Learning, Diffusion and the Industry Life Cycle

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Abstract

Firm numbers initially rise and later fall as an industry evolves. This nonmonotonicity, termed as "shakeout", is not well explained in the existing literature which overlooks the dynamic structure of new product demand. In this paper, I explain the time path of industrial evolution as a competitive equilibrium outcome driven by the dynamic interaction among technology progress, income growth and, in particular, demand diffusion. When a new product is introduced, high-income consumers tend to adopt it first. The technology then improves with cumulative output (Learning by Doing) and the demand growth generates S-shaped diffusion as the product penetrates a positively skewed income distribution (Trickle Down Effect and Income Growth Effect). Eventually fewer new adopters are available and the number of firms starts to decline as the market gets satiated. It is shown that faster technological learning, higher mean income or larger market size contributes to faster demand diffusion and earlier industry shakeout. Empirical studies on the US and UK television industries as well as ten other US industries show that the model well explains the patterns of industrial evolution across countries and products.

1 Introduction

1.1 Questions on the Industry Life Cycle

As a new industry evolves from birth to maturity it is typically observed that price falls, output rises, and the number of firms initially rises and later falls (Gort and Klepper 1982, Klepper and Graddy 1990). In particular, the nonmonotonic time path of firm numbers, termed as "shakeout", has been the focus of many recent studies of industry economics. The big question is why there is a shakeout and when it occurs.

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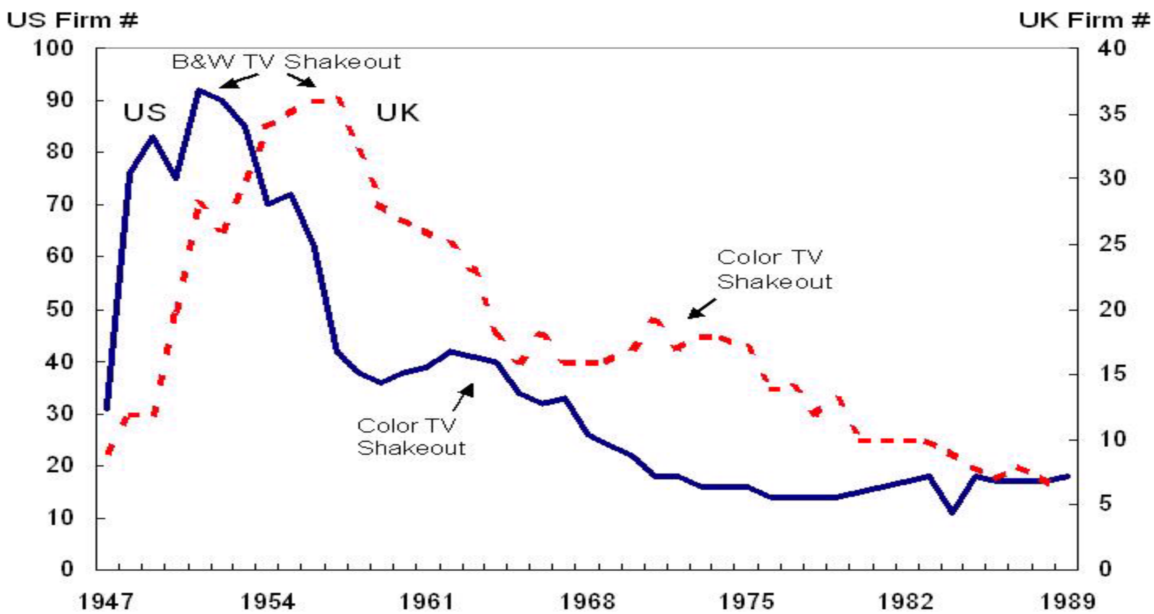

Figure 1: TV Industry Shakeout: US vs. UK

Most theories suggest that technological change is the key. It has been claimed that shakeout could be triggered by "emergence of the dominant design" (Utterback and Suárez 1993, Hopenhayn 1993), "gamble for a major innovation" (Jovanovic and MacDonald 1994), or "advantage of large firm size" (Klepper 1996, Klepper and Simons 2000). Some other explanations emphasize the demand uncertainty in new product markets. For example, the "uncertain profit" (Horvath, Schivardi and Woywode 2001) or "uncertain market size" (Rob 1991, Zeira 1987, 1999) can easily result in a mass entry and later shakeout.

Although all the theories mentioned above are able to generate a nonmonotonic time path of firm numbers, there are certain other facts that they do not explain. For example, let us look at Figure 1, which shows the time path of firm numbers in the US and UK television industry. The television was commercially introduced into the US and UK at the same time after the WWII, and the two markets were separately developed for the following two decades because of their different technical standard.[1] This natural experiment shows that the patterns of industrial evolution were very similar across countries, but the mass entry and shakeout for TV's in the UK was uniformly lagged behind the US.

Can any of the existing theories explain the TV shakeout and its different timing

[1]The UK adopted the 405-line screen standard in 1943, but other nations proceeded to adopt standard with higher resolutions. The UK standard remain anomalous through 1964, when some UK broadcasts began using the internationally common PAL 625-line color standats. Hence through 1964 and longer, UK market was isolated from the foreign competition. See Levy (1981).

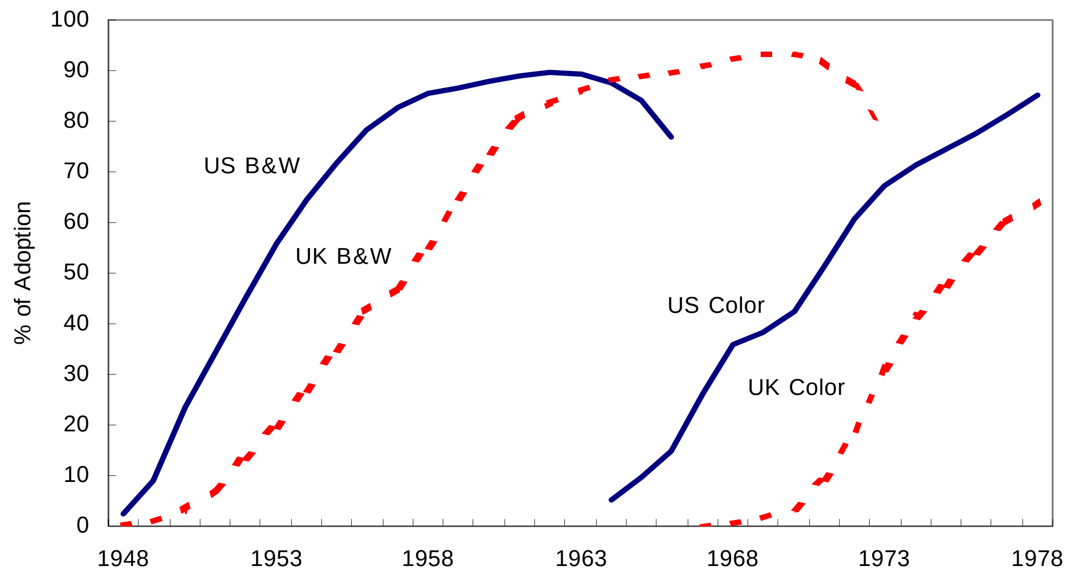

Figure 2: TV Adoption: US vs. UK

across countries? The answer is negative. On one hand, industry studies (Arnold 1985, LaFrance 1985) show that there was no dramatic technological change that accounts for the shakeout in either country. On the other hand, the demand uncertainty could not have caused the shakeout repeatedly since at least the UK producers can easily learn about the market from the US experience. Moreover, the TV shakeout had little to do with foreign competition because the import and export were very insignificant long after the shakeout occurred in each country.[2]

It is questions like this that motivate this study. In this paper, we are going to construct a new theory not only to explain the general pattern of industry life cycle but also to reveal how country-specific factors, the income distribution and market size in particular, shape this process. As part of this effort we will take the TV industry dynamics as an example to bring the theory to data.

1.2 My Hypothesis

One critical problem with the aforementioned theories is that they overlook an especially important issue about new products – the demand diffusion. New products are not adopted by potential customers simultaneously. Rather, the timing of adoption

[2] In 1950s, US and UK were the two largest TV producers in the world, but imports and exports were nil for both nations. Imports started to increase in 1960s as Japan took off, but did not reach 10% of domestic production until 1965 in US, and until 1970 in UK. Data sources: *Television Factbook* (US), *Monthly Digest of Statistics* (UK).

is distributed in some fashion over the population. Without taking that into consideration, their analyses of the industry life cycle tend to be incomplete or incorrect.

In this paper, I study explicitly the demand diffusion and its dynamic effects on the industrial evolution. When a new product is introduced, high-income consumers tend to adopt it first. The technology then improves with cumulative output (Learning by Doing) and the demand growth generates S-shaped diffusion as the product penetrates a positively skewed income distribution (Trickle Down Effect and Income Growth Effect). Eventually fewer new adopters are available and the number of firms starts to decline as the market gets satiated. Therefore, the industry life cycle is explained as a competitive equilibrium outcome driven by the dynamic interaction among technology progress, income growth and, in particular, demand diffusion. It is shown that faster technological learning, higher mean income or larger market size contributes to faster demand diffusion and earlier industry shakeout. This new theory provides a good explanation for the industrial evolution across many products and countries. For example, in the case of TV, it was mainly the lower per capita income and smaller market size in the UK than the US that led to a slower diffusion of television (Figure 2) and hence a lagged industry shakeout.

1.3 Relation to Other Research

By exploring the dynamic interaction among technological learning, demand diffusion and the evolution of market structure, this paper connects the studies of industry economics with research in otherwise separate fields. For example, in the marketing literature, the diffusion of new products has been studied for the purpose of demand forecast and monopoly pricing (Bass 1969, Kalish 1983, Horsky 1990). In the growth literature, the learning by doing is one of the most important engine for long run growth (Arrow 1962, Lucas 1993, Jovanovic & Rousseau 2002, Matsuyama 2003). In the international trade literature, the most celebrated “product cycle theory” claims that the demand for new consumer goods is initially greatest in high-income countries, and diffuse to lower-income countries later on (Vernon 1966, Stokey 1991 and Grossman & Helpman 1991). In the technology adoption literature, it has been found that per capita GDP is one of the key variable that explains the diffusion rate of new technology across nations (Comin & Hobijn 2003). However, all these studies have so far been unconnected with the study of industry dynamics. This paper is the first step to fill this gap, which shows that the typical pattern of industrial evolution is closely related and consistent with the findings in those fields.

1.4 Road Map

The paper is organized as follows. Chapter 2 models the supply structure of a competitive industry and reveals the equilibrium relation between the firm numbers and the relative industry GDP. Chapter 3 derives the market demand for a new nondurable good. In particular, it shows how to endogenize the demand diffusion by explicitly modeling consumers' heterogeneity of income and preference. Chapter 4 puts together the supply and demand, and introduces the law of motion for technology and income. Chapter 5 characterizes the dynamic industry equilibrium and discusses the time path of price, output and market structure. Chapter 6 extends the model to durable goods. Chapter 7 estimates our model with the data of the US and UK TV industries and ten other US industries. Chapter 8 contains concluding remarks.

2 The Supply Structure

The typical industry life cycle features falling price, rising output and nonmonotonic time path of firm numbers. In this section, by modeling the supply structure of a competitive industry we reveal some important relation among these variables, namely the comovement of the firm numbers and the relative industry GDP.

2.1 The Model

Assume a competitive industry produces one homogenous product. There are M potential producers that differ in their ability $\theta \in (0, \infty)$ for working in this industry. This ability θ, distributed with cdf function $S(\theta)$, can be interpreted as the efficiency of management. Anything else being equal, a more efficient firm produces more. Each period, a firm that actively produces in this industry has to pay a fixed cost C, which corresponds to the foregone earning of the entrepreneur who runs the firm. For a typical firm, x and y respectively denote the input and output. The production function is assumed to be $y = \theta A x^{\alpha}$ where A is the technology and $0 < \alpha < 1$ is the "span of control" parameter[3]. Let P denote the price of output, w the price of input. We also assume that firms can enter and exit freely.[4]

Each period, firm θ takes the market price P as given to maximize the profit:

$$\pi_\theta = \max_{y_\theta, x_\theta} \quad P y_\theta - w x_\theta - C$$

$$s.t. \quad y_\theta = \theta A x_\theta^{\alpha}$$

and get the solution:

$$\begin{aligned} y_\theta^* &= \left(\frac{\alpha P A^{\frac{1}{\alpha}} \theta^{\frac{1}{\alpha}}}{w}\right)^{\frac{\alpha}{1-\alpha}}; \qquad x_\theta^* = \left(\frac{\alpha P A \theta}{w}\right)^{\frac{1}{1-\alpha}}; \\ \pi_\theta &= (1-\alpha)(\alpha)^{\frac{\alpha}{1-\alpha}} w^{\frac{-\alpha}{1-\alpha}} (P A \theta)^{\frac{1}{1-\alpha}} - C \end{aligned}$$

[3] The "span of control" parameter captures the idea of managerial diseconomy of scale, and helps pin down the optimal firm size. See Lucas (1978).

[4] This assumption can be relaxed. See Appendix A for the discussion.

The free entry and exit condition ensures that the marginal firm, the lowest-ability player allowed in the industry, breaks even. The marginal firm's ability is denoted by $\tilde{\theta}$, and we get

$$C = (1-\alpha)(\alpha)^{\frac{\alpha}{1-\alpha}} w^{\frac{-\alpha}{1-\alpha}} (PA\tilde{\theta})^{\frac{1}{1-\alpha}}$$

The market price is then determined to be:

$$P = \frac{C^{1-\alpha} w^{\alpha}}{(1-\alpha)^{1-\alpha}(\alpha)^{\alpha} A\tilde{\theta}} \tag{1}$$

and we can solve more explicitly each firm's choice:

$$y^*_{\theta} = (\frac{\alpha C}{(1-\alpha)w})^{\alpha} A\theta^{\frac{1}{1-\alpha}}\tilde{\theta}^{\frac{\alpha}{\alpha-1}}; \qquad x^*_{\theta} = \frac{\alpha C}{(1-\alpha)w}\theta^{\frac{1}{1-\alpha}}\tilde{\theta}^{\frac{1}{\alpha-1}}; \tag{2}$$

$$\pi_{\theta} = [(\theta/\tilde{\theta})^{\frac{1}{1-\alpha}} - 1]C \tag{3}$$

The total market supply Y is the sum of individual firms' outputs:

$$Y = M\int_{\tilde{\theta}}^{\infty} y^*_{\theta} dS(\theta) = (\frac{\alpha C}{(1-\alpha)w})^{\alpha}\tilde{\theta}^{\frac{\alpha}{\alpha-1}} AM \int_{\tilde{\theta}}^{\infty} (\theta^{\frac{1}{1-\alpha}}) dS(\theta) \tag{4}$$

The corresponding number of firms is

$$N = M\int_{\tilde{\theta}}^{\infty} dS(\theta) \tag{5}$$

At equilibrium, the market supply equals the market demand. Equation 1 and 4 then implies the industry GDP to be

$$PY = \frac{C}{1-\alpha}\tilde{\theta}^{\frac{1}{\alpha-1}} M \int_{\tilde{\theta}}^{\infty} (\theta^{\frac{1}{1-\alpha}}) dS(\theta) \tag{6}$$

If we further assume that C, the foregone earning of the entrepreneur, grows with the mean income μ of the economy, e.g. $C = \phi\mu$, and the other parameters α, M and $S(\theta)$ are time-invariant, the following proposition suggests an important time-series relation between the firm numbers N and the relative industry GDP, PY/μ.

