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The dynamics of technological adoption in hardware/software systems: the case of compact disc players

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We examine the diffusion of a hardware/software system. For such systems there is interdependence between the hardware-adoption decisions of consumers and the supply decisions of software manufacturers. Hence there can be bottlenecks to the diffusion of the system. We consider the CD industry and estimate the (direct) elasticity of adoption with respect to CD player prices and the (cross) elasticity with respect to the variety of CD titles. Our results show that the cross elasticity is significant. Our model can be used to quantify the effect of various policies aimed at speeding up the diffusion of a system.

1. Introduction

■ **Objective of article.** The last two decades have witnessed a great proliferation of high-tech consumer electronic products. The successful diffusion of these products is often contingent upon the availability of complementary products. For example, the success of a computer operating system depends on how many software applications can be run on it. Similar statements apply to video game base units and video games, HDTV and television programming, CD players and compact discs, and so on.

One classical anecdote illustrating the critical role of the complementary product is that of the failure of the Betamax video cassette recorder (VCR) technology. The

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Betamax technology was apparently—"on its own"—as good as the competing incompatible VHS technology.[1] Nonetheless, by 1981, VHS held a 66% share of the VCR installed base.[2] When prerecorded video cassettes became important in the early 1980s, rental stores preferred to carry VHS tapes because of their compatible installed-base advantage. The dearth of Betamax tapes "tipped" the market to VHS, which became the de facto standard in 1988. This case illustrates that the feedback between the component parts of a system are important in determining the eventual adoption or failure of a technology and, if a technology is adopted, its speed of adoption. The strength of such feedback effects varies from system to system, so just how important they are is an empirical question.

The aim of this article is to undertake such an empirical study. We do this for CD systems, which consist of CD players—labelled the "hardware"—and of compact discs—labelled the "software." More precisely, we consider the diffusion of CD players and the increased variety of CD titles as driven by two factors: (1) "direct" factors, namely, the decreasing costs of CD players and the decreasing cost of installing CD-pressing capacity, and (2) "cross" factors, i.e., the increased tendency of consumers to adopt a CD player in response to an increased variety of CD titles (and vice versa). We construct and estimate a structural model of system diffusion using the direct and cross factors. Our main finding is that both the direct and cross effects are significant.

We are able to empirically measure these effects because (i) in the case of CD players, hardware prices are essentially exogenous (see Section 2) and (ii) we have cost instruments for CD variety. We expand on this and, more generally, on our econometric approach in the body of the article.

After generating estimates for both the direct and the cross effects, we argue that they can be used for further analysis of business and government policies. In particular, when a new technology is introduced, a question that often arises is how to allocate resources to encourage its adoption. In principle, an enterprise, or the government, can subsidize the new technology, it can ensure greater availability of the complementary product by forward integration into its production, or it can increase the availability of the complementary product by making the new technology backward-compatible with old versions of the complementary product. The natural question is which of these strategies (or which combination of strategies) is the most effective, or in other words, where do you get the greatest bang for your buck? Estimates of the elasticity of adoption with respect to own and cross variables (which we derive in this article) can help answer that question.

The article proceeds as follows. In the remainder of this section we provide a brief review of related literature. In Section 2 we discuss the evolution of the CD industry, describe our dataset, and provide preliminary econometric evidence that there is interdependence between software and hardware. In Section 3 we build a model based on the structure of the industry. In Section 4 we estimate the model. In Section 5 we provide applications of the model. Section 6 concludes.

□ **Brief literature review.** The idea of network externalities was first enunciated by Rohlfs (1974). In the mid-1980s, Katz and Shapiro (1985, 1986) and Farrell and Saloner (1985) extended this idea to the oligopoly context and examined the social and

[1] Park (1997) cites a 1982 *Consumer Reports* publication that tested various VCR models. The report concluded that there was no significant difference in the characteristics or qualities of the two platforms.

