Technological Innovation and Market Turbulence: The Dot-com Experience*

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Abstract

This paper explains market turbulence, such as the recent dot-com boom/bust cycle, as equilibrium industry dynamics driven by the synergy between new and existing technologies. When a major technological innovation arrives, a wave of new firms implement the innovation and enter the market. However, if the innovation complements existing technology, some new entrants later will be forced out as more and more incumbent firms succeed in adopting the innovation. It is argued that the diffusion of internet technology among traditional brick-and-mortar firms was indeed the driving force behind the rise and fall of dot-coms as well as the sustained growth of e-commerce. Systematic empirical evidence from retail and banking industries supports the theoretical findings.

JEL classification: E30; L10; O30

Keywords: Technology diffusion; Industry dynamics; Shakeout

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1 Introduction

1.1 Motivation

Technological innovation is one of the most fundamental impulses that set and keep the market economy in motion. It incessantly transforms production and consumption as well as organization of firms and industries, destroying old ones and creating new ones – a process that Schumpeter named "creative destruction." The recent internet innovation and following dot-com boom/bust cycle has presented itself, although in an unconventional sense, as a dramatic example of this process.

Internet technology became commercially available in the mid-1990s. Soon after, the potential of electronic commerce was discovered. A huge wave of companies, so-called "dot-coms," were then formed to conduct business via the internet. A typical dot-com firm is an internet pure play that operates only from its online website. Its ability to reach customers in vast geographic regions via the internet, while not having to invest in building physical facilities, has been among its most attractive features for investors and entrepreneurs.[1] During a short period in the late 1990s, about 7,000-10,000 new substantial dot-com companies were established,[2] most with a vision of generating huge market values after taking the firm public. The boom fueled tremendous excitement throughout the business world.

However, spring 2000 was a turning point. The dot-com stock index began to fall and bottomed out mid-2001, when the dot-com exit rate hit its peak. The stock index stabilized afterward, while dot-com exit continued, though at a decreasing rate. Between spring 2000 and spring 2003, nearly 5,000 dot-com companies exited

[1] Although dot-com firms do not have to invest in physical stores, they may still have to invest in storage facilities and warehouses. However, the costs of those are generally negligible compared to operating many store fronts.

[2] Data Source: Webmergers.com, a San Francisco-based company that monitors the dot-com mergers and acquisitions. Webmergers.com counts as "substantial" all dot-com companies that have received some formal outside funding from venture capitalists or other investors.

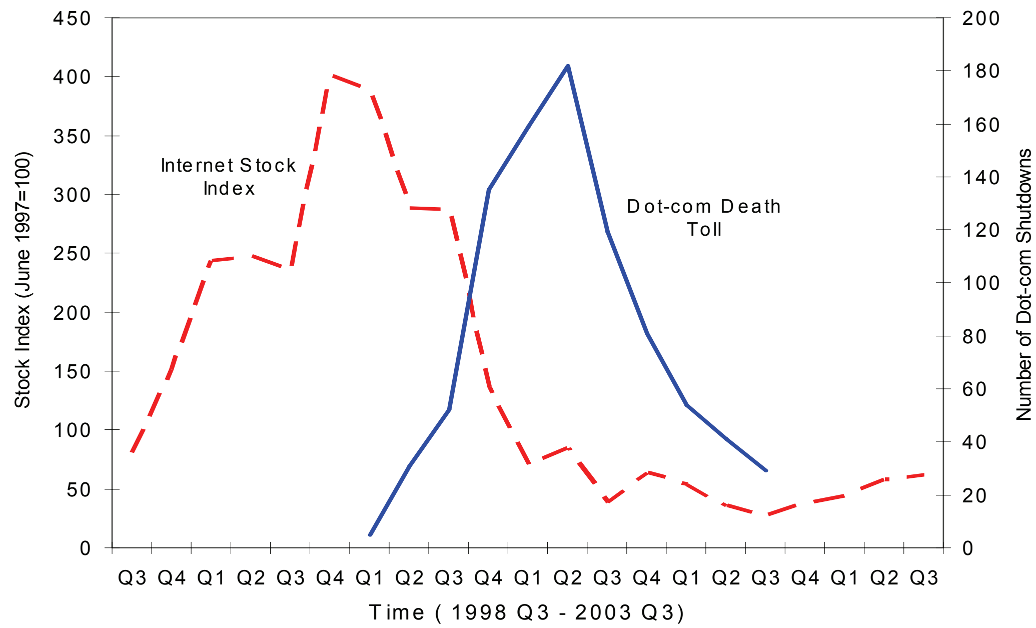

Figure 1: Internet Stock Index and Dot-com Death Toll

the market.[3] From peak to bottom, the Dow Jones internet stock index[4] plummeted by 93 percent, and the Nasdaq composite lost 78 percent of its value. The Dow Jones internet stock index and the number of dot-com shutdowns are plotted in Figure 1.

What can explain this striking boom/bust cycle of dot-coms? Several theories address this question. Most of them appeal to financial bubbles, rational or irrational (Shiller (2000), Abreu and Brunnermeier (2003), Ofek and Richardson (2003), LeRoy (2004)). However, as Garber (2000) has persuasively argued, "[bubble] is a fuzzy word filled with import but lacking a solid operational definition. Thus, one can make whatever one wants of it." More important, even if a bubble did exist, it still remains

[3] According to Webmergers.com, at least 3,892 dot-coms were sold and 962 closed or declared bankruptcy.

[4] Dow Jones defines an internet stock as the stock of a company that generates more than 50 percent of its annual revenues directly from the internet. With 40 components, the Dow Jones internet stock index represents roughly 80 percent of the total market cap of the internet sector.

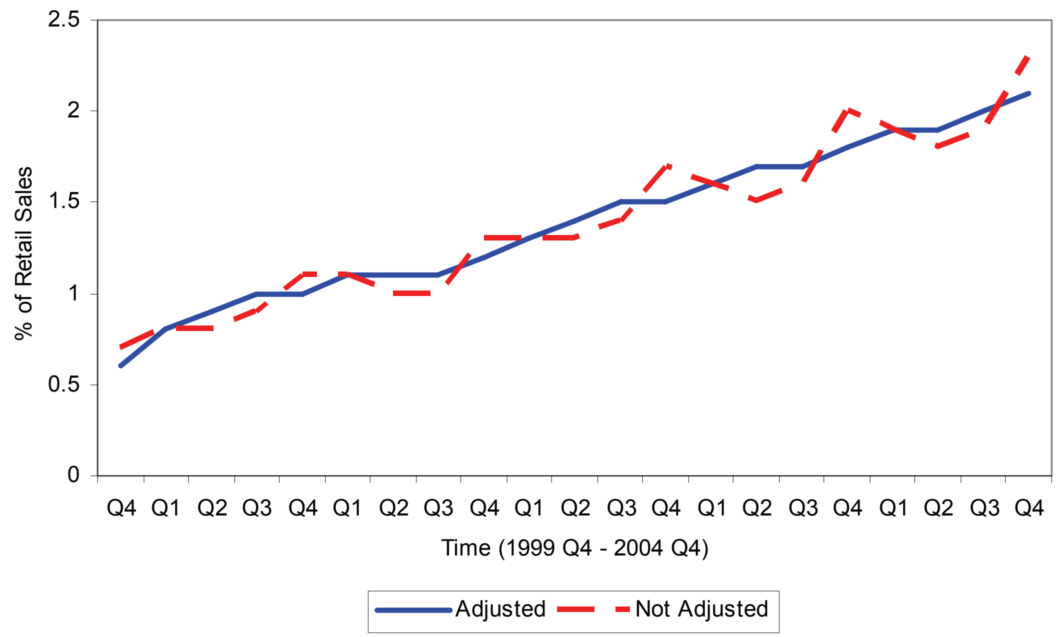

Figure 2: U.S. Retail E-Commerce Sales as a Percent of Total Retail Sales

a puzzle what changes of real fundamentals, if any, could have induced the bubble to form and burst in the first place. Some other theories try to build more upon economic foundations, especially the uncertainties in new markets; e.g., the uncertainties about profitability (Pastor and Veronesi (2006), Horvath, Schivardi and Woywode (2001)), pre-production (Jovanovic (2004)) or potential market size (Barbarino and Jovanovic (2005), Zeira (1999), Rob (1996)). Those factors certainly have played important roles in the new economy, but some key issues still have been overlooked. In particular, the nature of competition in the internet-related market has not been fully understood and analyzed.

To illustrate this point, Figure 2 presents the time trend of U.S. retail e-commerce sales as a percent of the total retail sales.[5] It clearly shows the growth of e-commerce

[5]Data Source: The Census Bureau of the Department of Commerce. Retail e-commerce sales are estimated from the Monthly Retail Trade Survey (MRTS), where about 11,000 retail firms are selected randomly. Their sales then are weighted and benchmarked to represent the complete

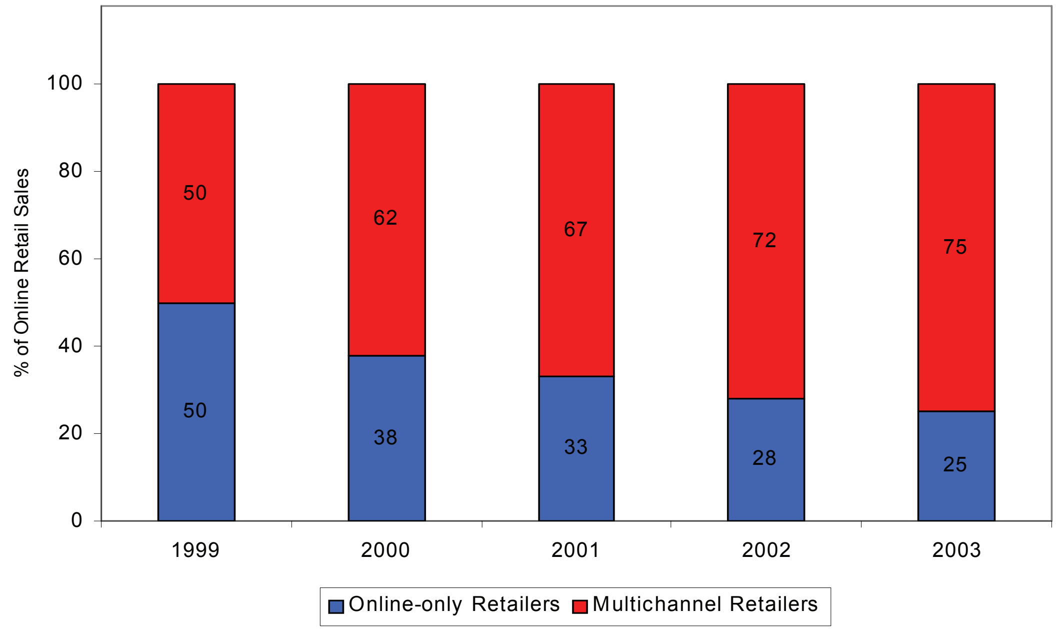

Figure 3: Percentage of Online Retail Sales: Dot-coms vs. Multichannel Retailers

was strong and stable despite the dramatic shakeout of dot-com companies. What drove this sustained growth? The evidence in Figure 3, showing the composition of retail e-commerce through time,[6] suggests the increasing online success of traditional brick-and-mortar firms was a major driving force.[7] Therefore, to better understand the rise and fall of dot-coms, we have to look into the dynamic competition among firms of different types in the market – in particular, online pure plays verse traditional brick-and-mortar firms.

universe of more than two million retail firms. The MRTS sample covers all retailers whether or not they are engaged in e-commerce. Online travel services, financial brokers and dealers, and ticket sales agencies are not classified as retail and are not included. The estimates are adjusted for seasonal variation and holiday and trading-day differences, but not for price changes.