Proposition 1 *In a competitive market, the number of firms is positively related with the relative industry GDP, i.e.* $\partial N/\partial(PY/\mu) > 0$.

Proof. Equation 5 and 6 imply

$$\frac{\partial N}{\partial(PY/\mu)} = \frac{\partial N}{\partial\tilde{\theta}}\frac{\partial\tilde{\theta}}{\partial(PY/\mu)} > 0$$

Hence the proposition is proved. ■

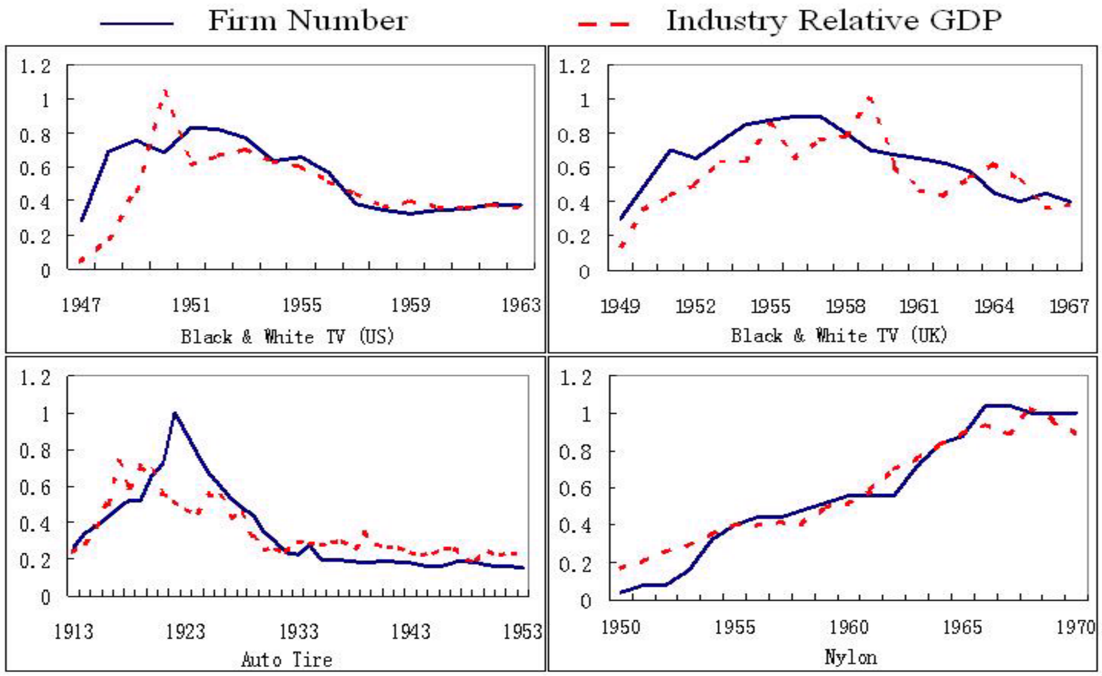

Figure 3: Firm Numbers and Relative Industry GDP: Evidence I

2.2 Examples and Remarks

There should be no surprise to find out that the model implies a comovement between the number of firms N and the relative industry GDP, PY/μ. In fact, the earning of the marginal entrepreneur increases with PY (the total industry GDP) and his opportunity cost is determined by μ (the mean income of the economy). It follows that the ratio PY/μ keeps track with the viable number of firms.

In some special cases, we can further show that the number of firms is proportional to the relative industry GDP, i.e. $N = z(PY/\mu)$ where $z > 0$ is a constant.

Example 1 *If θ follows a Pareto distribution, N is proportional to PY/μ.*

Proof. Assuming θ follows a Pareto distribution, we have

$$dS(\theta)/d\theta = \{ \begin{array}{ll} aL^a/\theta^{a+1} & \text{if } \theta \geq L \\ 0 & \text{if } \theta < L \end{array}$$

where $a > 0$, $L > 0$. Assuming $a > 1/(1-\alpha)$, Equation 6 implies that

$$PY = \frac{\phi\mu M}{1-\alpha}\tilde{\theta}^{\frac{1}{\alpha-1}} \int_{\tilde{\theta}}^{\infty} (\theta^{\frac{1}{1-\alpha}}) \frac{aL^a}{\theta^{a+1}} d\theta = \frac{\phi\mu a L^a M}{a(1-\alpha)-1}\tilde{\theta}^{-a}$$

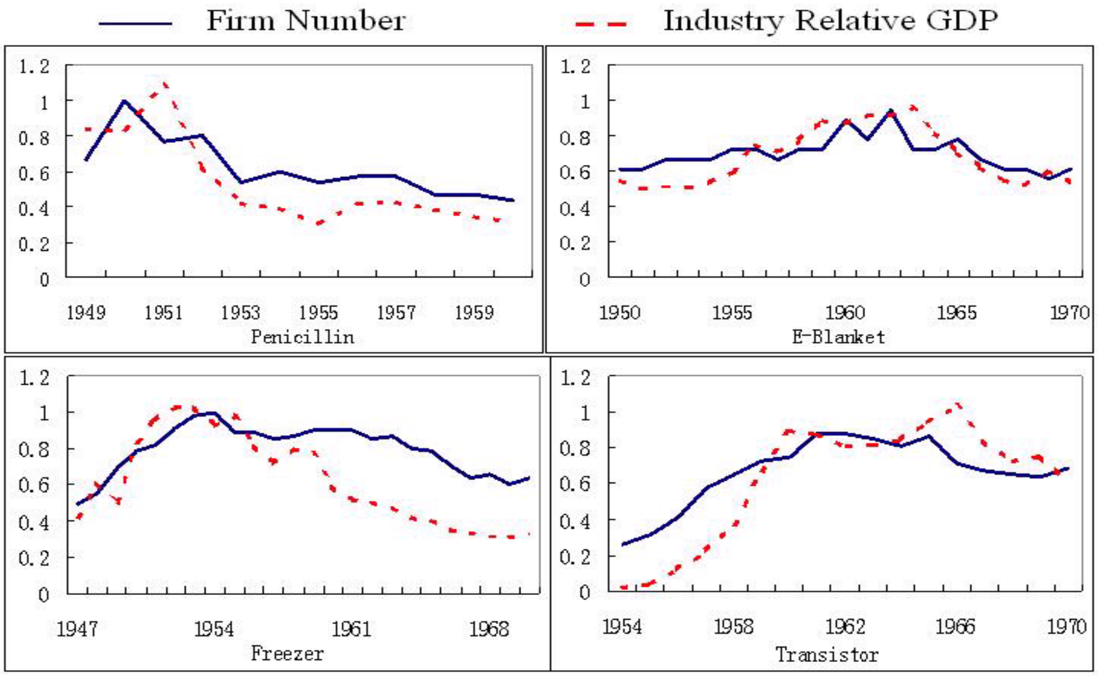

Figure 4: Firm Numbers and Relative Industry GDP: Evidence II

and Equation 5 implies that

$$N = M \int_{\tilde{\theta}}^{\infty} \frac{aL^a}{\theta^{a+1}} d\theta = ML^a \tilde{\theta}^{-a}$$

Therefore

$$N = z(PY/\mu) \qquad \text{where} \qquad z = \frac{a(1-\alpha)-1}{\phi a}$$

which proves that N is proportional to PY/μ. ■

Example 2 *If θ follows a degenerate distribution, N is proportional to PY/μ.*

Proof. Assuming firms are identical in ability θ, we have

$$PY = \frac{\phi\mu}{(1-\alpha)} N$$

Therefore

$$N = z(PY/\mu) \qquad \text{where} \qquad z = \frac{1-\alpha}{\phi}$$

which proves that N is proportional to PY/μ. ■

To derive Proposition 1, we have assumed that α, M and $s(\theta)$ are constant over time. The empirical evidence we have suggests that for many industries these assumptions work quite well. Figure 3 and 4 present the data for the US and UK Black & White TV industries as well as six other US industries. In those cases, we can clearly see the comovement of the firm numbers and the relative industry GDP. For most of our following analyses, we will maintain these assumptions. Moreover, we will show in Appendix B that it is possible to relax some of those assumptions but retain the essence of our analysis. More empirical evidence of Proposition 1 will be presented in section 7.4.

3 The Demand Structure

Now let us turn to the demand side. To explain the industrial evolution, it becomes crucial to understand the dynamic nature of market demand for a new product. In this chapter, we propose a novel analysis on this subject.

3.1 Questions on the Traditional Wisdom

It has long been a challenge to explain the demand of new products. In the economics and marketing literature, the most popular theory of new product diffusion focuses on the social contagion effect, i.e. people imitate early adopters. This explanation has been formally established by introducing the logistic curve and its variants since 1950s (Griliches 1957, Mansfield 1961 and Bass 1969).

The simple logistic curve has the property that the hazard rate of adoption rises with cumulative adoption.

$$\frac{\dot{F}_t}{1 - F_t} = vF_t$$

where F_t is the fraction of consumers who have adopted the product at time t, and v is a constant contagion parameter.

It implies the following adoption process, which has traditionally fit data very well.

$$F_t = \frac{1}{[1 + (\frac{1}{F_0} - 1)e^{-vt}]} \tag{7}$$

However, some serious problems arise for this conventional wisdom. In particular, the following puzzles can not be explained:

- Why a new product diffuses faster in some regions (countries) than others?
- Why a new product diffuses faster in some consumer groups than others?

Appliance	1% Penetration in the US Market	Leading Years of Penetration (US-UK) 1%	20%	50%
B &W TV	1948	+1	+2	+5
Color TV	1961	+9	+8	+7
Cloth Washer	1916	+18	+35	+38
Cloth Dryer	1950	0	+20	
Dishwasher	1922	+35		
Electric Blanket	1948	+7	+2	+3
Freezer	1947	+21	+19	
Motor Car	1908	0	+41	
Radio	1923	0	+4	+12
Refrigerator	1925	+21	+29	+30
Vacuum Cleaner	1913	+2		+14

Table 1: Diffusion Comparison of Household Appliance: US vs. UK

- Why some new products diffuse faster than others?

Since the social contagion theory assumes that adopters are homogenous and the diffusion parameters F_0, v are exogenous, it has no answer for the above questions. To seek the answer, we may look at some cross-country empirical evidence.

Table 1 compares the diffusion of household appliance between the US and the UK.[5] The data shows clearly that the US adopts new products uniformly earlier and faster than the UK. It suggests that the diffusion rates are not arbitrarily determined, and some country-specific factors must play important roles. This conjecture is further confirmed by the evidence in Figure 5, which plots the TV adoption rate verse per capita GDP for 104 countries in 1980.[6] At that time, TV was surely no longer a new product in the world market so that there leaves little room for the social contagion theory to explain any part of the diffusion. Instead, the cross-country heterogeneity of adoption is so clearly related with the heterogeneity of income across countries. Therefore, we expect a better diffusion theory to explicitly consider the heterogeneity of adopters.

3.2 My Approach

This paper is a new exploration on this subject, in which we endogenize the demand diffusion by explicitly modeling the heterogeneity of consumers.[7] As the result, we

[5]Data Source: Bowden & Offer (1994).

[6]Data Source: *UN Common Database.*

[7]In studying the diffusion of new technology among producers, Paul David (1969) suggests that a positive skewed distribution of firm size may result in a S-type diffusion curve. Here the idea is extended to study the diffusion of consumer goods. For related work, see Horsky (1990).

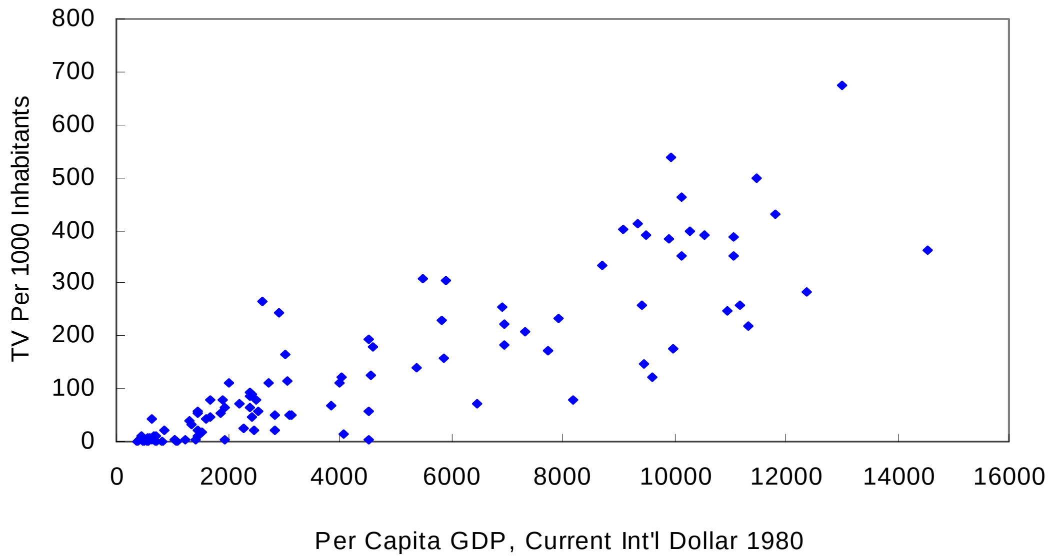

Figure 5: Per Capita GDP and TV Adoption in 104 Countries, 1980

will be able to explain not only the presence of logistic diffusion curves, but also how the diffusion process is shaped by economic forces like price and income. The model is presented as follows.

