Income Distribution, Market Size and the Evolution of Industry*

Zhu Wang†

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Abstract

An industry typically experiences initial mass entry and later shakeout of producers over its life cycle. However, the timing of the evolution varies substantially across markets. By exploring the dynamic interactions between technology progress and demand diffusion, our theory suggests that the cross-market differences of industrial evolution are largely the result of underlying demand factors. Particularly, higher consumer income or larger market size tends to drive faster demand diffusion and earlier industry shakeout. A comparative study on the US and UK television industries supports the theoretical findings.

Keywords: Product diffusion, Industry Life Cycle, Shakeout

JEL Classification: D30, O30, L1

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†Federal Reserve Bank of Kansas City, 925 Grand Boulevard, Kansas City, MO 64198. Email: zhu.wang@kc.frb.org. The views expressed herein are solely those of the author and do not necessarily reflect the views of the Federal Reserve Bank of Kansas City or the Federal Reserve System.
1 Introduction

1.1 Motivation

As an industry evolves from birth to maturity, we typically observe that price falls, output rises, and the net 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 industrial economics. The big question is when and why a shakeout will occur.

To answer this question, most existing theories emphasize supply-side factors, particularly inter-firm differences in technology. It has been shown that shakeout can be triggered by “emergence of dominant design” (Utterback and Suárez 1993), “race of innovation” (Wang 2007, Jovanovic and MacDonald 1994), and “scale economies in R&D” (Klepper and Simons 2000, Klepper 1996). Some other explanations point to uncertainties in new product markets, for example, “uncertain profit” (Horvath, Schivardi and Woywode 2001) or “uncertain market size” (Barbarino and Jovanovic 2006, Zeira 1999, Rob 1991) can also result in a mass entry and later shakeout.

Although these theories have advanced our understanding of industry shakeout, some important issues are still underexplored. Particularly, the impacts of demand characteristics on industry life cycles have been largely overlooked. As a result, it remains difficult to explain certain empirical facts. For example, Fig. 1 plots the number of firms in the US and the UK television industries. The television was commercially introduced into the US and the UK at the same time after WWII, but the two markets were segmented for the following two decades by technical standards. This natural experiment shows that the patterns of industrial evolution are very similar across countries, but the mass entry and shakeout of TV producers were uniformly lagged behind in the UK.

What can explain this cross-country difference of the timing of shakeout? The existing theories do not provide us adequate answers. Many industry studies (Klepper and Simons 1996, Arnold

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1 An exception is Hopenhyan (1993), where some demand issues are discussed briefly.
2 Data source: Simons (2002), Television Factbook (various issues).
3 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 standard. Hence through 1964 and even later, the UK TV market was isolated from foreign competition. See Levy (1981).
1985, LaFrance 1985) document numerous technological changes in the TV industry that may have a major cumulative effect on inter-firm heterogeneity, but they do not directly explain the timing of shakeout, let alone the cross-country differences. Market uncertainty could not have caused the shakeout either because at least the UK producers could easily learn from the US market experience. Moreover, the TV shakeouts, especially the Black & White TV shakeouts, had little to do with foreign competition since the TV import and export were negligible at the time.4

1.2 A New Hypothesis

In this paper, we propose a demand-side theory to explain the industry shakeout. A new product, over its life cycle, typically experiences strong demand growth early on but this growth gradually diminishes as the market matures. This suggests that demand characteristics can have influential, sometimes critical, effects on industry evolution. Without taking that into account, the analyses

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4In the 1950s, the US and the UK were the two largest TV producers in the world, while imports and exports were nil for both countries. Imports started to increase in the 1960s as Japanese production took off, but did not reach 10% of domestic production until 1965 in the US, and until 1970 in the UK. Data sources: Television Factbook (US), Monthly Digest of Statistics (UK).
on industry life cycle would be incomplete.

In this paper, we study an important mechanism driving the industry life cycle, and reveal how market-specific demand factors, the income distribution and market size in particular, shape this process. When a new product is introduced into a market, high-income consumers tend to adopt it first. The technology then improves with cumulative production (Learning by Doing) and the product subsequently penetrates lower-income groups (Trickle Down Effect and Income Growth Effect). Eventually fewer new adopters are available and the number of firms starts to decline. It is shown that higher consumer income or larger market size drives faster demand diffusion and earlier industry shakeout. This new theory offers a demand-side explanation for the varying patterns of industrial evolution across markets. For example, it suggests that lower per capita income and smaller market size in the UK led to slower diffusion of TV (Fig. 2) and hence lagged shakeout.5

1.3 Related Research

This paper complements existing theories of industry life cycle by exploring the previously largely ignored demand side. Meanwhile, it links the study of industrial evolution to research in other

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5 Data source: Television Factbook (various issues), Bowden and Offer (1994).
fields. In the marketing literature, diffusion of new products has been studied to forecast demand and pricing (Bass 1969, Kalish 1983, Horsky 1990). In the growth literature, learning by doing is one of the most important sources of technology progress (Arrow 1962, Lucas 1993, Jovanovic and Rousseau 2002, Matsuyama 2003). In the international trade literature, the most celebrated “product cycle theory” claims that demand for new consumer goods is initially greatest in high-income countries, and gradually diffuses to low-income countries (Vernon 1966, Stokey 1991, Grossman and Helpman 1991). In the technology adoption literature, it has been found that per capita GDP is one of the key variables that explain the diffusion of new technology across countries (Comin and Hobijn 2004). Those researches so far have not been connected with the study of industrial evolution. This paper is a first step to fill this gap, and shows that the typical pattern of industrial evolution is closely related and consistent with the findings in those fields.

1.4 Road Map

This paper is organized as follows. Section 2 presents a dynamic equilibrium model for a competitive industry. It shows that industrial evolution is driven endogenously by underlying demand factors. Particularly, larger and wealthier markets tend to speed up the initial growth and shakeout of an industry. Section 3 takes our theory to data. A comparative study on the US and UK television industries supports our theoretical findings. Section 4 offers concluding remarks.

2 The Model

2.1 The Demand Structure

2.1.1 Traditional View

In order to explain industrial evolution, it is crucial to understand the dynamics of new product demand. In the economics and marketing literature, the popular explanation relies on social contagion, i.e., consumers imitate early adopters. This idea has been formalized by introducing the logistic model and its variants since the 1950s (Griliches 1957, Mansfield 1961, Bass 1969).
The logistic model assumes the hazard rate of adoption rises with cumulative adoption, i.e.,

\[
\frac{\dot{F}_t}{1 - F_t} = vF_t \implies F_t = \frac{1}{1 + \left(\frac{1}{F_0} - 1\right)e^{-vt}},
\]

where \(F_t\) is the fraction of adopters at time \(t\), and \(v\) is a constant contagion parameter.

Although the logistic model has traditionally fit data very well, some important issues remain unclear. In particular, assuming homogenous adopters and exogenous diffusion parameters, the model does not explain why diffusion rates are so different historically across countries (regions), consumer groups, and products. Therefore, in many studies following this approach, ad hoc assumptions had to be added to the contagion framework (e.g., assuming diffusion parameters to be function of traits like region, consumer type or product).

However, the key question is – how much does the contagion effect really matter? Figure 3 plots the TV adoption rate against per capita GDP for 104 countries in 1980.\(^6\) At that time, TV was no longer a new product so the contagious spread of information can not explain the huge cross-country differences of adoption.\(^7\) Meanwhile, the figure shows evidently that TV adoption is strongly related with income across countries.