[2] See Gabel (1991). The JVC lead was due in part to the fact that JVC cassettes initially had a longer playing time. In the early adoption period (1976–1980), consumers primarily used VCRs to record television programs in order to replay them at a later time.

private incentives to achieve compatibility in a single-product network. Chou and Shy (1990) and Church and Gandal (1992) show how network effects arise when there are complementary products. All these formulations are static. Dynamic formulations include Katz and Shapiro (1992) and Kandori and Rob (1998); these models, however, focus on the adoption decision of consumers and not on the software industry.

A small literature has empirically examined technological adoption of hardware/software systems. Greenstein (1993), Gandal (1994), Saloner and Shepard (1995), Park (1997), and Gandal, Greenstein, and Salant (1999) all provide indirect evidence that the value of the hardware depends on the variety of (compatible) complementary software. Economides and Himmelberg (1995) estimate a dynamic model of network growth for fax machines; in this case there is no complementary product for that industry. Bayus (1987) also examined the relationship between hardware and software purchases for the CD industry. His focus is on forecasting the rate of diffusion (using time trends) rather than examining the underlying factors that affect the diffusion process. Our article focuses on the latter issue: It differs from Bayus (1987) in that we develop and estimate a model that is based on price and interaction effects.

None of these articles formally models both sides of a market with complementary products (that is, both the consumer-adoption *and* software-supply sides.) Hence, while the articles do find evidence that compatibility matters to consumers, their framework does not enable the examination of either the business or the public-policy questions that we address: without estimating the system, it is not possible to conduct counterfactuals.

In a policy paper, Farrell and Shapiro (1992) examine the role of standard setting in HDTV. To provide support for their policy conclusions (which are based on the belief that there is feedback from software to hardware), they examine the adoption of other technologies, including CD players. Their analysis, however, is based solely on price changes, i.e., it does not take into account the fact that the growth in CD players is partly due to the growth in compatible CD titles. They recognize this and note that "the number of titles available is likely driven by the installed base of sets [CD players] .... A simultaneous-equations model would be required to properly explore the evolution of the industry" (p. 72). In this article, we develop and estimate such a model.

2. The CD industry

■ **A brief description of the CD industry.** Compact disc technology was developed by Philips in 1979 and introduced to the United States by Philips and Sony in 1983. To encourage adoption as well as sell their software products (Philips owned Polygram Records and Sony owned CBS Records of Japan), Sony and Philips licensed their technology quite liberally. McGahan (1991b) and Grindley and McBryde (1992) note that by 1981, more than 30 firms had signed licensing agreements to use the Philips technology and that other firms had withdrawn competing prototypes. Consequently, by the early 1980s, CD players had become a fairly standardized product produced by many firms.

This conclusion is based on McGahan (1991a). There she notes that since the Philips standard was universally adopted (by more than 30 firms) and since Philips disseminated information about the manufacturing process to all the licensees, all manufacturers had the same information about the manufacturing process. She also notes that with one exception—the laser assembly—all components used in manufacturing CD players were widely available to all electronics manufacturers. In particular, she notes that the "injection-molding process for manufacturing the players would be similar to the one used to produce videotape, cassette, and receiver housings" (p. 3).

Additionally, "necessary plastics and metals would be exactly the same as those used in the other components" (p. 3). Finally, and perhaps most important, she notes that since "optical scanning technologies were widely available among consumer electronics firms, CD players would almost surely sound similar" (p. 3).

Our theoretical model as well as our estimation approach are guided by these features of the CD player market: Our theoretical model assumes that the market is perfectly competitive, so that prices in it are equal to marginal costs. Consequently—when we estimate the model—we take hardware prices as exogenously given.

Things are different on the software side, the production of compact discs. Most firms in this market are large record companies that integrated into the production of compact discs. The first compact disc pressing plant in the United States was opened by Sony/CBS Records of Japan in 1984. The second plant was opened by Philips/Polygram Records. Subsequent entrants included Capital/EMI (another record company). Hence the production of CD titles was done by a relatively small number of large firms. Consequently, we model this as an oligopolistic industry, prices in it being endogenous.

Since the production of compact discs involves recording and pressing, we include two components of cost in our model. One is the fixed cost of installing disc-pressing capacity; the other is the marginal cost, which includes the "physical" cost of producing a disc and the royalty per disc sold paid to the recording artist.

