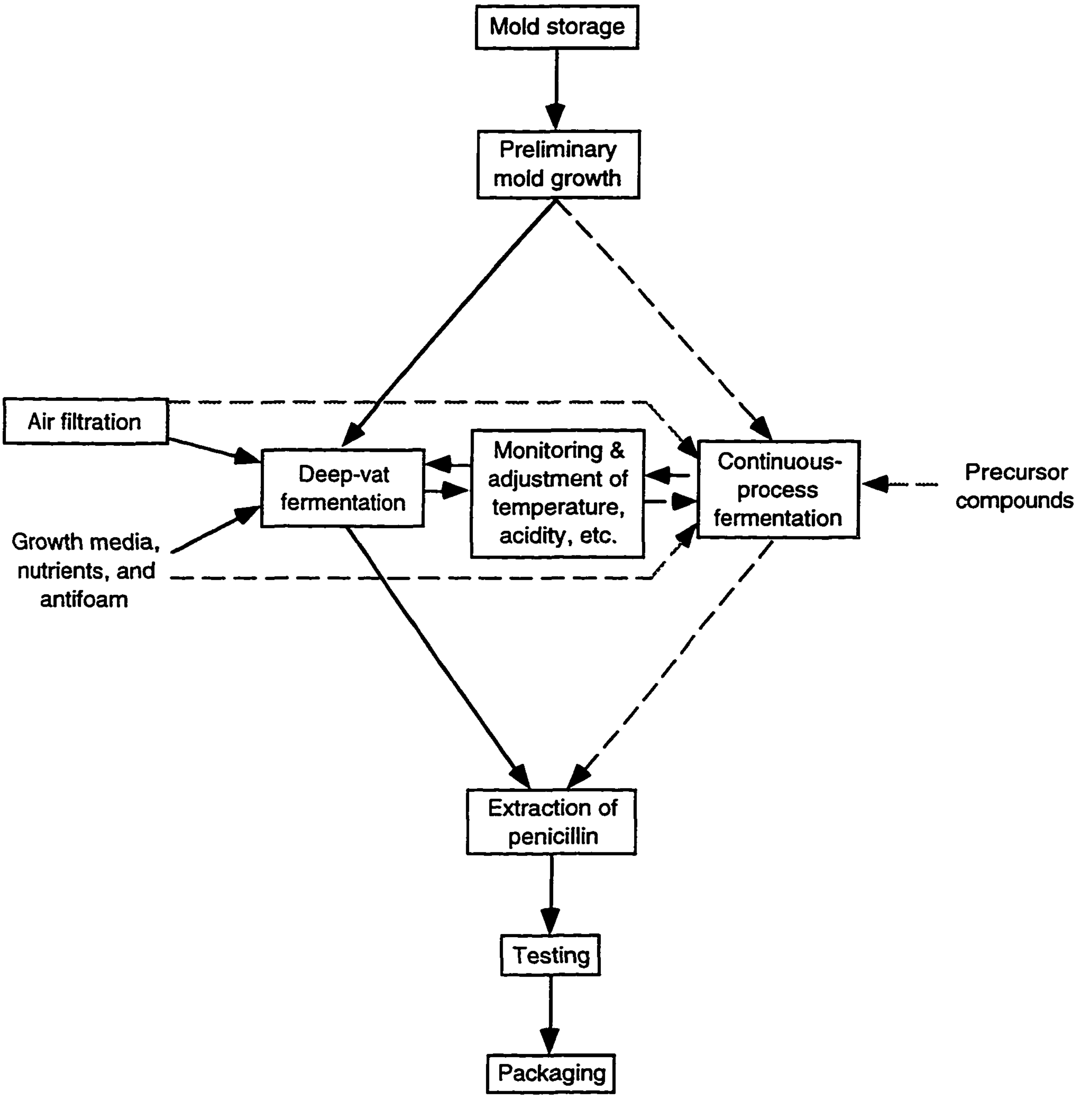


Figure 5.6. The penicillin manufacturing process. Dashed lines indicate that continuous-process fermentation eventually replaced batch-processed deep-vat fermentation.

Process improvements in penicillin were continual and dramatic, allowing average real prices to fall from $5,290 per pound in 1945 to $89 per pound in 1955 and about $15 per pound in the late 1970s.[50] Process improvement was central to competition in commodity penicillin markets. Costs fell with continual improvements in yield per liter of production broth (Figure 5.5). Yield improvements reduced costs throughout the process (Figure 5.6), not just in fermentation, by requiring less growth, extraction, and testing.[51] Data on productivity and cost data are not available for other aspects of the manufacturing process. Consequently, no check can be made on whether any single invention may have triggered the shakeout. Nevertheless, it is noteworthy that the industry's rapid productivity improvement was continual, from World War II through the 1980s, and that firms kept their process improvements shrouded in secrecy to hide apparently continual, incremental improvements the knowledge of which added up to a considerable competitive advantage.

Refinement Inventions

While the Banbury mixer apparently did not cause the tire industry's shakeout as proposed by Jovanovic and MacDonald (1994b), the drum tire machine is a credible candidate for a refinement invention in the tire industry. In the other industries an in-depth literature search did not uncover any credible candidates. In televisions and penicillin, information on process innovation is sufficiently poor as to leave considerable uncertainty.

Dominant Design

Utterback and Suárez (1993) propose dominant designs for seven industries, including automobiles and televisions. As automobiles was a key industry in the development of Abernathy and Utterback's technological product life cycle theory and the idea of dominant designs (Abernathy, 1978), and since I wanted to gain a solid understanding of the dominant design theory, I began this research by studying the automobile industry. The television receiver industry was also included in the sample, in part to provide a clear example of the dominant design theory of shakeouts. The empirical test starts with dominant designs that have been identified, the all-steel closed body in automobiles and the 21-inch set and RCA color standards in televisions. Then it moves on to consider the theory in all four products.

The All-Steel Closed Body

Utterback and Suárez (1993) identify Dodge's all-steel closed body, introduced in 1923, as the dominant design that caused the automobile industry's shakeout.[52] In fact, the innovation came too late to have caused the shakeout, according to the firm counts described in chapter four. Utterback (1987, p. 38) and Utterback and Suárez (1993) chose for their count of firms a list compiled by Fabris (1966, pp. 178-217), which unfortunately happens to be inappropriate. Fabris (1966, p. 27) deliberately excludes from his data sample all automobile producers that exited before 1924.[53] This exclusion makes it impossible to date correctly a shakeout that began before 1924. With no exit until 1924, no shakeout can be apparent before 1924, and not surprisingly, the data based on Fabris' list show a dropoff in number of firms beginning in 1924. Were pre-1924 exitors excluded from the firm lists of chapter four, they would also show a shakeout beginning in 1924. The 1923 all-steel closed body was apparently chosen because it coincides with the shakeout dated based on Fabris' list, but since the shakeout actually began around 1909, the all-steel closed body cannot explain the shakeout in the automobile industry.

Nevertheless, the presses used to produce steel closed bodies might have helped to intensify the shakeout in the 1920s. Drawing on case studies by his research assistants, Abernathy (1978, pp. 18-19, 183-187) describes the consequences of Dodge's new design. The design led to the decline of small producers, he says, because they could not afford to invest in expensive steel presses needed to produce steel car bodies.[54] However, the expense of the presses did not automatically preclude small firms, which could still buy bodies from third-party manufacturers. Even the major producers continued to buy from third parties. In the 1920s, GM and Ford bought pressed steel from Budd, and even by

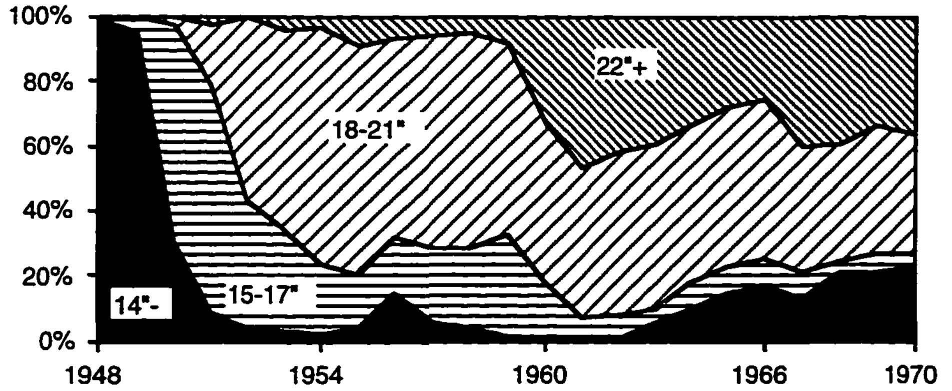


Figure 5.7. Screen sizes of black-and-white TV picture tubes, as a percentage of industry sales, 1948-1970. Source: Electronic Industries Association (1959, pp. 36-37; 1962, p. 48; 1969, p. 58; 1971, p. 64).

1946 Ford outsourced over 40% of its pressed steel (communication with David Hounshell). Also, other reasons existed for the increased pace of shakeout in the 1920s: falling prices, a declining virgin market, increased rapidity of style change, and delayed effects of the 1920-1922 recession.[55] Steel body presses perhaps helped to accelerate the shakeout in the 1920s, since firms forced to buy bodies solely from third parties may have had some cost or style disadvantages, but there is little evidence to support this hypothesis.[56]

The 21-Inch Set and RCA Color Standards

Utterback and Suárez (1993, pp. 8, 11-14) identify two product standards as the dominant design that caused the television industry's shakeout. These standards, the 21-inch set and the RCA color broadcast system, both emerged around 1953, three years after the shakeout began. Larger picture tubes became more popular as new tube designs developed and as prices fell (Figure 5.7).[57] But the size of picture tubes was largely irrelevant to manufacturing. Television manufacture was a process of assembly. To manufacture a larger size, one simply inserted a larger picture tube into a larger box, along with all the other necessary components which were largely independent of screen size. Aside from Utterback and Suárez's suggestion, speculation that the 21-inch set resulted in a stabilization of product standards, changes in the manufacturing process, or a shift in the competitive process is found nowhere in the literature. There is no evidence that the 21-inch set played any role in the shakeout.

As for RCA's color standard, it also was irrelevant to the shakeout. The RCA standard did not affect the design of black-and-white televisions, and color set sales remained minuscule until the 1960s. As discussed earlier in this chapter, and as seen in the industry output data of chapter four, black-and-white television, not color, was the focus of competition during the 1950s.

Possible Dominant Designs in All Four Products

A dominant design, as a set of product standards, is difficult to identify. Standards generally emerge throughout the history of a product, as illustrated by the lists in table 5.6.[58] These lists are far from complete, and indeed it is often difficult to tell what features should be declared standard because data about the percentage of unit sales that have particular features are rarely available. Furthermore, where multiple standards interact to form a dominant design, the definition of the dominant design is subjective. Rather than attempting to identify all possible dominant designs and their repercussions for firms, I use a more objective, quantifiable approach.

According to the dominant design theory, product innovation is important early in the history of a product, but with the dominant design comes a shift to process innovation. Firms try to produce the standardized product at low cost, and they are no longer concerned that changes in the product will require costly changes in production lines. To test for the predicted decrease in product innovation and increase in process innovation, I gathered either direct evidence on innovation patterns or indirect evidence on the resulting improvements to products and processes. The evidence is scattered and undoubtedly imperfect, but it nevertheless provides an objective assessment of which of the four products are likely to fit the dominant design theory.

Table 5.6. Some Product-Design Standards for the Four Products

Automobiles	Tires
gasoline-powered engines (became more common than steam & electric circa 1900-1905) one-piece cylinder block (after 1908) self-starters (1913) steering wheel on left side of dashboard (by 1914) closed bodies (1915-1920s) four-wheel hydraulic brakes (circa 1927) various safety equipment (post-WWII) some other standards: headlights, horns, heaters, rear-view mirrors, safety glass	carbon black as a coloring agent (by 1912) straightside tires & rims (1910-1930) cords in place of fabric (1912-1927) carbon black as a strengthening agent (1912 through 1920s) low-pressure balloon shape (1920s & early 1930s) synthetic rubber mixed with natural rubber (beginning in WWII) wider and flatter shape (after 1941) radial tires (1970s-1980s)
Televisions	**Penicillin**
US monochrome broadcast standards (1941) US color broadcast standards (1953) gradual convergence in picture quality and reliability some other standards: rectangular rather than round tubes, remote controls, automatic tuning, solid-state electronics, jacks for VCRs/speakers/cable boxes	pure crystalline forms developed by the end of World War II after World War II, penicillin experienced de-standardization, as new varieties of the product were developed

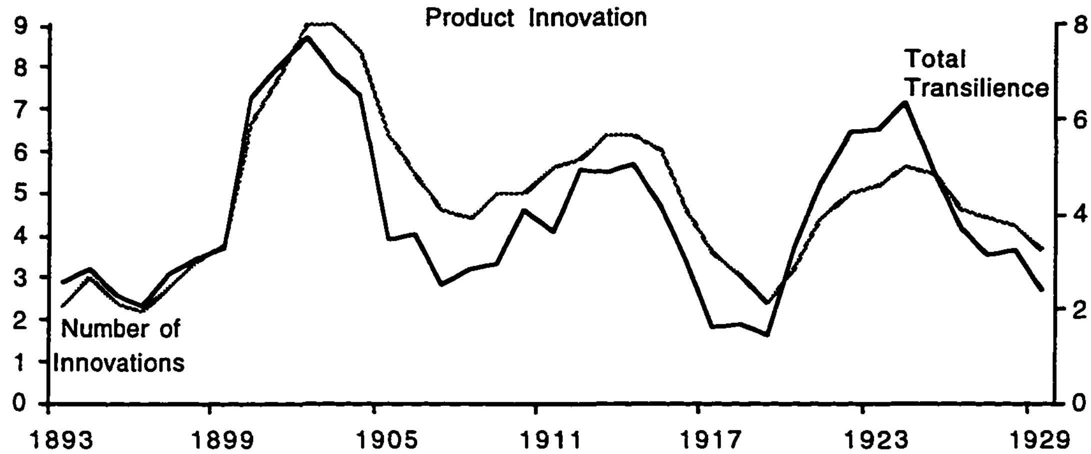
In automobiles, Abernathy, Clark, and Kantrow's (1983) list of innovations, used above in constructing tables 5.3 and 5.4, provides the richest available measures of product and process innovation as a function of time. The list can be used to generate both counts of innovations and importance rankings. Following Abernathy *et al.*, I squared the 1-7 importance rank of each innovation to estimate its "transilience," or impact on the industry, and summed across all product and process innovations in each year to come up with annual indexes of product and process innovation. I fit the following equation to each index in the years 1893-1929, which covers the pre-shakeout and shakeout eras before the Great Depression:[59]

$$Y_t = \alpha + \beta\,(t - 1893) + \gamma d \cdot (t - s) + \varepsilon,$$

where Y_t is the value of the index in year t, t is the year, s is the date of the shakeout, 1909, and d is a 0-1 dummy variable that equals 1 in all years after 1909. In addition, I fit the equation using the year 1921 instead of 1909, in case a dominant design (such as the adoption of closed bodies) might have caused the shakeout's 1921-1929 acceleration.

If process innovation increases and product innovation decreases over time during the shakeout, then $\beta + \gamma$ should be positive in the equation for process innovation and negative in the equation for product innovation. Alternatively, if the rate of growth of process innovation increases and the rate of growth of product innovation slows, then γ should be positive for process innovation and negative for product innovation. Figure 5.8 shows five-year unweighted moving averages of the raw data on product and process innovation. Table 5.7 shows the estimates of the coefficients, with standard errors in parentheses. If a dominant design caused the shakeout in automobiles, one might expect a pattern strong enough to be statistically significant. However, not only are the standard errors large compared to the estimates, but also the signs of the estimated coefficients do not fit the theory. Regardless of whether one dates the dominant design as occurring in 1909 or 1921, the estimates of γ and $(\beta + \gamma)$ are negative for both product and process innovation. The positive estimates of β suggest that both product and process innovation increased until the shakeout began, and the negative estimates of $(\beta + \gamma)$ indicate a decline in both product and process innovation after the start of the shakeout. Thus, the evidence for automobiles does not indicate the shift in innovation patterns predicted by the dominant design theory, and the estimates yield no indication of a marked rise in process innovation.

An indirect method to test for a shift in emphasis from product to process innovation is to measures changes in product quality and productivity, which presumably result from innovation. From 1899 to 1909, real value added per wage earner grew by 1.7% annually (Day and Thomas, 1928, pp. 134 and 145). The growth increased to 7.3% annually from 1909 to 1914, then slowed to -0.7% from 1914 to 1923. This trend supports the dominant design view during the period 1909 to 1914, but fails to explain why the shakeout continued after 1914. If one is willing to accept capital-labor ratios as a



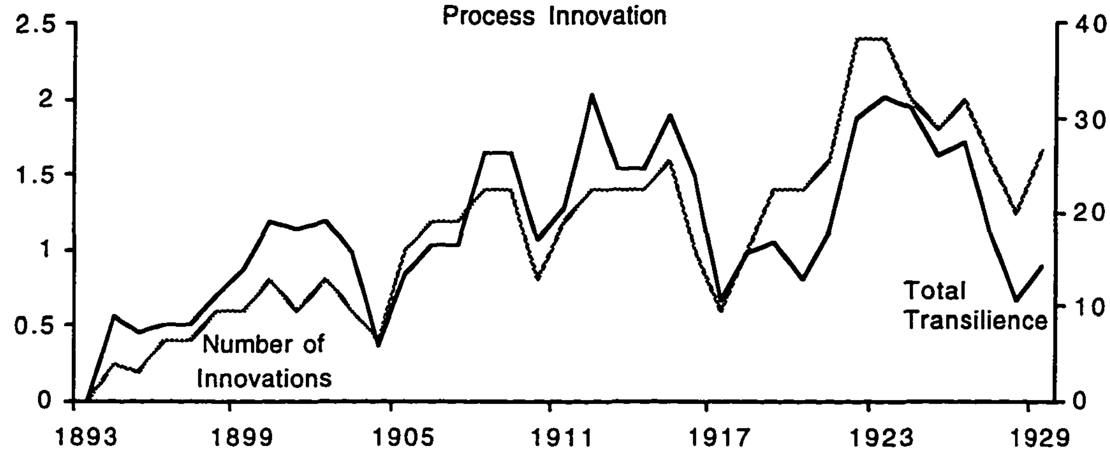


Figure 5.8. Five-year unweighted moving averages of product and process innovation for automobiles. Total transilience (black line) is the sum of squared 1-7 importance ranks of each year's innovations. Source: Based on Abernathy, Clark, and Kantrow (1987, pp. 155-179).

Table 5.7. Time trend regressions of product innovation and process innovation, 1893-1929

		Slope change in 1909		
Y_t	$\hat{\alpha}$	$\hat{\beta}$ (S.E.)	$\hat{\gamma}$ (S.E.)	$\hat{\beta}+\hat{\gamma}$
product innovations	35.44	0.61 (1.42)	-1.06 (2.14)	-0.45
process innovations	4.01	1.25 (0.89)	-1.32 (1.34)	-0.07
		Slope change in 1922		
Y_t	$\hat{\alpha}$	$\hat{\beta}$ (S.E.)	$\hat{\gamma}$ (S.E.)	$\hat{\beta}+\hat{\gamma}$
product innovations	39.14	0.10 (0.69)	-1.05 (3.46)	-0.96
process innovations	8.24	0.64 (0.44)	-1.59 (2.17)	-0.96

crude proxy for productivity, an additional source is available. Lewchuk (1987, p. 60) shows data from a Ford archive suggesting that the US motor vehicle industry's capital-labor ratio rose little from 1899 to 1909 (from $2574 per worker in 1899 down to $2007 in 1904 and up again to $2624 in 1909), but much from 1909 to 1919 (from $2624 per worker in 1909 to $3945 in 1914 and $6225 in 1919), in support of the dominant design view with a 1909 shakeout date. Thus, the direct and indirect tests for a shift from product to process innovation yield conflicting results, so that whether the automobile industry experienced the predicted shift from product to process innovation after 1909 is unclear.

For a 1921 acceleration of the shakeout, Scoville (1936, pp. 188-189) shows that labor productivity improved rapidly in the 1910s, but almost not at all in the 1920s. Katz (1970, p. 247) indicates that from 1904 to 1921 the annual growth in the capital-labor ratio in the automobile industry was 9.8%, with the growth accelerating through 1921. After 1921 the capital-labor ratio fell, remaining below its 1921 value until 1927, with an average annual growth from 1921 to 1927 of 1.9%. Changes in automobile production processes, and hence process innovation, can also be gauged by proxy series on price and vertical integration. Prices of automobiles decreased sharply until about 1920, then leveled off. Vertical integration declined in 1926-1932, to rise again in the mid-1930s, according to data from Katz (1970, p. 260). These indirect measures concur with the analysis based on Abernathy, Clark, and Kantrow's data, all contradicting the idea that a dominant design caused the acceleration of the shakeout in the 1920s.

For tires, televisions, and penicillin, extensive lists of innovations are not available. Nevertheless, in tires and penicillin crude indicator variables are available, and I use them to test the dominant design theory. In tires, tire mileage lifetime is the available measure of product innovation, and value added per man hour and tires produced per man hour are measures of process innovation. Tire mileage lifetime (miles traveled before replacement) grew by a greater rate after 1920, rising 67% between 1910 and 1920 versus 200% between 1920 and 1930 (Gaffey, 1940, p. 39).[60] Value added per man-hour grew faster before 1919, rising by 17% per year in 1914-1919 versus less than 5% per year in 1919-1931 (Gaffey, 1940, p. 77).[61] Growth in output per man hour was slightly larger after 1919, rising by 7.8% per year in 1909-1919 versus 9% per year in 1921-1929 (French, 1991, pp. 31 and 52). Thus, two of the three indicators suggest a shift from process to product innovation, the reverse of the pattern predicted by the dominant design theory, and only one indicator barely matches the predicted pattern.

In penicillin, the yield of penicillin per liter of broth rose by 16% per year in 1949-1958 versus 8% per year in 1958-1978 (Calam, 1987, p. 120). Thus, this crude measure suggests that at the time of the shakeout process innovation decreased, rather than increased. Indeed, enormous amounts of process engineering were done during World War II, at the outset of the industry. Product innovation can be measured roughly by penicillin papers and patents, since very few papers and patents involve manufacturing processes. The number of papers and patents rose steadily over time and were much greater after 1959, when semisynthetic penicillins were developed (Achilladelis, 1993). Thus, the available evidence suggests a gradual increase in product innovation and decrease in process innovation, opposite the dominant design theory.

Dominant Designs

The dominant designs proposed by Utterback and Suárez (1993) do not appear to be credible causes of the shakeouts in automobiles and televisions. However, the adoption of steel body presses may have helped to accelerate the automobile industry shakeout in the 1920s, and perhaps the advent of closed rather than open steel bodies created a dominant design that broadened the use of steel body presses. Crude tests for a shift from mostly product to mostly process innovation at the time of each shakeout, carried out in all the products except televisions, in most cases contradict the dominant design theory. Thus, while there is possible evidence of a dominant design accelerating a shakeout that was already ongoing, there is no evidence that dominant designs caused the shakeouts.

Size and Skill

In contrast to the preceding theories, the size-and-skill theory does not focus on any single detectable innovation. Instead, the theory involves a gradual process driven by an advantage to larger firms. The theory assumes that substantial portions of firms' R&D costs remain constant regardless of output size, so that larger firms achieve lower per-unit costs than small firms. The "R&D" efforts spread over a firm's output might include laboratory work; improvements in design, use, and layout of machinery; production scheduling and employee management; sourcing decisions; investigation of possible capital machinery purchases; and absorption of knowledge about innovation outside the firm.[62] Measures of spreadable R&D are not available,[63] but descriptions of research and engineering in the four products concur that most R&D projects, once complete, could be applied across multiple production lines, allowing per-unit costs of R&D to fall with firm size.[64]

The theory predicts that larger firms, given the incentive of lower per-unit R&D costs, innovate more than smaller firms and hence gain further competitive advantage. The prediction is borne out in the history of the four products. In automobiles, Ford's early leadership came from a car that used novel product innovations to outperform and outcompete others of its time, and its continuing leadership came from process innovation (Nevins and Hill, 1954; Hounshell, 1984). In the 1920s, General Motors captured the highest market share by emulating Ford's process innovations while remaining attentive to new developments in product design (Raff, 1991).[65] In tires, the industry's Akron-based leaders, Goodrich, Goodyear, and Firestone, had labor productivities about 30% greater than the national average, achieving the industry's lowest labor costs despite paying higher wages (Gaffey, 1940, pp. 154-156). In televisions, empirical studies of competitive strategy and survival in the black-and-white and color eras indicate that the largest firms innovated more and achieved the highest quality, which were the key correlates of firm survival (Datta, 1971; Willard, 1982). In penicillin, the World War II pioneers of penicillin manufacturing processes began and remained as the largest producers, and the leading antibiotics manufacturers dominated the development of lucrative new forms of penicillin (US Tariff Commission, 1945-1991; Federal Trade Commission, 1958, pp. 89-95 and 107-109). Thus, in all four products the largest firms were leaders in product and process innovation.

The theory predicts that large firms have an advantage and an incentive to innovate especially for process innovation, and in automobiles—the only product for which relevant data are available—this predicted pattern is precisely what the data show. Abernathy, Clark, and Kantrow's (1983) list of innovations shows an innovative leadership of large firms especially for process innovation. During 1893-1910, 1911-1921, and 1922-1929, the pre-shakeout, shakeout, and accelerated shakeout eras, Ford and GM together accounted for 8%, 14%, and 31% respectively of the industry's product innovations, but 50%, 64%, and 87% of process innovations.

According to the size-and-skill theory, not only do larger firms innovate more, but also they thereby achieve greater productivity than smaller firms. The size-productivity relationship can be tested in automobiles and tires. An unusual government report shows the relationship between plant size and value added per labor hour in 1935 and 1937 (US Bureaus of the Census and Labor Statistics, 1938, 1939). Because of the wide range of sizes involved, plant size and firm size are almost perfectly correlated. In 1935, motor vehicle plants with 1 to 5 workers had $1.29 of value added per wage-earner hour, versus $2.06 for plants with at least 2,501 workers (table 5.8). Between these two categories, value added increased almost monotonically with plant size. A similar pattern occurred for motor vehicles in 1937, except that plants with fewer than 20 employees managed to do even better than plants with 101 to 500 employees, though not as well as larger plants. In tires and tubes, value added per wage earner hour increased monotonically in 1935, and almost monotonically in 1937. Correcting for differences in payrolls makes little difference

Table 5.8. Value added per wage-earner man-hour, by plant size

	Automobiles*		Tires**	
Wage earners	1935	1937	1935	1937
1 to 5	$1.29	$1.87		
6 to 20	1.61		$1.02	
21 to 50	1.80	1.49		$1.43
51 to 100	1.38	1.79	1.44	
101 to 500	1.84	1.63		1.67
501 to 2,500	1.91	2.16	1.80	2.13
2,501 & over	2.06	2.03	2.04	2.02

*Motor vehicles, not including motorcycles
**Rubber tires and inner tubes
Source: U.S. Bureaus of the Census and of Labor Statistics (1938, pp. 30, 40; 1939, pp. 50, 75).

Table 5.9. Value added less wages and salaries per wage-earner man-hour, by plant size

	Automobiles*		Tires**	
Wage earners	1935	1937	1935	1937
1 to 5	$ .05	$ .72		
6 to 20	.50		$ .35	
21 to 50	.81	.59		$ .66
51 to 100	.44	.68	.58	
101 to 500	.95	.66		.84
501 to 2,500	1.08	1.14	.90	1.16
2,501 & over	1.18	.97	.92	.64

*Motor vehicles. not including motorcycles
**Rubber tires and inner tubes
Source: U.S. Bureaus of the Census and of Labor Statistics (1938, pp. 30, 40; 1939, pp. 50, 75).

in the conclusions (table 5.9). In motor vehicles, the corrected value added per wage earner hour rose almost monotonically with plant size in 1935 and 1937, except that the smallest plants in 1937 did better than firms with up to 500 employees. In tires and tubes the increase was monotonic in 1935, and in 1937 monotonic except for the largest plants, which scored slightly below plants with 21 to 100 employees. The fallback of the largest tire plants in 1937 probably resulted from strikes that paralyzed the industry's large Akron plants (Nelson, 1988, p. 214). While not surprisingly the data contain considerable noise, they fall close to the monotonic pattern predicted by the size-and-skill theory. Thus, both innovation patterns and productivity-size relationships conformed to the size-and-skill theory's prediction that larger firms innovate more and achieve greater manufacturing efficiency than smaller firms.

Conclusions: Technological Tests

Despite an extensive analysis of technological change in the four products, in only one product did the evidence suggest a plausible refinement invention. While the Banbury mixer apparently did not trigger the tire industry's shakeout as proposed by Jovanovic and MacDonald (1994b), another invention, the drum tire-building machine, may have caused or contributed to the shakeout. Similarly, dominant designs proposed by Utterback and Suárez (1993) for automobiles and tires turn out to be implausible candidates for causes of those industries' shakeouts. While steel body presses might have accelerated the shakeout in automobiles in the 1920s, after the shakeout had already begun, closed steel bodies may have been a consequence, rather than a cause, of the use of body presses. Data on time trends of product and process innovation also largely contradict the dominant design theory of shakeouts; rather, process innovation seems to have been important even early in each product, and the time trends in innovation are often directly opposite the predicted patterns. The size-and-skill theory's prediction that larger firms innovate more and achieve lower costs than smaller firms is consistent with what evidence is available. Larger firms were unusually innovative (in automobiles, especially for process innovation) and had especially high productivity. The next chapters test the three theories in other ways, examining patterns of entry, survival, and profits.

6

Entry

The three theories point out widely differing rationales for entry or the lack of entry. In the innovative gamble theory, firms respond to market opportunities to earn an expected profit, entering when there is a profit to be made—at the outset of the industry and again when the refinement invention makes possible the innovative gamble. In the dominant design theory, firms often break into the market by creating new product features. When the dominant design reduces opportunities to create novel features, entry slows. In the size-and-skill theory, firms enter if they have sufficient R&D-related skill to survive given the current prices in the industry. When increased competition drives down prices, firms must have more and more skill until eventually entry ceases because no entrant can earn a profit at its small initial size, no matter how skilled it may be. Thus, the theories suggest several interesting themes for empirical study.

Despite these differences, the theories' observable predictions about entry are similar. The theories all predict that entry falls around the time of a shakeout. In the innovative gamble and size-and-skill theories, entry drops to near zero. In Hopenhayn's variant of the dominant design theory, substantial entry continues. But without resorting to tests of stylizations of the models, there is no way to test whether entry falls to "near zero" versus whether "substantial" entry continues. Instead, one may ask whether entry decreased at all at the times of the four shakeouts.

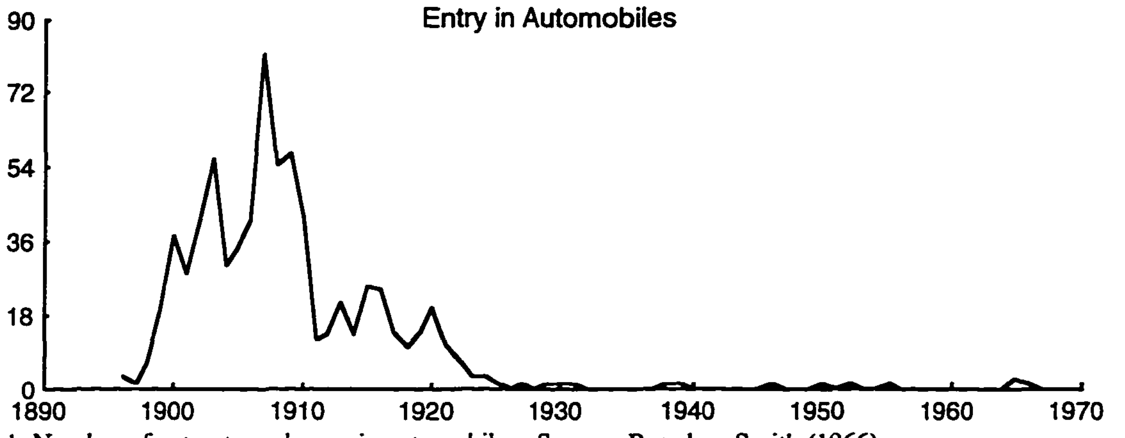


Fig. 6.1. Number of entrants each year in automobiles. Source: Based on Smith (1966).

In fact, entry did decrease at the times of the shakeouts, in accordance with the theories' mutual prediction. In automobiles, as Figure 6.1 shows, the annual number of entrants increased rapidly after the initial 4 entrants in 1895. In 1900, 37 firms entered, and by 1907 entry grew to its highest ever, with 81 entrants in one year. In the three years 1908 through 1910 there were 55, 57, and 42 entrants respectively, but in 1911 the number of entrants fell to 12. Over the period 1911 to 1921, an average of only 16 firms entered each year. After 1922 with six entrants, entry dropped off permanently to tiny amounts, with an average of one entrant per year from 1923 to 1929, and 0.3 entrant per year from 1930 to 1966.

Turning to the alternative sources of automobiles data, Thomas's (1965) more inclusive list shows a similar entry pattern, displayed in Figure 6.2. After the five initial entrants in 1895, the annual number of entrants gradually rose, reaching a peak of 92 entrants each year in 1907 and 1908. Thereafter entry fell off somewhat, averaging 30 firms each year from 1909 to 1923. Then in 1924-1929, almost no entry occurred, with an average of 0.5 entrants per year. Carroll's inclusive source shows a similar pattern, with the number of entrants rising rapidly in the late 1800s to a peak of over 300 entrants in

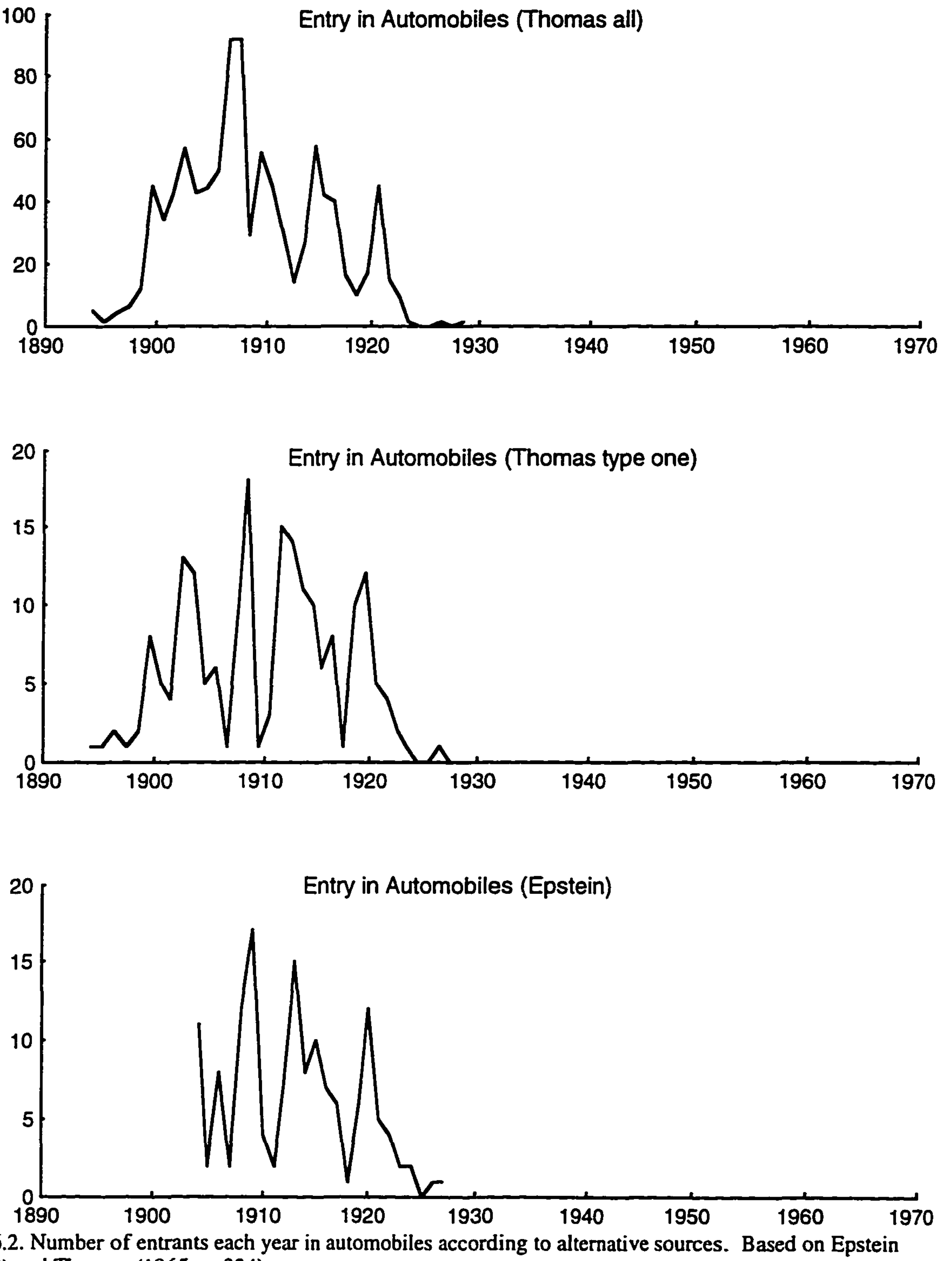


Fig. 6.2. Number of entrants each year in automobiles according to alternative sources. Based on Epstein (1928) and Thomas (1965, p. 324).

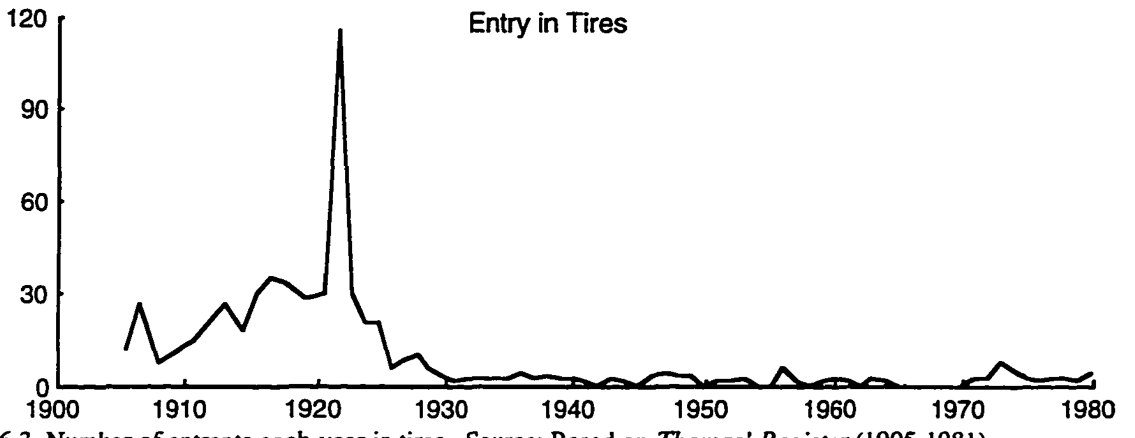


Fig. 6.3. Number of entrants each year in tires. Source: Based on *Thomas' Register* (1905-1981).

1900, dropping off temporarily, and then rising to a peak of nearly 400 entrants in 1910 (Carroll and Hannan, 1995, p. 205). After that the annual number of entrants dropped off to an average of around 240 firms per year in 1911-1914, 70 firms per year in 1916-1923, and fewer than 20 firms per year thereafter through the 1960s. The more exclusive lists by Thomas (1965) and Epstein (1928), which include much smaller numbers of firms, show substantial entry continuing from about 1900 to 1922. According to these sources, entry peaked in 1909 with 17 (Epstein) or 18 (Thomas) entrants, and by the mid-1920s fell to near zero. Thomas's exclusive list records an average of 0.3 firms per year entering in 1923-1929, and Epstein's list records an average of 1 firm per year in 1924-1927. Thus, all the sources concur that entry peaked around 1907-1910, then dropped off rapidly and reached near-zero entry starting in the mid-1920s.

In tires, the data do not cover the industry's earliest years. Automobile tires were produced starting in 1896, but *Thomas' Register of American Manufacturers*, the source of the tire industry data, began publication in 1905. Nevertheless, the data start well before the shakeout, and according to both *Thomas' Register* and other accounts the number of producers was still small as of 1905. Figure 6.3 shows the entry data for tires. Entry rose

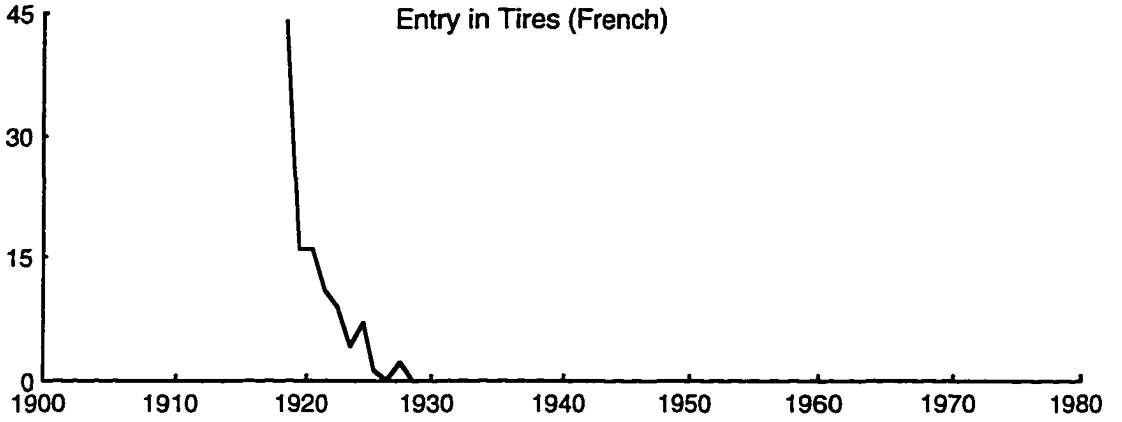


Fig. 6.4. Number of entrants each year in tires. Source: French (1986, p. 33; 1991, p. 48).

through the 1910s, reached an average of 28 firms per year during 1913-1921, and then jumped to an all-time high of 115 entrants in 1922. In 1923-1925, the annual number of entrants dropped to an average of 23 firms, and thereafter the number fell off quickly, averaging eight firms per year in 1926-1929, and two firms per year in the 1930s.

French's (1986) alternative data on tires suggest an earlier peak in the annual number of entrants. As Figure 6.4 indicates, his data show 44 entrants in 1919, with the number falling thereafter. The data include 16 entrants each year in 1920 and 1921, an average of 8 entrants each year in 1922-1925, and an average of only 0.25 entrants per year during 1926-1937. Thus, both data series on tires suggest a similar rise and fall in entry, with a possible spike of entry circa 1919-1922, and an almost complete cessation of entry starting in the mid- to late-1920s.

In televisions, as in tires, the sample begins after the start of the industry. Experimental sales in New York City began around December, 1938, but substantial commercialization did not begin until after World War II.[66] The entry data based on *Television Factbook* begin in 1949, two years before the peak in the number of firms. Seventeen firms entered in 1949, and 39 in 1950. After that, entry dropped off, with an

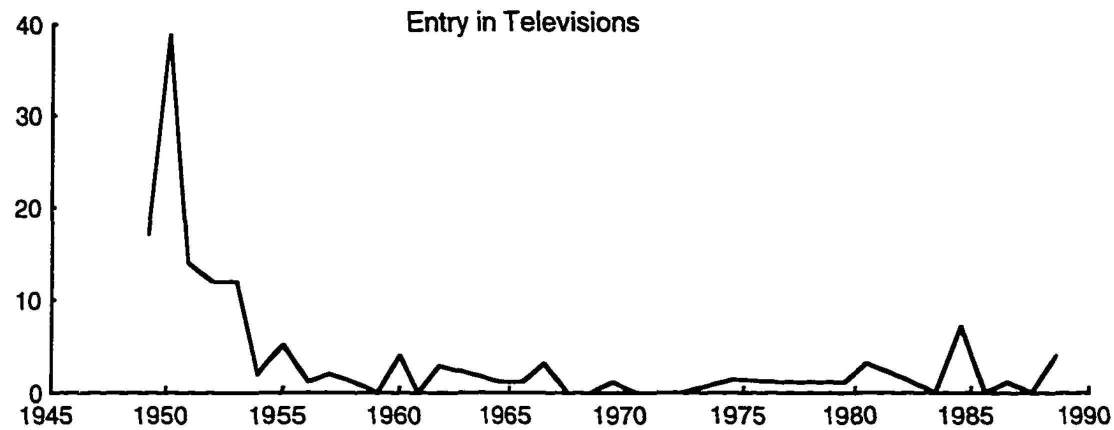


Fig. 6.5. Number of entrants each year in televisions. Source: Based on *Television Factbook* (1948-1990).

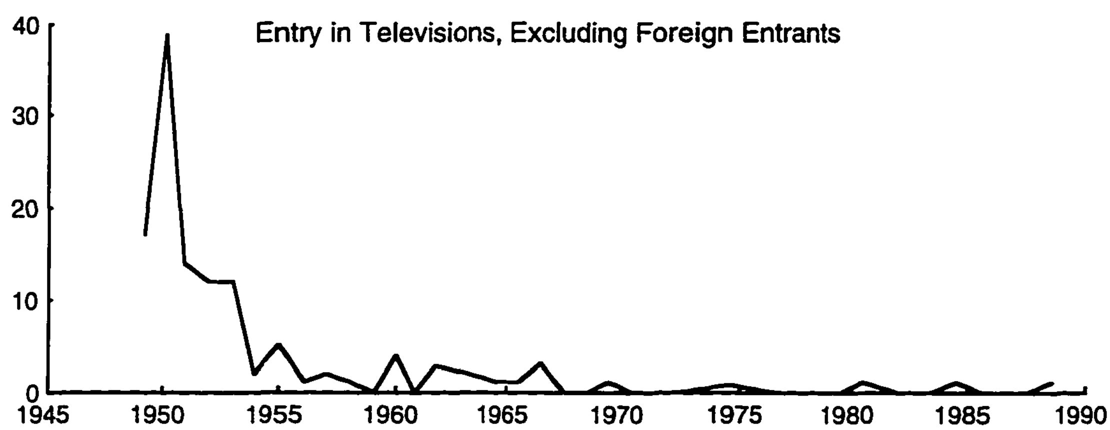


Fig. 6.6. Number of entrants each year in televisions, excluding foreign entrants. Source: Based on *Television Factbook* (1948-1990).

average of 13 firms entering each year in 1951-1953, and an average of 1.5 firms per year in 1954-1989. The entrants in the late 1970s and 1980s were mostly Japanese, Taiwanese, and European producers that had long been producing overseas, and established US manufacturing facilities. Once these entrants are excluded, the number of entrants averages 0.9 firms per year in 1954-1989, and 0.2 firms per year in 1972-1989 (Figure 6.6). Thus televisions, like automobiles and tires, experienced a dropoff in entry at the time of the shakeout and a further dropoff around a decade later.