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\(^6\)Data source: *UN Common Database.*

\(^7\)Sometimes, the social contagion model is interpreted more broadly to include network effects of consumption.
2.1.2 A New Approach

This paper is hence motivated to take a different approach. Without assuming a social contagion framework, we derive logistic diffusion from a demand function generated by the heterogeneity of consumers.8 This alternative approach clearly shows the diffusion process is driven by economic forces such as price and income.

The model is as follows. Assume a new nondurable product sells for price $P$ in the market.9 An individual consumer adopts it only if her disposable income $I_d$ for that product allows her to do so, i.e.,

$$y = \begin{cases} 
1 & \text{if } I_d \geq P, \\
0 & \text{if } I_d < P.
\end{cases}$$

Consumers are heterogenous in their disposable income $I_d$ for this new product. This heterogeneity comes from their different incomes and preferences. For an individual consumer, we assume that the disposable income $I_d$ is the product of her total income $I$ ($I \geq 0$) and propensity of spending $c$ ($1 \geq c \geq 0$), i.e., $I_d = cI$, where $I$ and $c$ are independently distributed over the population. This immediately suggests that new products achieve higher adoption in high-income groups.10 This finding is strongly supported by empirical evidence (as shown in Fig. 4), but is not implied by the social contagion model.11

Empirically, the disposable income $I_d$ may not be directly observable, but it can be inferred from observables. In particular, for a given distribution of preference $c$, a higher mean (inequality) of total income $I$ implies a higher mean (inequality) of disposable income $I_d$. Moreover, given that

However, as Bowden and Offer (1994) show, the US enjoyed a uniformly faster adoption than the UK in consumer appliances including TV, Cloth Washer, Cloth Dryer, Dishwasher, Electric Blanket, Freezer, Radio, Refrigerator, Vacuum Cleaner and etc. Many of them certainly have little, if any, network effects of consumption.

8This idea is not totally new. In fact, the downward demand curve sometimes is interpreted as individuals with highest willingness to pay buy the good first, followed by those with a lower willingness to pay. However, the method that we link consumers’ willingness to pay to their income distribution and explicitly derive logistic diffusion curves is new.

9Note that introducing durability does not change the main analysis (see Appendix B).

10Denote $H(c)$ as the cdf function for $c$. For a given income group, the fraction of adopter is $\Pr(I_d \geq P \mid I) = 1 - H(P/I)$ and it rises with $I$.

11Data source: The US data is from Bogart (1972), the UK data is from Emmett (1956).
Figure 4: TV Penetration Rates by Income Class: US and UK

$I_d$ is distributed over the positive domain $[0, \infty)$, its distribution tends to be positively skewed. Although possible candidates for this group of distributions are not unique, we choose the log-logistic distribution for this analysis (Figure 5 fits the log-logistic distribution with US family income in 1970). As we will see, the log-logistic distribution provides an easily tractable example, and more important, it helps derive the typically observed logistic diffusion curves.

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

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

Accordingly, the mean $E(I_d)$ and Gini coefficient $g(I_d)$ are determined as

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

where $\Gamma$ denotes the gamma function $\Gamma(\omega) \equiv \int_0^\infty i^{\omega-1} \exp(-i) \, di$.

\footnote{Data source: Statistical Abstract of the United States.}
We can then rewrite the cdf function as:

\[
G_{I_d}(x) = 1 - \frac{1}{1 + \left(\frac{\Gamma(1+g)\Gamma(1-g)}{E(I_d)}x\right)^{1/g}},
\]

where \( g \equiv g(I_d) \).

Recall \( I_d = cI \), where \( c \) and \( I \) are independently distributed. Let \( \mu = E(I) \) so \( E(I_d) = E(c)\mu \). We can now derive the adoption rate \( F \) as a function of price \( P \), mean income \( \mu \) and other parameters:

\[
F = 1 - G_{I_d}(P) = \frac{1}{1 + \eta(P/\mu)^{1/g}}, \tag{2}
\]

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

### 2.1.3 Endogenous vs. Exogenous Diffusion

Introducing log-logistic distribution offers a natural approach to endogenize the logistic diffusion process. To see this, let us assume that the price declines at a constant rate \( P_t = P_0e^{-\rho t} \), and mean income grows at a constant rate \( \mu_t = \mu_0e^{zt} \). Then we can rewrite Eq. (2) as
Comparing Eq. (3) with Eq. (1), it becomes clear that our new formula is equivalent to the logistic model under very reasonable assumptions. In particular, the diffusion parameters traditionally treated exogenously now have clear economic meanings – the contagion parameter $v$ is determined by the price decline rate and income growth rate, and the initial condition $F_0$ is the fraction of adopters who can afford the new product at the initial price and mean income:

$$v = (\rho + z)/g, \quad F_0 = \frac{1}{1 + \eta[P_0/\mu_0]^{1/g} e^{-(\rho + z)/g}}.$$  

Assuming constant price decline and income growth is just a convenient approximation to illustrate our model. In the following theoretical analysis, we will take a step further to model the time path of price as an endogenous learning-by-doing process, and reveal the dynamic interactions between technology progress and demand diffusion. After that, in the empirical analysis, we use real price and income data to calibrate the adoption equation. The results suggest our endogenous diffusion model fits data better than the social contagion model.

### 2.2 The Supply Structure

Now let us turn to the supply side, where a homogenous good is produced in a competitive industry. There are $M$ potential producers who differ in their efficiency $\theta \in (0, \infty)$, and $\theta$ is distributed with cdf function $S(\theta)$.

13 Each period, an active firm in the industry incurs an opportunity cost $C$, which corresponds to the foregone earnings of the human capital needed to run the firm.\footnote{$\theta$ may include any firm-specific factors that affect production efficiency, such as management ability, physical location, industry experience and etc.}

14 For a typical firm, the production function is $y = \theta Ax^\alpha$, where $x$ and $y$ are input and output respectively, $A$ is the technology parameter, and $0 < \alpha < 1$ is the “span of control” parameter.\footnote{$C$ captures the foregone earnings of firm human capital that are compensated from the production residual, such as the management group and R&D team. For simplicity, $C$ is assumed to be identical across firms. However, allowing $C$ to be heterogenous would not change our analysis.}

15 Let $P$ denote the output price and $w$ denote the input price. We also assume firms are free to enter and exit. Let $P$ denote the output price and $w$ denote the input price. We also assume firms are free to enter and exit. See Lucas (1978).
An individual firm, indexed by its efficiency \( \theta \), has zero measure. Each period, firm \( \theta \) takes the market price \( P \) as given to maximize its profit:

\[
\pi_\theta = \max_{y_\theta} P y_\theta - w x_\theta - C \quad \text{s.t.} \quad y_\theta = \theta x_\theta^2,
\]

and gets the following solution:

\[
y_\theta^* = \left( \frac{\alpha P A^{\frac{1}{\alpha}} \theta^{\frac{1}{\alpha}}}{w} \right)^{\alpha - \gamma}, \quad \pi_\theta = (1 - \alpha) \left( \frac{\alpha P A \theta}{w^\alpha} \right)^{\frac{1}{1-\alpha}} - C.
\]