□ **Data and data sources.** We obtained quarterly data on CD player sales for the 1985–1992 period from the Electronics Industries Association. For reasons of confidentiality, this series was given as an index. The index series of quarterly CD player sales is shown in Figure 1. (Note the strong third and fourth quarter or "Christmas" effect.)

FIGURE 1

QUARTERLY SALES INDEX (1985: 1 = 100)

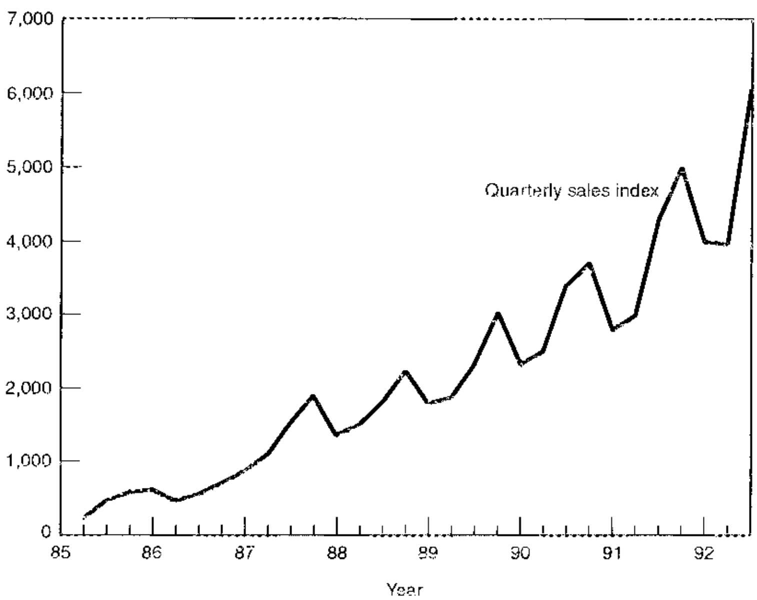
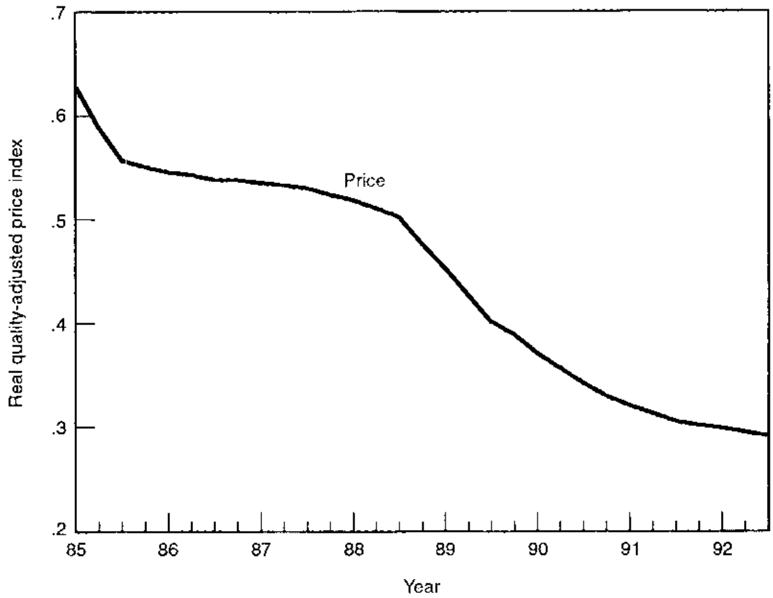


