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CREATIVE DESTRUCTION IN INDUSTRIES

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ABSTRACT

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Abstract

Most industries go through a "shakeout" phase during which the number of producers in the industry declines. Industry output generally continues to rise, however, which implies a reallocation of capacity from exiting firms to incumbents and new entrants. Thus shakeouts seem to be classic creative destruction episodes.

Shakeouts of firms tend to occur sooner in industries where technological progress is rapid. Existing models do not explain this. Yet the relation emerges naturally in a vintage-capital model in which shakeouts of firms accompany the replacement of capital, and in which a shakeout is the first replacement echo of the capital created when the industry is born. We fit the model to the Gort-Klepper data and to Agarwal's update of those data.

1 Introduction

Schumpeter argued that creative destruction happens in waves. By "creative destruction" he meant the replacement of old capital – physical and human – by new capital and of old firms by new firms. The driving force behind these waves of creative destruction is technological change, thought Schumpeter.

Whether such creative destruction waves are to be seen at the aggregate level or not, they have been documented in many industries. The "shakeout" episodes that Gort and Klepper (1982) documented are classic creative destruction episodes: During a shakeout, a substantial fraction of firms exits, and yet industry output on average continues to rise implying that aggregate capacity does not fall. The capacity withdrawn by the exiting firms is replaced by incumbents and new entrants.

Several explanations for these creative-destruction episodes have been advanced. When the entire economy is involved, the shock that prompts the wave may be a system-wide reform or deregulation (Atkeson and Kehoe 1993), or the arrival of a

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new general-purpose technology, a topic surveyed by Jovanovic and Rousseau (2006). At the level of an individual industry, four broad sets of explanations for such creative destruction waves have been put forward:

Temporary demand declines.—Caballero and Hammour (1994) find that if replacement of capital causes interruptions in production, it is optimal to replace capital when demand temporarily drops, for then the foregone sales are at their lowest. Klenow (1998) finds that when, in addition, the productivity of new capital rises with cumulative output, a firm will replace capital when the recovery is about to start. This raises the productivity growth of the new capital.

Technological advances.—A new technology like the assembly line can raise the efficient scale of firms in an industry, thereby crowding some of them out. This is argued by Hopenhayn (1993) and Jovanovic and MacDonald (1994). There is little doubt, for instance, that the arrival of the assembly-line technology raised the optimal scale of auto-manufacturing plants and caused a large reduction in the number of auto producers. Related to this, Utterback and Suarez (1993) argue similarly that a dominant design emerges, the winning model, which forces other models out and with them some other producers as well. In a similar vein, Klepper (1996) argues that larger firms will find it more profitable to do R&D because they can spread the result over a larger number of units, and eventually drive smaller firms out through a series of cost-reducing innovations, which amounts to there being dynamic increasing returns at the firm level during an industry's early stage.

Exit after learning through experience.—The shakeout usually comes after a wave of entry. That was clearly the case in the automobile and the automobile-tire industries, for instance. Most of the entrants in the entry wave would, some time later, find out that their ideas and methods, their products and technologies they used, were ill-suited for the industry at hand, and would consequently exit. Jovanovic (1982) argued that this mechanism could explain some other phenomena, but Horvath, Schivardi and Woywode (2003) point out that it can also help explain a shakeout conditional on there being a run-up in entry at some point in the industry's life.

Consolidations for other reasons.—Firms that exit during a shakeout are often acquired by other firms in the same industry. Consolidations and merger waves can occur for reasons unrelated to drops in demand and to advances in technology. Deregulation, for instance, has led to merger waves in the airlines and banking industries (Andrade *et al.* 2001), and both have consequently seen sharp reductions in the numbers of producers.

All these explanations make sense. One obvious explanation for creative destruction episodes seems, however, to have gone unnoticed: Producers exit an industry when their capital comes up for replacement. Before its optimal replacement date, the sunk costs in the capital stock will tend to keep a firm in the industry even if, on other grounds, it may prefer to exit. So, for example, when a plant reaches the age when it needs to be replaced, its owner may decide that the moment is then right

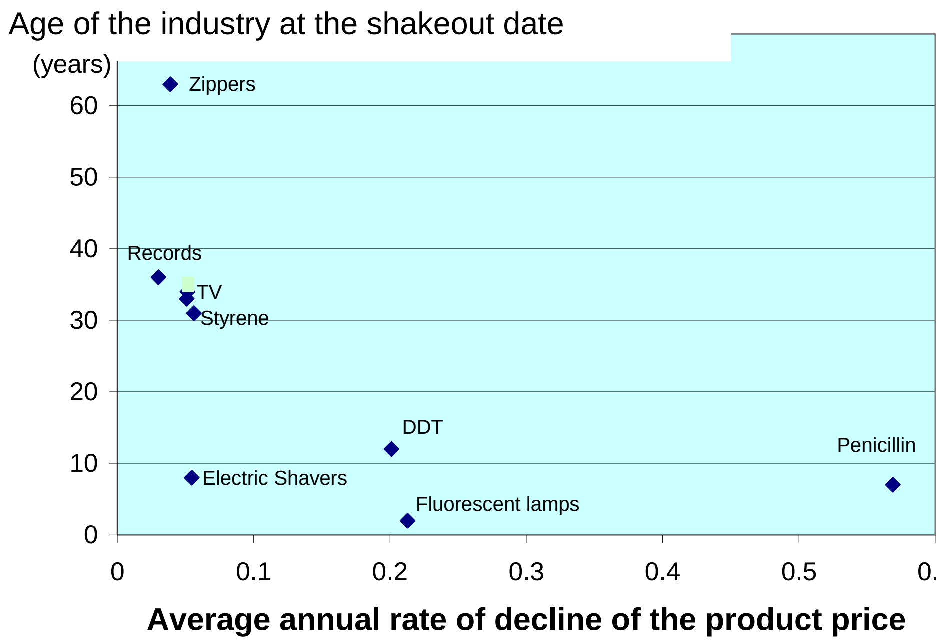


Figure 1: Technological progress and industry age at shakeout

to move out of the industry and let some other firm – incumbent or a new entrant – provide the new capacity. Viewed in this way, a shakeout is but an "echo" of the burst of investment that occurs when an industry comes into being. This explanation is suggested by the pattern shown in Figure 1.[1] The pattern is that the shakeout occurs earlier in those industries in which technological progress – as measured by the rate at which its product price declined prior to the shakeout – is faster.[2]

As we shall show, the same pattern is present in subsequent echoes – the higher the technological progress, the more frequent the echoes. A related pattern emerges at the more aggregative, two-digit level: Sectors that face more rapidly declining equipment-input prices experience higher rates of entry and exit (Samaniego, 2006). In other words, a sector that enjoys a high rate of embodied technological change will have a high rate of entry and exit, i.e., higher creative destruction. Our model will explain this fact too.

All technological change in our model is embodied in capital, which means that TFP should be constant when one adjusts inputs for quality. During the shakeout, a

[1]Gort and Klepper time the start of the skakeout when net entry becomes negative for an appreciable length of time. The shakeout era typically begins when the number of producers reaches a peak and it typically ends when the number of producers again stabilizes at a lower level.

[2]Table 7 of Gort and Klepper (1982) reports the number of years until shakeout for 39 industries. But only for 8 of them does Table 5 report data on the rate of price decline up to the shakeout. These are the eight reported in Figures 1 and 3.

fraction of the capital stock is replaced by new capital; the number of efficiency units of capital stays the same but the productivity of capital per *physical* unit rises.

The novelty here is not in the model but in the application. Using this model Mitchell (2002) and Aizcorbe and Kortum (2004) analyze industry equilibrium in steady state, i.e., the stationary case in which the effect of initial conditions has worn off, and after any possible spikes that may be caused by initial conditions have worn off. Jovanovic and Lach (1989) analyze the transitional dynamics but cannot generate a shakeout or repeated investment echoes. Closest to us analytically are Boucekkine *et al.* (1997), and we shall say more about their paper as we proceed.

Plan of the paper.—Section 2 presents the model and states three propositions. The tests of the first two are described in Section 3 while Section 4 is devoted to an analysis of repeated investment spikes. Section 5 presents the model's implications for TFP growth and Section 6 concludes the paper. The Appendix contains some proofs.

2 Model

Consider a small industry that takes the rate of interest and the price of its capital as given at unity. The product is homogeneous, and technology improves exogenously at the rate g. To use a technology of vintage t, however, a firm must buy capital of that vintage. The productivity of vintage-0 capital is normalized to 1, and so the productivity of vintage-t capital is e^{gt}.

Each firm is of measure zero and takes prices as given. Let $p(t)$ be industry price, $q(t)$ industry output, $D(p,t)$ the demand curve, and r the constant interest rate. The demand curve may also be defined for all t, including $t < 0$, but production is not feasible before date zero.[3] To ensure that the market will receive a spike of capital at date zero, we let $D(0,0) = \infty$, and assume that D is continuous in t.

The price of capital is unity. Capital must be maintained at a cost of c per unit of time; c does not depend on the vintage of the capital, nor on time. Capital cannot be resold; it has a salvage value of zero.

Let $K(s,t)$ be the date-t stock of capital of vintage s or older, not adjusted for quality. There is no labor. Industry output at time t then equals the total number of efficiency units of capital:

$$q(t) = \int_{\max(0,t-T)}^{t} e^{gs} K(ds,t), \tag{1}$$

where T is the age at which a unit of capital is retired – this number turns out to be a constant in equilibrium, so we shall simply assume this in the notation henceforth. We shall then verify, in Proposition 1, that a constant-T equilibrium exists.

[3] Alternatively, we may assume that the ability to produce is always there, but that demand only materializes at date zero. Less extreme variations are discussed later.

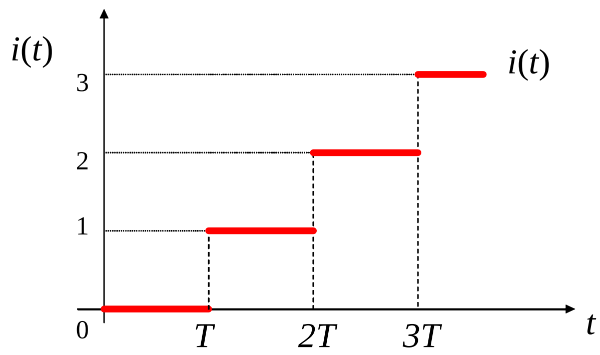


Figure 2: THE BEHAVIOR OF THE FUNCTION $i(t)$.