The free entry and exit condition ensures that the marginal firm \( \tilde{\theta} \) breaks even, i.e., \( \pi_{\tilde{\theta}} = 0 \). Accordingly, the market price is determined as

\[
P = \frac{C^{1-\alpha} w^\alpha}{(1 - \alpha)^{1-\alpha} \alpha A \bar{\theta}^{\frac{1}{1-\alpha}}}. \quad (4)
\]

Then, we can solve more explicitly each firm’s choice:

\[
y_{\theta}^* = \left( \frac{\alpha C}{(1 - \alpha) w} \right)^\alpha A \theta^{\frac{1}{1-\alpha}} \theta^{-\frac{\alpha}{1-\alpha}}, \quad \pi_{\theta} = [(\theta/\tilde{\theta})^{\frac{1}{1-\alpha}} - 1]C. \quad (5)
\]

The total market supply \( Y \) is the sum of active firms’ outputs:

\[
Y = M \int_{\tilde{\theta}}^\infty y_{\theta}^* dS(\theta) = \left( \frac{\alpha C}{(1 - \alpha) w} \right)^\alpha A \theta^{\frac{1}{1-\alpha}} \int_{\tilde{\theta}}^\infty (\theta^{\frac{1}{1-\alpha}}) dS(\theta). \quad (6)
\]

The corresponding number of firms is

\[
N = M \int_{\tilde{\theta}}^\infty dS(\theta). \quad (7)
\]

The supply-side structure in our model is a stylized representation of a competitive industry. It conveniently derives the key industry variables of interest while allowing for firm heterogeneity.\textsuperscript{16} In spite of its simplicity, the model fits industry data very well, as shown in Section 3.

\textsuperscript{16} Assuming heterogeneous firms allows us to explore some interesting issues of industry life cycle, including firm entry, exit and growth as well as the evolution of market concentration and profitability (see Section 2.4.3).
2.3 The Industry Equilibrium

2.3.1 The Momentary Equilibrium

Combining the demand and supply analyses, we are now ready to derive the industry equilibrium. At a point of time, the industry equilibrium implies that industry price $P$, output $Y$, marginal producer $\tilde{\theta}$ and firm numbers $N$ are uniquely determined by the following conditions:

\[ P = \frac{C^{1-\alpha}w^\alpha}{(1-\alpha)^{1-\alpha}(\alpha)^\alpha A\tilde{\theta}}, \quad (8) \]

\[ Y = (\frac{\alpha C}{(1-\alpha)w})^\alpha \tilde{\theta}^{\alpha-\alpha} AM \int_\theta^\infty (\theta^{\alpha-\alpha}) dS(\theta), \quad (9) \]

\[ Y = mF = \frac{m}{1 + \eta(P/\mu)^{1/\eta}}, \quad (10) \]

\[ N = M \int_\theta^\infty dS(\theta). \quad (11) \]

Notice that $m$ denotes the total number of consumers. It is reasonable to assume that the ratio $M/m$ is a constant, and does not vary with the population size.

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

2.3.2 Law of Motion

Technological Learning  Technology progress is commonly observed over industry life cycle. One most important source is learning by doing. Accordingly, we assume that technology $A$ is determined by the cumulative industry output:
\[ A_t = A_0(Q_t)^\gamma, \]  

(12)
in which \( Q_t = \int_0^t Y(s)ds + Q_0 \) and \( \gamma \) is the learning rate.

Equation (12) implies that only aggregate cumulative output matters for each producer’s productivity. In fact, a firm’s own contribution to \( Q \) may matter more, especially at high frequencies (Irwin and Klenow 1994, Thompson and Thornton 2001). However, at lower frequencies, the distinction between own and outside experience should fade given a wide range of channels through which information diffusion can occur.\(^{17}\)

**Income Growth** The mean income \( \mu \) is an economy-wide variable. It is reasonable to assume \( \mu \) grows at an exogenous rate \( z \). Meanwhile, the foregone earning \( C \) of firm human capital may grow with the mean income \( \mu \). Therefore,

\[ \begin{align*}
\mu_t &= \mu_0 e^{zt}, & \text{where } & \mu_0 > 0, \ z > 0; \\
C_t &= \phi \mu_t, & \text{where } & \phi > 0.
\end{align*} \]

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

\[ w_t = \sigma \mu_t^\psi, \quad \text{where } \sigma > 0, \ \psi < 1. \]

**2.3.3 The Dynamic Equilibrium**

The above law of motion equations suggest two fundamental driving forces for the industry evolution – technological learning (due to cumulative production) and income growth. As the initial adoption of a new product starts, these two forces interact with each other to generate further technology progress and demand diffusion (see Fig. 6). The dynamic industry equilibrium can then be summarized as follows: 

\(^{17}\)Lieberman (1987) lists many of these channels: employees may be hired away, products can be reverse-engineered, patents can be invented around or infringed, and etc.
Figure 6: Product Diffusion under Technology and Income Change

\[
\frac{P_t}{\mu_t} = \frac{(\phi)^{1-\alpha}(\sigma \mu_t^{\psi-1})^\alpha}{(1-\alpha)^{1-\alpha}(\alpha)^\alpha A_t \theta_t},
\]  
(13)

\[
Y_t = \left(\frac{\alpha^\phi \mu_t^{1-\psi}}{(1-\alpha)\sigma}\theta_t^{-\alpha} A_t M \int_{\theta_t}^{\infty} \left(\theta^{-1-\alpha}\right) dS(\theta),
\]  
(14)

\[
Y_t = m F_t = \frac{m}{1 + \eta(P_t/\mu_t)^{1/\theta}},
\]  
(15)

\[
N_t = M \int_{\theta_t}^{\infty} dS(\theta),
\]  
(16)

\[
A_t = A_0(Q_t)^{\gamma} \quad \text{where} \quad Q_t = \int_0^t Y(s) ds + Q_0,
\]  
(17)

\[
\mu_t = \mu_0 e^{2t}.
\]  
(18)

Now we are ready to characterize the time path of industrial evolution.
2.4 The Industrial Evolution

2.4.1 Industry Dynamics: Characterization

Under the assumption of learning by doing, the market demand equation (15) implies a first-order differential equation

\[ \dot{Q}_t = f(Q_t, t) = \frac{m}{1 + \eta \left( \frac{P_t}{\mu_t}(Q_t, t) \right)^{1/g}}. \]  

(19)

where the relative price \( P_t/\mu_t \) is a function of \( (Q_t, t) \), and the function is determined by the equilibrium conditions (13) - (15) as follows

\[ m \left( \frac{P_t}{\mu_t} \right)^{1/g} = \frac{\alpha \mu_t^{1-\psi}}{\sigma} \left( \frac{P_t}{\mu_t} \right)^{\frac{\alpha}{\sigma}} A_t^{1-\alpha} M \int_0^\infty \frac{(1-\alpha)^{1-\alpha} (\alpha)^{\frac{\psi-1}{\sigma}} \theta^{\frac{1}{1-\alpha}}} {(1-\alpha)^{1-\alpha} (\alpha)^{\frac{\psi-1}{\sigma}} A_t \mu_t} dS(\theta), \]

(20)

where \( A_t = A_0 (Q_t)^\gamma \), \( \mu_t = \mu_0 e^{zt} \).

Note that given an initial value, there is a unique \( Q(t) \) path satisfying Eq. (19).\(^{18}\) And given a \( Q(t) \) path we can then solve for the paths of everything else. The following theorems list some properties of the solution.

**Lemma 1:** In a competitive market, the number of firms \( N \) increases with the relative industry GDP, \( PY/\mu \).