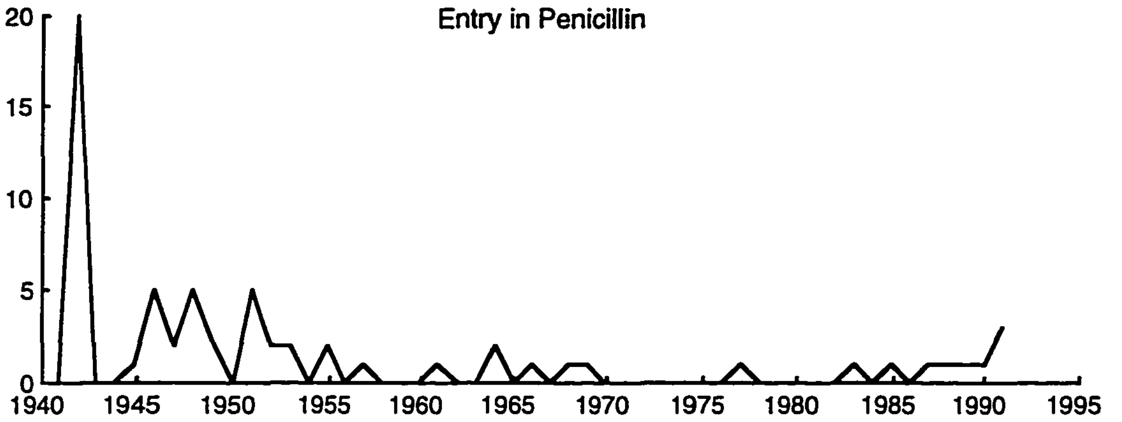


Fig. 6.7. Number of entrants each year in penicillin. Sources: *Thomas' Register of American Manufacturers* (1945-1993), US Tariff Commission (1945-1991), Federal Trade Commission (1958), and Elder (1970a).

In penicillin, most firms entered during World War II or shortly after. The combined dataset using *Thomas' Register*, *Synthetic Organic Chemicals*, and other sources shows twenty entrants during World War II. Immediately after World War II, substantial entry occurred for 6-10 years, with an average of 3 entrants per year in 1946 to 1951, and 2 entrants each year in 1952, 1953, and 1955. Thereafter, entry fell off to an average of 0.3 entrant per year in 1956-1982. An anomalous increase in entry occurred starting in 1983, with an average of 1 entrant per year from 1983 to 1992, perhaps the result of new developments in biotechnology.

All four products experienced the dropoff in entry predicted by the theories. In automobiles, tires, and televisions, entry was low initially, rose gradually to a peak around the time of the shakeout, then dropped off gradually until reaching near-zero entry rates. In penicillin, the pattern was the same except that most of the entry was compressed into a relatively brief period, during World War II and a few years afterward.[67] In tires, and to a lesser degree in the other products, the peak in entry involved a surge in the number of entrants over a period of one or a few years. In tires, *Thomas' Register* recorded 115

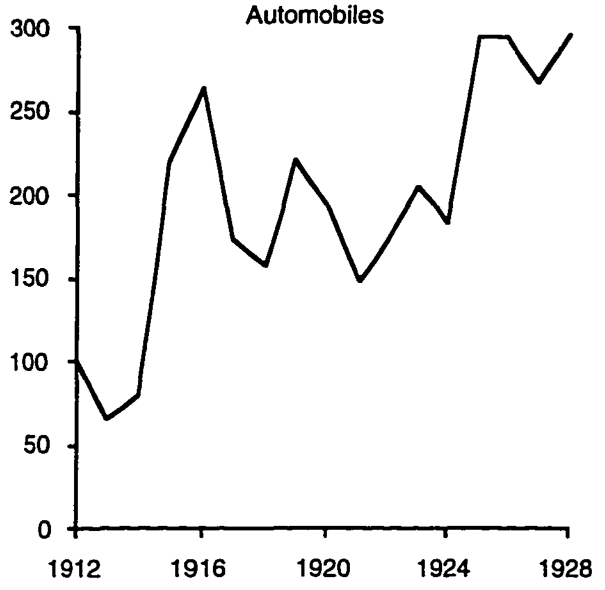


Figure 6.9. Index of stock prices plus dividends weighted by net value of firms' outstanding stock of publicly traded automobile companies excluding General Motors relative to the same index for all publicly traded companies. Constructed from data in Cowles (1934, pp. 61, 168-9, 240-2, and 460-1).

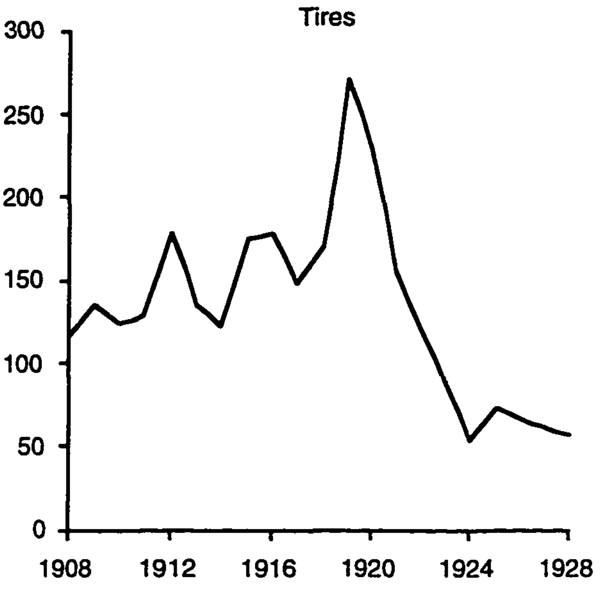


Figure 6.10. Index of stock prices plus dividends weighted by net value of firms' outstanding stock for twelve tire manufacturers relative to the same index for all publicly traded companies. Constructed from data in Cowles (1934, pp. 168-9, 202-3, and 461).

entrants in 1922, almost four times the number of entrants in any other year. Assuming these surges in entry are legitimate rather than artifactual, one might wonder why they occurred.

Many reasons for entry have been speculated upon (e.g., Geroski, 1991b), but frequently they involve high expected returns to entry. Following Jovanovic and MacDonald (1994b), I used changes in stock prices to measure the expectation of profits in automobiles and tires. In automobiles, stock price data are available beginning in 1912, as shown in Figure 6.9. The index of stock prices plus dividends for all publicly traded automobile companies other than GM relative to the same index for traded firms in all industries nearly quadrupled from 1914 to 1917. During this period, the annual number of entrants was one-third higher than in the surrounding four years. In tires, a comparable stock price index nearly doubled from 1918 to 1920 (Figure 6.10). Assuming some delay in entry or in *Thomas' Register*'s recording of information, the doubling of stock prices corresponds roughly with the quadrupling of entry in 1922.

Historians have explained the surges in expected profits (hence stock prices) and entry as a result of World War I. According to Bardou et al. (1982, p. 84), the war created an economic boom that stimulated the automobile industry. Indeed, in the two years from 1914 to 1916 output increased 182%, rising from 548,000 to 1,526,000 automobiles (Figure 4.5). Similarly tire production increased 70% in one year from 1915 to 1916, plus another 15% from 1916 to 1917. According to French (1991, p. 39), this increase in output plus the end of wartime controls on tire manufacturing in December 1918 contributed to the record number of entrants, which he dates as occurring in 1919.

The innovative gamble theory proposes an alternative reason for a surge in entry: the invention of a new technology, which creates new opportunities for profit. The surge in tire stock prices conforms to the view that the stock prices of incumbents surge at the time of a refinement invention, when incumbents are well-positioned to take advantage of the new technology. The surge of entry in tires also conforms to the view that tire firms entered to undertake an innovative gamble. However, Jovanovic and MacDonald's (1994b) assessment that the surges in tire industry stock prices and entry resulted from a refinement invention conflicts with French's explanation based on the World War I economic boom and the end of wartime controls. Indeed, historians of the industry have nowhere suggested that the surge in entry around 1919-1922 had anything to do with new technologies. While conceivably historians have been wrong to assert the importance of the post-war economic boom rather than the effects of some invention, Jovanovic and MacDonald present no evidence to support such a claim, and, not withstanding the discussion to come in the next chapter, the war-time boom seems a more appropriate explanation of the surges in stock prices and entry. Firms seem to have adopted drum tire-building machines in the mid-1920s, and there is no evidence that stockholders anticipated so far in advance the coming impact of drum tire machines.

7

Industry Aggregate Exit Rates

The shakeout theories differ in their predictions about industry-aggregate exit rates and about which firms survive. Not surprisingly, most theories predict that entry goes down and exit goes up at the time of shakeouts. Yet despite that more exit and less entry is guaranteed to yield a dropoff in the number of firms, the increased exit prediction is not ubiquitous. Both the size-and-skill theory and Hopenhayn's variant of the dominant design theory do not predict a rise in firms' exit rates. In the size-and-skill theory, the exact pattern of exit depends on complex interactions among several of the theory's parameters, so that no prediction is available about whether the exit rate should increase, stay the same, or even fall at the time of the shakeout. In Hopenhayn's (1993) stylized model, the exit rate always falls during a shakeout. The model points out that if firms grow large when they innovate successfully based on a newly-dominant technology, then it is only necessary to assume a hazard rate that declines with firm size in order to get a situation where the exit rate falls during the shakeout. With a higher fraction of large firms remaining after some firms have innovated, the industry's overall exit rate falls.

In contrast, in Utterback and Suárez's (1993) dominant design theory, before the dominant design firms survive especially because of competency at product innovation, but the onset of a dominant design leads to a shift in the required competitive competency. With process innovation suddenly the key to survival, many existing producers are annihilated, leaving only those incumbents, and a few entrants, that manage to succeed at process innovation. In the innovative gamble theory as well, the technological event causes a marked increase in exit rate, as firms that lose the gamble exit the industry. While other reasons for exit surely exist, they are taken to be noise compared to the sudden increase in exit (and hence in exit rate) due to the gamble. Thus, the dominant design and innovative gamble theories both predict an increase in exit rate caused by a technological event.

The theories also differ in their views about how time of entry affects firms' chances of survival. All three theories (except for Hopenhayn's variant of the dominant design theory) predict that earlier entrants have higher survival rates than later entrants. In the innovative gamble theory, entrants after the refinement invention occurs have less experience with the technology than incumbents have, and hence they have less chance to succeed at the gamble and to survive. In the dominant design theory, pre-dominant design entrants are presumed to have gained more experience in the industry than later entrants, and hence to have higher chances of survival. Whether the advantage of pre-dominant design entrants has anything to do with the dominant design, or whether it results from an advantage to earlier entry independent of the time of the dominant design, is unclear. In any case, Suárez and Utterback (1991) assert that the advantage should be especially important at young ages but should die away as firms gain age and experience. Thus, at young ages pre-dominant design entrants should have higher survival rates than post-dominant design entrants. The size-and-skill theory, in contrast, predicts that early entrants should have an advantage especially at old ages. At old ages, the earlier a firm entered, the more time it has had to grow large, and hence the more advantage it has. Because of this advantage to larger firms, the last members of each cohort of firms are forced out of the industry in reverse order of entry. Thus, earlier entrants have a higher probability of survival at old ages. Earlier entrants may or may not have a higher probability of survival at young ages (in fact, in the stochastic version of the size-and-skill theory, Klepper (1995) makes the stylized prediction that earlier entrants always have a *lower* survival rate at

Table 7.1. Predictions of the Theories Related to Exit.

	Technological Event		Advantage to Advantaged
	Innovative Gamble	Dominant Design	Size and Skill
Exit (Survival)	Hazard rate rises when the shakeout occurs. "No" exit before the shakeout.	Hazard rate rises when the shakeout occurs. (Hopenhayn: Hazard rate falls.)	No prediction.
Exit (Survival) by Firm Entry Year	Entrants just before the shakeout (just after the refinement) have a higher hazard rate than incumbents.	Especially in their first year of existence, pre-dominant design entrants have lower hazard rates. (Hopenhayn: No difference.)	At old ages, earlier entrants have lower hazard rates. At young ages, this difference is less pronounced or possibly reversed.

young ages), but the higher survival rate at old ages should always be especially pronounced. For convenience, Table 7.1 catalogues the theories' predictions about exit.

As a first step in examining how the theories contribute to an understanding of when, why, and how much exit occurred in the four products, this chapter presents industry-aggregate data on exit rates and compares the data with the theories' predictions. To see how the exit rate patterns contributed to the overall change in number of firms, and hence to the shakeout, I also include data on the numbers of firms, entrants, and exitors in each year. Since exit rates are subject to considerable noise, I present a five-year moving average of exit rates in addition to the raw numbers.

Exit and the Shakeout

Figure 7.1 shows the data for automobiles. The exit rate and its moving average appear in the top panel of the graph. That panel shows exit rates going from 0 to 33% of firms exiting per year, for the years 1893 to 1968. According to the data, the exit rate was exactly zero up to 1899, but then climbed to an average of 15% per year during the first decade of the 1900s. After the peak in number of firms in 1909 (bottom panel), with 274

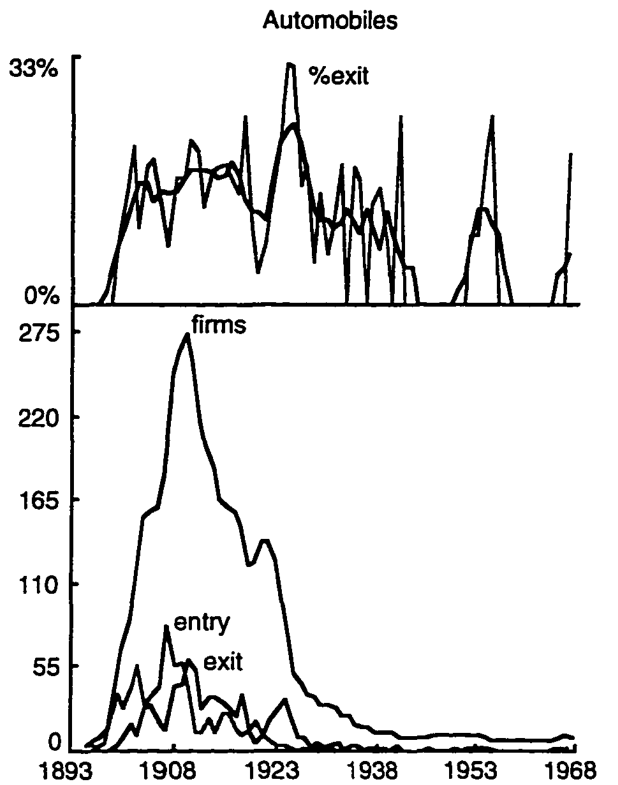


Figure 7.1. Exit rate, firms, entry, and exit in automobiles. Source: Based on Smith (1968).

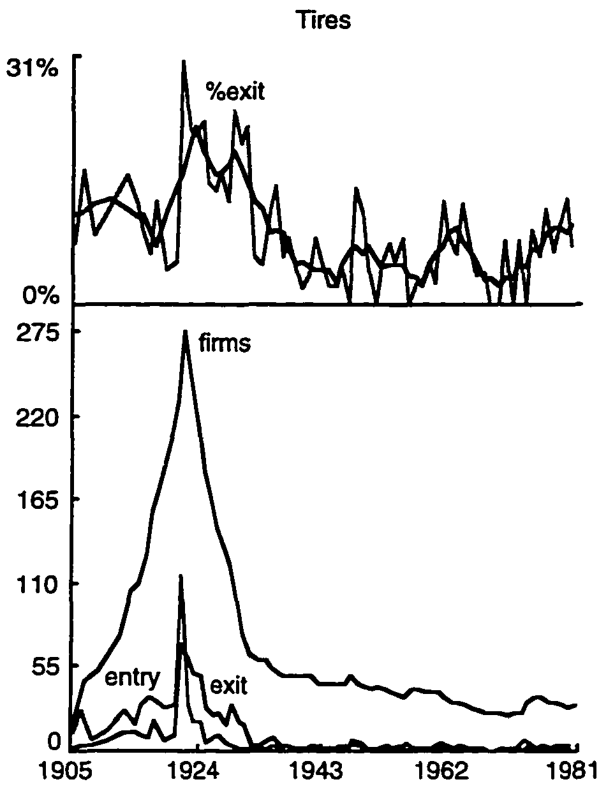


Figure 7.2. Exit rate, firms, entry, and exit in tires. Source: Based on *Thomas' Register* (1905-1981).

firms, the exit rate rose slightly to 21% during the two years after the peak (note the slight rise in the gray raw data line on the top panel of the graph), then fell back to about the same amount as before, with an average of 18% for the whole decade of the 1910s. The dips and rises in exit rate around the time of the shakeout were small compared to changes in exit rate at other times, such as the fall to 4% in 1920 and the rise to 32% in 1924-1925. The first substantial change in exit rate that lasted for an extended period occurred after 1928, with an average exit rate of 10% during 1928-1940. During and after World War II, the exit rate dropped off considerably to an average of 4% per year. Thus, if anything the exit rate in automobiles remained surprisingly flat around the time of the shakeout, and only starting in 1928 and more in 1940 did the exit rate undergo any kind of lasting change.

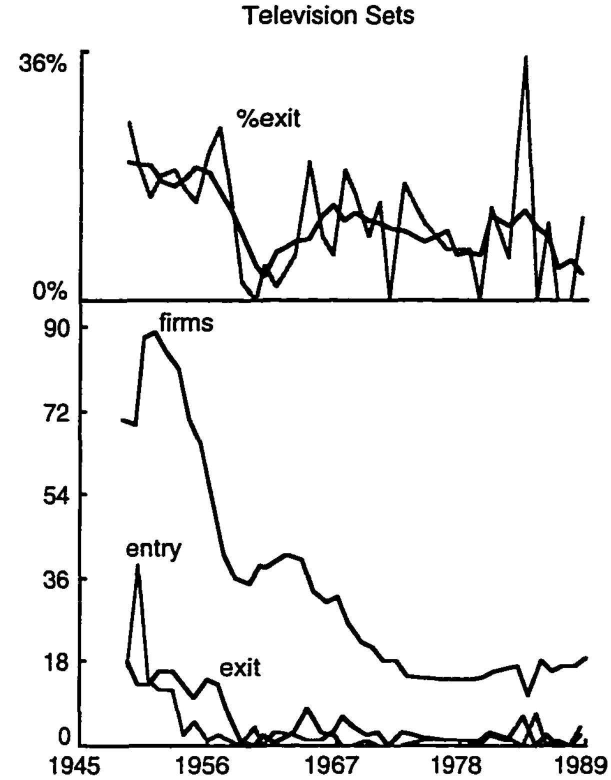


Figure 7.3. Exit rate, firms, entry, and exit in televisions. Foreign entrants into US production are excluded. Source: Based on *Television Factbook* (1948-1990).

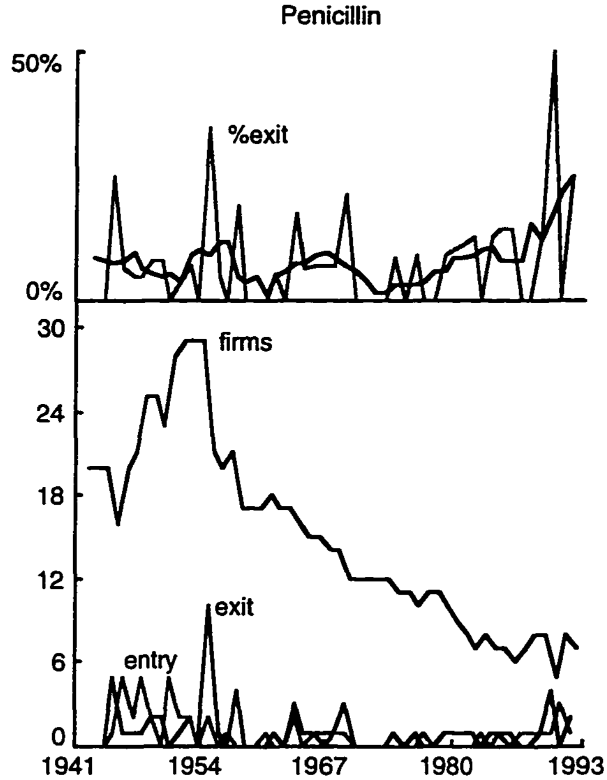


Figure 7.4. Exit rate, firms, entry, and exit in penicillin. Sources: Based on *Thomas' Register of American Manufacturers* (1945-1993), US Tariff Commission (1945-1991), Federal Trade Commission (1958), and Elder (1970a).

In tires, analyzed in Figure 7.2, a contrasting pattern occurred. The exit rate averaged 10% per year until one year before the peak number of 275 firms, then shot up to a record of 30% during the one year that preceded the peak. During the ensuing ten years the exit rate averaged 19% per year. But by 1932, the exit rate had dropped off substantially, to an average of 6% per year through 1980. Thus, in tires the exit rate rose around the time of the shakeout, as predicted by the technological event theories.

In televisions, yet another pattern occurred. As Figure 7.3 depicts, the exit rate in the three years preceding the peak in number of firms averaged 20% per year. During the shakeout, the average actually fell slightly, to an average of 18% per year in the first seven years of the shakeout and 3% per year in the next five years. In the color television era, the average picked up again starting in 1964, for an average of 13% until the end of the series in 1989. In this product, the exit rate appears to have fallen, if anything, during the shakeout.

Penicillin, like automobiles, did not experience much change in exit rate during the shakeout. Figure 7.4 shows that the exit rate averaged 5.6% per year before the shakeout began in 1955, then 6.1% per year up to 1978. Thereafter, throughout the 1980s and up to 1992, the exit rate increased, averaging 12% per year during that period.

Among all four products, tires experienced an increase in exit rate at the time of the shakeout, televisions experienced a decrease, and automobiles and penicillin had roughly constant exit rates until two decades after their shakeouts began. On the whole, the exit rates seem to have remained surprisingly steady. The exit patterns surely do not stem from a common underlying process in which exit causes shakeouts. Rather, the common pattern underlying all four products is the dropoff in entry at the time of the shakeout.

As can be seen from the bottom panels of Figures 7.1-7.4, in each product the annual number of entrants dropped off just when the number of firms began to fall. In automobiles, a further dropoff in entry occurred in the 1920s, just when the shakeout began to accelerate. It appears that the shakeouts resulted from changes in the rate of entry, not from changes in the probability of exit.

Alternative Data Sources

The conclusion that changes in entry, not the probability of exit, resulted in the shakeouts is also supported by the alternative data sources on automobiles and tires. In automobiles, Thomas's (1965) more comprehensive data depict an exit rate that remains roughly constant when the shakeout begins after 1909, going from 25% per year during 1901-1909 to 21% per year during 1909-1918 (Figure 7.5). The exit rate was higher

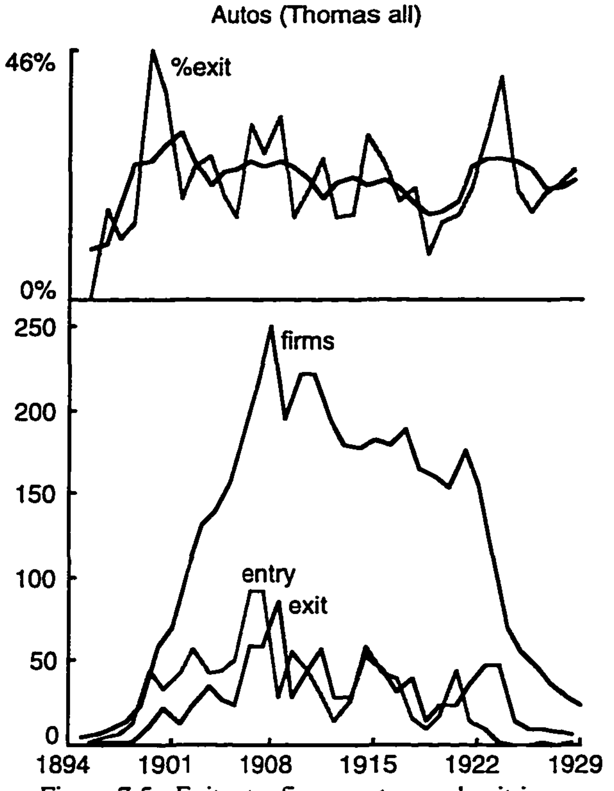


Figure 7.5. Exit rate, firms, entry, and exit in automobiles. Source: Thomas (1965, p. 324).

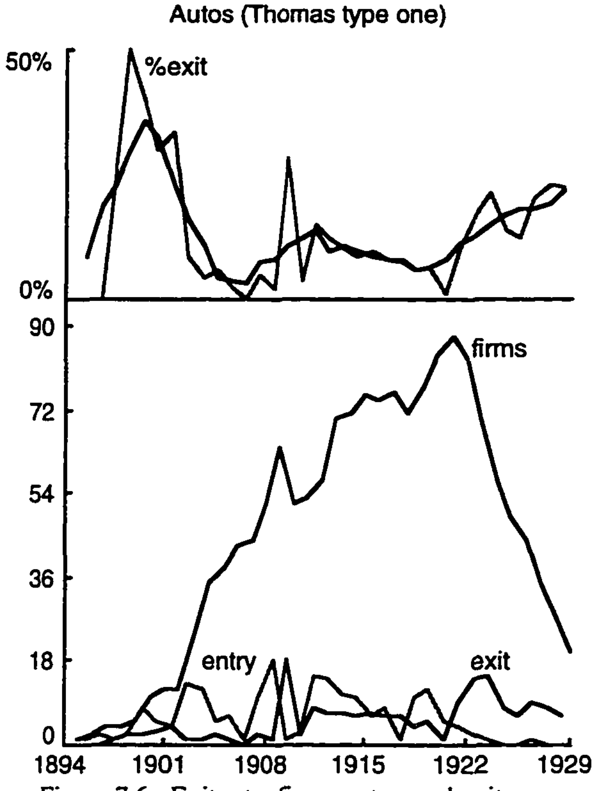


Figure 7.6. Exit rate, firms, entry, and exit in automobiles. Source: Thomas (1965, p. 324).

during 1899-1901 (42%) and lower during 1918-1921 (13%). It increased during 1922-1924 (36%) but was moderate during the rest of the 1920s (20%). According to Thomas's less comprehensive data (Figure 7.6), the exit rate was low from 1902 to the beginning of 1909 (4%), jumped up to 28% for the single year 1909, then dropped down to a moderate amount from 1910 through the end of 1921 (8%), and rose again in the rest of the 1920s (19%). Both of Thomas's series include exitors before 1900, suggesting that despite the characterization of zero exit before 1900 based on Smith (1968), the exit rate may in fact have been comparable before and after 1900. Epstein's (1928) data (Figure 7.7), much like Thomas's less inclusive data, show an increase in the exit rate to 22% during 1910 and also high exit rates during the years 1923 through 1926 (15%). In other years the exit rate

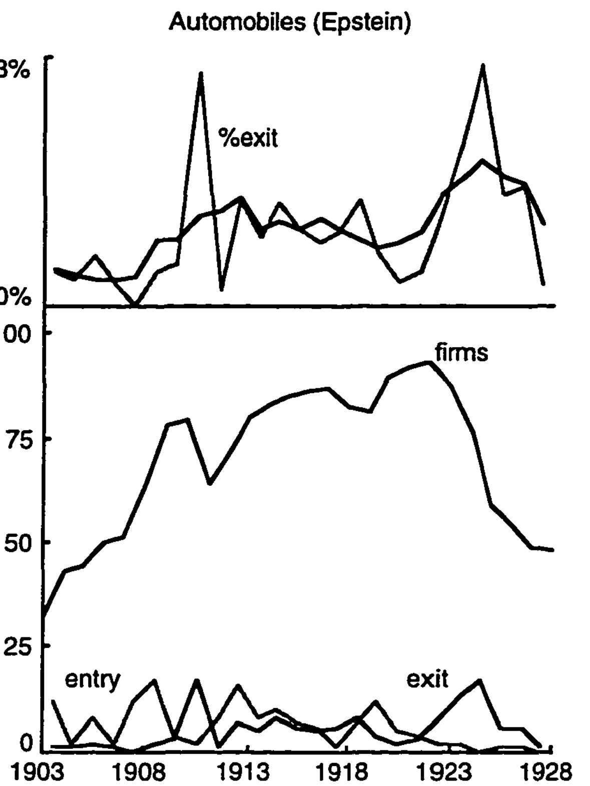


Figure 7.7. Exit rate, firms, entry, and exit in automobiles. Source: Based on Epstein (1928).

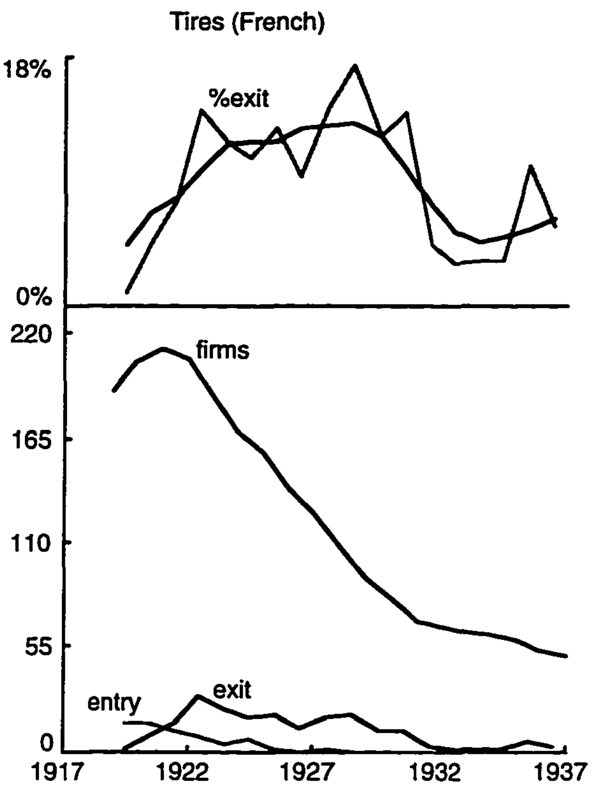


Figure 7.8. Exit rate, firms, entry, and exit in tires. Source: French (1986, p. 33; 1991, p. 48).

averaged 5%. The data compiled by Carroll show fairly constant numbers of firms and numbers of exitors from 1900 through the late 1910s, suggesting that the exit rate remained roughly constant before and after the peak in the number of firms.[68] Thus, all the sources on automobiles concur that the exit rate remained roughly constant before and after the peak number of firms, and that the exit rate increased in the mid-1920s.

In tires, French's (1986, 1991) data concur with data compiled from *Thomas' Register* to suggest that the exit rate indeed increased after the shakeout began. According to his data, the exit rate averaged 4% during the three years 1919 through 1921. Then the data show a sudden three-fold increase in exit rate, averaging 13% through the end of 1930. In 1931 through 1936 the exit rate fell to an average 6% per year. Thus, this alternative series concurs that in tires, unlike the other products, both an increase in exit rate and a decrease in entry contributed to the shakeout in the number of producers.

Types of Exit

The exit patterns discussed above result from the combination of three different types of exit: permanent cessation of production, temporary cessation of production, and merger. The rare phenomenon of temporary cessation of production can occur because of a decision to stop making a product followed by a reversal of the decision. For example, the J. Stevens Arm and Tool Company manufactured the Stevens-Duryea automobile from about 1902 through 1915, when the company shut down production for lack of working capital. Production resumed with a 1920 model after several former employees and two other people bought the rights to the Stevens-Duryea car and the factory in which it had been produced. However, apparent cessation of production can also arise for spurious reasons, for example when a company moves to a new city and a trade register is slow to record the company's resumption of production in the new locale.

For the survival analyses performed in chapter nine, the few cases in which temporary cessation of production occurred are simply treated as if production had continued throughout the cessation period. This method has the advantage that it corrects any erroneous cases of cessation of production. Furthermore, it is almost a necessity because an explicit treatment of cessation and resumption of production in the statistical models to be used would enormously complicate the models and the procedures needed to estimate them.

The term "merger" is used loosely here, and includes any kind of voluntary or involuntary acquisition or combination involving two or more producers. If a firm merely changed ownership without two producers of the same product (e.g., automobiles) being combined under a single ownership structure, then the firm is treated simply as continuing its previous existence unaffected. When merger did occur, the larger of the two producers is counted as the acquiring firm, regardless of which firm actually did the acquisition. For example, William C. Durant in 1915 used Chevrolet as a shell company to regain control of General Motors, which he had created in 1908 and lost control of in 1910, but it would be silly to say that General Motors had been absorbed into Chevrolet. Rather, Chevrolet was absorbed into General Motors and became one of its many divisions. Thus, in 1910 Chevrolet is treated as exiting by merger.

In the case of Chevrolet it is easy to know that this division continued to exist to the present, but in most instances it is unknown (unless one decided to do considerably more work on this aspect of the data) what happened to the merged firm after it was absorbed, so it is not possible to treat the merged firm as continuing until some specific date, such as when its division was closed down. Furthermore, merged firms generally appear to have been in questionable financial health at the time of the merger, suggesting that they are likely to have exited even if they were not absorbed. Nevertheless, I test the sensitivity of conclusions to the treatment of mergers in the case of automobiles, using the extreme opposite assumption that the merged firms continued their existence as independent divisions until the exit of the entire absorbing firm and of all firms that absorbed it in turn. Figure 7.9 compares the exit rate, number of firms, and annual numbers of entrants and exitors for automobiles under the usual treatment of merger and under this extreme assumption. The usual treatment and the adjusted treatment yield almost identical patterns. Regardless of how mergers are treated, the annual exit rate was roughly constant before and after the shakeout began. The overwhelming impression is still that the shakeout resulted not from a change in exit rate, but from the cessation of entry. In the adjusted treatment, the exit rate appears to be lower than in the unadjusted version starting in the late 1920s, since the fraction of exit that occurred by merger was substantial during those years but quite small in earlier years.

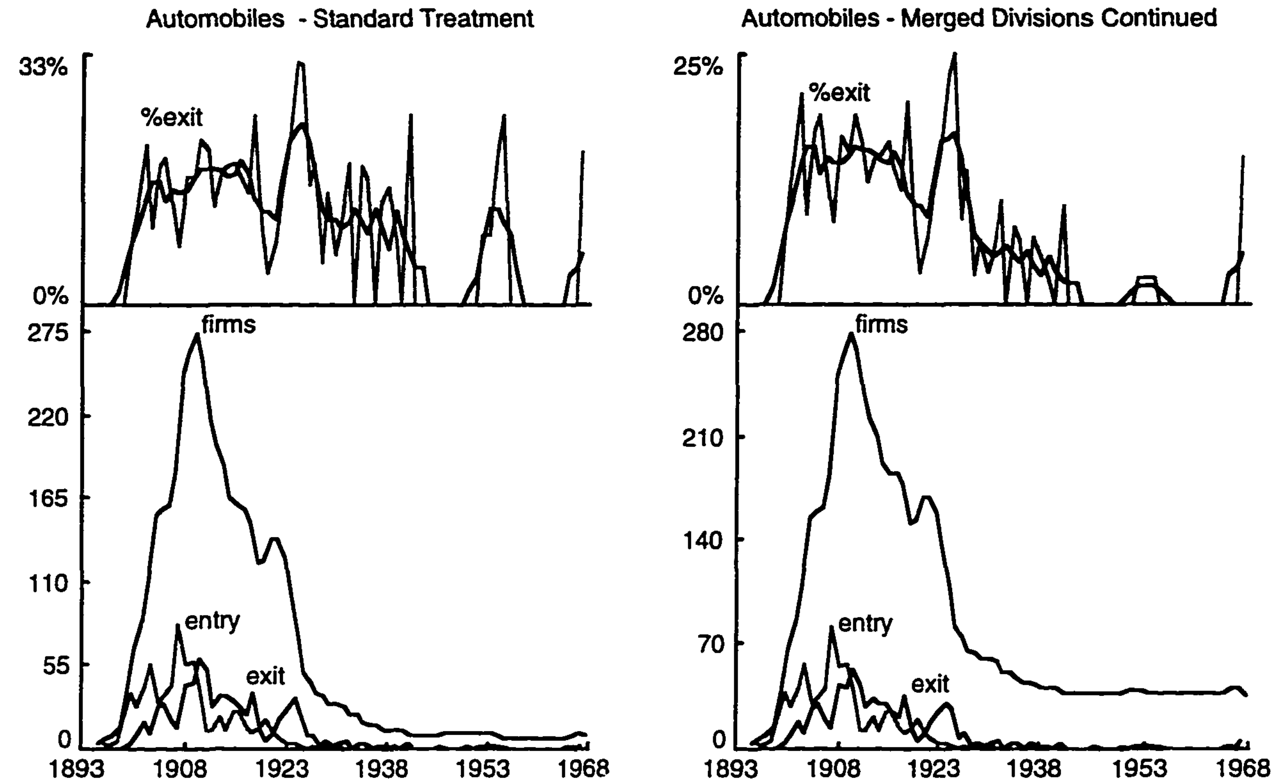


Figure 7.9. A comparison of two different treatments of mergers in the automobile industry. Source: Based on Smith (1968). Merger information was sometimes augmented using Kimes and Clark (1989) and Gunnell (1992).

Mergers tended to involve older firms that entered early, as shown in Table 7.2. In tires and television sets, the average entry dates of firms that merged were six and two years earlier than the average entry dates of firms that exited by ceasing production, and in automobiles the average entry dates were almost identical between the two groups. In all three products, the average age at merger was substantially higher than the average age at cessation of production, with a difference of two years in automobiles, seventeen years in tires, and twelve years in televisions. Because mergers involved older firms that entered earlier, the treatment of mergers as equivalent with permanent cession of production biases the empirical results against the size-and-skill theory. In an alternative treatment in which

Table 7.2. Average Entry Dates and Ages for Mergers versus Permanent Cessation of Production.

		Type of Exit: Permanent Cessation of Production	Merger
	Automobiles	1908.3	1908.6
Avg. Entry Date	Tires	1921.1	1915.0
	Televisions	1951.4	1949.5
	Automobiles	5.95	8.15
Avg. Age at Death	Tires	6.76	23.79
	Televisions	6.30	18.15

firms that exit by merger were said to survive beyond the date of merger, the merged firms would appear to have longer lifetimes. This would decrease the exit rate especially for early entrants at old ages, changing the empirical results exactly in the direction that supports the size-and-skill theory, suggesting a greater pattern of advantage to the advantaged.

Furthermore, it can be seen from Figure 7.10 that the statistical effects of choosing an alternative treatment of mergers are likely to be limited by the small number of mergers in each product relative to the number of firms exiting by permanent cessation of production. The figure shows evidence for automobiles, tires, and television sets. Because of limited space at the bottom of each panel in the figure, the term "M." is often used to indicate merger, and "T.c." to indicate temporary cessation of production. As discussed in chapter four, data on mergers were not collected for penicillin, but Figure 7.11 shows for that product exit broken down into permanent and temporary cessation of production.

In every case but one, temporary cessation is a minor phenomenon. The sole exception is televisions, for which some 15-25% of exits in the first five years of data resulted from temporary cessation. If one were to change the treatment of temporary cessation of production so that it is not included in the exit rate calculations, the decrease in exit rate would be lessened, making the television industry have an exit rate that remained close to constant before and after the peak in number of firms.

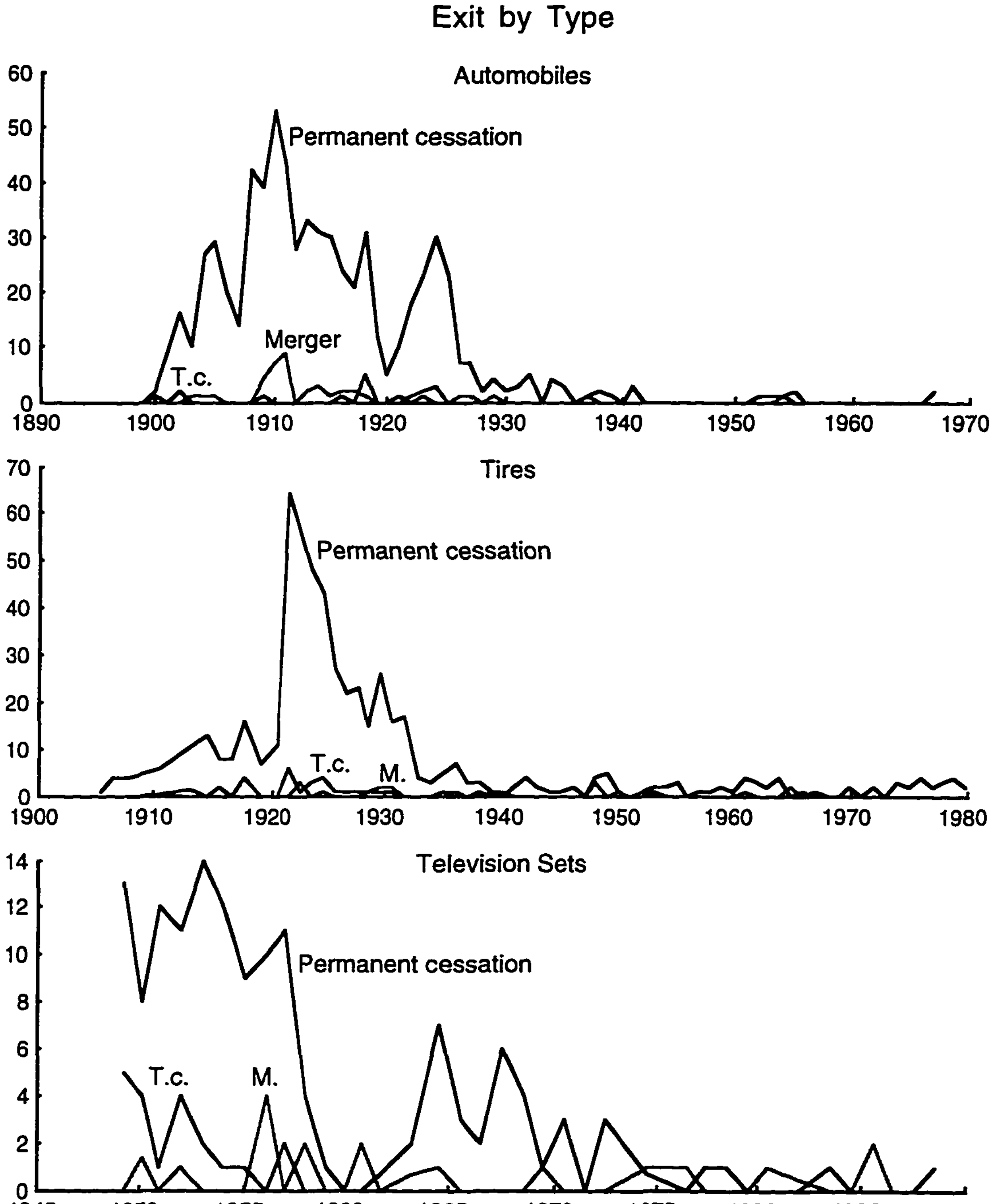


Figure 7.10. Number of exits by type in automobiles, tires, and television sets. "T.c." indicates temporary cessation of production, and "M." indicates merger.

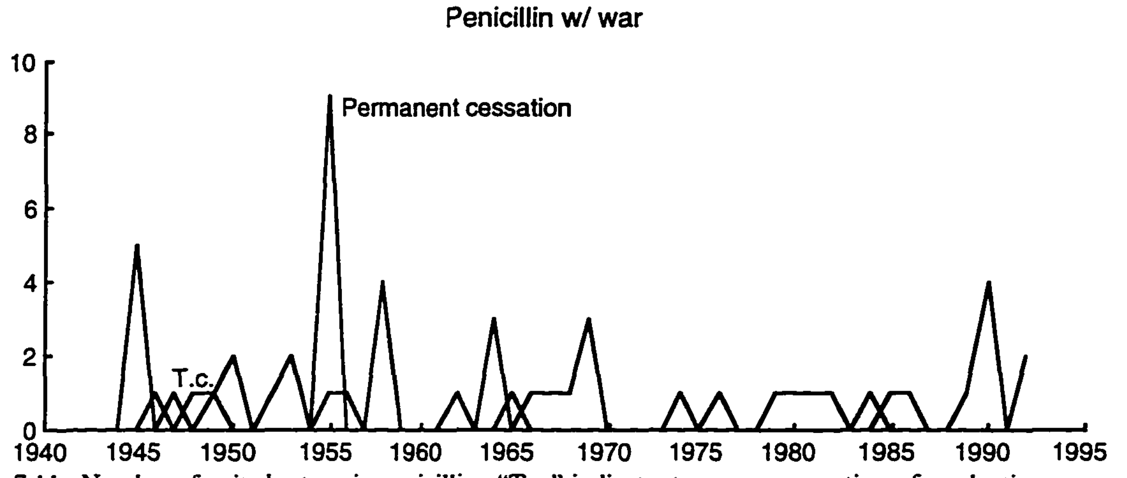


Figure 7.11. Number of exits by type in penicillin. "T.c." indicates temporary cessation of production.

Exit Rates—Conclusion

The consideration of alternative data sources and alternative treatments of merger and temporary cessation of production has done little to alter the key impressions based on Figures 7.1-7.4. Because of the treatment of mergers, the statistical tests to come may be biased against finding an advantage to early entrants at old ages. Because of the treatment of temporary cessation of production, ignoring exit by temporary cessation would lessen the apparent decrease in exit rate at the time of the shakeout in televisions. Regardless, the overwhelming impression is that exit rates did not consistently rise at the time of the shakeouts. If a technological event indeed causes an increase in exit rate at the time of a shakeout, as indicated by Utterback and Suárez (1993) and Jovanovic and MacDonald (1994b), then the only product consistent with this expected pattern is tires. Nor do exit rates consistently fall as in Hopenhayn's stylized version of the dominant design theory. Rather, a decrease in entry, not a change in the probability of exit, is the consistent reason for the shakeouts in the four products.

8

Statistical Survival Models

A more thorough investigation of the determinants of exit rates, including tests of how survival patterns relate to time of entry, requires techniques that allow explicit modeling of the exit process. These techniques must allow for the inclusion of variables such as whether a shakeout is underway, time of entry, age, and any covariates thought to be relevant as control variables. They should allow for statistical tests of significance to see whether observed patterns apparently occurred for reasons other than chance, provide tools that allow a clear understanding of what patterns are found in the data, and facilitate a comparison between fitted models and actual patterns. To examine how the theories' predictions can help explain exit patterns in the four products, I draw on a body of statistical techniques known variously as event history analysis, transition analysis, or survival analysis.[69]

Survival Analysis Models

In this body of statistics, the exit rate is known as the "hazard rate." Formally, the hazard rate $h(a, \underline{x}(t))$ is the probability that a firm will exit (at age a_d) during the next infinitesimal part da of its lifetime, given that it has survived to age a:

$$h(a, \underline{x}(t)) = \lim_{da \to 0} \frac{P[a \le a_d < a + da | a_d \ge a, \underline{x}(t)]}{da}.$$

The hazard rate is a function of age, a, and a vector of time-varying covariates, $\underline{x}(t)$. Only certain functional forms for $h(a, \underline{x}(t))$ have proven to be mathematically tractable for parametric methods, and statistical analysis requires choosing a form that is both tractable and flexible enough to accommodate the theories in question.

In proportional hazard forms, $h(a, \underline{x}(t)) = g(a)\ f(\underline{x}(t))$, so that a function of covariates multiplies a baseline function of age. $f(\underline{x}(t))$ is generally represented as $f(\underline{x}(t)) = \exp(\underline{\lambda}'\underline{x}(t))$, a convenient and flexible form that ensures a nonnegative hazard.[70] For g(a), forms that are tractable and make interpretation of results practical yield the exponential and Gompertz models as well as a variant of the Weibull model:

Exponential: $h(a, \underline{x}(t)) = \gamma \exp(\underline{\lambda}'\underline{x}(t))$.

Gompertz: $h(a, \underline{x}(t)) = \exp(\gamma a)\ \exp(\underline{\lambda}'\underline{x}(t))$.

Weibull variant: $h(a, \underline{x}(t)) = a^{\gamma} \exp(\underline{\lambda}'\underline{x}(t))$.