[6]Data Source: *The State of Online Retailing*, an annual survey conducted by Shop.org, Boston Consulting Group and Forrester Research.

[7]Improvement of internet technology and changes of consumer preference for e-commerce probably also played a role in the process.

1.2 A New Hypothesis

This paper proposes a new explanation as follows. When a major technological innovation (e.g., the internet) arrives, a wave of new firms (e.g., dot-coms) enter the market to compete with the incumbents (e.g., brick-and-mortar firms). This entry is especially facilitated by the lower entry cost associated with the innovation (e.g., lower physical investment of dot-coms). However, if the technological innovation is complementary to the existing technology, some new entrants later will be forced out as more and more incumbent firms succeed in adopting the innovation (e.g., becoming so-called "click-and-mortar" firms). During this process, the contribution of the new technology to the total industry output (e.g., share of e-commerce in total commerce) keeps rising, while the share of new pure-play entrants (e.g., dot-coms) keeps falling.

To formalize this idea, this paper develops an industry life cycle model based on Jovanovic and MacDonald (1994), in which forward-looking firms make optimal decisions on entry, exit and technology adoption in a competitive market. However, unlike Jovanovic and MacDonald (1994), the new model allows the new entrants to bypass the old technology and emphasizes the role sunk cost and technological complementarity play in industrial evolution. Without assuming aggregate uncertainty, this model generates mass entry and exit of dot-coms as the result of a complementary technological innovation – the internet. Adding aggregate uncertainty to the model does not change the main analysis, but it helps explain the timing and financial losses of the shakeout. Moreover, this paper considers explicitly each firm's individual uncertainty in adopting new technology, which explains the delayed adoption of the internet among incumbent firms as well as the high market-to-book value for those successful adopters (e.g., dot-coms and click-and-mortar firms).

The above theoretical findings are supported by systematic empirical evidence. Exploring an original dataset of the top 400 e-retailers across 14 major retail categories, it is found that incumbent multi-channel retailers enjoy a substantial advantage over dot-com entrants in both online and total sales. That advantage stems from the synergy between the online and offline channels as well as many forms of complementary assets that incumbent firms possess. A similar pattern also is found in the banking industry, in which incumbent multi-channel banks dominate the dot-coms.

The point that pure-play entrants are outrun by traditional firms who adopt new technology is not specific to the internet. Similar synergistic advantages have been observed in the diffusion of other technologies, for example, FM radio broadcasting. During the late 1940s, business opportunities created by FM technology were aggressively pursued by both new FM stations and the established AM stations diversifying into FM broadcasting. The new playing field then was dominated by the AM incumbents who owned more than 90 percent of the FM stations by the early 1950s.[8] The fact that AM stations embraced FM technology to take advantage of synergies as well as to deter entry by independent FM stations is similar to the clash between dot-coms and traditional firms adopting internet as a sales channel. Moreover, our theory is consistent with the well-established empirical finding in industrial evolution literature that incumbent firms in general possess substantial advantages over new entrants and hence have a better chance to survive industry shakeouts.[9]

It is worth noting the differences between this paper and some existing game-theoretical work that tries to explain how the nature of e-commerce technology affects the entry and diversification decisions of different firm types. One example is Dinlersoz and Pereira (2006), which studies the endogenous timing of adopting e-commerce for traditional firms and dot-com entrants. Consistent with the findings in this paper, they show consumers' loyalty to the incumbent firm is a source of complementarities (transferable reputation) that may give a traditional firm advantage over a dot-com in adopting e-commerce. However, it is technically too difficult for a game-theoretical model to track industry dynamics, so Dinlersoz and Pereira (2006) assume only one traditional firm and one dot-com can exist in the market. In con-

[8] Sterling and Kittross (2002) and *Federal Communications Commission Annual Report*. I thank the referee for suggesting this example.

[9] See Klepper and Simons (2005) for studies on automobiles, televisions, tires and penicillin.

trast, this paper assumes a competitive economy and de-emphasizes the richness of the strategic approach in favor of a focus on the interplay between individual firm decision making and aggregate industry characteristics. As a result, it provides a more suitable framework to study the overall trends of industrial evolution.

1.3 Road Map

The paper is organized as follows. Section 2 presents the model, which studies competitive industry dynamics generated by an exogenous technological innovation. In particular, it shows that a shakeout of pure-play entrants tends to occur if the innovation complements the traditional technology. Section 3 applies the model to the innovation of e-commerce, which features low entry costs and strong complementarity with traditional brick-and-mortar technology, to explain the mass entry and exit of dot-coms. Empirical analysis on retail and banking industries supports our theoretical findings. Section 4 offers final remarks.

2 Model

2.1 Background

The model is cast in discrete time and infinite horizon. The environment is a competitive market for a homogenous good. On the demand side, the behavior of consumers is summarized by a time-invariant market demand curve $D(P)$, which is continuous and strictly declining.[10] On the supply side, there is a continuum of firms with total mass fixed at unity. Each firm maximizes the present discounted value of its profits.

At each time t, a firm decides whether to stay in the industry. If it does, the firm receives a profit flow that depends on the market price and its technology state.

[10] The model assumes there is one demand curve for the combined online and offline market. However, this assumption is not crucial. The analysis also holds for the alternative setting where the online demand is separate from the offline.

Otherwise, it exits and gets an alternative return of π^θ. A firm's technology can be at one of four states in the context of the internet economy. The first is a primitive one, θ, in which the firm cannot produce in the industry and thus earns zero net revenue to participate. All firms are endowed with this technology. The second one, b, is the traditional technology of production (b refers to the *brick* – brick-and-mortar). The third one, c, is a technological innovation (c refers to the *click* – dot-com). The last one, h, is a combination of the traditional technology and the innovation (h refers to the *hybrid* – click-and-mortar).

Before innovation c arrives, only technology states θ and b are available. A firm can either choose to stay out and earn π^θ, or pay a fixed cost, S_b, to obtain technology b to produce in the industry. After innovation c arrives, firms then have more options. In particular, if a firm pays a fixed cost, S_c, it may learn how to implement new technology c, though the success is random and occurs with probability σ.[11] As a result, two new types of firms may appear in the industry in addition to the traditional *brick* one. For example, if a type-θ firm succeeds in entering with technology c, it then becomes a *click* firm; if an incumbent *brick* firm succeeds in adopting the new technology, it then becomes a *hybrid* firm. Therefore, driven by the technological innovation and its diffusion, the market equilibrium generates time paths of product price P_t, industry output Q_t and entry and exit of each type of firm. These time paths are thus the foci of our study.

2.2 Pre-Innovation Equilibrium

Firms are endowed with technology θ beforehand. The market for the homogenous good then starts at time 0 when technology state b becomes available. Although all firms have the opportunity to continue earning a profit π^θ from working somewhere else, some of them may choose to enter this market. Those entrants pay a once-

[11] Alternatively, we may assume incumbent firms have a different success rate σ than new entrants. That allows the model to be more flexible, but does not add much to the analysis.

and-for-all fixed cost S_b to implement technology b. The corresponding return is a profit flow of π_t^b, which is a standard profit function that depends on price P_t and technology b; i.e., $\pi_t^b = \max_{q_t^b}\{P_t q_t^b - C_b(q_t^b)\}$, where C_b refers to the convex cost function for technology b, and q_t^b is a *brick* firm's optimal output (notice $q_t^b = \partial\pi_t^b/\partial P_t$ and $\partial q_t^b/\partial P_t > 0$).

For simplicity, technology b is assumed to be a standard practice that involves no uncertainty to implement, and any future innovations such as technology c may arrive at a probability too small to affect a firm's decision. Therefore, at each time $t \geq 0$, optimal firm behavior implies

$$U_t^\theta = \pi^\theta + \max\{\beta U_{t+1}^\theta, \beta U_{t+1}^b - S_b\}, \tag{1}$$

$$U_t^b = \max\{\pi^\theta, \pi_t^b\} + \beta U_{t+1}^b, \tag{2}$$

where U_t^θ (U_t^b) is the maximum value of a firm with technology θ (b) at time t, and β is the discount factor.

The corresponding equilibrium is straightforward. Because of free entry, there exists a price level P^* at which firms are indifferent about entry or not. Hence,

$$\beta U_{t+1}^\theta = \beta U_{t+1}^b - S_b,$$

which implies that

$$\frac{\beta\pi^\theta}{1-\beta} = \frac{\beta\pi^b(P^*)}{1-\beta} - S_b,$$

so that

$$\pi^b(P^*) = \pi^\theta + \frac{1-\beta}{\beta}S_b. \tag{3}$$

In addition, the demand equals supply at the equilibrium; hence,

$$Q = D(P^*) = N^b q^b(P^*), \tag{4}$$

where N^b is the number of *brick* firms in this market.

Using Equations 3 and 4, we can solve for the equilibrium price P^*, the number of firms N^b, an individual firm's output q^b as well as the market total output Q. It implies a simple industry dynamic path: At time 0, firms decide whether to enter the new market. N^b of them then pay a cost S_b to enter and stay there afterward. Since it takes one period to transform the technology from state θ to b, no firm is able to produce in the new market at time 0. From time 1, the industry has a fixed price P^* and output $Q = D(P^*) = N^b q^b(P^*)$, and no further entry or exit will occur.

2.3 Post-Innovation Equilibrium

At time T, innovation c arrives as an unexpected shock and triggers a market turbulence. Now that firms have more options because of the technological progress, they have to reconsider entry and exit. The value of each type of firm at each time $t \geq T$ is as follows:

$$\begin{aligned} V_t^\theta \quad = \quad & \pi^\theta + \max\{\beta V_{t+1}^\theta, \beta V_{t+1}^b - S_b, \beta[\sigma V_{t+1}^c + (1-\sigma)V_{t+1}^\theta] - S_c, \\ & \beta[\sigma V_{t+1}^h + (1-\sigma)V_{t+1}^b] - S_b - S_c\}, \end{aligned} \tag{5}$$

$$V_t^b = \max\{\pi^\theta, \pi_t^b\} + \max\{\beta V_{t+1}^b, \beta[\sigma V_{t+1}^h + (1-\sigma)V_{t+1}^b] - S_c\}, \tag{6}$$

$$V_t^c = \max\{\pi^\theta, \pi_t^c\} + \max\{\beta V_{t+1}^c, \beta V_{t+1}^h - S_b\}, \tag{7}$$

$$V_t^h = \max\{\pi^\theta, \pi_t^b, \pi_t^c, \pi_t^h\} + \beta V_{t+1}^h. \tag{8}$$

Equations 5 to 8 say the following:

- A firm with primitive technology θ may choose to continue staying out of this market or pay a fixed cost S_b to enter with technology b, or pay a fixed cost S_c in hopes of entering with technology c (the probability of success is σ). In addition, it is possible for the firm to pay both costs, S_b and S_c, to implement technologies b and c at the same time. By doing that, it may enter as a *hybrid* firm if it succeeds in adopting innovation c (the probability is σ), or it may become a traditional *brick* firm if it fails (the probability is $1 - \sigma$).