**Proof.** Note Eqs. (13) and (14) suggest that \( PY/\mu \) is determined as

\[ \frac{PY_t}{\mu_t} = \frac{1}{1 - \alpha} \phi t \frac{\sigma}{\alpha} \text{M} \int_0^\infty \frac{(1-\alpha)^{1-\alpha} (\alpha)^{\frac{1}{1-\alpha}} \theta^{\frac{1}{1-\alpha}}} {(1-\alpha)^{1-\alpha} (\alpha)^{\frac{1}{1-\alpha}} A_t \mu_t} dS(\theta), \]

which decreases with the endogenous variable \( \hat{\theta} \). Meanwhile, Eq. (16) suggests that the number of firms \( N \) also decreases in \( \hat{\theta} \). Therefore, \( N \) and \( PY/\mu \) always move in the same direction at equilibrium. 

**Theorem 1 (Unique Shakeout):** Given a log-logistic distribution of the disposable income, there exists a unique shakeout for the firm numbers \( N \) and the relative industry GDP \( PY/\mu \).

**Proof.** Lemma 1 suggests that we can use \( PY/\mu \) to characterize the shakeout. See Appendix A for the proof. 

\(^{18}\)Since \( f \) is continuously differentiable, it satisfies the Lipschitz condition \( |f(x, t) - f(y, t)| \leq L |x - y| \), where \( L = \sup |\partial f/\partial Q| \).
Theorem 2 (Comparison Theorem): Everything else being equal, the relative price $P_t/\mu_t$ falls more quickly, the diffusion $F_t$ proceeds faster and the timing of shakeout $t^\ast$ arrives earlier if (1) technology is better (higher $Q_0$, higher $A_0$ or higher $\gamma$); (2) mean income is higher (higher $\mu_0$ or higher $\zeta$); (3) market size is larger (higher $m$); (4) input price is lower (lower $\phi$, lower $\sigma$ or lower $\psi$).

**Proof.** See Appendix A for the proof. ■

2.4.2 Industry Dynamics: An Intuitive Illustration

Intuitively, the industry dynamics can be illustrated as follows. First of all, as shown in Lemma 1, the number of firms $N$ follows the relative industry GDP $PY/\mu$ at equilibrium. In fact, in a competitive market, the profit of the marginal firm increases with $PY$ (the industry GDP) while its opportunity cost increases with $\mu$ (the mean income of the economy). It then follows that the ratio $PY/\mu$ tracks the viable number of firms. This result is strongly supported by industry evidence (see Section 3).

Then, in order to explain industry shakeout, we need to understand the time path of the relative industry GDP. An intuitive analysis can be shown in a familiar demand-supply framework. First, Eq. (15) 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:

$$F = \frac{1}{1 + \eta(P/\mu)^{1/\eta}},$$  \hspace{1cm} (21)

and the inverse demand function is convex ($\partial^2(P/\mu)/\partial F^2 > 0$) for $F \in (0, \frac{1}{\eta})$, and concave ($\partial^2(P/\mu)/\partial F^2 < 0$) for $F \in (\frac{1}{\eta}, 1)$.

Second, Eqs (13) and (14) suggest that the supply curve is upward sloping on $(P/\mu, F)$, and shifts to the right as the technology $A$ or mean income $\mu$ increases. The normalized industry supply $F$ is given as

$$F = \left(\frac{\alpha \mu^{1-\psi}}{\sigma}\right)^{\frac{1}{1-\alpha}} P^\alpha (P/\mu)^{\frac{\alpha}{1-\alpha}} A^{\frac{1}{1-\alpha}} M \int_{\frac{1}{1-\alpha}}^{\infty} \frac{(\theta^{1/\alpha} (\phi \mu^{\psi-1})^\alpha)}{(1-\alpha)^{1-\alpha}(\theta A(P/\mu))^{\alpha}} \theta^{1-\alpha} dS(\theta).$$  \hspace{1cm} (22)

Plotting the demand and supply curves on the graph of $(P/\mu, F)$ for a given technology $A$ and mean income $\mu$, we can then pin down the momentary equilibrium with Fig. 7.
For the dynamic analysis, we need to notice an important property of the demand function (21) in terms of its price/income elasticity,

\[ \varepsilon = \left| \frac{\partial F/F}{\partial (P/\mu)/(P/\mu)} \right| = \frac{(1 - F)}{g}, \]

which decreases with \( F \) and equals one at \( F^* = 1 - g \). It suggests something crucial for the time path of the relative industry GDP, \( PF/\mu \), as well as the firm numbers \( N \): if an industry starts from an initial condition that \( F_0 < 1 - g \), the supply curve keeps shifting to the right as the technology or mean income improves and the industry achieves the unique shakeout at \( F^* = 1 - g \).

Figure 7 illustrates that both technology progress and income growth drive industrial evolution, but through different mechanisms.

- In the presence of technology progress (\( \gamma > 0 \)) but no income growth (\( z = 0 \)), the supply curve shifts to the right due to cumulative production. As a result, the industry relative price

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19 It is clear that our results hold more generally than the log-logistic case. The only key assumption we need is the decreasing price/income elasticity, which captures the life-cycle pattern of new product demand. Introducing log-logistic distribution allows us to justify this assumption with observed logistic diffusion curves and uncover the effects of income distribution on demand diffusion.
as well as the absolute price $P$ keeps falling, and the product penetrates lower-income groups. Eventually, the demand growth is overtaken by the technology progress so fewer firms are needed. Meanwhile, the aggregate demand becomes inelastic and the shakeout begins.

- In the presence of income growth ($z > 0$) but no technology progress ($\gamma = 0$), the supply curve shifts to the right due to income growth. Although the absolute price $P$ may not fall (e.g., $\partial P / \partial t > 0$ for $0 \leq \psi < 1$), the relative price $P/\mu$ keeps falling and induces more adoption.\(^{20}\) Eventually, as the market demand becomes inelastic, the growth of industry profit is outstripped by the growth of firms’ foregone earnings so the shakeout begins.

- In the presence of both technology progress ($\gamma > 0$) and income growth ($z > 0$), the supply curve shifts to the right due to both cumulative production and income growth, and the two forces interact with each other to drive demand diffusion and industry shakeout.

With Fig. 7, it is also easy to understand the comparative dynamics proved in Theorem 2: If the technology is better (higher $Q_0$, higher $A_0$ or higher $\gamma$), mean income is higher (higher $\mu_0$ or higher $z$), market size is larger (higher $m$) or input price is lower (lower $\phi$, lower $\sigma$ or lower $\psi$), it contributes to cumulative production and/or income growth so the supply curve shifts to the right faster. As a result, demand diffusion and shakeout are sped up.

The above discussion provides a meaningful explanation for varying patterns of industrial evolution across markets. For example, applying to the US and UK TV industries, it suggests that the US, due to its higher per capita income and larger market size, tend to achieve faster demand diffusion and earlier shakeout than the UK.

### 2.4.3 Industry Dynamics: Further Implications

Our model also delivers rich implications on other aspects of the industry life cycle. Recall firms are different in size and profit due to their heterogenous efficiency (i.e., $\partial y_0 / \partial \theta > 0$ and $\partial \pi_0 / \partial \theta > 0$).