The Weibull model is normally written as $(\gamma + 1)\ a^{\gamma} \exp(\underline{\lambda}'\underline{x}(t))$, but for purposes of this research the above form is just as tractable and facilitates a clearer interpretation of results. Another approach, Cox's partial likelihood estimation method, is often used to allow $\underline{\lambda}$ to be estimated without specifying g(a). However, the partial likelihood approach is abandoned here because it is intractable with datasets in which many firms exit simultaneously.[71]

In non-proportional forms, the effects of the x-variables are different at different ages. The empirical tests will require such forms, for example to analyze whether earlier entrants have higher survival rates at young versus old ages. Furthermore, the empirical tests require a model in which x-variables can have both an effect that multiplies the hazard independent of age and an effect that changes with age (both proportional and non-proportional effects). While many statistical survival models include a non-proportional hazard, commonly used statistical models do not allow these two kinds of effects to be separated. The exception is a body of techniques that closely approximate true continuous survival models by using logistic regressions. The logistic regression approaches have many advantages, among them the ease with which time-varying independent variables and interval censoring can be incorporated into analyses. Unfortunately, they also suffer from disadvantages, including the fact that with interval censoring—ages of death known only to within a continuous range of values—they cannot properly account for intervals of varying length. Given the disadvantages, I decided to forgo the commonly used approaches and instead developed models based on the Gompertz and Weibull forms given above by incorporating additional independent variables into the constant parameter γ:

Gompertz: $h(a, \underline{x}(t)) = \exp(\underline{\gamma}' \underline{x}_\gamma(t)\, a)\ \exp(\underline{\lambda}' \underline{x}_\lambda(t))$.

Weibull variant: $h(a, \underline{x}(t)) = a^{\underline{\gamma}' \underline{x}_\gamma(t)} \exp(\underline{\lambda}' \underline{x}(t))$.

I developed new statistical software, as described later in this chapter, to make it possible to analyze these models.

To understand the form of these models, it is useful to rewrite them, using the identity $e^{k \log Z} = Z^k$ for the Weibull-variant model, as:

Gompertz: $h(a, \underline{x}(t)) = e^{\lambda_0}\, e^{\gamma_0 a}\, e^{\underline{\lambda}_+' \underline{x}_{\lambda+}(t)}\, e^{\underline{\gamma}_+' \underline{x}_{\gamma+}(t)\, a}$.

Weibull variant: $h(a, \underline{x}(t)) = e^{\lambda_0}\, e^{\gamma_0 \log(a)}\, e^{\underline{\lambda}_+' \underline{x}_{\lambda+}(t)}\, e^{\underline{\gamma}_+' \underline{x}_{\gamma+}(t) \log(a)}$.

The terms $\underline{\lambda}_+$ and $\underline{x}_{\lambda+}(t)$ indicate the vectors $\underline{\lambda}$ and $\underline{x}_\lambda(t)$ without the constant terms λ_0 and 1, and the similar γ terms are defined likewise. Note that the Weibull variant model is equivalent to the Gompertz model with log(a) substituted for a. The first term in each model, e^{λ_0}, is constant. The term $e^{\gamma_0 f(a)}$, $f(a) = a$ for the Gompertz model and $f(a) = \log a$ for the Weibull-variant model, allows the hazard rate to decline (if $\gamma_0 < 0$) or increase (if $\gamma_0 > 0$) with age even without any change in the x-variables. The term $e^{\underline{\lambda}_+' \underline{x}_{\lambda+}(t)}$ allows x-variables to have an effect on the hazard that is independent of age. And the term $e^{\underline{\gamma}_+' \underline{x}_{\gamma+}(t)\, f(a)}$ allows x-variables to have an effect that grows stronger or weaker as age increases. Any of these terms can be left out of the models by setting the parameter values to zero. For example, later in this chapter a piecewise constant function of age will be substituted in place of the terms $e^{\lambda_0}\, e^{\gamma_0 f(a)}$, using $\lambda_0 = 0$ and $\gamma_0 = 0$.

The different forms of age-dependence in the Gompertz and Weibull variant models yield different functional forms for the effect of $\gamma_0 + \underline{\gamma}_+' \underline{x}_{\gamma+}(t)$ on the hazard rate. In each

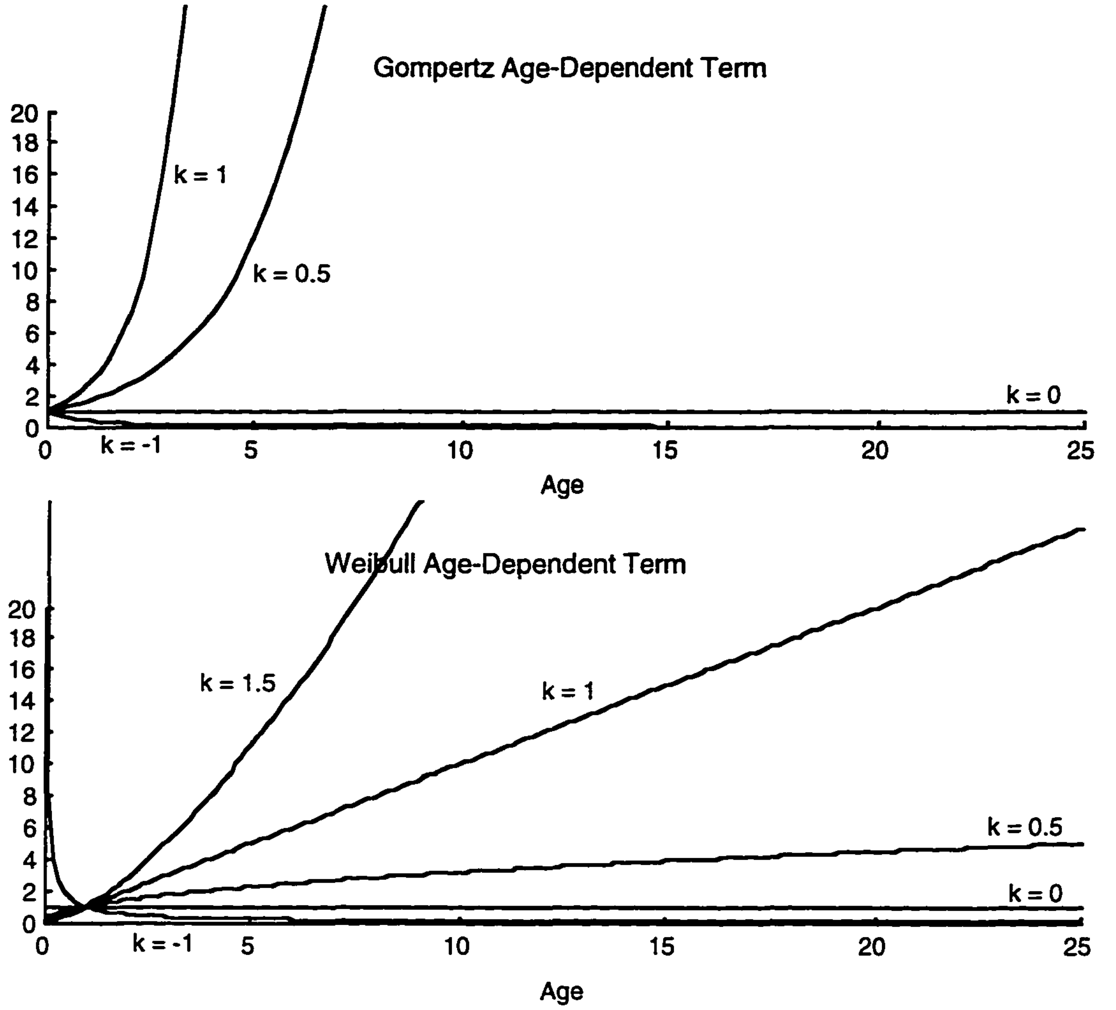


Figure 8.1. The effect on the hazard resulting from the age-dependent terms of the Gompertz and Weibull-variant models.

case, the hazard rate equals an age-independent term times the age-dependent term. When $\gamma_0 + \underline{\gamma}_+' \underline{x}_{\gamma+}(t)$ equals zero, the age-dependent term is just the exponent of zero, or one, and the hazard is equal to the age-independent term alone. When $\gamma_0 + \underline{\gamma}_+' \underline{x}_{\gamma+}(t)$ is positive, the age-dependent term increases either exponentially with age (in the Gompertz model) or with a power of age (in the Weibull-variant model). When $\gamma_0 + \underline{\gamma}_+' \underline{x}_{\gamma+}(t)$ is negative, the age-dependent term decreases similarly.

Figure 8.1 illustrates the possible functional forms using different values of $k = \gamma_0 + \underline{\gamma}_+' \underline{x}_{\gamma+}(t)$ for each of the two models. For positive values of k, the Weibull model allows the hazard to increase linearly with age, or to increase less rapidly at older ages. In contrast, the exponential function of the Gompertz model requires that with positive values of k, the hazard increases more and more rapidly at older ages. Similarly, with negative values of k, the dropoff in the age-dependent term is mediated by age. In the Gompertz model, the hazard continues to be halved in the same number of years regardless of whether those years are young ages or old ages. In the Weibull model, the number of years required for the age-dependent term to be halved continually increases with age. To see these relationships mathematically, consider plotting the hazards on a logarithmic scale rather than a linear scale. On this scale, the rate of change of the hazard with respect to age is:

$$\text{Gompertz:} \qquad \frac{d}{da}\log(e^{ka}) = k.$$

$$\text{Weibull variant:} \qquad \frac{d}{da}\log(a^{k}) = \frac{k}{a}.$$

Intuitively, it seems logical to expect that the effects of age, and of most independent variables interacted with age, would grow less rapidly at older ages than at younger ages, suggesting that the Weibull variant model is likely to be more appropriate than the Gompertz model. Also, previous researchers have found a better fit from the Weibull than from the Gompertz model (e.g., Hannan and Freeman, 1989, pp. 247-250, 268-270). Nevertheless, both forms will be compared against the evidence to see which seems to provide the best fit. Of the shakeout theories, only Hopenhayn (1993) specifies how the hazard rate should vary with age, yielding a complicated result for which one of the two models should provide an adequate first approximation.[72]

Representation of the Theories

Each of the three shakeout theories can be formulated in terms of the Gompertz and Weibull-variant models specified above. Since which model is most appropriate depends on which function of age seems to best fit the empirical facts, the function of age used in

Table 8.1. Terminology Used in Constructing the Hazard Models.

$h(a, \underline{x}(t))$	hazard rate	t_r	time of refinement invention
a	age of firm	t_p	time of peak number of firms
t	time (that is, the date, e.g. 1927)	Δ	when t_r is unknown, $t_r = t_p + \Delta$, where Δ is varied to probe the sensitivity of the results
$\underline{x}(t)$	vector of time-varying covariates	s	shakeout dummy (= 1 once the shakeout has begun, 0 before)
$\underline{x}_\lambda(t)$	subset of $\underline{x}$ that has an effect on the hazard independent of age	er	entry after refinement dummy (= 1 for firms that enter after the refinement, 0 for other firms)
$\underline{x}_\gamma(t)$	subset of $\underline{x}$ that interacts with age to affect the hazard	es	entry after shakeout dummy (= 1 for firms entering after the peak number of firms, 0 for others)
$\underline{x}_c(t)$	control variables subset of $\underline{x}_\lambda$	ey	entry year (date) of firm
$\underline{x}_{\lambda+}(t)$	subset of $\underline{x}_\lambda$ that does not include the constant term 1	tr	time since refinement (= a - ar)
$\underline{x}_{\gamma+}(t)$	subset of $\underline{x}_\gamma$ that does not include the constant term 1	ts	time since shakeout began (= a - as)
λ_0	log hazard rate when $a = 0$ and $\underline{x} = \underline{0}$	ar	age of firm at time of refinement
γ_0	first element of $\underline{\gamma}$	as	age of firm when shakeout began
$\underline{\lambda}$	vector of coefficients of $\underline{x}_1(t)$		
$\underline{\gamma}$	vector of coefficients of $\underline{x}_2(t)\, f(a)$		
$\underline{\lambda}_c$	vector of coefficients of $\underline{x}_c(t)$		

the age-dependent term will be denoted simply as $f(a)$, allowing for either the Gompertz form ($f(a) = a$) or the Weibull form ($f(a) = \log a$). Each model will be specified and tested in turn.

Innovative Gamble

In testing empirically the innovative gamble theory of Jovanovic and MacDonald (1994b), the date of any refinement invention, t_r, is unobserved. However, the refinement can be detected by its ensuing surge of entry. If a surge of entry precedes the shakeout, I will use the date of the surge for t_r. If no distinctive surge occurs, I will experiment with possible refinement dates t_r by choosing $t_r = t_p \pm \Delta$, where t_p is the date of the peak number of firms and Δ will be assigned different values, including 0, to probe the sensitivity of the results to choice of Δ.[73] (Table 8.1 catalogues terminology used in representing the theories.)

In the theory, the hazard rate for incumbents rises after the refinement, not necessarily immediately but rather when the shakeout begins. Also, the hazard during the shakeout is higher for post-refinement entrants than for incumbents. Let s = 1 if the time t is after the peak in number of firms ($t > t_p$), and s = 0 otherwise. Let er = 1 for entrants after the refinement (after t_p), and er = 0 otherwise. To capture the greater hazard of incumbents during the shakeout and the greater hazard of post-refinement entrants than incumbents, s and er are included in $\underline{x}_\lambda$, and each should have a positive coefficient.

The effects of the refinement decline eventually, as only successful innovators are left surviving. Define ts as the time since the refinement. To capture a declining effect of the refinement, allowing the hazard to fall back to normal after the wave of exit by firms that fail at the innovative gamble, $s \cdot ts$ is included in the model. If as predicted the hazard eventually falls back to normal, the coefficient of $s \cdot ts$ should be negative.

Furthermore, the effects of post-refinement entry decline with time since entry. Entrants initially have a disadvantage compared to incumbents, because of their lesser experience with the technology, but the disadvantage goes away once they successfully innovate based on the refinement. As the post-refinement entrants get older, they increasingly are represented by successful innovators, since unsuccessful firms exit. To capture the dwindling of the higher hazard due to post-refinement entry, $er \cdot f(a)$ is included in the model, where $f(a) = a$ in the Gompertz model or log(a) in the Weibull-variant model. If the effect of post-refinement entry eventually goes away, the coefficient of $er \cdot f(a)$ should be negative.

The model can be expressed in the form:

$$h(a, \underline{x}(t)) = \exp(\lambda_0 + \lambda_1 s + \lambda_2 er + \lambda_3 s \cdot ts + \underline{\lambda}_c{}' \underline{x}_c(t)) \exp([\gamma_0 + \gamma_1 er] f(a)),$$

where $\underline{x}_c(t)$ is a vector of any other variables that might affect the hazard rate proportionally (see below) and $\underline{\lambda}_c$ is a vector of the corresponding coefficients. Note that ts = a - as, where as is the age of the firm at time t_p. With the Gompertz model, substituting ts = a - as yields

$$h(a, \underline{x}(t)) = \exp(\lambda_0 + \lambda_1 s + \lambda_2 er - \lambda_3 s \cdot as + \underline{\lambda}_c{}' \underline{x}_c(t)) \exp([\gamma_0 + \gamma_1 er + \lambda_3] \cdot a).$$

With the Weibull-variant model, the logarithmic function $f(a)$ makes it impossible to obtain an exact representation of the model. A very close approximation is to include $s \cdot ts$ as an independent variable that remains constant over discrete time periods of about one year, using the value of ts in the middle of each period. The variable ts can be transformed using a logarithm, yielding a form that matches with the Weibull model's logarithmic age transformation. This resulting model is

$$h(a, \underline{x}(t)) = \exp(\lambda_0 + \lambda_1 s + \lambda_2 er + \lambda_3 \log(\overline{s \cdot ts}) + \underline{\lambda}_c' \underline{x}_c(t)) \exp([\gamma_0 + \gamma_1 er] \cdot \log a),$$

where $\overline{s \cdot ts}$ is the discrete approximation to $s \cdot ts$. The theory predicts that $\lambda_1 > 0$, $\lambda_2 > 0$, $\lambda_3 < 0$, and $\gamma_1 < 0$.

Dominant Design

Utterback and Suárez (1993) predict that the hazard rate rises at the time of the dominant design, when the shakeout occurs. Let s = 1 if the time t is after the peak in number of firms ($t > t_p$), and s = 0 otherwise. Let es = 1 for entrants after the shakeout begins, and es = 0 otherwise. To capture the greater hazard during the shakeout, s is included in $\underline{x}_\lambda$, and it should have a positive coefficient. To capture an effect of post-dominant design entry, es is also included, and should have a positive coefficient since the later group of entrants is presumed to have a higher hazard rate.

The effects of the dominant design might decline eventually. To capture a declining effect of the dominant design, $s \cdot ts$ is included in the model, where as before ts is the time since the shakeout began. To capture a declining effect of post-dominant design entry, $es \cdot ts$ is included in the model. If the effects decline with time since the dominant design, the coefficients of $s \cdot ts$ and $es \cdot ts$ should be negative. The effect of post-dominant design entry es should decline at old ages, since Suárez and Utterback (1991) expect the strongest effect at young ages. To capture a declining effect of post-dominant design entry, $es \cdot f(a)$ is included in the model. If es has an effect, then the coefficient of $es \cdot f(a)$ should be negative.

The resulting model is

$$h(a, \underline{x}(t)) = \exp(\lambda_0 + \lambda_1 s + \lambda_2 es + \lambda_3 s \cdot ts + \underline{\lambda}_c' \underline{x}_c(t)) \exp([\gamma_0 + \gamma_1 es] \cdot f(a)),$$

where as before $\underline{x}_c(t)$ is a vector of age-independent control variables and $\underline{\lambda}_c$ is a vector of the corresponding coefficients. Note that ts = a - as, where as is the age of the firm at time t_p. With the Gompertz model, substituting ts = a - as yields

$$h(a, \underline{x}(t)) = \exp(\lambda_0 + \lambda_1 s + \lambda_2 es - \lambda_3 s \cdot as + \underline{\lambda}_c' \underline{x}_c(t)) \exp([\gamma_0 + \gamma_1 es + \lambda_3 s] \cdot a).$$

With the Weibull model, the discrete approximation $\overline{s \cdot ts}$ must be used in place of $s \cdot ts$, as in the innovative gamble theory. Also as before, using the logarithmic transformation of the Weibull form yields the model

$$h(a, \underline{x}(t)) = \exp(\lambda_0 + \lambda_1 s + \lambda_2 es + \lambda_3 \overline{s \cdot ts} + \underline{\lambda}_c' \underline{x}_c(t)) \exp([\gamma_0 + \gamma_1 es] \cdot \log a).$$

The theory predicts that $\lambda_1 > 0$, $\lambda_2 > 0$, $\lambda_3 < 0$, and $\gamma_1 < 0$.

Hopenhayn's (1993) variant of the dominant design theory predicts that the hazard rate falls permanently with the onset of the shakeout, yielding $\lambda_1 < 0$. This prediction relies in part on the characterization that date of entry has no influence on the hazard rate, $\lambda_2 = 0$. Hence, the alternative possibility shown by his model is the case $\lambda_1 < 0$, $\lambda_2 = 0$, $\gamma_1 = 0$, and $\gamma_2 = 0$.

Size and Skill

Klepper's (in press) theory predicts that earlier entrants have an advantage over later entrants, particularly at old ages. As the theory does not specify the form of the relationship between time of entry and the hazard, I try several different forms to test the sensitivity of the conclusions to choice of functional form. Let ey, the "entry year," denote the date at which a firm begins production of the product being studied. Let the effect of entry year at young ages enter the model via the term g(ey), and the effect at old ages be denoted via the term $g(ey) \cdot f(a)$. Since the theory provides no basis for choosing g(ey) or $f(a)$, I investigate the sensitivity of the conclusions to a range of functional forms. For $f(a)$ I use a and log(a), the Gompertz and Weibull forms of age-dependence. For g(ey), the functional forms investigated are described later in this chapter.

If the theory is correct, the advantage to earlier entrants should be particularly strong at old ages. In fact, as long as exceptional circumstances do not yield a much higher hazard rate for later entrants at young ages, the effect of entry year should increase with age. In the extreme form of Klepper's (1995) stochastic variant of his model, the advantage of early entrants always increases with age, because a stylization of the model ensures that at the youngest ages, earlier entrants actually have a higher hazard rate than later entrants. If this form of the model is in fact realistic, the coefficient of $g(ey) \cdot f(a)$ should be positive. Regardless of whether one believes this prediction of the extreme form, in every case the sum of the two terms, $\lambda_1 g(ey) + \gamma_1 g(ey) \cdot f(a)$, should yield at old ages a lower hazard rate for earlier entrants relative to later entrants (or, *vice versa*, a higher hazard rate at old ages for later entrants).

The resulting model is

$$h(a, \underline{x}(t)) = \exp(\lambda_0 + \lambda_1 g(ey) + \underline{\lambda}_c' \underline{x}_c(t)) \exp([\gamma_0 + \gamma_1 g(ey)] \cdot f(a)).$$

The theory predicts that $\gamma_1 > 0$, or at least that the values of λ_1 and γ_1 are such that the sum of terms $\lambda_1 g(ey) + \gamma_1 g(ey) \cdot f(a)$ is substantially greater than zero at old ages.

Age, Time, Entry Date, and Other Covariates

The hazard rate of each firm at each point in time depends on a complex web of interrelationships involving the characteristics of firms and potential entrants, processes of selection of fitter firms, competitive conditions, supply and demand, and other characteristics, all of which evolve over time. The three theories studied here are attempts to characterize key features of the overall complex system. In reformulating and testing the theories as hazard models, it is critical to understand how these variables may interact when placed in statistical models, and to understand how these variables relate to processes already embodied in the theories.

Age Dependence of the Hazard

A "liability of newness" (Stinchcombe, 1965) for firms has been predicted by organization theorists, explained by economists (Jovanovic, 1982) and found by organizational ecologists (e.g. Hannan and Freeman, 1989) and economists (e.g. Evans, 1987; Dunne et al., 1989). In general, the finding is that hazard rates decline roughly monotonically with age. Brüderl and Schüssler (1990) caution that the true pattern may involve a "liability of adolescence." In aggregate data on West German businesses, they find that the hazard rate has an inverted-U shape, increasing at young ages and then decreasing. While other sources have not generally confirmed an inverted-U shape, it would be wise to choose a functional form that allows for this possibility.

The reason for the lower hazard rate of old firms is not at all clear from previous empirical work. Different theories suggest different reasons for the decline in the hazard. One reason often cited is that firms change over time, either developing internal practices needed to operate effectively or gaining resources that improve their competitive fitness. In the size-and-skill theory, the size part of the theory portrays just such an accumulation of a resource, size, allowing the hazard to decline with age because older firms have had more time to grow large.

A second reason often cited for the higher survival rate of old firms is a selection process that tends to eliminate weaker firms, leaving mostly stronger firms by the time they reach old ages. In the context of statistical survival models, the selection of fitter individuals has been considered under the heading of unobserved heterogeneity, discussed later in this chapter. The size-and-skill theory makes its predictions in part by explicitly addressing unmeasured heterogeneity, since the skill part of the theory involves distributions of firms' R&D competency, which affects firms' abilities to survive. The selection process resulting from firm skill leaves behind more-skilled firms and thus tends to yield a hazard that declines with age, but the decline in the hazard is counteracted by increasing requirements for survival.

The innovative gamble and dominant design theories do not address the age dependence of hazard rates. Nevertheless, with both these theories and the size-and-skill theory, it may be that the hazard declines with age for reasons not incorporated in the theories. Therefore, it is desirable to find a way to control for unmeasured effects of age without biasing the estimates of coefficients central to the theories.

The approach most commonly used is a parametric representation of the effect of age. For example, including the constant term γ_0 in the Gompertz and Weibull-variant models allows the hazard to change either as an exponential function of age or as a power of age, as was illustrated in Figure 8.1. The models can be rewritten as follows:

$$\exp(\gamma_0 f(a))\ \exp(\lambda_0 + \underline{\lambda}'_{+}\underline{x}_{\lambda+}(t) + \underline{\gamma}'_{+}\underline{x}_{\gamma+}(t)\cdot f(a)).$$

Explicitly separating the term $\exp(\gamma_0 f(a))$ from the rest of the model helps to clarify the role of this term, in which unspecified effects on the hazard are presumed to be correlated with whatever parametric function is chosen for age. For example, the legitimacy of producers in the eyes of customers and regulators might increase as the firms grow older, yielding a lower hazard rate, as suggested by organizational ecologists. The term $\exp(\gamma_0 f(a))$ multiplies the rest of the hazard model, for example possibly causing the hazard to equal the value indicated by the rest of the model at age a_1, but to be 50% lower by age a_2. Of course, the hazard may also vary with age as a function of variables explicitly incorporated in the rest of the model.

Since there is no theoretical basis on which to assume a specific parametric form for the age-varying effect of unknown variables, it may be better to choose a much more flexible form for this term of the model. Another commonly-used approach is the Cox proportional hazards model, which makes no assumption about some "baseline" effect of age, but as discussed above the proportional hazards model is intractable given the data available in this study. An equivalent approach for data with discrete time periods is to assign each age period a dummy variable. This approach results in a piecewise constant

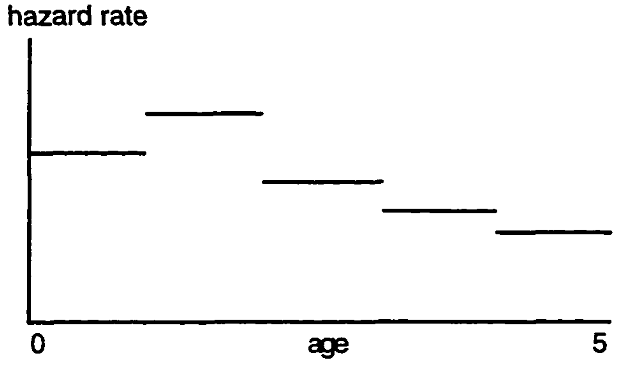


Figure 8.2. A piecewise constant baseline hazard.

baseline hazard such as that illustrated in Figure 8.2. The resulting model is termed "semiparametric" because while most of the model is specified parametrically, the age-interaction term is specified in a non-parametric manner.

This semiparametric approach of assigning a separate dummy variable to each period works well as long as sample sizes are large at all ages and as long as all firms have identical ages of interval censoring. In the data studied here, sample sizes are large at young ages but decline rapidly with age. Furthermore, the ages of interval censoring are different for different firms. For example one firm may have appeared in the 1906 and 1907 editions of *Thomas' Register* (survival from age 0 to 1) but may have disappeared by the next edition of the *Register*, published in 1909 after a one-year publication lapse (exit between ages 1 and 3), and another firm may have survived between the 1921 and 1922 editions of the *Register* (survival from age 0 to 1) but may have disappeared by the 1923 edition (exit between ages 1 and 2). In this simple example the second interval censoring period was twice as long for the first firm as for the second. With these data, there is too little information to estimate a separate dummy variable for each age at very old ages and for each fractional difference in age that results from interval censoring periods that turn out to be non-integer. Thus, a completely nonparametric approach to constructing this term of the model cannot be used, and the model cannot be specified in the manner that is called semiparametric.

Table 8.2. Age periods used for a piecewise constant baseline hazard.

Number of Firms in the Sample	Breakpoint of Age Periods
100+	0 1 2 3 4 5 6 7 8 9 10 12 14 16 18 20 30 40 ∞
50 to 99	0 1 2 3 4 5 6 8 10 12 16 20 40 ∞
30 to 49	0 2 4 6 10 15 20 ∞
10 to 29	0 5 10 ∞

However, a very close approximation is to allow the baseline hazard to vary over discrete periods that start out with a length of one year, but increase in length at older ages, depending on the sample size available. This almost-semiparametric approach is the one used to model the age-related effect of unknown variables for the statistical survival analyses carried out in this research. After two experiments with slightly more fine-grained periods, I arrived at a choice of periods that seems to yield results not unduly affected by the random fluctuations associated with small sample sizes. Table 8.2 shows the periods chosen. With a sample of at least 100 firms, a separate dummy is allowed every year from age zero to ten, every two years from age ten to twenty, and every ten years from age twenty to forty, and a single dummy variable is used thereafter. With smaller samples, dummies are chosen to cover longer periods. For example, with a sample of 40 firms, the dummies chosen span the ages 0-2, 2-4, 4-6, 6-10, 15-20, and 20+.

In practice, the dummies at the upper end of the age range must be restricted even further to avoid biasing the estimates associated with entry date. To understand why, consider dividing entrants into two groups, early and late. In automobiles, for example, entrants might be divided into those that entered by 1905 and those that entered in 1906 and later. Suppose that early entrants often achieve a low hazard rate by age ten, so that many survive to age twenty, but no late entrants have a lower hazard rate in old ages so that after age 10, none of them survive to age 20. Then a dummy variable for age 10+ would absorb all the effect of the low hazard of early entrants at old ages, attributing the low hazard to being age 10+ rather than to entering early, despite that the high versus low hazards of late versus early entrants at old ages suggests that some cause associated with entry year (or perhaps the interaction of entry year and age) is responsible for the high survival rate of firms remaining by age 10, rather than the high survival rate being the result of an unknown effect associated solely with age. This problem does in fact arise in analyzing the data, and to address it I require that no new age dummies be used once the sample size of any particular cohort of entrants (e.g., early or late entrants) becomes small.

Again, the solution is to require a sufficient sample size. As it turns out in the case of these data, the problem can be solved by allowing the almost-semiparametric age dummies to change until the age at which the sample size drops below 100 firms. In any case, the age dummies are allowed to change at least until after age 8. For example, while the data on penicillin include only 56 firms, dummies are still used for periods of one year from ages zero to six, a two-year dummy is used for ages six to eight, and a final dummy is used for ages eight and older.

Thus, the almost-semiparametric age dummies provide a flexible form by which to control for unknown age-related effects on the hazard, while still allowing the coefficients of variables central to the theories to be estimated without bias. The dummies are incorporated in the model in place of the parametric term $\exp(\gamma_0 f(a))$. (The constant term involving λ_0 must also be removed, as it would be redundant with the dummies.) This approach allows for non-monotonic effects of age, as with the liability of newness found by Brüderl and Schüssler (1990). Known variables that are thought to interact with age to determine the hazard can still be incorporated in the model in both age-independent and age-dependent terms.

Time Dependence of the Hazard

The hazard rate is also likely to vary with time. Economic booms and recessions, world wars, price wars, industry overcapacity, legislative changes, and other causes all might affect the hazard irrespective of firms' ages. Again, one could try to choose some parametric form for the effect of time, but a monotonic form is unlikely to be valid, and there is far less justification than with age to know what form might be appropriate. Closely-spaced dummy variables for each year are not appropriate because the sample sizes are too small to support so many dummies. The coefficient of entry year would again be biased by including dates in the early years of a sample, when the sample size for late entrants is zero or small, or by including dates in the late years of the sample, when, as will become apparent, not only is the overall sample size small but also the problem recurs that the sample disproportionately includes one cohort of entrants. And finally, the coefficient of the shakeout dummy used to estimate the innovative gamble and dominant design theories would be biased similarly. In fact, a statistical model including a shakeout dummy as well as dummy variables for each period would not even be identified. An alternative approach is required.

Therefore, to measure national economic growth, I used annual percentage changes in US gross domestic product.[74] I also included these percentage changes lagged by one and two years. I left industry output data out of the analysis because of concerns that including this endogenous variable may bias the estimates of key variables to be estimated, not to mention that the necessary data are unavailable in many years of many of the products. I used the gross domestic product variables in additional analyses, not reported here, to verify that the conclusions based on each analysis are robust to the inclusion of the GDP variables. Indeed, I found that inclusion of the GDP variables had little influence on the other coefficients of the statistical models.

To capture long-term effects of causes such as price wars or industry overcapacity, I sometimes add a dummy variable for extended periods in which high exit occurred. In no case do I use such a dummy for a time when the sample size of any cohort of entrants is small, nor do I include this high-exit dummy when testing the innovative gamble or dominant design theories because it would bias the estimated coefficient of the shakeout dummy. The very concept requiring the shakeout dummy is that if an increase in the exit rate occurs, that increase results from the refinement invention or dominant design, not from some unknown cause captured in high-exit dummy. Where a high-exit dummy is used, the extended period of high exit is judged simply by using the exit rate graph. Among the four products, high-exit dummies are included for automobiles from 1922.5 to 1927.5 and in tires from 1921.0 to 1932.1. (The uneven dates result from the fact that, for example, automobile producers known to exist in 1922 are dated as being in production at time 1922.5, and from the uneven publication times of *Thomas' Register*.) In both cases, the high exit rates at these times is notable from the exit rate data shown in chapter seven.

Thus, while it is impossible to control for every effect of a boom, recession, war, price war, or other exogenous time-varying process that may affect the hazard, at least the primary effects of changes in GDP can be considered. Furthermore, when testing effects of entry date without including a shakeout dummy, extended periods of high exit can be controlled for. The latter type of control turns out to be useful because it explains why unusually high hazard rates occur for different cohorts of entrants at different ages.

Entry Date Dependence of the Hazard

All three theories predict an effect of firms' entry dates on the hazard. For the innovative gamble and dominant design theories, the effect of entry date is easy to represent by using a dummy variable es that equals one for all entrants after the technological event and zero for all earlier entrants. The increased hazard of late entrants should be strong at young ages and dissipate as firms grow old. To allow for this effect, I include an additional term $es \cdot f(a)$. If post-technological event entrants have an unusually high hazard rate at young ages, the estimated coefficient of es should be positive and the estimated coefficient of $es \cdot f(a)$ should be negative. I explore the sensitivity of the conclusions to choice of functional form by considering both the Gompertz and Weibull forms $f(a) = a$ and $\log(a)$.

The size-and-skill theory predicts a continuous effect of entry date. The theory does not specify a functional form for the effect of entry date, and hence I consider a range of plausible functional forms and explore the sensitivity of the results to the choice of functional form. I first analyze differences in the hazard rates of different entry groups by dividing entrants into cohorts according to their dates of entry. Then I also consider continuous functions of ey. I use three continuous functions:

$$(1)\ g(ey) = \log(ey - \min(ey) + 1)$$

$$(2)\ g(ey) = \sqrt{\log(ey - \min(ey) + 1)}$$

$$(3)\ g(ey) = \log(\log(ey - \min(ey) + 1) + 1)$$

A function at least as strong as the logarithmic form (1) appears to be necessary to fit the data. Using g(ey) = ey would imply an exponential increase in the hazard rate with ey, resulting in increasingly large differences between later cohorts of entrants. In fact, as can be seen from plots of survival patterns shown in chapter nine, the opposite pattern seems to hold: the biggest difference in the effect of entry year seems to occur early in the history of the industry, and differences among later entry cohorts are less pronounced. In form (1), taking the logarithm of ey gets rid of the exponentially increasing pattern that seems to fit so poorly with empirical facts. Instead, the hazard is allowed to increase (or decrease) as a power of the entry date,

$$h = [\log(ey - \min(ey) + 1)]^{\lambda_1} \exp[...],$$

where exp[...] represents the remaining terms of the model. In forms (2) and (3), the additional square root or logarithm emphasizes differences between entrants early in the industry's history, and de-emphasizes differences between entrants at later times.

Again, the size-and-skill theory predicts that the effect of entry year varies with age. To examine whether late entrants have unusually high hazard rates at old ages, I include the term $g(ey) \cdot f(a)$. If late entrants have above-normal hazard rates at old ages, but not at young ages, then the estimated coefficient of g(a) should be near zero and the estimated coefficient of $g(ey) \cdot f(a)$ should be greater than zero.

Estimation

Before proceeding with the statistical tests of the shakeout theories, I explain the procedures used for maximum likelihood estimation of model parameters. In this research, unique features of the data required non-standard treatment of the estimation procedure, and I describe these traits of the data and explain how I dealt with them. Given the many unusual requirements of the estimation, pre-existing software could not handle the data analysis, so I created a new statistical analysis program to carry out the estimations. I explain how I tested the program to ensure that it yields the correct estimates. Finally, I discuss possible random variation in the shakeout date and biases that could result from unobserved differences in firm characteristics.

Derivation of the Likelihood Function

Central to any survival analysis estimation are data on survival lengths. For this study of firm survival, a survival length is the amount of time between when a company began producing a product and when it ceased production. Statistical survival models predict the probability of surviving a given length of time as a function of observable variables. For expositional purposes, I begin with the simplest case, including independent variables $\underline{x}$ that remain constant over time, and then explain how the statistical methods extend to more complicated situations, including the use of time-varying variables $\underline{x}(t)$.

The probability of surviving from age zero until at least age a is known as the survivorship function, $S(\underline{x}, a)$. For any hazard function $h(\underline{x},a)$, it can be shown by the solution of a differential equation that the probability of surviving until at least age a is $S(\underline{x},a) = \exp(-\int_0^a h(\underline{x},\alpha)d\alpha)$.[75] The probability of *not* surviving until age a is $[1 - S(\underline{x}, a)]$. From this function, one can compute the probability density function $f(a, \underline{x})$ for the age at which a firm stops surviving, as $f(\underline{x},a) = \frac{d}{da}[1 - S(\underline{x},a)]$. Equivalently, $f(a, \underline{x}) = S(\underline{x}, a)\, h(\underline{x},a)$.

For the Gompertz and Weibull-variant models, $h(\underline{x},a) = \exp(A + B\, a)$ and $h(\underline{x},a) = \exp(A + B \log a)$, respectively, where $A = \underline{\lambda}' \underline{x}_\lambda$ and $B = \underline{\gamma}' \underline{x}_\gamma$. Solving for the survivorship functions $S(\underline{x}, a)$ yields

$$S(\underline{x}, a) = \begin{cases} \exp\left[-\frac{\exp(A)}{B}(\exp(B \cdot a) - 1)\right] & \text{Gompertz model, } B \neq 0 \\ \exp[-\exp(A) \cdot a] & B = 0 \\ \exp\left[-\frac{\exp(A)}{B+1} a^{B+1}\right] & \text{Weibull-v. model, } B > -1. \end{cases}$$

Note that if $B \leq -1$, the Weibull-variant model predicts an infinite hazard at age zero, and $S(\underline{x}, a) = 0$ for all $a > 0$. Hence the Weibull-variant model is constrained to have $B > -1$, but this constraint will be removed below. Solving next for the density functions $f(\underline{x}, a)$ at the age of "death" d yields

$$f(\underline{x}, d) = \begin{cases} \exp\left[-\frac{\exp(A)}{B}(\exp(B \cdot d) - 1)\right] \exp(A + B \cdot d) & \text{Gompertz, } B \neq 0 \\ \exp[-\exp(A) \cdot d] \exp(A) & B = 0 \\ \exp\left[-\frac{\exp(A)}{B+1} d^{B+1}\right] \exp(A)\, d^B & \text{Weibull-v., } B > -1. \end{cases}$$

This function describes the probability density for the age of exit of a single firm.

The likelihood function for the exit ages of all firms equals the multiple of the density functions for the individuals firms. Substituting A_i, B_i, $\underline{x}_i$, and d_i in place of A, B, $\underline{x}$, and d, to denote that the values of these variables may differ for different firms, the likelihood function is

$$L = \prod_{i=1}^{n} f(\underline{x}_i, d_i).$$

This function is the basis for maximum likelihood estimation of the model parameters.

In the research reported here, several features of the data complicate the derivation of the likelihood function. First, the times of exit d_i are not known for all firms, since some firms were still listed as producers in the last year of the dataset. This feature is known as right-censoring of the data, and is a routine complication in statistical survival analyses. To deal with this problem, the probability of survival from age zero *at least* until age d_i replaces the probability of survival from age zero until exit occurs at exactly age d_i. Thus, for right-censored firms, $f(\underline{x}_i, d_i)$ is replaced in the likelihood function by $S(\underline{x}_i, d_i)$. Let $\delta_i = 0$ if firm i is censored and 1 if it is not. Then

$$f(\underline{x}_i, d_i, \delta_i) = \begin{cases} \exp\left[-\frac{\exp(A_i)}{B_i}(\exp(B_i \cdot d_i) - 1)\right] [\exp(A_i + B_i \cdot d_i)]^{\delta_i} & \text{Gompertz, } B_i \neq 0 \\ \exp[-\exp(A_i) \cdot d_i] [\exp(A_i)]^{\delta_i} & B_i = 0 \\ \exp\left[-\frac{\exp(A_i)}{B_i + 1} d_i^{B_i + 1}\right] [\exp(A_i)\, d^{B_i}]^{\delta_i} & \text{Weibull - v., } B_i > -1. \end{cases}$$

As before, the likelihood function is the multiple of the density functions of all firms, or

$$L = \prod_{i=1}^{n} f(\underline{x}_i, d_i, \delta_i),$$

allowing maximum likelihood estimation of the model parameters.

A less routine problem is the unavailability of data during the early years of some products, known as left-truncation of the sample. In this case, the true ages of firms that predate the sample are unknown. One solution is to determine the original entry dates of these firms, by gathering more data. Then the true ages of all firms are known. To avoid biasing the estimated parameters when estimating the models, firms that predate the sample must be included only for those ages when they were originally included in the sample. Since firms that exited before the sample began are unknown and are not included in the data, it would bias the results to include the early years of firms that survived until the sample began but not the years of firms that exited before the sample began. The likelihood function is built up as before, but now using the probability of surviving from age a_E to age $a > a_E$, where a_E is the age of a firm when it enters the sample. The probability of surviving from age a_E to age a is

$$S'(\underline{x}, a_E, a) = \exp(-\int_{a_E}^{a} h(\underline{x}, \alpha) d\alpha),$$

and from this formula the likelihood function can be built up as before, resulting in a likelihood function involving

$$f(\underline{x}_i, a_E, d_i, \delta_i) = \begin{cases} \exp\left[-\frac{\exp(A_i)}{B_i}\left(\exp(B_i \cdot d_i) - \exp(B_i \cdot a_E)\right)\right] \left[\exp(A_i + B_i \cdot d_i)\right]^{\delta_i} & \text{G., } B_i \neq 0 \\ \exp[-\exp(A_i) \cdot (d_i - a_E)] \left[\exp(A_i)\right]^{\delta_i} & B_i = 0 \\ \exp\left[-\frac{\exp(A_i)}{B_i + 1}\left(d_i^{B_i+1} - a_E^{B_i+1}\right)\right] \left[\exp(A_i)\, d^{B_i}\right]^{\delta_i} & \text{W.-v., } B_i > -1. \end{cases}$$

This approach is used for one product, typewriters, studied in the second empirical section of this dissertation.

In most products, an alternative approach is preferable in cases of left-truncation. Since true entry dates of firms that predate the sample are usually available for long-lived firms, but not for shorter-lived firms, inclusion of true entry dates in only those cases where information is available would bias the sample. The hazard rates of early entrants would appear unrealistically low. Therefore, for most analyses, I simply treat the first year of data as if it were the first year of production. Typewriters is the sole exception because that industry greatly predated *Thomas' Register* and because information that is unusually inclusive of short-lived firms—hence relatively unbiased information—is available to date the original entry of typewriter firms. In the other products studied in this dissertation, with the exception of a single product (adding and calculating machines) analyzed in the second empirical section, the sample begins soon after the introduction of the product, and a very small percentage of firms predates the sample. With these methods of handling products for which data are not immediately available at the inception of the industry, left-truncation should have minimal effect on the coefficient estimates of the models.

A third complication, interval censoring, involves the publication times of the data. The data are discrete rather than continuous. Normally this problem is ignored in estimation, because annual data are thought to be close enough to continuous that the results are not seriously biased. In this case, however, a further complication exists. The data are not truly annual, because in some instances publication gaps of up to three years separate the listings. Three-year gaps might create problems in estimation, and any estimation procedure that treated these gaps as being equal in duration to one-year gaps could yield biased estimates. To overcome these problems, the likelihood function can be expressed in terms of variable-length, discrete time periods. Let E_i and J_i denote the volume numbers of the first and last registers in which firm i was listed, and let a_{ij} denote the age of firm i when data for volume j of the trade register were collected by the people who compiled the register. Thus, a_{iE_i} and a_{iJ_i} are the ages of firm i at the times when data for volumes E_i and J_i were collected. Note that, except for right-censored firms, $J_i + 1$ is the volume of the trade register when the firm was no longer listed in the register, and the age corresponding to this volume is a_{iJ_i+1}. The probability of surviving from age a_{iE_i} to age a_{iJ_i}, and then exiting during the period from a_{iJ_i} to a_{iJ_i+1} if $\delta_i = 1$, is

$$f^*(\underline{x}_i, a_{iE}, a_{iJ_i}, a_{iJ_i+1}, \delta_i) = S^*(\underline{x}_i, a_{iE}, a_{iJ_i}) \left[1 - S^*(\underline{x}_i, a_{iJ_i}, a_{iJ_i+1})\right]^{\delta_i}.$$

The full resulting likelihood function is shown below, in conjunction with the case of time-varying data.

A fourth complication is this time-varying nature of the data, $\underline{x}_i(t)$ rather than simply $\underline{x}_i$. If the data remain constant within discrete time periods, the survivorship function and probability density function can still be determined using integration by parts. If the discrete time periods of the data correspond to the interval-censoring periods between publication of trade registers, the functional forms are especially compact. This compact form allows computation of maximum likelihood estimates with roughly 5% of the computation time required by the non-compact form.[76] Furthermore, assuming that $\underline{x}_i(t)$ does not change between periods j and j+1 fits the problem, since the independent variables used here generally fit fairly neatly with the times of trade listings.

Let subscript j denote the interval-censoring period (or equivalently, the data period) immediately following the jth edition of the trade register. Thus, A and B are written A_{ij} and B_{ij}, explicitly denoting the variation of the data across different time periods. The likelihood function allowing for interval censoring and time-varying data is

$$L = \prod_{i=1}^{n} \left\{ \left[1 - \exp\left(-F_{iJ_i} \exp\left(A_{iJ_i}\right)\right) \right]^{\delta_i} \times \prod_{j=E_i}^{J_i - 1} \left[\exp\left(-F_{ij} \exp\left(A_{ij}\right)\right) \right] \right\},$$

$$\text{where } F_{ij} = \begin{cases} \dfrac{\exp(B_{ij} a_{ij+1}) - \exp(B_{ij} a_{ij})}{B_{ij}} & \text{for the Gompertz model, } B_{ij} \neq 0 \\ a_{ij+1} - a_{ij} & B_{ij} = 0 \\ \dfrac{a_{ij+1}^{B_{ij}+1} - a_{ij}^{B_{ij}+1}}{B_{ij} + 1} & \text{for the Weibull-v. model, } B_{ij} \neq -1 \\ \log(a_{ij+1}) - \log(a_{ij}) & B_{ij} = -1. \end{cases}$$

Lancaster (1990, pp. 170-172) shows that for a class of models including these, the likelihood function is single-peaked. This facilitates estimation of the model's coefficients and the execution of log-likelihood tests for the significance of the estimates.

B_{ij} is no longer constrained to be greater than -1 for the Weibull-variant model. The only case in which a constraint holds is for $j = 0$ when the firm enters the sample at age zero. However, the data used here never contain instances in which firms enter at age zero. To see why, consider a trade register that compiled its lists at times 1948.0, 1949.0, and 1950.0. If a firm first appeared as a producer in the 1949.0 list, then it is known to have entered sometime between 1948.0 and 1949.0. The firm's entry date could be incorporated into the model as some kind of random variable, but that would greatly complicate the specification of the model and the estimation procedure. Instead, it is treated as beginning production halfway through the preceding period, in this example at time 1948.5. Firms that entered in the first period are assumed to have begun production 0.5 year before the first date of the register.

In theory, firms that survive less than 0.5 year would be unlikely to appear in any edition of an annual register. If the firms in the sample were counted as beginning at age 0 instead of age 0.5, the estimated coefficients would be biased by including in the sample the periods from age 0 to 0.5. Firms would appear to have an unrealistically high survival rate from age 0 to 0.5 because of the exclusion of the especially short-lived firms that never survive to age 0.5. While in practice there may be few manufacturing firms that produce a product for less than six months, I nonetheless use the formally correct approach here and only include firms beginning at age 0.5 (for some firms this entry age differs slightly from 0.5 because interval-censoring periods may not be exactly one year long). This formally correct approach has an added benefit: for the Weibull-variant model, B_{ij} can take any value regardless of the time period. This flexibility is important because it allows complete freedom of the parameters $\underline{\lambda}$ in B, alleviating any concerns about how a constraint on B might affect the parameter estimates.