Assume a new nondurable product sells for price P in the market.[8] An individual consumer will adopt it only if her disposable income I_d on that product allows her to do so, i.e.

$$y = \begin{cases} 1 & \text{if} \quad I_d \geqslant P \\ 0 & \text{if} \quad I_d < P \end{cases}$$

Consumers are heterogenous in their disposable income I_d on this new product. This heterogeneity comes from their different income and preference. In particular, we assume that the disposable income I_d is the product of her total income I $(I \geq 0)$ and propensity of spending c $(1 \geq c \geq 0)$[9], i.e.

$$I_d = cI$$

with I and c independently distributed over the population. A proposition follows immediately.

Proposition 2 *New products diffuse faster in higher-income groups.*

[8]It is assumed here that the new product is a nondurable good. In chapter 6 and 7 we will see that introducing durability does not change much the analysis.

[9]Assuming a constant fraction of spending on a certain consumption category is equivalent to assuming a Cobb-Douglas utility function for individual consumers.

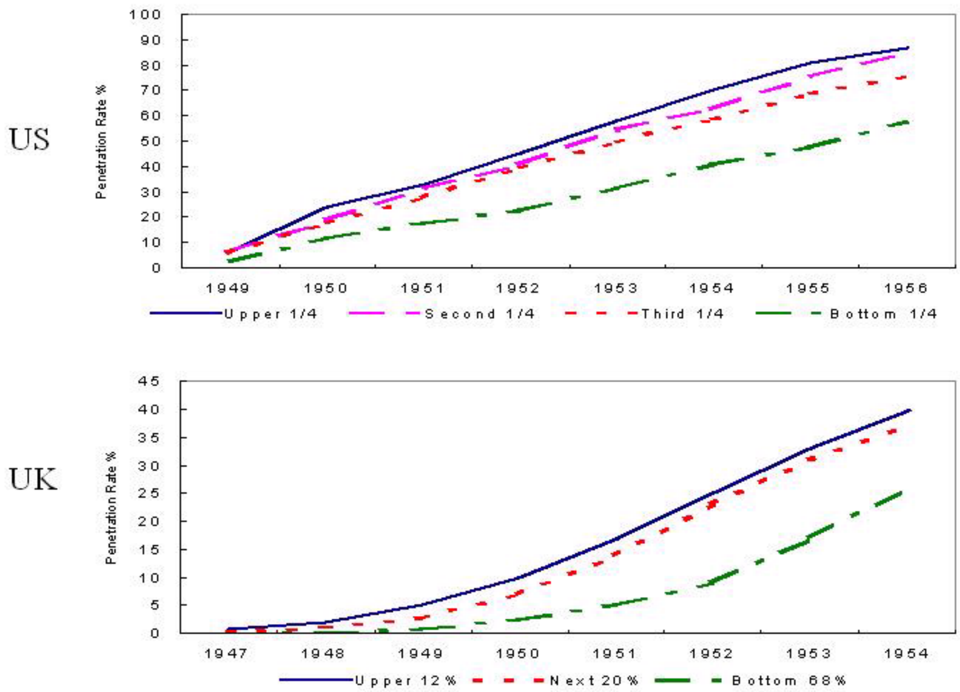

Figure 6: TV Penetration Rates by Income Class: US and UK

Proof. Denote $H(c)$ to be the cdf function of c. Since I and c are independent, for a given income group the fraction of people who adopt the new product is

$$\Pr(I_d \geqslant P \mid I) = \Pr(cI \geq P \mid I) = H(I/P)$$

and it rises with I. ■

Proposition 2 actually states a well-known fact of new product diffusion. In Figure 6 we present the penetration rates of the Black & White TV in different income groups in the US and UK at its early years.[10] It clearly shows that new products diffuse faster in higher-income groups.

Since the disposable income I_d is generally not observable, we would like to learn more about it from the observables. The following lemma gives the clue.

Lemma 1 *A higher mean (inequality) of total income I implies a higher mean (inequality) of disposable income I_d.*

Proof. Since I and c are independently distributed, we have the mean of disposable income $E(I_d)$ increases with the mean income $\mu = E(I)$:

$$E(I_d) = E(c)\mu \Longrightarrow dE(I_d)/d\mu > 0$$

[10] Data source: the US data is from Bogart (1972); the UK data is from Emmett (1956).

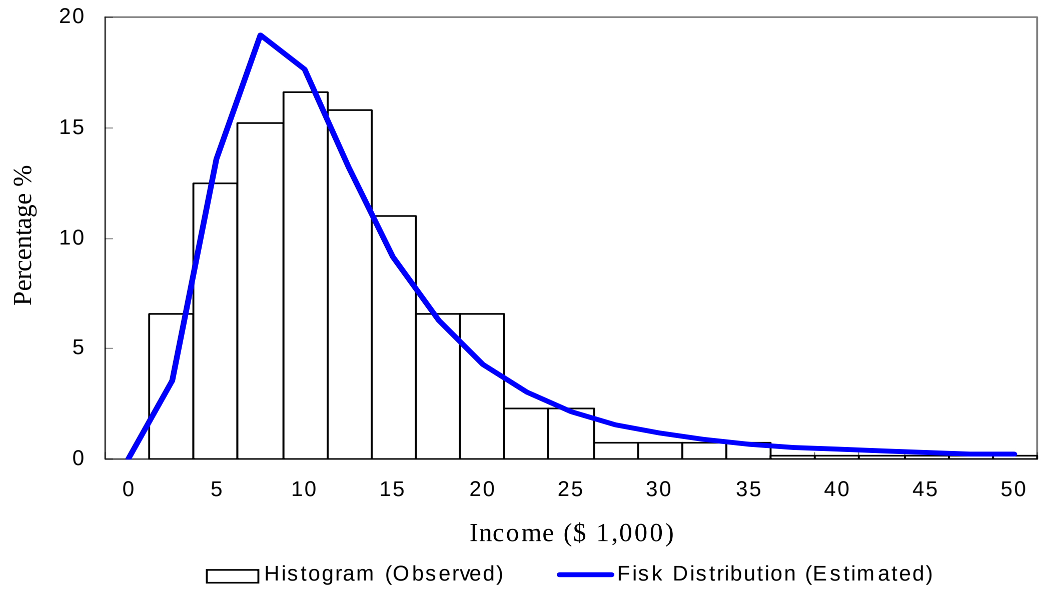

Figure 7: US Family Income Distribution 1970

and the coefficient of variation of the disposable income, $v(I_d) = \sqrt{Var(I_d)}/E(I_d)$, increases with $v(I)$:

$$v(I_d) = \sqrt{(v^2(c) + 1)(v^2(I) + 1) - 1} \Longrightarrow dv(I_d)/dv(I) > 0$$

Hence Lemma 1 is proved. ■

Lemma 1 establishes the relations between the unobserved disposable income and the observed income so that our theory can be applied to empirical work later on.

3.3 An Explicit Formulation: Log-logistic Distribution

To take our analysis a step further, we have to model the disposable income more explicitly. By the way of constructing the disposable income, we know that I_d is distributed over the domain $[0, \infty)$, so its distribution tends to be positively skewed. The possible candidates for this group of distribution are far from unique, so the best thing we can do is to pick a reasonable one.

In the following discussion, we introduce the log-logistic distribution as our specific example. Though not as well known as its sister distribution, the log-normal, the application of log-logistic distribution has a long history in economics. Its use can be traced back to the study of Lomax (1954) on business failure rates, and to Fisk (1961) on the size distribution of income[11]. The reason for us to pick the log-logistic

[11] Figure 7 shows an example of using the Fisk (log-logistic) distribution to fit US family income 1970. See McDonald (1984).

distribution here is not only because it can serve as an easily tractable representative of the larger group of positively skewed distributions, but also because it connects our study to the typically observed logistic diffusion curves as we will show next.

The log-logistic distribution is defined as the distribution of a variate whose logarithm is logistically distributed. Assume that the disposable income I_d follows the log-logistic distribution. The cdf function is given as

$$G_{I_d}(x) = 1 - \frac{1}{1 + a_1 x^{a_2}}$$

with the mean $E(I_d)$ and Gini coefficient[12] $g(I_d)$ given as

$$E(I_d) = a_1^{-1/a_2}\Gamma(1 + \frac{1}{a_2})\Gamma(1 - \frac{1}{a_2}); \qquad g(I_d) = \frac{1}{a_2}$$

Hence, we may rewrite the cdf function into a more meaningful form:

$$G_{I_d}(x) = 1 - \frac{1}{1 + (\frac{\Gamma(1+g)\Gamma(1-g)}{E(I_d)} x)^{1/g}}$$

where $g = g(I_d)$.

Given $E(I_d) = E(c)\mu$, we can now derive the adoption rate F to be a function of price, mean income and other parameters:

$$F = 1 - G(P) = \frac{1}{1 + \eta(P/\mu)^{1/g}} \tag{8}$$

where $\eta = (\Gamma(1 + g)\Gamma(1 - g)/E(c))^{1/g}$.

3.4 Endogenous Diffusion vs. Exogenous Diffusion

The appealing feature of introducing the log-logistic distribution is that we can easily endogenize the logistic diffusion curves. To see this, let us assume that the price declines at a constant rate $P_t = P_0 e^{-\rho t}$, and mean income grows at a constant rate $\mu_t = \mu_0 e^{xt}$. Then we can rewrite equation 8 as follows

$$F_t = \frac{1}{1 + \eta[P_0/\mu_0]^{1/g} e^{-(\rho+x)t/g}} \tag{9}$$

Comparing the equation 9 and 7, we realize that our endogenous diffusion formula is actually equivalent to the logistic model under very reasonable assumptions. Notice that the diffusion parameters traditionally treated as exogenous variables are now given clear economic meanings: the contagion parameter v is determined by the

[12] The coefficient of variation, an alternative measure of income inequality, is also only determined by the parameter a_2.

growth rate of price and income, and the initial condition F_0 is the fraction of adopters who can afford the new product at the beginning of time.

$$v = (\rho + x)/g \qquad F_0 = \frac{1}{1 + \eta[P_0/\mu_0]^{1/g}}$$

This result is also empirically plausible. Sultan et al. (1990) analyzed the parameter estimates of 213 published application of the logistic model and its extension. They report the average value of $v = 0.38$. Jeuland (1993, 1994) finds that the value of v is rarely greater than 0.5 and rarely less than 0.3. Assigning reasonable values of Gini coefficient and growth rates of income and price, our model can easily generate the value of v within that range. Further empirical analysis will be presented in section 7.6.

4 The Industry Equilibrium

Given the above analyses, we are now ready to put together the supply and demand to derive the industry equilibrium.

4.1 The Momentary Equilibrium

At a point of time, given the value of parameters, the industry equilibrium implies (1) Individual firms take the price as given and maximize their profits; (2) Individual consumers take the price as given and maximize their utility; (3) Industry price, output and firm numbers are uniquely determined to clear the market. All the findings are summarized in the following equations.[13]

$$P = \frac{C^{1-\alpha} w^{\alpha}}{(1-\alpha)^{1-\alpha}(\alpha)^{\alpha} A\tilde{\theta}} \tag{10}$$

$$Y = (\frac{\alpha C}{(1-\alpha)w})^{\alpha} \tilde{\theta}^{\frac{\alpha}{\alpha-1}} AM \int_{\tilde{\theta}}^{\infty} (\theta^{\frac{1}{1-\alpha}}) dS(\theta) \tag{11}$$

$$Y = mF = \frac{m}{1 + \eta(P/\mu)^{1/g}} \tag{12}$$

$$N \;=\; M \int_{\tilde{\theta}}^{\infty} dS(\theta) \propto \frac{PY}{C} \tag{13}$$

[13]Notice that although we have so far assumed that individual consumers can only make unit purchase and the disposable income has a log-logistic distribution, they are harmless simplifications and can be relaxed. The proof is available from the author.

Notice m denotes the total number of potential consumers. Since the number of potential consumers and producers are both closely related to the population size, it is reasonable to assume that the ratio M/m is a constant.

This is a system of four equations with four unknowns. The solution shows that the equilibrium values of P, Y, $\tilde{\theta}$ and N are endogenously determined by the four important parameters: technology A, mean income μ, foregone earning C and input price w. With reasonable assumptions on the law of motion for those parameters, we will then be able to characterize the time path of industrial evolution.

4.2 Law of Motion Equations

4.2.1 Learning-by-Doing Technology Progress

Technology progress is commonly observed over the industry life cycle. Many theoretical and empirical work (Arrow 1962, Boston Consulting Group 1972 and etc.) have identified that learning by doing is one of the most important driving force. The productivity gains, closely linked to growth in cumulative output, typically stem from a wide variety of underlying sources, including improvement in capital equipment, better product and process designs, and improved organizational and individual skills. Therefore, in our context, we assume that the technology A is determined by the cumulative industry output as follows.

$$A_t = A_0(Q_t)^\gamma \tag{14}$$

in which $Q_t = \int_0^t Y(s)ds + Q_0$ and γ is the learning rate.

The above formula implies that only aggregate cumulative output matters to every producer's productivity. In fact, a firm's own contribution to Q seems to matter more than that of others, especially at high frequencies (Irwin & Klenow 1994, Thompson & Thornto 2001). However, at lower frequencies, the distinction between own and outside experience should fade given the wide range of channels by which information diffusion can occur.[14] Therefore, we take equation 14 as a reasonable formulation.

4.2.2 Income Growth and Its Effects

Since the mean income of the economy is determined outside any single industry, we assume it grows at an exogenous rate x,

$$\mu_t = \mu_0 e^{xt} \qquad \text{with} \quad \mu_0 > 0, \;\; x > 0$$

[14] Lieberman (1987) lists many of the channels. Employees may be hired-away by rival firms. Products can be examined and reverse-engineered. Patents can be invented around or even infringed without penalty. Consultants and contractors may disseminate information on new products and processes. Moreover, productivity improvements often stem form learning by capital equipment suppliers, whose innovations become available to all firms in the industry.