\(^{20}\)In the international economics literature, the “Balassa-Samuelson Effect” says a non-tradable good typically has a higher price in a richer country due to the higher foregone earnings 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 finding that it is the relative price $P/\mu$ rather than the absolute price $P$ that drives the demand diffusion.
Assume each individual firm’s efficiency $\theta_t$ is fixed over time. Because the efficiency threshold $\tilde{\theta}_t$ for participating the industry falls before the shakeout and rises afterwards, our model implies high-efficiency firms enter the industry earlier and survive longer. This provides an alternative explanation for the so-called “first-mover advantage”: It is not the action of moving first creates advantages for firms, but rather it is the firms who have advantages that move first.

This result can be generalized. In fact, it does not require a fixed $\theta_t$ for each individual firm over time. As a simple example, consider

$$\ln \theta_t = \ln \theta + \varepsilon_t, \quad (23)$$

where $\theta$ is an individual firm’s fixed efficiency, and $\varepsilon_t$ are i.i.d. random shocks. This implies that the overall distribution of $\theta_t$ is time-invariant, but individual firms have idiosyncratic shocks.\(^{21}\) As a result, there are both entry and exit before and after the shakeout, but the net number of firms evolves as our model predicts. Moreover, because firm efficiency is time persistent, early entrants tend to be relatively larger and survive longer. This result is consistent with well-established findings of industry studies on firm age and size effects (Evans 1987a, 1987b, Dunne, Roberts and Samuelson 1988, 1989, Audretsch 1991). Simons (2002) shows this is particularly true for the US and UK TV industries.

As technology improves, firms’ outputs tend to grow. Under the assumption (23), the model suggests that individual firms tend to have the same proportionate growth, consistent with “Gibrat’s Law”.\(^{22}\) To see this, notice Eq. (5) implies

$$\ln(y_{\tilde{\theta},t}^*) = \alpha \ln \frac{\alpha \phi}{(1-\alpha)\sigma} + \alpha(1-\psi) \ln \mu_t + \ln(A_t) - \frac{\alpha}{1-\alpha} \ln \tilde{\theta}_t + \frac{1}{1-\alpha} (\ln \theta + \varepsilon_t),$$

which suggests

$$\ln \frac{y_{\tilde{\theta},t}^*}{y_{\tilde{\theta},t-1}^*} = \alpha(1-\psi) \ln \frac{\mu_t}{\mu_{t-1}} + \ln \frac{A_t}{A_{t-1}} - \frac{\alpha}{1-\alpha} \ln \frac{\tilde{\theta}_t}{\tilde{\theta}_{t-1}} + \frac{1}{1-\alpha} (\varepsilon_t - \varepsilon_{t-1}).$$

Because $\partial Y/\partial t > 0$, Eq. (14) implies

$$\alpha(1-\psi) \ln \frac{\mu_t}{\mu_{t-1}} + \ln \frac{A_t}{A_{t-1}} - \frac{\alpha}{1-\alpha} \ln \frac{\tilde{\theta}_t}{\tilde{\theta}_{t-1}} > 0.$$  

\(^{21}\) For example, if $\ln \theta$ and $\varepsilon_t$ are normally distributed, $\theta_t$ then has a time-invariant log-normal distribution.

\(^{22}\) Alternatively, if we assume $\ln \theta_t = \lambda \ln \theta_{t-1} + \varepsilon_t$ with $0 < \lambda < 1$ and $\varepsilon_t$ i.i.d. normally distributed, $\theta_t$ also follows a time-invariant log-normal distribution but the growth of firm decreases in size. The other results remain unchanged. This is consistent with findings of Evans (1987a, 1987b) and Dunne, Roberts and Samuelson (1988, 1989).
Hence, given $1^{-1}(\varepsilon_t - \varepsilon_{t-1})$ are i.i.d., firms are statistically growing at the same positive rate.

Furthermore, as the industry evolves, the market concentration ratio displays a “U” shape over time, while industry profitability follows an inverted "U". To see this, denote $\lambda_q$ as the market share for the top $q$ firms surviving the period of interest. We have

$$\lambda_q = \frac{M \int_{S^{-1}(1-q/M)} y_0^\ast dS(\theta)}{M \int_{\tilde{\theta}}^\infty y_0^\ast dS(\theta)} \implies \frac{d\lambda_q}{d\theta} > 0.$$ 

Because the efficiency threshold $\tilde{\theta}$ falls before the shakeout and rises afterwards, so is the market concentration. Meanwhile, because industry profitability $\pi/\mu$ decreases in $\tilde{\theta}$,

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

it rises before the shakeout and falls afterwards.23

3 Data

In this section, we fit our model to the US and UK TV industry data. Because TV is a consumer durable good, we need to modify our model to take into account the durability issue. However, this does not affect our analytical results (see Appendix B).

3.1 TV Industry Data

The origin of TV industry can be traced back to the US and the UK in the 1930s. However, WWII curtailed TV production in both countries and it was not until after the war that TV market got off the ground. In our study, we focus on the evolution of the TV industry from the late 1940s to the late 1960s, namely the Black & White TV age. During this period, the US and the UK were the two major countries that pioneered TV adoption and production, and these two markets were segmented by standards.

We construct a US and UK TV dataset, which includes annual data on the number of TV producers, TV output, value of TV output, household numbers, TV adoption rate, nominal GDP per capita, and CPI for each country. Also, we collect the annual TV licence fee for the UK, and

23 Note that an individual firm may have idiosyncratic efficiency shocks, so its profitability does not necessarily coincide with the industry trend.
TV adoption rates across the 48 continental US states in the 1950s and 1960s. A detailed data description is in Appendix C.

3.2 Model Specification

Our theoretical model uses a system of equations to determine firm numbers, price, adoption, and output. Equations (13) - (18) are equilibrium conditions for a nondurable good, while the modified equations in Appendix B cover the case of durable goods. In the following empirical study, we fit our model with TV price and adoption data by assuming a degenerate distribution for firm efficiency $S(\theta)$. This is a restricted but easy specification. In fact, with identical firms, the price and adoption equations imply two simple linear regressions:

$$\frac{P_t}{\mu_t} = \frac{(\phi)^{1-\alpha}(\sigma_t^{1-\alpha})^{\alpha}}{(1-\alpha)^{1-\alpha}(\alpha)^{\alpha}A_t} \ln(P_t/\mu_t) = \kappa + \alpha(\psi - 1) \ln(\mu_t) - \gamma \ln(Q_{t-1}) + \varepsilon_t, \quad (24)$$

$$F_t = \frac{1}{1 + \eta(P_t/\mu_t)^{1/g}} \implies \ln\left(\frac{1}{F_t} - 1\right) = \beta + \frac{1}{g} \ln(P_t/\mu_t) + \epsilon_t, \quad (25)$$

where $\kappa$ and $\beta$ are constants, $\varepsilon_t$ and $\epsilon_t$ are random errors. The OLS then yields consistent parameter estimates.$^{24}$

Assuming homogenous firms is just one way to calibrate our model, and we use it as an illustrative example. The results show that our model fits data well under this specification. Of course, if we allow heterogenous firms and assume a more flexible distribution for $S(\theta)$, our model could fit data even better with additional freedom.

3.3 Comparing Theory and Data

3.3.1 Firm Numbers

Lemma 1 suggests that in a competitive market, the number of firms follows the relative industry GDP. We test this prediction using the US and the UK TV industry data as follows:

$$\ln N_t = a + b \ln(PY/\mu)_t + \nu_t, \quad (M-1)$$

where $\nu_t$ is assumed to be a Gaussian white noise process.