- A traditional *brick* firm has the option to work somewhere else, stay in the market with technology b, or pay a fixed cost S_c to implement technology c. If it succeeds in adopting c (the probability is σ), it then transforms itself into a *hybrid* firm; if it fails, it stays as a *brick* firm (the probability is $1-\sigma$).

- A *click* firm has the option to work somewhere else, stay in the market with technology c, or pay a fixed cost S_b to implement technology b. If it invests S_b, it then transforms itself into a *hybrid* firm.

- A *hybrid* firm does not have to invest in any new technology and can implement whatever technology θ, b, c or h it wants to pursue the highest profit.

Depending on the values of parameters, a number of equilibrium time paths can result. To keep the discussion more focused, we assume the investment S_b is too large for any type of firm to find it profitable from time T on. This condition is likely to be satisfied in the dot-com context. Empirical evidence in section 3 shows many brick-and-mortar firms have become major online players, while few dot-coms have ever developed substantial offline channels.[12] Therefore, Equations 5 to 8 can be simplified as follows:

$$V_t^\theta = \pi^\theta + \max\{\beta V_{t+1}^\theta, \beta[\sigma V_{t+1}^c + (1-\sigma)V_{t+1}^\theta] - S_c\}, \tag{9}$$

$$V_t^b = \max\{\pi^\theta, \pi_t^b\} + \max\{\beta V_{t+1}^b, \beta[\sigma V_{t+1}^h + (1-\sigma)V_{t+1}^b] - S_c\}, \tag{10}$$

$$V_t^c = \max\{\pi^\theta, \pi_t^c\} + \beta V_{t+1}^c, \tag{11}$$

$$V_t^h = \max\{\pi^\theta, \pi_t^b, \pi_t^c, \pi_t^h\} + \beta V_{t+1}^h. \tag{12}$$

As we will see, the equilibrium industry dynamics depend on how innovation c is related to the traditional technology b.

[12] Some dot-coms did develop an offline presence. For example, ING Direct, the largest dot-com bank, opened four brick-and-mortar locations, referred to as *cafes*; RedEnvelope, a major dot-com gift store, started catalog services. However, these types of offline operations are typically limited in scope and scale.

2.4 Characterization: A Complementary Innovation

If the innovation complements the traditional technology (i.e., $\pi_t^h > \pi_t^c$ and $\pi_t^h > \pi_t^b$), the industry tends to experience a shakeout of new entrants. Still, we have to distinguish the following two cases: $\pi_t^h > \pi_t^b > \pi_t^c$ and $\pi_t^h > \pi_t^c > \pi_t^b$. Let us start with the first one.

2.4.1 Case 1: $\pi_t^h > \pi_t^b > \pi_t^c$

In the first case, we assume $\pi_t^h > \pi_t^b > \pi_t^c$ and $q_t^h > q_t^b > q_t^c$. Denote the mass of participating firms in the four technology states at time t to be $n_t \equiv (n_t^\theta, n_t^b, n_t^c, n_t^h)$. The market equilibrium path can be characterized as follows.

At time T, given the entry cost S_c is sufficiently small, N^θ type-θ firms attempt to enter the market with technology c. For those firms, the free entry condition requires

$$\beta V_{T+1}^\theta = \beta[\sigma V_{T+1}^c + (1-\sigma)V_{T+1}^\theta] - S_c,$$

which implies

$$V_{T+1}^c - V_{T+1}^\theta = \frac{S_c}{\beta\sigma}. \tag{13}$$

Because S_c is sufficiently small, the existing N^b *brick* firms also find it profitable to adopt the new technology.[13] Since it takes one period for the adoption to take effect, there is no change in price and output at time T.

At time $T+1$, among all the N^θ entry attempts, a fraction σ turns out to succeed. Hence there are $n_{T+1}^c = \sigma N^\theta$ *click* firms in the market. Also, as long as there are *click* firms in the market, no *brick* firm will choose to exit since $\pi_t^b > \pi_t^c \geq \pi^\theta$. Among all the N^b *brick* firms, a fraction σ succeeds in adopting technology c; hence, the number of *hybrid* firm becomes $n_{T+1}^h = \sigma N^b$. The rest of the *brick* firms will have to try

[13] In other words, the complementary gain from upgrading technology b to h needs to be large enough. Here, we assume $V_t^h - V_t^b > S_c/(\beta\sigma)$ holds for all $t \geq T+1$ so that *brick* firms always find it profitable to upgrade.

upgrading in the next period. As the supply increases, the price falls, and no more type-θ firms will find it profitable to enter.

After time $T+1$, as more and more *brick* firms succeed in adopting the innovation, the output keeps rising and the price keeps falling. The price eventually reaches a critical value P^c at time T^c so that *click* firms become indifferent about staying or exiting the market.

Hence for $T+1 \leq t < T^c$, the number of each type of participating firm is

$$\begin{aligned} n_t^b &= N^b(1-\sigma)^{t-T}, \qquad n_t^c = N^\theta \sigma, \\ n_t^h &= N^b - n_t^b = N^b[1-(1-\sigma)^{t-T}]. \end{aligned}$$

At time T^c, the price reaches a critical value P^c for which

$$\pi^c(P^c) = \pi^\theta,$$

so some *click* firms start to exit. As a result, we have

$$D(P^c) = n_{T^c}^c q^c(P^c) + n_{T^c}^b q^b(P^c) + n_{T^c}^h q^h(P^c),$$

which implies that

$$n_{T^c}^c = \frac{D(P^c) - N^b(1-\sigma)^{T^c-T} q^b(P^c) - N^b[1-(1-\sigma)^{T^c-T}] q^h(P^c)}{q^c(P^c)}, \tag{14}$$

so that the number of exiting *click* firms $x_{T^c}^c$ is

$$x_{T^c}^c = N^\theta \sigma - n_{T^c}^c. \tag{15}$$

For $t > T^c$, as the rest *brick* firms continue adopting the innovation, more *click* firms exit to keep the price at P^c. At each time, the number of exiting firms x_t^c is determined by

$$x_t^c q^c(P^c) = (n_t^h - n_{t-1}^h)(q^h(P^c) - q^b(P^c)).$$

It implies that

$$x_t^c = \frac{N^b \sigma (1-\sigma)^{t-(T+1)} (q^h(P^c) - q^b(P^c))}{q^c(P^c)}. \tag{16}$$

In the long run, if $n^c_{T^c} q^c(P^c) \geq n^b_{T^c}[q^h(P^c) - q^b(P^c)]$, not all *click* firms will exit, and the market will keep price at P^c and output at $D(P^c)$. However, if $n^c_{T^c} q^c(P^c) < n^b_{T^c}[q^h(P^c) - q^b(P^c)]$, then the market price will eventually fall again and the shakeout of *brick* firms is also possible.

To complete the model, notice that N^θ and T^c meet the following conditions:

$$V^c_{T+1} - V^\theta_{T+1} = \sum_{t=T+1}^{T^c-1} \beta^{t-(T+1)}[\pi^c(P_t) - \pi^\theta] = \frac{S_c}{\beta\sigma}, \tag{17}$$

where for $T^c - 1 \geq t \geq T + 1$, P_t is determined by

$$P_t = D^{-1}\{N^\theta \sigma q^c(P_t) + N^b(1-\sigma)^{t-T} q^b(P_t) + N^b[1-(1-\sigma)^{t-T}]q^h(P_t)\}, \tag{18}$$

and for $t = T^c$, $P_t < P^c$ for P_t that solves Equation 18.

Several further results can be derived from the model.

Proposition 1 *The value of a successful click entrant increases from $V^\theta + S_c$ at time T to $V^\theta + \frac{S_c}{\beta\sigma}$ at time $T+1$, and then falls back to V^θ at time T^c and afterward.* [14]

Proof. Given free entry, Equation 9 implies the value of a successful *click* entrant increases from $V^\theta + S_c$ at time T to $V^\theta + \frac{S_c}{\beta\sigma}$ at time $T+1$; given free exit, Equation 11 implies the value of a *click* firm equals V^θ at time T^c and afterward. In the meantime, for $T^c > t \geq T + 1$, the value of a *click* firm is

$$V^c_t = V^\theta + \sum_{\tau=t}^{T^c-1} \beta^{\tau-t}[\pi^c(P_\tau) - \pi^\theta],$$

which implies V^c_t decreases in t. ■

[14] A successful *click* entrant enjoys an increase of market-to-book value initially; i.e., $V^c_{T+1}/(V^\theta + S_c) > 1$. This is due to survivor bias and consistent with empirical findings. Using Thomson Venture Economics dataset, Hochberg et al. (2005) shows that for VC funds raised in 1998 and 1999, on average only 20 percent of a fund's portfolio companies (presumably most were dot-coms) had successfully exited via IPO or M&A as of November 2003. Using the same dataset, Gompers et al. (2005) reports that for internet and computer companies that successfully went public, the average Q value jumped to 6 in 2000, and fell to 2 in 2001 and to 1.5 in 2003.

Proposition 2 *Click firms start exiting at time T^c, but the number of exits continues to fall after time $T^c + 1$.*

Proof. Equation 16 implies x_t^c decreases in t for $t \geq T^c + 1$. ■

Furthermore, the share of output attributable to the innovation c continues to increase from time $T + 1$, but the contribution of pure-play entrants is falling. In the context of the internet economy, it implies that e-commerce's share in total output is rising but dot-coms' share in e-commerce is falling (recall Figure 2 and 3). To illustrate this, we assume for a *hybrid* firm, the share ω of sales is conducted via the online channel and counted as e-commerce sales.

Proposition 3 *If ω is large, the share of output attributable to the innovation c continues to increase from time $T + 1$, but the contribution of click firms is falling.*

Proof. Denote s the share of output attributable to the innovation c and s_c the contribution of *click* firms. Hence,

$$s_t = 1 - \frac{N^b(1-\sigma)^{t-T} q^b(P_t) + (1-\omega) N^b [1-(1-\sigma)^{t-T}] q^h(P_t)}{D(P_t)}, \qquad s_{c,t} = \frac{n_t^c q^c(P_t)}{s_t D(P_t)}.$$

Assume $\partial(q^b/q^h)/\partial P \geqslant 0$. If $\omega > 1 - (q^b(P^c)/q^h(P^c))$, s_t increases in t and $s_{c,t}$ decreases in t for $t \geq T + 1$.[15] ■

In summary, Case 1 offers the following findings, as illustrated in Figure 4.

- No *click* firm exits through time $T^c - 1$. The number of exits turns positive at time T^c and falls after time $T^c + 1$. Meanwhile, the total number of *click* firms peaks from time $T + 1$ to $T^c - 1$ and falls afterward.

- The value of a successful *click* entrant increases from $V^\theta + S_c$ at time T to $V^\theta + \frac{S_c}{\beta\sigma}$ at time $T + 1$, and then falls back to V^θ at time T^c and afterward.