Also as we discussed in Section 2.1 the foregone earning of the entrepreneur C grows with the mean income μ, hence we have

$$C_t = \phi\mu_t \qquad \text{with} \qquad \phi > 0$$

The law of motion for the input price w is a little complicated. Since we assume there is only one input in our model, w is actually a composite price index for both labor and non-labor inputs. Though the price of labor inputs may grow with the mean income, the price of non-labor inputs like capital and materials does not. Therefore, it is reasonable to assume that $d(w/\mu)/d\mu < 0$. A simple formulation is

$$w_t = \sigma\mu_t^{\psi} \qquad \text{with} \qquad \sigma > 0, \quad \psi < 1$$

4.3 The Dynamic Equilibrium

With the above discussion, we can now summarize the dynamic equilibrium into the following system of equations:

$$\frac{P_t}{\mu_t} = \frac{(\phi)^{1-\alpha}(\sigma\mu_t^{\psi-1})^{\alpha}}{(1-\alpha)^{1-\alpha}(\alpha)^{\alpha}A_t\tilde{\theta}_t} \tag{15}$$

$$Y_t = \left(\frac{\alpha\phi\mu_t^{1-\psi}}{(1-\alpha)\sigma}\right)^{\alpha}\tilde{\theta}_t^{\frac{\alpha}{\alpha-1}}A_t M\int_{\tilde{\theta}_t}^{\infty}(\theta^{\frac{1}{1-\alpha}})dS(\theta) \tag{16}$$

$$Y_t = mF_t = \frac{m}{1+\eta(P_t/\mu_t)^{1/g}} \tag{17}$$

$$N_t = M\int_{\tilde{\theta}_t}^{\infty} dS(\theta) \propto \frac{P_tY_t}{\mu_t} \tag{18}$$

$$A_t = A_0(Q_t)^{\gamma} \quad \text{where} \quad Q_t = \int_0^t Y(s)ds + Q_0 \tag{19}$$

$$\mu_t = \mu_0 e^{xt} \tag{20}$$

Now it becomes clear that the driving forces of the industry dynamics are the technological learning and the income growth (law of motion equations 19 and 20). After the initial adoption of a new product, these two forces contribute to further technology progress and demand diffusion, and keeps this process going (See Figure 8 for an illustration). In the next section, let us find out how this recursive dynamic process drives an industry through its life cycle, and why we typically observe the number of firms initially rises and later falls.

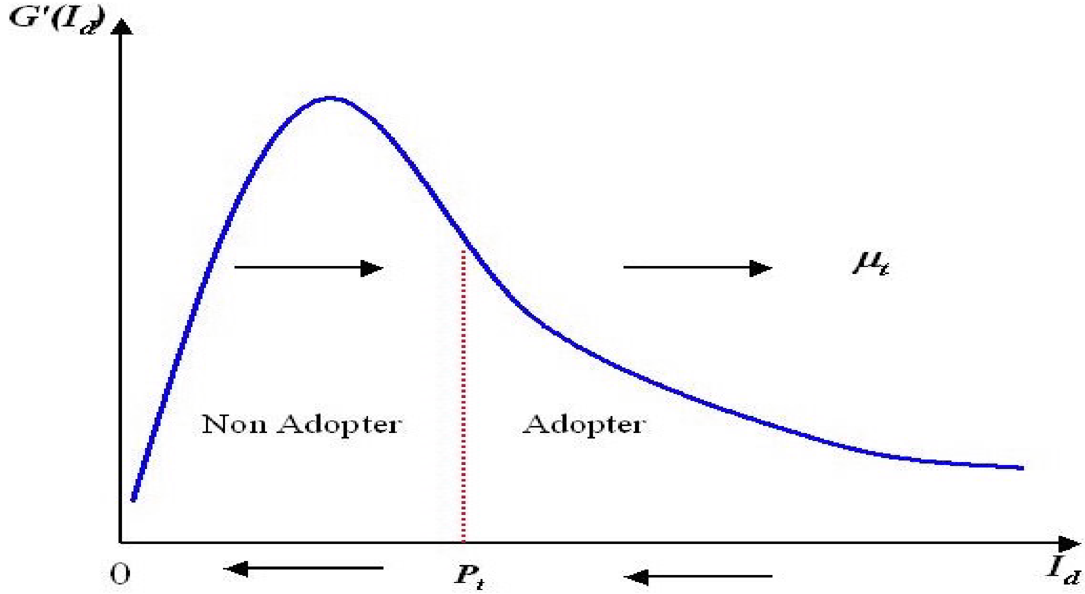

Figure 8: Product Diffuses as Technology and Income Change

5 The Industry Dynamics: Characterization

With the assumption of learning-by-doing technology progress, the market demand equation 17 implies a first-order differential equation

$$\dot{Q}_t = f(Q_t, t) = \frac{m}{1 + \eta(\frac{P}{\mu}(Q_t, t))^{1/g}} \tag{21}$$

where the relatively price P_t/μ_t is a function of (Q_t, t), and the function is determined by the equilibrium conditions 15 - 17 as follows

$$\frac{m}{1+\eta(P_t/\mu_t)^{1/g}} = (\frac{\alpha\mu_t^{1-\psi}}{\sigma})^{\frac{\alpha}{1-\alpha}} (P_t/\mu_t)^{\frac{\alpha}{1-\alpha}} A_t^{\frac{1}{1-\alpha}} M \int_{\frac{(\phi)^{1-\alpha}(\sigma\mu_t^{\psi-1})^{\alpha}}{(1-\alpha)^{1-\alpha}(\alpha)^{\alpha} A_t P_t/\mu_t}}^{\infty} (\theta^{\frac{1}{1-\alpha}}) dS(\theta) \tag{22}$$

$$\text{where} \qquad A_t = A_0(Q_t)^{\gamma}; \qquad \mu_t = \mu_0 e^{xt}$$

Theorem 1 ***(Existence and Uniqueness Theorem):*** *There exists one and only one solution $Q(t)$ of $\dot{Q}_t = f(Q_t, t)$ for $t \geq 0$ which satisfies $Q(0) = Q_0$.*

Proof. Given f is continuously differentiable, it satisfies the Lipschitz condition

$$\mid f(x,t) - f(y,t) \mid \quad \leq \quad L \mid x - y \mid$$

where $L = \sup \mid \partial f / \partial Q \mid$. Theorem 1 then follows Theorem 5 of p23 in Birkhoff & Rota (1968). ■

Theorem 2 ***(Comparison Theorem):*** *Anything else being equal, it leads to a higher Q_t (hence higher A_t) at any time t if*

- *the technology is better (higher Q_0, higher A_0 or higher γ) or*
- *the mean income is higher (higher μ_0 or higher x) or*
- *the market size is larger (higher m) or*
- *the input prices is lower (lower ϕ, lower σ or lower ψ).*

Proof. We have shown above that f satisfies the Lipschitz condition. Also we have $\partial f/\partial Q_0 > 0$ for $t = 0$ and $\partial f/\partial A_0 > 0, \partial f/\partial\gamma > 0$, $\partial f/\partial\mu_0 > 0$, $\partial f/\partial x > 0, \partial f/\partial m > 0$, $\partial f/\partial\phi < 0$, $\partial f/\partial\sigma < 0, \partial f/\partial\psi < 0$ for any given (Q_t, t). Hence Theorem 2 follows Theorem 8 and Corollary 2 of p25-26 in Birkhoff & Rota (1968). ■

5.1 Price and Output Dynamics

Given the above results, we can now characterize the time path of industry price and output.

Proposition 3 *The relative price P_t/μ_t keeps falling and output Y_t keeps rising over time.*

Proof. Equation 22 implies that $\partial(P_t/\mu_t)/\partial A_t < 0$ and $\partial(P_t/\mu_t)/\partial\mu_t < 0$. Since $A_t = A_0(Q_t)^\gamma$ and $\mu_t = \mu_0 e^{xt}$ are strictly increasing with time, we have $\partial(P_t/\mu_t)/\partial t < 0$. Furthermore, equation 17 implies $\partial Y_t/\partial(P_t/\mu_t) < 0$ so we have $\partial Y_t/\partial t > 0$. Hence Proposition 3 is proved. ■

Proposition 4 *Anything else being equal, it leads to a lower relative price P_t/μ_t and higher adoption rate F_t at any time t if*

- *the technology is better (higher Q_0, higher A_0 or higher γ) or*
- *the mean income is higher (higher μ_0 or higher x) or*
- *the market size is larger (higher m) or*
- *the input prices is lower (lower ϕ, lower σ or lower ψ).*

Proof. Let us take the case of γ as an example. Theorem 2 shows $\partial A_t/\partial\gamma > 0$ *for any time* t. Equation 22 then implies that

$$\frac{\partial(P_t/\mu_t)}{\partial\gamma} = \frac{\partial(P_t/\mu_t)}{\partial A_t}\frac{\partial A_t}{\partial\gamma} < 0$$

and equation 17 implies that

$$\frac{\partial F}{\partial\gamma} = \frac{\partial F}{(P_t/\mu_t)}\frac{\partial(P_t/\mu_t)}{\partial\gamma} > 0$$

Similarly we can prove the rest results. ■

Notice that Proposition 3 and 4 are both about the industry relative price P/μ rather than the absolute price P. In our model, it is indeed the relative price only that matters for the analysis. The time path of absolute price can not be pinned down without making further assumptions. See Section 5.3 for more discussion.

5.2 The Shakeout

By the term "shakeout", we mean the nonmonotonic time path of the firm numbers, which initially rises and later falls. It can be characterized by the following propositions .

Proposition 5 *(Existence and Uniqueness of Shakeout) Given a log-logistic distribution of the disposable income, there exists a unique shakeout.*

Proof. With a log-logistic distribution of the disposable income, the number of firms as well as the relative industry GDP is given by

$$N_t \propto \frac{P_t Y_t}{\mu_t} = (P_t/\mu_t)\frac{m}{1+\eta(P_t/\mu_t)^{1/g}}$$

Therefore

$$\partial N_t/\partial t = \frac{\partial N_t}{\partial(P_t/\mu_t)}\cdot\frac{\partial(P_t/\mu_t)}{\partial t}$$

As shown in Proposition 3, $\partial(P_t/\mu_t)/\partial t < 0$. Moreover, we have

$$\partial N_t/\partial(P_t/\mu_t) \lesseqqgtr 0 \quad \text{for} \quad P_t/\mu_t \gtreqqless [\frac{g}{\eta(1-g)}]^g$$

Therefore, the unique shakeout occurs at $(P_t/\mu_t)^* = [\frac{g}{\eta(1-g)}]^g$ and the corresponding adoption rate is $F^* = 1-g$. If $P_0/\mu_0 > [\frac{g}{\eta(1-g)}]^g$, the number of firms initially rises and later falls. If $P_0/\mu_0 < [\frac{g}{\eta(1-g)}]^g$, the number of firms declines from the very beginning. ■

Proposition 6 *(Timing of Shakeout) Anything else being equal, it leads to an earlier industry shakeout if*

- *the technology is better (higher Q_0, higher A_0 or higher γ) or*
- *the mean income is higher (higher μ_0 or higher x) or*
- *the market size is larger (higher m) or*
- *the input prices is lower (lower ϕ, lower σ or lower ψ).*

Proof. Let us consider the effect of γ on the timing of shakeout as an example. Denote the timing of shakeout to be t^*.

At the time of shakeout t^*, we have $\partial(P_tY_t/\mu_t)/\partial t = 0$ and $\partial^2(P_tY_t/\mu_t)/\partial t^2 < 0$.

$$\frac{\partial(P_tY_t/\mu_t)}{\partial t} = 0 \Longrightarrow \frac{\partial(P_t/\mu_t)}{\partial t}\frac{m}{1+\eta(P_t/\mu_t)^{1/g}}\{1 - \frac{\eta/g}{\eta + [P_t/\mu_t]^{-1/g}}\} = 0$$

Since $\frac{\partial(P_t/\mu_t)}{\partial t} < 0$, we have

$$J = \frac{m}{1+\eta(P_t/\mu_t)^{1/g}}\{1 - \frac{\eta/g}{\eta + [P_t/\mu_t]^{-1/g}}\} = 0 \quad \text{and} \quad \frac{\partial J}{\partial(P_t/\mu_t)} < 0$$

Notice that Proposition 4 suggests $\partial(P_t/\mu_t)/\partial\gamma < 0$. Therefore,

$$\frac{\partial t^*}{\partial \gamma} = -\frac{\partial^2(P_tY_t/\mu_t)/\partial t\partial\gamma}{\partial^2(P_tY_t/\mu_t)/\partial t^2} = -\frac{\frac{\partial(P_t/\mu_t)}{\partial t}\frac{\partial J}{\partial(P_t/\mu_t)}\frac{\partial(P_t/\mu_t)}{\partial\gamma}}{\partial^2(P_tY_t/\mu_t)/\partial t^2} < 0$$

Hence a higher γ leads to an earlier shakeout. Similarly, we can prove the rest results. ■

5.3 Industry Dynamics: An Intuitive Illustration

In fact, the industry dynamics can be illustrated more intuitively as follows. First, Equation 17 implies that there is a downward-sloping demand curve on $(P/\mu, F)$. Notice that only the normalized demand $F = Y/m$ matters for our discussion:

$$F = \frac{1}{1+\eta(P/\mu)^{1/g}} \tag{23}$$

Second, Equation 15 and 16 suggest that the supply curve is upward sloping on $(P/\mu, F)$, and shifts to the right if the technology A or mean income μ is higher. The normalized supply F is given as

$$F = (\frac{\alpha\mu^{1-\psi}}{\sigma})^{\frac{\alpha}{1-\alpha}}(P/\mu)^{\frac{\alpha}{1-\alpha}}A^{\frac{1}{1-\alpha}}\frac{M}{m}\int_{\frac{(\phi)^{1-\alpha}(\sigma\mu^{\psi-1}\ )^{\alpha}}{(1-\alpha)^{1-\alpha}(\alpha)^{\alpha}A(P/\mu)}}^{\infty}(\theta^{\frac{1}{1-\alpha}})dS(\theta) \tag{24}$$

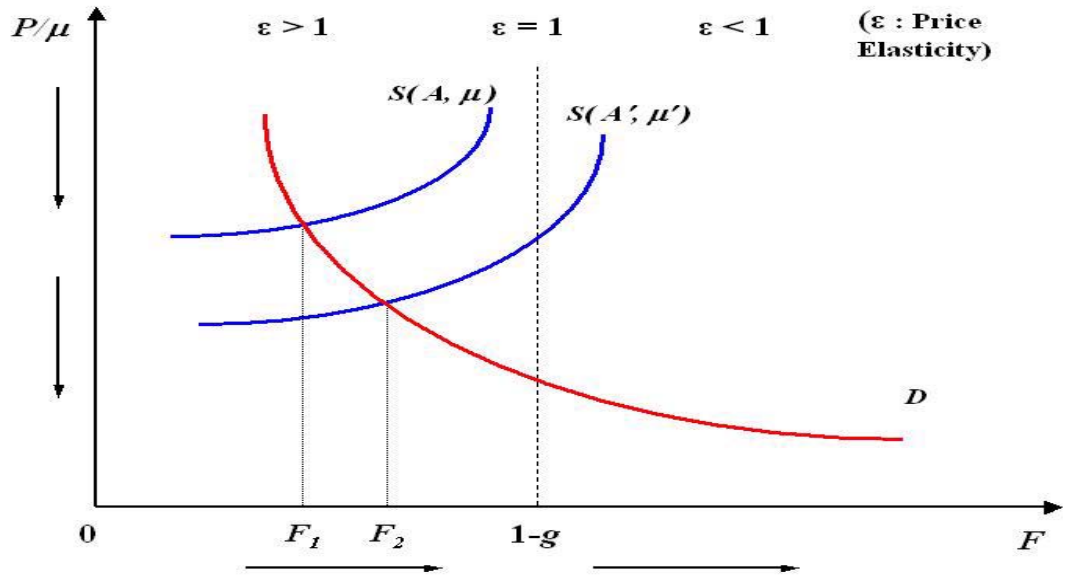

Figure 9: Industry Life Cycle: An Illustration

Plotting the demand and supply curves on the graph of $(P/\mu, F)$ for a given technology A and mean income μ, we can then pin down the solution for the static equilibrium with Figure 9.