$^{24}$Note that the two equations (24) and (25) are recursive since each of the endogenous variables can be determined sequentially and the errors from each equation are independent of each other.
The regression results are reported in Table 3.1. For both industries, the null hypothesis \( b \leq 0 \) is rejected and the \( R^2 \) values are fairly high. This confirms the comovement between \( N \) and \( PY/\mu \). As shown by Fig. 8, TV firm numbers and relative industry GDP are highly synchronized.

Table 3.1. TV Firm Numbers

<table>
<thead>
<tr>
<th>Data</th>
<th>( \hat{b} )</th>
<th>( b \leq 0 )</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>US (1947-1963)</td>
<td>0.31 (0.12)</td>
<td>R</td>
<td>0.32</td>
</tr>
<tr>
<td>UK (1949-1967)</td>
<td>0.57 (0.11)</td>
<td>R</td>
<td>0.60</td>
</tr>
</tbody>
</table>

R: Rejected at 5% level.

The regression (M-1) was also applied to 20 other US industries in Gort & Klepper (1982) dataset and delivers consistent results. See Wang (2006).

As shown in Fig. 8, \( N \) and \( PY/\mu \) may not be perfectly synchronized. This suggests some factors outside our model may also play a role in industry evolution. For example, \( \alpha \) or \( S(\theta) \) may change over time, \( C \) may include time-varying components other than \( \mu \), or there may be distortions to the competitive market environment. However, we may want to abstract from those complications for at least two reasons. First, the empirical evidence suggests our theory does capture a major trend in industrial evolution. Second, by restricting the effects of additional supply factors, we constrain the role that the inter-firm heterogeneity can play in industry evolution. This allows us to focus on the effects of demand factors and distinguish our theory from the supply-side literature.
3.3.2 Price

Three models are fitted with the TV price data. Model (P-2), derived from Eq. (24), regresses the relative TV price on real per capita income and cumulative industry output. The parameters recovered are the changing rate of relative input price $\alpha(\psi - 1)$ and the technological learning rate $\gamma$. For comparison, we also fit two additional models. In Model (P-1), the relative TV price is regressed on a time trend, whose coefficient is the average price change rate. In Model (P-3), the US cumulative output is included to fit the UK relative TV price. Because the UK TV industry was lagged behind the US, this regression assesses how much the UK producers may have benefited from the US technology spillover.

\[
\ln\left(\frac{P_t}{\mu_t}\right) = \kappa + \omega t + \varepsilon_t, \tag{P-1}
\]

\[
\ln\left(\frac{P_t}{\mu_t}\right) = \kappa + \alpha(\psi - 1) \ln(\mu_t) - \gamma \ln(Q_{t-1}) + \varepsilon_t, \tag{P-2}
\]

\[
\ln\left(\frac{P_{uk,t}}{\mu_{uk,t}}\right) = \kappa + \alpha(\psi - 1) \ln(\mu_{uk,t}) - \gamma \ln(Q_{uk,t-1} + hQ_{us,t-1}) + \varepsilon_t, \tag{P-3}
\]

where $\mu$ is real per capita GDP in 1953 dollars (pounds) and $Q$ is cumulative output.

<table>
<thead>
<tr>
<th>Data</th>
<th>Model</th>
<th>$\omega$ (S.E.)</th>
<th>$\alpha(\psi - 1)$ (S.E.)</th>
<th>$-\gamma$ (S.E.)</th>
<th>$h$ (S.E.)</th>
<th>adj.$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>US</td>
<td>(P-1)</td>
<td>-0.08* (0.005)</td>
<td></td>
<td></td>
<td></td>
<td>0.93</td>
</tr>
<tr>
<td>(1948-1963)</td>
<td>(P-2)</td>
<td>-2.61* (0.36)</td>
<td>-0.06* (0.02)</td>
<td></td>
<td></td>
<td>0.97</td>
</tr>
<tr>
<td>UK</td>
<td>(P-1)</td>
<td>-0.05* (0.003)</td>
<td></td>
<td></td>
<td></td>
<td>0.94</td>
</tr>
<tr>
<td>(1949-1967)</td>
<td>(P-2)</td>
<td>-1.26* (0.23)</td>
<td>-0.08* (0.02)</td>
<td></td>
<td></td>
<td>0.96</td>
</tr>
<tr>
<td>(P-3)</td>
<td></td>
<td>-1.26* (0.71)</td>
<td>-0.08* (0.25)</td>
<td>0.003</td>
<td></td>
<td>0.96</td>
</tr>
</tbody>
</table>

* Statistically significant at 5% level.

The regression results are reported in Table 3.2. All the parameter estimates have the expected sign and most are statistically significant.\footnote{Note the regressions may arguably involve nonstationary time series. However, the OLS still consistently estimates the parameters as long as the equations are correctly specified. Also, because the Model (P-3) requires a nonlinear regression using very limited data, it is not surprising to see the parameter estimates are not statistically significant.} Model (P-1) shows that the relative TV price fell more...
rapidly in the US than the UK. The learning by doing equation, Model (P-2), suggests that the US advantage was due to its larger cumulative output and faster drop of input price. Figure 9 shows the Model (P-2) fits the TV price data very well.

Because the TV industry developed faster in the US, some may suspect that UK producers learned from US experience. Model (P-3) tests this hypothesis by including US cumulative output in the UK price regression using nonlinear least squares. Compared with the results from Model (P-2), we find that including the US experience does not improve fitting for the UK price data. Moreover, the magnitude of $h$, the coefficient of US spillover, is very small if it exists at all. This finding supports that these two markets were technologically segmented at the time.

### 3.3.3 Adoption

We fit four models with the TV adoption data. First, if the diffusion is a social contagion process, Eq. (1) implies the regression:

$$\ln\left(\frac{1}{F_t} - 1\right) = \beta + wt + \epsilon_t,$$

(A-1)

Note that the faster drop of input price may also be related to the larger cumulative output. As another channel of learning by doing, this can be easily added to our theoretic model and reinforce our findings.
where $\beta = \ln(\frac{1}{1-\delta} - 1), w = -v$.

For a consumer durable like the TV, if the price declines at an approximately constant rate, i.e., $P_{t+1}/P_t = \rho$, our endogenous adoption equations (26) and (27) in Appendix B suggest

$$\ln\left(\frac{1}{F_t} - 1\right) = \beta + \frac{1}{g} \ln(P_t/\mu_t) + \epsilon_t,$$  
(A-2)

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

For robustness, we also apply our endogenous model to a panel regression using TV adoption data across 48 continental US states in 1950, 1955, 1959 and 1963:

$$\ln\left(\frac{1}{F_{i,t}} - 1\right) = \beta + \frac{1}{g} \ln(R_{i,t}/\mu_{i,t}) + u_i + \epsilon_t,$$  
(A-3)

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

In contrast to the US, the UK government imposes a TV licence fee, which is a tax on TV ownership. Our theory predicts this should further delay TV adoption and shakeout in the UK. Including the TV licence fee into our endogenous model, Eqs. (26) and (27) in Appendix B suggest the following regression:

$$\ln\left(\frac{1}{F_t} - 1\right) = \beta + \frac{1}{g} \ln(R + \frac{L_t}{\mu_t}) + \epsilon_t,$$  
(A-4)

where $R = [1 - \frac{1-\delta}{1+\rho}]$ is the TV rental rate, $L_t$ is the TV licence fee at year $t$.