FIGURE 2

PRICE



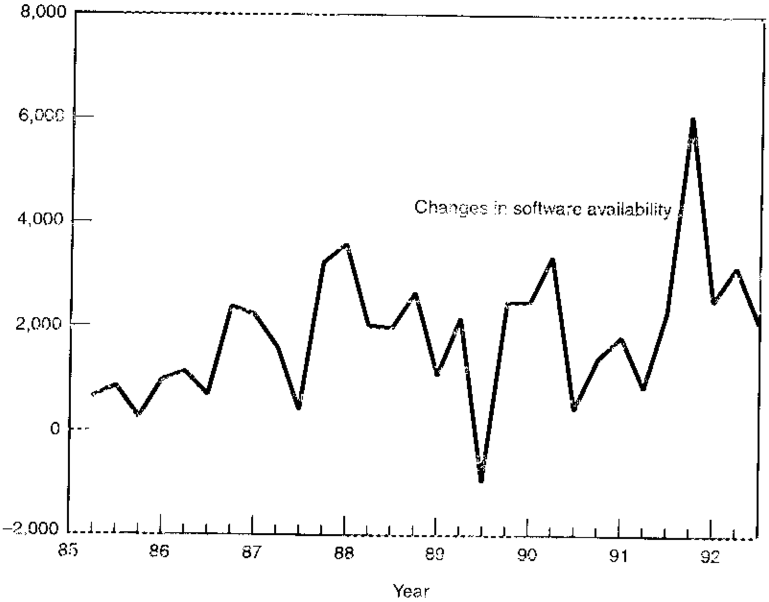
The CD player industry experienced technological progress during our sample period, 1985–1992, reflected in declining prices and improved characteristics of players. We account for this by constructing a quality-adjusted price series. We received data on prices and characteristics for all CD players sold in the United States for the 1983–1992 period from Glenn MacDonald. As reported in Horstmann and MacDonald (1995), these data come from *Audio* magazine and are based on third-quarter prices. The series they collected runs through the third quarter of 1992. Correspondingly, our analysis focuses on the period between the first quarter of 1985 through the third quarter of 1992. Using these data, we estimated a hedonic price regression. A description of the data and the regression results are reported in the Appendix. Based on that analysis, we have third-quarter quality-adjusted prices for our sample period. Quality-adjusted prices for the remaining quarters were obtained by linear interpolations. We then converted nominal to real quality-adjusted prices using the Consumer Price Index. The resulting series is called PRICE. Figure 2 shows that PRICE fell by approximately 54% during the 1985–1992 period. PRICE fell slowly from the middle of 1985 to 1989 and then began to fall more quickly.[3] As noted above, we treat PRICE as being exogenous.

Our data on compact disc availability from 1985 to 1992 comes from a series of Schwann publications. Schwann guides, which are published quarterly, list all compact discs available by major music category: classical, popular, and jazz. Compact disc availability was calculated by multiplying the average number of titles per page in the Schwann guides by the number of pages in the relevant category. We then aggregated across the categories to obtain total compact disc availability, denoted VARIETY. The series DVARIETY, which is the change in compact disc availability from quarter to quarter, is shown in Figure 3.

[3] Our estimates are consistent with data provided by Grindley (1995). He includes a graph that indicates that U.S. CD player prices fell by 33% in the 1985–1990 period.

FIGURE 3

CHANGES IN SOFTWARE AVAILABILITY (CD TITLES)



Our data on the fixed cost of capacity installation for producing compact discs (software) come from a Harvard Business School study on compact discs that was prepared by McGahan (1991a). In her study she cites industry estimates of the fixed cost of installing disc-pressing capacity. McGahan provides yearly estimates for each of the first four years of our sample period and an additional "long-run" estimate. We use the long-run cost estimate as the cost for "year eight" and interpolate—between years four and eight—to fill in years "five" through "seven." We further interpolate to obtain quarterly observations. We report the resulting series in terms of the per-unit cost of disc-pressing capacity per year (i.e., the cost of setting up a plant divided by the number of discs it can press per year). We denote it by FIXED; it is shown in Figure 4.