Evolution of the capital stock: No capital is in the industry at date zero. Capital evolves smoothly except for a countable set of dates, at which a positive fraction of the industry's capacity is replaced, and at which we observe an investment spike. Since the inter-spike waiting times are T, and since the first spike occurs at $t = 0$, the date of the i'th investment spike is iT, for $i = 0, 1, 2, ...$ Let $i(t) = \max\{i \mid iT \leq t\}$ be the integer index of the most recent spike. We illustrate the function $i(t)$ in Figure 2.

We shall show that in equilibrium, all the capital created at one spike date is replaced at the following spike date. Therefore the capital stock never embodies capital created at more than a single spike date. For calculating the capital stock, that is, only the immediately preceding spike will matter. Let X_i denote the size of the i'th investment spike. At date t, then, the amount of capital accounted for by the last spike is $X_{i(t)}$. So referring to Figure 2, for $t \in (2T, 3T)$, say, the contribution of capital created by the last spike would be X_2. In general, the date-t distribution of capital by vintage is

$$K(s,t) = I_{\{s-i(t)T \geq 0\}} X_{i(t)} + \int_{\max(0,t-T)}^{s} x(u)\,du, \tag{2}$$

where I_A is the indicator function of the set A, and where $x(t)$ is the industry-investment flow at date t.

Equilibrium.—The definition of equilibrium is simple if $x(t) > 0$ for all t (we shall later provide conditions – in (10) – that guarantee this outcome). Such an equilibrium consists of a product-price function $p(t)$, a retirement-age of capital, T, investment flows $x(t)$, and investment spikes X_i accruing at dates iT, $(i = 0, 1, ...)$ that satisfy

1. *Optimal retirement of capital*: Since price declines monotonically, it is optimal to replace vintage-t capital as soon as its revenue equals its maintenance cost:

$$e^{gt} p(t+T) = c. \tag{3}$$

2. *Optimal investment*: If investment $x(t) > 0$, the present value of a new capital good must equal its cost. The present value of the net revenues derived from that (vintage-t) unit of capital was

$$1 = \int_t^{t+T} e^{-r(s-t)} \left(e^{gt} p(s) - c\right) ds. \tag{4}$$

If $x(t) = 0$ at some dates, (4) may become a strict inequality.[4]

3. *Market clearing*:

$$D(p[t], t) = e^{gi(t)T} X_{i(t)} + \int_{\max(0,t-T)}^{t} e^{gs} x(s)\, ds. \tag{5}$$

Existence of a constant-T equilibrium.—Because the supply of entrants is infinitely elastic, the time path of $p(t)$ depends on the cost side alone. We now show that $p(t)$ declines at the rate g. That is, for some initial price p_0,

$$p(t) = p_0 e^{-gt}. \tag{6}$$

In that case, (3) implies

$$p_0 e^{-gT} = c, \tag{7}$$

while (4) implies

$$1 + c\frac{1 - e^{-rT}}{r} = p_0 \frac{1 - e^{-(r+g)T}}{r+g}. \tag{8}$$

Equations (7) and (8) are to be solved for the pair (p_0, T). If we eliminate p_0, we reach the implicit function for T alone:

$$\left(\frac{r+c}{c}\right)(r+g) = ge^{-rT} + re^{gT}, \tag{9}$$

for $t \geq 0$.

Proposition 1 *Eq. (9) has unique solution for* $T \equiv \tilde{T}(r, c, g)$.

Proof. The LHS of (9) is constant and exceeds $r+g$. On the other hand, the RHS of (9) is continuous and strictly increases from $r+g$ to infinity, having the derivative $rg\left(e^{gT} - e^{-rT}\right) > 0$ for $T > 0$. Therefore the two curves have exactly one strictly positive intersection. ■

Having got T, we now use (7) to solve for the last unknown: $p_0 = ce^{g\tilde{T}(r,c,g)}$.

[4]Proposition 4 of Boucekkine *et al.* (1997) covers that case.

Sufficient conditions for $x(t) > 0$ for all t.—Proposition 1 relies on the assumption that investment is always positive. A necessary and sufficient condition for that to be true is that output be increasing. That condition is that for all t,

$$\frac{d}{dt}D(p,t) = \frac{\partial D}{\partial p}\frac{dp}{dt} + \frac{\partial D}{\partial t} = gp\left|\frac{\partial D}{\partial p}\right| + \frac{\partial D}{\partial t} > 0. \tag{10}$$

Thus it is possible for the time-derivative of D to be negative, but not too negative to offset the positive effect on output of the fall in price. Now, condition (10) is of limited value because it involves the endogenous variable p. One can, however, reduce (10) to a condition on primitives in some special cases. Take the case where population grows at the rate γ_t and where each consumer's demand is iso-elastic, i.e., the case where $D(p,t) = Ap^{-\lambda}\exp\left(\int_0^t \gamma_s ds\right)$, (10) is equivalent to

$$g\lambda > -\gamma_t$$

for all $t \geq 0$. Thus (10) can hold even if population is declining, as long as its rate of decline, γ_t, never exceeds $g\lambda$.

Propositions 2-4 state the results that we shall test. The first result follows directly from implicitly differentiating (9) and is derived in the Appendix:

Proposition 2 *The replacement cycle is shorter if technological progress is faster:*

$$\frac{\partial T}{\partial g} = -\frac{\frac{r+c}{c} + (gT-1)e^{gT}}{g^2\left(e^{gT} - e^{-rT}\right)} < 0. \tag{11}$$

Thus, industries with higher productivity growth should have an earlier shakeout.[5]

The second relation emerges between two variables that in the model should be equal to each other. Let

$$y \equiv \frac{X_0}{q_T}$$

be the fraction of capacity replaced at the first shakeout, and let

$$z \equiv \frac{q_0}{q_T}$$

be the initial output of the industry relative to its output at the shakeout date. From (7), $p_0 = ce^{gT}$. Then from (5) ,

$$q_0 = D\left(ce^{gT}, 0\right) = X_0$$

Since *all* of the initial capacity is replaced at T, it must mean that $X_0 = q_0$ and that therefore

[5] We interpret g as an invariant property of an industry. But it can be interpreted as applying only to a given epoch in the lifetime of a given industry, and subject to occasional shifts. In Aizcorbe and Kortum (2005), e.g., one can think of such shifts as tracing out the relation between technological change and the lifetime of computer chips.

Proposition 3 *The fraction of capacity replaced at T depends inversely on output growth over the period $[0, T]$:*

$$y = z. \tag{12}$$

The restriction in (12) holds regardless of why output has grown. Output may have grown because the demand curve shifted out, or it may have grown because demand is elastic so that the price decline led output to grow. The end result in (12) is the same.

The third relation concerns the rate at which investment echoes or investment spikes die off. Let X_n be the size of the n'th investment spike. We then have

Proposition 4 *Investment spikes decay geometrically. That is,*

$$X_n = e^{-gTn} X_0 \tag{13}$$

for $n = 1, 2, ...$

Proof. Because $p(t)$ is continuous at T, the number of efficiency units replaced at the spikes is a constant, X_0. which means that $X_n = e^{-gT} X_{n-1}$. The absolute size of each spike is a fraction, e^{-gT}, of the previous one. ■

The spike dates remain T periods apart, at $0, T, 2T, 3T, ...$ The spikes occur regularly because technological progress occurs at the steady rate g. Thus we offer an explanation for periodic creative destruction episodes that, since it does not rely on recurring shocks, is different from the one that Caballero and Hammour offer.

Relation to vintage-capital growth models.—Proposition 4 gives us an opportunity to relate this to the general equilibrium vintage-capital models of Johansen (1959) and Arrow (1962) who assume a production function for final goods that is Leontieff in capital and labor. In that case the maintenance cost is like a wage multiplied by the labor requirement per machine. The paper is especially close to Boucekkine, Germain, and Licandro (1997) (BGL)who, unlike Arrow, emphasize transitional dynamics and echo effects. These general-equilibrium models become like ours when the instantaneous utility of consumption is linear so that the interest rate is constant. Our Proposition 4 is equivalent to BGL's Propositions 5 and 7. The main difference is that at T we have a spike, whereas in their model retirement is distributed on an interval.

The remaining parameters of the model are the maintenance cost c and the rate of interest r. The following claim is proved in the Appendix:

Proposition 5

$$(i) \quad \frac{\partial T}{\partial c} < 0. \quad \textit{And, if } gc < r^2, \quad (ii) \quad \frac{\partial T}{\partial r} > 0.$$

A rise in the maintenance cost, c, reduces the lifetime of capital as one would expect. Since replacing capital constitutes an investment, when the rate of interest rises that form of investment is discouraged, and it will occur less frequently.

3 Tests

Gort and Klepper measure an industry's age from the date that the product was commercially introduced, i.e., from the date of its first sales. The shakeout period is defined as the epoch during which the number of firms is declining. An "exit" occurs when a producer of a product stops making it. The producer can continue to exist as a firm that makes other products. The model is about the replacement of capital where the number of its units declines for the first time at T, whereas Gort-Klepper report the exit and replacement of *firms*, and the shakeout is the date when the number of firms first declines.

3.0.1 Capital replacement and exit

The model assumes that capital is operated by measure-zero firms of indeterminate size. We hypothesize that a fraction of machines replaced are in firms that will themselves exit and be replaced by new firms. The argument is that if the firm needed to exit for some unrelated reason, then the appropriate time to do so would be when its plant and equipment need replacing. This is more likely to be so if used capital markets do not function well, or if the firm finds it hard to sell off an unwanted division. Instead of replacing its equipment at T, the firm can exit and let others bring the new equipment into the industry. This assumption gets varying support from evidence on

1. *The trading of patent rights.*—Serrano (2006) finds that the probability of a patent being traded rises at its renewal dates.

2. *Higher embodied technical progress raises exit.*—Samaniego (2006) finds that where the prices of machinery inputs fall faster, the firms using those machines experience higher rates of exit.