Statistical Software

To carry out a maximum likelihood estimation using the above likelihood function, I created a new statistical program as part of my Survival! data analysis software. The statistical program converts survival data into a form amenable to analysis and carries out estimations. The program is unique in several ways. It automatically handles time-varying covariates without requiring additional programming, when used in conjunction with the Survival! software. It allows the Gompertz and Weibull-variant models used here to have both age-dependent and age-independent covariates. It provides the capability to handle interval-censoring and the non-zero starting ages associated with left-truncation of a sample, as well as the right-censoring addressed in most survival analysis programs. It incorporates techniques that help to ensure convergence on a solution in cases where other programs may be unable to obtain a solution. It performs some checks to help ensure that a model is identified, and it automatically estimates previously-unidentified models after removing offending terms (this allows the inclusion of variables that are valid in some datasets, but are for example always zero in others, so that the variables are only included in a model for relevant datasets). And finally, it automates analyses involving multiple models and datasets, and it coordinates multiple workstation computers on a network so that lengthy tasks can be sped up by using multiple computers. Persons interested in using the software should contact this author.

This new statistical program is not a subject of this dissertation, but nevertheless it is critical to show that the estimates and standard errors resulting from the program are valid. To ensure that it obtains correct results, I used several mutually-reinforcing methods. First, I checked the computation of the likelihood function against results computed by hand. The results agree to a high precision, with a round-off error that is typically less than one part in one billion. (I created special high-precision calculation methods to reduce problems of round-off error and numerical overflow, which otherwise would occur frequently with the Gompertz and Weibull-variant models.)

Second, I created analytical routines to compute the gradient of the log-likelihood function and compared the analytical gradients against numerically computed gradients. The two agree closely, except in special regions of the parameter space (around $B = 0$ in the Gompertz model and $B = -1$ in the Weibull model) where the numerical computations are inaccurate. (Using an analytical gradient allows a more efficient process of maximum likelihood estimation and more accurate calculation of standard errors.)

Third, I checked a special case of the model against results obtained from SAS. I used a simple exponential model without time-varying data, and treated the data as if exit occurred at a known time, the end of the interval-censoring period, instead of at an unknown time during the interval-censoring period. I estimated the model as a function of a constant and of entry year normalized to have a minimum value of zero, using the data for automobiles. Table 8.3 shows the results obtained from SAS and from my Survival! statistical program. The precision chosen for the table is the maximum precision that was printed out by SAS (SAS does not report p-values below 10^{-4}). The results are identical except that the estimates of the constant term differ by one part in one billion. Thus, all the parts of the Survival! program used in this estimation seem to function properly.

Table 8.3. Comparison of Estimates Using SAS and Survival!

Variable	— SAS — Estimate	S.E.	P-value	— Survival! — Estimate	S.E.	P-value
Constant	-2.09393857	0.064707	< 0.0001	-2.09393859	0.064707	$1 * 10^{-12}$
Entry year	0.0230631	0.003929	< 0.0001	0.0230631	0.003929	$2 * 10^{-9}$

Table 8.4. Comparison of True Model Estimates with Random Model Estimates

Model Term	True Values	Random Est. 1	Random Est. 2	Random Est. 3
λ_0	-2.751	-2.511***	-2.985***	-2.875***
		(0.268)	(0.223)	(0.240)
λ_1	0.478	0.342**	0.476**	0.594**
		(0.222)	(0.201)	(0.211)
γ_1	-0.014	0.001	0.013	-0.032
		(0.048)	(0.046)	(0.046)

Fourth, I generated random test data for a known hazard model and used the program to estimate the Gompertz model based on the randomly-generated data. I estimated the model $h(a, \underline{x}(t)) = \exp[\lambda_0 + \lambda_1 \log(ey) + \gamma_1 \log(ey)\, a]$ using the data for automobiles and found the estimates shown in the first column of data in Table 8.4. I labeled these estimates as "true" values and generated random data based on the "true" model. After creating the random data, I estimated the model. The table shows three sets of estimates, based on three random datasets, with standard errors in parentheses. The estimates lie scattered on both sides of the true values, as one would expect if the estimates are unbiased. Furthermore, the standard errors seem to be about the right size, since in one out of nine estimates the estimated value differs from the true value by an amount greater than the standard error, and then by an amount only slightly larger than the standard error. Thus, to the degree of accuracy that can be seen here, the estimation seems to yield correct estimates and standard errors.

Sample Sizes and the Timing of the Shakeout

If a product has few firms, random deviations are likely to affect the timing of the shakeout. For example, if a dominant design appeared in 1960 and caused a shakeout, chance patterns of entry and exit in the previous five years could cause the number of firms to fall beginning in 1955. Random variation in the timing of the shakeout could affect coefficient estimates, but is not accounted for in significance tests.[77] Therefore, significance tests may yield overconfident findings in small industries. In general, the increased uncertainty in products with few firms will be dealt with by presenting results first for products with large sample sizes. This way, readers can easily discern patterns in the large sample products, without being distracted by results from small samples, yet the small-sample results will still be available for inspection.

Unobserved Heterogeneity

Unmeasured firm traits such as managerial competency are likely to play a major role in determining whether firms survive. The size-and-skill theory posits that such characteristics affect firms' R&D competencies and thereby partially determine which firms exit. In fact, the predictions of the size-and-skill theory depend on the presence of just such unmeasured characteristics. However, the innovative gamble and dominant design theories do not account for unmeasured firm characteristics, and as a result their estimated coefficients could be biased.

"Unobserved heterogeneity," as such unmeasured traits are termed, often complicates the estimation of survival models. Consider the proportional hazards model

$$h(a, \underline{x}(t)) = g(a) \exp(\underline{\lambda}'\underline{x}(t) + \varepsilon).$$

The ε represents a measurement error or unobserved variable that is correlated over time. In the most extreme case, there is perfect correlation over time, so that ε is an unmeasured trait of firms. In this case, it can be shown (Lancaster, 1990, pp. 58-65) that an effect of ε is to bias the coefficient estimate λ_i toward zero for any variable x_i that remains the same (or roughly the same) over time. In non-proportional hazards models, the problem is likely to be worse for variables that take effect at old ages, because if ε has an important effect on survival, it is at old ages when selection has left surviving mostly firms with low ε. The reader should keep in mind this bias in connection with estimates for the innovative gamble and dominant design models.

9

Survival

I begin the statistical analyses by testing for the increased hazard said to arise from an innovative gamble or a dominant design. Then I examine the predictions of these theories that at young ages, entrants after the refinement invention or dominant design have lower hazard rates than earlier entrants. Finally, I examine the advantage-to-the-advantaged view of the size-and-skill theory, which predicts that earlier entrants have a lower hazard rate than later entrants particularly at old ages.

Technological Events and Hazard Rates

Both of the technological event theories predict that the hazard rate rises when the event occurs, then falls back to normal as the effects of the event dissipate. In the innovative gamble, the hazard rises when firms that lose the gamble are forced out of the industry. Eventually, the losing gamblers all exit, and the hazard rate returns to normal. In the dominant design view, firms that might have been good at product innovation but have no particular skill at process innovation are forced out of the industry when the product becomes standardized. Eventually, only firms that are good at process innovation remain, and the reason for the increased hazard no longer exists. It has already been seen, in chapter seven, that industry aggregate exit rates in fact remained roughly constant at the time of the shakeout, except in tires where the exit rate rose with the shakeout, and in televisions where the exit rate may have even decreased. The statistical analyses provide a more sophisticated means to probe changes in the hazard rate, to see if firms' hazard rates in fact remain constant at the times of the shakeouts once characteristics of the firms are taken into account.

A critical characteristic to consider is the age distribution of firms. In human demographics, changing age distributions can obscure or exaggerate changes in death rates, because the aggregate death rate increases or decreases with the percentage of senior citizens in the population. In industries as well, effects associated with age might obscure or exaggerate changes in the exit rate. If older firms have higher survival rates, opposite the pattern in human populations, the aggregate hazard rate might remain constant at the time of the shakeout if the hazard rate of firms of a given age rise, tending to increase the aggregate hazard rate, at the same time as the average age of firms in the sample rises, tending to decrease the aggregate hazard rate. Therefore, I begin by analyzing the "baseline hazard" of firms as a function of their age. I start with automobiles, where I use dummy variables beginning and ending at age 0.5, 1.5, *et cetera*, to correspond with the interval censoring periods of the automobiles data. Table 9.1, column 1 shows the estimates resulting from this baseline hazard model for automobiles.[78] The numbers in each cell indicate the estimated coefficients of each term in the model, and the numbers in parentheses indicate standard errors. According to the estimates, the hazard for firms up to 1.5 years old is exp(-2.27), or 10% per year. At age 1.5 to 2.5, the estimated hazard rate increases to exp(-1.37), or 25% per year. The hazard rate drops slightly after age 5.5, to exp(-1.79) = 17% per year, and then falls further after age 9.5, to exp(-2.43) = 9% per year. Figure 9.1 shows a plot of this estimated hazard as a function of age.

The second statistical analysis probes whether firms of a given age experienced a change in hazard rate at the time of the shakeout. Column 2 of Table 9.1 shows the results of a model in which a dummy variable for the onset of the shakeout is included along with

Table 9.1. Technological Event Analyses, Automobiles

	1 Age Baseline Only	2 Shakeout	3 Gompertz time since shakeout	4 Weibull-v. time since shakeout
Age 0.5 to 1.5	-2.27*** (0.12)	-2.43*** (0.13)	-2.43*** (0.13)	-2.43*** (0.13)
Age 1.5 to 2.5	-1.39*** (0.08)	-1.57*** (0.10)	-1.57*** (0.10)	-1.57*** (0.10)
Age 2.5 to 3.5	-1.38*** (0.09)	-1.59*** (0.11)	-1.59*** (0.11)	-1.59*** (0.11)
Age 3.5 to 4.5	-1.50*** (0.11)	-1.72*** (0.13)	-1.72*** (0.13)	-1.72*** (0.13)
Age 4.5 to 5.5	-1.35*** (0.12)	-1.59*** (0.13)	-1.59*** (0.13)	-1.59*** (0.13)
Age 5.5 to 6.5	-1.81*** (0.16)	-2.05*** (0.18)	-2.05*** (0.18)	-2.05*** (0.18)
Age 6.5 to 7.5	-1.75*** (0.17)	-2.02*** (0.19)	-2.02*** (0.19)	-2.02*** (0.19)
Age 7.5 to 8.5	-1.70*** (0.19)	-1.99*** (0.20)	-1.99*** (0.20)	-1.99*** (0.20)
Age 8.5 to 9.5	-1.66*** (0.20)	-1.96*** (0.21)	-1.96*** (0.21)	-1.96*** (0.21)
Age 9.5 & up	-2.45*** (0.09)	-2.79*** (0.13)	-2.71*** (0.14)	-2.76*** (0.14)
Shakeout		0.35*** (0.09)	0.40*** (0.09)	0.40*** (0.13)
S TS			-0.008 (0.006)	
S logTS				-0.03 (0.06)
LL	-1949.31	-1941.01	-1939.99	-1940.86

In each cell, the first number indicates the estimated coefficient of the variable indicated at left, and the number in parentheses indicates its standard error. The columns numbered 1 through 4 pertain to four separate statistical models. These data are based on Smith (1968). * p < .05, ** p < .01, *** p < .001

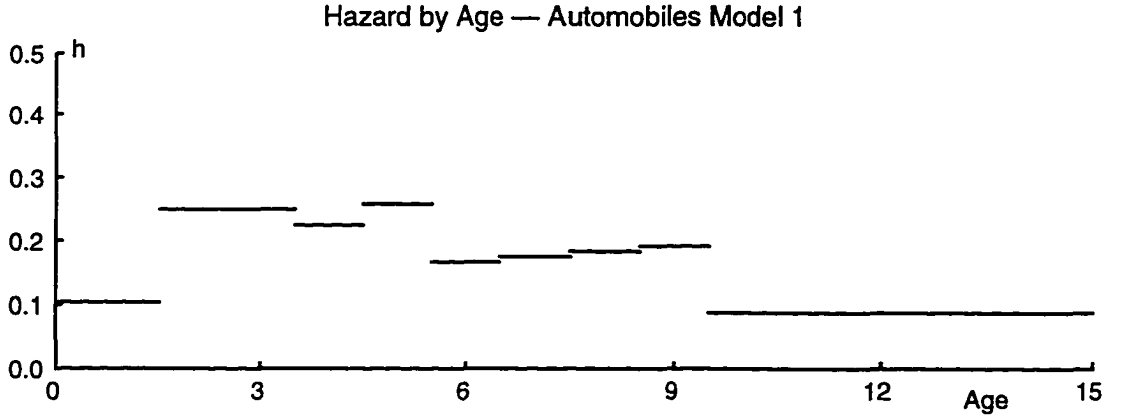


Figure 9.1. The predicted hazard rate according to model 1, automobiles.

the age dummies. The estimated coefficient of the shakeout dummy is 0.35, and since exp(0.35) = 1.42, the coefficient indicates that the hazard rate of firms of a given age rose by 42% with the onset of the shakeout. Thus, while industry aggregate exit rates did not rise at the time of the shakeout, nevertheless firms seem to have experienced unusually high hazard rates at this time, once the age distribution of firms is considered. This effect is highly significant: the estimated coefficient 0.35 for the shakeout dummy has a standard error of only 0.09, shown in parentheses after the estimate. As indicated by the asterisks in the table, the probability of obtaining an estimate this large would be less than 0.001 if the true coefficient were zero ($p < .001$).

The technological event theories predict the effects of the event should decline with time after the shakeout begins. Eventually, after the exit of unsuccessful innovative gamblers or of firms that do not succeed at low cost production of a dominant design, the hazard rate should return to normal. Models 3 and 4 in Table 9.1 test for this dropoff in the effect of the shakeout by adding to the model an additional term, the shakeout dummy times a function of the amount of time since the shakeout began. Model 3 uses the shakeout dummy multiplied by the amount of time since the shakeout began, and model 4 uses the shakeout dummy multiplied by the logarithm of this amount of time. The theories do not specify which form is most appropriate, so using both forms provides a check on the sensitivity of the conclusions.

Examining the coefficients in columns 3 and 4 of Table 9.1, the models again depict an increase in the hazard rate at the time of the shakeout. Now the hazard rate appears to rise even more with the onset of the shakeout, for an increase of 49% (since $\exp(0.40) = 1.49$), and in both cases the increase is highly significant. Examining next the decline in the hazard after the shakeout begins, both models indeed show a declining hazard rate. In the model 3, the variable S TS (shakeout times time since shakeout) has an estimated coefficient of -0.008. In model 4, the variable S logTS has an estimated coefficient of -0.03. However, both of these estimates are exceedingly small and statistically insignificant. In the model 3, the increased hazard at the time of the shakeout persists for 50 years after the shakeout began. That is, after the shakeout the estimated hazard rises by the multiple $\exp(0.40 - 0.008\ TS)$, which does not return to its normal value of 1 until $TS = 50$. In the model 4 the estimated hazard does not return to normal until over 600,000 years after the shakeout begins! To see this, note that $\exp(0.40 - 0.03 \log TS)$ equals 1 only when $0.40 = 0.03 \log TS$, i.e., when $TS = 617{,}000$.

Table 9.2. Technological Event Analyses, Tires

	1 Age Baseline Only	2 Shakeout	3 Gompertz time since shakeout	4 Weibull-v. time since shakeout
Age 0 to 1	-1.79*** (0.35)	-2.08*** (0.36)	-2.11*** (0.37)	-2.23*** (0.37)
Age 1 to 2	-1.98*** (0.21)	-2.12*** (0.23)	-2.14*** (0.23)	-2.18*** (0.23)
Age 2 to 3	-1.48*** (0.17)	-1.62*** (0.18)	-1.62*** (0.18)	-1.62*** (0.18)
Age 3 to 4	-1.87*** (0.20)	-2.06*** (0.21)	-2.08*** (0.20)	-2.10*** (0.20)
Age 4 to 5	-1.65*** (0.22)	-1.80*** (0.23)	-1.80*** (0.22)	-1.78*** (0.22)
Age 5 to 6	-1.96*** (0.30)	-2.18*** (0.30)	-2.18*** (0.30)	-2.19*** (0.30)
Age 6 to 7	-1.65*** (0.32)	-1.81*** (0.32)	-1.82*** (0.31)	-1.80*** (0.32)
Age 7 to 8	-2.79*** (0.34)	-3.07*** (0.36)	-3.07*** (0.35)	-3.08*** (0.36)
Age 8 to 9	-1.22*** (0.25)	-1.37*** (0.26)	-1.37*** (0.26)	-1.33*** (0.26)
Age 9 to 10	-2.86*** (0.39)	-3.13*** (0.40)	-3.14*** (0.39)	-3.14*** (0.39)
Age 10 to 12	-2.60*** (0.23)	-3.00*** (0.26)	-3.00*** (0.26)	-2.95*** (0.26)
Age 12 & up	-2.93*** (0.10)	-3.26*** (0.13)	-3.01*** (0.14)	-2.94*** (0.14)
Shakeout		0.34*** (0.09)	0.54*** (0.09)	0.89*** (0.12)
S TS			-0.019*** (0.004)	
S logTS				-0.30*** (0.05)
LL	-1787.96	-1780.03	-1766.51	-1762.62

* p < .05, ** p < .01, *** p < .001

Model 3 fits the data slightly better than model 4. However, even with model 3, adding the term S TS to the model provides only a modest improvement in fit compared to the model 2, which does not include S TS. While the increased hazard at the time of the shakeout does appear to decline over time, the decline is exceedingly modest and adds little to model 2's predictive ability. It appears that the hazard did not simply rise temporarily as predicted by the technological event theories. The hazard rose permanently! Competition seems to have intensified after 1909, and it stayed intensified well past the middle of the century.

Turning next to tires, a similar pattern is apparent. Table 9.2 shows the estimates for tires. Tire firms had a fairly low hazard rate until age two (14% per year from age 1 to 2), but the hazard rate rose to 23% per year from age 2 to 3, and then gradually declined with older ages, reaching 5% per year above age 12. Adding a shakeout dummy shows a highly significant, 40% increase in the hazard rate starting after 1922. Next, adding the

Table 9.3. Technological Event Analyses, Televisions

	1 Age Baseline Only	2 Shakeout	3 Gompertz time since shakeout	4 Weibull-v. time since shakeout
Age 0 to 1	-1.27** (0.46)	-1.32** (0.47)	-1.32** (0.47)	-1.32** (0.47)
Age 1 to 2	-1.45*** (0.42)	-1.69*** (0.45)	-1.69*** (0.45)	-1.69*** (0.45)
Age 2 to 3	-2.31*** (0.46)	-2.47*** (0.48)	-2.48*** (0.48)	-2.48*** (0.48)
Age 3 to 4	-1.99*** (0.45)	-2.44*** (0.52)	-2.40*** (0.52)	-2.41*** (0.52)
Age 4 to 5	-2.15*** (0.47)	-2.55*** (0.52)	-2.53*** (0.52)	-2.54*** (0.52)
Age 5 to 6	-1.90*** (0.50)	-2.34*** (0.57)	-2.33*** (0.57)	-2.35*** (0.57)
Age 6 to 7	-2.77*** (0.63)	-3.11*** (0.66)	-3.11*** (0.66)	-3.12*** (0.66)
Age 7 to 8	-2.14*** (0.41)	-2.76*** (0.55)	-2.77*** (0.55)	-2.79*** (0.56)
Age 8 & up	-2.35*** (0.14)	-2.77*** (0.29)	-2.86*** (0.31)	-2.82*** (0.33)
Shakeout		0.42* (0.25)	0.36 (0.26)	0.35 (0.32)
S TS			0.009 (0.013)	
S logTS				0.04 (0.14)
LL	-470.23	-468.85	-468.60	-468.80

Foreign entrants into US production are excluded. * p < .05, ** p < .01, *** p < .001

S TS or S logTS term to the model shows a significant but very slow dwindling of the post-1922 increase in hazard rates. Using the Gompertz form, model 3, the 72% increase in the hazard after 1922 does not seem to have dwindled away until 1950. Using the logarithmic Weibull form of model 4, which has the better fit in this case, the 144%-higher hazard appears to have returned to normal only by 1946. As in automobiles, the increased hazard starting in the 1920s appears to fit with the technological event theories, but the return to normal hazard rates after the exit of unsuccessful firms takes a surprisingly long time.

In televisions, Table 9.3 shows the estimated coefficients for the four models. Here, the *Television Factbook* data do not show an especially low hazard rate at young ages. Rather, the hazard appears to have been high early on (around 28% from age 0 to 1) and then dropped off by around age 2 to a fairly constant hazard rate of around 10-15% per year. The shakeout dummy in model 2 shows a significant, 52% increase in the hazard rate after 1951. However, the increase is not significant in models 3 and 4, once the variable S TS or S logTS is added to the model. Furthermore, in models 3 and 4 not only is there

Table 9.4. Technological Event Analyses, Televisions Including Foreign Entrants

	1 Age Baseline Only	2 Shakeout	3 Gompertz time since shakeout	4 Weibull-v. time since shakeout
Age 0 to 1	-1.27** (0.46)	-1.32** (0.47)	-1.32** (0.47)	-1.32** (0.47)
Age 1 to 2	-1.46*** (0.42)	-1.71*** (0.45)	-1.70*** (0.45)	-1.70*** (0.45)
Age 2 to 3	-2.32*** (0.46)	-2.48*** (0.48)	-2.48*** (0.48)	-2.49*** (0.48)
Age 3 to 4	-2.00*** (0.45)	-2.44*** (0.52)	-2.41*** (0.52)	-2.42*** (0.52)
Age 4 to 5	-2.16*** (0.47)	-2.56*** (0.52)	-2.54*** (0.52)	-2.56*** (0.52)
Age 5 to 6	-1.90*** (0.50)	-2.34*** (0.57)	-2.33*** (0.57)	-2.35*** (0.57)
Age 6 to 7	-2.81*** (0.63)	-3.16*** (0.66)	-3.15*** (0.66)	-3.16*** (0.66)
Age 7 to 8	-2.07*** (0.40)	-2.69*** (0.54)	-2.71*** (0.55)	-2.72*** (0.55)
Age 8 & up	-2.35*** (0.14)	-2.77*** (0.29)	-2.87*** (0.31)	-2.82*** (0.33)
Shakeout		0.42* (0.25)	0.36 (0.26)	0.36 (0.32)
S TS			0.010 (0.013)	
S logTS				0.04 (0.14)
Foreign	-2.81** (1.00)	-2.91** (1.01)	-3.16** (1.06)	-2.99** (1.04)
LL	-475.10	-473.70	-473.41	-473.65

* p < .05, ** p < .01, *** p < .001

no significant dwindling of the increased hazard, but in fact the hazard actually appears to have *increased* with time after 1951. Contrary to the technological event theories' prediction that the hazard temporarily increases after a technological event occurs, competition seems to have continually intensified in the television set industry.

Nor are the conclusions about televisions any different if foreign entrants into US production are added to the sample. These late entrants, listed in *Television Factbook* beginning in the 1970s and 1980s, have an unmeasured amount of experience in other countries before beginning production in the US. To control for the fact that their true ages differ from the ages based on entry into *Television Factbook*, I simply include in the models a dummy variable to indicate foreign entrants. Table 9.4 shows the estimated coefficients once foreign entrants are added. Again, the hazard rate is high until age 2 and lower at older ages. Perhaps not surprisingly given that foreign entrants were already highly successful producers and were much older than is apparent in the dataset, the foreign entrant dummy in each model predicts a 94-96% reduction in the hazard rate of foreign entrants compared to US producers. The shakeout dummy shows a significant,

Table 9.5. Technological Event Analyses, Penicillin

	1 Age Baseline Only	2 Shakeout	3 Gompertz time since shakeout	4 Weibull-v. time since shakeout
Age 0 to 1	-3.95 (3.32)	-4.98 (3.36)	-5.01 (3.36)	-4.95 (3.36)
Age 1 to 2	-2.68 (3.00)	-2.56 (3.02)	-2.63 (3.02)	-2.52 (3.02)
Age 2 to 3	-1.90 (2.87)	-2.83 (2.90)	-2.81 (2.90)	-2.84 (2.90)
Age 3 to 4	-1.70 (2.77)	-1.50 (2.78)	-1.55 (2.78)	-1.46 (2.78)
Age 4 to 5	-2.69 (2.58)	-3.73 (2.62)	-3.66 (2.62)	-3.81 (2.63)
Age 5 to 6	-2.91 (2.16)	-2.59 (2.17)	-2.64 (2.17)	-2.52 (2.18)
Age 6 to 8	-3.98*** (0.81)	-5.10*** (0.95)	-5.00*** (0.96)	-5.23*** (0.98)
Age 8 & up	-2.90*** (0.20)	-4.03*** (0.41)	-4.02*** (0.41)	-4.00*** (0.41)
Shakeout		1.21*** (0.37)	1.05** (0.44)	1.49** (0.53)
S TS			0.011 (0.015)	
S logTS				-0.13 (0.18)
LL	-185.32	-179.90	-179.64	-179.65

* p < .05, ** p < .01, *** p < .001

52% increase in the hazard after 1951, just as for the data without foreign producers. The estimated coefficients of S TS and s logTS are almost identical to those in the US-only dataset, again indicating a hazard that actually increased over time after 1951.

In penicillin, despite a small sample size, the same conclusions are strikingly clear. Table 9.5 shows the coefficient estimates for this product. The hazard rate is particularly low below age 2, with a baseline hazard rate of 2% from age 0 to 1 and 7% from age 1 to 2, but the hazard rises to 15-18% at ages 2 to 4, and then drops off again, reaching 6% at age 8 and higher. Adding the shakeout dummy in model 2, the hazard rate apparently rose 240% after 1955, when the shakeout began. Adding the further variable S TS or S logTS, the coefficients show either an insignificant increase over time in the hazard rate after it rose 190% around 1955, or a barely perceptible, insignificant decrease in the hazard rate following a 340% increase at the time of the shakeout.

Thus, in all four products the hazard rate apparently rose at the time of the shakeout, and thereafter the hazard rate remained high. If a refinement invention or dominant design triggered the shakeout, the hazard rate should have returned to normal not long after the event, after the exit of firms unable to successfully innovate based on the refinement or unable to convert to low-cost production of the standardized product. This return to a normal hazard rate did not occur. Rather, a much more persistent process seems to have been responsible for a lasting increase in the hazard rate. Competition intensified enormously by the time the shakeout began, and it continued just as intensely for decades afterward.

By examining alternative possible dates of the refinement or dominant design, one can examine whether the rise in the hazard rate in fact occurred at the time of the shakeout, or whether the hazard rate had begun to rise even earlier. Furthermore, because there may be some random variation in the date when a shakeout begins, examining alternative dates allows a more robust test of whether technological events might have triggered the shakeouts. Accordingly, I varied the shakeout dates in models 5 and 6 above, going from six years before until three years after the shakeout date. The period of up to six years preceding the shakeout should allow ample time to capture any effects that might have had a delayed impact on the shakeout.

Tables 9.6 and 9.7 show the estimated coefficients of S and of S TS or S logTS when the shakeout date is varied. Table 9.8 shows the log-likelihoods of the estimated models. Examining first Table 9.6, in automobiles and tires the estimated hazard rate rose with the variable S even if the shakeout date used to determine when $S = 1$ is varied considerably. In automobiles, the biggest increase in the hazard is apparent with a shakeout date zero to two years before the peak in the number of firms, and in tires the biggest increase occurred one year before the peak. According to the log-likelihoods in Table 9.8, the best fit occurred in automobiles two years before the true shakeout date and in tires one year before the true date. In televisions, the hazard rose at the time of every alternative shakeout date, except with the single case of a Weibull-variant model and a date two years before the peak in the number of firms, immediately after the sample begins. The best fit in televisions occurs with a division one year after the peak number of firms. In penicillin, the pattern is sensitive to the choice of an alternative date and to whether the

Table 9.6. Coefficients of S when the Shakeout Date is Varied

Shakeout Date	Automobiles	Tires	Televisions	Penicillin
	Gompertz Model			
-6	0.41** (0.17)	0.08 (0.11)		0.01 (0.48)
-5	0.23* (0.14)	0.23* (0.11)		0.06 (0.46)
-4	0.17 (0.12)	0.31** (0.10)		0.23 (0.45)
-3	0.26* (0.11)	0.30** (0.10)		0.58 (0.44)
-2	0.44*** (0.11)	0.68*** (0.10)	0.08 (0.32)	0.72 (0.44)
-1	0.38*** (0.10)	0.83*** (0.10)	0.30 (0.28)	0.67 (0.44)
0	0.38*** (0.09)	0.54*** (0.09)	0.36 (0.26)	1.05** (0.44)
+1	0.26** (0.09)	0.37*** (0.09)	0.40 (0.25)	-0.60 (0.51)
+2	0.20* (0.09)	0.27** (0.10)	0.26 (0.26)	-0.29 (0.51)
+3	0.32*** (0.09)	0.13 (0.10)	0.14 (0.27)	0.01 (0.50)
	Weibull-Variant Model			
-6	0.18 (0.21)	-0.12 (0.16)		-0.56 (0.64)
-5	-0.05 (0.18)	0.12 (0.15)		-0.44 (0.59)
-4	-0.17 (0.16)	0.23 (0.15)		-0.23 (0.60)
-3	-0.02 (0.15)	0.15 (0.13)		0.35 (0.57)
-2	0.33** (0.14)	0.93*** (0.13)	-0.10 (0.38)	0.65 (0.55)
-1	0.29* (0.13)	1.29*** (0.13)	0.21 (0.34)	0.69 (0.56)
0	0.35** (0.13)	0.89*** (0.12)	0.35 (0.32)	1.49** (0.53)
+1	0.15 (0.13)	0.71*** (0.13)	0.49 (0.32)	-1.28 (0.81)
+2	0.01 (0.14)	0.61*** (0.14)	0.40 (0.33)	-0.65 (0.76)
+3	0.27* (0.14)	0.40** (0.15)	0.32 (0.36)	0.01 (0.70)

Table 9.7. Coefficients of S TS or S logTS when the Shakeout Date is Varied

Shake. Date	Automobiles	Tires	Televisions	Penicillin
	Gompertz Model			
-6	0.004 (0.005)	-0.007* (0.003)		0.030** (0.012)
-5	0.005 (0.005)	-0.007** (0.003)		0.030** (0.012)
-4	0.005 (0.005)	-0.009** (0.003)		0.028* (0.012)
-3	0.003 (0.005)	-0.009** (0.003)		0.022* (0.013)
-2	-0.001 (0.005)	-0.016*** (0.004)	0.015 (0.012)	0.019 (0.013)
-1	-0.002 (0.005)	-0.020*** (0.004)	0.012 (0.013)	0.019 (0.014)
0	-0.004 (0.006)	-0.019*** (0.004)	0.009 (0.013)	0.011 (0.015)
+1	-0.003 (0.006)	-0.018*** (0.004)	0.007 (0.013)	0.046** (0.017)
+2	-0.001 (0.006)	-0.017*** (0.004)	0.008 (0.014)	0.040* (0.018)
+3	-0.007 (0.006)	-0.015*** (0.004)	0.010 (0.015)	0.034* (0.018)
	Weibull-Variant Model			
-6	0.135* (0.059)	0.052 (0.053)		0.460** (0.193)
-5	0.162** (0.059)	0.003 (0.052)		0.433** (0.184)
-4	0.193*** (0.059)	-0.019 (0.051)		0.397* (0.188)
-3	0.160** (0.057)	0.020 (0.043)		0.252 (0.181)
-2	0.055 (0.056)	-0.219*** (0.050)	0.186 (0.141)	0.158 (0.179)
-1	0.045 (0.056)	-0.358*** (0.051)	0.108 (0.135)	0.121 (0.182)
0	0.001 (0.057)	-0.298*** (0.052)	0.044 (0.136)	-0.125 (0.177)
+1	0.051 (0.060)	-0.283*** (0.054)	-0.033 (0.139)	0.580* (0.256)
+2	0.101 (0.064)	-0.278*** (0.057)	-0.048 (0.145)	0.412* (0.243)
+3	0.004 (0.066)	-0.227*** (0.060)	-0.055 (0.152)	0.225 (0.228)

Table 9.8. Log-likelihoods when the Shakeout Date is Varied

Shake. Date	Automobiles	Tires	Televisions	Penicillin
		Gompertz Model		
-6	-1939.93	-1785.56		-181.94
-5	-1941.64	-1783.44		-181.95
-4	-1942.21	-1781.05		-181.85
-3	-1940.62	-1781.05		-181.19
-2	-1934.67	-1760.50	-469.41	-180.81
-1	-1936.03	-1747.30	-468.90	-181.11
0	-1935.41	-1766.51	-468.60	-179.62
+1	-1940.02	-1775.02	-468.42	-181.64
+2	-1941.76	-1778.58	-469.16	-182.18
+3	-1938.25	-1781.36	-469.58	-182.33
		Weibull-Variant Model		
-6	-1937.72	-1787.46		-182.01
-5	-1938.27	-1787.18		-181.90
-4	-1937.24	-1785.90		-181.84
-3	-1936.85	-1785.87		-181.65
-2	-1934.19	-1763.30	-469.23	-181.43
-1	-1935.81	-1739.51	-469.01	-181.77
0	-1935.73	-1762.62	-468.78	-179.63
+1	-1939.80	-1771.98	-468.50	-182.17
+2	-1940.60	-1775.53	-469.27	-183.08
+3	-1938.95	-1780.26	-469.75	-183.51

Gompertz or Weibull-variant model is used, but the best fit occurs at the time of the peak, when the hazard rose as predicted.

Turning next to the coefficients of S TS and S logTS in Table 9.7, it is apparent that in all four products, the higher hazard rate persisted or even grew after the start of the shakeouts. The coefficients in the table are positive as often as they are negative. Furthermore, even when they are negative, they are tiny in comparison to the increased hazard rates shown in Table 9.6. When the coefficients in Table 9.6 are negative, the coefficients in Table 9.7 are highly positive, indicating that regardless of which alternative shakeout date is used, the high hazard persists long after the chosen date.

Entrants Before and After Technological Events

The innovative gamble and dominant design theories predict that entrants after the time of the refinement invention or dominant design are at a disadvantage compared to earlier entrants. Earlier entrants have gained more experience with the technology and, in the dominant design theory, may have accumulated other advantages related to earlier entry. As a result, post-technological event entrants are predicted to have a higher hazard rate than earlier entrants. The relative disadvantage of post-event entrants should hold at young ages, but not at old ages. In the case of the innovative gamble theory, eventually all firms remaining in the industry are those who have successfully innovated based on the refinement, and hence among the remaining firms, early and late entrants become technological equals by the time they reach old ages. In the dominant design theory, similarly, eventually the only late entrants who remain are those who were able to adapt to low-cost production of the dominant design.

To test for a higher hazard rate among later entrants, I use a dummy variable ES that is 1 for any firm that entered during the shakeout and 0 otherwise. This dummy is added to the variables already included in models 3 and 4. Table 9.9 shows the resulting estimates for automobiles. Regardless of whether the model includes S TS or S logTS, adding the ES dummy has the predicted effect, as evidenced in columns 5 and 6. The coefficient of the late-entry dummy is positive and significant, with the coefficients 0.23 and 0.30 indicating a 26-35% higher hazard rate for firms that entered after 1909. Thus, entrants during the shakeout, after the time of any refinement invention or dominant design, indeed have a disadvantage compared to earlier entrants.

Next, I check to see whether the disadvantage of early entrants holds at young ages and decays with age, as predicted by the theories. To each model, I add an additional term that interacts the shakeout entry dummy ES with a function of age. For the Gompertz-form model, I add ES times age to model 5, yielding model 7. For the Weibull-variant model, I

Table 9.9. Entry After a Technological Event, Automobiles

	5 ES, with Gompertz TS	6 ES, with Weibull-v. TS	7 Decay w/ Age, Gompertz TS	8 Decay w/ Age, Weibull-v. TS
Age 0 to 1.5	-2.45*** (0.13)	-2.46*** (0.13)	-2.37*** (0.13)	-2.29*** (0.13)
Age 1.5 to 2.5	-1.58*** (0.10)	-1.59*** (0.10)	-1.54*** (0.10)	-1.53*** (0.10)
Age 2.5 to 3.5	-1.59*** (0.11)	-1.59*** (0.11)	-1.59*** (0.11)	-1.62*** (0.11)
Age 3.5 to 4.5	-1.71*** (0.13)	-1.71*** (0.13)	-1.75*** (0.13)	-1.79*** (0.13)
Age 4.5 to 5.5	-1.57*** (0.13)	-1.56*** (0.13)	-1.64*** (0.14)	-1.69*** (0.14)
Age 5.5 to 6.5	-2.02*** (0.18)	-2.01*** (0.18)	-2.13*** (0.18)	-2.17*** (0.18)
Age 6.5 to 7.5	-1.98*** (0.19)	-1.96*** (0.19)	-2.11*** (0.19)	-2.15*** (0.20)
Age 7.5 to 8.5	-1.93*** (0.20)	-1.91*** (0.20)	-2.09*** (0.21)	-2.11*** (0.21)
Age 8.5 to 9.5	-1.89*** (0.22)	-1.86*** (0.22)	-2.06*** (0.22)	-2.07*** (0.23)
Age 9.5 & up	-2.54*** (0.16)	-2.52*** (0.17)	-2.78*** (0.17)	-2.73*** (0.18)
Shakeout	0.30** (0.11)	0.42*** (0.13)	0.42*** (0.11)	0.53*** (0.13)
S TS	-0.013* (0.006)		-0.013* (0.007)	
S logTS		-0.14* (0.07)		-0.13* (0.08)
ES	0.23* (0.11)	0.30* (0.13)	-0.23 (0.15)	-0.37* (0.22)
ES Age			0.085*** (0.018)	
ES logAge				0.47*** (0.11)
LL	-1937.75	-1938.27	-1928.11	-1930.12

* p < .05, ** p < .01, *** p < .001

add ES times the logarithm of age to model 6, yielding model 8. If the prediction is right, the estimated coefficients of the terms ES Age and ES logAge should be negative. But in fact, as evident from columns 7 and 8 of Table 9.9, the empirical pattern is exactly opposite the prediction. Not only are the coefficients of ES Age and ES logAge positive—in fact, significantly positive—but also the coefficients of ES alone become negative once the interaction terms are included, and significantly negative in the Weibull-variant model. In other words, the estimated coefficients show that entrants during the shakeout initially had a *lower* hazard rate than pre-shakeout entrants at comparable young ages, but the hazard rates of shakeout entrants grew rapidly as they became older, resulting in the higher hazard rates of later entrants apparent in models 5 and 6. Thus, the reason for the positive estimated coefficient of ES in models 5 and 6 is that post-shakeout entrants had such a higher hazard rate at old ages that the effect overwhelms the unusually low hazard of post-shakeout entrants at young ages.

The growth of the hazard rate with age for entrants during the shakeout was apparently quite rapid. According to the Gompertz model 7, which best fits the data, entrants during the shakeout had a 17% lower hazard rate when they entered the sample at age 0.5 than did pre-shakeout entrants at the same age. By 2.7 years old, the hazard rate of entrants during the shakeout had climbed to a rate equivalent to that of 2.7-year-old, pre-shakeout entrants. By ages 5 and 10, the later entrants had hazard rates 22% and 86% higher, respectively, than firms of the same age that had entered before the shakeout. According to the Weibull-variant model 8, which does not fit as well, the hazard rate of post-shakeout entrants was at the ages 0.5, 2.2, 5, and 10 years, respectively, 50% lower, equal, 47% greater, and 104% greater compared to the hazard for earlier-entering firms. Thus, both of these models show a clear disadvantage at *old* ages for automobile firms that entered during the shakeout.

In models 5-8, the conclusions about the effect of the shakeout on the hazard rate are similar to the conclusions in models 1-4. The estimates for the shakeout dummies indicate a substantial, statistically significant increase in the hazard rate of firms of a given age. The effect of the shakeout seem to decline with time, and in models 5-8, unlike models 1-4, the coefficients of S TS and S logTS become significant. However, the estimates still indicate that the effects of the shakeout persist for decades.

In tires, Table 9.10 presents the estimates for the four models. Again, entrants during the shakeout, that is, post-1922 entrants, had a higher hazard rate than pre-shakeout entrants. The Gompertz model in column 5 yields an insignificant estimate of a 20% higher hazard rate for shakeout entrants than for pre-shakeout entrants, but the much better-fitting Weibull-variant model yields a significant estimate of a hazard 51% higher for shakeout entrants than for earlier entrants. Again, when the terms ES Age and ES logAge are included in the models in columns 6 and 7, not only do these terms not show a significant decline with age in the increased hazard of post-shakeout entrants, but in fact the

Table 9.10. Entry After a Technological Event, Tires

	5 ES, with Gompertz TS	6 ES, with Weibull-v. TS	7 Decay w/ Age, Gompertz TS	8 Decay w/ Age, Weibull-v. TS
Age 0 to 1	-2.14*** (0.37)	-2.35*** (0.38)	-2.09*** (0.37)	-2.30*** (0.39)
Age 1 to 2	-2.15*** (0.23)	-2.22*** (0.23)	-2.13*** (0.23)	-2.21*** (0.23)
Age 2 to 3	-1.63*** (0.18)	-1.64*** (0.18)	-1.61*** (0.18)	-1.64*** (0.18)
Age 3 to 4	-2.08*** (0.21)	-2.12*** (0.20)	-2.07*** (0.20)	-2.12*** (0.20)
Age 4 to 5	-1.80*** (0.23)	-1.78*** (0.22)	-1.80*** (0.22)	-1.78*** (0.22)
Age 5 to 6	-2.17*** (0.30)	-2.19*** (0.30)	-2.18*** (0.30)	-2.19*** (0.30)
Age 6 to 7	-1.80*** (0.32)	-1.77*** (0.32)	-1.81*** (0.32)	-1.78*** (0.32)
Age 7 to 8	-3.06*** (0.35)	-3.04*** (0.36)	-3.07*** (0.36)	-3.05*** (0.36)
Age 8 to 9	-1.36*** (0.26)	-1.28*** (0.26)	-1.37*** (0.26)	-1.29*** (0.26)
Age 9 to 10	-3.11*** (0.39)	-3.08*** (0.39)	-3.14*** (0.39)	-3.09*** (0.39)
Age 10 to 12	-2.95*** (0.26)	-2.84*** (0.26)	-3.00*** (0.26)	-2.86*** (0.26)
Age 12 & up	-2.92*** (0.15)	-2.72*** (0.16)	-2.98*** (0.16)	-2.73*** (0.16)
Shakeout	0.49*** (0.10)	0.94*** (0.13)	0.51*** (0.10)	0.95*** (0.13)
S TS	-0.023*** (0.005)		-0.023*** (0.005)	
S logTS		-0.42*** (0.07)		-0.42*** (0.07)
ES	0.18 (0.12)	0.41** (0.13)	0.04 (0.15)	0.33 (0.20)
ES Age			0.020 (0.013)	
ES logAge				0.05 (0.10)
LL	-1765.44	-1758.19	-1764.36	-1758.05

* p < .05, ** p < .01, *** p < .001

disadvantage of post-shakeout entrants appears to have gotten worse, though not significantly so, as they grew older. According to the Gompertz model, the hazard rate was 6%, 16%, and 28% higher for shakeout entrants at age 1, 5, and 10 years, respectively, compared to pre-shakeout entrants at the same ages. According to the better-fitting Weibull-variant model, the hazard rate was 39%, 51%, and 56% higher at ages 1, 5, and 10 for shakeout than pre-shakeout entrants. As in automobiles, in tires the hazard rate indeed appears to have been greater for entrants during the shakeout than for pre-shakeout entrants, but the effect increased rather than decreased with age, opposite the pattern that would be expected to result from a technological event.

In televisions, again the pattern is the same. Table 9.11 shows the estimated coefficients for the four models. The estimates for models 5 and 6 indicate hazard rates that were 26% or 42% higher for entrants during the shakeout than for previous entrants,

Table 9.11. Entry After a Technological Event, Televisions

	5 ES, with Gompertz TS	6 ES, with Weibull-v. TS	7 Decay w/ Age, Gompertz TS	8 Decay w/ Age, Weibull-v. TS
Age 0 to 1	-1.35** (0.47)	-1.36** (0.47)	-1.28** (0.47)	-1.29** (0.48)
Age 1 to 2	-1.67*** (0.45)	-1.68*** (0.45)	-1.67*** (0.45)	-1.69*** (0.46)
Age 2 to 3	-2.47*** (0.48)	-2.45*** (0.48)	-2.48*** (0.48)	-2.48*** (0.48)
Age 3 to 4	-2.31*** (0.53)	-2.33*** (0.53)	-2.47*** (0.53)	-2.44*** (0.55)
Age 4 to 5	-2.44*** (0.53)	-2.41*** (0.53)	-2.59*** (0.54)	-2.54*** (0.55)
Age 5 to 6	-2.23*** (0.58)	-2.16*** (0.59)	-2.42*** (0.59)	-2.32*** (0.62)
Age 6 to 7	-3.02*** (0.66)	-2.96*** (0.67)	-3.17*** (0.67)	-3.08*** (0.69)
Age 7 to 8	-2.61*** (0.58)	-2.46*** (0.62)	-2.94*** (0.61)	-2.71*** (0.70)
Age 8 & up	-2.67*** (0.37)	-2.46*** (0.44)	-2.93*** (0.40)	-2.65*** (0.50)
Shakeout	0.24 (0.29)	0.32 (0.33)	0.44 (0.31)	0.43 (0.35)
S TS	0.003 (0.015)		0.004 (0.015)	
S logTS		-0.09 (0.18)		-0.07 (0.18)
ES	0.23 (0.24)	0.35 (0.28)	-0.23 (0.37)	0.05 (0.47)
ES Age			0.069* (0.041)	
ES logAge				0.17 (0.22)
LL	-468.17	-468.06	-466.90	-467.75

Foreign entrants are excluded. * p < .05, ** p < .01, *** p < .001

Table 9.12. Entry After a Technological Event, Televisions Including Foreign Entrants

	5 ES, with Gompertz TS	6 ES, with Weibull-v. TS	7 Decay w/ Age, Gompertz TS	8 Decay w/ Age, Weibull-v. TS
Age 0 to 1	-1.34** (0.47)	-1.35** (0.47)	-1.28** (0.47)	-1.28** (0.48)
Age 1 to 2	-1.68*** (0.45)	-1.69*** (0.45)	-1.69*** (0.45)	-1.70*** (0.46)
Age 2 to 3	-2.48*** (0.48)	-2.46*** (0.48)	-2.48*** (0.48)	-2.49*** (0.48)
Age 3 to 4	-2.32*** (0.53)	-2.34*** (0.53)	-2.48*** (0.53)	-2.47*** (0.54)
Age 4 to 5	-2.46*** (0.53)	-2.43*** (0.53)	-2.62*** (0.54)	-2.57*** (0.55)
Age 5 to 6	-2.23*** (0.58)	-2.16*** (0.58)	-2.43*** (0.59)	-2.34*** (0.61)
Age 6 to 7	-3.07*** (0.66)	-3.00*** (0.67)	-3.23*** (0.67)	-3.14*** (0.68)
Age 7 to 8	-2.55*** (0.57)	-2.40*** (0.61)	-2.90*** (0.61)	-2.69*** (0.69)
Age 8 & up	-2.69*** (0.37)	-2.47*** (0.44)	-2.96*** (0.40)	-2.69*** (0.49)
Shakeout	0.24 (0.29)	0.33 (0.33)	0.45 (0.31)	0.45 (0.34)
S TS	0.004 (0.015)		0.005 (0.015)	
S logTS		-0.09 (0.18)		-0.07 (0.18)
ES	0.22 (0.24)	0.35 (0.28)	-0.26 (0.37)	0.01 (0.47)
ES Age			0.072* (0.041)	
ES logAge				0.20 (0.22)
Foreign	-3.15** (1.06)	-2.96** (1.03)	-3.15** (1.06)	-3.01** (1.03)
LL	-473.00	-472.90	-471.58	-472.50

* p < .05, ** p < .01, *** p < .001

though the increase was not significant. When the age interaction terms are included in models 7 and 8, the better-fitting Gompertz model 7 indicates a hazard that was actually

Table 9.13. Entry After a Technological Event, Penicillin

	5 ES, with Gompertz TS	6 ES, with Weibull-v. TS	7 Decay w/ Age, Gompertz TS	8 Decay w/ Age, Weibull-v. TS
Age 0 to 1	-5.01 (3.36)	-4.96 (3.36)	-5.07 (3.36)	-4.64 (3.35)
Age 1 to 2	-2.62 (3.02)	-2.62 (3.02)	-1.68 (3.05)	-1.85 (3.05)
Age 2 to 3	-2.81 (2.90)	-2.83 (2.90)	-3.23 (2.92)	-3.09 (2.92)
Age 3 to 4	-1.54 (2.78)	-1.56 (2.78)	-0.85 (2.80)	-1.17 (2.80)
Age 4 to 5	-3.67 (2.63)	-3.74 (2.63)	-4.53* (2.69)	-4.40 (2.68)
Age 5 to 6	-2.63 (2.18)	-2.60 (2.18)	-2.12 (2.20)	-2.36 (2.19)
Age 6 to 8	-5.02*** (0.98)	-5.11*** (0.98)	-6.17*** (1.20)	-5.93*** (1.17)
Age 8 & up	-4.05*** (0.56)	-3.78*** (0.55)	-4.79*** (0.65)	-4.22*** (0.63)
Shakeout	1.08* (0.55)	1.37** (0.57)	1.74** (0.60)	1.79** (0.62)
S TS	0.011 (0.016)		0.013 (0.017)	
S logTS		-0.17 (0.20)		-0.17 (0.20)
ES	-0.05 (0.63)	0.36 (0.62)	-2.18* (1.05)	-1.63 (1.27)
ES Age			0.327** (0.118)	
ES logAge				1.25* (0.65)
LL	-179.64	-179.49	-176.32	-177.60

* p < .05, ** p < .01, *** p < .001

18% *lower* at age 0.5 for entrants during the shakeout than for previous entrants, and that actually increased with age, yielding an equivalent hazard rate at age 3.3, and a hazard that was 12% and 58% higher at ages 5 and 10, respectively, compared to pre-shakeout entrants. The only term outside of the age baseline that is significant is ES Age in the better-fitting Gompertz model, and that coefficient actually indicates a rapid increase with age in the hazard rate of late entrants. The lower initial hazard rate of the later entrants is highly significant statistically, but not the ensuing increase in hazard rate. The Weibull-variant model 8 shows a hazard rate that at ages 0.5, 0.75, 5, and 10 years was 7% lower (since log(0.5) < 0), equal, 38% higher, and 58% higher for entrants during the shakeout than for pre-shakeout entrants of equivalent age. When foreign entrants are included in the sample in Table 9.12, the estimations yield almost identical findings, showing the same disadvantage to later entrants especially at old ages.