For the dynamic analysis, we first notice there is an important property of the demand function 23 for the price elasticity:

$$\varepsilon = \mid \frac{\partial F/F}{\partial(P/\mu)/(P/\mu)} \mid = \frac{(1-F)}{g}$$

which is decreasing with F and achieves unit elasticity at $F^* = 1 - g$. It suggests something crucial for the time path of firm number $N \propto \frac{P}{\mu}F$: If an industry starts from an initial condition that $F_0 < 1 - g$, the supply curve will keep shifting to the right as the technology and mean income improves and the industry achieves the unique shakeout at $F^* = 1 - g$.

With Figure 9, we can clearly identify the two driving forces of industrial evolution and discuss their effects as follows.

- Technology Progress. In the presence of technology progress ($\gamma > 0$) but no income growth ($x = 0$), the supply curve shifts to the right due to cumulative production. As the result, the industry relative price P/μ as well as the absolute price P keeps falling, and the product penetrates into the lower income groups. Eventually, the market demand becomes inelastic and the shakeout comes in.

- Income Growth. In the presence of income growth ($x > 0$) but no technology progress ($\gamma = 0$), the supply curve shifts to the right due to income growth. Though the absolute price P may not fall (e.g. $\partial P/\partial t > 0$ if $0 \leq \psi < 1$), the industry relative price P/μ keeps falling and more consumers adopt the new product.[15] Eventually, as the market demand turns inelastic to the relative price, the growth of the industry profit is outstripped by the growth of the foregone earnings of entrepreneurs so the shakeout comes in.

- Technology Progress and Income Growth. In the presence of both technology progress ($\gamma > 0$) and income growth ($x > 0$), the supply curve shifts to the right due to both cumulative production and income growth, and the two driving forces reinforce each other. As the result, we observe the demand diffusion and industry shakeout.

With Figure 9, it is also easy to understand how the parameters affect the rate of diffusion and timing of shakeout as we proved in Proposition 4 and 6: if the technology is better (higher Q_0, higher A_0 or higher γ), the mean income is higher (higher μ_0 or higher x), the market size is larger (higher m) or the input prices is lower (lower ϕ, lower σ or lower ψ), it contributes to the cumulative production or (and) income growth so the supply curve shifts faster to the right. As the result, the industry achieves faster demand diffusion and earlier shakeout.

The above discussion provides a meaningful explanation for the cross-country difference of industrial evolution. For two countries like the US and the UK, the income inequality and consumer preference are very similar. As Lemma 1 suggests, their Gini coefficient g of the disposable income should be close, so is the shakeout adoption level $F^* = 1 - g$. Therefore, given that the law of motion for technology and income are alike, the US as the relative richer and larger country tends to enjoy faster demand diffusion as well as earlier industry shakeout.

5.4 Survival, Concentration and Profit Dynamics

Our model also offers clear predictions for the firm survival, market concentration and profit dynamics. First, since firms are heterogenous in their ability, we have the following lemma:

Lemma 2 *The higher the ability, the larger the firm size and profit.*

Proof. Equations 2 and 3 imply: $\partial y_\theta^*/\partial\theta > 0$, $\partial x_\theta^*/\partial\theta > 0$ and $\partial\pi_\theta/\partial\theta > 0$. ■

[15] In the literature of international economics, it is termed as the "Balassa-Samuelson Effect" that a non-tradable good typically has a higher price in a richer country due to the higher foregone earning for producing it. However, in spite of the higher price, the consumers in a richer country typically consume more of the good given their higher income. It is consistent with our model that it is the relative price P/μ rather than the absolute price P that determines the demand diffusion.

If we assume that each individual firm's ability is fixed over time, Lemma 2 just implies that high-ability firms enter the industry earlier and survive longer.

Proposition 7 *High-ability firms enter the industry earlier and survive longer.*

Proof. The minimum ability requirement $\tilde{\theta}$ falls before the shakeout and rises afterwards. It is straightforward to see that a high-ability firm satisfies that requirement earlier and longer than a low-ability one. ■

This result can be easily generalized. For example, given a time-invariant distribution of firm ability, even if each firm has idiosyncratic ability shocks we would still observe that early entrants tend to survive longer as long as the shocks are time persistent. In fact, this result is consistent with the well-established finding of industry studies that hazard rates typically decline with firm ages (Dunne, Roberts and Samuelson 1988, Audretsch 1991). Simons (2002) shows that it is particularly true for the TV industries in the US and the UK.

As the technology improves each firm's output typically grows over time. Our model suggests that all the firms surviving in the industry would have the same proportionate growth, which is usually called the "Gibrat's Law".

Proposition 8 *The surviving firms in the industry grow at the same positive rate.*

Proof. Equation 2 implies

$$y_\theta^* = (\frac{\alpha\phi\mu^{1-\psi}}{(1-\alpha)\sigma})^\alpha A\theta^{\frac{1}{1-\alpha}}\tilde{\theta}^{\frac{\alpha}{\alpha-1}} \Longrightarrow \frac{\dot{y}_\theta^*}{y_\theta^*} = \alpha(1-\psi)\frac{\dot{\mu}}{\mu} + \frac{\dot{A}}{A} - \frac{\alpha}{1-\alpha}\frac{\dot{\tilde{\theta}}}{\tilde{\theta}}$$

Since Proposition 3 shows $\partial Y/\partial t > 0$, Equation 16 implies that

$$\alpha(1-\psi)\frac{\dot{\mu}}{\mu} + \frac{\dot{A}}{A} - \frac{\alpha}{1-\alpha}\frac{\dot{\tilde{\theta}}}{\tilde{\theta}} > 0$$

at any time. Hence all the surviving firms grow at the same positive rate. ■

Also the market concentration ratio changes inversely with the number of firms.

Proposition 9 *For the top x firms, the market share declines before the shakeout and rises afterwards.*

Proof. *Denote λ_x to be the market share for the top x firms that survive the period of interest. We have*

$$\lambda_x = \frac{M\int_{S^{-1}(1-x/M)}^{\infty} y_\theta^* dS(\theta)}{M\int_{\tilde{\theta}}^{\infty} y_\theta^* dS(\theta)} = \frac{\int_{S^{-1}(1-x/M)}^{\infty} \theta^{\frac{1}{1-\alpha}} dS(\theta)}{\int_{\tilde{\theta}}^{\infty} \theta^{\frac{1}{1-\alpha}} dS(\theta)} => \frac{d\lambda_x}{dN} = \frac{d\lambda_x}{d\tilde{\theta}}\frac{d\tilde{\theta}}{dN} < 0$$

Hence the proposition is proved. ■

If we keep track with the profit of a firm, Equation 3 suggests that the relative profit π_θ/μ rises before the shakeout and falls afterwards, and so is the industry profit π/μ.

Proposition 10 *An individual firm's relative profit π_θ/μ as well as the industry relative profit π/μ rises before the shakeout and falls afterwards.*

Proof. Equation 3 and 5 implies

$$\pi_\theta/\mu = [(\theta/\tilde{\theta})^{\frac{1}{1-\alpha}} - 1]\phi \Longrightarrow \frac{d(\pi_\theta/\mu)}{dN} = \frac{d(\pi_\theta/\mu)}{d\tilde{\theta}}\frac{d\tilde{\theta}}{dN} > 0$$

$$\pi/\mu = M\int_{\tilde{\theta}}^{\infty}[(\theta/\tilde{\theta})^{\frac{1}{1-\alpha}} - 1]\phi dS(\theta) \Longrightarrow \frac{d(\pi/\mu)}{dN} = \frac{d(\pi/\mu)}{d\tilde{\theta}}\frac{d\tilde{\theta}}{dN} > 0$$

Hence the proposition is proved. ■

6 Extension to Durable Goods

So far our theoretical work is built on the consumer nondurable goods. However, the analysis can be readily extended to durables. This extension will not only be of its own theoretical interest, but also help the next empirical work.

It is the durability issue that complicates the analysis for durable goods. For a durable good, the consumers actually pay the rental price for the service from the stock of the good, and the producers are paid the output price to supply the increment of stock to meet the demand. Therefore, some modifications are needed for our original model.[16]

First, we have to derive the rental price from the output price. At equilibrium, the output price is the discounted sum of expected future rents, i.e.

$$P_t = E_t\sum_{\tau=t}^{\infty}\frac{(1-\delta)^{\tau-t}}{(1+r)^{\tau-t}}R_\tau$$

where r is the market interest rate and δ is the depreciation rate. It implies that the rental price can be written into the following form

$$R_t = [1 - \frac{1-\delta}{1+r}E_t(\frac{P_{t+1}}{P_t})]P_t$$

Second, the output Y_t for durable goods is made of two parts. One is the demand growth of the stock $m(F_t - F_{t-1})$. The other is the replacement demand $\delta m F_{t-1}$. Hence we have

[16]The model is now set in discrete time so that it can be directly brought to the empirical study in the next chapter.

$$Y_t = m(F_t - F_{t-1} + \delta F_{t-1})$$

Given these modifications, we can then summarize the market equilibrium equations for durable goods as follows:

$$\frac{P_t}{\mu_t} = \frac{(\phi)^{1-\alpha}(\sigma\mu_t^{\psi-1})^{\alpha}}{(1-\alpha)^{1-\alpha}(\alpha)^{\alpha}A_t\tilde{\theta}_t} \tag{25}$$

$$Y_t = (\frac{\alpha\phi\mu_t^{1-\psi}}{(1-\alpha)\sigma})^{\alpha}\tilde{\theta}_t^{\frac{\alpha}{\alpha-1}}A_t M\int_{\tilde{\theta}_t}^{\infty}(\theta^{\frac{1}{1-\alpha}})dS(\theta) \tag{26}$$

$$R_t = [1 - \frac{1-\delta}{1+r}E_t(\frac{P_{t+1}}{P_t})]P_t \tag{27}$$

$$F_t = \frac{1}{1+\eta(R_t/\mu_t)^{1/g}} \tag{28}$$

$$Y_t = m(F_t - F_{t-1} + \delta F_{t-1}) \tag{29}$$

$$N_t = M\int_{\tilde{\theta}_t}^{\infty} dS(\theta) \propto \frac{P_t Y_t}{\mu_t} \tag{30}$$

Notice that if $\delta = 1$, the case of full depreciation, the equilibrium equations above get back to what we have before for nondurable goods.

Introducing the learning-by-doing technological progress

$$A_t = A_0(Q_{t-1})^{\gamma} \qquad \text{where} \qquad Q_t = \sum_{\tau=0}^{t} Y_{\tau} \tag{31}$$

and constant income growth

$$\mu_t = \mu_0 e^{xt} \tag{32}$$

we can then characterize the industry dynamics.

As we go through the empirical study in the next chapter, we will see that with some minor reinterpretation most theoretical analyses that we have for the nondurable goods remain unchanged for the durable goods, and are supported by the data.

7 Empirical Study: TV Industry Life Cycles

In this chapter I use the data of TV, a durable good, to estimate our model. The TV dataset that we have not only provides rich information of new product diffusion, but also allows us to do cross-country comparisons between the US and the UK.

The start of TV industry can be traced back to 1930s, when innovation and first production of Black & White TV occurred in the US and the UK. However, WWII resulted in the curtailment of TV production in both countries and it was not until after the war that the TV market got off the ground. In this study, I focus on the TV industrial evolution from late 1940s to late 1960s, namely the B&W TV age in the US and the UK. During that period, the US and the UK were the two major countries that pioneered the TV adoption and production, and these two markets were segmented.

7.1 Hypotheses

Our model has the following important implications that we are interested to find in data:

- The number of firms is positively related with the relative industry GDP;
- The relative price declines with the mean income and cumulative output;
- The log-logistic distribution well explains the adoption;
- The demand equation well explains the output;
- Other things being equal, a higher mean income or larger market size leads to a faster demand diffusion and earlier industry shakeout.

7.2 Estimation Strategy

Before we jump into the data, we may have to figure out the estimation strategy. For a consumer nondurable goods, it is the system of equations 15 - 20 that we should go for estimation. For a consumer durable good like TV, it is the system of equations 25 - 32. Since both of them involve a system of equations, we then have to deal with the issue of simultaneity. There are two approaches that we consider as follows.

- OLS (Ordinary Least Squares): If the heterogeneity of firms is negligible, OLS yields consistent parameter estimates. Indeed under the assumption of identical firms, the system of equations for a nondurable good can be simplified as follows.

$$\frac{P_t}{\mu_t} = \frac{(\phi)^{1-\alpha}(\sigma\mu_t^{\psi-1})^{\alpha}}{(1-\alpha)^{1-\alpha}(\alpha)^{\alpha}A_t} \Longrightarrow \ln(P_t/\mu_t) = \kappa + \alpha(\psi-1)\ln(\mu_t) - \gamma\ln(Q_{t-1}) + \varepsilon_t \tag{33}$$

$$F_t = \frac{1}{1+\eta(P_t/\mu_t)^{1/g}} \Longrightarrow \ln(\frac{1}{F_t} - 1) = \beta + \frac{1}{g}\ln(P_t/\mu_t) + \epsilon_t \tag{34}$$

where κ and β are constants, ε_t and ϵ_t are random errors. For a durable good, the price equation 33 is the same, and the adoption equation 34 holds if the consumer expects the price to decline at an approximately constant rate which typically fits well with data. Then the system of equations 33 and 34 becomes *recursive* since each of the endogenous variables can be determined sequentially and the errors from each equation are independent of each other. In a system of this sort, the OLS is the appropriate estimation procedure.