□ **Informal analysis of the data.** Before spelling out a structural model and estimating it, we informally examine the data by running ordinary least squares (OLS) regressions of (i) hardware sales on changes in variety, price, and quarterly dummies and (ii) changes in variety on CD player sales, fixed costs, and quarterly dummies.[4]

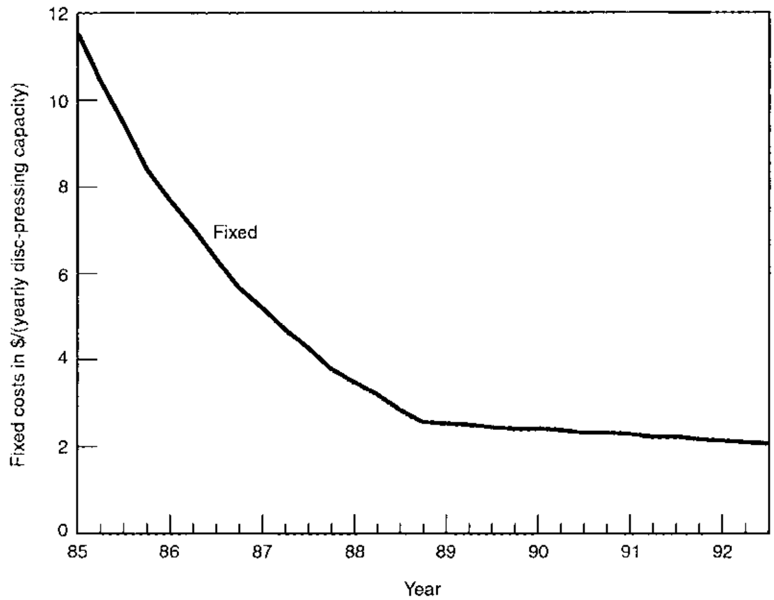
The results of our analysis are reported in Table 1. Since VARIETY and SALES are probably endogenous, in Table 2, we employ instrumental-variable (IV) regressions using PRICE, PRICE^2, FIXED, and FIXED^2 as instruments in both equations.

The coefficients in the hardware-sales equations have the expected signs—negative for PRICE and positive for DVARIETY—and are statistically significant in both the OLS and IV regressions. In the case of the variety equation, the coefficient on FIXED is insignificant in both cases, while the coefficient on SALES is marginally significant in the OLS regression in Table 1 and insignificant in the instrumental-variables regression in Table 2.

[4] QUARTER2 is a dummy variable that takes on the value one if it is the second quarter of the year, etc.

FIGURE 4

FIXED COSTS OF CAPACITY INSTALLATION



In doing this analysis, we have chosen variables that seemed "natural" and have confirmed that some degree of feedback between these variables is present. The results also indicate that the feedback in the variety equation is weaker than the feedback in the hardware-sales equation. While these results are suggestive, this still leaves open the question of which software variable affects which hardware variable, and vice versa, and why these are the "right" variables to use. In the next section we construct a theoretical model of durable-good adoption that suggests that the right variables are

TABLE 1 Informal OLS Regressions

	Dependent Variable			
	Change in Variety (DVARIETY)		SALES	
Independent Variables	Coefficient	*t*-statistic	Coefficient	*t*-statistic
CONSTANT	1,562.17	1.67	6,663.22	12.73
QUARTER2	−136.09	−.23	57.69	.23
QUARTER3	−1,301.17	−2.21	835.97	3.18
QUARTER4	388.19	.64	478.52	1.84
FIXED	−53.13	−.41		
SALES	.36	1.62		
PRICE			−12,053.45	−13.04
DVARIETY			.24	2.88
	Adjusted R^2 = .317	DW = 1.73	Adjusted R^2 = .897	DW = 1.29
Number of observations	30		30	

TABLE 2 **Informal IV Regressions**
Instruments: PRICE, PRICE², FIXED, and FIXED²

	Dependent Variable			
	Change in Variety (DVARIETY)		SALES	
Independent Variables	Coefficient	*t*-statistic	Coefficient	*t*-statistic
CONSTANT	1,775.02	1.79	5,143.70	4.91
QUARTER2	−126.28	−.22	122.09	.35
QUARTER3	−1,257.25	−2.11	1,263.57	3.00
QUARTER4	423.82	.70	250.39	.66
FIXED	−80.46	−.59		
SALES	.30	1.25		
PRICE			−10,370.70	−6.78
DVARIETY			.61	2.79
		DW = 1.73		DW = 1.99
Number of observations	30		30	

cumulative CD player sales and *cumulative* CD title variety. That conclusion comes from the fact that—when network effects are present—what matters to potential hardware adopters and to software suppliers is the installed base of the cross product, i.e., its cumulative value. After constructing the theoretical model, we estimate it in Section 4.