### Table 3.3. TV Adoption

<table>
<thead>
<tr>
<th>Data</th>
<th>Model</th>
<th>$w$ (S.E.)</th>
<th>$R$ (S.E.)</th>
<th>$1/g$ (S.E.)</th>
<th>adj.$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>United States</td>
<td>(A-1)</td>
<td>-0.34* (0.06)</td>
<td>0.84</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1948-1963)</td>
<td>(A-2)</td>
<td>4.52* (0.44)</td>
<td>0.95</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(A-3)</td>
<td>5.38* (0.30)</td>
<td>0.55</td>
<td></td>
<td></td>
</tr>
<tr>
<td>United Kingdom</td>
<td>(A-1)</td>
<td>-0.35* (0.04)</td>
<td>0.94</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1949-1967)</td>
<td>(A-2)</td>
<td>6.46* (0.61)</td>
<td>0.94</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(A-4)</td>
<td>0.25* (0.11)</td>
<td>8.56* (0.97)</td>
<td>0.95</td>
<td></td>
</tr>
</tbody>
</table>

* Statistically significant at 5% level.

---

29 This is a reasonable description of the TV price data, as suggested by the regression (P-1).
The regression results are reported in Table 3.3. We find that the endogenous diffusion models (A-2) and (A-4) fit the data better than the contagion Model (A-1) (as shown in Fig. 10) and offer higher $R^2$ values. Of course, this result by itself may not fully reject the contagion model, but at least it suggests our theory provides a reasonable alternative. Model (A-3) reports the panel estimates using the fixed-effect model.\footnote{The random-effect model is rejected by the Hausman specification test.} Notably, the results are very close to Model (A-2), which lends more credence to our theory.

\subsection*{3.3.4 Output}

Given TV adoption, output fitting is straightforward. As a durable good, the TV demand takes the simple form as Eq. (28) in Appendix B:

\[ Y_t = m_t(F_t - F_{t-1} + \delta F_{t-1}) + v_t, \]

where $m_t$ is the number of households at time $t$, and $\delta$ is the annual depreciation rate. It implies that annual output consists of two parts: first-time purchases $m_t(F_t - F_{t-1})$ by new adopters, and replacement purchases $m_t\delta F_{t-1}$ by existing adopters.
Given the data of $Y_t$, $m_t$, and $F_t$, the only parameter estimate is the depreciation rate $\delta$. Although assuming a constant $\delta$ might seem restrictive, the regression results (Table 3.4) suggest the model does fit the data well (Fig. 11).

### Table 3.4. TV Output

<table>
<thead>
<tr>
<th>Data</th>
<th>$\delta$ (S.E.)</th>
<th>adj.$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>US (1948-1963)</td>
<td>0.10* (0.005)</td>
<td>0.84</td>
</tr>
<tr>
<td>UK (1949-1967)</td>
<td>0.08* (0.009)</td>
<td>0.53</td>
</tr>
</tbody>
</table>

* Statistically significant at 5% level.

#### 3.3.5 Shakeout

The above empirical results allow us to explore the specific roles that demand factors played in driving TV shakeouts in the US and the UK. Notice that over the sample period, per capita GDP in the UK was only 70% of the US level, and the UK had only one third as many households as the US. Therefore, our theory suggests that the relative TV price $P_t/\mu_t$ should be sustainedly higher in
the UK compared to the US. This prediction is supported by the data, as shown in Fig. 12 (a).\textsuperscript{31} Note the TV licence fee exacerbated the cost of adoption in the UK.

How did the difference in relative price $P_t/\mu_t$ affect the timing of TV shakeout? Recall the demand of a durable good is given by Eq. (28) in Appendix B:

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

where $m_t(F_t - F_{t-1})$ are first-time purchases by new adopters and $\delta m_t F_{t-1}$ are replacement purchases by existing adopters. The UK’s sustainedly higher $P_t/\mu_t$ delayed the mass adoption of TV so that the peak of first-time purchases came much later than the US, as predicted by our theory. The data for $(F_t - F_{t-1})$ is plotted in Fig. 12 (b).

Comparing Fig. 11 with Fig. 12 (b), we notice that in the US, TV output outpaced what first-time purchases would predict. This was due to replacement purchases and population growth.\textsuperscript{32} However, industry output did level off in the early 1950s, and relative industry GDP, as well as the number of firms, started to decline at that time (see Fig. 8). In the UK, replacement purchases

\textsuperscript{31}The absolute TV price in the UK was not necessarily higher than the US as discussed in Footnote 20. Using both official exchange rate and the PPP, we find the absolute TV price was lower in the UK.

\textsuperscript{32}During 1948-1963, the number of households grew at 2% annually in the US and 0.5% in the UK.
and population growth were moderate so the TV output was mainly driven by first-time purchases, which continued growing until 1959. Consequently, relative industry GDP and the number of firms did not decline until then (see Fig. 8).

4 Concluding Remarks

This paper complements the existing industry life cycle literature by exploring the previously largely ignored demand side. First, it shows that demand changes alone could drive a shakeout. Second, it connects characteristics of demand, including income distribution and market size, to industry life cycle dynamics including timing of shakeout and observed adoption rates.

The demand analysis in this paper assumes a log-logistic income distribution, but our findings of industrial evolution hold more generally. The only key assumption we need is the decreasing price/income elasticity of demand through the life cycle of a new product. Introducing log-logistic distribution allows us to justify this assumption with observed logistic diffusion curves and uncover the effects of income distribution on new product demand.

On the supply side, we assume a stylized portrayal of firms. Firms face decreasing returns to scale in the short run, and they can change their production scales without adjustment costs. Moreover, the span of control parameter $\alpha$ and the efficiency distribution $S(\theta)$ are assumed to be time-invariant. These simplifications allow our theory to focus on demand characteristics and explain the major trend of industrial evolution. However, this by no means rules out other explanations for shakeouts, such as the supply-side theories. Rather, they are good complements. Particularly, the number of firms and the relative industry GDP are not perfectly synchronized, which suggests that some factors outside our model may also play important roles.

Here are a few final comments. First, a competitive market does not internalize spillover of learning, so the industry equilibrium derived in the model is not Pareto optimal. A social planner would prefer a faster demand diffusion and earlier industry shakeout.

Second, the demand structure in the paper is constructed for consumer goods. To extend it to producer goods, we may need to consider the size distribution of producers in place of the income distribution of consumers (see Sullivan and Wang 2006 for an example).
Third, quality changes in goods may also play a role in industrial evolution. On the demand side, it suggests hedonic price could be used to model demand adoption. On the supply side, quality change may offer firms another dimension to compete with each other (see Klepper 1996 for a model on product innovation and industry shakeout).

Finally, the close-country framework in the paper can be generalized. In an open world economy, a country may specialize in certain industries to exploit its comparative advantages. Then the world income distribution and world market size will shape the industry life cycle.

Acknowledgments


Appendix A. Proofs.

Theorem 1 (Unique Shakeout): Given a log-logistic distribution of the disposable income, there exists a unique shakeout for the firm numbers \( N \) and the relative industry GDP \( \frac{PY}{\mu} \).