3. *Exit and efficiency.*—Baily *et al.* (1993, Table 3) find that the least productive plants are the most likely to exit and Deily *et al.* (2000, Table 2) show that the least efficient private hospitals are more likely to close.

4. *Exit and age.*—The hypothesis implies that oldest firms or, at least, oldest plants should close first. Evidence does not support this, but we should remember that there are other reasons why firms exit and other reasons why plants close. Agarwal and Gort (1996, Figure 2) show that hazard rates for *firm* exit tend to rise once age exceeds 30 or 40 years, and perhaps this is because their capital is old and needs replacing.

As suggested by this discussion, we shall begin by proxying the age, T, of an industry at its first replacement spike, by the industry's age at which the shakeout of its firms begins. And as suggested by (6), we shall proxy the rate of technological progress, g, by the rate at which the price of the product declines.

3.1 Testing (11): The timing of the shakeout

Since replacement episodes are in the model caused by technological progress, we first check if industries with higher productivity growth experience earlier shakeouts. That is, we ask whether industries with a high g have a low T as Proposition 2 claims and, if so, how well the solution for T to (9) fits the cross-industry data on g and T. GK report eight industries for which they can measure price over the entire pre-shakeout stage; there also are two industries in which the shakeout had not yet begun, but for which we have price information. We reproduce the numbers in Table 1:

PRODUCT NAME	$\hat{g}$	$\hat{T}$
DDT$^{(-)}$	0.20	12
Electric shavers$^{(-)}$	0.05	8
Fluorescent lamps$^{(+)}$	0.21	2
Penicillin$^{(+)}$	0.57	7
Phonograph records$^{(-)}$	0.03	36
Styrene$^{(+)}$	0.06	31
Television$^{(-)}$	0.05	33
Zippers$^{(-)}$	0.04	63
Ball-point pens	0.07	>28
Nylon	0.03	>34

Table 1: THE DATA IN FIGURES 1 AND 3.

We now describe the procedure by which we choose the model's parameters. By Proposition 1, a unique solution to (9) for T exists, denoted it by $\tilde{T}(r, c, g)$. We estimate T to be the date that Gort and Klepper find that Stage 4 (the shakeout stage) begins in their various industries. For industry i we call this variable $\hat{T}_i$. In view of (6), we estimate g by the rate of product-price decline in that industry. We call this variable $\hat{g}_i$. We do not have observations on r and c, so we set $r = 0.07$ and estimate c to minimize the sum of squared deviations of the model from the data for the eight industries for which we have complete information on both g and T:

$$\min_c \left\{ \sum_{i=1}^{8} \left[\hat{T}_i - \tilde{T}(0.07, c, \hat{g}_i) \right]^2 \right\}.$$

The data and the implicit function $\tilde{T}(g, r, c)$ fitted to them are shown in Figure 3. The estimate is $c = 0.039$ (s.e. $= 0.013$, $R^2 = 0.53$).

Our estimate of c is in the range of typical maintenance spending. McGrattan and Schmitz (1999) report that in Canada, total maintenance and repair expenditures have averaged 5.7 percent of GDP over the period from 1981 to 1993, and 6.1 percent

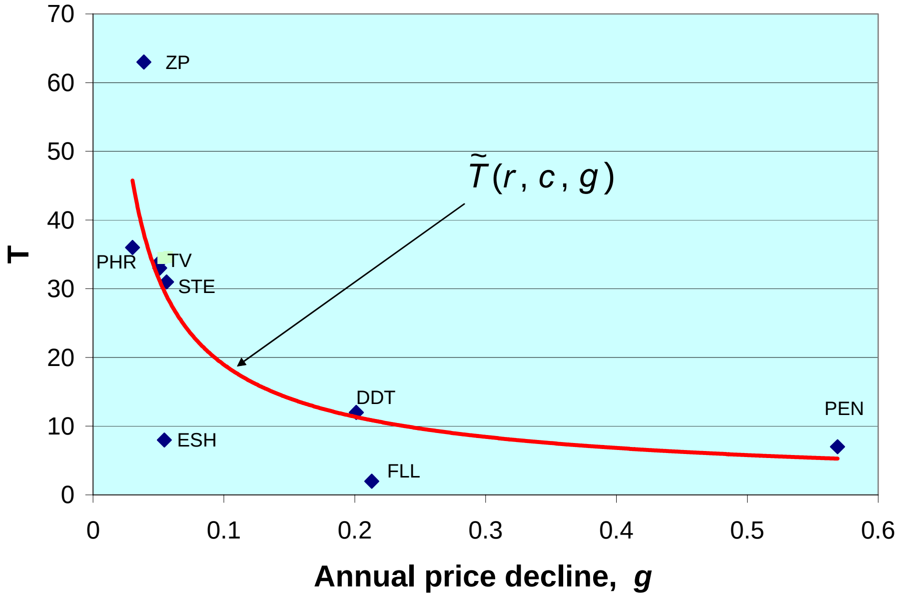


Figure 3: THE RELATION BETWEEN $\hat{T}$ AND $\hat{g}$

if one goes back to 1961. These estimates are relative to output, however, whereas ours are relative to the purchase price of the machine which is normalized to unity. Relative to output, maintenance costs are one hundred percent at the point when the machine is retired (this is equation [3]). Maintenance costs are constant over the machine's lifetime, whereas the value of the machine's output relative to the numeraire good is e^{gT} when the machine is new. Now e^{gT} averages around $e^{1.7} = 5.5$ – see Figures 10 and 11 – so that as a percentage of output, maintenance spending ranges between 18 and 100 percent. Therefore, c must stand partly for wages to workers as a fixed-proportion input as in the original vintage-capital models like Arrow (1962) and Johansen (1959) that had a fixed labor requirement.

3.1.1 Testing (11) using an alternative definition of T

We now entertain a different definition of T; one that may provide a better test of the model, and one that will provide us with more observations. The main reason for doing this is that in many industries that GK cover, what they call "Stage 1" may not contain what we would call an investment spike. During stage 1, only a few firms enter, a number that is in some industries – autos and tires, e.g., – much smaller than the number of firms that exit during the shakeout.

The model predicts a date-zero investment spike $X_0 = D(p_0, 0)$, without which there would be no exit spike at date T. Not all the GK industries will fit this, however. Indeed, GK state that rarely is a product's initial commercial introduction immediately followed by rapid entry. Autos, e.g., had very low sales early on, and it took years for sales to develop.[6] Therefore the spike is better defined at or around the time when the entry of firms was the highest. Moreover, in GK, for many industries, the shakeouts were not completed until a few years after they first began. It may thus be more appropriate to designate the shakeout date as the midpoint of the shakeout episode instead of as the start date of the shakeout episode.

In light of this, let $\widehat{T}$ be the time elapsed between the industry's "Takeoff" date (which is when Stage 2 begins) and the midpoint of the the industry's shakeout episode (the midpoint of Stage 4). This revised definition for $\widehat{T}$ calls for adjusting $\widehat{g}$ to be the rate of the average annual price decline between the takeoff date (which comes after the industry has completed stage 1), and the first shakeout date. This allows us to enlarge the sample. The additions were as follows:

1. For six of the GK industries, complete information for price-declines in Stages 2 and 3 (but not Stage 1) is available. They can now be added to the analysis.
2. The two censored observations listed in table 1 will also be added,
3. We replace the GK information for the TV by that reported in Wang (2006), who compiled the data from the Television Factbook. This change may better reflect the history of the TV industry as GK dated the birth of the industry as early as 1929, while according to Wang, the commercial introduction of TV starts only in 1947.

The estimation procedure.—The inclusion of the two censored observations leads us to use maximum likelihood. We set $r = 0.07$ and assume that the distribution of c over industries is log- normal: For all firms in industry i, $\ln c_i$ is a draw from $N(\ln \overline{c}, \sigma^2)$, where $\bar{c}$ is the mean over all industries and σ^2 is the variance. We then estimate $\overline{c}$ and σ to fit the model to the data; the details are in the Appendix.

The estimate of $\bar{c} = 0.078$ is a bit higher than with the previous sample. This is because T is smaller under the new definition, and a higher replacement cost is needed to generate the earlier replacement. Figure 4 plots the predicted T for the industry with the estimated mean value of c. The fit is not quite as good as before, and, indeed, it looks at first sight that the line of best fit should should be a bit lower. Note, however, that Nylon and Ball-point pens are censored points and that their true realizations, if we were to observe them, would lie above the line, and in effect they act to pull the line up.

[6]Klepper and Simons (2005), however, do find an initial spike for TVs and Pennicyllin – both start out strong after WW2. There may be a problem with the TV birthday being set at 1929 as GK have it. During WW2 the Government had banned the sale of TVs.