- 2SLS (Two-Stage Least Squares): If the heterogeneity of firms is not negligible, we have to confront the problem of simultaneity. Notice that in the case of non-durable goods, equation 33 actually is a reduced-form linear equation for price. Hence it can be estimated with OLS in the first-stage regression and the fitted values of the dependent variable $\ln(\frac{P_t}{\mu_t})$ will by construction be independent of the error terms ε_t and ϵ_t. In the second-stage regression, the adoption equation 34 can then be estimated by replacing the variable $\ln(\frac{P_t}{\mu_t})$ with the first-stage fitted variable. However, for durable goods, equation 33 may be less robust since the lagged adoption rate is involved.

In the following study, we will mainly report the results from OLS since the results of 2SLS are very similar. For either case, we should be aware of the limitation of the procedures.

7.3 Data

To test the above hypotheses, yearly data of 7 variables for the B&W TV industry in both the US and the UK is collected. It includes the number of TV producers, TV output, value of TV output, household numbers, TV adoption rate, nominal GDP per capita and CPI. Two additional datasets are also used to extend our empirical analysis. One is the Gort & Klepper (1982) dataset, which covers the firm numbers, price and output for many US industries from their beginning years until 1970. The other is a panel dataset of B&W TV diffusion across 49 US continental states in 1950s and 1960s. A detailed description of data is provided in Appendix C.

7.4 Firm Numbers and Industry GDP

Proposition 1 states that the number of firms is positively related with the relative industry GDP. To test it rigorously, we apply the following regression to the US and UK B&W TV industries as well as ten other industries in the original Gort & Klepper (1982) dataset. For each industry, we use the time-series data of firm numbers, price,

Product	*Data Range*	b $(S.E.)$	$b \leq 0$	$b = 1$	$adj.R^2$	$Corr$ $(N, PY/\mu)$
Black & White TV (US)	1947-1963	0.31 (0.12)	R	R	0.28	0.61
Black & White TV (UK)	1949-1967	0.57 (0.11)	R	R	0.57	0.72
Blanket, Electrical	1950-1970	0.43 (0.08)	R	R	0.55	0.75
Computer	1955-1970	0.10 (0.02)	R	R	0.59	0.63
Freezer	1947-1970	0.31 (0.07)	R	R	0.42	0.69
Nylon	1950-1970	1.65 (0.13)	R	R	0.89	0.97
Penicillin	1949-1960	0.49 (0.10)	R	R	0.67	0.78
Pens, Ball Point	1951-1970	1.01 (0.25)	R	N	0.45	0.81
Styrene	1943-1970	1.04 (0.29)	R	N	0.30	0.42
Tapes, Recording	1958-1970	0.73 (0.08)	R	R	0.90	0.92
Tires, Automobile	1913-1953	1.30 (0.13)	R	R	0.72	0.78
Transistors	1954-1970	0.29 (0.02)	R	R	0.92	0.88

R: Reject; N: Not Reject (at 5% significance level).

Table 2: Testing Proposition 1

output and per capita GDP from the birth year up to 15-25 years later.[17]

$$\ln N_t = a + b \ln(PY/\mu)_t + \nu_t$$

where ν_t is assumed to be a Gaussian white noise process.[18]

For all 12 products that we include in the test, we reject the hypothesis $b \leq 0$ at 5% significance level. It suggests that Proposition 1 explains the data very well. Furthermore, it is also interesting to see that for some products like Ball Point pen and Styrene, we can not reject the hypothesis $b = 1$ at 5% significance level. These empirical findings are summarized in Table 2.

[17] The defination of each product may change over time as new substitutes are introduced, e.g. Personal Computer was introduced after Mainframe Computer, Synthetic Penicillin after Natually Produced Penicillin, Color TV after Black & White TV and etc. Therefore, we limit our analysis to the time period when each product can be clearly defined.

[18] We also check alternative assumptions that the error term has time trend or serial correlation. The results are very similar.

Data	Model	ω (S.E.)	$\alpha(\psi-1)$ (S.E.)	$-\gamma$ (S.E.)	c (S.E.)	$adj.R^2$
US	(P-1)	-0.08^* (0.005)				0.93
1948-1963	(P-2)		-2.61^* (0.38)	-0.06^* (0.02)		0.97
UK	(P-1)	-0.05^* (0.003)				0.94
1949-1967	(P-2)		-1.26^* (0.23)	-0.08^* (0.02)		0.96
	(P-3)		-1.26 (0.71)	-0.08 (0.25)	0.003 (0.77)	0.96

* Statistically significant at 5% level.

Table 3: US and UK TV Price Estimation

7.5 Price Estimation

Our model implies that the relative price decreases with the mean income and cumulative production. To see that, we estimate the following three equations:

$$\ln(P_t/\mu_t) = \kappa + \omega t + \varepsilon_t \qquad \text{Model (P-1)}$$

$$\ln(P_t/\mu_t) = \kappa + \alpha(\psi-1)\ln(\mu_t) - \gamma\ln(Q_{t-1}) + \varepsilon_t \qquad \text{Model (P-2)}$$

$$\ln(P_{uk,t}/\mu_{uk,t}) = \kappa + \alpha(\psi-1)\ln(\mu_{uk,t}) - \gamma\ln(Q_{uk,t-1} + cQ_{us,t-1}) + \varepsilon_t \qquad \text{Model (P-3)}$$

where μ_t is the real per capita GDP in 1953 dollar (pound) and Q is the cumulative output.

In Model (P-1), the relative price is estimated with a time trend only. It provides its average annual declining rate. In Model (P-2), the relative price is estimated with the real per capita income and cumulative industry output. It provides the changing rate of relative input price $\alpha(\psi-1)$ and the technological learning rate γ. In Model (P-3), the cumulative output of the US production is included in the estimation of the UK TV relative price so we can estimate how much the UK producers benefited from the technology spillover from the US.

The results are shown in Table 3. All the parameter estimators have the expected sign and highly statistically significant.[19] The estimation of Model (P-1) shows that the US enjoyed a much faster average declining rate of the relative TV price than the UK. By estimating the learning by doing equation, Model (P-2) suggests that the

[19] One concern is that the regressions may involve nonstationary time series so that the t test becomes less meaningful. However, OLS still consistently estimates the parameters as long as the regression equations are correctly specified.

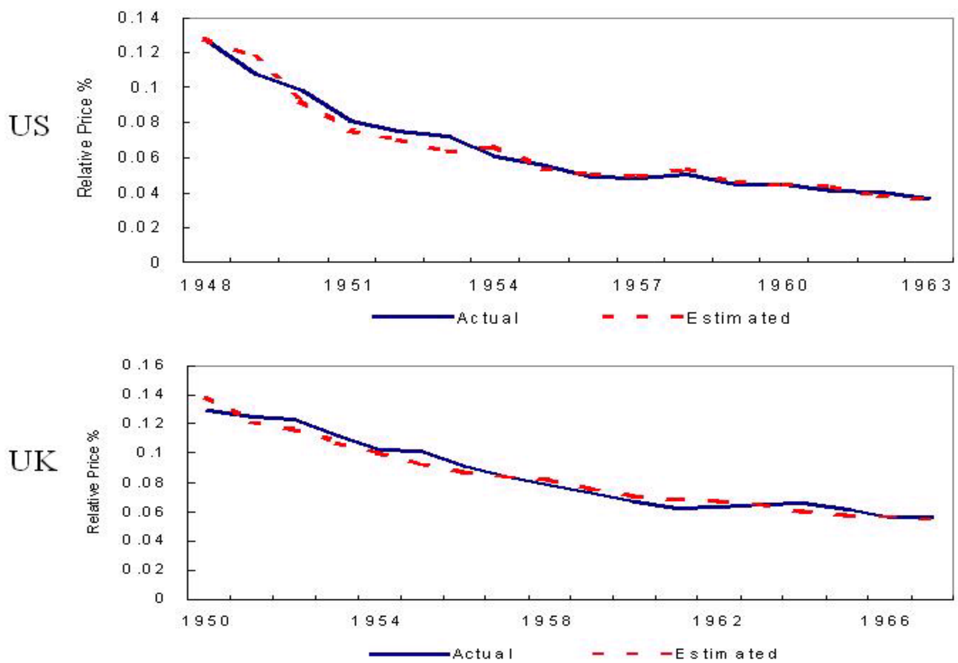

Figure 10: TV Relative Price Estimation: US and UK

US advantage may be due to a faster declining rate of input price in addition to the larger cumulative output. Figure 10 provides the data fitting using Model (P-2).

Since the TV industry was developed much earlier and faster in US, one immediate question is whether and how much the UK producers could have learned from the US experience. Model (P-3) tests this hypothesis by including the US cumulative output into UK relative price equation. The regression is conducted using nonlinear least squares. Comparing the estimation results of Model (P-2) and (P-3), we find that introducing the US experience does not improve fitting the UK price data, and the parameter estimators are almost unchanged. Moreover, the magnitude of the coefficient of US experience is very small if it exists at all. This finding confirms our previous assumption that the US and the UK TV markets were segmented due to their different technical standard.

7.6 Adoption Estimation

There are three models that we estimate for the B&W TV adoption. First, if the diffusion is an exogenous contagion process, we have the logistic model:

$$\ln(\frac{1}{F_t} - 1) = \beta + wt + \epsilon_t \qquad \text{Model (A-1)}$$

where $\beta = \ln(\frac{1}{F_0} - 1)$, $w = -v$.

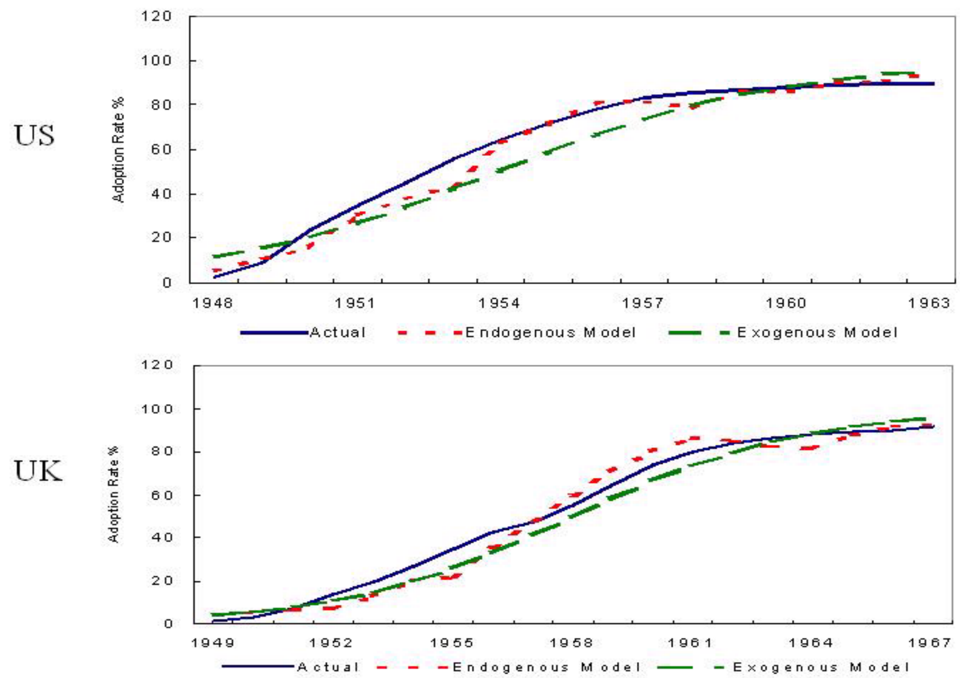

Figure 11: TV Adoption Estimation: US and UK

For a consumer durable good like TV, if we assume that the decision makers predict a constant price declining rate, i.e. $E_t(\frac{P_{t+1}}{P_t}) = \rho$ with $1 > \rho > 0$, the adoption equation 34 suggests

$$\ln(\frac{1}{F_t} - 1) = \beta + \frac{1}{g}\ln(P_t/\mu_t) + \epsilon_t \qquad \text{Model (A-2)}$$

where $\beta = \ln\eta + \frac{1}{g}\ln(1 - \frac{1-\delta}{1+r}\rho)$.

To check the robustness of our estimation, we further conduct a panel-data estimation using the TV diffusion data across 49 continental states of US at year 1950, 1955, 1959 and 1963.

$$\ln(\frac{1}{F_{i,t}} - 1) = \beta + \frac{1}{g}\ln(P_t/\mu_{i,t}) + u_i + \epsilon_t \qquad \text{Model (A-3)}$$

where $F_{i,t}$ is the TV adoption rate of state i at time t, $\mu_{i,t}$ is the per capita income of state i at time t, u_i is the fixed effect of state i.

The results are shown in Table 4. We find that Model (A-2) has higher R^2 value than Model (A-1), which implies a better fitting of data using endogenous diffusion model. Model (A-3) reports the panel-data estimation using the fixed-effect model (random-effect model is rejected by the Hausman specification test), with the results very close to what we estimate using Model (A-2). See Figure 11 for the data fitting using Model (A-1) and (A-2).

Data	Model	w (S.E.)	$1/g$ (S.E.)	$adj.R^2$
United States	(A-1)	-0.34^* (0.06)		0.84
1948-1963	(A-2)		4.52^* (0.44)	0.95
	(A-3)		5.38^* (0.30)	0.55
United Kingdom	(A-1)	-0.35^* (0.04)		0.94
1949-1967	(A-2)		6.46^* (0.61)	0.94

* Statistically significant at 5% level.

Table 4: US and UK TV Adoption Estimation

7.7 Output Estimation

Having explained the adoption rate of B&W TV, we now estimate the annual output. The demand function takes the simple form as equation 29:

$$Y_t = m_t(F_t - F_{t-1} + \delta F_{t-1}) + \upsilon_t$$

where m_t is the household number at time t, δ is the annual depreciation rate. It implies that the annual output consists of two parts: the first purchase from the new adopters and the replacement purchase from the existing adopters.