3. Model formulation

■ **Generalities.** In our model, hardware is a homogeneous, infinitely durable product. The market for hardware is competitive, so hardware is provided at marginal cost. We denote the price of hardware in period t by P_t, where P_t is strictly decreasing in t as a result of exogenous technological progress.

Software firms are infinitely lived and maximize profit, which is the discounted stream of their per-period profits. A software firm that enters the market at time t incurs a fixed cost of capacity installation denoted F_t and begins selling its software products in each period beginning with $t + 1$. Let n_t denote the number of software-producing firms in the market in period t; let m be the common number of varieties that each firm produces, and let N_t be the total variety of software that is available in period $t + 1$. Then $N_t = mn_t$. Software is assumed to provide service for one period only.[5] Exogenous reductions in F_t and increases in the size of the hardware installed base induce more software firms to enter over time.

Consumers are also infinitely lived and are differentiated by a taste parameter, θ, which measures their eagerness to own the system. Let $G(\theta)$ denote the measure of consumers with $\tilde{\theta} < \theta$. We assume G has support $[0, \overline{\theta}]$, with $\overline{\theta} < \infty$ and $G(\overline{\theta}) = M < \infty$. Consumers maximize lifetime utility, which is the discounted value of the stream of period utilities. Each consumer who buys a unit of hardware at time t has a demand for software varieties (specified below) in each period beginning with $t + 1$.

Y_t is the "installed base" of hardware in period t, that is, the measure of consumers who have purchased hardware by the end of period t; this gives the size of the software

[5] Consumers frequently listen to (and receive benefits from) a compact disc in the period immediately following the purchase and then listen to it less often in later periods.

market in period $t + 1$. Different individuals buy the system at different dates depending on the size of their θ. Y_t increases over time because the price of hardware, P_t, decreases, because the variety of software, N_t, increases, and because the price of software decreases.

The timing is as follows. In each period, (1) some consumers make initial hardware purchases, (2) consumers with hardware purchase software, (3) some software firms enter the software market and install capacity, and (4) established software firms sell their software products to consumers with hardware. We assume that all these actions occur simultaneously. Then we go to the next period—with new values of N_t, Y_t, F_t, and P_t—and the same set of actions is repeated.

In the following subsections we describe competition in the software industry and the software-entry decision. We then describe consumer preferences over hardware/software systems and the consumer-adoption decision.

□ **Software market.** Within a period, t, denote the per-consumer demand for software variety i by $D_i(p_1, \ldots, p_N)$, where N is the number of software varieties available in that period, and p_j is the price of variety j, $j = 1, \ldots, N$. We assume that demands are symmetric: $D_j(p'_1, \ldots, p'_j, \ldots, p'_N) = D_i(p_1, \ldots, p_i, \ldots, p_N)$, whenever $p'_j = p_i$ and $(p'_k)_{k \neq j}$ is a permutation of $(p_k)_{k \neq i}$. We assume a constant marginal cost of compact disc production, s, which includes the "physical" cost of pressing a disc and the royalty per disc paid to the recording artist. The per-consumer profit function, $(p_i - s)D_i(p_1, \ldots, p_N)$, is assumed quasi-concave in p_i.

Given the symmetry of demands and the quasi-concavity of the profit functions, there exists an equilibrium in which all firms charge the same price per disc, denoted p. This equilibrium is characterized by $p = s - D_1(\overline{p})/[\partial D_1(\overline{p})/\partial p_1]$, where $D_1(\overline{p}) \equiv D_1(p, \ldots, p)$ and $\partial D_1(\overline{p})/\partial p_1$ is the partial derivative of the demand for the "first" variety of software with respect to its own price evaluated at $p_1 = p_2 = \ldots = p_n = p$.