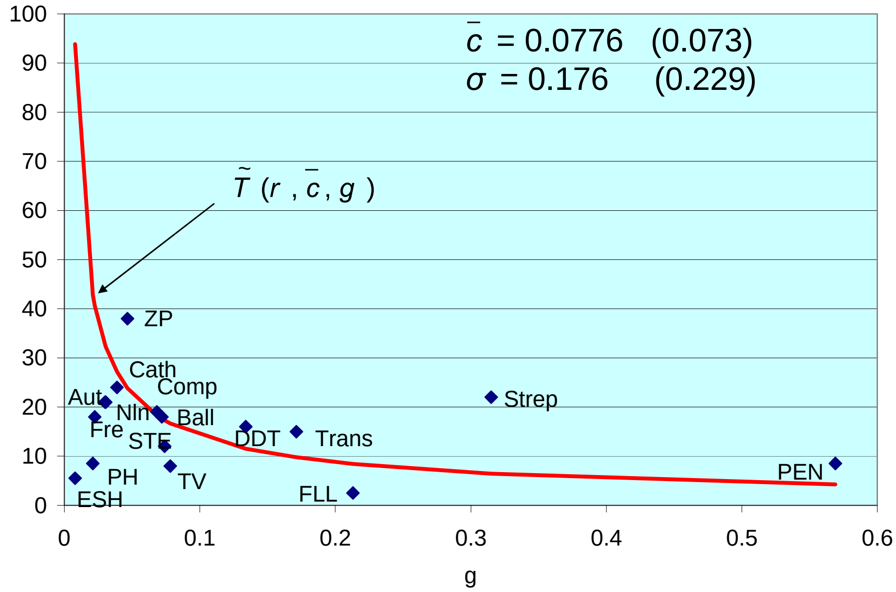


Figure 4: $\hat{T}$ AND $\hat{g}$ USING THE ALTERNATIVE DEFINITION OF T

3.1.2 Other explanations for the negative $\hat{T} - \hat{g}$ relation

Demand declines.—On the face of it, this seems like a plausible alternative explanation for the negative relation between $\hat{T}$ and $\hat{g}$. The gist of the argument can be collapsed into a two-period example, suppose demand either stays constant or that it declines, and that the outcome is unpredictable. Then a demand decline produces a shakeout ($T = 2$) and a decline in p, whereas without a decline there is no shakeout ($T = +\infty$) and no decline in p. This seemingly plausible argument does not, however, meet with support in GK's sample. Among the industries where output fell during the shakeout, which in Table 1 are marked with a superscript $^{(-)}$, the average pair $\left(\hat{g}^{(-)}, \hat{T}^{(-)}\right) = (0.07, 30.4)$, whereas among the industries where output rose, marked with a superscript $^{(+)}$, the average pair $\left(\hat{g}^{(+)}, \hat{T}^{(+)}\right) = (0.28, 13.3)$. Yet the demand hypothesis implies the opposite: Prompted by the decline in output, $\hat{g}^{(-)}$ should have exceeded $\hat{g}^{(+)}$, and $\hat{T}^{(-)}$ should have been lower than $\hat{T}^{(+)}$.

Technological change.—Our argument uses technological change in a vintage-capital context. Both components are needed for the conclusions to hold. We would argue that the second component, which is missing in the other papers we listed under this heading, is essential. It is the new vintages of capital that must replace old vintages sooner when technological progress is faster. Progress manifests itself through a falling p, and so the relation emerges in a straightforward way. An extension of Klepper (1996) should imply that leading firms would squeeze out the inefficient fringe more quickly in industries where there is more technological opportunity and, hence, faster-declining product prices. The difference between our model and his concerns the fate of the firms in the first cohort of entrants: In our model, the first cohort is the least efficient whereas in Klepper's model it is the *most* efficient because it has done the most research .

Exit after learning through experience.—The argument of Horvath *et al.* (2003) would need to be augmented with some reason for why a run-up in entry should come sooner in those industries where p is declining rapidly. Such an argument would then explain why the shakeout itself would occur earlier.

Consolidations for other reasons.—Again, one would need a reason for why consolidations should occur sooner in industries where technological change is more rapid.

3.2 Testing (12)

Testing Proposition 3 requires that we estimate the fraction of capacity replaced and the growth of output when the industry reaches age T. Equation (12) says that if we regress y on z we should get a perfect fit. We calculate $\widehat{z}_i$ from GK's table 5 as the inverse of the rate of output increase from the date industry i was born up to the date when the number of firms in the industry peaked. But we do not have data on capacity replaced; we do have estimates on the fraction of firms that exit during the shakeout. We calculate $\hat{y}_i =$ GK's Table 4 column 3. This is the total decrease in the number of firms for a period of time that lasted for on average 5.4 years, after which the number of firms in the industry peaked. Hence $\widehat{y}_i$ is the upper bound on the number of firms that exited at time T.

Because exiting firms are smaller than other firms, the fraction of firms that exits does not equal the fraction of industry capacity withdrawn by the exiting firms: Evans (1987) and Dunne, Roberts and Samuelson (1988) find that firm size is positively associated with survival. Since small firms have a greater tendency to exit than large firms, the fraction of capacity that is scrapped is smaller than the fraction of firms that exit. Table 2 of Dunne *et al.* shows that the size of exiting firms is about 35 percent of the size of non-exiting firms. Therefore the fraction of firms should be roughly three times the fraction of capacity replaced. In other words, Proposition 3 together with the size adjustment implies the regression equation $\hat{y}_i = 3\hat{z}_i + u_i$, where i denotes the industry. Firms may also exit for reasons that are outside the model.[7] Therefore we add a constant, b_0, to the RHS of the regression equation in order to represent these other forms of exit. Thus, we estimate the relation

$$\hat{y}_i = b_0 + b\hat{z}_i + u_i,$$

[7] In our model, it is always the oldest capital that is replaced and, on these grounds, the oldest firms that exit. Now Figure 2 of Agarwal and Gort (1996) shows that this is not true in any of the five stages. The exit hazard does tend to rise beyond a certain age, however, indicating an additional reason for exit among the oldest firms in the sample. Nevertheless, the fraction of firms exiting is, at best, a noisy measure of the fraction of the capacity replaced, and that is how we interpret it.

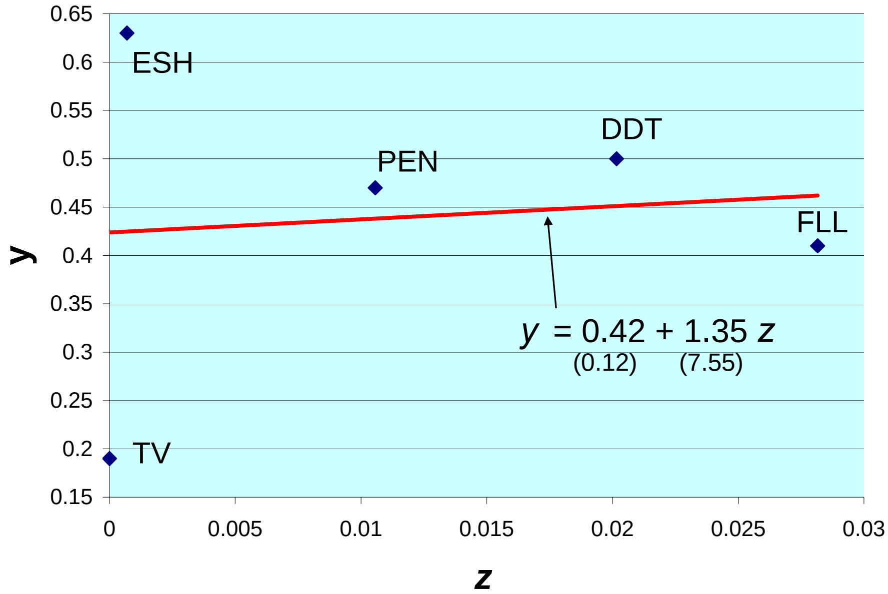


Figure 5: TESTING (12): THE RELATION BETWEEN y AND z.

where b represent the fraction of firms that exit in response to capacity replacement. The estimates are in Figure 5.[8] There are too few observations to allow us to tell if b differs significantly from 3.

3.2.1 Tests of (12) with the alternative definition of T

The alternative definition of T takes the date of the first spike to be the takeoff date of an industry, i.e., the start of GK's Stage 2. In that case, if we ignore as negligible the capacity created before the takeoff date, $\widehat{z}$ should equal the inverse of the rate of output increase between the takeoff date and the start of Stage 4, i.e., the date at which the number of firms in the industry peaked. There are 5 industries in GK for which output data, as well as information on $\widehat{y}$, are available from the takeoff date to the shakeout date but not earlier. These industries can now be added to the analysis. For the TV industry we use the information from Wang (2006) in place of GK. The results are described in Figure 6. The slope is marginally significant, but far lower than the model predicts.

[8] GK's Table 5 reports complete information on the rate of output increase up to the shakeout for 10 industries. But only for five of these is there also information on the rate of firm exit during the shakeout in GK's table 4.

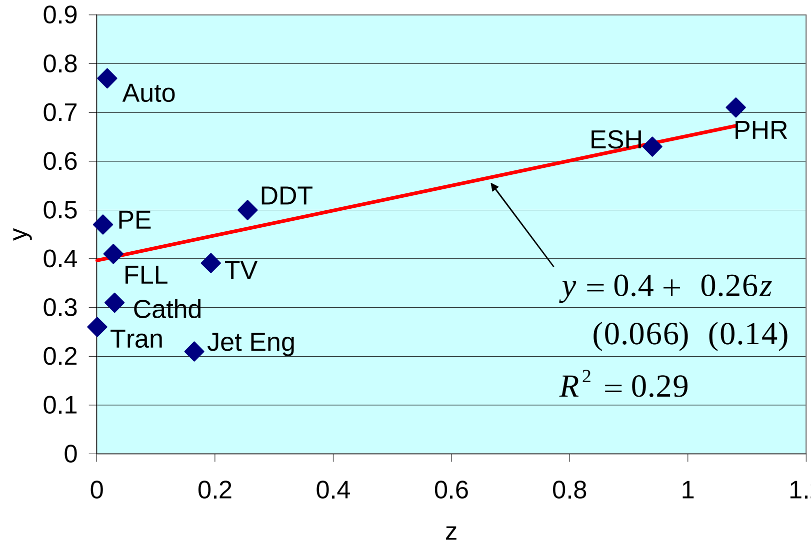


Figure 6: Testing (12) with the alternative definition of T

4 Entry and Exit Spikes

Shakeouts should diminish geometrically in absolute terms as (13) shows. Moreover, exit spikes should coincide with entry spikes. This section tests these implications using Agarwal's extension and update of the Gort-Klepper data, described fully in Agarwal (1998). The products are listed and some statistics on them presented in Table 2 of the Appendix.

The evidence hitherto is mixed: Cooper and Haltiwanger (1993) report evidence of industry-wide retooling spikes, but Gort and Klepper did not report second shakeouts, though this may in part be because the Gort-Klepper data rarely cover industry age to the point $t = 2T$ where we ought to observe a second shakeout. In any case, Agarwal's data cover more years and contain entry and exit separately, and we shall use them to study this question.