Proof. Lemma 1 suggests that we can use \( \frac{PY}{\mu} \) to characterize the shakeout. Given a log-logistic distribution, Eq. (15) suggests

\[
\frac{PY_t}{\mu_t} = (P_t/\mu_t) \frac{m}{1 + \eta(P_t/\mu_t)^{1/g}}.
\]

Hence,

\[
\frac{\partial \left( \frac{PY_t}{\mu_t} \right) / \partial t}{\partial (P_t/\mu_t) / \partial t} = \frac{\partial (PY_t)}{\partial (P_t/\mu_t)} \left( \frac{\partial (P_t/\mu_t)}{\partial t} \right).
\]
Equation (20) implies that $\dot{\theta}$ decreases with $\dot{\tau}$ and $\ddot{\tau}$. Since $A_t = A_0 (Q_t)^{\gamma}$ and $\mu_t = \mu_0 e^{z t}$ are strictly increasing with time $t$, we have $\partial (P_t / \mu_t) / \partial t < 0$. In addition, we have

$$\frac{\partial (P_t / \mu_t)}{\partial (P_t / \mu_t)} \leq 0 \quad \text{for} \quad P_t / \mu_t \geq \frac{g}{\eta (1 - g)}.$$ 

Therefore, the unique shakeout occurs at $(P_t / \mu_t)^* = \left[ \frac{g}{\eta (1 - g)} \right]^g$ and the corresponding adoption rate is $F^* = 1 - g$. If $P_0 / \mu_0 > \left[ \frac{g}{\eta (1 - g)} \right]^g$, the firm numbers as well as the relative industry GDP initially rise and later fall. If $P_0 / \mu_0 < \left[ \frac{g}{\eta (1 - g)} \right]^g$, the firm numbers and the relative industry GDP decline from the very beginning.

**Theorem 2 (Comparison Theorem):** Everything else being equal, the relative price $P_t / \mu_t$ falls more quickly, the diffusion $F_t$ proceeds faster and the timing of shakeout $t^*$ arrives earlier if (1) technology is better (higher $Q_0$, higher $A_0$ or higher $\gamma$); (2) mean income is higher (higher $\mu_0$ or higher $\xi$); (3) market size is larger (higher $m$); (4) input price is lower (lower $\phi$, lower $\sigma$ or lower $\psi$).

**Proof.** Let us take $\gamma$ as an example, and the other proofs are similar. The proof takes the following three steps: (1) Equations (19) and (20) define $\dot{Q}_t = f(Q_t, t)$, where $f$ satisfies the Lipschitz condition. Since $\partial f / \partial \gamma > 0$ for any given $(Q_t, t)$, a higher $\gamma$ leads to a higher $Q_t$ (hence higher $A_t$) at any time $t$. This result follows Theorem 8 and Corollary 2 of p. 25-26 in Birkhoff and Rota (1969).

(2) With $\partial A_t / \partial \gamma > 0$ at any time $t$, Eqs. (20) and (15) imply that a higher $\gamma$ leads to a lower relative price and higher adoption:

$$\frac{\partial (P_t / \mu_t)}{\partial \gamma} = \frac{\partial (P_t / \mu_t)}{\partial A_t} \frac{\partial A_t}{\partial \gamma} < 0, \quad \frac{\partial F_t}{\partial \gamma} = \frac{\partial F_t}{\partial (P_t / \mu_t)} \frac{\partial (P_t / \mu_t)}{\partial \gamma} > 0.$$ 

(3) At the time of shakeout $t^*$, $\partial (P_t Y_t / \mu_t) / \partial t = 0$ and $\partial^2 (P_t Y_t / \mu_t) / \partial t^2 < 0$, so

$$\frac{\partial (P_t Y_t / \mu_t)}{\partial t} = 0 \Rightarrow \frac{\partial (P_t / \mu_t)}{\partial t} = \frac{m}{1 + \eta (P_t / \mu_t)^{1/g}} \left\{ 1 - \frac{\eta / g}{\eta + [P_t / \mu_t]^{-1/g}} \right\} = 0.$$ 

Since we have proved in Theorem 2 that $\frac{\partial (P_t / \mu_t)}{\partial t} < 0$, we have

$$J = \frac{m}{1 + \eta (P_t / \mu_t)^{1/g}} \left\{ 1 - \frac{\eta / g}{\eta + [P_t / \mu_t]^{-1/g}} \right\} = 0 \quad \text{and} \quad \frac{\partial J}{\partial (P_t / \mu_t)} < 0.$$
Therefore,
\[
\frac{\partial t^*}{\partial \gamma} = - \frac{\partial^2 (P_t Y_t / \mu_t) / \partial t \partial \gamma}{\partial^2 (P_t Y_t / \mu_t) / \partial t^2} = - \frac{\partial (P_t / \mu_t) \partial (P_t / \mu_t)}{\partial^2 (P_t Y_t / \mu_t) / \partial t^2} < 0.
\]

Hence a higher $\gamma$ leads to an earlier shakeout. ■

Appendix B. Durable Goods

We have discussed consumer nondurable goods in the paper. The analysis can be readily extended to durables. This extension is not only of its own theoretical interest, but also adds to our empirical work.

The issue of durability complicates the analysis, because for a durable good, consumers pay a rental price for the service provided by the stock of the good, and producers are paid with the output price to supply the increment of stock to meet the demand. Therefore, some modifications are needed for our original model.

First, we need to derive the rental price from the output price. At equilibrium, the output price is the discounted sum of future rents, i.e.,
\[
P_t = \sum_{\tau=t}^{\infty} \frac{(1 - \delta)^{\tau-t}}{(1 + r)^{\tau-t}} R_{\tau},
\]
where $r$ is the market interest rate and $\delta$ is the depreciation rate. It implies that the rental price $R_t$ can be written into the following form
\[
R_t = [1 - \frac{1 - \delta}{1 + r}(P_{t+1} / P_t)]P_t,
\] (26)
and the consumers make their adoption decisions based on this rental price
\[
F_t = \frac{1}{1 + \eta(\bar{R}_t / \mu_t)^{1/g}}.
\] (27)

Second, the output $Y_t$ for durable goods is made of two parts. One is first-time purchases by new adopters $m(F_t - F_{t-1})$. The other is replacement purchases by existing adopters $\delta m F_{t-1}$. Therefore, total output is
\[
Y_t = m(F_t - F_{t-1} + \delta F_{t-1}).
\] (28)

The rest of the equilibrium conditions are the same as those for nondurable goods. Notice that when $\delta = 1$, Eqs. (27) and (28) are equivalent to what we derived for nondurable goods.
As before, assuming learning-by-doing technology progress and constant income growth, we can characterize the industry dynamics. The study in Section 3 shows, with minor reinterpretation, most our theoretical analyses for nondurable goods remain unchanged for durable goods and are supported by the data.

Appendix C. Data Details

US-UK TV Dataset – The US data starts as early as 1946 when the Black & White TV was initially introduced, and ends at 1963 when the sales 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 and Williamson (2003) and CPI is from International Historical Statistics: the Americas, 1750-1993. We also collect data for the TV adoption rate and personal income across 48 continental US states at year 1950, 1955, 1959 and 1963, for which the TV adoption rate is drawn from the Television Factbook and the personal income is drawn from the Statistical Abstract of the United States. The UK data also starts from 1946 but ends at 1967 (a little later than the US) 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 as population (from UN Common Database) divided by average household size (from UN Demographic Yearbook). The TV adoption rate is from Table AI of Bowden and Offer (1994) and TV licence fee is from the BBC press office. The nominal GDP per capita is from Officer (2003) and the CPI is from International Historical Statistics: Europe, 1750-1993.

References