Denote the equilibrium markup by $\varphi(n_t)$ $(\equiv -D_1(\overline{p})/[\partial D_1(\overline{p})/\partial p_1])$ and assume $\varphi'(n) < 0$, so that the equilibrium software price is declining in the number of software firms in the market; this is consistent with the properties of common spatial competition models. Further, let $f(n) \equiv mD(p)\varphi(n)/N = D(p)\varphi(n)/n$. The period $t + 1$ operating profit of a software firm is then $\pi_{t+1} = Y_t f(n_t)$, since, by symmetry, each software firm has an equal portion $(mD(p)Y_t/N_t = D(p)Y_t/n_t)$ of the market, and the profit earned per disc is $p - s = \varphi(n)$.

Consider now the entry decision of software firms. If a firm enters in period t, it pays the entry fee F_t and earns the profit stream $(\pi_{t+1}, \pi_{t+2}, \ldots)$, generating a discounted profit of

$$-F_t + \delta\pi_{t+1} + \delta^2\pi_{t+2} + \ldots, \tag{1}$$

where δ is a discount factor common to all consumers and firms. If a software firm enters in period $t + 1$, it generates a discounted profit—evaluated as of period t—of

$$-\delta F_{t+1} + \delta^2\pi_{t+2} + \delta^3\pi_{t+3} + \ldots. \tag{2}$$

In a free-entry equilibrium firms must be indifferent between these two options. This implies

$$F_t - \delta F_{t+1} = \delta\pi_{t+1} = \delta Y_t f(n_t), \tag{3}$$

where the left-hand side of the above equation represents the gain from waiting, while the right-hand side represents the cost of waiting.[6] We assume $F_t - \delta F_{t+1}$ is decreasing over time; this ensures that the number of software firms keeps increasing. Taking the natural logarithms of both sides of (3), we obtain

$$\log f(n_t) = -\log \delta - \log Y_t + \log(F_t - \delta F_{t+1}). \tag{4}$$

We return to this equation below. The model can be enriched to allow for the possibility of differential entry fees, reflecting the fact that some firms are more efficient than others. In such a case, the fixed fee for a particular firm would be $F_t q(n_t)$ if it entered at time t and $F_{t+1} q(n_t)$ if it entered at time $t + 1$. The second term is the "firm-specific" component that does not change over time. An examination of (3) reveals that this equilibrium condition would be qualitatively unchanged. The left-hand side would be the same and the right-hand side would be $\delta Y_t z(n_t)$, where $z(n_t) = f(n_t)/q(n_t)$.[7]

□ **Hardware market.** There is no stand-alone value to either hardware or software. Consider consumer θ's hardware-adoption decision. If he purchases in period t, his outlay is P_t and he enjoys the stream of utility $(CS(p_{t+1}), CS(p_{t+2}), \ldots)$, where $CS(\cdot)$ is the consumer surplus and p_τ is the (common) equilibrium price of software in period τ. This generates a net discounted benefit of

$$-P_t + \theta[\delta CS(p_{t+1}) + \delta^2 CS(p_{t+2}) + \ldots]. \tag{5}$$

Likewise, if the consumer purchases in period $t + 1$, he generates a net discounted benefit (evaluated as of period t) equal to

$$-\delta P_{t+1} + \theta[\delta^2 CS(p_{t+2}) + \delta^3 CS(p_{t+3}) + \ldots]. \tag{6}$$

Let θ_t be the consumer indifferent between these two. Then, subtracting (5) from (6), we obtain

$$P_t - \delta P_{t+1} = \theta_t \delta CS(p_{t+1}) = \theta_t \delta CS(s + \varphi(n_t)) = \theta_t \delta g(n_t). \tag{7}$$

Taking the natural logarithms of the two sides, we obtain

$$\log(\theta_t) = \log(P_t - \delta P_{t+1}) - \log \delta - \log g(n_t). \tag{8}$$

We assume that $P_t - \delta P_{t+1}$ is decreasing in t; this ensures that the installed base keeps increasing.

□ **Econometric specification.** To take the model to the data, we make three functional-form assumptions: $G(\theta) = \tau\theta^{\beta_1}$, $g(n) = an^{\eta} = a(N/m)^{\eta}$, and $f(n) = bn^{\gamma} = b(N/m)^{\gamma}$. These assumptions are different from what is usually done; for instance, people assume a bell-shaped distribution over θ. However, the assumptions give us tractable functional

[6] McGahan (1991b) notes that when Philips/Polygram considered building a processing plant, it explicitly weighed the cost of waiting (the loss of early sales) with the benefit of waiting (the forecasted decline in the cost of building new capacity).