A procedure for detecting spikes must recognize the following features of the data:

(A) *Length of histories differ by product.*—Coverage differs widely over products, from 18 years (Video Cassette Recorders) to 84 years (Phonograph Records)

(B) *The volatility of entry and exit declines as products age.*—The model predicts that the volatility of entry and exit should decline with industry age. Other factors also imply such a decline: (i) Convex investment costs at the industry level, as in Caballero and Hammour (1994), and (ii) Firm-specific c's. Both (i) and (ii) would transform our X_n from spikes into waves and, eventually, ripples.[9]

[9] Spikes may also dissipate because (i) A positive shock to demand would start a new spike and

Hodrick-Prescott residuals in entry and exit rates.—Roughly speaking, we shall say that a spike in a series Y_t occurs whenever its HP residual is more than two standard deviations above its mean. "Roughly", because of adjustments for (A) and (B) above. We constrain industry i's trend, τ, by

$$\sum_{t=2}^{A_i} (\tau_t - \tau_{t-1}) \leq a A_i^b,$$

where A_i is the age at which an industry's coverage ends. We set $a = 0.005$ for both series. Because both series are heteroskedastic, with higher variances in earlier years, we chose $b = 0.7$ for both entry and exit (If b were unity, an industry with longer coverage would have a larger fraction of its observations explained by the trend). The trend therefore explains about the same fraction of the variation in short-coverage industries as in long-coverage industries.

This fixes problem (A), but not (B): The HP residual, $u_t \equiv Y_t - \tau_t$, is still heteroskedastic, the variance being higher at lower ages. To fix this, we assumed that the standard-deviation was age specific and equal to

$$\sigma_t = \sigma_0 t^{-\gamma}, \tag{14}$$

where $\sigma_0 \geq 0$ and $\gamma \geq 0$ are product-specific parameters estimated by maximizing the normal likelihood[10]

$$\prod_{t=1}^{A_i} \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp\left(-\frac{1}{2}\left[\frac{u_t}{\sigma_t}\right]^2\right).$$

The spike-detection algorithm.—If at some date the HP residual is more than two standard deviations above its mean of zero, then that date is a spike date. But we shall allow for the possibility that unusually high replacement will take up to three periods. Thus we shall say that a series Y_t in a certain time window is above 'normal' if one or more of the following events occurs

1-period spike:	$u_t > 2\sigma_t,$
2-period spike:	$u_t > \sigma_t$ and $u_{t+1} > \sigma_{t+1},$
3-period spike:	$u_t > \frac{2}{3}\sigma_t$ and $u_{t+1} > \frac{2}{3}\sigma_{t+1}$ and $u_{t-1} > \frac{2}{3}\sigma_{t-1}.$

series of echoes following it; these would mix with the echoes stemming from the initial investment spike, (*ii*) Random machine breakdowns at the rate δ would transform (13) into $X_n = e^{-(g+\delta)Tn} X_0$, which decays faster with n

[10] Although the HP residuals are not independent and probably not normal either, this procedure still appears to have removed the heteroskedasticity in the sense that the spikes were as likely to occur late in an industry's life as they were to occur early on.

The cutoff levels of 2, 1, and $\frac{2}{3}$ times σ_t were chosen in the expectation that each of the three events would carry the same (small) probability of being true under the null. The latter depends on the distribution and the serial correlation of the u_t which we do not know. But, again for the normal case, these probabilities turned out to be roughly the same. That is,

$$1 - \Phi(2) = 0.023, \quad (1 - \Phi(1))^2 = 0.025, \text{ and } \left(1 - \Phi\left(\frac{2}{3}\right)\right)^3 = 0.016.$$

Table 2 (Appendix) summarizes the results. The 33 products are listed alphabetically and are so numbered. To explain the table, let us focus on product 23, Phonograph Records and read across the row. Records were first commercialized, i.e., sold, in 1908. Being the oldest product, it also is the product for which we have the most observations, 84, since (with one exception) the series all end in 1991. The next four entries are the exit and entry spikes, by age of industry and by calendar year. There are seven one-year spikes and one two-year spike, this being the last exit spike. The 1934 exit spike is labelled in red because it falls in the GK shakeout region the dates of which are in the last column of the table. See Figure 7 where the GK shakeout region is shaded. The remaining columns report the correlations between the entry and exit series. The raw series are negatively correlated – when the industry is young, entry is higher than exit, and later the reverse is true – but the correlation is slight (-0.07). The trends (i.e., the τ's) are more negatively correlated (-0.27). The HP residuals, on the other hand, are *positively* correlated; our model suggests that this should be so because the spikes should coincide. The correlations averaged across products are at the bottom of the table.

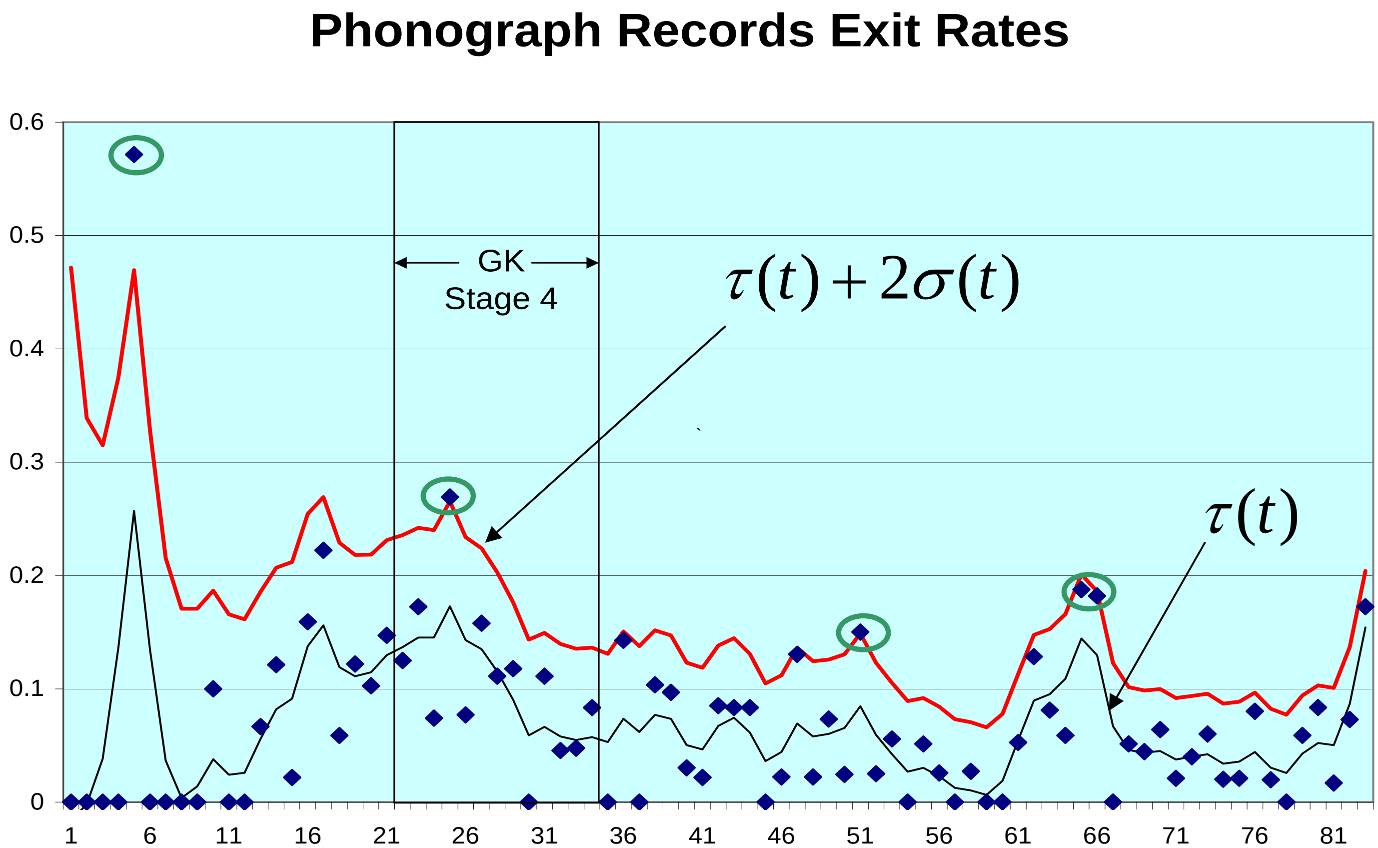
Figure 7 plots the exit and entry series for Phonograph records, in each case plotting the HP trend and the two-standard-deviation band. Spikes are circled in green. Let us note the following points:

1. For both entry and exit the spikes are evenly distributed, and this is true in most industries.[11] This suggests that the heteroskedasticity adjustment in (14) is adequate.

2. The number of entry and exit spikes is equal – four entry and four exit spikes. But only the final, fourth spikes coincide in that they are within one year of each other. There were only five other products (10, 11, 25, 27, and 32) for which this was so.

3. The second exit spike is well in the GK region, but there should also have been an entry spike in that region. Over all the industries the number of entry spikes

[11] Since neither the entry nor the exit rate is defined in the first year of the raw series, both series begin in the second year. Thus "Year t" of the entry and exit rate series refers to element $t + 1$ of the raw data series. So if each raw series starts in "year 0," the entry and exit series start in year 1.