[15] For example, if $\partial(q^b/q^h)/\partial P = 0$, e.g., the cost function is $C_x(q) = \alpha_x q^\beta$ (where $x = h, b$ and $\beta > 1$), the condition for ω is simply $\omega > 1 - (\alpha_h/\alpha_b)^{1/(\beta-1)}$.

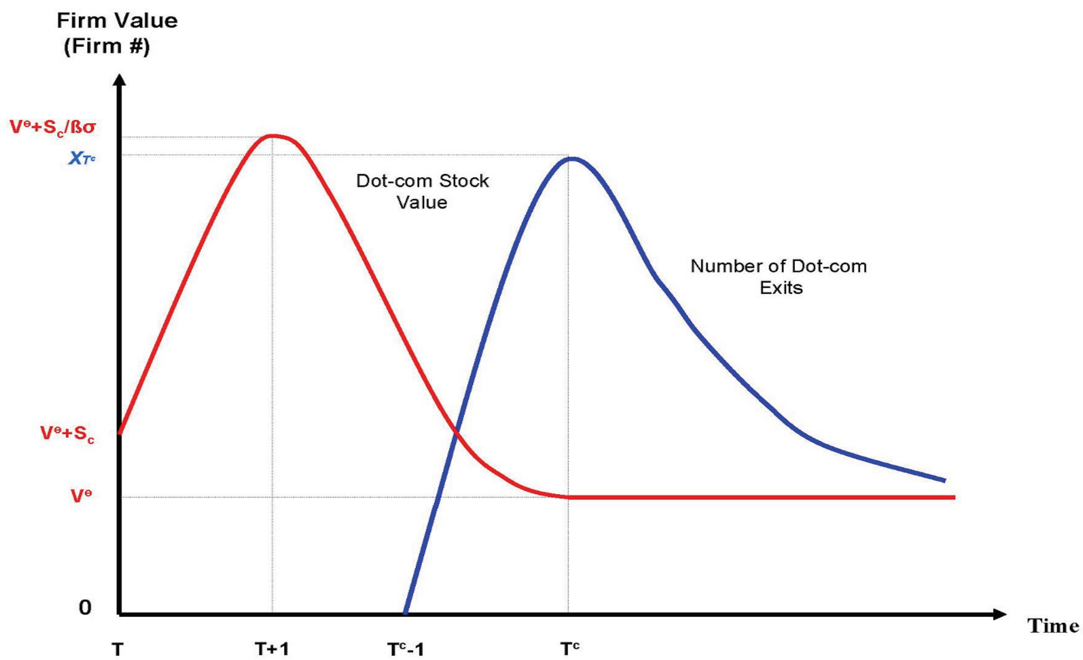

Figure 4: Stock Value and Firm Exits: A Complementary Innovation

- Through time, as more firms adopt the innovation c, the industry output Q_t increases and price P_t decreases up to time T^c or possibly even afterward.
- The share of output attributable to the innovation c continues to increase from time $T+1$, but the contribution of *click* firms is falling.

2.4.2 Case 2: $\pi_t^h > \pi_t^c > \pi_t^b$

The above analysis can be similarly applied to the second case, in which we have $\pi_t^h > \pi_t^c > \pi_t^b$ and $q_t^h > q_t^c > q_t^b$. Notice that the equilibrium industry dynamics through time $T+1$ are the same as in Case 1. At time T, N^θ type-θ firms, as well as N^b existing *brick* firms, attempt to adopt innovation c, but the price and output do not change. At time $T+1$, σN^θ *click* firms and σN^b *hybrid* firms succeed in implementing the new technology. As the supply increases, the price falls and no more type-θ firms will find it profitable to enter.

After time $T+1$, more and more *brick* firms succeed in upgrading; hence, the output keeps rising and the price keeps falling. The price will then reach a critical value P^b so that $\pi^b(P^b) = \pi^\theta$ and some *brick* firms are no longer active in the market.

However, the remaining *brick* firms, active or inactive, may continue upgrading their technology. Consequently, if the price eventually falls to the critical value P^c at which $\pi^c(P^c) = \pi^\theta$, *click* firms then start to exit (though it is also possible that the price may not fall enough to ever induce exit by *click* firms).

2.5 Extensions

As discussed, the dot-com shakeout tends to occur if the *hybrid* is the most profitable business model, but the order of exits for *click* firms and *brick* firms may vary due to their relative efficiency to each other. More generally, if firms are heterogenous in efficiency within the *click* or *brick* group, it is even possible to see *click* firms and *brick* firms exit at the same time. In contrast, if the internet innovation dominates the old technology (i.e., $\pi_t^c > \pi_t^h$ and $\pi_t^c > \pi_t^b$), the dot-com shakeout would not occur (see the Appendix for a detailed discussion).

Furthermore, what does the model say about the financial losses incurred during the dot-com shakeout? So far, assuming no aggregate uncertainty in the market, the shakeout does not cause financial losses to the overall dot-com sector.[16] However, it is plausible that some aggregate uncertainty exists. In fact, it took time for the market participants to understand the competitive disadvantage of the online-only business model. Therefore, aggregate financial losses were likely to occur as the result of overentry of dot-coms.

To see this, assume that firms have to make their decisions to adopt the internet innovation at time T based on their expected profits: $E_T(\pi^c)$ and $E_T(\pi^h)$. If *ex ante*

[16] Notice some new entrants, who fail to adopt the innovation and exit, do have financial losses. However, that risk is idiosyncratic and can be insured; e.g., a dot-com investor may diversify her investment portfolio across many entry attempts.

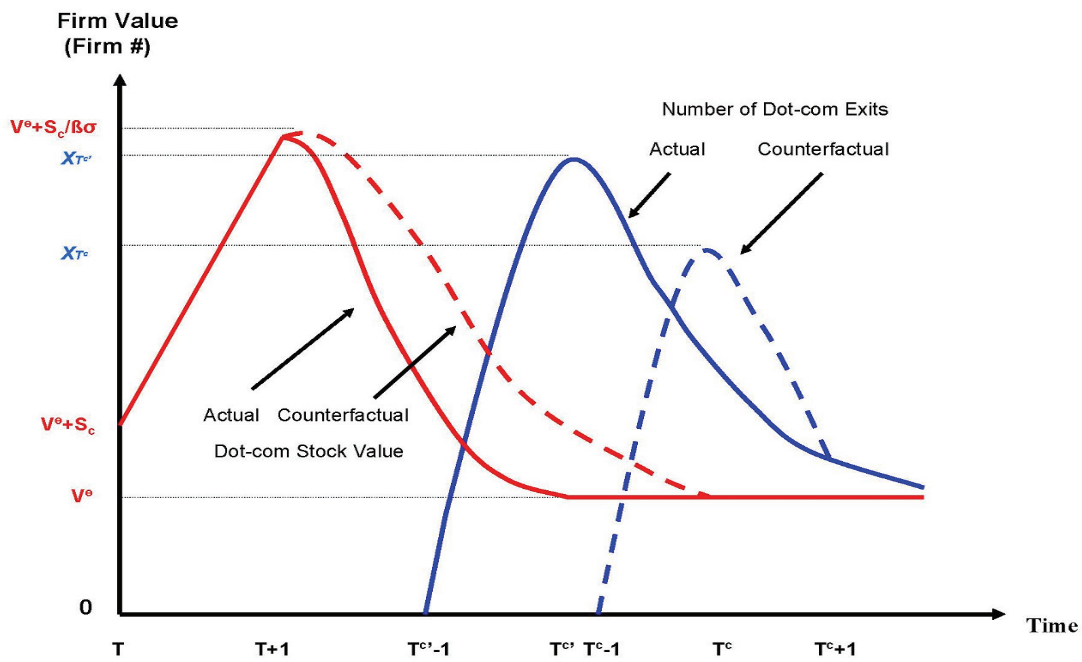

Figure 5: Industry Dynamics: Actual vs. Counterfactual

the market expects the innovation to dominate the old technology, this may result in overentry of dot-com firms (i.e., $N^{\theta\prime} > N^{\theta}$). When the truth is revealed *ex post* (at time $T+1$), we then observe that all entrants suffer financial losses.[17] The industry dynamics under imperfect information (actual paths) and perfect information (counterfactual paths) are compared in Figure 5. Given overentry, the shakeout begins earlier and becomes more severe than the counterfactual case.

To elaborate on this, we may use $N^{\theta\prime}, P_t^{\prime}, V_t^{c\prime}, T^{c\prime}, x_t^{c\prime}$ for the corresponding notations under imperfect information. Notice that $N^{\theta\prime}(> N^{\theta})$ is now exogenously given at time $T+1$, so that Equation 18 has to be rewritten as

$$P_t^{\prime} = D^{-1}\{N^{\theta\prime}\sigma q^c(P_t^{\prime}) + N^b(1-\sigma)^{t-T}q^b(P_t^{\prime}) + N^b[1-(1-\sigma)^{t-T}]q^h(P_t^{\prime})\},$$

[17] Some other factors may also induce overentry; e.g., overestimating market demand or first-mover advantage, underestimating the learning rate of incumbent firms. However, the analyses would be similar.

which implies a lower price path: $P'_t < P_t$. Because exit starts the first time $T^{c\prime}$ when $P'_{T^{c\prime}} < P^c$, the shakeout then begins earlier; i.e., $T^{c\prime} < T^c$. Meanwhile, all dot-coms suffer a loss of value; i.e., for $T^c > t \geq T+1$,

$$V_t^{c'} - V_t^c = \sum_{\tau=t}^{T^{c'}-1} \beta^{\tau-t}[\pi^c(P'_\tau) - \pi^c(P_\tau)] - \sum_{\tau=T^{c\prime}}^{T^c-1} \beta^{\tau-t}[\pi^c(P_\tau) - \pi^\theta] < 0.$$

In addition, the number of dot-com exits is larger. Equations 14 and 15 imply that the actual cumulative number of exits at time T^c is greater than the counterfactual case:

$$(\sum_{t=T^{c\prime}}^{T^c} x_t^{c\prime}) - x_{T^c}^c = N^{\theta\prime}\sigma - N^\theta\sigma > 0.$$

After time T^c, Equation 16 suggests that the number of actual exits is the same as the counterfactual case:

$$x_t^{c\prime} = \frac{N^b\sigma(1-\sigma)^{t-(T+1)}(q^h(P^c) - q^b(P^c))}{q^c(P^c)} = x_t^c.$$

3 Empirical Analysis

The above discussions suggest that in a market impacted by a significant technological innovation, the shakeout of new entrants tends to occur if the following conditions are met: (1) the innovation creates some advantages for pure-play entrants (e.g., low entry and/or operational costs); (2) the innovation is complementary to the existing technology; and (3) it takes time for the innovation to diffuse among the incumbents using traditional technology. The evolving history of e-commerce suggests that those are indeed the features of doing business via the internet.

3.1 E-commerce Overview

In the early days of e-commerce, the market was excited about the potential competitive advantages that internet firms had over traditional firms. By eliminating physical operations, online pure plays enjoyed substantially low entry costs into the market. Internet firms also enjoyed further advantages, including: access to wider markets; lower inventory costs; ability to bypass intermediaries; lower menu costs enabling more rapid response to market changes; ease of bundling complementary products; and ease of offering 24/7 access.