In penicillin, despite the small sample size for that product, the finding of an old-age disadvantage to entrants during the shakeout are all the more striking. Depending on whether one uses the Gompertz model 5 or the Weibull-variant model 6, entrants during the shakeout appear to have an insignificant advantage of a 5% lower hazard rate than earlier entrants of the same age, or an insignificant disadvantage of a 43% higher hazard (Table 9.13). But when the term ES Age or ES logAge is added, regardless of whether the Gompertz or Weibull-variant form is used, later entrants are estimated to have a strong survival advantage at young ages that changes to a strong disadvantage at old ages. In both cases, the shift from advantage to disadvantage among late entrants is statistically significant. Using the better-fitting Gompertz model, entrants during the shakeout have at ages 0.5, 5, 6.7, and 10 years a hazard rate that is 87% lower, 42% lower, equal, or 197% higher compared to pre-shakeout entrants of the same ages. Using the Weibull-variant model, entrants during the shakeout have at ages 0.5, 3.6, 5, and 10 years a hazard rate that is 92% lower, equal, 49% higher, and 255% higher compared to equivalent-age pre-shakeout entrants. Thus, despite the small sample size in penicillin, the estimates strikingly agree with the same patterns found in the other three products.

Timing of the Late-Entry Disadvantage

Given the recurrent finding of a disadvantage to entrants during the shakeout at old ages, one might ask whether the advantage to earlier entrants even occurred beginning at the time of the shakeout, or whether in fact the difference between the two groups of entrants occurred at some earlier date. In televisions and penicillin, the sample of entrants before the shakeout involves too short a time span or number of firms to answer this question, but an answer is possible for automobiles and tires. I divide the pre-shakeout entrants into two groups, those that entered more than five years before the shakeout began, and those that entered within the five years preceding the shakeout. I add a dummy variable for the late pre-shakeout entrants, termed "pre-shakeout group 2," denoted as EPreS2. As before, I also interact this variable with age to test how the hazard of the pre-shakeout group 2 firms compares to that of the group 1 firms at young and old ages.

Table 9.14 shows the resulting estimates for automobiles. Columns 9 and 10 are similar to columns 5 and 6 in the previous tables, except that now two dummies are used, one for each of the two groups of later entrants. As before, the age baseline is used, as well as the shakeout dummy and its interaction with time since the shakeout began. The estimates for these variables are similar to the estimates in models 3 and 4. However, in models 9 and 10, after controlling for the differences in entry cohorts, the effect of the shakeout appears to be smaller and insignificant. Looking next at the estimated coefficients of EPreS2 and ES, both groups of entrants had higher hazard rates, by a highly significant margin, compared to the hazard rate of entrants in pre-shakeout group 1. According to the estimates of the Gompertz model 9, without including an age-interaction term, pre-shakeout 2 entrants had a 65% higher hazard rate than pre-shakeout 1 entrants of the same age, and shakeout entrants had a 95% higher hazard rate than pre-shakeout 1 entrants. The slightly better-fitting Weibull-variant model 10 shows a similar but even stronger pattern, in which pre-shakeout 2 entrants had a 70% higher hazard rate than pre-shakeout 1 entrants, and shakeout entrants had a 123% higher hazard rate. As shown in Table 9.15, using the Gompertz model shakeout entrants appear to have had a 19% higher hazard rate than pre-shakeout 2 entrants of the same age, and using the Weibull-variant model the shakeout entrants apparently had a statistically significant 31% higher hazard rate. Late entrants appear to have had a disadvantage not because they entered after the shakeout began, but simply because they entered late, regardless of when the shakeout began. Furthermore, the disadvantage of late entrants apparently intensified with time.

When the age-interaction terms are added in models 11 and 12, the pattern of disadvantage to late entrants at old ages becomes all the more apparent. In both the Gompertz and Weibull models, the hazard rates of the two late entry groups appear to have been comparable at young ages, but to have diverged at old ages. The increase in the hazard with age occurred almost twice as quickly for the shakeout entrants as for the pre-

Table 9.14. Distinguishing Pre-Shakeout Entrants, Automobiles

	9 Entry Dummies, Gompertz TS	10 Entry Dummies, Weibull-v. TS	11 Decay w/ Age, Gompertz TS	12 Decay w/ Age, Weibull-v. TS
Age 0 to 1.5	-2.67*** (0.14)	-2.69*** (0.14)	-2.45*** (0.14)	-2.24*** (0.16)
Age 1.5 to 2.5	-1.77*** (0.11)	-1.80*** (0.11)	-1.61*** (0.11)	-1.57*** (0.12)
Age 2.5 to 3.5	-1.75*** (0.12)	-1.77*** (0.12)	-1.66*** (0.12)	-1.68*** (0.12)
Age 3.5 to 4.5	-1.85*** (0.13)	-1.86*** (0.13)	-1.81*** (0.13)	-1.87*** (0.13)
Age 4.5 to 5.5	-1.69*** (0.14)	-1.68*** (0.14)	-1.70*** (0.14)	-1.78*** (0.14)
Age 5.5 to 6.5	-2.12*** (0.18)	-2.10*** (0.18)	-2.18*** (0.18)	-2.26*** (0.19)
Age 6.5 to 7.5	-2.05*** (0.19)	-2.02*** (0.19)	-2.16*** (0.19)	-2.23*** (0.20)
Age 7.5 to 8.5	-1.98*** (0.20)	-1.94*** (0.20)	-2.13*** (0.21)	-2.19*** (0.22)
Age 8.5 to 9.5	-1.91*** (0.22)	-1.86*** (0.22)	-2.10*** (0.22)	-2.13*** (0.23)
Age 9.5 & up	-2.42*** (0.16)	-2.34*** (0.17)	-2.75*** (0.18)	-2.65*** (0.19)
Shakeout	0.01 (0.12)	0.14 (0.14)	0.22 (0.14)	0.35* (0.16)
S TS	-0.013* (0.007)		-0.016* (0.007)	
S logTS		-0.18* (0.08)		-0.21** (0.08)
EPreS2	0.50*** (0.11)	0.53*** (0.11)	0.15 (0.15)	-0.07 (0.20)
EPreS2 Age			0.035** (0.013)	
EPreS2 logAge				0.33** (0.11)
ES	0.67*** (0.15)	0.80*** (0.17)	0.08 (0.21)	-0.02 (0.28)
ES Age			0.081*** (0.020)	
ES logAge				0.50*** (0.13)
LL	-1927.50	-1927.03	-1919.47	-1918.81

* p < .05, ** p < .01, *** p < .001

Table 9.15. EPreS2 versus ES Entrants, Automobiles

	9 Entry Dummies, Gompertz TS	10 Entry Dummies, Weibull-v. TS	11 Decay w/ Age, Gompertz TS	12 Decay w/ Age, Weibull-v. TS
ES - EPreS2	0.17 (0.11)	0.27* (0.13)	-0.08 (0.16)	0.05 (0.24)
Diff Age			0.047** (0.019)	
Diff logAge				0.17 (0.13)
LL	-1927.50	-1927.03	-1919.47	-1918.81

* p < .05, ** p < .01, *** p < .001

shakeout 2 entrants. In Table 9.15, the term Diff Age represents the difference between the two shakeout dummies, ES - EPreS2, interacted with age. For the Gompertz model, but not for the better-fitting Weibull-variant model, the estimate of Diff Age of 0.047 shows a statistically significant divergence in the rate of increase in the hazard rates of the two late-entry groups. Returning to Table 9.14, the estimates for the Gompertz model indicate that pre-shakeout group 2 entrants had hazard rates that were 18%, 38%, and 65% higher than those of pre-shakeout group 1 entrants at age 0.5, 5, and 10 years respectively, and shakeout entrants had hazard rates that were 13%, 62%, and 144% higher at the same ages. With the better-fitting Weibull-variant model, pre-shakeout group 2 entrants had hazard rates that were 24% lower, 62% higher, and 103% higher than pre-shakeout group 1 entrants at ages 0.5, 5, and 10, and shakeout entrants had hazard rates that were 31% lower, 119% higher, and 210% higher at the same ages. Thus, the pattern of disadvantage to late entrants at old ages was striking, grew over time, and began well before the start of the shakeout in automobiles.

In tires, Table 9.16 shows the estimated hazard rates for the pre-shakeout 2 entrants, which entered in the five years preceding the peak in the number of firms, and the shakeout entrants compared to the pre-shakeout 1 entrants. The estimates for the two entry group dummies in models 9 and 10 again show that the pre-shakeout 2 entrants had a higher hazard rate than earlier entrants, so that the increase in the hazard rate for later entrants apparently occurred well before the shakeout began. The hazard rate was highest for the shakeout entrants. Entrants within the five years preceding the shakeout had hazard rates 49 or 63% above the hazards of the earliest entrants at the same ages, depending on whether the Gompertz or the better-fitting Weibull-variant model is used, and entrants during the shakeout had exit rates 67 or 137% higher. In each model, the differences between the pre-shakeout 1 entrants and the two later groups entrants are highly significant. The difference between the two later groups is significant if the Weibull-variant model is used (Table 9.17).

Adding the age-interaction terms to the model, the predicted effect of a higher hazard rate at young ages holds, but it holds for entrants in the five years preceding the shakeout as well as for entrants during the shakeout. For both groups, the higher hazard at young ages is strongly significant. At age 0.5 years, the pre-shakeout 2 entrants are estimated to have had hazard rates 87% or 108% higher than the earliest entrants,

Table 9.16. Distinguishing Pre-Shakeout Entrants, Tires

	9 With Gompertz TS	10 With Weibull-v. TS	11 Decay w/ Age, Gompertz TS	12 Decay w/ Age, Weibull-v. TS
Age 0 to 1	-2.25*** (0.37)	-2.53*** (0.38)	-2.35*** (0.37)	-2.73*** (0.42)
Age 1 to 2	-2.26*** (0.23)	-2.38*** (0.23)	-2.36*** (0.23)	-2.46*** (0.25)
Age 2 to 3	-1.75*** (0.18)	-1.80*** (0.18)	-1.83*** (0.19)	-1.86*** (0.19)
Age 3 to 4	-2.15*** (0.21)	-2.22*** (0.20)	-2.19*** (0.21)	-2.24*** (0.20)
Age 4 to 5	-1.88*** (0.23)	-1.87*** (0.23)	-1.91*** (0.23)	-1.89*** (0.23)
Age 5 to 6	-2.21*** (0.30)	-2.24*** (0.30)	-2.23*** (0.30)	-2.23*** (0.30)
Age 6 to 7	-1.84*** (0.31)	-1.80*** (0.31)	-1.84*** (0.31)	-1.78*** (0.31)
Age 7 to 8	-3.04*** (0.35)	-3.01*** (0.35)	-3.04*** (0.35)	-2.97*** (0.35)
Age 8 to 9	-1.37*** (0.26)	-1.29*** (0.26)	-1.36*** (0.26)	-1.27*** (0.26)
Age 9 to 10	-3.07*** (0.39)	-3.02*** (0.39)	-3.05*** (0.40)	-2.98*** (0.39)
Age 10 to 12	-2.84*** (0.26)	-2.69*** (0.25)	-2.79*** (0.26)	-2.63*** (0.26)
Age 12 & up	-2.76*** (0.16)	-2.50*** (0.16)	-2.68*** (0.17)	-2.45*** (0.17)
Shakeout	0.24* (0.12)	0.71*** (0.14)	0.19 (0.13)	0.64*** (0.15)
S TS	-0.025*** (0.005)		-0.022*** (0.005)	
S logTS		-0.48*** (0.07)		-0.46*** (0.07)
EPreS2	0.40*** (0.12)	0.49*** (0.12)	0.64*** (0.16)	0.67** (0.22)
EPreS2 Age			-0.031** (0.013)	
EPreS2 logAge				-0.09 (0.11)
ES	0.51*** (0.16)	0.84*** (0.17)	0.56** (0.21)	1.06*** (0.28)
ES Age			-0.004 (0.016)	
ES logAge				-0.12 (0.12)
LL	-1760.05	-1750.40	-1756.59	-1749.77

* p < .05, ** p < .01, *** p < .001

Table 9.17. EPreS2 versus ES Entrants, Tires

	9 With Gompertz TS	10 With Weibull-v. TS	11 Decay w/ Age, Gompertz TS	12 Decay w/ Age, Weibull-v. TS
ES - EPreS2	0.12 (0.12)	0.36** (0.13)	-0.07 (0.16)	0.39* (0.22)
Diff Age			0.027 (0.017)	
Diff logAge				-0.03 (0.12)
LL	-1760.05	-1750.40	-1756.61	-1749.77

* p < .05, ** p < .01, *** p < .001

depending on whether the Gompertz or the better-fitting Weibull-variant model is used, and entrants during the shakeout are estimated to have had hazard rates 75% or 214% higher at the same age. Furthermore, the effect of late entry persisted even at very old ages. There were small declines in the increased hazard as firms grew older, but the declines were insignificant except with the less-well-fitting Gompertz model for the EPreS2 group only.

At ages 5 and 10 years, respectively, the Gompertz model indicates that pre-shakeout 2 entrants had 63% and 40% higher hazard rates than pre-shakeout 1 entrants, and the Weibull-variant model indicates that pre-shakeout 2 entrants had 69% and 59% higher hazard rates. For entrants during the shakeout at ages 5 and 10, the Gompertz model indicates that these particularly late entrants had hazard rates 72% and 68% greater than those of the earliest entrants, and the Weibull-variant model indicates hazard rates 138% and 119% higher. According to the Gompertz model, the higher hazard due to late entry did not disappear until age 21 for pre-shakeout 2 entrants and age 140 for shakeout entrants, and according to the Weibull-variant model, the higher hazard rates are predicted to persist for thousands of years. Thus, in tires as well as in automobiles, the disadvantage caused by late entry began with entrants well before the start of the shakeout, and it persisted essentially forever.

As expected in the technological event theories, post-shakeout entrants appear to have had a higher hazard rate than pre-shakeout entrants. Yet the higher hazard rate of later entrants does not appear to have resulted from any single, temporary event. If a technological event had caused the higher hazard of late entrants, the hazard of late entrants should have been especially high at young ages, but returned to normal at old ages, once firms that were unable to adapt to the refinement invention or dominant design had exited the industry. In fact, exactly the opposite pattern typically occurred. At young ages, late entrants in all products except tires had comparable hazard rates to earlier entrants, in many cases even lower hazard rates than earlier entrants. But as late entrants grew older, their hazard rates grew dramatically above the hazard rates of earlier entrants with the same age. In tires, late entrants did have higher hazard rates at young ages, but the high hazard persisted at old ages as well. Furthermore, dividing pre-shakeout entrants in automobiles and tires into two groups showed that a disadvantage of late entry already existed five years before the shakeouts began. The later pre-shakeout entrants had higher hazard rates at old ages than the earlier pre-shakeout entrants, and the disadvantage at old ages was even stronger for entrants during the shakeout. Thus, some continual process, rather than a single technological event, seems to have put later entrants at an increasing disadvantage, and their disadvantage appears to have been important particularly at old ages.

The Old-Age Advantage of Early Entrants

The size-and-skill theory predicts an advantage to earlier entrants at old ages because earlier entrants have more time to grow larger. Once firms are large, they can afford to do more R&D, not simply because they have more money to spend but because the per-unit costs of R&D are lower. Other reasons may exist for an advantage to older or larger firms, but regardless of the source of the advantage, an advantage-to-the-advantaged dynamic results. Firms that have an advantage are most likely to maintain or improve their advantage. Firms at a disadvantage are most likely to remain at a disadvantage or to be put at an even further disadvantage with time. Time of entry matters because the earliest entrants to the industry have the most time to grow large and capture an advantage. Among the early-entering firms, those with the most expertise, leadership, and luck eventually come to dominate the industry. Later entrants grow over time as well, but since they start out small in comparison to earlier entrants which have already had time to grow, they are unlikely ever to achieve the preeminence of the early-entering leaders. Late-entering firms are able to break into the industry only because they are particularly skilled innovators, and while their skill may give them normal exit rates at young ages, they are doomed to increasingly high exit rates at old ages. Successive cohorts of entrants reach extinction in reverse order of entry.

The size-and-skill theory makes no predictions about the specific functional form of the relationship between time of entry and the hazard rate. Before performing statistical analyses based on particular functional forms, it is therefore useful to use nonparametric statistical techniques to examine the dependence of the hazard rate on time of entry. I use the Kaplan-Meier method of estimating survival rates, a commonly used method that provides unbiased estimates of survival rates for the firms in each cohort. I divide firms with different entry times into cohorts, intentionally creating separate cohorts for firms that entered in the earliest years of each product, as well as in the late years after entry declined to small numbers, in case survival patterns are different for especially early and late entrants than compared to firms at intermediate times. In the Kaplan-Meier plots included here, cohorts have been chosen to emphasize differences in survival rates among earlier- and later-entering firms, but when I plotted similar curves with cohorts chosen to equalize sample sizes, the results were similar to those shown here.

The Kaplan-Meier curves show the percentage of firms in each cohort that were still surviving as a function of the ages of the firms. In each plot, the left-hand axis indicates the percentage of firms surviving, and the bottom axis indicates age. The percentage survival figures are plotted on a logarithmic scale, facilitating the ability to read hazard rates, as well as the percentage of firms surviving. With a logarithmic scale, a straight line on the graph implies a constant hazard rate equal to negative one times the slope of the line.

Figure 9.2 illustrates the pattern predicted by the size-and-skill theory as it should appear in the Kaplan-Meier plots. A hypothetical earliest cohort of entrants is represented by curve 1. The percentage of firms surviving in this cohort drops off from 100% at age zero to a lower percentage at greater ages. Assuming a baseline hazard rate that declines with age, the slope of survival curve 1 becomes increasingly shallow as the hazard rate falls. A later cohort of entrants, cohort 2, has a hazard rate at young ages comparable to that of cohort 1, so the percentage of firms surviving in cohort 2 initially remains the same as that in cohort 1. But as the cohort two entrants reach old ages, their hazard rates increase. The slope of curve 2 gets steeper as the hazard increases and the cohort 2 firms are forced out of the industry. Similarly, a third cohort of even later entrants initially has hazard rates comparable to those of earlier entrants, but as the firms in this cohort grow older, their hazard rate increases and they are rapidly forced out of the industry.

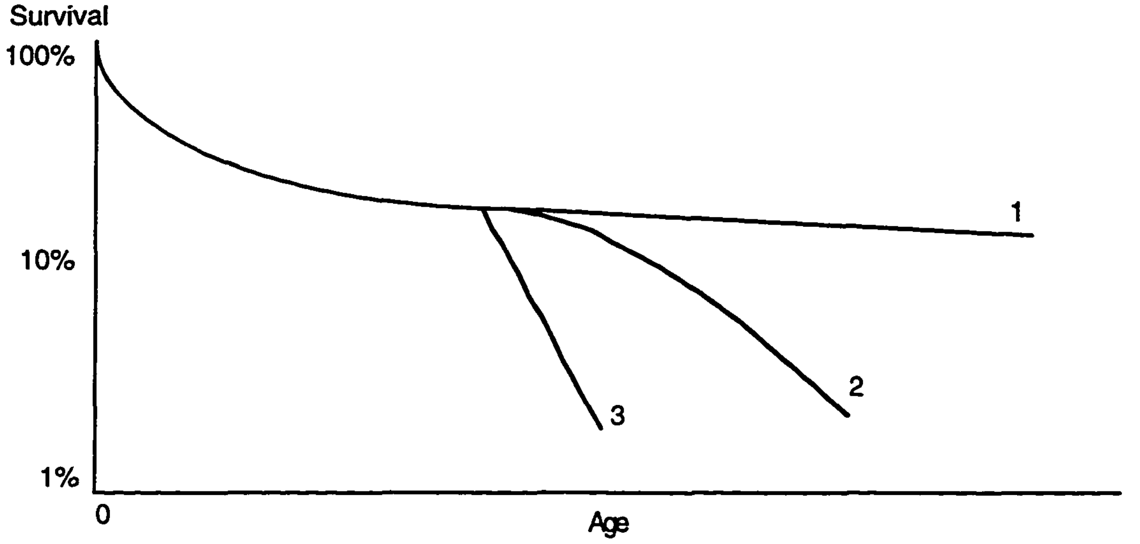


Figure 9.2. Survival pattern predicted by the size-and-skill theory.

Figure 9.3 shows the actual Kaplan-Meier survival curves for automobiles. Entrants are divided into five cohorts: 1895-1904, 1905-1909, 1910-1916, 1917-1922, and 1923-1967. The thicker lines show earlier-entering cohorts. The dates of entry of the cohorts are also noted in the figure, as "1895-04," "05-09," *et cetera*. The curves lie on top of each other initially, indicating comparable hazard rates through about age five. After age five, the hazard rate for the earliest cohort fell substantially, so that the thickest curve drops off less rapidly and emerges above the other curves. The other cohorts, in contrast, continued with their early hazard rates largely unchanged—the slopes of their curves remain nearly constant. At very old ages, the earliest entry cohort experienced a declining hazard rate, but among the later entrants, the hazard rate remained roughly constant or perhaps even increased, most notably in the case of the 1923-1967 entrants. Thus, the automobiles data appear to match with the prediction that later entrants have higher hazard rates at old ages. The biggest disparity was between entrants in the 1895-1904 group and all later entrants. The later entrants all died out by age 26, and a few early entrants came to

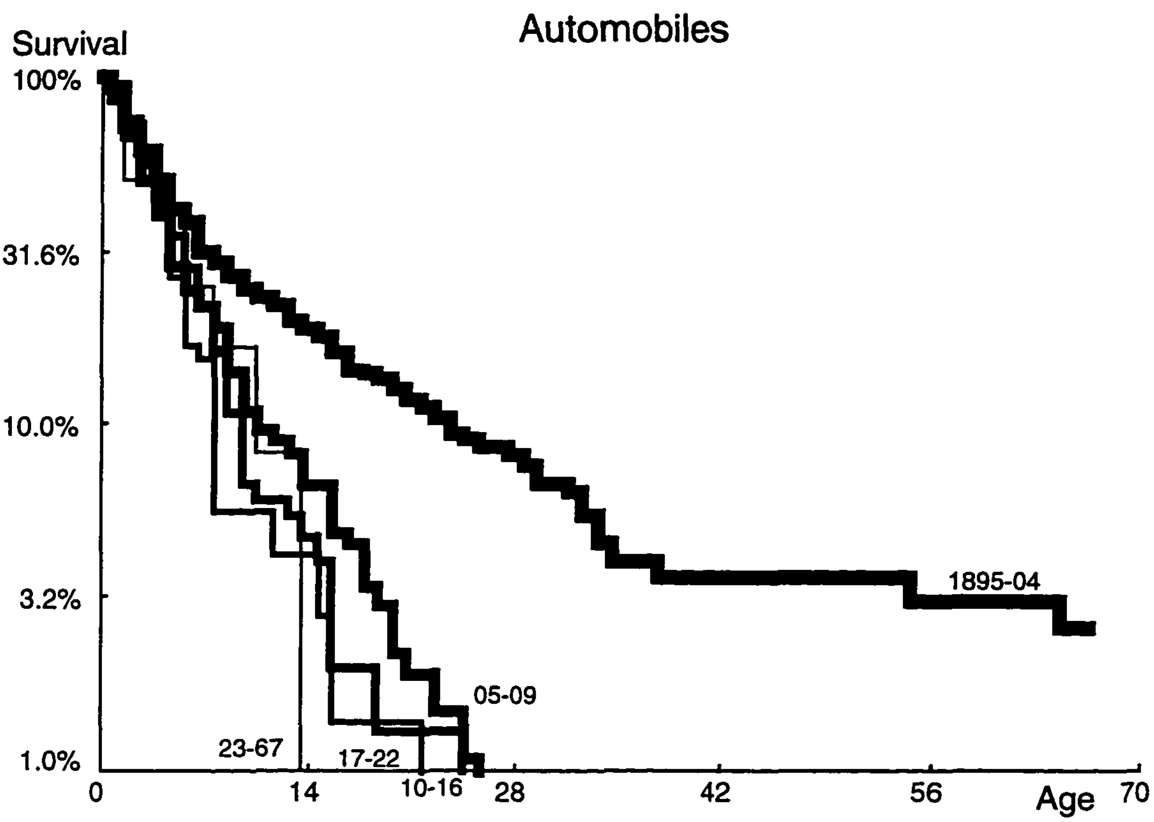


Figure 9.3. Kaplan-Meier survival plots of entrants by cohort in automobiles.

dominate the industry. Among the later entrants, there seems to have been a very slight disparity between cohorts, since the last firms in each cohort exited at an increasingly young age.

In tires, Figure 9.4 shows the survival curves for entrants in 1905-1906, 1907-1916, 1917-1921, 1922-1932, and 1932-1980. Again, a pattern of early-mover advantage is apparent, with the biggest difference occurring between the earliest entrants and all later entrants. The first two cohorts had comparable hazard rates until about age five, when the hazard rate of early entrants diminished. Because of their higher hazard rate after age five, the percentage of 1907-1916 entrants remaining dropped below the percentage of remaining 1905-1906 entrants. The 1917-1921 and 1922-1932 entrants experienced higher hazard rates even at young ages, so that their survival percentages quickly fell below those of earlier entrants. Among the later cohorts, if one ignores the 1933-1980 entrants, the

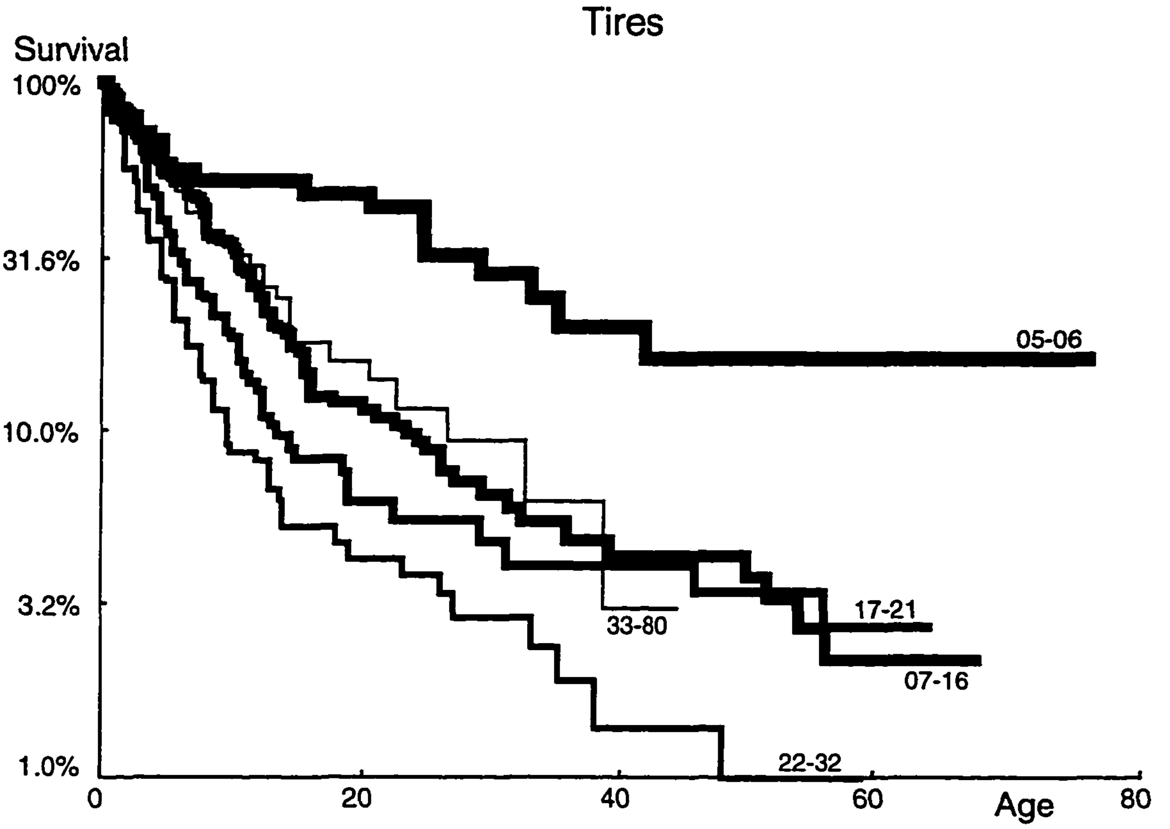


Figure 9.4. Kaplan-Meier survival plots of entrants by cohort in tires.

increase in the hazard rate with entry year is almost monotonic. Except for the crossing of the 1907-1916 and 1917-1921 cohort curves at nearly age 60, when sample sizes are minuscule, the survival percentages of earlier cohorts were always greater than those for later cohorts.

The 1933-1980 entrants, in contrast, appear to have had unusually low hazard rates, not as low as 1905-1906 entrants, but slightly lower than the hazard of 1907-1916 entrants. These late entrants were few, and the virtually-monotonic rise in hazard rates with entry date among the earlier entry cohorts suggests that the late entrants must have been unusual to be able to avoid the trend. I examined the late entrants in tires to try to find any signs that these firms might have been unusual, for example producers of specialized products such as racing tires, but the search did not reveal any clear signs that the firms

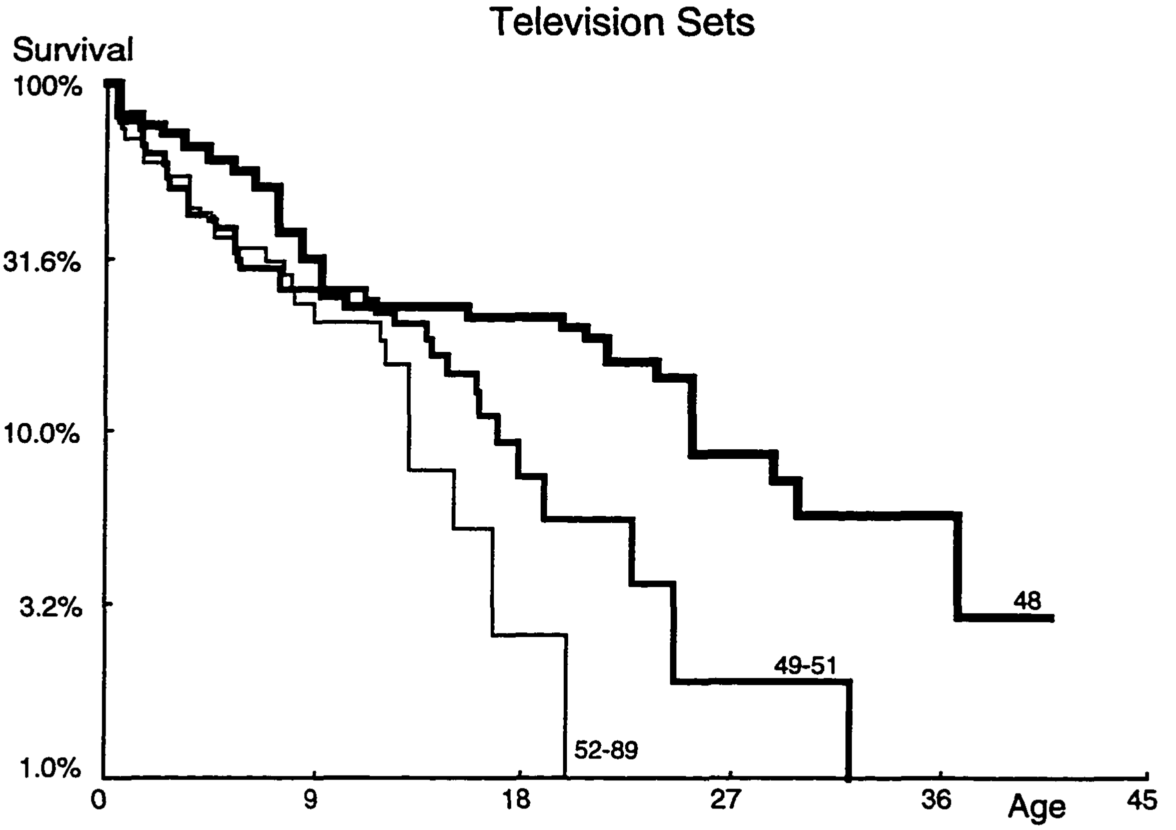


Figure 9.5. Kaplan-Meier survival plots of entrants by cohort in televisions. Foreign entrants are excluded.

were unusual. The only possible explanation that resulted from the search is that many of the firms seem similar in name or address to firms that had been listed in the trade register long ago. Perhaps they were the same firms that had moved and/or changed their names, but without more specific indications that the firms were the same, I chose not to guess in favor of this easy explanation. The nature of these late entrants remains a mystery. In any case, despite their higher survival rates, these firms captured very little market share; the eventual market leaders all entered much earlier. The tires data show a nearly monotonic pattern of advantage to earlier entrants within the other cohorts, and even considering the unusual 1933-1980 entrants, there is a clear disparity in hazard rates at old ages between the 1905-1906 entrants and all later entrants.

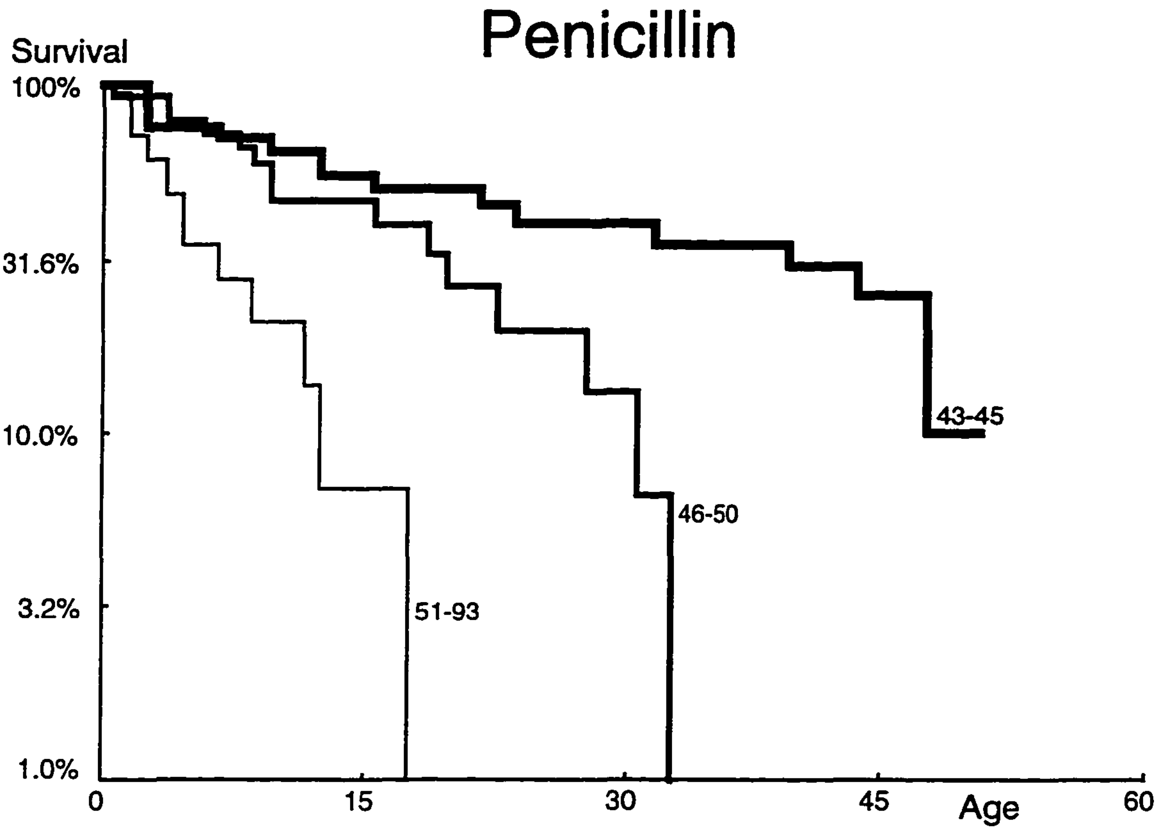


Figure 9.6. Kaplan-Meier survival plots of entrants by cohort in penicillin.

In televisions, an advantage to early entry is mostly apparent at old ages. Firms that entered by 1948, when *Television Factbook* began listing manufacturers of television sets, had a lower hazard rate than later entrants until about age six (Figure 9.5). However, an increased hazard in the next three years of age brought the percentage of surviving 1948 entrants down to a level comparable to that of entrants in 1949-1951 and 1952-1989. The hazard rates of the latest entrants increased after age 12, with the latest entry cohort experiencing the greatest increase in hazard rate. Thus, televisions fits the prediction of the advantage-to-the-advantaged view that later entrants have increased hazard rates at old ages. Indeed, little advantage to earlier entry is apparent in the survival data until after age 12, but thereafter the survival rates of the three entry cohorts diverged dramatically.

Finally, consider the Kaplan-Meier curves for penicillin shown in Figure 9.6. Firms are divided into three groups, distinguishing entrants in 1943-1945, 1946-1950, and

1951-1993. The hazard rates below age seven were comparable for the first two cohorts of entrants, but the last cohort began with a higher hazard rate. By old ages, the hazard rates of the three cohorts diverged increasingly, showing a strong advantage to early entry. By age 17, all entrants in the third cohort had exited. The second cohort fared somewhat better, with the last of its producers forced out of the industry by age 33. In contrast, the 1943-1945 entrants still had firms remaining at age 50.

The nonparametric analyses using Kaplan-Meier survival curves indicate that in each product, earlier entrants had lower hazard rates at least by old ages. In tires and penicillin, an advantage to early entry was apparent at young ages as well. The caricature made by Klepper's (1995) stochastic variant of the size and skill model that later entrants have *lower* hazard rates at young ages seems in most cases to be unrealistic. But always the essential, advantage-to-the-advantaged prediction of the size-and-skill model is strongly evident. In each product, by the time they reach old ages, later entrants have substantially higher hazard rates than earlier entrants.

The biggest differences in hazard rates arises between the first cohort and later cohorts. Apparently, in order to achieve lower probabilities of exit, firms had to enter in the earliest years of these products. After the earliest years, the hazard rate increased relatively little with time of entry. It seems there were windows of opportunity in each product, during which firms had to enter if they wished to achieve an early-mover advantage.

In three of the products, the window of opportunity began at the inception of the industry, but automobiles is a suggestive counterexample. When the first cohort of entrants into automobile manufacture are subdivided into those that entered in 1895-1900 versus entrants in 1900-1905, the later group of entrants had much higher survival rates in the long run, and it includes the forerunners of General Motors, Ford, and Chrysler, which became the industry's leading producers. Entrants in 1895-1900 were concentrated in the Northeastern part of the country and disproportionately included makers of steam and electric automobiles, technologies that turned out to fare poorly in contrast to gasoline automobiles. Entrants in 1900-1905 included many more Detroit-area manufacturers, who may have benefited from each other's research and from developing gasoline-powered engines, which became the dominant engine design. Thus, the window of opportunity in tires may have begun after the beginning of the industry, lasting from about 1900 to 1905. In the other products, the windows of opportunity for entry began immediately after the inception of each industry and lasted at most until about 1906 in tires, 1948 in televisions, and 1945 in penicillin.

The Old-Age Advantage of Early Entrants: Functional Form

The finding that the lower hazard rate of earlier entrants held particularly for entrants in the earliest years of each product compared to all later entrants provides a basis on which to consider functional forms with which to represent entry year in the parametric statistical models. Since the theories do not imply any particular functional form, I tested the sensitivity of the results to the choice of any of three functional forms that allow for the finding of the greatest effect of entry year in the earliest years of each product. I considered three different functional forms discussed in chapter eight to allow for a range of possibilities in terms of how rapidly the effects of later entry grow with age for entrants at different times.

These analyses consistently showed an advantage to early entrants that persisted or grew into old ages. Appendix 1 reports the estimates for these models, which include as independent variables a baseline function of age, g(ey), and g(ey) interacted with age, using both Gompertz and Weibull functions of age. After trying each of the three functional forms in each product, in addition to variations in which I used max(g(ey)) - g(ey) in place of g(ey) to allow the advantage of early entrants to increase with age, so that the age baseline alone estimated the hazard rate of the latest entrants, I found the estimated dependence between hazard rates of late (or early) entrants and age to be highly sensitive to the functional form of the model. Since the true form of the dependence of the hazard on entry year and age is unknown, this sensitivity makes it unclear whether at young ages later entrants had higher hazard rates than earlier entrants. Regardless, if late entrants were estimated to have high hazard rates at young ages, those high hazards persisted into old ages, and if late entrants did not appear to have high hazard rates at young ages, their hazard rates nonetheless increased as they grew old. Thus, a clear early mover advantage at old ages resulted from these analyses.

Best-Fit Entry Cohorts

As an alternative to testing the continuous functional forms for the dependence of the hazard rate on entry date and age, I used a best-fit technique to determine dates at which a division of entry cohorts provided a good fit for the statistical model. The Kaplan-Meier survival plots are suggestive that there existed windows of opportunity for entry, after which entrants fared relatively poorly in long-run competition. To capture this possibility, I used one entry cohort for all entrants before a specific date EY* and another cohort for all entrants afterward. Instead of choosing the cohorts based on subjective perceptions of a window of opportunity, I varied EY* to see what division provided the best fit for the statistical models. I tried every date from one year after the start of each sample until thirty years after the start, or until the sample size was so small as to yield enormous standard errors. I used this approach in three different models. Each model incorporated a baseline function of age; the dummy variable Early, which equaled 1 for all firms that entered up to EY* years after the first entrant and 0 for all later-entering firms; and the interaction term Early times $f(a)$. The three models differed only in the function of age, $f(a)$, used. For $f(a)$, I tried the Gompertz and Weibull functions of age and, alternatively, a dummy variable that divided age into groups with age less than or greater than eight years.[79] The

Table 9.18. Advantage to Early Entrants at Alternative Entry Year Breakpoints, for Automobiles.

EY*	LL	Early & Young	Early & Old
1	-1939.365	-1.641* (0.709)	-0.168 (0.456)
2	-1937.900	-1.791** (0.709)	-0.250 (0.417)
3	-1938.536	-1.125** (0.411)	-0.263 (0.364)
4	-1938.625	-0.716** (0.240)	-0.146 (0.273)
5	-1939.617	-0.427** (0.154)	-0.207 (0.224)
6	-1938.333	-0.373** (0.132)	-0.361* (0.204)
7	-1936.363	-0.330** (0.113)	-0.474** (0.186)
8	-1926.693	-0.317*** (0.098)	-0.862*** (0.178)
9 *	-1919.976	-0.339*** (0.094)	-1.039*** (0.176)
10	-1920.169	-0.405*** (0.090)	-0.920*** (0.173)
11	-1923.058	-0.386*** (0.086)	-0.841*** (0.174)
12	-1933.007	-0.229** (0.084)	-0.726*** (0.179)
13	-1937.445	-0.123 (0.084)	-0.658*** (0.184)
14	-1936.004	-0.212** (0.087)	-0.762*** (0.213)
15	-1935.919	-0.202* (0.092)	-0.904*** (0.235)
16	-1934.098	-0.224** (0.093)	-1.068*** (0.247)
17	-1935.386	-0.168* (0.096)	-1.068*** (0.247)
18	-1938.428	-0.107 (0.100)	-0.953*** (0.260)
19	-1939.637	-0.160 (0.103)	-0.856** (0.288)
20	-1941.787	-0.196* (0.111)	-0.561 (0.347)
21	-1941.778	-0.271* (0.122)	-0.340 (0.419)
22	-1942.264	-0.263* (0.132)	-0.340 (0.419)
23	-1941.780	-0.319* (0.141)	-0.360 (0.457)
24	-1940.114	-0.445** (0.154)	-0.685 (0.589)
25	-1942.103	-0.402* (0.192)	-0.653 (0.716)
26	-1943.602	-0.239 (0.240)	-0.653 (0.716)
27	-1943.833	-0.205 (0.293)	-0.653 (0.716)
28	-1943.987	-0.121 (0.305)	-0.653 (0.716)
29	-1944.060	0.021 (0.357)	-0.653 (0.716)
30	-1944.062	0.000 (0.381)	-0.653 (0.716)

conclusions are similar to those discussed above: at the entry cohort divisions that are local minima of the likelihood function, later entrants sometimes appear to have had higher hazard rates at young ages, but consistently appear to have had higher hazard rates at old ages.