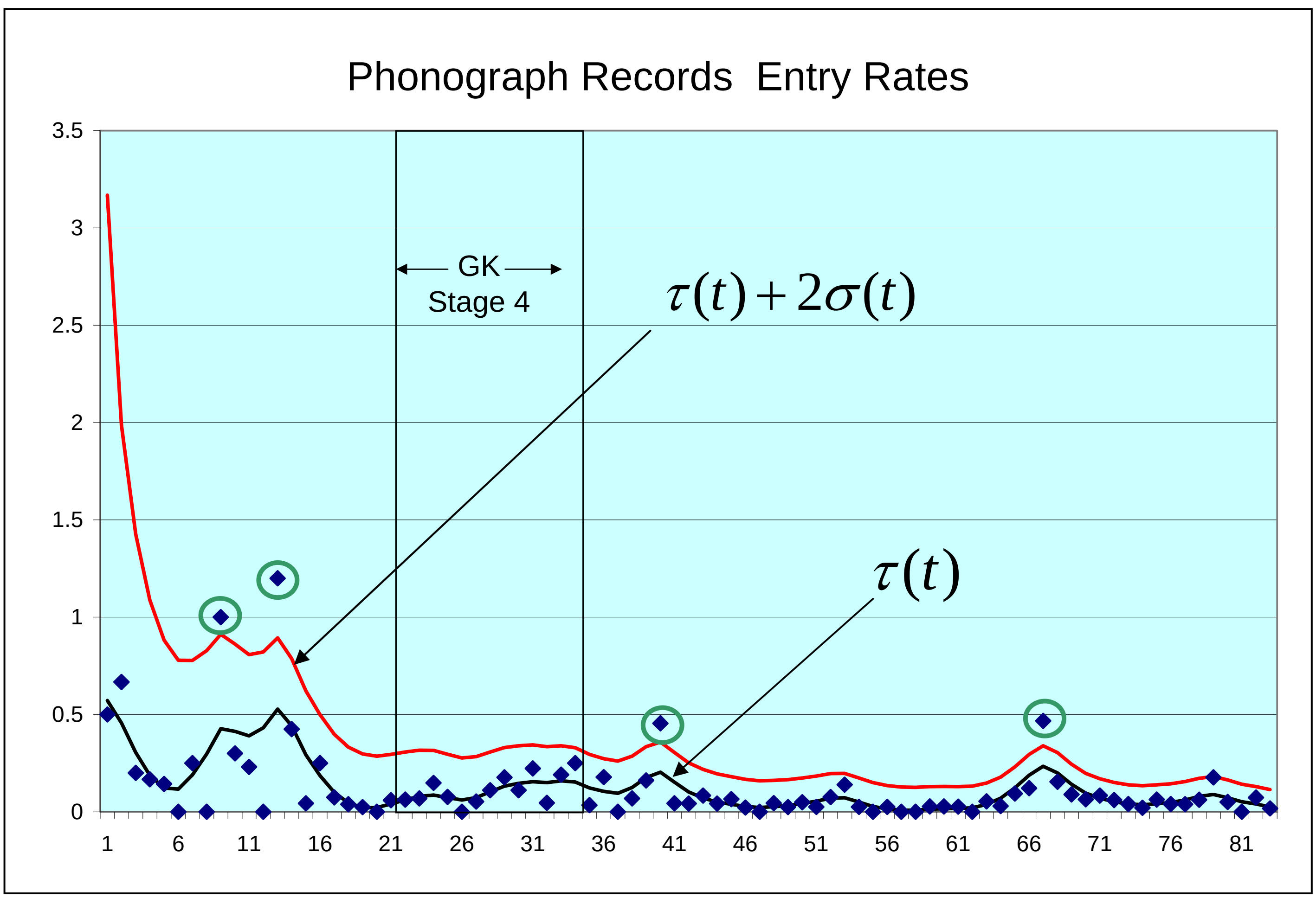


Figure 7: How the spikes were determined for the case of the Phonograph-Record Industry

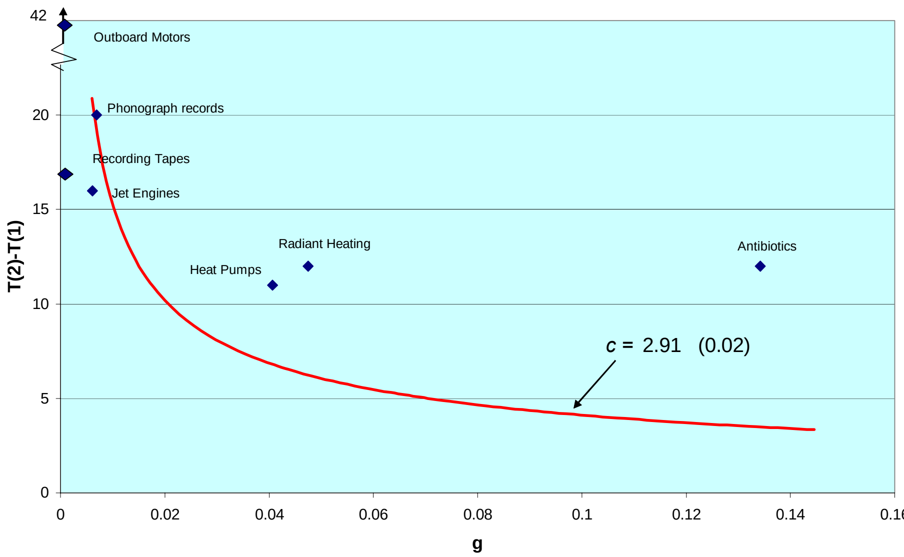


Figure 8: EXITS: THE RELATION BETWEEN $\hat{T}_2 - \hat{T}_1$ AND $\hat{g}$

(67 in all) is slightly less than the number of entry spikes (79 in all), for the nine industries in which the GK region does contain an Agarwal spike, it is *always* an exit spike – see the red numbers in Table 2.

4. Just as our model predicts, however, $T_{2,i} - T_{1,i}$ is negatively related to $\hat{g}_i$. That is, analogously to the result in Figures 3, the first exit spike is followed sooner by the second exit spike in those industries i where prices decline faster. We now calculate $\widehat{g}$ as the rate of average price decline during the years covered by $T_2 - T_1$. To maximize the number of observations, we include products for which price information is available for as little as 70% of the time during the years covered by $T_2 - T_1$. For *Outboard Motors* and *Recording Tapes*, however, price went up during those years which is inconsistent with the model. But they both had above-average $T_2 - T_1$ values, 42 and 17 respectively, and while we did not include them in the estimation routine, we include them in Figure 8, setting $\hat{g}$ to zero in both cases.

5. The same test is also done on entry spikes. Once again, $T_{2,i} - T_{1,i}$ is negatively related to $\hat{g}_i$. The results are in Figure 9.[12] At first it may seems like a better fit could be obtained at a lower value of $\bar{c}$ which would raise the red curve upwards. The problem, however, is that a fall in c raises T by much more when g is low, as one can verify from Proposition 5 and more intuitively from (7), so that the curve moves clockwise.

[12] For both plots $\bar{c}$ solves $\min_c RSS = \min_c \sum_{i=1}^{n} \left(\widehat{T}_i - \overline{T}(r, c, \widehat{g}_i) \right)^2$.

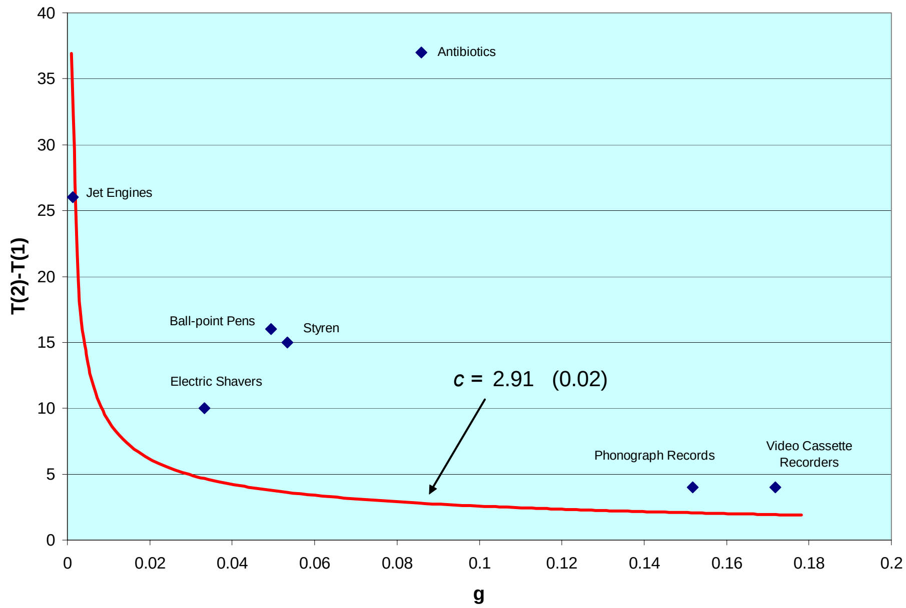


Figure 9: ENTRY: THE RELATION BETWEEN $\hat{T}_2 - \hat{T}_1$ AND $\hat{g}$

5 Implications for productivity growth

The model has no labor, and so TFP is simply the productivity of capital.[13] If the price of capital used to deflate investment spending were per unit of quality, then all the technological progress would appear in the capital stock, the resulting measure of the capital stock would be given by (1) and would equal output, with TFP being constant at unity. On the other hand, if no adjustment is made for quality so that the price index used to deflate investment was unity, then the capital stock would be given by $K(t,t)$ as given by (2) when evaluated at $s = t$, and TFP would equal

$$\text{TFP}_t = \frac{q_t}{K(t,t)}. \tag{15}$$

Thus TFP rises smoothly until the shakeout date, and then it experiences an upward jump during the shakeout when the number of physical units of capital falls, but the number of their efficiency units stays unchanged.

[13] One way to add labor to the model is to have one worker per machine, and to interpret c as the wage. Labor productivity would then be the same as the productivity of the physical units of capital and would equal the expression in (15). A shakeout would be accompanied by a sharp decline in employment.

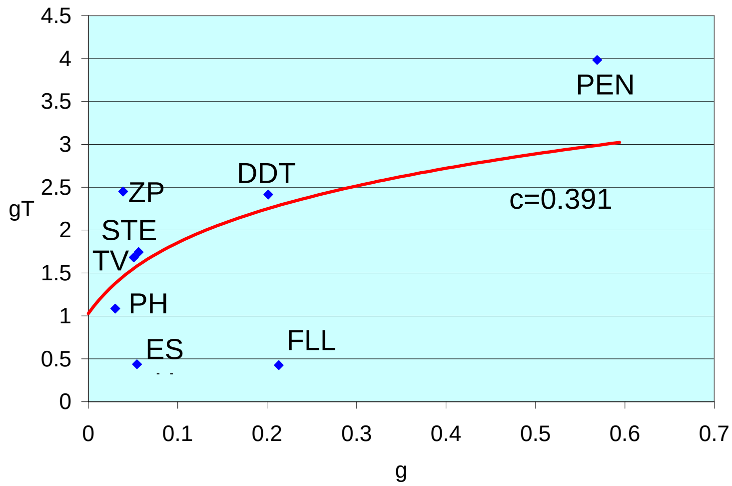


Figure 10: TFP GROWTH AND THE MAX/MIN TFP RATIO – PREDICTED AND ACTUAL

5.0.2 TFP growth vs. dispersion

Faster TFP-growing industries should show greater TFP dispersion in our model. Dwyer (1998) has derived the same relation in a similar model. He also estimated the relation in a group of textile industries. The relation was positive and significant.[14] Dwyer measured dispersion by the TFP ratio of the tenth percentile plants to the ninetieth percentile plants. TFP growth ranged from about two percent to about eight percent and the TFP ratio ranged between 2.4 to 4.6.