However, eschewing physical space for cyberspace did not come without consequences. Above all, online and offline channels are not perfect substitutes. Internet shopping fits better with standardized goods and services, such as buying books, which do not require personal contact with the item. Conversely, it is less suited for "experience" goods and services, such as clothing, for which customers need first-hand experience with the item. Additionally, internet firms had to incur extra costs by running high-tech systems that require a more expensive labor force, and also by offering more physical delivery channels.

Most important, traditional firms were entering the online business to explore the synergy between the online and offline channels. The sources of synergy include common infrastructures, common operations, common marketing, and common customers.[18] The synergy also is embodied in the many forms of complementary assets that incumbent firms possess, such as existing supplier and distributor relationships, experience in the market, a customer base, and others that can enable them to take better advantage of an innovation like e-commerce. Eventually, traditional firms were able to capitalize on these synergies to beat the dot-coms at their own game.

[18] An example of a common infrastructure is when a firm relies on the same logistics system or shares the same IT infrastructure for both online and offline sales. An order processing system shared between e-commerce and physical channels is a good example of a common operation. This can enable, for example, improved tracking of customers' movements between channels, in addition to cost savings. E-commerce and physical channels also may share common marketing and sales assets, such as a common product catalog, a experienced sales force, or advertisements and promotions. Moreover, e-commerce and physical outlets in click-and-mortar firms often target the same potential buyers. This enables a click-and-mortar firm to better meet customers' needs for both convenience and immediacy. For example, it can allow consumers to buy a product online and return it offline, or try a product in the store before purchasing it online. See Steinfield (2002) for detailed discussions.

3.2 Hypotheses

Several implications of the model are empirically testable. The relative profitability of different firm types is of particular importance and interest, and is the primary focus of our following empirical analysis.

Other implications, such as the entry/exit patterns and the adoption sequence, also are interesting.[19] Although we do not formally test them, we nevertheless show our theoretical predictions are largely consistent with the data throughout the paper.[20] Lieberman (2005) and Dinlersoz and Pereira (2006) provide additional evidence on this for several retail sectors.

3.3 The Retail Industry

Retail is an industry that has widely adopted e-commerce, and multi-channel retailers seem to enjoy advantages over dot-coms. According to *Retail Forward*'s annual study, dot-coms comprised 23 of the top 50 e-retailers in 1999, but the number dropped to 11 in 2004 as reported by *Internet Retailer*. However, the evidence to date is largely anecdotal, and counterexamples can easily be found. For example, the dot-com giant, Amazon, has continued as the largest online retailer with sales of $6.9 billion in 2004. This surpasses the online sales of the top multi-channels, including: Office Depot ($3.1 Billion); Sears ($1.7 Billion) or Walmart ($0.78 billion), and therefore, a systematic

[19] Note that website adoption by traditional firms may be a less accurate measure of their online entry. In the theory, online entry is defined as successful adoption of the internet technology. Conceptually, it requires more than just starting an online business, but also doing so correctly. In this sense, improvement and expansion of online services is indeed a crucial part of the entry process.

[20] The entry and exit of dot-coms are described in section 1.1. Systematic data on website adoption by traditional retailers is not available but the adoption was certainly rising over time. Particularly, right before and during the dot-com shakeout, major offline retailers were busy launching or re-launching (overhauling) their websites. As a result, they captured an increasing online market share as shown in Figure 3. In section 3.4, more systematic data is presented for the banking industry, which shows a similar pattern.

empirical analysis is needed to fully address this issue.

3.3.1 Data

The empirical analysis uses an original dataset from two primary sources: *Internet Retailer* and *Compustat*. We briefly describe here the dataset and market definition.

The first data source, *Internet Retailer,* identifies the 400 largest online retailers by their 2004 internet sales.[21] It provides a comprehensive coverage of the online retail universe: the top 400 e-retailers generated combined online sales of more than $51 billion and accounted for more than 90 percent of the total U.S. internet retail sales (excluding motor vehicle sales, travel, financial and ticket-related services) in 2004.[22] Also, with additional help from the *Internet Retailer,* we are able to identify the type of each retailer (dot-com vs. multi-channel) and even divide multi-channel retailers further into traditional store retailers and traditional direct retailers (e.g., catalog and mail order retailers). The second data source, *Compustat,* reports annual total sales of publicly traded firms. It adds information of total sales (online plus offline sales) for 275 firms in the top 400 e-retailer list.

Following *Internet Retailer*'s definition, the 400 retailers are divided into 14 merchandising categories based on their primary business: Beaut (Health/Beauty), Book (Books/CD/DVDs), Cloth (Apparel/Accessories), Dept (Department Store/Mass Merchant), Drug (Drug/Food), Elect (Computer/Electronics), Flow (Flowers/Gifts), Hard (Hardware/Home Improvement), House (Housewares/Home Furnishings), Jewel (Jewelry), Offi (Office Supplies), Spec (Specialty/Non-Apparel), Sport (Sporting Goods), and Toys (Toys/Hobbies). We then test if multi-channel retailers have competitive

[21] Whenever possible, *Internet Retailer* obtained the data from the retail company. If the company would not provide the data, *Internet Retailer* formed estimates based on other sources. Companies were then given the opportunity to respond to the estimates.

[22] According to the U.S. Census Bureau, U.S. internet retail sales totaled $69 billion in 2004, of which about 20 percent were automobile sales via auto dealers' websites. Online travel services, financial brokers and dealers, and ticket sales are not classified as retail and are not included.

advantage over dot-coms in each retail category. Detailed data summary statistics are provided in Appendix Table A1 and A2.

In the following analysis, we use sales data to compare firms' profitability. Within a competitive framework, as assumed in the model, the sale/output/profit comparisons are consistent. However, the comparison may become somewhat cloudy in a non-competitive environment where price differences across retailers can play a role. Empirical evidence suggests that price dispersion does exist in many internet retail sectors (Baye, Morgan and Scholten (2004)) and prices of internet pure-plays are often lower than prices of hybrids (Pan, Ratchford and Shankar (2004)). Therefore, our competitive model should be viewed as a first-order approximation.[23]

The data of both online sales and total sales are based on 2004 information. Ten years after the birth of internet retail and five years after the start of the dot-com shakeout, the retail industry should have absorbed the technology shock of the internet and evolved into a new steady state. Hence, this allows for a meaningful comparison of market performance between firm types across retail categories. While using solely 2004 information may have a selection bias since we only see the survivors of the dot-com crash in the data, it in fact reinforces our argument regarding the multi-channel firms' advantage: Even the best pure-plays (i.e., survivors) cannot match the performance of multi-channel retailers.

3.3.2 Multi-channel Retailers vs. Dot-coms

To identify the advantage of multi-channel retailers over dot-coms, we first treat the internet as a separate marketplace from the offline. We then test the hypothesis that multi-channel retailers enjoy greater online sales than dot-coms.

[23]Note that some retail sectors in the data have a small number of observations but that does not necessarily mean those markets are not competitive. In fact, because firms are selected by their ranking of online sales, many firms are not included in our sample.

The regression is set up as follows:

$$\ln(WEBSALE) = CONSTANT + \sum_{i=1}^{13} \lambda_i * CATEGORY_i + \sum_{i=1}^{14} \gamma_i * CATEGORY_i * MULTI + \mu, \qquad \text{(R1)}$$

where $\ln(WEBSALE)$ is the logarithm of online sales, $CATEGORY_i$ is the category dummies (=1 if in category i; =0 otherwise), $MULTI$ is the firm type dummy (=1 if multi-channel; =0 if dot-com), and μ is the random error (likely being heteroskedastic). The estimation results are reported in Appendix Table A3.[24]

The γ_i, by definition, is the average additional online sales of a multi-channel retailer over a dot-com in category i. The estimation results confirm the multi-channel firms' advantage and also show that the advantage varies across retail categories. Among all 14 categories, it is found that a multi-channel firm tends to sell more online than a dot-com ($\gamma_i > 0$) in 10 categories, of which the advantage is statistically significant in 6 categories (i.e., the null hypothesis $\gamma_i \leq 0$ is rejected based on a one-sided t test). In the other four categories, a multi-channel firm tends to sell less than a dot-com on average ($\gamma_i < 0$), but only in one category (Drug/Food) is the difference statistically significant (i.e., the null hypothesis $\gamma_i \geq 0$ is rejected based on a one-sided t test).[25]

For the ten retail categories in which multi-channel firms are found to perform better, the average difference of online sales between a multi-channel firm and a dot-com ranges from 7 percent (Housewares/Home Furnishings) to 263 percent (Office Supplies). We also notice that the four categories in which dot-coms are likely to do better are Drug/Food, Department Store/Mass Merchant, Jewelry and Book/CD/DVDs. One potential explanation is that products in these categories tend to be standard goods and easy to transport. Therefore, the spillovers from the offline channels to

[24] We also ran separate regressions by retail category and got consistent results.

[25] Statistical insignificance of some results may be driven by the small sample problem, but the overall advantage of multi-channel retailers is clearly evident.

the online channel (e.g., product display, customer consultation and distribution networks) are less important than other categories.

However, treating the internet as a separate marketplace is an extreme assumption that may underestimate the performance of multi-channel retailers by ignoring the spillovers from the online channel to the offline channels. Therefore, we also ran the above regression R1 using total sales (online plus offline) as the dependent variable, assuming that the online and offline sales compete in the same marketplace. This may be another extreme assumption, but at least we know the truth should lie somewhere in between.[26] The regression results are also reported in Appendix Table A3, which clearly shows that multi-channel firms dominate dot-coms in every retail category, and the advantage is so economically and statistically significant that there is no comparison. This result is consistent with our general intuition. Consider Amazon and Walmart for example – the largest dot-com retailer versus the largest multi-channel retailer. Amazon had \$6.9 billion online and total sales in 2004, while Walmart had \$0.78 billion online sales but \$285 billion total sales.[27]

Using market share instead of average sales per firm, Figure 9 in the Appendix shows a consistent pattern. In the four categories where dot-coms have greater average online sales per firm than multi-channel firms, dot-coms also get larger online market shares (i.e., more than 50 percent). However, in the remaining ten categories, the dot-coms' online market shares are dominated by multi-channel firms. In terms of total sales (online plus offline), multi-channel firms dominate dot-coms in every retail category (see Figure 10 in the Appendix).[28]

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[26] Note that adding offline sales to online sales for multi-channel retailers can never weaken our findings, so it actually provides an upper-bound estimate of multi-channel retailers' advantage.

[27] Amazon and Walmart are both in the Department Store/Mass Merchant category. Note that Amazon is also the largest online book store. However, regardless which category Amazon is counted in (Dept or Book), it does not change our empirical findings throughout the paper.

[28] In fact, dot-coms' market shares in total sales are overestimated in Figure 10 because many multichannel retailers' total sales are not available to be included in the calculation.

3.3.3 Store Retailers, Direct Retailers vs. Dot-coms

So far, the multi-channel retailers are treated as a single group. However, the data suggests some important differentiation within the multi-channel group. In particular, some multi-channel retailers, such as Walmart, specialize in store retailing, while others focus on direct retailing (catalog/mail order, sales representative, or telemarketing), such as L.L. Bean. Based on each company's historical merchandising channels and primary business, we have identified 53 direct retailers out of 282 multi-channel retailers.