Tables 9.18-9.22 show estimates of the critical terms of the model with an age division at eight years. The coefficients of the baseline function of age are not shown. In Table 9.18, which pertains to automobiles, the first column, EY*, indicates the entry year breakpoint used in each of the thirty different statistical analyses. The breakpoint is relative to the first date of entry in the industry. In this case, the asterisk by breakpoint 9 indicates that when entrants up to nine years after the first entrant are compared with all later entrants, the model has the best fit. Apparently, the difference between earlier and later entrants is most pronounced when comparing firms that entered by the year 1904 with all later entrants. The second column of the table indicates the log-likelihood of the fitted model at each entry year breakpoint. The highest log-likelihood, -1919.976, occurs at breakpoint 9. The monotonic rise in the likelihood function in the eight years before breakpoint 9, and the monotonic fall in the next thirteen years, is consistent with the idea that entrants can be divided into two cohorts with substantial differences in survival probabilities. The only other breakpoint at which there is barely a local minimum of the likelihood function is at EY* = 24, suggesting a slight discontinuity between entrants before and after 1920, with the later group faring worse at old ages than the earlier group.

The third and fourth columns of the table show the coefficients of dummy variables for early entrants at young (≤ 8 years) and old (> 8 years) ages. Negative numbers indicate higher survival rates for early entrants. Regardless of what breakpoint is chosen, early entrants appear to have had a higher survival rate at old ages, and except at the badly fitting breakpoints 29 and 30, there appears to have been at least some advantage to early entry at young ages as well. With a breakpoint of EY* = 9, the 224 early entrants had a 29% lower hazard rate than the 503 later entrants at age ≤ 8, and a 65% lower hazard rate at age > 8 (both differences highly significant). Thus, at the best-fitting entry year breakpoint in automobiles, early entrants appear to have had an advantage that increased as they grew older.

In tires, Table 9.19 shows the estimates for the alternative breakpoints. The best-fitting breakpoint occurs at EY* = 13 or EY* = 14. The break occurs at the time of a two-year gap in publication of *Thomas' Register*, explaining why the estimates for the two breakpoints are identical. The breakpoint divides the 272 firms that entered by 1918 from the 361 that entered later. With this breakpoint, the earlier entrants apparently had 46% and

Table 9.19. Advantage to Early Entrants at Alternative Entry Year Breakpoints, for Tires.

EY*	LL	Early & Young	Early & Old
1	-1775.006	-0.710* (0.306)	-1.197*** (0.327)
2	-1778.537	-0.224 (0.182)	-1.001*** (0.278)
3	-1778.537	-0.224 (0.182)	-1.001*** (0.278)
4	-1781.251	-0.180 (0.163)	-0.762*** (0.242)
5	-1781.251	-0.180 (0.163)	-0.762*** (0.242)
6	-1782.650	-0.305* (0.139)	-0.391* (0.173)
7	-1782.521	-0.305* (0.139)	-0.400* (0.173)
8	-1782.521	-0.305* (0.139)	-0.400* (0.173)
9	-1777.079	-0.536*** (0.125)	-0.173 (0.151)
10	-1775.111	-0.566*** (0.119)	-0.142 (0.147)
11	-1770.195	-0.597*** (0.113)	-0.323* (0.144)
12	-1767.027	-0.577*** (0.106)	-0.466*** (0.143)
13 *	-1764.761	-0.618*** (0.102)	-0.420** (0.143)
14 *	-1764.761	-0.618*** (0.102)	-0.420** (0.143)
15	-1774.932	-0.445*** (0.099)	-0.359** (0.147)
16	-1774.359	-0.442*** (0.099)	-0.417** (0.151)
17	-1781.688	-0.132 (0.109)	-0.523*** (0.153)
18	-1781.688	-0.132 (0.109)	-0.523*** (0.153)
19	-1782.411	-0.037 (0.118)	-0.521*** (0.154)
20	-1782.001	0.008 (0.125)	-0.549*** (0.156)
21	-1781.104	0.123 (0.138)	-0.575*** (0.159)
22	-1781.393	0.155 (0.143)	-0.553*** (0.159)
23	-1781.046	0.197 (0.146)	-0.551*** (0.159)
24	-1779.440	0.291* (0.153)	-0.581*** (0.161)
25	-1778.335	0.278* (0.156)	-0.652*** (0.164)
26	-1777.981	0.310* (0.159)	-0.651*** (0.164)
27	-1777.897	0.319* (0.160)	-0.650*** (0.164)
28	-1777.333	0.364* (0.163)	-0.648*** (0.164)
29	-1777.328	0.367* (0.167)	-0.654*** (0.165)
30	-1777.263	0.355* (0.168)	-0.674*** (0.167)

34% lower hazard rates at young and old ages, respectively, than later entrants (both differences highly significant). A local minimum in the log-likelihood also occurs at EY* = 1, indicating that substantial explanatory power is also available by comparing entrants by 1906 with all later entrants. This differential corresponds with the unusually low hazard rate of the earliest cohort in Figure 9.4. These extremely early entrants had a hazard rate 51% lower than later entrants at age ≤ 8, and 70% lower at age > 8. Thus, a clear advantage at all ages is apparent for entrants before 1920, the division with the most explanatory power, and especially for entrants by 1906, a division also suggested by the likelihoods.

Table 9.20. Advantage to Early Entrants at Alternative Entry Year Breakpoints, for Televisions.

EY*	LL	Early & Young	Early & Old
1 *	-465.209	-0.329* (0.192)	-0.795** (0.289)
2	-467.160	-0.187 (0.204)	-0.758** (0.310)
3	-466.613	-0.250 (0.218)	-0.917** (0.343)
4	-467.541	-0.054 (0.254)	-0.946** (0.370)
5	-468.030	-0.108 (0.275)	-0.944* (0.410)
6	-468.095	-0.040 (0.283)	-0.944* (0.410)
7	-468.296	-0.131 (0.300)	-0.882* (0.423)
8	-468.841	-0.235 (0.302)	-0.718 (0.444)
9	-468.841	-0.235 (0.302)	-0.718 (0.444)
10	-468.841	-0.235 (0.302)	-0.718 (0.444)
11	-468.841	-0.235 (0.302)	-0.718 (0.444)
12	-468.192	-0.505 (0.320)	-0.856 (0.546)
13	-468.192	-0.505 (0.320)	-0.856 (0.546)
14	-468.675	-0.536 (0.369)	-0.831 (0.627)

Foreign entrants are excluded. Above EY* = 14, the number of entrants is too small to yield reliable estimates.

In televisions, the breakpoint occurs immediately after the start of the industry.[80] The 72 firms that entered TV set production by early 1949 had 28% lower hazard rates at young ages, and 55% lower hazard rates at old ages, than the 94 later entrants (both differences significant). Table 9.20 shows the results of an analysis excluding foreign entrants into US production, but when foreign entrants are included and a dummy variable is added to the model to indicate those firms, the results are nearly identical, yielding in Table 9.21 the same best-fitting breakpoint. Thus, regardless of whether foreign entrants are included, the best-fitting breakpoint indicates an advantage to earlier entrants, particularly at old ages.

In penicillin, the best fitting division separates the 57 producers that entered by 1950 from the 22 later entrants. As Table 9.22 indicates, the earlier entrants had hazard rates 76% and 78% lower, at ages ≤ 8 and > 8 respectively, than the hazard rates of later entrants (both differences highly significant). A local minimum also indicates higher survival rates for firms that entered during World War II than for all later entrants. As in

Table 9.21. Advantage to Early Entrants at Alternative Entry Year Breakpoints, for Televisions Including Foreign Entrants.

EY*	LL	Early & Young	Early & Old
1 *	-470.186	-0.329* (0.192)	-0.784** (0.289)
2	-472.146	-0.186 (0.204)	-0.742** (0.311)
3	-471.643	-0.250 (0.218)	-0.894** (0.344)
4	-472.589	-0.056 (0.253)	-0.914** (0.371)
5	-473.083	-0.109 (0.273)	-0.903* (0.412)
6	-473.150	-0.042 (0.281)	-0.901* (0.412)
7	-473.318	-0.130 (0.298)	-0.842* (0.422)
8	-473.832	-0.230 (0.301)	-0.681 (0.442)
9	-473.832	-0.230 (0.301)	-0.681 (0.442)
10	-473.832	-0.230 (0.301)	-0.681 (0.442)
11	-473.832	-0.230 (0.301)	-0.681 (0.442)
12	-473.224	-0.498 (0.319)	-0.801 (0.541)
13	-473.224	-0.498 (0.319)	-0.801 (0.541)
14	-473.707	-0.524 (0.369)	-0.762 (0.617)
15	-472.910	-0.624 (0.412)	-1.907 (1.261)
16	-472.910	-0.624 (0.412)	-1.907 (1.261)
17	-472.910	-0.624 (0.412)	-1.907 (1.261)
18	-472.910	-0.624 (0.412)	-1.907 (1.261)
19	-473.734	-0.313 (0.549)	-1.722 (1.257)
20	-473.734	-0.313 (0.549)	-1.722 (1.257)
21	-473.734	-0.313 (0.549)	-1.722 (1.257)
22	-473.852	-0.168 (0.641)	-1.635 (1.262)
23	-473.852	-0.168 (0.641)	-1.635 (1.262)
24	-473.852	-0.168 (0.641)	-1.635 (1.262)
25	-473.852	-0.168 (0.641)	-1.635 (1.262)
26	-473.852	-0.168 (0.641)	-1.635 (1.262)
27	-473.539	-0.179 (0.764)	-2.066 (1.471)
28	-473.539	-0.179 (0.764)	-2.066 (1.471)
29	-473.408	-0.210 (0.749)	-2.301 (1.597)
30	-473.264	-0.242 (0.735)	-2.623 (1.811)

the other three products, earlier entrants in penicillin apparently had a substantially lower hazard rate than later entrants, and the advantage was quite pronounced at old ages.

Accounting for Market Exit Rates

From the figures in chapter seven, aggregate exit rates appear to have been particularly high during certain eras in each product's history. In automobiles, exit rates were unusually high from 1922 to 1927, perhaps because of the widespread introduction of steel closed-body presses. In tires, exit rates increased starting in 1921, and higher exit

Table 9.22. Advantage to Early Entrants at Alternative Entry Year Breakpoints, for Penicillin.

EY*	LL	Early & Young	Early & Old
1	-179.466	-0.878* (0.467)	-1.101** (0.393)
2	-179.466	-0.878* (0.467)	-1.101** (0.393)
3	-179.853	-0.984* (0.467)	-0.963** (0.392)
4	-181.693	-0.731* (0.414)	-0.818* (0.397)
5	-180.923	-0.763* (0.406)	-0.963** (0.403)
6	-177.248	-1.347*** (0.409)	-1.275** (0.498)
7 *	-176.440	-1.421*** (0.405)	-1.527** (0.545)
8 *	-176.440	-1.421*** (0.405)	-1.527** (0.545)
9	-178.346	-1.180** (0.408)	-1.972*** (0.617)
10	-179.158	-1.066** (0.413)	-1.972*** (0.617)
11	-180.042	-0.913* (0.422)	-1.972*** (0.617)
12	-180.042	-0.913* (0.422)	-1.972*** (0.617)
13	-181.542	-0.998* (0.437)	-1.581* (0.738)
14	-181.542	-0.998* (0.437)	-1.581* (0.738)
15	-181.916	-0.958* (0.456)	-1.581* (0.738)
16	-181.916	-0.958* (0.456)	-1.581* (0.738)
17	-181.916	-0.958* (0.456)	-1.581* (0.738)
18	-181.916	-0.958* (0.456)	-1.581* (0.738)
19	-181.916	-0.958* (0.456)	-1.581* (0.738)
20	-181.916	-0.958* (0.456)	-1.581* (0.738)
21	-181.916	-0.958* (0.456)	-1.581* (0.738)
22	-182.378	-0.880* (0.482)	-1.581* (0.738)
23	-182.378	-0.880* (0.482)	-1.581* (0.738)
24	-182.378	-0.880* (0.482)	-1.581* (0.738)
25	-182.378	-0.880* (0.482)	-1.581* (0.738)
26	-182.006	-1.207** (0.490)	-1.685* (1.023)
27	-182.006	-1.207** (0.490)	-1.685* (1.023)
28	-182.006	-1.207** (0.490)	-1.685* (1.023)
29	-182.006	-1.207** (0.490)	-1.685* (1.023)
30	-182.006	-1.207** (0.490)	-1.685* (1.023)

persisted through 1932. In televisions, the industry experienced unusually high exit rates during the color TV set era, in 1964-1971. These periods of higher exit are apparent in the Kaplan-Meier survival plots shown previously. For example, entrants in tires in 1905-1906 had unusually high hazard rates especially at ages 16-27.

The periods of higher exit, which occur at different ages for different entry cohorts, may affect the estimated coefficients for early entrants at young and old ages. Therefore, I control for these periods of higher exit by adding a dummy variable to the model that equals

Table 9.23. Advantage to Early Entrants at Alternative Entry Year Breakpoints, for Automobiles, Accounting for Market Exit in 1922-1927.

EY*	LL	Early & Young	Early & Old
1	-1916.626	-1.568* (0.709)	1.479* (0.842)
2	-1915.326	-1.717** (0.709)	1.537* (0.822)
3	-1916.085	-1.055** (0.411)	0.840 (0.549)
4	-1916.527	-0.646** (0.240)	0.553 (0.364)
5	-1917.905	-0.356* (0.155)	0.214 (0.272)
6	-1917.234	-0.301* (0.133)	0.010 (0.243)
7	-1916.251	-0.255* (0.114)	-0.128 (0.217)
8	-1909.225	-0.242** (0.100)	-0.505** (0.203)
9 *	-1904.140	-0.262** (0.095)	-0.651*** (0.199)
10	-1905.186	-0.323*** (0.092)	-0.469** (0.195)
11	-1908.302	-0.297*** (0.089)	-0.402* (0.195)
12	-1915.976	-0.114 (0.087)	-0.442* (0.198)
13	-1918.065	0.020 (0.089)	-0.485** (0.203)
14	-1918.490	-0.039 (0.094)	-0.479* (0.233)
15	-1917.933	0.013 (0.102)	-0.657** (0.258)
16	-1917.010	-0.000 (0.104)	-0.791** (0.272)
17	-1916.725	0.081 (0.108)	-0.853*** (0.274)
18	-1917.010	0.196* (0.116)	-0.802** (0.288)
19	-1917.774	0.182 (0.121)	-0.803** (0.314)
20	-1918.641	0.225* (0.134)	-0.723* (0.373)
21	-1919.507	0.215 (0.148)	-0.652 (0.449)
22	-1918.941	0.286* (0.161)	-0.727 (0.454)
23	-1919.494	0.238 (0.169)	-0.765 (0.495)
24	-1920.250	0.059 (0.177)	-0.865 (0.620)
25	-1920.423	0.116 (0.210)	-0.892 (0.750)
26	-1920.347	0.167 (0.250)	-0.941 (0.761)
27	-1920.544	-0.080 (0.294)	-0.690 (0.776)
28	-1920.580	-0.000 (0.307)	-0.770 (0.781)
29	-1920.579	0.017 (0.357)	-0.788 (0.801)
30	-1920.566	-0.063 (0.381)	-0.708 (0.812)

one during the years of apparent higher exit and zero at other times. Tables 9.23-26 show the results of best-fit analyses for automobiles, tires, and televisions. The tables are similar to Tables 9.18-22 above.

In automobiles, adding the market exit dummy for 1922-1927, the best fit still occurs with a breakpoint at EY* = 9, separating the 224 entrants 1895-1904 from the 503 later entrants (Table 9.23). The coefficients of EY≤EY* and EY≤EY* Age are smaller than in the previous analysis, indicating that some of the previous effects attributed to EY≤EY* and EY≤EY* Age may have been a result of the higher exit during 1922-1927. However,

Table 9.24. Advantage to Early Entrants at Alternative Entry Year Breakpoints, for Tires, Accounting for Market Exit in 1921-1932.

EY*	LL	Early & Young	Early & Old
1	-1720.742	-0.225 (0.311)	-0.983* (0.454)
2	-1720.999	0.312 (0.192)	-1.313*** (0.341)
3	-1720.999	0.312 (0.192)	-1.313*** (0.341)
4	-1722.899	0.365* (0.174)	-1.115*** (0.303)
5	-1722.899	0.365* (0.174)	-1.115*** (0.303)
6	-1725.707	0.287* (0.154)	-0.720** (0.238)
7	-1725.598	0.287* (0.154)	-0.727** (0.238)
8	-1725.598	0.287* (0.154)	-0.727** (0.238)
9	-1728.717	0.092 (0.146)	-0.368* (0.218)
10	-1728.409	0.078 (0.142)	-0.377* (0.215)
11	-1723.358	0.065 (0.137)	-0.622** (0.214)
12	-1716.782	0.113 (0.131)	-0.896*** (0.214)
13	-1717.183	0.008 (0.124)	-0.781*** (0.209)
14	-1717.183	0.008 (0.124)	-0.781*** (0.209)
15	-1718.047	0.101 (0.113)	-0.884*** (0.205)
16	-1716.445	-0.018 (0.107)	-0.835*** (0.200)
17	-1712.573	-0.049 (0.109)	-0.964*** (0.198)
18	-1712.573	-0.049 (0.109)	-0.964*** (0.198)
19	-1712.374	-0.095 (0.118)	-0.936*** (0.202)
20	-1711.680	-0.200 (0.127)	-0.856*** (0.204)
21	-1710.838	-0.269* (0.143)	-0.827*** (0.211)
22	-1711.321	-0.323* (0.151)	-0.758*** (0.214)
23	-1711.622	-0.307* (0.155)	-0.772*** (0.216)
24	-1711.693	-0.247 (0.164)	-0.853*** (0.222)
25 *	-1709.734	-0.317* (0.169)	-0.857*** (0.226)
26	-1709.915	-0.306* (0.173)	-0.867*** (0.228)
27	-1710.004	-0.299* (0.175)	-0.872*** (0.229)
28	-1710.481	-0.246 (0.178)	-0.917*** (0.231)
29	-1710.836	-0.234 (0.181)	-0.924*** (0.234)
30	-1710.665	-0.239 (0.182)	-0.937*** (0.236)

the coefficients are still highly significant, and indicate that the earlier entrants had a 23% lower hazard rate than later entrants at ages 0 to 8, and a 48% lower hazard rate at ages greater than 8.

In tires, after including the market exit dummy for 1921-1932, the best-fitting division occurs at EY* = 25 separating the 557 entrants by 1930 from the 76 later entrants (Table 9.24). With this division, entrants by 1930 up to age eight are estimated to have had a 27% lower hazard rate than later entrants at the same ages (a slightly significant result), and after age eight the earlier entrants are estimated to have had a 58% lower hazard rate

Table 9.25. Advantage to Early Entrants at Alternative Entry Year Breakpoints, for Televisions, Accounting for Market Exit in 1964-1971.

EY*	LL	Early & Young	Early & Old
1 *	-463.780	-0.276 (0.195)	-0.510 (0.348)
2	-465.600	-0.108 (0.211)	-0.630* (0.374)
3	-465.179	-0.150 (0.228)	-0.748* (0.410)
4	-465.567	0.105 (0.270)	-1.039* (0.457)
5	-466.083	0.091 (0.296)	-1.034* (0.506)
6	-465.967	0.171 (0.304)	-1.114* (0.510)
7	-466.106	0.135 (0.330)	-1.077* (0.545)
8	-466.964	0.035 (0.336)	-0.806 (0.565)
9	-466.964	0.035 (0.336)	-0.806 (0.565)
10	-466.964	0.035 (0.336)	-0.806 (0.565)
11	-466.964	0.035 (0.336)	-0.806 (0.565)
12	-466.866	-0.263 (0.354)	-0.656 (0.666)
13	-466.866	-0.263 (0.354)	-0.656 (0.666)
14	-467.188	-0.300 (0.395)	-0.607 (0.760)

Foreign entrants are excluded. Above EY* = 14, the number of entrants is too small to yield reliable estimates.

(highly significant). This result appears to explain the apparently unusually high survival rate of post-1932 entrants in the Kaplan-Meier plot of Figure 9.4. Their high survival rates are explained by the fact that they did not have to survive through the high-exit period of the 1920s.

Next, compare the 272 entrants by 1918 with the 361 later entrants. This division after 1918 was the best-fitting division before including a market exit dummy. Through age eight the pre-1919 entrants apparently had a 1% higher hazard rate than later entrants (an insignificant difference), but above age eight pre-1919 entrants are estimated to have had a 54% lower hazard rate (highly significant). Comparing the 25 entrants by 1906 with the 608 later entrants, the results are similar, with a 20% lower hazard rate for early entrants through age eight (an insignificant difference), and a 63% lower hazard rate for early entrants after age eight (highly significant).

In televisions, adding a dummy variable for higher exit during 1964-1971, the best-fitting division still occurs at EY* = 1 (Table 9.25). However, the advantage of earlier entrants is slightly less and no longer significant. The 72 firms that entered by early 1949

Table 9.26. Advantage to Early Entrants at Alternative Entry Year Breakpoints, for Televisions including Foreign Entrants, Accounting for Market Exit in 1964-1971.

EY*	LL	Early & Young	Early & Old
1 *	-468.726	-0.274 (0.195)	-0.503 (0.348)
2	-470.546	-0.105 (0.211)	-0.618* (0.373)
3	-470.170	-0.148 (0.228)	-0.728* (0.410)
4	-470.565	0.106 (0.269)	-1.008* (0.455)
5	-471.087	0.093 (0.295)	-0.994* (0.503)
6	-470.970	0.173 (0.303)	-1.072* (0.507)
7	-471.090	0.138 (0.328)	-1.034* (0.538)
8	-471.914	0.041 (0.334)	-0.770 (0.557)
9	-471.914	0.041 (0.334)	-0.770 (0.557)
10	-471.914	0.041 (0.334)	-0.770 (0.557)
11	-471.914	0.041 (0.334)	-0.770 (0.557)
12	-471.867	-0.255 (0.353)	-0.598 (0.652)
13	-471.867	-0.255 (0.353)	-0.598 (0.652)
14	-472.187	-0.288 (0.393)	-0.531 (0.734)
15	-471.361	-0.445 (0.426)	-1.394 (1.259)
16	-471.361	-0.445 (0.426)	-1.394 (1.259)
17	-471.361	-0.445 (0.426)	-1.394 (1.259)
18	-471.361	-0.445 (0.426)	-1.394 (1.259)
19	-471.759	-0.247 (0.553)	-1.480 (1.253)
20	-471.759	-0.247 (0.553)	-1.480 (1.253)
21	-471.759	-0.247 (0.553)	-1.480 (1.253)
22	-471.826	-0.154 (0.649)	-1.518 (1.253)
23	-471.826	-0.154 (0.649)	-1.518 (1.253)
24	-471.826	-0.154 (0.649)	-1.518 (1.253)
25	-471.826	-0.154 (0.649)	-1.518 (1.253)
26	-471.826	-0.154 (0.649)	-1.518 (1.253)
27	-471.532	-0.144 (0.775)	-1.952 (1.494)
28	-471.532	-0.144 (0.775)	-1.952 (1.494)
29	-471.409	-0.177 (0.759)	-2.157 (1.639)
30	-471.275	-0.212 (0.744)	-2.448 (1.873)

had a 24% lower hazard rate than later entrants, and the 94 later-entering had a 40% lower hazard rate. Table 9.26 shows the estimates when foreign entrants are included. The inclusion of foreign entrants makes little difference in the results.

Conclusions

An examination of industry aggregate exit rates in chapter seven showed that, except in tires, aggregate exit rates did not increase at the times of the shakeouts. In the aggregate, the shakeouts resulted not from increased exit rates, but from decreases in the numbers of entrants. However, the statistical analyses provided a means to probe these findings in more detail. It became apparent after adjusting for the effects of a changing age distribution on the hazard that, while the *aggregate* exit rate did not in general increase at the times of the shakeouts, the probabilities of exit for firms of a given age did increase. When the shakeouts began, older firms' exit probabilities increased to be more comparable to the exit probabilities that in the past had been characteristic of younger firms.

Entrants during the shakeout did have higher exit probabilities, as predicted in the innovative gamble and dominant design theories, but their exit probabilities remained high even at old ages. The sustained high exit rates of later entrants suggest that some continual disadvantage affected these firms, rather than merely a single technological event forcing existing firms to adapt and the losers to exit. If a single technological event had caused the shakeout, the exit rates of later entrants should have returned to normal after the losers left the industry, leaving behind only firms that were adept at the reigning technology. Furthermore, the differences between earlier and later entrants appear to have occurred not at the times of the shakeouts, but even earlier. In fact, typically differences in hazard rates were most apparent between the earliest entrants and all later entrants, and the differences tended to grow over time. This early-mover advantage, connected with its nearly ubiquitous manifestation at old ages, suggests a pattern in which some early entrants manage to gain a nearly unshakable advantage and come to dominate their respective industries.

10

Profits

The innovative gamble and size-and-skill theories both make predictions about time-trend variations in firm profits. According to the innovative gamble theory, profits stabilize immediately after entrants populate a new industry. Potential entrants can earn the greatest expected return by entering as soon as possible after the industry's inception, since the quickest attempt to enter yields the most possible time to develop the product. Enough entry occurs to yield normal expected returns to attempted entry, and no further entry takes place until the time of the refinement invention.

When the refinement invention occurs, incumbents' previous experience with the technology gives them an advantage compared to new entrants. The profits of the average incumbent rise temporarily as some incumbents successfully innovate based on the refinement. Profits eventually fall again as more firms innovate based on the refinement. The profit predictions are tested here using return on investment data that pertain primarily to large, successful incumbents. Because of this bias toward successful firms, the predicted rise and fall of profits among incumbents should be especially apparent in the data, if indeed a refinement invention had the effect on profits predicted by the innovative gamble theory.

In contrast, the size-and-skill theory predicts a gradual decline in profits. As firms gradually expand and new firms enter, the supply of the product increases and the price falls. Firms' manufacturing costs fall as well, but even for the largest firms, the falling prices eventually outpace falling costs and profit margins decrease as well. The return on investment data shown here tend to be available only for the large, successful producers. For these firms, return on investment might rise for a short while at the beginning of the industry, but soon the aggregate trend of declining profit should prevail. Profits do not rise at the time of the shakeout, but simply continue their inexorable decline.

Figures 10.1 through 10.4 present the return on investment data needed to test the predictions of the innovative gamble and size-and-skill theories. In automobiles and tires, the data are sales-weighted average firm rates of return on investment.[81] In televisions, few market share data are available for the period 1947-1960, and I use an unweighted average of return on investment. Two series are presented, one for all television producers for which return on investment data could be obtained, the other restricted to firms that primarily produced televisions, in order to investigate whether the inclusion of diversified firms would bias the results.[82] In automobiles and tires, firms produced those products almost exclusively, except for one diversified firm, US Rubber, which is excluded from the sample. In penicillin, firms produced many different products, and return on investment data would not reveal the trend in profits related to the manufacture of penicillin. Instead, I use data on net profit as a percentage of sales based on a report by the Federal Trade Commission (1958, pp. 211-212). The data distinguish profit rates for the older forms of penicillin, which were subject to severe price competition, from profit rates for lucrative new forms of penicillin that were patented and produced by few firms.

In the four products, the figures all indicate unusually high initial rates of return. In automobiles and tires, rates of return exceeded 40% initially, and in televisions they approached 20%. In penicillin, firms enjoyed a net profit equal to more than 20% of the value of sales. Qualitative evidence from historians is available for earlier years, and suggests that profits in automobiles and tires were even greater. Early automobiles were in such demand that producers generally could obtain advance payments sufficient to pay for

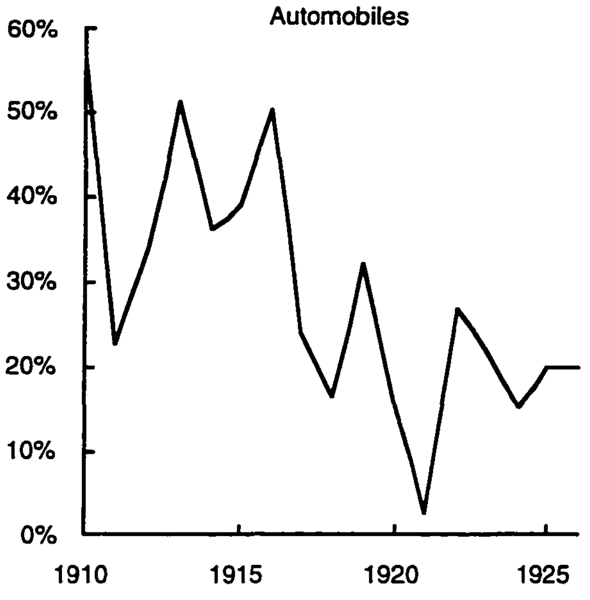


Figure 10.1. Net profits as a percentage of net worth for nine major firms. Source: Epstein (1928, p. 256).

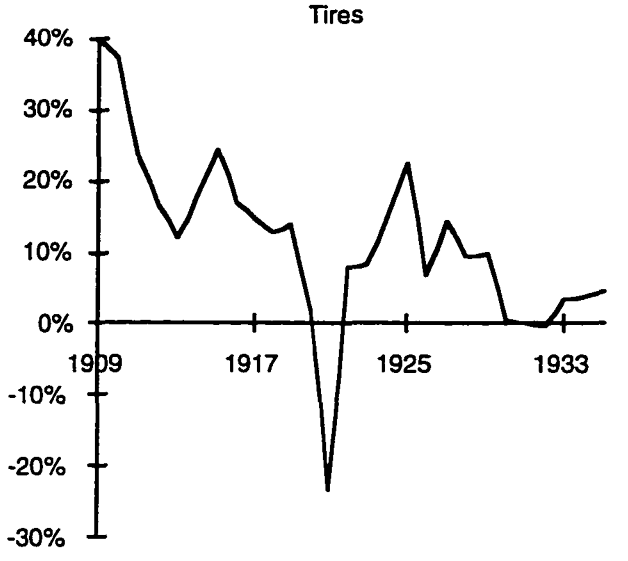


Figure 10.2. Output-weighted industry average net income to owner's equity of tire producers. Source: Based on Bray (1959, pp. 72, 102, 104, 151-152, 192-193).

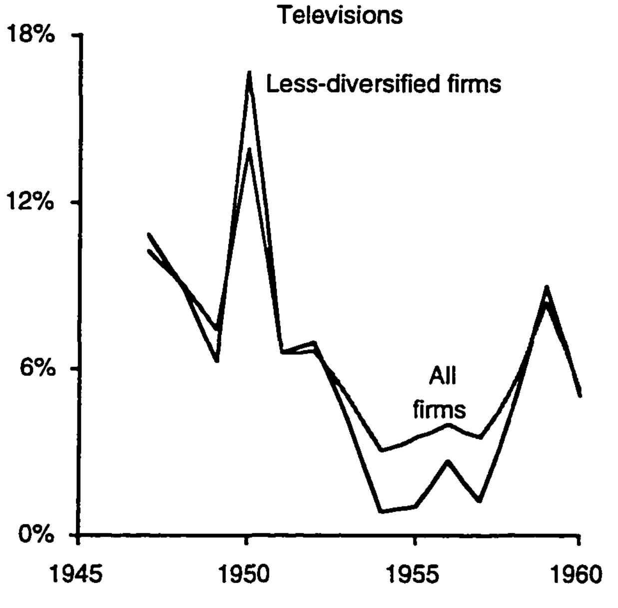


Figure 10.3. Average net income as a percentage of total assets for television firms. Sources: *Moody's Industrials* (1948-1961), Datta (1971, pp. 273 and 296).

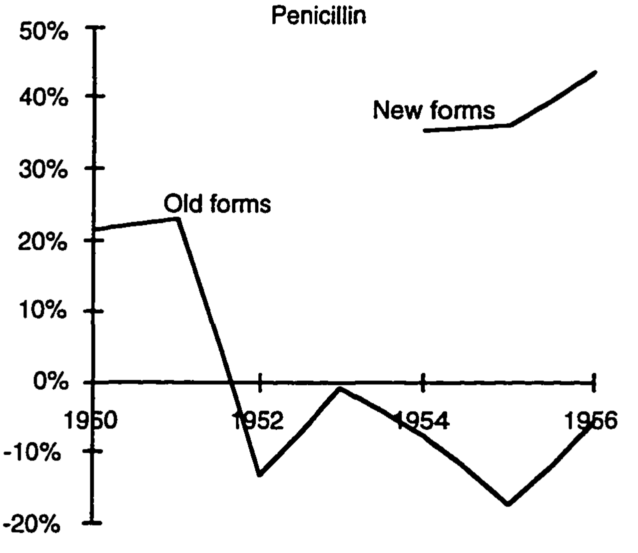


Figure 10.4. Net profit as a percentage of sales, for old and new forms of penicillin. Source: Federal Trade Commission (1958, pp. 211-2).

their capital costs as well as labor and materials (Katz, 1970, pp. 22-28). In tires, early profits seem to have frequently yielded a 100% per year return on investment (Sobel, 1954, p. 13).

The profit patterns all indicate a compression in profits over time. By the shakeout eras, the rates of return of tire, television, and old-form penicillin producers were at or below normal levels. Only in automobiles were rates of return still above normal in the shakeout era, explaining why only that product still had substantial numbers of entrants after the shakeout began, in the 1910s.

Only in televisions are the data consistent with the idea that the profit rate of incumbent firms may have risen at the time of a refinement invention. However, some more continual process seems to have affected profits, by gradually and steadily compressing firms' rates of return. In the case of automobiles and tires, this process apparently required decades before profit rates reached normal rates of return.

Cross-Industry Comparison & Conclusion

11

Forty-Nine Products with a Broad Range of Behaviors

The first section of this dissertation analyzed four products that experienced severe shakeouts. The evidence on technological change, entry, survival, and profits all suggested a process in which early entrants came to dominate, eventually gaining such an advantage over new entrants that entry ceased almost entirely, and the number of firms dropped off because early entrants always managed to outcompete others. This section asks whether the findings of the first section—that shakeouts appear to have resulted from a growing advantage to dominant, early-entering producers, causing entry to drop off and exit to continue—are distinctive to products that experienced severe shakeouts. It analyzes a broad cross-section of products to see whether this pattern of early-mover advantage leading to a decline in entry and continued exit is distinctive to industries that experience severe shakeouts. If the advantage-to-the-advantaged dynamic is indeed the key to shakeouts, industries with no shakeouts or less pronounced shakeouts than others should exhibit less early-mover advantage at old ages and should experience more entry at later stages of the industry than industries with relatively severe shakeouts.

The analyses described here trade detail for a broad sample. Information about innovation and other forms of data that would require many months to collect for a single industry (if the information exists at all) is eschewed in favor of more readily available information. I use information that pertains only to the participation of manufacturers in product industries. To study industry shakeouts, it is particularly important to have such data, since it is patterns in the entry and exit of manufacturers that determine the number of manufacturers in an industry at any given time. For narrowly-defined product categories, no many-industry database of firm participation has been available. This dissertation uses a unique, newly-collected database.

Cross-Industry Data

As in the preceding chapters, the data used here list which firms made a product in which years. Hence they show patterns in entry, exit, and the number of firms. The data come from *Thomas' Register of American Manufacturers*, an annual trade publication, plus the other sources discussed in chapter four. Forty-nine products were chosen, based mainly on Gort and Klepper (1982), but with several alterations necessitated by concerns about collecting clean and meaningful data. Two products (automobiles and typewriters) had not been included in the original group, and were added to broaden the sample of products with strong shakeouts while using products for which much information was available. Table 11.1 lists the forty-nine products. Every year of the *Register* was used from when the product first appeared in the *Register*, usually just after it began commercial production, to 1980.

Thomas' gathers its information via agents sent around the US. It attempts to survey literally every US manufacturer. In case of errors or omissions, listed companies and users of the *Register* are encouraged to send a letter to correct the problem. Thus the data are quite comprehensive and there are mechanisms to make sure it is sound. However, since the data obviously cannot be perfect, it is important to investigate their reliability.

Table 11.1. The Forty-Nine Products.

adding and calculating machines	polariscopes
automobiles	radar: marine, airborne, & other
baseboards, radiant heating	radio transmitters
blankets, electric	reactors, nuclear
compressors, freon	readers, microfilm
computers	records, phonograph
crystals, piezo	saccharin
DDT	shampoo
electrocardiographs	shavers, electric
engines, jet-propelled	streptomycin
engines, rocket	styrene
fluorescent lamps, general line	tanks, cryogenic
fluorescent light bulbs	tapes, recording
freezers, home & farm	telemeters
gauges, beta-ray	television sets
gyroscopes	tents, oxygen
heat pumps	tires
lasers	transistors
missiles, guided	trees, artificial Christmas
motors, outboard	tubes, cathode ray
nylon	turbines, gas
paints, rubber & rubber base	typewriters
penicillin	windshield wipers
pens, ball-point	zippers
photocopy machines	

Reliability of Thomas' Register

The reliability of the *Register* can be judged by comparing it to detailed histories of companies and to other lists of manufacturers. Compared with detailed knowledge of individual cases, there sometimes seem to be errors. Most noticeably, there are often delays before *Thomas'* notices that a new company has begun to produce the product or has ceased production. These delays might cause patterns in the data to be delayed by one or a few years. Compared with other sources listing which firms manufactured each product in given years, the overall shakeout patterns and their timing are similar. In automobiles, sources that exclude the tiniest firms showed a shakeout beginning circa 1921, whereas four sources (including the *Register*) that include tiny firms showed a shakeout beginning circa 1910. In tires, televisions, and penicillin, the shakeout patterns and timing are roughly similar to those given by independent sources. The main differences between sources appear to stem from definitions of what should be counted as a manufacturer and from collection methods. Some sources exclude very small firms, or collect information in a way that fails to notice these small firms. No source is perfect; even the US Census of Manufactures fails to include many firms because firms below a given sales volume are not required to report. Other trade and government sources often lack information about small and regional manufacturers, or simply fail to notice a large percentage of firms. While there is generally no reason to expect that alternative data sources are preferable to *Thomas' Register*, I will use multiple data sources wherever possible to ensure valid results.

Reliability of the *Register* is most important for this study in the following sense. For the analyses in this section of the dissertation, the longitudinal patterns in the number of firms, entry, and exit must be comparable across the *Thomas' Register* samples. For two reasons, the samples appear to be comparable. First, the *Register* seeks to include all manufacturers of a product, even tiny ones, for every product, and by sending its agents across the US it can find even the tiniest manufacturers. This provides a consistent means of data collection. While of course data collection errors occurred and some manufacturers were overlooked, it seems safe to treat these errors as noise rather than as a consistent bias that affects the timing and shape of the shakeout. Second, as described above, comparison with other sources, where available, has shown the *Register* patterns to be quite reliable for recording longitudinal patterns in the number of firms, entry, and exit.

Thomas' Register lists manufacturers under headings for particular products. Under the heading, each firm is listed separately, along with its address and often a brief description of its product. In some cases, a note after the heading refers to related topics. Some headings in *Thomas' Register* are broadly defined, while others are tightly focused. An outstanding example of broad definition is computers, which includes a scattering of firms making products such as electronics for gas-station pumps and plastic slide rules for aeronautical navigation, as well as powerful multi-purpose electronic computers. Some headings include component makers, and others include quite different product niches (e.g.

"adding and calculating machines" includes makers of tabulators and perhaps even cash registers as well as adding machines). However, the majority of products are narrowly-defined and have virtually no problem of confusion with other products. I have carefully defined which of the *Register*'s listings to use for a given product, including what to do when the *Register*'s headings split or merge over time or when only a subset of firms (denoted in the *Register*) under a heading make a given product. To check how well-defined each product is, I use detailed information in the *Register* about the products manufactured by firms. I assign subjective ratings to each product indicating how well-defined it is, and use the ratings to check whether results differ (or are less pronounced) for the less well-defined products.

Mergers and Acquisitions

Thomas' Register does not track mergers and acquisitions of most firms. While analyzing the data, I will look for possible mergers, acquisitions, name changes, and address changes. Obvious changes, such as changes in name but not address, or changes in address but not name, have already been coded as being a single firm regardless of the change. For less obvious cases, I have created a computerized check to assist in the process. The first word of each firm's name is compared with every other firm's name, to see if that word is also present (as a whole word) anywhere in any other name. If the first one or two words in a name are single letters, as in "A. J. Thompson Company," then the first two or three words are used instead of the first word alone. In addition, every word and number in every firm's street address, with the exception of certain common words such as "Street," is compared with every word in every other firm's address, for firms in the same US state, to find any matching words. None of the comparisons is case-sensitive. All the matches found are used to create a list of suggested matches.

These possible mergers, acquisitions, name changes, and address changes are checked by hand. If, in the same year or nearby years, two firms in a spreadsheet have the same name but different addresses, they are assumed to be the same firm: either separate parts of one firm, or a single part that moved its manufacturing location, or some combination thereof. Exceptions are made for very common names separated by wide gaps of time (for example, companies whose name begin with "American" and that are separated by a gap of two decades when neither existed). If two firms have the same address but different names, and the first name stopped being listed just when the second began to be listed, they are assumed to be a single manufacturer that changed names and perhaps ownership. If however two firms with different names were listed simultaneously at the same address, they are assumed to be separate manufacturers sharing the same building. This procedure seems to give reasonable accuracy in distinguishing which firms listed separately in the *Register* were really the same firm. While some error is unavoidable, the remaining error seems to be small relative to other error in the data.[83]

Mergers (including acquisitions) are not distinguished in the data. A merger appears as an exit of one of the merged companies. There is no methodical way to distinguish mergers using the *Thomas' Register* data. The majority of firms appearing in the *Register* are tiny and are never considered for mergers. Nevertheless, it is worthwhile to keep in mind that some of the apparent "exits" in the data are actually mergers.

Advantage-to-the-Advantaged and Shakeout Severity

Table 11.2 lists the sample of products in descending order according to the severity of their shakeouts. The table also indicates the total number of firms N that ever participated in producing each product, and the time of the peak in the number of firms manufacturing the product. The four products studied earlier include the three products with the most severe shakeouts, automobiles, television sets, and tires, as well as the product with the eighth-most severe shakeout, penicillin.

Table 11.2. The Products According to Severity of Shakeout.

Product	N	Peak	Severity
Automobiles	727	1909.5	97.4
Television Sets	166	1951.5	96.6
Tires, Pneumatic	633	1922.0	90.9
DDT[84]	81	1952.4	90.5
Streptomycin	19	1953.4	84.6
Windshield Wiper Mechanisms	204	1925.1	81.4
Saccharin	104	1918.0	79.5
Penicillin	79	1954.4	75.9
Shavers, Electric	58	1938.4	74.2
Adding Machines	270	1927.1	70.4
Radio Transmitters	330	1962.4	69.7
Tents, Oxygen	50	1961.4	66.7
Typewriters	158	1922.0	65.8
Blankets, Electric	42	1962.4	64.7
Freezers, Home & Farm	138	1954.4	63.9
Telemeters	81	1971.4	58.3
Flour. Light Fixtures, General Line	674	1952.4	54.5
Paints, Rubber & Rubber Base	238	1966.4	52.5
Reactors, Nuclear	82	1965.4	52.2
Missiles, Guided	481	1962.4	52.1
Radar, Marine, Airborne, Other	496	1962.4	50.3
Trees, Artificial Christmas	111	1965.4	45.0
Polariscopes	103	1971.4	43.8
Gyroscopes	119	1970.4	42.9
Electrocardiographs	53	1964.4	41.2
Tubes, Cathode Ray	101	1959.4	34.1
Engines, Jet-Propelled	62	1964.4	32.1
Baseboards, Radiant Heating	48	1972.4	29.6
Photocopy Machines	72	1968.4	27.6
Styrene	135	1980.4	25.6
Motors, Outboard	116	1966.4	24.1
Fl. Lamps, Complete Tubes	88	1960.4	23.3
Gauges, Beta-Ray	18	1973.4	22.2
Shampoo	567	1949.4	17.8
Tanks, Cryogenic	119	1977.4	16.2
Nylon	814	1967.4	15.1
Engines, Rocket	27	1971.4	14.3
Computers	855	1971.4	13.8
Crystals, Piezo	81	1963.4	12.5
Zippers	219	1977.4	12.2
Pens, Ballpoint	331	1975.4	4.6
Readers, Microfilm	90	1978.4	3.3
Compressors, Freon	63	1980.4	0
Heat Pumps	77	1979.4	0
Lasers	215	1979.4	0
Records, Phonograph	241	1979.4	0
Tapes, Recording	133	1979.4	0
Transistors	194	1979.4	0
Turbines, Gas	127	1979.4	0

Table 11.3. Products in the Reduced Sample.

Product	N	Peak	Severity
Automobiles	727	1909.5	97.4
Television Sets	166	1951.5	96.6
Tires	633	1922.0	90.9
Windshield Wiper Mechanisms	204	1925.1	81.4
Saccharin	104	1918.0	79.5
Adding Machines	270	1927.1	70.4
Typewriters	158	1922.0	65.8
Freezers, Home & Farm	138	1954.4	63.9
Paints, Rubber & Rubber Base	238	1966.4	52.5
Radar, Marine, Airborne, Other	496	1962.4	50.3
Trees, Artificial Christmas	111	1965.4	45.0
Polariscopes	103	1971.4	43.8
Gyroscopes	119	1970.4	42.9
Tubes, Cathode Ray	101	1959.4	34.1
Styrene	135	1980.4	25.6
Motors, Outboard	116	1966.4	24.1
Shampoo	567	1949.4	17.8
Tanks, Cryogenic	119	1977.4	16.2
Zippers	219	1977.4	12.2
Pens, Ballpoint	331	1975.4	4.6
Lasers	215	1979.4	0
Records, Phonograph	241	1979.4	0
Tapes, Recording	133	1979.4	0
Turbines, Gas	127	1979.4	0

In order to examine how the severity of shakeouts relates to patterns of early-mover advantage, entry, and exit, a precise definition of severity is necessary. I use the following method, which yields severity as a number between 0 and 100. Let t_p be the year with the peak number of firms.[85] Let t_z be the year after which the average annual decrease in number of firms is less than 1% over each of the subsequent 5-year, 10-year, 15-year, etc. periods.[86] The shakeout severity is defined as $100 \times (t_p - t_z) / t_p$.

Products with a small sample size N have large random variation in peak date, severity of the shakeout, and other measures. Because of this random variation, patterns in the data can be difficult to perceive. Therefore, I initially focus only on those products for which the sample contains at least 100 firms. At the same time, I exclude any products that appear to be unusually broadly defined or ill-defined in *Thomas' Register of American*

Manufacturers: radio transmitters, fluorescent light fixtures, guided missiles, nylon, computers, and transistors. The resulting sample appears in Table 11.3.

Analyses in the Reduced Sample

I begin by analyzing the entry patterns in the reduced sample of products. In the four products, entry dropped off around the times of the shakeouts. To examine whether the shakeouts in other products involved a dropoff in entry, rather than a shift to a new equilibrium in which continued exit balanced entry, I count the number of firms that entered each industry 10-20 years after the peak in the number of firms, and compare it to the number of firms that entered in the ten years immediately preceding the shakeout. Allowing ten years after the peak before counting entrants allows time for the entry rate to settle in case it does not settle immediately, as in automobiles. Counting entrants throughout the ensuing ten-year period yields enough time for a reasonable sample size while still allowing comparability between products, since many products do not have much more than 20 years after the peak in the number of firms. When periods of fewer than ten years are available before the shakeout or a decade later than the shakeout, I use shorter-length periods at each end as necessary, but if periods of at least five years are not available, I do not compute any figure. I divide the number of entrants in the post-peak period by the total number in the two periods and multiplied by 100 to yield the percentage of entrants in the two groups that entered after the peak. This measure of late entry, termed Late Entry I, appears in Table 11.4. Products with a peak number of firms near the beginning or end of the sample have too short a period in which to count numbers of early or late entrants, and appear in the table with a period.

Among the products for which Late Entry I can be calculated, the first ten products in the table all indicate that well under 50% of the entrants in the two groups entered after the shakeout had begun. Apparently products with more severe shakeouts experienced some decrease in entry between the pre-shakeout period and the later period. The method of computation of these figures typically does not allow comparison with products that had little or no shakeout, because their peak number of firms usually occurs at or near the end of the sample, leaving too little time to compute the measure.