Given the data of Y_t, m_t and F_t, the only parameter to estimate is the depreciation rate δ. Though a constant depreciation rate seems to be a strong assumption, the estimation results in Table 5 suggest that it does explain the data pretty well. See Figure 12 for the data fitting.

	Data Range	δ (S.E.)	$adj.R^2$
US	1948-1963	0.10^* (0.005)	0.84
UK	1949-1967	0.08^* (0.009)	0.53

* Statistically significant at 5% level.

Table 5: US and UK TV Output Estimation

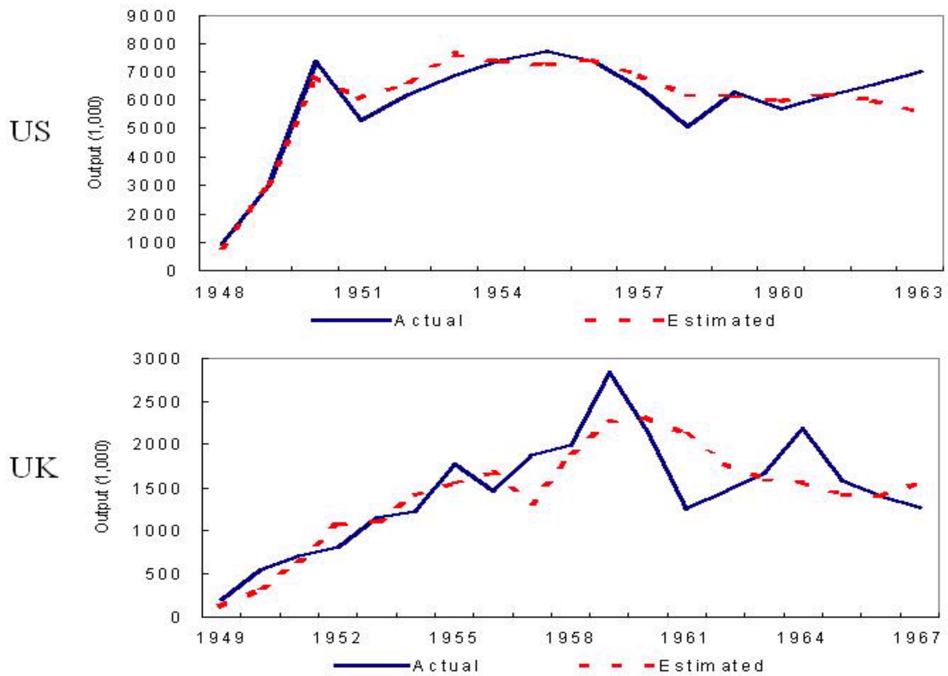

Figure 12: TV Output Estimation: US and UK

7.8 Mean Income, Market Size, Diffusion and Shakeout

Our regressions have so far explained pretty well the time path of price and output for the US and UK B&W TV industries. With the assistance of our theoretical analysis, we now explore the roles that the mean income and market size play in shaping the TV industrial evolution.

The fact is for the period that we study, the per capita GDP of the UK was 70-80% of the US and the population of the UK is one third of the US. As our model suggests, the lower mean income together with the smaller market size would lead to a sustainedly higher TV price-income ratio in the UK than the US.[20] Therefore, the diffusion of TV in UK was delayed. See Figure 13 (a) for the data plotting of TV price-income ratio.

How did this delayed diffusion affect the timing of shakeout for a consumer durable good like TV? Notice that the early demand of durable goods is mainly the first purchase, i.e.

$$Y_t \approx m(F_t - F_{t-1}) \tag{35}$$

where m is assumed to be a constant market size. Given the sustainedly higher TV

[20] The absolute price of B&W TV in the UK was not necessarily higher than the US as we discuss in section 5.3. Using both official exchange rate and PPP, I find that the price was actually lower in the UK.

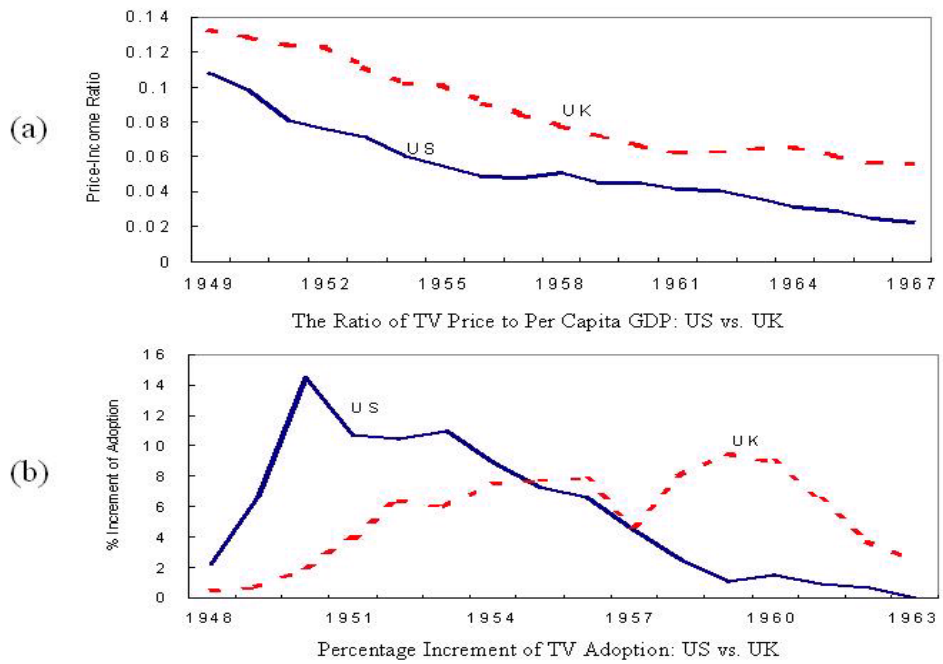

Figure 13: TV Relative Price and Adoption Increment: US vs. UK

price-income ratio P_t/μ_t in the UK, the market expansion was postponed so that the peak of first purchase came in much later than the US. The data of adoption increment $(F_t - F_{t-1})$ is plotted in Figure 13 (b).

In the US case, we notice that the actual output declined less severe than what we calculate with equation 35, which was due to the fast population growth in US during that period.[21] However, the industry output did level off in early 1950s, and the relative industry GDP as well as the firm numbers declined at that time. In the case of UK, where the population grew much slower, the time path of actual output is very close to what we calculate with equation 35, which kept increasing until 1959. Hence the relative industry GDP as well as the firm numbers had not declined until then.

8 Concluding Remarks

This paper offers a new theory of industrial life cycle, in which the industry shakeout is explained as a competitive equilibrium outcome. It reveals the roles that technological learning, income distribution and market size play in shaping how industries evolve

[21] During 1948-1963, the average annual growth rate of household number was 2% in US, but only 0.5% in UK.

from birth to maturity. Since the competitive market does not internalize the spillover of learning by doing, the equilibrium we describe is not Pareto optimal. A social planner would prefer a faster demand diffusion and earlier shakeout.

In the paper, the technology progress is assumed to be the productivity gains generated from learning by doing. A further extension of the model would be to study other forms and sources of technology progress and their dynamic effects, e.g. the quality change of new products, product differentiation and firms' endogenous R&D decisions.

In the paper, we have assumed a close-country framework but it can be easily generalized. In a world with free trade, a country may specialize on some certain industries to explore her comparative advantage. If that is the case, it should be the world income distribution and world market size that shape the industry life cycle.

A Appendix

A.1 Supply Structure: Entry with Sunk Cost

In the supply-side analysis, we assume that firms can enter and exit freely. It helps transform the original dynamic problem into a period-by-period static calculation and simplify the analysis. However, this assumption can be relaxed. Below we show an example in which entry incurs a fixed amount of sunk cost and firms have to make dynamic decisions on entry and exit. As the result, we can still obtain the positive relation between the firm numbers and industry GDP at equilibrium.

The setup of the model is almost the same as before. However, we now assume that there is a fixed entry cost K for each firm. K does not depreciate, but has no salvage value if a firm exits. Furthermore, we assume that firms are identical and share a constant death rate $1-\phi$ every period. If a firm dies, her output is zero in that period.

At time t, the technology A_t is given. A representative firm takes the price P_t as given to maximize her value,

$$V_t = \max\{0, \phi[\pi(P_t,\, A_t) + \beta V_{t+1}]\} \tag{36}$$

where the profit function is given as before

$$\pi_t = (1-\alpha)(\alpha)^{\frac{\alpha}{1-\alpha}} w^{\frac{-\alpha}{1-\alpha}} (P_t A_t)^{\frac{1}{1-\alpha}} - C \tag{37}$$

If entry occurs at time t and $t+1$, the value of each firm can be pinned down by the fixed entry cost K. Then equation 36 implies the period profit π_t to be

$$K = \frac{\phi \pi_t}{1-\phi\beta} \tag{38}$$

The market price P_t is now solved by equations 37 and 38 as follows:

$$P_t = \frac{(K(1-\phi\beta)+\phi C)^{1-\alpha} w^\alpha}{\phi^{1-\alpha}(1-\alpha)^{1-\alpha}\alpha^\alpha A_t} \tag{39}$$

It implies that the optimal output per firm becomes

$$y_t^* = (\frac{\alpha P A^{\frac{1}{\alpha}}}{w})^{\frac{\alpha}{1-\alpha}} = \frac{\alpha^\alpha (K(1-\phi\beta)+\phi C)^\alpha A_t}{\phi^\alpha(1-\alpha)^\alpha w^\alpha} \tag{40}$$

Then the active firm number N_t at time t can be shown to be proportional to industry GDP given equation 39 and 40

$$N_t = z P_t Y_t$$

where $z = \phi(1-\alpha)/[K(1-\phi\beta)+\phi C]$.

Since the analysis above depends on the assumption of continuing entry, we have to justify its existence to complete the proof. Notice that equation 39 implies that price P falls over time as technology A improves. Therefore, when the market demand is price elastic (at the early stage of diffusion) the required number of active firm N will keep rising, which implies entry has to occur each period. However, even when the market demand turns inelastic and shakeout starts, entry can still continue to occur as long as $P_t Y_t > \phi P_{t-1} Y_{t-1}$ holds period by period.

Some other scenarios may also exist. For example, if the technology progress is so dramatic that the entry stops and continuing exit starts sometime after the shakeout. In that case, the industry jumps to another equilibrium path. The incumbent firms become indifferent between staying and leaving, so equation 36 implies that the firm value drops to zero, and every active firm breaks even each period. A similar proof as above suggests that the market price is then determined to be

$$P_t = \frac{C^{1-\alpha} w^\alpha}{(1-\alpha)^{1-\alpha}\alpha^\alpha A_t}$$

The number of firm is still proportional to the industry GDP though now the proportionality changes to $z = (1-\alpha)/C$. Along this path, we have $P_t Y_t < \phi P_{t-1} Y_{t-1}$ holds period by period.

Notice that higher death rate would prolong the number of periods in which entry takes place. In the extreme, suppose firms have to die after a single period– then we are back to the original model, with the interpretation that the fixed cost of production can also include the entry cost, and nothing changes (except that now the path of N is also the path of entry).

A.2 Industry Life Cycle with Increasing Span of Control

In the paper, we have shown with empirical evidence that the relative industry GDP is a good indicator for the number of firms. However, it is possible to find counterexamples. A dramatic case is the automobile, for which the firm shakeout came in around 1910 but the relative industry GDP kept rising up to the Great Depression. Does that mean our theory is not consistent with the fact?

Not necessarily! Recall that the comovement between the firm numbers and the relative industry GDP is derived on the assumption that the span of control parameter α is constant over time. In the case of automobile industrial evolution, this assumption is less likely to be valid. In particular, as the assembly line was introduced in 1910s the industry became more and more capital intensive. During that process, the technology progress indeed realized also through the increasing span of control α. If we take this into account, it is possible for the number of firms to deviate from the relative industry GDP so the shakeout of firm numbers should come in earlier. However, this extension does not necessarily invalidate our analysis in the paper. In the following, we construct an example with endogenously increasing span of control and show the essence of our previous analysis still holds.

For simplicity, we assume the industry has identical firms. The production function is

$$y = \phi_\alpha A x^\alpha$$

where $\phi_\alpha = (1-\alpha)^{-(1-\alpha)}\alpha^{-\alpha}$.

Assume that there is only labor input, and the entrepreneur's forgone earning equals the worker's wage, i.e. $C = w$, and mean income of the economy is fixed. We then have the momentary industry equilibrium conditions as follows:

$$P = \frac{C}{A} \tag{41}$$

$$Y = mF = \frac{m}{1+\eta(P/\mu)^{1/g}} \tag{42}$$

$$N = \frac{1-\alpha}{C} PY \tag{43}$$

Assume that the technology progress results from learning by doing as follows

$$A_t = A_0 Q_t^\gamma; \qquad \alpha = 1 - \alpha_0 Q_t^{-\lambda}$$

where $Q_t = \int_0^t Y(s)ds + Q_0$. Characterizing the dynamic of this system, we can see most our previous analyses stay unchanged except the shakeout of firm numbers now starts earlier than that of GDP. This can be illustrated as follows.

Lemma 3 *The number of firms starts declining when price elasticity falls to* $1+\lambda/\gamma$.