To see if differences exist in the online-offline synergy between traditional store retailers and direct retailers, we run the following regression:

$$\begin{aligned} \ln(WEBSALE) &= CONSTANT + \sum_{i=1}^{13} \lambda_i * CATEGORY_i \\ &\quad + \sum_{i=1}^{14} \alpha_i * CATEGORY_i * STORE \\ &\quad + \sum_{i=1}^{14} \beta_i * CATEGORY_i * DIRECT + \mu, \qquad \text{(R2)} \end{aligned}$$

where $\ln(WEBSALE)$ and $CATEGORY$ are defined as before, and $STORE$ and $DIRECT$ are dummies for firm type ($STORE$=1 if multi-channel store retailer, =0 otherwise; $DIRECT$=1 if multi-channel direct retailer, =0 otherwise). The regression results are shown in Appendix Table A4.[29]

The α_i (β_i), by definition, is the average additional online sales of a multi-channel store (direct) retailer over a dot-com in category i. With some refinement, the estimation results confirm our previous findings. Among all 14 categories, a store retailer sells more online on average than a dot-com ($\alpha_i > 0$) in 8 categories, of which the advantage is statistically significant in 3 categories (i.e., the null hypothesis $\alpha_i \leq 0$ is rejected based on a one-sided t test). A dot-com sells more online than a store retailer ($\alpha_i < 0$) in the other 6 categories, but only the difference in the Drug/Food

[29] We also ran separate regressions by retail category and got consistent results.

category is statistically significant (i.e., the null hypothesis $\alpha_i \geq 0$ is rejected based on a one-sided t test). Among the 11 categories where observations are available, a multi-channel direct retailer sells more online on average than a dot-com ($\beta_i > 0$) in 9 categories, of which the advantage is statistically significant in 5 categories. Moreover, direct retailers are not found to be disadvantaged in the category of Drug/Food , but they are at a disadvantage in Office Supplies. On average, direct retailers appear to enjoy a greater online advantage than store retailers. Among the 11 categories where observations are available, direct retailers generate more online sales per firm than store retailers ($\alpha_i < \beta_i$) in 9 categories, and in 4 categories the advantage is statistically significant.

Running the regression R2 using total sales as the dependent variable, we find that both traditional store and direct retailers dominate dot-coms in every retail category. Moreover, store retailers are typically larger in total sales than direct retailers ($\alpha_i > \beta_i$) in all categories except Sporting Goods, and in five categories the advantage is statistically significant. The regression results are also shown in Appendix Table A4.

The above findings are summarized in Figure 6.[30] Several results may need further clarification. First, an individual direct retailer tends to sell more online than an individual store retailer. It is reasonable to think that direct retailers may be able to better adapt to the online technology, or their product lines are simply more suitable for the online environment. Given the fact that direct retailers typically have smaller total sales, they in general rely more on their online channels than the store retailers; i.e., the ratio of online sales to total sales is higher for direct retailers. Second, the greater online sales per firm does not necessarily mean that direct retailers have contributed more to the dot-com shakeout than store retailers. Because the number of direct retailers is small, less than one fifth in the multi-channel group, their effects were rather limited. In fact, the cross-category pattern of multi-channel retailers' advantage, in both online and total sales, is mainly driven by the store-retailers.

[30] Due to no observation of direct retailers, Figure 6 covers 10 categories instead of 14.

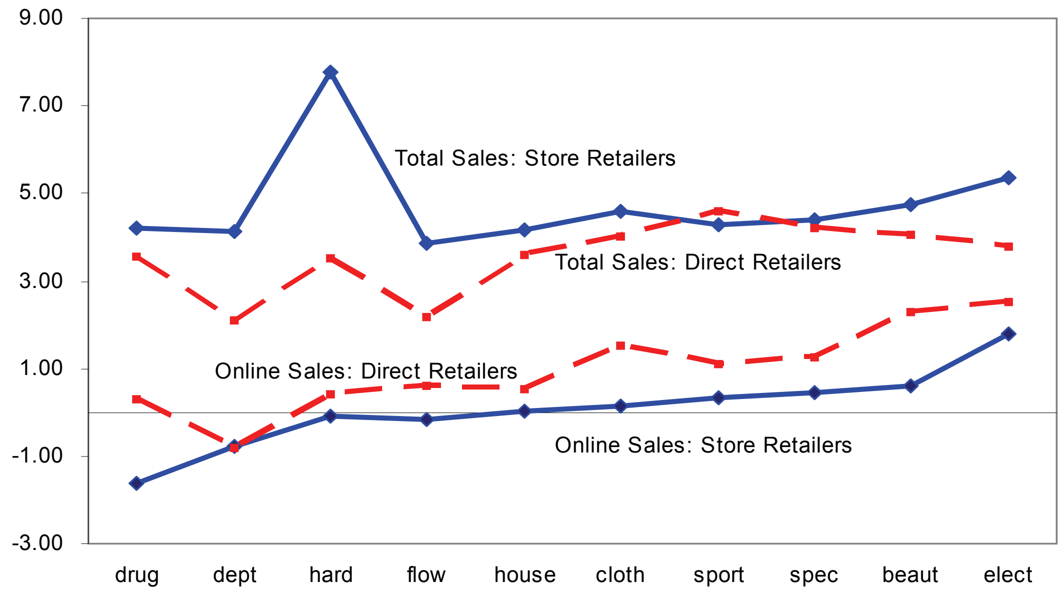

Figure 6: Log Difference of Sales Per Firm: Store (Direct) Retailers Minus Dot-coms

Figures 9 and 10 in the Appendix present the market shares in online and total sales by each firm type, which clearly show the dominance of store retailers. Even so, our study of direct retailers does remind us that the sources of multi-channel synergy include not only the store channel, but also other offline channels as well as the broader assets that incumbents possess like brand, customer base and business relations.

3.4 The Banking Industry

In addition to retail, the history of online banking provides further support for our theory.

In the United States, internet banking started in 1995, when Wells Fargo became the first bank to offer online access to account statements, and Security First Network Bank became the first online-only bank. The next few years were more or less an experimental stage, during which the industry witnessed slow adoption of the internet

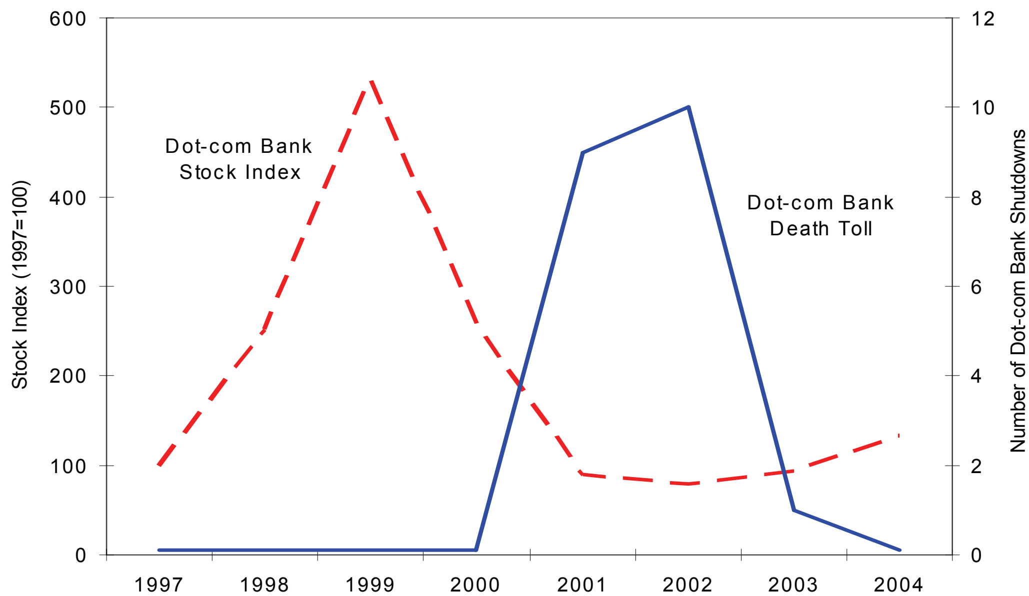

Figure 7: Dot-com Banks: Stock Index and Death Toll

technology. Through 1998, 6 percent of national banks offered transactional internet services, and seven banks offered online-only services. Then the diffusion of online banking took off in 1999 and 2000. By the end of 2000, 37 percent of national banks offered transactional internet banking, and about 40 new dot-com banks had entered the market.[31] However, a shakeout started striking the dot-com banks in 2001. As shown in Figure 7 (similar to Figure 1), the stock index for dot-com banks dropped by 80 percent,[32] and nearly half of the dot-com banks exited the industry by 2003.[33]

As suggested, the key to explaining the shakeout of dot-com banks is to compare the competitive position of pure internet banks against their competitors with brick-and-mortar branches. Similar to other e-commerce industries, the core strategy of

[31] Data Source: *Online Banking Report* and the Office of the Comptroller of the Currency (OCC).

[32] The stock index is calculated as the value-weighted sum of stock prices for six publicly owned dot-com banks, which include Security First Network Bank (SFNB), Next Bank (NXCD), Net Bank (NTBK), E*trade Bank (ET), USA Bancshares (USAB) and American Bank (AMBK).

[33] Data Source: *Online Banking Report*.

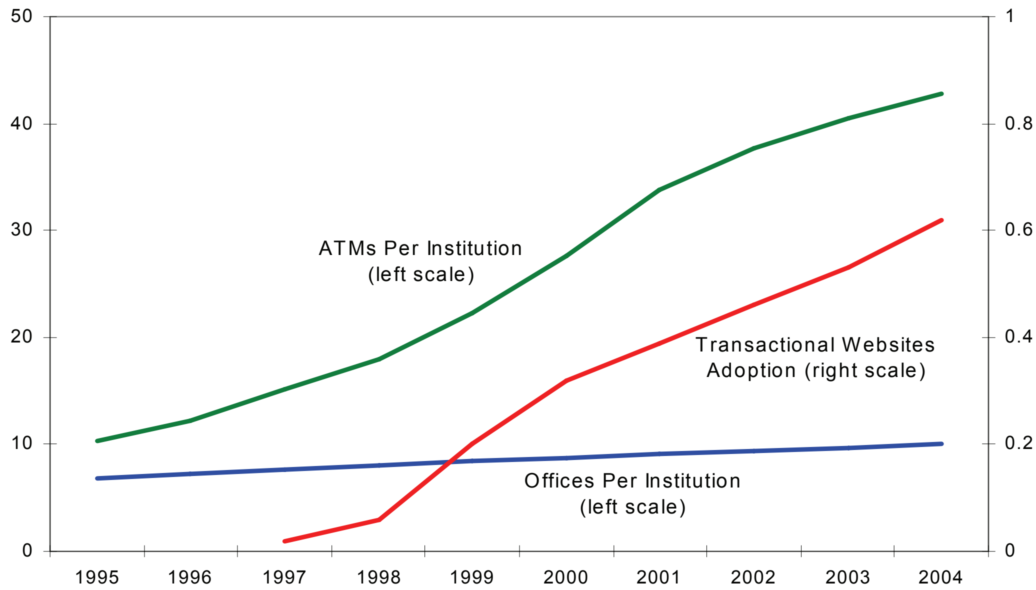

Figure 8: Evolution of Banking Service Delivery Channels

an internet-only banking model is to reduce overhead expenses by eliminating the physical branch channel. However, it turns out the online channel is not a perfect substitute for the branch channel, but a good complement. Figure 8 shows the number of ATMs as well as brick-and-mortar offices per bank has been increasing since the mid-1990s, together with the increasing adoption of online banking.[34]

Exploring the synergy between online and offline channels reveals that a click-and-mortar bank typically delivers standardized, low-value-added transactions such as bill payments, balance inquiries, account transfers and credit card lending through the inexpensive internet channel, while delivering specialized, high-value-added transactions such as small business lending, personal trust services and investment banking through the more expensive branch channel. By providing more service options to

[34]Note: Institutions include all FDIC-Insured depository financial institutions. Data on offices (headquarters and branches) is from *Summary of Deposits*; ATMs from the *ATM&Debit News*; and transactional websites from *Call Report* and the OCC.

its customers, a click-and-mortar bank is able to retain its most profitable customers and generate more revenue from cross-selling.