Our model cannot generate such large dispersion, even when we measure dispersion as the ratio of the most productive to the least productive producer. Figure 10 plots the logarithm of

$$\ln \frac{\mathrm{TFP}_{\max}}{\mathrm{TFP}_{\min}} = gT$$

as a function of g. It shows, in other words, the comparative steady state relation between inequality and growth.[15] The relation is positive, but for the less-than-ten-percent range of TFP growth (which would include all of Dwyer's industries), the most we can explain is a ratio of about 1.75. Table 5 of Aizcorbe and Kortum (2005) reports a result similar to the one portrayed in Figure 10 – when g is larger, gT should go up.

[14]At the two-digit level, Oikawa (2006) finds a positive relation between TFP growth and TFP dispersion measured by the standard deviation of the logs.

[15]Moreover, the model's implications for inequality have a curious discontinuity at $g = 0$. Namely, if g is really zero, then everyone should be using the same quality machine and there should be no TFP inequality. But a steady state with a very small g would have TFP inequality of at least unity.

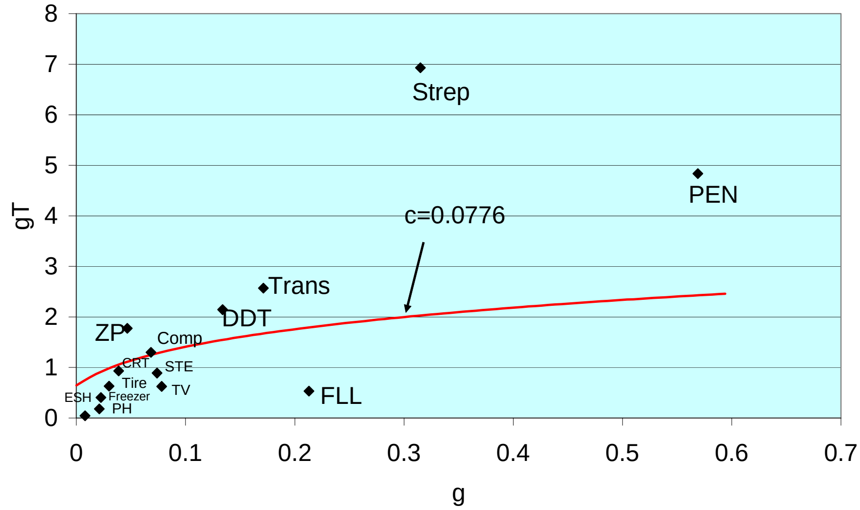


Figure 11: TFP GROWTH AND THE MAX/MIN TFP RATIO WITH THE ALTERNATIVE DEFINITION OF T – PREDICTED AND ACTUAL

Figure 10 is based on the information in Table 1, and on the least-squares estimate of c based on the first eight industries in that table, i.e., $c = 0.039$. If we switch to measuring T by the time between the industry's takeoff and the midpoint of the shakeout episode while adjusting the measure of g accordingly, and if we use the ML estimate of $\bar{c}$ reported in Figure 4, we get the results shown in Figure 11. Note that Figures 10 and 11 portray the very same information portrayed in Figures 3 and 4 – no new information is added. The difference is merely that the variable plotted on the vertical axis is gT instead of T. Since the data do not have T declining with g as fast as the model predicts, the relation between g and gT is steeper than the model predicts. This is especially evident in Figure 11.

A further difficulty with the model as an explanation of TFP dispersion is that the dynamics of TFP do not quite match the dynamics of actual plants in the data. In a word, too much *leapfrogging* goes on. In the data TFP-rank reversals are common, but they typically do not give the "last shall be first" implication. In our model, as in many other vintage-capital models, when a producer updates his capital, his productivity rises from the last percentile to the first percentile. A plant would move smoothly down the distribution of percentiles until it reached the last percentile, and it then would suddenly jump back up to the first percentile, and so on. Analysis of productivity transitions by Baily, Hulten, and Campbell (1993, Table 3) does not bear this out. Plants move up and down the various quintiles of the distribution and the transition matrix is fairly full. Moreover, births tend to be below average productivity.

On the positive side, a supporting fact in Baily *et al.*'s transition matrix is that

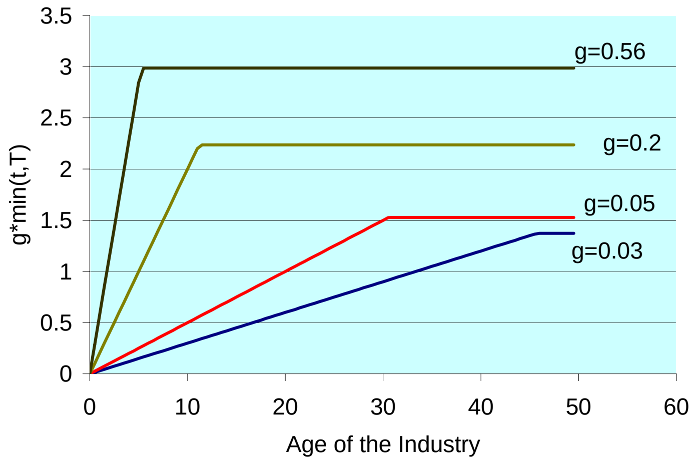


Figure 12: TRANSITIONAL DYNAMICS IN PRODUCTIVITY DISPERSION

more plants (14 percent) move from the bottom quintile to the top quintile than the reverse (5 percent). One reason why we do not see the dramatic "last shall be first" rank reversals is the tendency for a plant's TFP to grow as it ages.[16] Thus a new, cutting-edge plant does not immediately have the highest productivity. Rather, its productivity grows as it ages, as Bahk and Gort (1993), and Table 5 of Baily *et al.* (1993) document. This would explain why a new plant does not enter at the top of the distribution of TFP in the way that this model predicts and why, as Table 5 of Baily et al. (1993) shows they tend to rise from the bottom to the top TFP quintile by the time they are 10-15 years old.

5.0.3 Transitional dynamics in productivity dispersion

The model implies that in the initial stages of an industry's life, the distribution of TFP across producers should be fanning out. How fast it does so, however, should depend on the rate of technological progress, i.e., on g. This is the rate at which the productivity of new capital gains at the expense of old capital. But after the industry reaches age T, no further fanning out takes place, because old capital begins to be withdrawn. Thereafter, dispersion remains constant at its steady-state level. In Figure 12 we show how the fanning out process depends on the industry's growth rate by plotting, for four different values of g, the logarithm of

$$\ln \frac{\text{TFP}_{\max}}{\text{TFP}_{\min}} = g \min(t, T)$$

where t is the age of the industry.

[16]Parente (1994) models learning of the technology with the passage of time, and Klenow (1998) models learning as a function of cumulative output.

6 Conclusion

This paper started out with a graphical display of evidence that industry shakeouts of firms occur earlier in industries where technological progress is faster. We argued that other models of shakeouts were not able to explain this fact, whereas our vintage-capital model does so by predicting earlier replacement when capital-embodied technological progress is fast.

By inferring technological progress in the inputs from the decline in the price of the output as our model predicted, we could test several implications of the model, and we found that the model fit fairly well the negative relation between technological progress and the onset of the shakeout. We then tested other implications, most extensively those pertaining to repeated echoes of the initial entry spike where we found that, indeed, subsequent investment spikes are also more frequent where technological progress is fast.

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7 Appendix

Proof of Proposition 2.—Rewrite (9) as

$$ge^{-rT} + re^{gT} - \left(\frac{r+c}{c}\right)(r+g) \equiv \Phi\left(T, g, c, r\right) = 0.$$

We have $\frac{\partial\Phi}{\partial T} = rg\left(e^{gT} - e^{-rT}\right) > 0$. Therefore (11) follows if $\frac{\partial\Phi}{\partial g} > 0$. Now

$$\begin{aligned}
\frac{\partial\Phi}{\partial g} &= e^{-rT} + rTe^{gT} - \frac{r+c}{c} \text{ and, by eliminating } e^{-rT}, \\
&= \left(\frac{r+c}{c}\right)\frac{r+g}{g} - \frac{r}{g}e^{gT} + rTe^{gT} - \frac{r+c}{c} \\
&= \left(\frac{r+c}{c}\right)\frac{r}{g} - \frac{r}{g}e^{gT} + rTe^{gT} = \frac{r}{g}\left(\frac{r+c}{c} - e^{gT}\right) + rTe^{gT} \\
&= \frac{r}{g}\left(\frac{r+c}{c} + (gT-1)\,e^{gT}\right) > 0.
\end{aligned}$$

The strict inequality follows because (i) The function $(gT-1)\,e^{gT}$ is increasing in gT, with derivative $e^{gT}\left[1 + (gT-1)\right] = gTe^{gT}$, and because (ii) As $gT \to 0$, $(gT-1)\,e^{gT} \to -1$, so that at its smallest point, $\frac{\partial\Phi}{\partial g} = \frac{r^2}{gd} > 0$. Then, since $\frac{\partial T}{\partial g} = -\frac{\partial\Phi}{\partial g}/\frac{\partial\Phi}{\partial T}$, and since $\frac{\partial\Phi}{\partial T} > 0$, (11) follows. ■