Proof. Given $P_t = \frac{C}{A_0} Q_t^{-\gamma}$ and $1-\alpha = \alpha_0 Q_t^{-\lambda}$, we have

$$N_t = \frac{1-\alpha_t}{C} P_t Y_t = \alpha_0 A_0^{\lambda/\gamma} (P_t/C)^{1+\lambda/\gamma} Y_t$$

Hence, the peak of firm numbers is determined as follows,

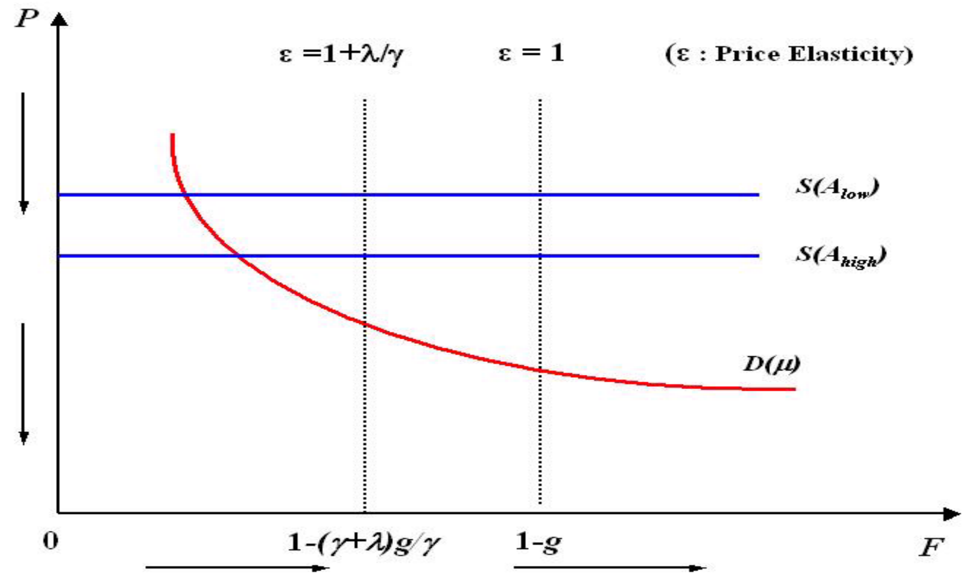

Figure 14: Industry Life Cycle with Increasing Span of Control

$$\frac{\partial N_t}{\partial t} = 0 => (1 + \lambda/\gamma)\frac{\dot{P}_t}{P_t} + \frac{\dot{Y}_t}{Y_t} = 0 => \varepsilon^* = 1 + \lambda/\gamma$$

■

Recall that the industry GDP starts declining at $\varepsilon^* = 1$. As we know that the demand function 42 has a declining price elasticity, the shakeout of firm numbers hence starts earlier at a lower critical adoption level, $1 - \frac{g(\lambda+\gamma)}{\gamma}$, instead of $1 - g$ for the industry GDP.

Using Figure 14, we can also check the effects of parameter changes.

Proposition 11 *Anything else being equal, it leads to a lower relative price P_t/μ_t and higher adoption rate F_t at any time t if*

- *the technology is better (higher Q_0, higher A_0 or higher γ) or*
- *the mean income is higher (higher μ) or*
- *the market size is larger (higher m).*

Proof. The proof is similar as before. All the conditions listed here will help move down the supply curve faster, hence leads to faster demand diffusion and earlier industry shakeout. ■

So far, we have not linked the foregone earning C and input price w to the mean income μ. What if we do? For the model to be analytically solvable, we no longer distinguish the entrepreneur's foregone earning from the input price, i.e. $C = w$. It is a little different from what we assumed in the paper: $C = \phi\mu$ and $w = \sigma\mu^{\psi}$ $(\psi < 1)$. Therefore, we have to discuss two special cases. In one case, $C = w = \phi\mu$, a higher mean income will be fully transferred into a higher production cost so that it does not result in a lower relative price P/μ for a given initial technology. Hence it does not lead to a faster diffusion and earlier shakeout. In the other case, if $C = w = \sigma\mu^{\psi}$ $(\psi < 1)$, a higher mean income will only be partly transferred into the production cost so that the relative price P/μ turns lower for a given initial technology. As the result, it does lead to a faster diffusion and earlier shakeout. The latter case is consistent with our finding in the paper.

A.3 The Data Used in the Empirical Work

US-UK TV Dataset – The US data starts as early as 1946 when the B&W TV was initially introduced, and ends at 1963 when the sale of color TV took off. Most of the data (the number of TV producers, TV output, value of TV output, household numbers and TV adoption rate) are drawn from periodic editions of *Television Factbook.* The nominal GDP per capita is from Johnston & Williamson (2003) and CPI is from *International Historical Statistics: the Americas*, 1750-1993. The UK data also starts from 1946 but ends a little later than the US at 1967 when the color TV was introduced. The number of TV producers is cited from Simons (2002). The TV output and value are from *Monthly Digest of Statistics (1946-1968).* The household numbers are calculated by population (from *UN Common Database*) divided by average household size (from *UN Demographic Yearbook*). The TV adoption rate is from Table AI of Bowden & Offer (1994). The nominal GDP per capita is from Officer (2003) and the CPI is from *International Historical Statistics: Europe, 1750-1993.*

Gort-Klepper Dataset – It covers time-series data of firm numbers (46 industries), price (23 industries) and output (25 industries) from the beginning of each industry up to 1970. 13 industries are selected for our empirical study because they have long enough coverage and continuos observations.

US TV Panel Dataset – It covers the TV adoption rate and personal income across 49 continental states of the US at year 1950, 1955, 1959 and 1963. The TV adoption rate is drawn from the *Television Factbook*, and the personal income is drawn from the *Statistical Abstract of the United States.*

References

[1] Arnold, Erik, (1985). *Competition and Technological Change in the Television Industry.* Macmillan, London.

[2] Arrow, Kenneth, (1962). "The Economic Implications of Learning by Doing," *Review of Economic Studies* 29(3), 155-173.

[3] Audretsch, David B., (1991). "New-Firm Survival and the Technological Regime," *Review of Economics and Statistics* 73:3, 441-450.

[4] Barbarino, A. and Boyan Jovanovic, (2003). "Shakeouts and Market Crashes," working paper, Department of Economics, University of Chicago.

[5] Bass, F. M., (1969). "A New Product Growth Model for Consumer Durables," *Management Science*, 15 (Jan.), 215-27.

[6] Becker, G. S., (1965). "A Theory of the Allocation of Time," *Economic Journal*, 75 (September), 493-517.

[7] Birkhoff, Garrett and Gian-Carlo Rota, (1969). *Ordinary Differential Equations.* Blaisdell Publishing Company.

[8] Bogart, Leo, (1972). *The Age of Television: A Study of Viewing Habits and the Impact of Television on American life.* F. Ungar Pub. Co., New York.

[9] Bonus, Holger, (1973). "Quasi-Engel Curves, Diffusions and the Ownership of Major Consumer Durables," *Journal of Political Economy*, 81, 3, 655-677.

[10] Boston Consulting Group, (1972). "Perspectives on Experience," *Technical Report*, Boston.

[11] Boston Consulting Group, (1978). "Cross Sectional Experience Curves," *Technical Report*, Boston.

[12] Bowden, Sue and Avner Offer, (1994). "Household Appliances and the Use of Time: The United States and Britain Since the 1920s," *Economic History Review*, New Series, 47 (Nov.), 725-748.

[13] Central Statistical Office, Great Britain, (1946-1970). *Monthly Digest of Statistics.*

[14] Comin, Diego and Bart Hobijn, (2003). "Cross-Country Technological Adoption: Making the Theories Face the Facts," working paper, Carnegie Rochester Conference on Public Policy.

[15] David, Paul, (1969). "A Contribution to the theory of Diffusion," mimeo, Research Center in Economic Growth, Stanford University.

[16] Dunne, Timothy, Mark J. Roberts, and Larry Samuelson, (1988). "Patterns of Firm Entry and Exit in U.S. Manufacturing Industries," *RAND Journal of Economics* 19:4, 495-515.

[17] Emmett, B.P., (1956). "The Television Audience in the United Kingdom," *Journal of the Royal Statistical Society*, Series A, 119, 3, 284-311.

[18] Filson, Darren, (2001). "The Nature and Effects of Technological Change over the Industry Life Cycle," *Review of Economic Dynamics*, (Mar.), 460-494.

[19] Fisk, Peter R., (1961). "The Graduation of Income Distributions," *Econometrica*, 29, 2, 171-185.

[20] Gort, Michael and Steven Klepper, (1982). "Time Paths in the Diffusion of Product Innovations," *The Economic Journal*, 92, (Sept.), 630-653.

[21] Griliches, Zvi, (1957). "Hybrid Corn: An Exploration in the Economics of Technological Change," *Econometrica*, 25, (Oct.), 501-522.

[22] Grossman, Gene M. and Elhanan Helpman, (1991). "Endogenous Product Cycles," *The Economic Journal*, 101, 1212-1229.

[23] Hopenhayn, Hugo A., (1993). "The Shakeout," *Economics Working Paper 33*, Universitat Pompeu Fabra.

[24] Horsky, Dan, (1990). "A Diffusion Model Incorporating Product Benefits, Price, Income and Information," *Marketing Science*, 9 (Autumn), 342-365.

[25] Horvath, Michael, Fabiano Schivardi and Michael Woywode, (2001). "On Industry Life-Cycles: Delay, Entry, and Shakeout in Beer Brewing," *International Journal of Industrial Organization*, 19, 1023-1052.

[26] Irwin, Douglas A. and Peter J. Klenow, (1994). "Learning-by-Doing Spillovers in the Semiconductor Industry," *Journal of Political Economy*, 102 (6), 1200-1227.

[27] Jeuland, A. P., (1994). "The Bass Model as a Tool to Uncover Empirical Generalizations in Diffusion of Innovation," Paper prepared for Empirical Generalizations Conference, Wharton School, February.

[28] Jovanovic, Boyan and Saul Lach, (1989). "Entry, Exit, and Diffusion with Learning by Doing," *American Economic Review*, 79 (Sept.), 690-699.

[29] Jovanovic, Boyan and G. M. MacDonald, (1994). "The Life Cycle of a Competitive Industry," *Journal of Political Economy*, 102 (Apr.), 322-347.

[30] Jovanovic, Boyan and Peter L. Rousseau, (2002). "Moore's Law and Learning-By-Doing," *Review of Economic Dynamics*, 5 (2), 346-375.

[31] Johnston, Louis and Samuel H. Williamson, (2003). "The Annual Real and Nominal GDP for the United States, 1789 - 2002," Economic History Services, URL : http://www.eh.net/hmit/gdp/.

[32] Kalish, Shlomo, (1983). "Monopolist Pricing with Dynamic Demand and Production Cost," *Marketing Science*, Vol. 2, No. 2, 135-159.

[33] Klepper, Steven and Elizabeth Graddy, (1990). "The Evolution of New Industries and the Determinants of Market Structure," *The Rand Journal of Economics*, 21 (1990), 27-44.

[34] Klepper, Steven, (1996). "Entry, Exit, Growth, and Innovation over the Product Life Cycle," *American Economic Review*, 86 (June), 562-583.

[35] Klepper, Steven and Kenneth Simons, (2000). "The Making of an Oligopoly: Firm Survival and Technological Change in the Evolution of the U.S. Tire Industry," *Journal of Political Economy*, 108, 4, 728-758.

[36] Klepper, Steven and Kenneth Simons, (2001). "Industry Shakeouts and Technological Change," mimeo.

[37] LaFrance, Vincent A., (1985). *The United States Television Receiver Industry: United States vs. Japan, 1960-1980.* Ph.D. Dissertation, Pennsylvania State University.

[38] Levy, Jonathan D., (1981). *Diffusion of Technology and Patterns of International Trade: The Case of Television Receivers.* Ph.D. Dissertation, Yale University.

[39] Lieberman, Marvin B., (1987). "The Learning Curve, Diffusion, and Competitive Strategy," *Strategic Management Journal*, 8, 5, 441-452.

[40] Lomax, K.S., (1954). "Business Failures: Another Example of the Analysis of Failure Data," *Journal of American Statistical Association*, 49,847-852.

[41] Lucas, Robert E., (1978). "On the Size Distribution of Business Firms," *The Bell Journal of Economics*, 9, 2, 508-523.

[42] Lucas, Robert E., (1988). "On the Mechanics of Economic Development," *Journal of Monetary Economics*, 22, 3-42.

[43] Lucas, Robert E., (1993). "Making a Miracle," *Econometrica*, 61, 251-272.

[44] Mahajan, Vijay, Eitan Muller and Frank M. Bass, (1995). "Diffusion of New Products: Empirical Generalizations and Managerial Uses," *Marketing Science*, 14, 3, 79-88.

[45] Mansfield, Edwin, (1961). "Technical Change and the Rate of Imitation," *Econometrica*, 29 (Oct.), 741-766.

[46] Matsuyama, Kiminori, (2002). "The Rise of Mass Consumption Societies," *Journal of Political Economy*, 110, 5, 1035-1070.

[47] McDonald, James B., (1984). "Some Generalized Functions for The Size Distribution of Income," *Econometrica*, 52 (May), 647-664.

[48] Mitchell, B.R., (1998). *International Historical Statistics : Europe, 1750-1993*. Stockton Press, New York.

[49] Mitchell, B.R., (1998). *International Historical Statistics : the Americas*, 1750-1993. Stockton Press, New York.

[50] Officer, Lawrence H., (2003). "The Annual Real and Nominal GDP for the United Kingdom, 1086 - 2000." Economic History Services, URL : http://www.eh.net/hmit/ukgdp/.

[51] Rob, Rafael, (1991). "Learning and Capacity Expansion under Demand Uncertainty," *Review of Economic Studies*, 58 (June), 655-675.

[52] Simons, Kenneth, (1995). *Shakeouts: Firm Survival and Technological Change in New Manufacturing Industries*, Ph.D. Dissertation, Carnegie Mellon University.

[53] Simons, Kenneth, (2001). "Product Market Characteristics and the Industry Life Cycle," working paper, Department of Economics, University of London.

[54] Simons, Kenneth, (2002). "Predictable Cross-Industry Heterogeneity in Industry Dynamics," working paper, Department of Economics, University of London.

[55] Stokey, Nancy L., (1991). "The Volume and Composition of Trade Between Rich and Poor Countries," *Review of Economic Studies*, 58, 63-80.

[56] Sultan, F., J. U. Farley and D. R. Lehmann, (1990). "A Meta-Analysis of Diffusion Models," *Journal of Marketing Research*, 27 (February), 70-77.

[57] *Television Factbook (1948-1970)*. Warren Publishing, Washington.

[58] Thompson, Peter and Rebecca A. Thornton, (2001). "Learning from Experience and Learning from Others: An Exploration of Learning and Spillovers in Wartime Shipbuilding," *American Economic Review*, December.

[59] United Nation, *Demographic Yearbook, 1955.*

[60] United Nation, *Common Database,* http://unstats.un.org/unsd/.

[61] Utterback, James and Fernando Suarez, (1993). "Innovation, Competition, and Industry Structure," *Research Policy*, 22, 1-21.

[62] Vernon, R., (1966). "International Investment and International Trade in the Product Cycle," *Quarterly Journal of Economics*, 80, 190-207.

[63] Wang, Zhu, (2003). "Learning-by-Doing Dynamics and Industrial Shakeouts," mimeo, Department of Economics, University of Chicago.

[64] Zeira, Joseph, (1987). "Investment as a Process of Search," *Journal of Political Economy*, 95 (Feb.), 204-210.

[65] Zeira, Joseph, (1999). "Information Overshooting, Booms and Crashes," *Journal of Monetary Economics*, 43, 237-257.