DeYoung (2005) compares the performance between internet-only full-service banks and their branching counterparts from 1997 to 2001.[35] The empirical results show internet-only banks on average have lower asset returns than incumbent branching banks as well as new branching entrants. This is primarily due to internet-only banks' lower interest margins and fee income, lower levels of loan and deposit generation, fewer business loans, and higher noninterest expense for equipment and skilled labor. These results are robust after controlling the effects of age and survivorship.

As more and more brick-and-mortar banks got online, the competitive pressure in the online banking market surely increased. According to *Call Report*, 75 percent of all depository institutions had adopted a website by 2004, compared with 35 percent in 1999. Meanwhile, 60 percent of the institutions reported websites with transactional capability in 2004 compared with less than 37 percent in 2000.[36] More importantly, traditional banks outran the dot-coms in online services. Based on research conducted by GomexPro, six dot-com banks ranked among the top ten for the "Best Online Banking Services" in 1999, but the number dropped to two in 2001, then to one in 2003.[37]

[35] Besides dot-com banks, two comparison groups of banks are investigated. One is incumbent branching banks, including 3,777 small, established banks and thrifts (with assets less than $1 billion that are at least 10 years old) in urban U.S. markets between 1997 and 2000. The other is new branching entrants, including 644 branching banks and thrifts newly chartered during the same sample period.

[36] *Call Report* started collecting website information for all FDIC-insured depository institutions in 1999, but the information of transactional websites was not available until 2003. An independent survey by the OCC reported 37 percent of national banks had adopted transactional websites by 2000. This suggests that the adoption of transactional websites by the overall banking population should be even lower.

[37] The total score of online services is evaluated as a weighted sum of scores in categories of functionality, ease of use, privacy/security and quality/availability, based on 150 to 300 criteria.

Consequently, the online-only banks steadily lost ground to their multi-channel competitors. As the Media Metrix online traffic data reveals, the number of unique visitors to multi-channel banks' websites climbed from 6.4 million in July 2000 to 13.4 million in July 2001 (a 110.5 percent increase), while the traffic to online-only banks fell from 1.2 million to 1.1 million (an 8.1 percent decrease) during the same period.[38] Meanwhile, the shakeout of online-only banks started in 2000, with the number of dot-coms declining from around 50 in 2000 to fewer than 30 in 2003.

Security First Network Bank, the first dot-com bank, was one of the casualties. Acquired by Royal Bank of Canada in 1998, its internet operations were discontinued in 2001. Other dot-com survivors generally have adjusted their strategies, trying to avoid head-on competition with big click-and-mortars. For example, ING Direct, the largest dot-com bank today, offers limited banking services and encourages its customers to keep their old bank accounts.

4 Final Remarks

This paper explains the recent dot-com boom/bust cycle as equilibrium industry dynamics driven by the complementarities in the adoption of the internet technology by traditional firms. Particularly, the dot-com shakeout occurred because the existing technology and assets allow the incumbent firms to take greater advantage of the internet innovation. In addition, we show that *ex ante* overestimation on dot-coms' potential may help explain the timing and financial losses of the shakeout.

With no externality involved, we can also show the competitive equilibrium is socially optimal. It implies that as long as the social planner does not have better information about the innovation than the market participants, there is no need for government intervention. This may explain why the U.S. government authorities

[38] During the same period, the number of unique visitors to the internet rose from 76.9 million to 92.2 million, a 19.8 percent increase, and the number of unique visitors to the overall banking websites rose from 10.4 million to 18.5 million, a 77.6 percent increase.

chose not to intervene during the dot-com market boom.

That pure-play entrants are outrun by traditional firms who adopt new technology is not entirely specific to the internet. The analysis may shed light on other cases, such as the diffusion of FM radio broadcasting, where synergies between existing and new technologies are significant. It also suggests a consistent explanation for the well-established empirical finding in industrial evolution literature that incumbent firms in general possess substantial advantages over new entrants and hence have a better chance to survive industry shakeouts.

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Appendix: A Dominant Innovation

If the innovation dominates the traditional technology (i.e. $\pi_t^c > \pi_t^h$ and $\pi_t^c > \pi_t^b$), no shakeout occurs to the new entrants. It can be shown as follows:

At time T, firms attempt to adopt innovation c. Because $\pi_t^c > \pi_t^h$, *hybrid* is not at all a profitable model. Hence, all *brick* and type-θ firms, if they choose to adopt the innovation, try transforming themselves into *click* firms. The free entry condition requires

$$V_{T+1}^c - V_{T+1}^\theta = \frac{S_c}{\beta\sigma}.$$

Because it takes one period for the technology upgrade to take effect, there is no change of price and output at time T. At time $T+1$, some *click* firms appear in the market. As the supply increases, the price falls, and no more firms will find it profitable to adopt the innovation. Hence, starting at time $T+1$, no further entry or exit will occur. Two possible equilibrium outcomes are discussed below.

The first equilibrium, with $\pi^b(P^*) \leq \pi^\theta$, does not allow the *brick* firms to remain in the market for $t \geq T+1$. It satisfies the following conditions:

$$\frac{\pi^c(P^*) - \pi^\theta}{1-\beta} = \frac{S_c}{\beta\sigma},$$

$$\pi^b(P^*) \leq \pi^\theta,$$

$$Q = D(P^*) = \sigma N^\theta q^c(P^*),$$

which imply that among N^θ attempts for technology upgrading at time T (notice that the N^θ attempts may include both type-θ and *brick* firms because they have the same opportunity cost π^θ), σN^θ firms succeed and produce at time $T+1$. Thereafter, only *click* firms are in the market and there will be no further dynamics.

The analysis can be similarly applied to the other case. The second equilibrium, with $\pi^b(P^*) > \pi^\theta$, allows the *brick* firms to remain in the market. The corresponding conditions are

$$\frac{\pi^c(P^*) - \pi^\theta}{1-\beta} = \frac{S_c}{\beta\sigma},$$

$$\pi^b(P^*) > \pi^\theta,$$

$$Q = D(P^*) = \sigma N^\theta q^c(P^*) + N^b q^b(P^*),$$

which imply that N^θ type-θ firms attempt to enter with technology c at time T (notice that no *brick* firm would try adopting innovation c because of the higher opportunity cost; i.e., $\pi^b(P^*) > \pi^\theta$), and a fraction σ of them succeed at time $T+1$. Thereafter, σN^θ *click* firms and N^b *brick* firms are in the market and there will be no further dynamics.

Table A1. **Summary Statistics: Online Retail Sales ($ million)**

Category	Firm Type	Firm #	Mean Sales	Std. Dev.	Min Sales	Max Sales	% of Sales
Overall	Dotcom	118	112.99	643.57	3.30	6921.12	26.06
	Multi	282	134.11	407.61	3.81	3257.42	73.94
	Total	400	127.88	488.42	3.30	6921.12	100.00
Beaut	Dotcom	6	25.03	13.86	8.90	48.08	9.91
	Multi	6	227.68	306.42	9.26	748.00	90.09
	Total	12	126.36	232.30	8.90	748.00	100.00
Book	Dotcom	11	79.01	146.14	4.65	506.23	51.12
	Multi	14	59.36	115.03	4.60	419.80	48.88
	Total	25	68.01	127.14	4.60	506.23	100.00
Cloth	Dotcom	17	31.07	44.53	3.58	184.00	11.26
	Multi	82	50.75	80.14	3.81	438.96	88.74
	Total	99	47.37	75.42	3.58	438.96	100.00
Dept	Dotcom	5	1568.95	2997.24	46.00	6921.12	55.41
	Multi	16	394.61	468.62	7.63	1740.00	44.59
	Total	21	674.22	1491.33	7.63	6921.12	100.00
Drug	Dotcom	5	152.27	129.22	36.25	360.10	53.58
	Multi	15	43.97	45.09	4.84	150.00	46.42
	Total	20	71.04	85.60	4.84	360.10	100.00
Elect	Dotcom	12	129.85	287.53	5.70	1000.00	10.93
	Multi	20	635.03	934.65	11.40	3257.42	89.07
	Total	32	445.59	791.51	5.70	3257.42	100.00
Flow	Dotcom	7	42.33	46.55	4.00	128.80	31.87
	Multi	9	70.36	106.71	4.56	307.47	68.13
	Total	16	58.10	84.53	4.00	307.47	100.00
Hard	Dotcom	3	26.29	18.60	11.00	47.00	16.36
	Multi	7	57.60	65.77	4.40	163.68	83.64
	Total	10	48.21	56.47	4.40	163.68	100.00
House	Dotcom	15	24.47	19.45	4.22	68.70	20.36
	Multi	33	43.51	88.81	4.80	477.50	79.64
	Total	48	37.56	74.58	4.22	477.50	100.00
Jewel	Dotcom	5	53.91	66.73	7.47	169.24	62.59
	Multi	6	26.86	18.13	5.36	52.40	37.41
	Total	11	39.15	46.31	5.36	169.24	100.00
Offi	Dotcom	3	10.98	4.56	6.80	15.85	0.51
	Multi	6	1061.84	1542.04	5.80	3100.00	99.49
	Total	9	711.55	1327.50	5.80	3100.00	100.00
Spec	Dotcom	19	21.64	19.12	3.30	69.70	23.96
	Multi	28	46.59	48.04	5.47	172.81	76.04
	Total	47	36.51	40.63	3.30	172.81	100.00
Sport	Dotcom	7	15.42	13.54	3.91	39.60	10.81
	Multi	27	32.98	45.46	4.02	200.18	89.19
	Total	34	29.36	41.40	3.91	200.18	100.00
Toys	Dotcom	3	19.08	16.57	8.00	38.13	8.87
	Multi	13	45.26	103.12	5.06	386.00	91.13
	Total	16	40.35	93.03	5.06	386.00	100.00

* Dotcom refers to online-only retailers; Multi refers to multichannel retailers who sell through both online and offline channels.