Table 11.4. Severity of Shakeouts and Decline in Entry.

Product	Severity	Late Entry I	Late Entry II
Automobiles	97.4	9.3	1.1
Television Sets	96.6	.	2.4
Tires	90.9	5.4	9.0
Windshield Wiper Mechanisms	81.4	24.1	27.0
Saccharin	79.5	9.6	33.0
Adding Machines	70.4	23.7	28.3
Typewriters	65.8	13.8	40.5
Freezers, Home & Farm	63.9	14.7	22.5
Paints, Rubber & Rubber Base	52.5	21.8	46.6
Radar, Marine, Airborne, Other	50.3	31.5	32.2
Trees, Artificial X-Mas	45.0	.	33.3
Polariscopes	43.8	.	64.6
Gyroscopes	42.9	.	93.2
Tubes, Cathode Ray	34.1	38.2	51.5
Styrene	25.6	.	65.1
Motors, Outboard	24.1	.	52.6
Shampoo	17.8	27.0	54.4
Tanks, Cryogenic	16.2	.	39.5
Zippers	12.2	.	57.9
Pens, Ballpoint	4.6	.	42.3
Lasers	0	.	58.7
Records, Phonograph	0	.	51.9
Tapes, Recording	0	.	60.2
Turbines, Gas	0	.	62.7

For comparison between products with varying degrees of shakeout, I compute a second measure, termed Late Entry II. This measure indicates the percentage of firms that entered in the latter half of the sample. This measure is also shown in Table 11.4. All three products with severity greater than 90% had fewer than 10% of firms enter in the latter half of the sample. Among the ten products with shakeouts of severity greater than 50%, all had fewer than 50% of entrants in the latter half of the sample. In contrast, among the fourteen products with severity less than 50%, eleven of the fourteen had more than 50% of entrants in the latter half of the sample. The Late Entry II measure has a mean value of 24.3 (standard deviation 15.6) for the ten products with shakeouts of severity greater than 50%, and a mean value of 56.3 (standard deviation 14.2) for the fourteen products with severity less than 50%.

This finding is not surprising in that shakeouts occur when either entry decreases, exit increases, or both. Nevertheless, it suggests that at least in general, products with fairly severe shakeouts do not generally experience simply a rise in hazard rates that balances continued entry. This is far from a proof that entry decreases in shakeouts because early-movers capture an advantage that makes further entry unprofitable. But at least it suggests that another possible pattern, involving a "revolving door" (Geroski, 1991b) of continued entry and exit, does not occur in industries with severe shakeouts.

Next, I examine whether a window of opportunity allowed earlier entrants to capture a strong early-mover advantage. I use the same technique as presented at the end of chapter seven, in which alternative breakpoints between entry cohorts are tried in order to find the breakpoint EY* that yields the best fit to the model. I allowed breakpoints up to EY* = 20 to reduce the computational demands of the analysis and because even if later breakpoints seem to fit better, the better fit could be an artifact of a small number of late entrants that by chance had unusually high or low hazard rates. As before, the model includes a baseline function of age, a dummy variable for early entrants of age less than or equal to eight, and another dummy variable for early entrants of age greater than eight. Early entrants are defined as all firms that entered before the breakpoint.

Table 11.5 presents the results of this analysis. For each product, the table reports the value of EY* that provided the best fit, and the estimated coefficients affecting the hazard rate for early entrants at ages up to eight and greater than eight. Standard errors appear in parentheses.

Among the first ten products, which had shakeouts of severity greater than 50%, the estimated coefficients indicate that all ten products had substantial early-mover advantages at old ages. Furthermore, the estimated coefficients are all substantially greater than their standard errors. In nine out of ten of these products, the advantage of earlier entrants increased from young ages to old ages, and in all of the nine cases the estimated coefficient either changed sign or more than doubled going from young to old ages.

Table 11.5. Tests for Early-Mover Advantage.

Product	Best EY*	EY≤EY* Age≤8	EY≤EY* Age>8
Automobiles	9	-0.34 (0.09)	-1.04 (0.18)
Television Sets	1	-0.33 (0.19)	-0.79 (0.29)
Tires	13-14	-0.62 (0.10)	-0.42 (0.14)
Windshield Wiper Mechanisms	19	0.44 (0.18)	-0.51 (0.29)
Saccharin	19-20	0.67 (0.27)	-0.43 (0.34)
Adding Machines	20	0.03 (0.16)	-0.68 (0.20)
Typewriters	26†	-0.87 (0.29)	-1.94 (0.78)
Freezers, Home & Farm	9	0.05 (0.26)	-1.16 (0.30)
Paints, Rubber & Rubber Base	7	0.05 (0.39)	-0.79 (0.35)
Radar, Marine, Airborne, Other	18	-0.17 (0.15)	-0.98 (0.24)
Trees, Artificial Christmas	16-20	-0.87 (0.61)	-1.23 (0.45)
Polariscopes	11-14	0.87 (0.54)	0.62 (0.62)
Gyroscopes	6-20	-7.83 (3.96)	-2.16 (1.10)
Tubes, Cathode Ray	5-7	0.01 (0.60)	-2.29 (1.02)
Styrene	15-17	-0.87 (0.60)	-0.89 (0.43)
Motors, Outboard	5	-0.90 (1.08)	-0.54 (1.33)
Shampoo	20	0.44 (0.18)	-0.16 (0.17)
Tanks, Cryogenic	7	-0.88 (*)	27.12 (*)
Zippers	7	-2.64 (1.09)	-0.34 (0.31)
Pens, Ballpoint	5	0.48 (0.18)	0.20 (0.24)
Lasers	3	-0.52 (0.29)	0.53 (0.76)
Records, Phonograph	1	1.29 (0.40)	-2.32 (0.84)
Tapes, Recording	15	-0.93 (0.27)	9.83 (214.96)
Turbines, Gas	14-16	-1.03 (0.55)	-0.53 (0.43)

†The typewriters sample begins in 1878 when backdated entry years are used for firms in *Thomas' Register*, as described in chapter seven. To avoid biasing the results for reasons discussed in chapter seven, only divisions during the publication of *Thomas' Register* are permitted. The value EY* = 26 divides firms that had entered by the first year of publication of the *Register* from all later entrants.

*Estimates have unknown but very large standard errors, due to problems in estimation.

In contrast, among the ten products with the least severe shakeouts, six of the ten products exhibit an early-mover advantage at old ages, and only two of the six negative coefficients are significant. Seven of the products exhibit early-mover advantage at young ages, and four of the six are significant. Three products exhibit a significant early-mover disadvantage at young ages, but in those cases the disadvantage decreased or disappeared by old ages.

Among the products that experienced shakeouts of severity greater than 50%, the estimated coefficient of EY≤EY* Age>8 averaged -0.87 (standard deviation 0.45). The products with severity less than 50% showed less old-age advantage, with the estimated coefficient of EY≤EY* Age>8 averaging 2.0 (standard deviation 7.8), or -0.46 (standard deviation 0.93) after the exclusion of products with standard errors of at least 1.0. In contrast, at young ages the products with more severe shakeouts appear to have had, if anything, less early-mover advantage. Among products that experienced shakeouts of severity greater than 50%, the estimated coefficient of EY≤EY* Age≤8 averaged -0.11 (standard deviation 0.46). For products with severity less than 50%, the estimated coefficient of EY≤EY* Age≤8 averaged -0.96 (standard deviation 2.2), or -0.11 (standard deviation 0.85) after the exclusion of products with standard errors of at least 1.0.

Products with severe shakeouts always exhibited strong early-mover advantages by the time firms reached old ages, and products with little or no shakeouts exhibited early-mover advantages less often, and less strongly, at old ages. An early-mover advantage at old ages appears to have held most strongly and most often in the products that experienced more severe shakeouts.

Analyses in the Full Sample

Tables 11.6 and 11.7 show the entry and early-mover advantage measures for the full sample of products. Among the full sample, the results involve considerable noise, but are otherwise similar to those seen in the reduced sample. The typical pattern for industries with severe shakeouts appears to be a strong early-mover advantage at old ages, resulting in a decrease in entry around the time of the shakeout.

In the full sample in Table 11.6, products with shakeouts of severity greater than 50% had a mean Late Entry II measure of 28.0 (standard deviation 18.9). In contrast, products with shakeouts of severity less than 50% had a mean Late Entry II measure of 54.6 (standard deviation 15.5). As expected, entry dropped off considerably more in the products with more severe shakeouts.

The early-entrant advantage measures in Table 11.7 again indicate a stronger old-age advantage to early entrants in products with more severe shakeouts. Among the products that experienced shakeouts of severity greater than 50%, the estimated coefficient of EY≤EY* Age>8 averaged -0.85 (standard deviation 0.61). The products with severity less than 50% showed less old-age advantage, with the estimated coefficient of EY≤EY* Age>8 averaging 0.83 (standard deviation 6.3), or -0.66 (standard deviation 0.98) after the exclusion of products with standard errors of at least 1.0. Of the fifteen products with the most severe shakeouts, ten exhibited a significant early-mover advantage at old ages, but of the fifteen with the least severe shakeouts, only four exhibited a significant early-mover advantage at old ages.

At young ages, early-mover advantages were less apparent, and the difference between the two groups of products is less clear. Among the products that experienced shakeouts of severity greater than 50%, the estimated coefficient of EY≤EY* Age≤8 averaged -0.43 (standard deviation 0.71). Among products with severity less than 50%, the estimated coefficient of EY≤EY* Age≤8 averaged -0.74 (standard deviation 1.8), or -0.19 (standard deviation 0.97) after the exclusion of products with standard errors of at least 1.0.

Thus the entry and early-mover advantage patterns in the broad sample of products suggest that products with more severe shakeouts tend to have a stronger early-mover advantage at old ages.

Table 11.6. Severity of Shakeouts and Decline in Entry, Full Sample.

Product	Severity	Late Entry % I	Late Entry % II
Automobiles	97.4	9.3	1.1
Television Sets	96.6	.	2.4
Tires	90.9	5.4	9.0
DDT	90.5	13.6	9.9
Streptomycin	84.6	6.7	10.5
Windshield Wiper Mechanisms	81.4	24.1	27.0
Saccharin	79.5	9.6	33.0
Penicillin	75.9	11.1	19.3
Shavers, Electric	74.2	.	15.5
Adding Machines	70.4	23.7	28.3
Radio Transmitters	69.7	48.6	58.2
Tents, Oxygen	66.7	15.4	42.0
Typewriters	65.8	13.8	40.5
Blankets, Electric	64.7	0.0	47.6
Freezers, Home & Farm	63.9	14.7	22.5
Telemeters	58.3	.	76.5
Fl. Light Fixtures, General Line	54.5	26.0	17.1
Paints, Rubber & Rubber Base	52.5	21.8	46.6
Reactors, Nuclear	52.2	.	26.8
Missiles, Guided	52.1	9.9	22.2
Radar, Marine, Airborne, Other	50.3	31.5	32.2
Trees, Artificial X-Mas	45.0	.	66.7
Polariscopes	43.8	.	64.6
Gyroscopes	42.9	.	93.2
Electrocardiographs	41.2	.	67.3
Tubes, Cathode Ray	34.1	38.2	51.5
Engines, Jet-Propelled	32.1	.	38.7
Baseboards, Radiant Heating	29.6	.	41.7
Photocopy Machines	27.6	.	54.3
Styrene	25.6	.	65.1
Motors, Outboard	24.1	.	52.6
Fl. Lamps, Complete Tubes	23.3	43.6	22.7
Gauges, Beta-Ray	22.2	.	38.9
Shampoo	17.8	27.0	54.4
Tanks, Cryogenic	16.2	.	39.5
Nylon	15.1	.	66.8
Engines, Rocket	14.3	.	37.0
Computers	13.8	.	79.0
Crystals, Piezo	12.5	48.0	38.3
Zippers	12.2	.	57.9
Pens, Ballpoint	4.6	.	42.3
Readers, Microfilm	3.3	.	78.1
Compressors, Freon	0	.	49.2
Heat Pumps	0	.	59.7
Lasers	0	.	58.7
Records, Phonograph	0	.	51.9
Tapes, Recording	0	.	60.2
Transistors	0	.	36.6
Turbines, Gas	0	.	62.7

Table 11.7. Tests for Early-Mover Advantage in the Full Sample.

Product	Best EY*	EY≤EY* Age≤8	EY≤EY* Age>8
Automobiles	9	-0.34 (0.09)	-1.04 (0.18)
Television Sets	1	-0.33 (0.19)	-0.79 (0.29)
Tires	13-14	-0.62 (0.10)	-0.42 (0.14)
DDT	14-15	-1.12 (0.34)	** (*)
Streptomycin	10	-1.35 (0.68)	-1.47 (1.05)
Windshield Wiper Mechanisms	19	0.44 (0.18)	-0.51 (0.29)
Saccharin	19-20	0.67 (0.27)	-0.43 (0.34)
Penicillin	7-8	-1.42 (0.41)	-1.53 (0.54)
Shavers, Electric	8-9	0.36 (0.33)	0.72 (0.56)
Adding Machines	20	0.03 (0.16)	-0.68 (0.20)
Radio Transmitters	11	0.52 (0.19)	-0.82 (0.33)
Tents, Oxygen	19	-0.56 (0.44)	-0.97 (0.43)
Typewriters	26†	-0.87 (0.29)	-1.94 (0.78)
Blankets, Electric	7-8	-0.84 (1.02)	0.27 (0.55)
Freezers, Home & Farm	9	0.05 (0.26)	-1.16 (0.30)
Telemeters	19	-1.60 (0.72)	-0.71 (0.44)
Fl. Light Fixtures, General Line	17	-0.04 (0.15)	-1.07 (0.20)
Paints, Rubber & Rubber Base	7	0.05 (0.39)	-0.79 (0.35)
Reactors, Nuclear	8	-1.64 (0.34)	-1.38 (0.62)
Missiles, Guided	14	-0.32 (0.15)	-1.33 (0.26)
Radar, Marine, Airborne, Other	18	-0.17 (0.15)	-0.98 (0.24)
Trees, Artificial X-Mas	16-20	-0.87 (0.61)	-1.23 (0.45)
Polariscopes	11-14	0.87 (0.54)	0.62 (0.62)
Gyroscopes	6-20	-7.83 (3.96)	-2.16 (1.10)
Electrocardiographs	17	-1.07 (0.74)	-1.46 (0.57)
Tubes, Cathode Ray	5-7	0.01 (0.60)	-2.29 (1.02)
Engines, Jet-Propelled	1	-0.96 (1.02)	0.92 (0.56)
Baseboards, Radiant Heating	20	-1.80 (0.55)	-1.81 (0.60)
Photocopy Machines	5	-1.61 (1.02)	-0.75 (0.47)
Styrene	15-17	-0.87 (0.60)	-0.89 (0.43)
Motors, Outboard	5	-0.90 (1.08)	-0.54 (1.33)
Fl. Lamps, Complete Tubes	9	0.24 (0.33)	-0.91 (0.40)
Gauges, Beta-Ray	5-6	1.18 (0.70)	-3.00 (0.55)
Shampoo	20	0.44 (0.18)	-0.16 (0.17)
Tanks, Cryogenic	7	-0.88 (*)	27.12 (*)
Nylon	18	-0.20 (0.14)	-0.74 (0.16)
Engines, Rocket	6	-0.74 (0.64)	-0.78 (0.68)
Computers	9	-2.57 (1.00)	-0.74 (0.35)
Crystals, Piezo	8	-1.21 (0.73)	0.29 (0.45)
Zippers	7	-2.64 (1.09)	-0.34 (0.31)
Pens, Ballpoint	5	0.48 (0.18)	0.20 (0.24)
Readers, Microfilm	4	2.06 (0.65)	-7.87 (2.62)
Compressors, Freon	8	-0.75 (0.49)	-1.07 (0.61)
Heat Pumps	11	-0.37 (0.40)	13.09 (*)
Lasers	3	-0.52 (0.29)	0.53 (0.76)
Records, Phonograph	1	1.29 (0.40)	-2.32 (0.84)
Tapes, Recording	15	-0.93 (0.27)	9.83 (214.96)
Transistors	12	0.54 (0.26)	0.27 (0.73)
Turbines, Gas	14-16	-1.03 (0.55)	-0.53 (0.43)

*Estimates have unknown but very large standard errors, due to problems in estimation.

**A reliable estimate could not be obtained.

12

Conclusion

This dissertation used three technology-related theories of industry shakeouts to guide an empirical exploration into the causes of shakeouts. It paid special attention to technology and technology-related theories, in part because the four products with severe shakeouts chosen for study turned out to involve extremely high rates of technological progress. Furthermore, the technological focus provided a fresh approach to analyze the role of technological change in determining market structure. Technological change appears to be at the root of the advantage-to-the-advantaged dynamic that results in shakeout and eventual concentration of industries in the grip of a few dominant producers. The findings have implications not only for future research but also for corporate strategy and national economic policy.

Empirical Patterns

The empirical analyses considered technological change, entry, survival, and profit. They considered four manufacturing industries, automobiles, tires, television sets, and penicillin, which experienced severe shakeouts and which span a range of technological types and historical eras. In each case, the empirical analysis extended from near the inception of the product until at least several decades later.

Technology

The four products experienced dramatic technological advance. Automobiles is famous for its implementation of mass production methods and its inventor-entrepreneurs. Tires in the early 1900s had the highest rate of productivity growth of any US industry. Television set quality and reliability improved dramatically over time, and later automated production methods led to considerable reductions in cost. Penicillin was developed in one of the largest World War II US R&D projects, followed in the next decades by continual improvements in production yield and by the laboratory development of new varieties of penicillin.

Technological change in the four products had enormous impacts on product quality and production cost, so that firms unable to keep up with the latest technology suffered severe competitive disadvantages. In some cases individual technological events such as the widespread adoption of steel body presses for closed-body automobiles, the drum tire building machine and the radial tire, color television, and semisynthetic penicillins increased competition or gave a disadvantage to smaller producers or an advantage to larger producers. Indeed, most of these technological events corresponded to periods of increased exit among producers.

The other kind of technological event, the dominant design crystallizing at approximately a single point in time, did not seem to occur. In three of the four products, designs standards accumulated gradually over time, and in the fourth, penicillin, the product became more diverse with time rather than more standardized. Among researchers of technology and industry, the view of dominant designs that seems to resonate deeply is that a highly standardized product emerges at the end of long periods of a product's evolution. This common view, not the idea of a sudden crystallization, seems appropriate for automobiles, tires, and televisions. Furthermore, at least in automobiles, tires, and penicillin, process innovation was critical even in the earliest years of each industry. Producers did not wait for a standardization of the product before pursuing process innovation, but devoted considerable attention to improving their production processes from the very inception of the industry.

Larger producers tended to achieve greater productivity and to innovate more than smaller firms. This tendency is obvious in the writings of historians, and also in what quantitative evidence is available on the variation of productivity patterns and innovation among firms of varying size. The leading automobile firms did most of the innovation, particularly process innovation, and in both automobiles and tires as of the 1930s larger plants achieved much higher productivity than smaller plants.

Entry

In all four products, the annual number of entrants dropped off around the time of the shakeout. Except in automobiles, the number of firms fell quickly to negligible levels. In automobiles, considerable entry continued for another 10-15 years before entry fell to negligible levels. Among the few late entrants, none became major producers, except for foreign television set manufacturers that began production in the US and had considerable past experience in their home countries. Not surprisingly, the entry patterns in the broader sample of forty-nine products also showed a strong tendency for larger decreases in entry among products with more severe shakeouts.

Survival

Aggregate exit rates typically remained approximately constant from before until during each of the shakeouts, except in tires where the exit rate increased. However, once firms' ages and entry times are taken into account, a considerably different picture emerged in the four products. Figure 12.1 illustrates the typical pattern of firms' hazard rates (probabilities of exit per unit of time) as a function of both age and time of entry. For ease of exposition, the hazard rate is plotted on a logarithmic scale. The earliest entrants, said to

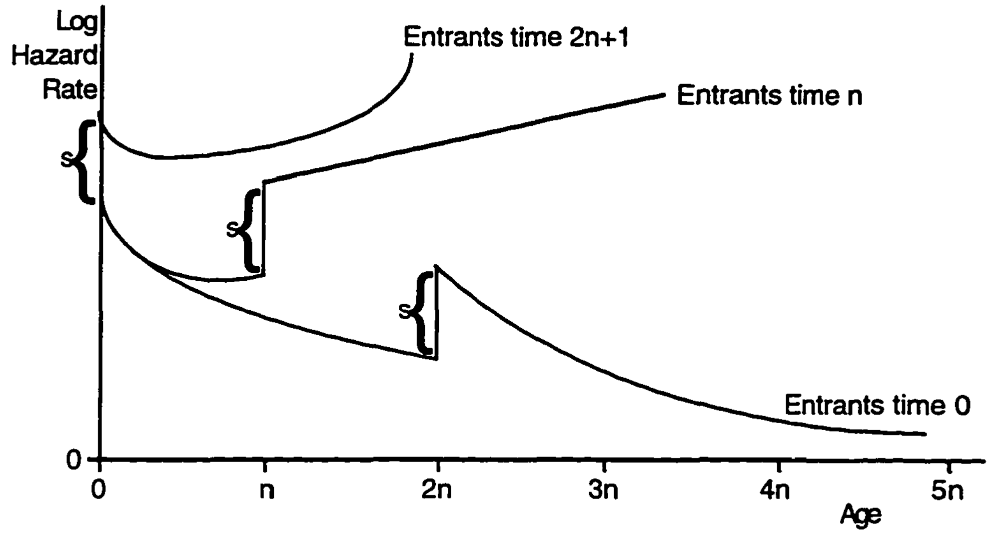


Figure 12.1. An example to illustrate the observed hazard rate patterns.

enter at time 0, are depicted in the bottom curve of the figure. The hazard rate of these earliest entrants decreased as they grew older from age 0 to age n and then to age 2n. But 2n years after they began production, the shakeout began, and their hazard rate increased by a multiple exp(s). Thus, the logarithm of their hazard rate increased by s. They immediately resumed their progression toward lower hazard rates at older ages.

Later entrants had a much different pattern in their hazard rates. Consider next the firms that entered n years after the earliest entrants. Typically, their hazard rate started out similar to those of the earliest entrants. Again the hazard rate declined as they grew older. But after some amount of time, typically 5-10 years, the hazard began to diverge from that of the earliest entrants, rising to greater values. When they reached n years of age, the shakeout began, and the hazard increased by a multiple exp(s), so that the logarithm of the hazard increased by s. Thereafter, their hazard rate typically continued to increase as they grew older. At some point, the last of these year-n entrants exited the industry, and the curve ends.

Entrants after the shakeout began, at time 2n + 1, started with the higher hazard rate associated with the shakeout. In practice, in some products (automobiles, penicillin, and possibly televisions) their initial hazard started somewhere in between that higher hazard rate and the initial hazard of earlier entrants (perhaps because less competent potential entrants chose not to enter, anticipating the higher probability of exit during the shakeout). Regardless, their hazard rate started to fall as they grew older. Around age 5-10, their hazard rate began to increase, diverging from that of earlier entrants and in fact growing even more quickly than the hazard rate of entrants at time n. Before the entrants from time n reached extinction, that is, at an age at least n + 1 years younger, the last firms that entered at time 2n + 1 left the industry.

Thus, with the exception of a few very late entrants, the last firms in each entry cohort departed from each industry approximately in the reverse of the order in which they entered. One factor involved in this pattern was the shakeout, which typically caused a permanent increase in firms' hazards. In the long term, only very early entrants remained in the industry.

To a reasonable approximation, each product seemed to have a window of opportunity, ending at some time $t^* < 2n$. Firms entering during the window had much lower hazard rates at old ages than later entrants. In contrast, firms that entered at different times before (or after) the window appeared to have relatively homogeneous hazard rates. In tires, the depiction of a single window of opportunity seemed less appropriate than in the other products, and the hazard rate seemed to change more continuously as a function of entry time.

Among the broad sample of products, industries with more severe shakeouts tended to have a stronger early-mover advantage at old ages. At young ages, the pattern was less certain, and the early-mover advantage at young ages appeared to be either less strong at old ages, or entirely non-existent.

Profit

Each of the four products started out with extremely high rates of return on investment for successful firms. Over time, as industry output increased, prices gradually decreased and, despite improvements in production cost that were often quite dramatic, rates of return also gradually decreased. Profits typically reached normal levels or lower sometime around the beginning of the shakeout. In automobiles, profits remained above normal for just over a decade after the shakeout began, and in this product the fall in profits to normal levels coincided with the cessation of entry and the most dramatic increase in the hazard rate.

Summary

The empirical patterns conform to a dynamic in which advantaged firms gain further advantage over time. An advantage that was likely technology-related apparently gave larger firms lower production costs and higher-quality products than other firms. Earlier entrants had more time to grow large and some of them captured positions of lasting dominance in their industry. As firms expanded, prices fell, and only those firms with cost and quality advantages were able to remain profitable. Eventually, entry stopped almost entirely as entry apparently became unprofitable. Those firms that did enter later did not capture large market shares and were generally short-lived. Exit of less-advantaged firms continued, and each industry moved steadily toward a smaller and smaller number of highly-advantaged firms.

The Shakeout Theories

This dissertation focused on three theories of technology and shakeouts. The goal was not simply to test the theories, but to use them to guide an analysis of the multiple factors that might play a role in shakeouts. The first two theories argue that a single technological event—a refinement invention or a dominant design—causes a shakeout by inducing a decline in entry combined with the mass-extinction of producers unable to convert to the new technology. The third theory, the size-and-skill theory, argues that the growing advantage of particularly skilled early entrants eventually puts potential entrants at such a disadvantage as to cause entry to cease, while exit continues because some of the expanding incumbents always have an advantage over others.

I began examining the technological event theories by focusing directly on technological change. For the innovative gamble theory, I searched the historical, economic, and trade literatures to find candidates for inventions or innovations that might have caused the shakeouts in the four products. In tires, the drum tire building machine seems a plausible refinement invention that apparently had a dramatic impact on firms' costs. In the other three products, I was not able to discover refinement inventions as described in the theory. I did uncover several inventions well after the shakeouts had begun that seemingly had substantial effects

For the dominant design theory, I searched for a shift from product to process innovation predicted to occur at the time of the shakeout. I examined time-series data such as counts of innovations, labor productivity, and product quality measures. In automobiles, data on innovation counts did not fit the theory, but labor productivity and capital-labor ratio data do suggest in increase in process innovations after the times of the shakeouts. In the other three products, the available data largely suggests a shift from process to product innovation, opposite the predicted pattern. Nevertheless, the technological evidence might be too limited to observe a refinement invention or a shift from product to process innovation, and I turned to indirect methods of testing the theories.

The technological event theories predict a decrease in entry and a rise in the probability of exit at the time of a shakeout. Entry dropped off as predicted, and the probability of exit increased after controlling for the changing age distribution of firms. However, the increased probabilities of exit did not decline as they should have once firms unable to survive in the new technological regime had exited. The technological event theories also predict that the technological disadvantage of later entrants should give them a higher probabilities of exit at young ages, and that their exit rates should return to normal after the exit of firms unable to adapt to the new technology. In fact, firms disadvantaged by entering after the technological event either experienced higher exit rates virtually forever, or actually experienced increasing hazard rates as they grew older. Also, dividing pre-shakeout entrants into two entry cohorts suggested that the difference between earlier and later entrants manifested itself much earlier than when the shakeout began.

The refinement invention theory also makes predictions about a surge in entry and in the profits of leading firms, triggered by the innovative gamble. The predicted surge in entry occurred only in tires, and in that product historians attributed the surge to an economic boom and deregulation after World War I. The profit rates of incumbents did not rise at the times of the shakeouts, with the possible exception of automobiles since quantitative profits data are not available before the times of the shakeouts.

The size-and-skill theory predicts a gradual pattern in which early entrants capture an early-mover advantage, entry ceases as prices fall and entry by potential entrants becomes unprofitable, and exit continues, driving down the number of producers. Technological tests of the theory were minimal because of the lack of available evidence. In automobiles evidence was available that matched with the predicted patterns of a higher innovation rate for larger firms, especially for process innovation. In automobiles and tires, data from the 1930s show the predicted higher productivity of larger firms. I again turned to indirect tests of the theory.

As expected by the size-and-skill theory, entry dropped off around the time of the shakeout. However, the theory does not predict the observed increase in exit at the times of the shakeouts. Essential to the theory is an early-mover advantage that is manifested as a higher hazard rate of later entrants, relative to earlier entrants, at old ages. As predicted, when they were compared at older ages, the hazard rate of later entrants was substantially greater than the hazard rate of earlier entrants of the same age. The difference between earlier and later entrants varied substantially with the choice of parametric models. As an alternative to arbitrarily choosing a parametric form, I used a model with a single window of opportunity, with the time of the window chosen by a best fit method. The results from this method consistently showed a higher hazard rate for later entrants at old ages. The theory also predicts that at least eventually profits fall steadily over time even for the largest firms, and this prediction matched with profitability data.

Among the alternative theories, aspects of each seem to be correct. Individual innovations sometimes caused an increase in hazard rates, but the increases did not typically occur at the times of the shakeouts. Hazard rates increased at the times of the shakeouts. And early entrants gained a lasting early-mover advantage whereas later entrants experienced increased hazard rates particularly at old ages.

Technology and Market Structure

Throughout this century, dating at least from Schumpeter, economists have considered how market structure may affect technological change in industries. And in the past two decades particularly, economic theorists have turned the issue around, asking how technological change may determine market structure. To date, the reasons for the empirical relationships that have been observed between technology and market structure are controversial and far from understood. The focus of this research on technology and industry shakeouts has been in part an attempt to improve understanding of the technology-market structure relationship.

The three shakeout theories provide unusually rich depictions of how technological changes might cause dramatic evolutionary patterns in market structure, resulting eventually in the concentration of an industry among a small number of producers. The evolutionary framework of the theories allowed a contrasting approach to the usual cross-sectional methods of analysis.

The shakeouts in the four products apparently resulted not from any single invention or design standard, but from a continual process in which advantaged firms accumulated more advantage, such as that modeled in the size-and-skill theory. Given the dramatic pace of technological change in the four products, as well as other evidence about patterns of technological change, it appears that technological change is deeply tied up in the advantage of dominant firms. In other words, some process such as R&D cost-spreading apparently led to the shakeouts and concentration in the four products.

The reasons for the advantage of early entrants need not have to do with the R&D cost-spreading argument of the size-and-skill theory. National advertising, distribution networks, reputation or product adoption among consumers, and in many countries even the establishment of political connections all might result in an advantage-to-the-advantaged dynamic. Nevertheless, the enormous rate of technological advance and the enormous amounts of money devoted to R&D in the four products suggest that technological change was deeply involved in competitive processes. Furthermore, the differences in manufacturing productivity between large and small firms suggest that larger firms captured a strong technology-related advantage.

Individual technological innovations, while they did not cause the shakeouts, appear to have had important competitive ramifications that affected industry concentration. Typically the exit rate rose at the times of such key events as the color TV era. Historians and industry analysts have devoted substantial attention to these topics and often document the purported reasons for the increased exit.

Research Implications

R&D cost-spreading should not be confused with the related concept of learning curves. Research on learning curves has typically argued that a sharp reduction in cost results as cumulative production increases, until eventually the progressive cost reduction bottoms out given a limited size of industry output. The reasons for progressive cost reduction in manufactured products in most cases remains unclear, although it is often attributed to individual learning on the part of production line workers, R&D employees, and managers, as well as to corporate-wide learning in which the entire corporation develops routines for worker interaction, production techniques, R&D know-how, and other useful traits that may not be embodied in the mind of a single employee. The progressive cost reduction in the four products studied here came from continual engineering and reengineering of production processes. But at least in automobiles, tires, and penicillin, the enormous attention and money devoted to process innovation, especially in the first decades of each product, led to dramatic productivity improvements that resulted from purposeful R&D, not from learning as a mere by-product of production. Furthermore, the survival patterns observed in the four products are not consistent with the bottoming-out of learning curves that is so widely discussed. If the learning curves bottomed out, then the biggest difference in firms' competitiveness should occur at young ages, when firms are on the steepest part of the learning curve. By the time they reach old ages, they should be comparable to each other, regardless of their order of entry, because they are all near the bottom of the learning curve. In fact, the data from the four products indicate that the consistent disparity between producers from different entry periods occurred at old ages, exactly when the learning curve hypothesis suggests there should be no difference.

Many related and very important topics have been left out of this study and are valuable directions for future research. How do niche markets affect evolutionary competitive processes and the survival or failure of firms? Does regional agglomeration play an important role in the development of industries and does it help to determine the eventual industry leaders? Have shakeouts been commonly experienced outside of the US? In the modern era of international competition, how do shakeouts and early-mover advantages manifest themselves, if it all, on an international scale, and what does this say about appropriate national policy?

Strategy Implications

The advantage-to-the-advantaged dynamic resulting from technological change suggests a strategy for businesses executives seeking to guide their businesses' growth and investment. An ideal investment involves a product that has perhaps already been introduced and that seemingly has a potential for large demand, but is in its early stage of development. It seems likely to experience a strong advantage-to-the-advantaged dynamic. This dynamic might be expected if production will require complicated processes that can be automated but that have great potential for customized engineering effort to continually bring down costs by creating or redesigning machinery, reorienting plant layouts and production flow, and otherwise improving and streamlining the production process. It may also occur in other situations, such as where national advertising and brand name reputation will have a large impact on buyers' purchasing decisions, so that national advertising costs can be spread over the number of units produced.

If a suitable new product is not available for investment, too-late entry to capture an advantage does not necessarily mean too-late entry to make a profit. Businesses may enter moderately late and still have temporary high profits. As prices fall, they may wish to carefully consider how much money to spend improving their product or lowering their manufacturing costs, depending on how long the improvements will forestall exit and what profit margins they are likely to have. Eventually, exit is likely to be inevitable. It would be prudent to consider in advance the most appropriate time and means of exit, how the assets of the company can be put to new uses or sold, and what the employees involved will do for their living after production ceases in the original market. In the meantime, though, the company has the potential to earn a substantial profit.

Early entry into a new market with an advantage-to-the-advantaged dynamic is not always a panacea. Only some of the early entrants are likely to succeed in the long run. Success is likely to require top-notch personnel and a commitment to long-range investment in R&D, expansion, and other necessities such as distribution networks, advertising, and branch assembly plants. Further, in modern high-technology industries, uncertainty abounds about how the technology is likely to evolve. In some products, entering early might involve a risk of adopting a technology that turns out to be inappropriate or unpopular, as with makers of steam-powered automobiles in the late 1800s. And of course, in some products established market leaders have been deposed by the development of alternative technologies that require an unrelated technological competency. For example, makers of vacuum tubes and mechanical calculators were unable to maintain their leadership upon the introduction of transistors and electronic calculators.

Businesses may intentionally wish to invest in products that are unlikely to have an advantage-to-the-advantaged dynamic. Products without an advantage to early entry, if they can somehow be identified, are likely to provide a much more survivable environment for late entrants than products like automobiles or television sets. Products with high rates of product innovation are much less likely to involve an early-mover advantage than those that necessitate high rates of process innovation, especially if existing product features can be easily and legally copied. Of course, other barriers to long-run success such as reputation, national advertising, and distribution networks could put entrants at a disadvantage, and obviously it would behoove potential entrants to consider these possible barriers.

Policy Implications

Of the four products studied here, automobiles, tires, and penicillin have been closely scrutinized under suspicion of anti-trust violations. The US Federal Trade Commission has created reports hundreds of pages long analyzing each industry's competitive practices. And televisions has been the subject of decades of lawsuits and international negotiations about competitive practices.

Regardless whether every producer behaves within the confines of the law, the advantage-to-the-advantaged dynamic impels the industry toward a state of high concentration with a few producers, or ultimately even a single producer. Suspicion of antitrust violation is no substitute for the truth. It would be inappropriate to declare a firm and its executives guilty solely on the basis of a company's large market share. Without investigating how a company achieved its large market share, there is no *a priori* basis on which to assume a guilty verdict.

Of course, bigger companies and more concentrated markets are not necessarily desirable. The R&D cost-spreading hypothesis suggests that bigger companies achieve lower production costs, because given their large size it is worthwhile for them to spend greater resources on process innovation. The same devotion of resources to product innovation is unlikely since it generally has relatively little effect on the sales or profits of leading firms. Government policy might be able to achieve optimal product *and* process innovation, by encouraging product innovation in industries that have gone through a shakeout and become tightly concentrated. It might do so, for example, by policies targeted to relevant industries that support university-industry research or government research, provide tax breaks for research, or mandate new product standards such as those for fuel efficiency and reduced emissions of pollutants.

Appendices

A1

Continuous Effects of Entry Year

This appendix presents estimates from models involving continuous effects of entry year, as described in chapter seven.

Table A1.1. Continuous Entry Year Effect, Gompertz Model, for Automobiles

	LogEntryYear	SqrtLogEntryYear	LogLogEntryYear
Age 0.5 to 1.5	-3.47*** (0.23)	-4.15*** (0.37)	-4.01*** (0.33)
Age 1.5 to 2.5	-2.55*** (0.21)	-3.22*** (0.35)	-3.08*** (0.32)
Age 2.5 to 3.5	-2.49*** (0.21)	-3.16*** (0.36)	-3.02*** (0.32)
Age 3.5 to 4.5	-2.56*** (0.22)	-3.24*** (0.36)	-3.09*** (0.32)
Age 4.5 to 5.5	-2.37*** (0.22)	-3.05*** (0.36)	-2.90*** (0.32)
Age 5.5 to 6.5	-2.78*** (0.25)	-3.45*** (0.38)	-3.31*** (0.34)
Age 6.5 to 7.5	-2.68*** (0.26)	-3.35*** (0.38)	-3.20*** (0.35)
Age 7.5 to 8.5	-2.58*** (0.26)	-3.25*** (0.38)	-3.10*** (0.35)
Age 8.5 to 9.5	-2.49*** (0.27)	-3.15*** (0.39)	-3.01*** (0.36)
Age 9.5 & up	-2.84*** (0.22)	-3.46*** (0.35)	-3.31*** (0.32)
g(ey)	0.48*** (0.08)	1.20*** (0.22)	1.40*** (0.24)
g(ey) Age	-0.01*** (0.00)	-0.02*** (0.01)	-0.03*** (0.01)
LL	-1926.00	-1925.30	-1924.76

Table A1.2. Continuous Entry Year Effect, Weibull-V. Model, for Automobiles

	LogEntryYear	SqrtLogEntryYear	LogLogEntryYear
Age 0.5 to 1.5	-3.70*** (0.34)	-4.97*** (0.48)	-4.76*** (0.45)
Age 1.5 to 2.5	-2.62*** (0.24)	-3.61*** (0.39)	-3.43*** (0.35)
Age 2.5 to 3.5	-2.49*** (0.22)	-3.32*** (0.36)	-3.16*** (0.33)
Age 3.5 to 4.5	-2.53*** (0.22)	-3.25*** (0.36)	-3.11*** (0.32)
Age 4.5 to 5.5	-2.32*** (0.23)	-2.96*** (0.36)	-2.82*** (0.32)
Age 5.5 to 6.5	-2.72*** (0.26)	-3.29*** (0.38)	-3.16*** (0.34)
Age 6.5 to 7.5	-2.62*** (0.27)	-3.14*** (0.38)	-3.01*** (0.35)
Age 7.5 to 8.5	-2.52*** (0.28)	-2.99*** (0.39)	-2.88*** (0.36)
Age 8.5 to 9.5	-2.44*** (0.30)	-2.87*** (0.40)	-2.75*** (0.37)
Age 9.5 & up	-3.00*** (0.29)	-3.19*** (0.40)	-3.10*** (0.37)
g(ey)	0.54*** (0.11)	1.65*** (0.28)	1.91*** (0.33)
g(ey) logAge	-0.10 (0.06)	-0.39*** (0.12)	-0.46*** (0.15)
LL	-1932.20	-1929.10	-1929.07

Table A1.3. Continuous Entry Year Effect, Gompertz Model, for Automobiles (Epstein)

	LogEntryYear	SqrtLogEntryYear	LogLogEntryYear
Age 0.5 to 1.5	-5.82*** (0.74)	-6.77*** (1.10)	-6.49*** (0.99)
Age 1.5 to 2.5	-4.42*** (0.63)	-5.38*** (1.03)	-5.09*** (0.91)
Age 2.5 to 3.5	-4.19*** (0.61)	-5.16*** (1.03)	-4.87*** (0.91)
Age 3.5 to 4.5	-4.59*** (0.64)	-5.57*** (1.05)	-5.28*** (0.93)
Age 4.5 to 5.5	-4.80*** (0.66)	-5.78*** (1.06)	-5.48*** (0.94)
Age 5.5 to 6.5	-4.22*** (0.62)	-5.22*** (1.04)	-4.92*** (0.92)
Age 6.5 to 7.5	-4.59*** (0.66)	-5.60*** (1.06)	-5.29*** (0.95)
Age 7.5 & up	-4.28*** (0.58)	-5.33*** (1.01)	-5.00*** (0.89)
g(ey)	0.82*** (0.21)	1.97*** (0.59)	2.26*** (0.65)
g(ey) Age	-0.01 (0.01)	-0.02 (0.02)	-0.02 (0.03)
LL	-453.32	-455.26	-454.98

Table A1.4. Continuous Entry Year Effect, Weibull-V. Model, for Automobiles (Epstein)

	LogEntryYear	SqrtLogEntryYear	LogLogEntryYear
Age 0.5 to 1.5	-6.42*** (1.14)	-7.64*** (1.33)	-7.42*** (1.28)
Age 1.5 to 2.5	-4.74*** (0.79)	-5.85*** (1.08)	-5.61*** (1.00)
Age 2.5 to 3.5	-4.38*** (0.67)	-5.42*** (1.02)	-5.17*** (0.92)
Age 3.5 to 4.5	-4.69*** (0.65)	-5.70*** (1.02)	-5.43*** (0.92)
Age 4.5 to 5.5	-4.83*** (0.66)	-5.81*** (1.04)	-5.54*** (0.93)
Age 5.5 to 6.5	-4.22*** (0.62)	-5.18*** (1.02)	-4.90*** (0.90)
Age 6.5 to 7.5	-4.55*** (0.67)	-5.50*** (1.05)	-5.22*** (0.93)
Age 7.5 & up	-4.22*** (0.61)	-5.11*** (1.02)	-4.81*** (0.90)
g(ey)	1.01** (0.34)	2.43*** (0.71)	2.89*** (0.85)
g(ey) Age	-0.14 (0.17)	-0.33 (0.29)	-0.44 (0.36)
LL	-453.31	-454.93	-454.63

Table A1.5. Continuous Entry Year Effect, Gompertz Model, for Tires

	LogEntryYear	SqrtLogEntryYear	LogLogEntryYear
Age 0 to 1	-2.29*** (0.39)	-2.28*** (0.40)	-2.33*** (0.40)
Age 1 to 2	-2.37*** (0.25)	-2.40*** (0.27)	-2.43*** (0.27)
Age 2 to 3	-1.84*** (0.22)	-1.88*** (0.24)	-1.89*** (0.23)
Age 3 to 4	-2.20*** (0.23)	-2.21*** (0.25)	-2.25*** (0.25)
Age 4 to 5	-1.95*** (0.25)	-1.96*** (0.27)	-2.00*** (0.27)
Age 5 to 6	-2.23*** (0.32)	-2.24*** (0.34)	-2.26*** (0.33)
Age 6 to 7	-1.87*** (0.34)	-1.90*** (0.35)	-1.92*** (0.35)
Age 7 to 8	-2.98*** (0.36)	-3.00*** (0.37)	-3.02*** (0.36)
Age 8 to 9	-1.37*** (0.27)	-1.40*** (0.29)	-1.40*** (0.29)
Age 9 to 10	-2.97*** (0.40)	-3.00*** (0.41)	-3.02*** (0.41)
Age 10 to 12	-2.67*** (0.27)	-2.70*** (0.29)	-2.72*** (0.29)
Age 12 & up	-2.59*** (0.16)	-2.56*** (0.17)	-2.57*** (0.17)
g(ey)	0.18*** (0.05)	0.31** (0.11)	0.41** (0.14)
g(ey) Age	-0.01*** (0.00)	-0.02*** (0.01)	-0.01*** (0.01)
LL	-1778.92	-1779.05	-1778.79

Table A1.6. Continuous Entry Year Effect, Weibull-V. Model, for Tires

	LogEntryYear	SqrtLogEntryYear	LogLogEntryYear
Age 0 to 1	-2.91*** (0.50)	-3.41*** (0.59)	-3.36*** (0.57)
Age 1 to 2	-2.60*** (0.29)	-2.98*** (0.37)	-2.93*** (0.36)
Age 2 to 3	-1.93*** (0.24)	-2.22*** (0.30)	-2.19*** (0.29)
Age 3 to 4	-2.20*** (0.24)	-2.42*** (0.28)	-2.38*** (0.27)
Age 4 to 5	-1.90*** (0.25)	-2.07*** (0.28)	-2.04*** (0.28)
Age 5 to 6	-2.14*** (0.32)	-2.28*** (0.34)	-2.25*** (0.34)
Age 6 to 7	-1.77*** (0.34)	-1.86*** (0.35)	-1.87*** (0.35)
Age 7 to 8	-2.84*** (0.36)	-2.92*** (0.37)	-2.92*** (0.36)
Age 8 to 9	-1.23*** (0.27)	-1.30*** (0.29)	-1.29*** (0.28)
Age 9 to 10	-2.85*** (0.40)	-2.89*** (0.41)	-2.91*** (0.41)
Age 10 to 12	-2.50*** (0.27)	-2.50*** (0.29)	-2.52*** (0.29)
Age 12 & up	-2.66*** (0.16)	-2.53*** (0.18)	-2.58*** (0.17)
g(ey)	0.30*** (0.09)	0.77*** (0.22)	0.93*** (0.26)
g(ey) Age	-0.13*** (0.04)	-0.33*** (0.09)	-0.38*** (0.11)
LL	-1781.90	-1780.00	-1780.12

Table A1.7. Continuous Entry Year Effect, Gompertz Model, for Televisions

	LogEntryYear	SqrtLogEntryYear	LogLogEntryYear
Age 0 to 1	-1.33** (0.48)	-1.39** (0.48)	-1.37** (0.48)
Age 1 to 2	-1.51*** (0.43)	-1.56*** (0.43)	-1.53*** (0.43)
Age 2 to 3	-2.40*** (0.48)	-2.47*** (0.49)	-2.44*** (0.48)
Age 3 to 4	-2.08*** (0.46)	-2.13*** (0.46)	-2.12*** (0.46)
Age 4 to 5	-2.27*** (0.47)	-2.31*** (0.48)	-2.28*** (0.48)
Age 5 to 6	-2.03*** (0.51)	-2.08*** (0.51)	-2.06*** (0.51)
Age 6 to 7	-2.87*** (0.63)	-2.89*** (0.63)	-2.90*** (0.63)
Age 7 to 8	-2.44*** (0.43)	-2.48*** (0.44)	-2.47*** (0.44)
Age 8 & up	-2.56*** (0.17)	-2.60*** (0.18)	-2.59*** (0.18)
g(ey)	0.06 (0.13)	0.14 (0.18)	0.16 (0.24)
g(ey) Age	0.02 (0.02)	0.03 (0.02)	0.04 (0.03)
LL	-466.54	-466.21	-466.22

Table A1.8. Continuous Entry Year Effect, Weibull-V. Model, for Televisions

	LogEntryYear	SqrtLogEntryYear	LogLogEntryYear
Age 0 to 1	-1.39** (0.49)	-1.48** (0.51)	-1.45** (0.51)
Age 1 to 2	-1.57*** (0.43)	-1.63*** (0.43)	-1.62*** (0.43)
Age 2 to 3	-2.47*** (0.48)	-2.54*** (0.49)	-2.54*** (0.49)
Age 3 to 4	-2.14*** (0.46)	-2.16*** (0.46)	-2.15*** (0.46)
Age 4 to 5	-2.29*** (0.47)	-2.33*** (0.48)	-2.32*** (0.48)
Age 5 to 6	-2.05*** (0.51)	-2.08*** (0.51)	-2.09*** (0.51)
Age 6 to 7	-2.88*** (0.63)	-2.90*** (0.63)	-2.91*** (0.63)
Age 7 to 8	-2.41*** (0.44)	-2.46*** (0.44)	-2.45*** (0.44)
Age 8 & up	-2.47*** (0.16)	-2.50*** (0.17)	-2.49*** (0.17)
g(ey)	0.15 (0.15)	0.29 (0.22)	0.36 (0.29)
g(ey) Age	0.03 (0.09)	0.02 (0.13)	0.03 (0.17)
LL	-467.50	-466.99	-467.09

Table A1.9. Continuous Entry Year Effect, Gompertz Model, for Televisions, Including Foreign Entrants

	LogEntryYear	SqrtLogEntryYear	LogLogEntryYear
Age 0 to 1	-1.32** (0.47)	-1.37** (0.48)	-1.35** (0.48)
Age 1 to 2	-1.51*** (0.43)	-1.55*** (0.43)	-1.55*** (0.43)
Age 2 to 3	-2.40*** (0.48)	-2.46*** (0.48)	-2.44*** (0.48)
Age 3 to 4	-2.10*** (0.46)	-2.12*** (0.46)	-2.11*** (0.46)
Age 4 to 5	-2.28*** (0.47)	-2.32*** (0.48)	-2.29*** (0.48)
Age 5 to 6	-2.03*** (0.51)	-2.08*** (0.51)	-2.07*** (0.51)
Age 6 to 7	-2.93*** (0.63)	-2.95*** (0.63)	-2.93*** (0.63)
Age 7 to 8	-2.38*** (0.42)	-2.43*** (0.43)	-2.42*** (0.43)
Age 8 & up	-2.57*** (0.17)	-2.61*** (0.19)	-2.59*** (0.18)
g(ey)	0.05 (0.13)	0.13 (0.18)	0.15 (0.24)
g(ey) Age	0.02 (0.02)	0.03 (0.02)	0.04 (0.03)
Foreign	-3.29*** (1.03)	-3.18*** (1.01)	-3.19*** (1.02)
LL	-471.22	-470.96	-470.96

Table A1.10. Continuous Entry Year Effect, Weibull-V. Model, for Televisions, Incl. Foreign Entrants

	LogEntryYear	SqrtLogEntryYear	LogLogEntryYear
Age 0 to 1	-1.35** (0.49)	-1.46** (0.51)	-1.43** (0.51)
Age 1 to 2	-1.57*** (0.43)	-1.62*** (0.43)	-1.61*** (0.43)
Age 2 to 3	-2.47*** (0.48)	-2.54*** (0.49)	-2.54*** (0.49)
Age 3 to 4	-2.13*** (0.46)	-2.17*** (0.46)	-2.16*** (0.46)
Age 4 to 5	-2.30*** (0.47)	-2.36*** (0.48)	-2.35*** (0.48)
Age 5 to 6	-2.07*** (0.51)	-2.10*** (0.51)	-2.09*** (0.51)
Age 6 to 7	-2.94*** (0.63)	-2.95*** (0.63)	-2.94*** (0.63)
Age 7 to 8	-2.34*** (0.43)	-2.40*** (0.43)	-2.39*** (0.43)
Age 8 & up	-2.47*** (0.16)	-2.51*** (0.17)	-2.49*** (0.17)
g(ey)	0.13 (0.15)	0.27 (0.22)	0.33 (0.28)
g(ey) Age	0.04 (0.09)	0.03 (0.13)	0.05 (0.16)
Foreign	-3.34*** (1.03)	-3.19*** (1.01)	-3.22*** (1.02)
LL	-472.26	-471.81	-471.89

Table A1.11. Continuous Entry Year Effect, Gompertz Model, for Penicillin

	LogEntryYear	SqrtLogEntryYear	LogLogEntryYear
Age 0 to 1	-4.91 (3.36)	-4.83 (3.37)	-4.85 (3.37)
Age 1 to 2	-2.77 (3.02)	-2.77 (3.02)	-2.77 (3.02)
Age 2 to 3	-2.82 (2.90)	-2.76 (2.91)	-2.79 (2.91)
Age 3 to 4	-1.78 (2.78)	-1.82 (2.78)	-1.82 (2.78)
Age 4 to 5	-3.63 (2.61)	-3.59 (2.62)	-3.60 (2.62)
Age 5 to 6	-2.99 (2.17)	-3.00 (2.17)	-3.00 (2.17)
Age 6 to 8	-4.90*** (0.90)	-4.87*** (0.91)	-4.88*** (0.91)
Age 8+	-3.37*** (0.27)	-3.34*** (0.27)	-3.36*** (0.27)
g(ey)	0.26 (0.17)	0.42 (0.30)	0.54 (0.37)
g(ey) Age	0.02 (0.01)	0.02 (0.02)	0.03 (0.03)
LL	-178.38	-179.27	-179.13

Table A1.12. Continuous Entry Year Effect, Weibull-V. Model, for Penicillin

	LogEntryYear	SqrtLogEntryYear	LogLogEntryYear
Age 0 to 1	-4.85 (3.40)	-4.85 (3.41)	-4.86 (3.41)
Age 1 to 2	-2.78 (3.05)	-2.81 (3.05)	-2.81 (3.05)
Age 2 to 3	-2.93 (2.91)	-2.90 (2.91)	-2.91 (2.91)
Age 3 to 4	-1.86 (2.79)	-1.88 (2.79)	-1.87 (2.79)
Age 4 to 5	-3.74 (2.62)	-3.72 (2.62)	-3.72 (2.62)
Age 5 to 6	-3.03 (2.17)	-3.07 (2.17)	-3.07 (2.17)
Age 6 to 8	-5.02*** (0.91)	-5.00*** (0.92)	-4.99*** (0.92)
Age 8+	-3.28*** (0.27)	-3.30*** (0.27)	-3.30*** (0.27)
g(ey)	0.27 (0.26)	0.46 (0.47)	0.59 (0.60)
g(ey) Age	0.08 (0.13)	0.09 (0.21)	0.12 (0.27)
LL	-178.98	-179.72	-179.58

A2

Notes

[1]More precise definitions and a discussion of alternative definitions appear later in the dissertation.