Proof of Proposition 4.—(i) We showed that $\Phi_T > 0$ in the proof of Proposition 2. Moreover, $\frac{\partial\Phi}{\partial c} > 0$ because the ratio $\frac{r+c}{c}$ is decreasing in c. Therefore $\frac{\partial T}{\partial c} = -\frac{\partial\Phi}{\partial c}/\frac{\partial\Phi}{\partial T} < 0$. (ii) When $gc < r^2$, $\frac{\partial T}{\partial r} = -\frac{\partial\Phi}{\partial r}/\frac{\partial\Phi}{\partial T}$

$$\begin{aligned}
\frac{\partial\Phi}{\partial r} &= -Tge^{-rT} + e^{gT} - \left(\frac{r+g}{c}\right) - \left(\frac{r+c}{c}\right) \text{ and, by eliminating } e^{gT}, \\
&= -Tge^{-rT} - \frac{ge^{-rT}}{r} + \left(\frac{r+c}{c}\right)\frac{(r+g)}{r} - \left(\frac{r+g}{c}\right) - \left(\frac{r+c}{c}\right) \\
&= -Tge^{-rT} - \frac{ge^{-rT}}{r} + \left(\frac{r+c}{c}\right)\frac{g}{r} - \left(\frac{r+g}{c}\right) \\
&= \frac{g}{r}\left(1 - e^{-rT}\right) - \left(\frac{r}{c} + Tge^{-rT}\right) < \frac{g}{r} - \frac{r}{c}.
\end{aligned}$$

so that then $\frac{\partial T}{\partial r} = -\frac{\partial\Phi}{\partial r}/\frac{\partial\Phi}{\partial T} > 0$. ■

Derivation of the Likelihood Function used for the estimates in Figure 4.—. Because $\widetilde{T}(r, c_i, \widehat{g}_i)$ does not admit a closed form solution, the exact functional relationship between $\widetilde{T}_i$ and c_i is unknown and we linearize it in c. After substituting $x_i = \log c_i$ and $g = \hat{g}_i$ into (9), it reads

$$\left(\frac{r}{e^{x_i}} + 1\right)(r + \hat{g}_i) = \hat{g}_i e^{-rT_i} + re^{\hat{g}_i T_i}. \tag{16}$$

Call the solution to this equation $T_i = \widetilde{T}_i\left(r, x_i, \widehat{g}_i\right)$. Taking total derivatives at $x_i = \overline{x}$ gives

$$-re^{-\overline{x}}\left(r + \hat{g}_i\right)dx_i = r\hat{g}_i\left(e^{\hat{g}_i\bar{T}_i} - e^{-r\bar{T}_i}\right)dT_i$$

where $\bar{T}_i \equiv \tilde{T}\left(0.07, \overline{x}, \hat{g}_i\right)$. Then so that

$$-\frac{dT_i}{dx_i} = e^{-\overline{x}}\frac{r + \hat{g}_i}{\hat{g}_i}\frac{1}{e^{\hat{g}_i\bar{T}_i} - e^{-r\bar{T}_i}} \equiv \beta_i$$

Hence $T_i \simeq \tilde{T}(0.07, \overline{x}, \hat{g}_i) - (x_i - \overline{x})\beta_i$. If $x_i \sim N(\overline{x}, \sigma^2)$, then approximately, $T_i \sim N(\bar{T}_i, \beta_i^2\sigma^2)$. The density of T_i is $f(T_i) = \frac{1}{\sqrt{2\pi}\beta_i\sigma}\exp\left(-\frac{1}{2}\left[\frac{T_i - \overline{T}_i}{\beta_i\sigma}\right]^2\right)$. Letting $F(T_i)$ denote its CDF, the likelihood is

$$L = \prod_{i=1}^{2}(1 - F_{T_i}(T_i))\prod_{i=3}^{n} f_{T_i}(T_i),$$

where $i = 1, 2$ denote the two censored observations.

	Product & yr of comm intr.	Length of raw series	EXIT spike dates in yrs since comm intro	EXIT spike dates in calendar yr	ENTRY spike dates in yrs since comm intro	ENTRY spike dates in calendar yr	Corr btw smoothd entry and exit rates	Corr btw entry and exit residuals	Corr btw entry and exit rates	G-K Stage 4
1	Antibiotics	44	7	1955	2	1950	-0.46	-0.04	-0.30	not in G-K
	1948		19	1967	39	1987				
			32	1980						
2	Artificial Christmas Trees	54	8	1946	35	1973	-0.52	-0.02	-0.21	1968-1969
	1938		18	1956	49	1987				
			43	1981						
			45	1983						
3	Ball-point Pens	44	23	1971	9-10	1957-58	0.81	-0.32	0.55	S4 not reached
	1948				26	1973-74				
4	Betaray Gauges	36	7	1963	7	1963	0.18	0.34	0.26	1973-
	1956				33	1989				
5	Cathode Ray Tubes	57	54	1989	10	1945	0.92	0.55	0.79	1963-1967
	1935				15	1950				
					52	1987				
6	Combination Locks	80	13	1925	21	1933	0.41	0.01	0.21	not in G-K
	1912		16	1928	29	1941				
			65	1977	53	1965				
			75	1987						
7	Contact Lenses	56	10	1946	6	1942	0.09	-0.15	-0.13	not in G-K
	1936		29	1965	12	1948				
			35	1971	30	1966				
					39	1975				
8	Electric Blankets	76	3	1919	6-7	1922-23	-0.13	0.07	-0.09	1962-1973
	1916		35	1951	30	1946				
			41	1957	46	1962				
			63	1979	70	1986				
			69-70	1985-86						
9	Electric Shavers	55	36	1973	36-39	1973-76	0.22	-0.09	-0.11	1938-1945
	1937				49	1986				
10	Electrocardiographs	50	6	1948	6	1948	0.25	0.41	0.37	1964-1969
	1942		32	1974	48	1990				
11	Freezers	46	27	1973	40	1986	0.41	-0.13	0.23	1947-1957
	1946									

Red = Is or may be in GK Stage 4 **Blue = Within 1 year of exit spike**

Table 2: Entry and Exit Statistics in Agarwal's data

	Product & yr of comm intr.	Length of raw series	EXIT spike dates in yrs since comm intro	EXIT spike dates in calendar yr	ENTRY spike dates in yrs since comm intro	ENTRY spike dates in calendar yr	Corr btw smthed entry and exit rates	Corr btw entry and exit residuals	Corr btw entry and exit rates	G-K stage 4
12	Freon Compressors	57	5	1940	3	1938	-0.21	-0.12	-0.17	1971-1973
	1935		**37**	**1972**	46	1981				
			52	1987						
13	Gas Turbines	48	20	1964	2	1946	-0.42	0.00	-0.22	1973-
	1944				36	1980				
					41	1985				
14	Guided Missiles	41	2	1953	8	1959	-0.32	-0.43	-0.41	1965-1973
	1951				35	1986				
15	Gyroscopes	77	10	1925	4	1919	0.36	0.10	0.24	1966-1973
	1915		31-32	1946-47	**30-32**	1945-47				
					39-40	1954-55				
16	Heat Pumps	38	5	1959	25	1979	-0.42	-0.08	-0.24	1970-1973
	1954		**16**	**1970**						
			32	1986						
17	Jet Engines	44	6	1954	**6**	1953-54	-0.26	0.42	0.07	1960-1962
	1948		22	1970	32	1980				
					35	1983				
18	Microfilm Readers	52	5-6	1945-46	8	1948	0.37	-0.24	-0.12	S4 not reached
	1940		16	1956	22-23	1962-63				
					33	1973				
					45	1985				
19	Nuclear Reactors	37	30	1985	**30**	1985	-0.57	0.12	-0.38	1965-1973
	1955		33	1988	35	1990				
20	Outboard Motors	79	22	1935	2-4	1915-17	-0.18	0.07	-0.08	1921-1923
	1913		67	1980	28	1941				
					34	1947				
					72	1985				
21	Oxygen Tents	60	**41**	**1973**	4	1936	-0.32	-0.17	-0.26	1967-1973
	1932		48	1980	56	1988				
			52-53	1984-85						
22	Paints	58	**39**	**1973**	13-14	1947-48	-0.41	0.04	-0.20	1967-1973
	1934		43	1977	20	1954				

Red = Is or may be in GK Stage 4 **Blue = Within 1 year of exit spike**

Table 2, continued

	Product & yr of comm Intr.	Length of raw series	EXIT spike dates in yrs since comm intro	EXIT spike dates in calendar yr	ENTRY spike dates in yrs since comm intro	ENTRY spike dates in calendar yr	Corr btw smthed entry and exit rates	Corr btw entry and exit residuals	Corr btw entry and exit rates	G-K stage 4
23	Phonograph Records	84	5	1913	9	1917	-0.23	0.08	-0.07	1923-1934
	1908		25	1933	13	1921				
			51	1959	40	1948				
			65-66	1973-74	67	1975				
24	Photocopying Machines	52	34	1974	42	1982	-0.30	-0.20	-0.25	1965-1973
	1940		39	1979						
25	Piezoelectric Crystals	51	13	1953	3	1943	-0.28	-0.06	-0.21	1955-1957
	1940		40	1980	45	1985				
26	Polariscopes	64	15	1943	18	1946	0.20	-0.26	-0.03	1964-1967
	1928		45	1973	23	1951				
					25	1953				
					44	1972				
27	Radar Antenna Assemblies	40	15	1967	4	1956	-0.50	-0.10	-0.32	1957-1968
	1952		21	1973	33	1985				
28	Radiant Heating Baseboards	45	25	1972	27	1974	-0.42	0.02	-0.19	1972-1973
	1947		37	1984						
29	Radiation Meters	43	no spike dates		6	1955	-0.28	0.20	-0.13	not in G-K
	1949				37	1986				
					41	1990				
30	Recording Tapes	40	11	1963	33	1985	-0.53	0.06	-0.31	1973-
	1952		28	1980						
31	Rocket Engines	34	32	1990	7	1965	-0.34	-0.08	-0.19	1973-
	1958				33	1991				
32	Styrene	54	17	1955	4-5	1942-43	-0.55	-0.09	-0.27	1966-1973
	1938				20-1	1958-59				
33	Video Cassette Recorders	18	no spike dates		7	1981	-0.33	-0.18	-0.11	not in G-K
	1974				11	1985				
	average	51.94					-0.11	-0.01	-0.07	
	max	84.00					0.92	0.55	0.79	
	min	18.00					-0.57	-0.43	-0.41	
	std deviation	14.97					0.40	0.22	0.27	

Red = Is or may be in GK Stage 4 **Blue = Within 1 year of exit spike**

Table 2, continued