Table A2. **Summary Statistics: Total Retail Sales ($ million)**

Category	Firm Type	Firm #	Mean Sales	Std. Dev.	Min Sales	Max Sales	% of Sales
Overall	Dotcom	118	112.99	643.57	3.30	6921.12	0.95
	Multi	157	8881.93	26157.75	55.83	285200.00	99.05
	Total	275	5119.26	20214.92	3.30	285200.00	100.00
Beaut	Dotcom	6	25.03	13.86	8.90	48.08	1.00
	Multi	4	3713.02	3637.76	211.68	7750.00	99.00
	Total	10	1500.23	2835.17	8.90	7750.00	100.00
Book	Dotcom	11	79.01	146.14	4.65	506.23	1.76
	Multi	7	6938.58	8001.81	266.72	22525.90	98.24
	Total	18	2746.62	5869.53	4.65	22525.90	100.00
Cloth	Dotcom	17	31.07	44.53	3.58	184.00	0.42
	Multi	51	2437.35	3657.40	200.00	19566.00	99.58
	Total	68	1835.78	3329.40	3.58	19566.00	100.00
Dept	Dotcom	5	1568.95	2997.24	46.00	6921.12	1.52
	Multi	15	33951.70	71268.26	649.00	285200.00	98.48
	Total	20	25856.01	62860.18	46.00	285200.00	100.00
Drug	Dotcom	5	152.27	129.22	36.25	360.10	0.41
	Multi	10	18696.05	17625.36	360.00	39897.00	99.59
	Total	15	12514.79	16780.48	36.25	39897.00	100.00
Elect	Dotcom	12	129.85	287.53	5.70	1000.00	0.57
	Multi	15	18012.44	26927.59	100.00	79905.00	99.43
	Total	27	10064.62	21736.32	5.70	79905.00	100.00
Flow	Dotcom	7	42.33	46.55	4.00	128.80	4.65
	Multi	5	1215.42	1829.73	55.83	4466.00	95.35
	Total	12	531.11	1258.37	4.00	4466.00	100.00
Hard	Dotcom	3	26.29	18.60	11.00	47.00	0.07
	Multi	3	36768.00	36172.98	750.00	73094.00	99.93
	Total	6	18397.14	30469.33	11.00	73094.00	100.00
House	Dotcom	15	24.47	19.45	4.22	68.70	1.86
	Multi	13	1491.03	1429.58	187.44	5150.00	98.14
	Total	28	705.37	1209.66	4.22	5150.00	100.00
Jewel	Dotcom	5	53.91	66.73	7.47	169.24	5.64
	Multi	2	2254.64	70.43	2204.83	2304.44	94.36
	Total	7	682.69	1075.61	7.47	2304.44	100.00
Offi	Dotcom	3	10.98	4.56	6.80	15.85	0.08
	Multi	4	10398.50	6766.94	275.43	14448.38	99.92
	Total	7	5946.71	7329.70	6.80	14448.38	100.00
Spec	Dotcom	19	21.64	19.12	3.30	69.70	1.48
	Multi	12	2274.48	2649.48	186.35	8666.00	98.52
	Total	31	893.71	1954.07	3.30	8666.00	100.00
Sport	Dotcom	7	15.42	13.54	3.91	39.60	1.11
	Multi	8	1205.63	840.97	233.00	2435.86	98.89
	Total	15	650.20	855.25	3.91	2435.86	100.00
Toys	Dotcom	3	19.08	16.57	8.00	38.13	0.27
	Multi	8	2688.31	3550.24	301.66	11100.00	99.73
	Total	11	1960.34	3221.41	8.00	11100.00	100.00

* Dotcom refers to online-only retailers; Multi refers to multichannel retailers who sell through both online and offline channels.

Table A3. Multichannel Effects: γ

Category	Online Sales	Total Sales
Beaut	1.18*	4.41***
	[0.76]	[0.80]
Book	-0.32	4.61***
	[0.54]	[0.74]
Cloth	0.41*	4.46***
	[0.32]	[0.33]
Dept	-0.78	3.46***
	[0.91]	[0.92]
Drug	-1.49***	4.14***
	[0.48]	[0.70]
Elect	1.89***	5.04***
	[0.60]	[0.70]
Flow	0.09	3.17***
	[0.72]	[0.83]
Hard	0.07	6.35***
	[0.67]	[1.28]
House	0.12	4.05***
	[0.31]	[0.37]
Jewel	-0.36	4.32***
	[0.60]	[0.51]
Offi	2.63***	6.21***
	[1.04]	[0.92]
Spec	0.65**	4.32***
	[0.29]	[0.44]
Sport	0.48*	4.40***
	[0.38]	[0.45]
Toys	0.13	4.58***
	[0.52]	[0.58]
Observations	400	275
Adjusted R^2	0.23	0.76

Robust Standard Errors in the brackets;

One-sided *t* test significance level: *** 1%, ** 5%, *10%.

Table A4. **Multichannel Effects: α (Store Retailer) and β (Direct Retailer)**

Category	Online Sales			Total Sales		
	α	β	α-β	α	β	α-β
Beaut	0.62	2.31***	-1.69*	4.75***	4.07***	0.68
	[0.96]	[0.59]	[1.08]	[0.68]	[1.39]	[1.52]
Book	-0.32	N/A	N/A	4.61***	N/A	N/A
	[0.55]			[0.75]		
Cloth	0.14	1.54***	-1.40***	4.60***	4.00***	0.61**
	[0.32]	[0.41]	[0.32]	[0.34]	[0.44]	[0.36]
Dept	-0.76	-0.82	0.05	4.14***	2.10**	2.04***
	[1.00]	[0.99]	[0.81]	[0.94]	[0.93]	[0.61]
Drug	-1.62***	0.29	-1.91***	4.20***	3.57***	0.63
	[0.48]	[0.38]	[0.29]	[0.77]	[0.39]	[0.66]
Elect	1.78***	2.50***	-0.72	5.35***	3.78***	1.57*
	[0.64]	[0.81]	[0.79]	[0.77]	[0.98]	[1.05]
Flow	-0.18	0.61	-0.79	3.85***	2.16**	1.69*
	[0.79]	[1.08]	[1.12]	[0.85]	[1.05]	[1.13]
Hard	-0.07	0.42	-0.49	7.76***	3.53***	4.23***
	[0.81]	[0.89]	[1.09]	[0.45]	[0.37]	[0.26]
House	0.01	0.54	-0.53	4.19***	3.60***	0.58
	[0.32]	[0.52]	[0.51]	[0.41]	[0.45]	[0.50]
Jewel	-0.37	N/A	N/A	4.32***	N/A	N/A
	[0.61]			[0.52]		
Offi	3.27***	-0.58***	3.85***	6.21***	N/A	N/A
	[1.02]	[0.21]	[0.99]	[0.94]		
Spec	0.44*	1.27***	-0.82*	4.39***	4.20***	0.19
	[0.29]	[0.53]	[0.52]	[0.49]	[0.82]	[0.95]
Sport	0.34	1.11*	-0.77	4.28***	4.60***	-0.32
	[0.38]	[0.69]	[0.64]	[0.57]	[0.47]	[0.57]
Toys	0.13	N/A	N/A	4.58***	N/A	N/A
	[0.52]			[0.59]		
Observations		400			275	
Adjusted R^2		0.28			0.78	

Robust Standard Errors in the brackets;

One-sided *t* test significance level: *** 1%, ** 5%, *10%;

N/A: not available because of no observation.

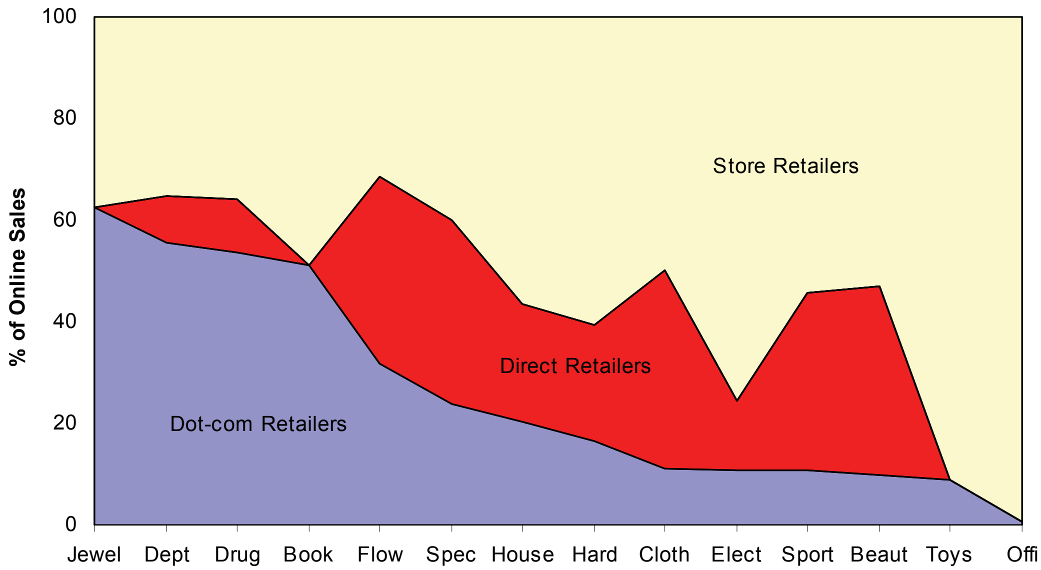

Figure 9: Market Shares in Online Sales

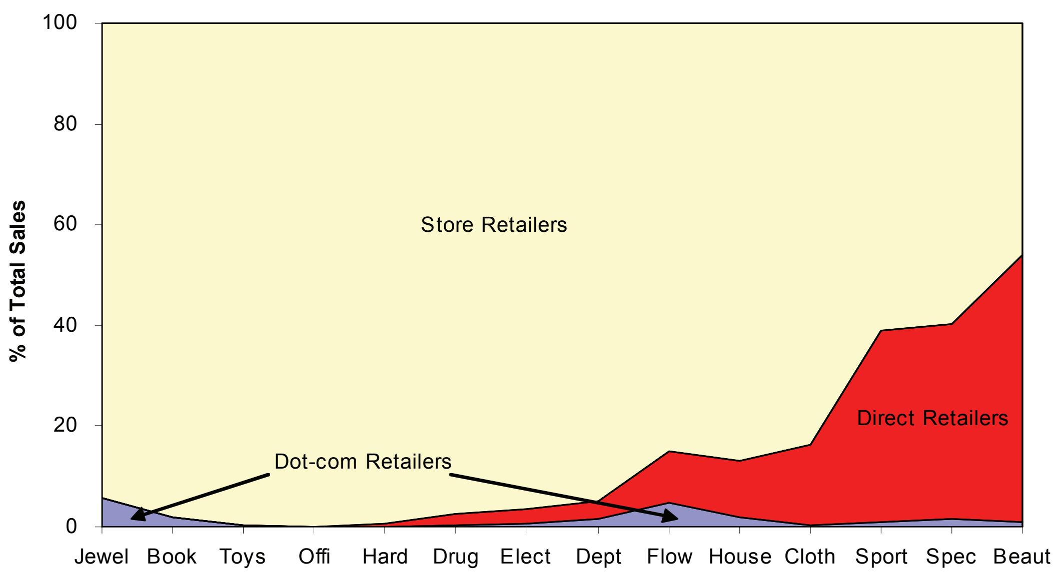

Figure 10: Market Shares in Total Sales (Online and Offline)