[2]The three theories have yet to be tested extensively. The first theoretical paper fits the innovative gamble theory to data from the tire industry and suggests an invention (the Banbury mixer) as the triggering event for the industry's shakeout. The second paper includes six qualitative case studies to explain quantitative data on entry, exit, and number of firms. A related paper by Hopenhayn includes no tests. The last paper explains how the theory predicts stylized patterns of industry evolution. I am aware of no other empirical tests of the theories to date.

[3]Thanks to John Miller for his dinosaur annihilation metaphors.

[4]Radical creative destruction that replaces incumbent producers with a new set of firms is likely to involve at least a temporary *increase* in the number of producers, rather than a dropoff. Hence, the changeover of producers is not likely to involve a shakeout according to the definition used here, of a dropoff in the number of producers.

[5]Cohen (1995) provides a detailed review of Schumpeterian and post-Schumpeterian treatments of technology-market structure relationships, explaining both empirical findings and recent reinterpretations of the meaning of the empirical patterns. The introduction to Phillips (1971) provides a useful framework for understanding how Schumpeter's

arguments varied over time, and how they compare to the views of Galbraith (1952) and to a broad range of economic research. For reviews of theoretical work on technology-structure relationships, see for example Reinganum's (1989) chapter in the *Handbook of Industrial Organization*.

[6]The effects of innovation on market structure have been examined in cross-sectional industry studies using instrumental variables to identify simultaneous equations in assumed equilibrium. For a brief summary, see Cohen (1995, pp. 193-194).

[7]For other studies that show shakeouts of varying degrees in manufacturing industries, see for example Epstein (1928) and Smith (1968) in automobiles, Swaminathan and Carroll (1995) in beer brewing, Mitchell (1984) in various categories of diagnostic medical imaging equipment, Utterback and Suárez (1993) in television sets and television picture tubes, and Majumdar (1982) in electronic calculators. Many other studies relate to service industries and to nonprofit organizations, such as Carroll and Hannan (1989), Carroll and Delacroix (1982), Amburgey, Kelly, and Barnett (1993), and Carroll (1995) in newspapers, Wholey at al. (1992, 1993) and Strang (1995) in health maintenance organizations, and Hannan and Freeman (1987, 1988) and Hannan (1995) in labor unions.

[8]The advantage of incumbents contrasts with a considerable literature suggesting that incumbents have lower chances than new firms to develop extreme innovations. See for example Majumdar's (1982) analysis of the replacement of mechanical with electronic calculators, Henderson's (1985) study of photolithographic alignment equipment manufacturers, and Ehrnberg and Sjoberg (1992).

[9]Cf. Utterback and Abernathy (1975), Abernathy (1978), Abernathy and Utterback (1978), and Utterback (1994).

[10]In Hopenhayn's (1993) theory, technological changes occur at random times and make worthless any previous improvements to production methods. Firms avoid doing process R&D if they think the technological changes are likely to occur. Eventually the

technological changes slow or stop, and firms race to improve their production processes. Successful firms expand. With a larger average firm size, the number of firms decreases, causing the shakeout.

Entry stabilizes at a level sufficient to keep total output equal to demand. Exit continues, but successful firms have lower probabilities of exit. It is because an increased fraction of firms have succeeded at innovation that the exit rate decreases during the shakeout. The technological changes occurring over time lower production costs, and hence result in declining prices and increasing industry output. Industry output and the number of firms might also rise over time because of demand growth (although sufficient growth would cause entry to exceed exit, yielding an increase in number of firms rather than a shakeout).

[11]This view also fits with evolutionary industry patterns discussed by Geroski (1991b).

[12]Another variant proposed by Hopenhayn involves falling costs. This variant assumes that firms that achieve lower costs expand, decreasing the number of firms and entry as in the theory discussed above. The assumption of lower cost simultaneous with growth is similar to assumptions and predictions of the technological shakeout theories.

[13]Define x_1 as the exit rate of pre-refinement entrants and x_2 as the exit rate of post-refinement entrants and let $m = x_2/x_1$. It can be shown that m is high when the shakeout begins, but falls to one as unsuccessful innovators exit, assuming a non-zero amount of random exit due to causes not predicted in the theory.

[14]Proof, using Jovanovic and MacDonald's notation: While exit of unsuccessful innovators occurs, $V_t^l = \pi^a$, i.e. the expected return to continued participation of unsuccessful innovators equals the profit that could be obtained by participating in alternative industries. The expected return from participation, V_t^l, is $\pi_t^l + \gamma\left[rV_{t+1}^h + (1-r)\pi^a\right] = \pi^a$ for all t when exit occurs. Since $V_{t+1}^h > \pi^a$, $\left[rV_{t+1}^h + (1-r)\pi^a\right] > \pi^a > 0$, and $\pi_t^l < \pi^a$. Since V_{t+1}^h decreases with t, π_t^l must increase with t for the equality to hold.

[15]This stylized result holds when one assumes two levels of skill, with random exit that occurs more often for less-skilled firms, plus exit whenever firms become unprofitable. Early entrants include both high- and low-skill firms, but later entrants must all be high-skilled in order to remain competitive against the early entrants which have had more time to grow large. At young ages, the early entrants have on average a probability of random exit in between the high- and low-skill values, but later entrants have the lowest possible probability, equal to the high-skill value.

[16]Expansion increases profit both because the firm sells more units and because it chooses to do more process R&D and hence achieves a lower production cost. Falling price decreases profit for the obvious reason.

[17]In the innovative gamble model, the convenient assumption of free-entry equilibrium implies that all entry occurs "instantaneously" at the outset of the product, and again "instantaneously" when the refinement invention appears. In the size-and-skill model, entry eventually becomes unprofitable for even the most competent potential entrants, and the existence of exceptional cases is ruled out so that there is "zero" entry.

[18]Of the four primary products in this study, the one product for which I am sometimes questioned about product definition is penicillin. Other antibiotics can be used to treat the same diseases as penicillin, so one might argue that antibiotics as a whole be defined as the relevant industry. But in fact, penicillin and other antibiotics have different side effects, different ramifications for the development of resistant organisms in patients, and different abilities to treat different kinds of disease. In practice, doctors who wish to use penicillin do so whenever they feel a particular drug is most appropriate. Were the price of penicillin exorbitant compared to the price of other antibiotics, doctors might choose other antibiotics instead, but penicillin has always been the least expensive of antibiotics.

[19]As an example, many firms that were forced out of the automobile industry managed to hang on considerably longer as truck manufacturers (Thomas' Register). Therefore, the

motor vehicle industry as a whole may have experienced a shakeout less dramatic than in automobiles alone. Exit from the automobile industry should not always be thought of as complete failure, but in some cases it is merely a resignation to limit production to only the truck market, rather than both the truck market and the more lucrative automobile market.

[20]Glenn Carroll's list of automobile producers apparently also includes tiny firms that never manufactured automobiles for sale, since it includes a few firms even in the 1880s, whereas the first sale of a US-manufactured automobile is usually dated to 1896.

[21]Smith (1966) and Epstein (1928) are the only sources from which I have collected the dates of survival of each automobile manufacturer. Thomas (1965) includes a count of the annual number of entrants and exitors, but he tells me that the roster of firms from which counts were computed has been thrown out.

[22]I date the peak in number of firms as occurring in 1951, not 1952, counting the peak as occurring in issue number 13 (15 July 1951) of the *Factbook* rather than issue number 14 (15 January 1952), but which issue has the peak number of producers depends on whether once includes "companies reported in TV manufacturing," but not ascertained to be manufacturers, in issue 14. Similarly, the two series differ slightly initially, perhaps because Utterback and Suárez chose to exclude the more questionable companies in the first two years of the *Factbook*.

[23]In penicillin, where mergers of producers appear to have been rare or nonexistent, data on mergers were not collected.

[24]According to the data based on *Television Factbook*, Philips, the European electronics firm, entered US production by buying Magnavox circa 1976. Around the same time, Matsushita Electric Corp. entered US production, with Panasonic and Quasar (formerly the US television production of Motorola) as subsidiaries. Sanyo, Toshiba, and others entered soon after.

[25]Penicillin production figures for 1945-1947 were estimated assuming a concentration of 0.7 billion Oxford units per pound (Federal Trade Commission, 1958, p. 355).

[26]Before this pool was established came the Selden patent, for which almost all firms in 1903-1911 paid royalties equal to 1.25% (0.8% starting in 1907) of list prices for retail sales (Epstein, 1928, pp. 227-235). The patent was widely licensed. It could not have propped up the number of firms through 1909, when the shakeout began, because there were no production quotas or other mechanisms that would support smaller producers. Court-imposed restrictions in the patent's scope rendered it obsolete in 1911.

[27]A series of magazine articles (Hounshell, 1984, pp. 260-261), plus a book by Arnold and Faurote (1915), carried detailed news of Ford's production methods to any interested readers. Ford took pride in showing off his production methods, and plant tours were common. For further information, see Hounshell (1984).

[28]The Clincher Tire Association licensed manufacturers to use clincher-type tires (French, 1991, p. 19). The Association set annual output quotas and minimum prices. Small and young firms got small quotas if any: in 1903 Goodyear was allowed 1.75% of the market, and Firestone was refused a license. While this gave some firms a hold on the industry before 1907, it also encouraged other firms to innovate around the clincher patent. One alternative, the straightside tire, was invented around 1900, put in production by 1905 by Goodyear, and licensed to other manufacturers in 1906. Firestone also developed its own straightside tire. In 1906 Firestone signed a contract with Ford to produce clincher tires at a price that undercut the Clincher Tire Association, and when auto makers backed up Firestone's move with a threat to enter tire production themselves, the Association began to collapse. In 1907, a court ruling declared that the clincher patent applied only to bicycle tires.

[29]If anything, firms that served broader markets were disadvantaged, because the patent royalties were assessed even for products that did not use the patents (Levy, 1981, pp. 154-155).

[30]In an October 1958 agreement reached with the US Justice Department, RCA agreed to license all existing patents, except some color TV patents, without royalties (Levy, 1981, pp. 158-160). All patents acquired by RCA during the next ten years were required to be licensed for reasonable royalties, and RCA would have nonexclusive license to use the patents of all firms which chose to be its licensees. A color patent pool was established for RCA's exempted color TV patents, with no royalties for firms that contributed whatever color patents they held (even if they held none), and with reasonable royalties for firms that chose to retain control of their color patents.

[31]Lilly, which had the first patent rights to procaine penicillin, was involved in interference lawsuits versus Pfizer, Merck, Bristol, and Dr. Simon L. Ruskin. The four firms settled amongst themselves once Ruskin was removed from the process. Ruskin continued his lawsuits until 1957, when he assigned his patent to Union Carbide Corp., which settled out of court. Lilly sued three unlicensed competitors for infringement, and all three eventually agreed to pay royalties to Lilly in return for licenses.

One might wonder whether licensing of procaine penicillin was restricted to some firms, and whether the firms that did not receive licenses were the ones forced out of the industry during the shakeout. This was not the case. *Synthetic Organic Chemicals*, which has annual lists of manufacturers making each type of penicillin, shows six companies that were making procaine penicillin in the early 1950s but stopped being listed as making any type of penicillin sometime between 1953 and 1959. Of these six, the FTC report (Federal Trade Commission, 1958) shows that at least five (all but Cutter) received licenses to produce procaine penicillin.

[32]By 1959, work by the scientist Sheehan and the company Beecham revealed a critical substance, 6-aminopenicillanic acid (6-APA), used by the Penicillium mold when it creates penicillin. By isolating this substance from the broth in which the mold was grown, modifying it chemically, and then using it in the broth for new batches of penicillin, new types of "semi-synthetic" penicillins were created with various useful properties. Efforts to improve penicillin tried to create forms of the drug that were more effective antibiotics, that could be ingested orally, and that provoked fewer allergic reactions.

[33]Since the cost to replace earlier machines with Banbury mixers seems to have been high, the Banbury mixers seem to have had a cost *dis*advantage before labor productivity gains are considered.

[34]French (1991, pp. 31 and 52) notes that between 1909 an 1919 the average annual labor productivity growth for rubber manufacturing was 7.8%, and tire manufacturing productivity doubled between 1921 and 1929. From 1909 to 1929, apparently, the industry led all other US manufacturing industries in its rate of productivity improvement.

[35]For information on process innovations in penicillin, see especially Elder (1970a), Federal Trade Commission (1958, pp. 34-45), Lyons (1970), Perlman (1970, pp. 25-27), Gaden (1956), and Sheehan (1982, pp. 62-75 and 160).

[36]While follow-on innovations to the moving assembly line must have occurred, they apparently were swamped in importance relative to other ongoing innovations. The primary impression conveyed by a study of the industry's technological history is one of enormous ongoing change made up of thousands of product and process innovations, most of them tiny and inconsequential, but in sum creating a tremendous pace of technological advance.

An excellent illustration of small innovations together yielding rapid technological advance is the development of mass production at Ford. New machines had to be designed and built for each step of the manufacturing process, and elaborate floor plans had to be drawn up to coordinate the flow of production between machines. Conveyors and gravity slides were designed and put into place to facilitate flow between machines. Workers were retrained to use the new machines. Experiments in timing and new methods of supervision were needed to ensure that workers worked efficiently and properly and that their work processes were well coordinated. Safety improvements had to be made. When workers began to complain about the feverish pace and repetitive nature of their work, causing high labor turnover and the beginnings of unionization, Ford made innovations in how he dealt with workers by giving out bonuses and instituting the famous "five-dollar day." At the core of Ford's factory were "perhaps a dozen or a dozen and half (*sic*) young, gifted mechanics.... [T]his group carried out production experiments and worked out fresh ideas in gauging, fixture design, machine tool design and placement, factory layout, quality control, and materials handling" (Hounshell, 1984, p. 220). Of Chrysler's later adoption of mass production techniques, Knudsen (1927, p. 66) writes:

> [A]ccuracy of our workmanship and uniformity of materials would be the parents of the speed which was to produce the required cost.
>
> The machine equipment was first tackled, with the result that all the old machines were discarded, new heavy type standard machines (not single purpose) were installed, and the fixtures strengthened so as to withstand the spring, which is the greater factor than wear. Sequence lines were established so as to pave the way for the conveyors which were to follow.... Gauges and indicators, particularly the latter, were devised for all operations of major importance, and the inspection system was given full opportunity to come into its own....

Raff (1991) points out an additional kind of innovation pursued by General Motors in the 1920s, the standardization of parts across its different product lines.

[37]The magneto integrated into the flywheel, detachable cylinder heads, and the all-steel open car body is nowhere discussed as having any unusual importance. Katz (1970, pp. 304-324) analyzes the competitive impact of branch assembly plants. However, his analysis is for the post-World War II industry, and effects in the 1910s and 1920s remain ambiguous. A rough estimate of the competitive impact of branch assembly plants can be

made by assuming that the efficiency of assembly plants in 1915 was below their efficiency in 1956, and that savings in shipping costs were comparable. Deflating the 1956 savings of assembly plants into 1915 dollars, this approach suggests that around 1915 the cost savings was under $35 per car. Katz (1970, p. 311) suggests that the savings in the 1910s and 1920s were probably lower. A $35 savings is substantial, but explains only part of the wide price differential between firms. Thus, branch assembly plants appear to have been one of many innovations that together gave innovators a competitive advantage.

[38]The major process innovations of 1896 (multiple cars produced according to one design) and 1901 (mass production rather than one-at-a-time production) are excluded from the search, because they are nearly all-encompassing, occurred much earlier than the shakeout, and have more to do with the product's creation than with any conceivable radical innovation.

[39]The 1924 and 1925 pyroxolin paint innovations, while listed separately by Abernathy, Clark, and Kantrow (1987), are in fact identical. Henry Ford wanted DUCO-pyroxolin paints for his company's cars, but the paints were made by DuPont, which had heavily invested in General Motors. To avoid buying from DuPont, Ford Motor Company duplicated DuPont's research and created similar multicolor pyroxolin paints (communication with David Hounshell).

[40]Straightside tires replaced older clincher tires. To mount a clincher tire, it was stretched over a wheel rim with hooked edges. Metal wires or "beads" in the tire caught inside the hooks, securing the tire to the rim. Straightside tires did not use their beads as hooks, but merely as circles with small enough circumference that tires would not come off the rims. One side of a rim was removed to allow a tire to be mounted, and then the side was bolted into place. Burton (1954) details this technology. Clincher tires had two disadvantages compared to straightside tires. First, the rim chafed against the tire edge, and sometimes the tire would get banged against the edge, causing the rim to cut through the tire. The rim

would then cut into the inner tube, causing a blowout. Second, installing and removing clincher tires was difficult work. Litchfield (1954, p. 87) writes, "In the larger [tire] sizes it might take an hour's work with an iron bar to force the tire into place—and it was still harder to take the tire off, particularly if it was rusted on."

41Cords replaced square-woven fabric in tires. Until the 1910s, automobile tires were made from layers of cotton fabric, impregnated with and surrounded by rubber. The cotton fibers rubbed back and forth, creating friction which helped to wear out the tires and increased the chance of blowouts. In cord tires, most of the side-to-side threads were eliminated from the cotton fabric, decreasing friction and wear. The remaining lengthwise threads were thick "cords" (Gaffey, 1940, p. 44; Allen, 1949, pp. 36-42).

42Average-sized high-pressure tires used 70-90 pounds of pressure per square inch. Balloon tires, in contrast, used about 30 pounds or less of pressure per square inch, and were much larger and heavier. Balloon tires absorbed shocks better, making drivers and passengers more comfortable. Early balloon tires had short lifespans, but within a few years after their adoption they were improved to a (presumably average) lifetime of 14,000 to 15,000 miles. By 1937 they could last 20,000 miles or more (Gaffey, 1940, pp. 44-45). French (1991, p. 50) claims that "Balloon tires required adjustments to production processes and used more rubber than previous casings, which increased materials and production costs to the disadvantage of small firms...." However, the initial low sales and quality problems suggest that competition from producers of balloon tires did not immediately put other firms out of business, nor can the late invention and adoption of balloon tires explain the entry pattern described in chapter six. Thus, while the balloon tire may have had competitive ramifications, it is unable to explain the tire industry's entry and exit patterns and came too late to explain the industry's shakeout.

43For the following reasons, other major tire innovations in table 5.3 do not seem to be appropriate candidates for a refinement invention that might have caused the industry's shakeout. Only innovations made in 1910-1925 are considered. Plantation rubber was available to all firms on the open market, and while large firms sometimes established large rubber stockpiles, they appear to have lost as often as gained money on the volatile raw rubber market. After switching from rubber tapped by tappers to rubber grown on plantations, firms managed to achieve somewhat lower costs, but conversion occurred mostly before the shakeout began. The use of carbon black as a reinforcing material in tires seems to have been easy to imitate. Radial tires were not practically applied until 1948, and did not develop a substantial US market until the 1970s (French, 1991, pp. 101-106). Many substances were tried out as antioxidants, to reduce degradation of tires from aging and exposure, and while aldehyde-amine antioxidants had the distinction that they did not simultaneously accelerate the curing of rubber, this distinction is of minor importance. Chutes, slides, conveyors, and the rearrangement of plant layouts had substantial impacts on costs in the 1920s (along with many other reasons for cost reduction), but these changes can hardly be lumped into a single category as stemming from any particular invention. 2-Mercaptobenzothiazole accelerator improved the rubber curing time greatly, decreasing the costs of some parts of the tire building process, but nowhere is it argued that this particular accelerator had a great impact on the competitive process.

[44]Before drum tire-building machines were used, tires were assembled around cores. After assembly, the tires would be pried off the cores, or collapsible or deflatable cores would be collapsed or deflated and removed from the tires. Builders carried the iron cores, weighing up to 250 pounds and more, on their shoulders (Allen, 1949, p. 30). Increasing mechanization gradually made the work less strenuous. Instead of building tires by manually stretching rubber plies onto cores (see illustration in Allen, 1949, p. 19), machines such as the Yoder machine were developed to automatically wrap rubber, fabric, and reinforcing bead wire around cores (Burton, 1954, pp. 119-121). In drum tire building, an alternative technique, the component parts of a tire were assembled loosely,

then formed into the proper shape inside a vacuum chamber. Drum tire building made the job easier and faster and required fewer workers with less specialized skills.

[45]Carlsmith (1934, p. 137) asserts that drum tire machines were responsible for the high productivity growth in 1925. His method of computation of productivity displacement treats displacement as a percentage of future output rather than past output, causing a slight difference between his aggregate data and the department-specific data of Figure 5.4.

[46]In 1962, sales of color television sets increased dramatically, to nearly 440,000 sets compared to less than 140,000 in 1961. In that year, Zenith, the monochrome industry leader, announced plans to produce color televisions. By 1963, Motorola was "the last major television set manufacturer" to enter (or re-enter) the color market (Willard, 1982, p. 174).

[47]In 1950, the Federal Communications Commission accepted the CBS mechanical color wheel system as the US color broadcast standard (Chisholm, 1987). One year later, CBS suspended production of color TV sets at the request of the US Office of Defense Mobilization, "to conserve critical materials" for the Korean war. RCA continued to improve its alternative color broadcast system, based on electronic rather than mechanical components. In response to industry-wide pressures, the FCC in 1953 reversed its decision, making RCA's system the color TV broadcasting standard.

[48]Shadow mask and curved shadow mask picture tubes were for use in color televisions (Herold, 1976). Hence they were not involved in the shakeout, which occurred while color television sales were relatively unimportant in the industry. Also, most varieties of television picture tubes were readily available for purchase from third-party manufacturers. Remote controls do not appear to have been important in television competition. While some advances in remote controls occurred during the 1950s, around when the shakeout began, even in 1962 they were not very important for TV set sales. In that year, *Consumer Bulletin* recommended against buying them, saying, "'Remotes' are expensive and add

complications (and thus service expense) to an already very complicated appliance" (Consumers' Research, Inc., 1962, p. 10). Portable receivers created a new segment of the television market. As usual, the manufacture of televisions was simply an assembly process, and any firms interested in creating portable TV sets could easily do so, as many did when sales of portables proved successful.

[49]Most firms adopted printed circuits in the mid-1950s, cutting labor costs by, according to the very least estimate, 20% (Levy, 1981, p. 66). However, printed circuits were adopted after the shakeout began, and since they were components that could be bought by any firm, all firms could achieve the resulting labor savings. Automatic component insertion may have given further cost reductions, but while it was tried out by Sylvania as early as 1955, it was otherwise not used for television manufacture for some time, and was adopted for making color televisions only in the 1970s (Willard, 1982, pp. 181-182). RCA and Sylvania advertised "space-age circuitry," but any perceived product quality advantage this provided was beaten back by Zenith's advertising campaign for "hand-wired, hand-crafted quality" (Willard, 1982, p. 182).

Printed circuit boards were boards on which electronic connections had been printed, with holes in appropriate places to insert electronic components. The components were placed into the board from above, with their wires protruding at the bottom. The wires would then be soldered to the board's printed connections. Printed circuit boards were soon widely used, and there appears to have been little difficulty in adopting them and adapting existing circuits to printed circuit form. Besides decreasing the industry's labor requirements, they had little impact on the assembly nature of the industry, making them unlikely candidates for a cause of the shakeout.

In automatic component insertion, originally a circuit board would move along a production line, having each component put in place by a separate insertion head (Levy, 1981, p. 68). Later, one insertion head inserted multiple components into the same circuit board. The circuit board was swiveled into position according to a pre-programmed sequence, and the same insertion head inserted each component in the sequence, allowing the entire job to be done at a single station. Automatic insertion equipment suitable for a wide variety of industrial processes was sold beginning in 1958 by the United Shoe Machinery Company. Automatic component insertion apparently was not widely used even by very successful firms until well after the shakeout had begun.

Dip soldering (or the related wave soldering) was developed as a labor-saving way to solder connections in a circuit board (Levy, 1981, p. 67). The board was moved along a conveyor, bottom side immersed, through a bath of liquid solder. Solder adhered to the printed copper lines along the bottom of the board, but not to the fiber board itself. Thus all connections could be soldered simultaneously. Little information is available about the effect of dip soldering on competitiveness.

[50]Aggregate penicillin prices are calculated from *Synthetic Organic Chemicals* (US Tariff Commission, 1945-1980), and are deflated into 1950 dollars using the consumer price index. The aggregate figures hide even more dramatic price reductions for the commodity forms of penicillin.

[51]On the manufacturing processes in general, see Perlman (1970). On fermentation, see Lyons (1970), Gaden (1956), and Calam (1987). On extraction, see Podbielniak, Kaiser, and Ziegenhorn (1970).

[52]A point of historical note is that the all-steel closed body was not in fact all steel, and that it was one step in a progression of different kinds of closed bodies. Closed wooden bodies existed at least by 1910 and probably before (Epstein, 1928, pp. 110-115). As Figure A3.1 illustrates, closed cars represented a gradually increasing share of the industry's production. In 1922 Hudson introduced a closed model costing only $50 to $100 more than its open cars with the same chassis. Within a year or two nearly all other manufacturers set similar prices, including Dodge (Thomas, 1965, p. 229). "All-steel"

closed bodies in the 1920s were wooden frames surrounded with steel (Federal Trade Commission, 1939, pp. 916-917). In the early 1930s steel tops began to replace older tops which were often made of fabric or imitation leather. Hudson claims to have made the first true all-steel bodies in 1935, although many different firms and engineers were involved in the development of such all-steel bodies.

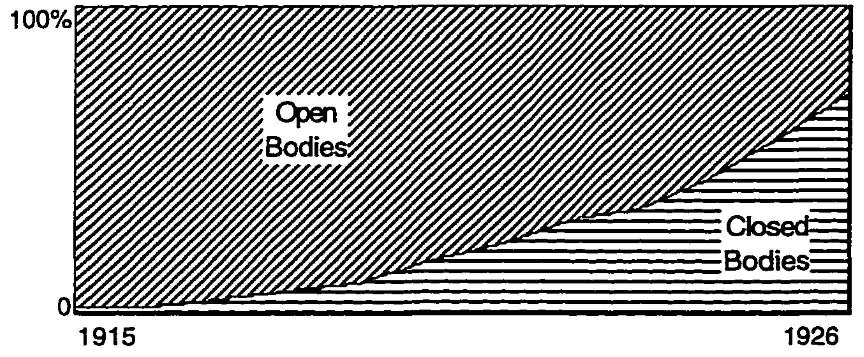


Figure A3.1. Closed car production as a percentage of passenger car output. Source: Epstein (1928, p. 112).

[53]Fabris' sample also excludes all firms that survived fewer than five years. And technically, the sample pertains to a number of "makes," or brands, of cars rather than to a number of producers.

[54]Hydraulic presses were developed to produce thousands of identical automobile body panels, made out of sheet steel with large, compound curves (e.g., Fortune, 1939). The presses replaced old hand-fitting procedures. As an idea of the cost of the necessary equipment, Essex spent $10 million to build a new plant for all-steel bodies with baked enamel finishes. Model changes added further expense, because they required retooling of the dies used in body presses. Chrysler retooled every two years, at a cost of $7 million (Fortune, 1939, p. 104). For a later period, Fisher, Griliches, and Kaysen (1962, p. 440) estimate industry aggregate retooling costs to have risen from $20 million, or $3 per car, in 1950, to $900 million, or $125 per car, in 1961. Like Abernathy, Flink (1988, p. 240) suggests that the expense of retooling drove most firms out of business.

[55]First, falling prices may have squeezed many firms' profit margins. Second, by 1920, 40% of American families owned cars, and by 1926 over three-fourths of American families owned cars (Griffin, 1926). The loss of a virgin market for automobiles meant that firms had trouble selling cars unless their cars were substantially better than inexpensive used ones available from dealers (Thomas, 1965, pp. 184-185). Third, annual model style change increased in the 1920s, though substantive product innovation probably decreased (Fabris, 1966). New styles and features induced customers to buy new rather than used cars. To gain the advantages of frequent style changes, firms had to spend a great deal of money on retooling costs. The expense may have been too great for many firms, increasing their risk of failure because their cars became outdated in style. Fourth, some increase in failures may have been caused by delayed effects of the recession of 1920 to 1922 (Epstein, 1928, pp. 187-88), Rae (1959, pp. 136-149), Thomas (1966, pp. 186-199).

[56]Any effects of steel body presses, if they occurred, may not have been the result of a dominant design. Rather, the closed steel body may have become popular merely because steel presses allowed low-cost production and hence low prices for closed-body cars. Also, continuous electric welding and rapid-drying paint, developed around the same time, helped to make closed-body cars competitive with open cars in production cost (Thomas 1965, pp. 227-228).

[57]The data in Figure 5.7 do not reveal what fraction of the 18-21" category was 21" televisions, but data in 1969 and 1970 show that in those years, 20-21" tubes made up only 27% and 32%, respectively, of the category (Electronic Industries Association, 1975). In the earliest years of Figure 5.7, minor discrepancies in the EIA data (in numbers and category definitions) were resolved by informed guesswork, but no matter how the discrepancies are resolved, it would have little effect on Figure 5.7.

[58]For information about standardization, consult, in addition to sources already mentioned in the text, the following sources: In automobiles, information on steam cars is available from Bergere (1962, pp. 19-20) and Flink (1988, pp. 6-7), and on electric cars from Adler (1978) and Flink (1988, pp. 8-10). Lists of steam and electric producers can be garnered from Kimes and Clark (1988), *Thomas' Register of American Manufacturers*, and Smith (1968). For self-starters and four-wheel brakes, see Epstein (1928, pp. 108-110). For safety equipment, see Eastman (1984). In tires, for synthetic rubber and radial tires, see French (1991). In televisions, LaFrance (1985, pp. 145-146) views product standardization in terms of a gradual convergence in "picture quality and reliability," where quality includes brightness, color resolution, and reception. However, for the establishment of monochrome and color broadcast standards, see Chisholm (1987), and for the replacement of round picture tubes with rectangular tubes, and other changes in displays, see, e.g., Herold (1976). In penicillin, to understand why penicillin experienced an explosion of variety rather than standardization, see, e.g., Elder (1970a) and Sheehan (1982).

[59]Using Abernathy, Clark, and Kantrow's (1983) series only through 1929 ensures that effects of the Great Depression cannot bias the statistical results.

[60]When tire lifetime is measured in years, the increase is again greater during the 1920s. From 1910 to 1920, the lifetime increased 75%, and from 1920 to 1930 it increased 93% (Gaffey, 1940, p. 39).

[61]Data from Day and Thomas (1928, pp. 134 and 145) show a similar pattern.

[62]The contrasting type of "R&D," where costs rise in proportion to output, might occur when firms buy machinery that is available in only one size at a fixed price. However, if the costs of choosing, installing, and learning to use the machinery are less than twice as high for twice the number of machines, then per-unit costs decline with firm size. All of these costs are included in the broad heading of "R&D" in the size-and-skill theory.

[63]In one industry, automobiles, the Abernathy, Clark, and Kantrow (1983) list of innovations allowed a crude investigation of whether a substantial amount of R&D effort was largely independent of size of output. I classified each innovation in the list from 1893 to 1929 as either (a) likely to have been available from suppliers, (b) possibly imitable with relatively little effort, (c) probably difficult to adopt without considerable effort, or (d) uncertain categorization. While in some cases the decision was subjective, most innovations were straightforward to classify. Table A3.1 shows the results of this exercise. Difficult-to-adopt product innovations constituted 30% of all product innovations and 50% of their squared 7-point importance ranks. For process innovations, difficult-to-adopt innovations constituted 40% of all product innovations and 60% of their squared importance ranks. Thus, much of the industry's innovations apparently required considerable effort to adopt. These innovations had to be created in large part inside of firms, but once created could be applied to any production volume.

Table A3.1. Numbers and summed squared 7-point ranks of product and process innovations, by estimated ease of adoption, 1893-1929

	Numbers of innovations			
	(a) Suppliers	(b) Easy to copy	(c) Effort to copy	(d) Uncertain
product	71	13	55	41
process	12	4	18	10
	Squared rankings			
	(a) Suppliers	(b) Easy to copy	(c) Effort to copy	(d) Uncertain
product	405	52	665	350
process	158	30	390	104

Source: Analysis by the author, based on Abernathy, Clark, and Kantrow (1987).

[64]The two other key assumptions of the size-and-skill theory are even less amenable to quantitative tests, but match with historical evidence (and indeed, they were chosen because of the fit with historical evidence). It is assumed that future output is related to current output, so that small firms do not choose to do extraordinary amounts of process R&D in hopes of capturing a large future market. Indeed, in the four products, the few small firms that did do substantial process R&D, such as Birmingham Iron Foundry with its Banbury

Mixer, sold their inventions throughout the industry and did not attempt to capture large market shares. The theory also assumes a distribution of skill, so that entrants at the same time are not equally competent. If it is not self-evident to the reader that firms differed in managerial and R&D competency, a quick browse through books like Kimes and Clark (1988), French (1991), Willard (1982), Federal Trade Commission (1958), and Sheehan (1982) will make it obvious that firms differed radically in managerial and research competencies.

[65]Consistent with General Motor's advance to industry leadership through innovation was its managerial reorganization in the early 1920s (Kuhn, 1986), which helped to foster R&D within and across divisions and to strengthen the company's research laboratories (Leslie, 1983).

[66]Chisholm (1987) includes a detailed history of the television industry's early commercial development. On sales of receivers for experimental broadcasts in 1938-1939, see circa p. 103. On the effects of World War II on the television industry, see circa p. 175.

[67]The compressed rate of entry in penicillin may have resulted from the US government's World War II penicillin program, whose massive R&D effort was second only to the Manhattan Project, and which established penicillin manufacturing techniques and encouraged investment.

[68]Carroll and Hannan (1995) do not include data on the number of exitors. The exit data referred to in chapter seven come from a thesis proposal by a student of Glenn Carroll. Given only these figures, it is difficult to deduce more accurate information about the exit rate than what is stated in the text of chapter seven.

[69]For an introduction to statistical techniques for survival analysis, see Lee (1992). Kiefer (1988) provides a shorter review. Lancaster (1990) provides an advanced treatment.

[70]Alternative formulations are available for $f(\underline{x}(t))$, yielding $h(a, \underline{x}(t)) = g(a)\ \underline{\beta}'\underline{x}(t)$ or $h(a, \underline{x}(t)) = g(a) / \underline{\beta}'\underline{x}(t)$. However, these formulations suffer from the disadvantage that some values of $\underline{x}(t)$ can predict an undefined negative hazard.

[71]Exact times of exit are not known for the industries studied here. Times of entry and exit are known to the nearest year or the nearest date of publication of a trade register, so that large numbers of firms exit at identical ages. This makes the partial likelihood approach, which draws information from the ordering of exit ages, intractable.

[72]Hopenhayn's (1993) model, if interpreted literally to draw out a result not in Hopenhayn's analysis, can be shown by the solution of differential equations to yield the form:

$$h(a) = \frac{qx + sy}{x + y} = \frac{qe^{-(q+r)a} + \dfrac{rs}{q+r}[e^{-sa} - e^{-(q+r+s)a}]}{e^{-(q+r)a} + \dfrac{r}{q+r}[e^{-sa} - e^{-(q+r+s)a}]},$$

where x is the fraction of firms in a given entry cohort that have not yet innovated by age a, y is the fraction that have innovated, q is the hazard rate of firms that have not yet innovated, r is the innovation rate, and s is the hazard rate of firms that have innovated ($s < q$). This form is not tractable statistically. Plotting this hazard function for some plausible parameter values shows that it roughly fits an exponentially declining hazard of the form $c + e^{\gamma_0 a}$, known as the Makeham model. While the Makeham model is also not very tractable because of a multi-peaked likelihood function, it is quite close to the Gompertz and Weibull forms, suggesting that one of the two should be an adequate first approximation: the Gompertz for c near zero, and the Weibull for c substantially greater than zero. Furthermore, the piecewise constant hazard chosen later in chapter eight to measure unknown age-related effects allows for more complex variations in the effect of age on the hazard, including the decline in the hazard to a non-zero constant c as specified in the Makeham model.

[73]The date t_p is defined explicitly later in this document, but for practical purposes it is the date with the highest number of firms ever in the industry, or the last such date if multiple dates have the highest number of firms.

[74]Gross domestic product is a concept that came into vogue in the later 1900s, and statistics for it have been computed back to 1959. Before the annual change in gross domestic product can be computed, annual change in gross national product will be used instead. In the 1960s, the two series are quite comparable, and they should be all the more comparable in earlier decades, when overseas investment was relatively low. Data come from Darney (1992, pp. 6, 8, 62) and Council of Economic Advisors (1994, p. 2).

[75]Let $p(a_{j+1}|a_j)$ be the probability of surviving to age a_{j+1} given that a firm has survived to a_j. From the definition of the hazard rate, it follows that

$$\frac{d}{da_{j+1}} p(a_{j+1}|a_j) = - h(\underline{x}, a_{j+1})\, p(a_{j+1}|a_j).$$

Since it is known that the firm survived to a_j, this differential equation has the initial condition $p(a_j|a_j) = 1$. Solving the equation subject to the initial condition yields

$$p(a_{j+1}|a_j) = \exp\left(-\int_{a_j}^{a_{j+1}} h(\underline{x}, a)da \right).$$

For a more general proof, see Lancaster (1990, pp. 85-88).

[76]Compare the case with a roughly equal number of data periods and interval censoring periods, but for which the periods do not coincide, with the case where the periods do coincide. In the first case, the interval-censoring periods over which survival or death occur must be divided into subperiods in which the data remain constant. This yields twice as many subperiods as either the number of data periods or the number of interval-censoring periods, roughly doubling the computational time requirement. Worse, the computation becomes much more convoluted. Where vector computations are possible with corresponding periods, each subperiod must be handled separately for the non-corresponding case, and then data from the subperiods must be combined to compute the

probability of survival in each interval-censoring period. With a variable number of subperiods per interval-censoring period, little vector computation is possible. With hardware or programming environments that optimize vector computations, vectorization allows an order-of-magnitude speed increase. The MatLab programming language in which I constructed the estimation software is just such a vector programming environment, and it is in MatLab that I observed a roughly 95% speed increase after trying the calculations both ways. The speed increase is critical for my purposes, since even with the 95% reduction, the estimates shown in this dissertation required hundreds of hours on fast workstation computers.

[77]I used statistical bootstrapping (e.g., Efron and Tibshirani, 1993) to obtain estimated standard errors and confidence intervals for the shakeout dates, accounting for random variation in firms' entry and exit dates. This method overexaggerates the variance in the timing of the shakeout in that it treats firms' entry and exit times as independent of the entry and exit times of other firms, whereas in fact the decision to enter or the chance being driven out of the industry through lack of profits is most likely conditioned by the number of firms remaining in the industry. On the other hand, this method does not attempt to account for any variance in shakeout dates that may result from exogenous events such as national economic trends. The bootstrap estimates of standard errors in the timing of the shakeouts are 0.4 year in automobiles (2.7 years using the data based on Epstein (1928)), 0.0 year in tires, 0.8 year in televisions, and 1.1 year in penicillin. The bootstrap sample consisted of 550 iterations, yielding results substantially more precise than with the 100-200 iterations usually thought sufficient for statistical bootstrap estimation. Thus, in the four products studied here, endogenous random variation in the timing of the shakeout appears to have been minimal.

[78]For automobiles, I use only the data based on Smith (1968). Because the data based on Epstein (1928) involve only five years after 1922, when the data indicate the start of the

shakeout, they provide little time with which to see an effect of a shakeout, and certainly insufficient time to look for a diminishment of the effect of the shakeout.

[79]Because of the exorbitant computational requirements for simultaneously testing alternative breakpoints of entry year and age, I chose a single age division at eight years, a point that often appears from the Kaplan-Meier survival plots to yield a substantial change in the inter-cohort differences in hazard rates.

[80]In televisions, entry year breakpoints after EY* = 14 show a relatively poor fit and enormous standard errors, although the coefficients still indicate that earlier entrants had higher survival rates at young ages than later entrants.

[81]In the industry average return on investment data for tires, I include Firestone beginning in 1909, Goodyear beginning in 1909, Goodrich beginning in 1912, Mansfield beginning in 1912, General beginning in 1916, and Dayton in 1916 and from 1919 on.

[82]The degree of television specialization was determined by estimating each firm's television sales from its share of the market reported in Datta (1971) and comparing it to its overall sales in *Moody's Industrials*. For a majority of firms market share data were not available; these firms were treated as diversified only when total company sales was at least $100 million. An exception was Arvin Industries, which was classified as diversified based on Willard (1982, p. 214).

[83]Some improvements in the matching technique could be made using lists at the back of each year's *Thomas' Register*, which for leading manufacturers gives information about name changes, subsidiary or affiliate status, and mergers and acquisitions, but these improvements would require large amounts of time and money for little return.

[84]Unlike the other products, DDT may have experienced much of its decrease in number of producers as a consequence of a decrease in market size, since use of DDT decreased after the publication of Rachel Carson's (1962) *Silent Spring*, particularly when it was banned for use in US agriculture in 1972. While the peak in the number of firms in DDT occurred

earlier, almost all of the decrease in number of firms occurred after 1962 and particularly after 1972.

[85]Following Klepper and Graddy (1990), if two or more years have the same peak number of firms, I define t_p to be the year with greatest average number of firms in the three subsequent years, or as the last year of data if the last year has the peak number of firms.

[86]This method for determining t_z is identical to Klepper and Graddy's (1990) definition of the end of their stage two. If no t_z is found because the shakeout has not yet ceased, I use for t_z the last year available in the sample.

A3

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