[7] We thank Ed Glaeser for this point.

forms to estimate, and the insight of the model—that one should use cumulative variables—is not dependent on these functional forms.

Noting that cumulative sales up to period t equal $Y_t = M - G(\theta_t)$, and substituting the three functional-form assumptions into (4) and (8), yields the consumer-adoption equation (9) and the software-entry equation (10):

$$\log(M - Y_t) = \beta_0 + \beta_1 \log(P_t - \delta P_t) + \beta_2 \log N_t + \epsilon_{1,t}, \tag{9}$$

$$\log(N_t) = \alpha_0 + \alpha_1 \log(F_t - \delta F_{t+1}) + \alpha_2 \log Y_t + \epsilon_{2,t}, \tag{10}$$

where $\beta_0 \equiv \log m^{\eta\beta_1}\tau/(a\delta)^{\beta_1}$, β_1 is the parameter in G, $\beta_2 \equiv -\eta\beta_1$, $\epsilon_{1,t}$ is a noise term, $\alpha_0 \equiv \log(bm^{-\gamma}\delta^{-1/\gamma})$, $\alpha_1 \equiv 1/\gamma$, $\alpha_2 \equiv -1/\gamma$ (γ is the parameter in f), and $\epsilon_{2,t}$ is a noise term. Note that $\alpha_1 = -\alpha_2$.

□ **Interpretation of parameters.** Before we report our empirical results, we interpret the parameters. α_1 and β_1 are the direct (price) effects, and we expect them to be negative and positive, respectively. (The price-effect coefficient, β_1, is positive because the dependent variable in the consumer-adoption equation is the *residual market*, $M - Y_t$, rather than cumulative sales, Y_t. A similar remark applies to β_2.) On the other hand α_2 and β_2 are the cross effects—the impact of the availability of the complementary product—and we expect them to be positive and negative, respectively. The significance with which α_2 and β_2 are different from zero measures the strength of the cross effects, i.e., it measures the significance and direction of feedbacks between the components of the system. If both α_2 and β_2 are significantly different from zero, we have a two-way feedback; otherwise, it is one-way feedback or no feedback at all.

□ **Multiple equilibria.** Before we estimate the model, we note that multiple equilibria are typical when there are complementary products.[8] Our model is no exception. First of all, there is the stable degenerate equilibrium where no one adopts the hardware and no one supplies the software, i.e., $Y_t = 0$ for all t. This is the good old story about self-confirming expectations. Second, there are two equilibria with positive Y_t's. Substituting the value for $\log(N_t)$, from (10), into (9) and rewriting yields the following expression.

$$\log(M - Y_t)Y_t^{-\beta_2\alpha_2} = (\beta_0 + \beta_2\alpha_0) + \beta_1 \log(P_t - \delta P_{t+1}) + \alpha_1\beta_2 \log(F_t - \delta F_{t+1}) + \beta_2\epsilon_{2,t} + \epsilon_{1,t}. \tag{11}$$

Since α_2 is positive and β_2 is negative, the exponent on Y_t on the left-hand side of equation (11) is positive. Hence, the left-hand side is a hump-shaped curve, while the right-hand side is constant. So equation (11) has two solutions. The smaller positive solution is where the curve is upward sloping, so it is unstable. The larger positive solution is where the curve is downward sloping, and so it is stable. We interpret our data and the coefficients we estimate as corresponding to the positive stable solution.

4. Estimation of theoretical model

■ To perform the estimation, we needed to choose a value for M. By the end of 1991, 16.2% of all households in the United States had purchased a CD player. At that time, our index of cumulative CD sales stood at 51,091 (recall from Section 2 that—

[8] See Shy (1995) for further discussion.

for reasons of confidentially—we are using an *index*, not actual sales). If all households would adopt a CD player, our index would reach 315,000. Hence this number is a lower bound for the size of the *potential market*. There are approximately 2.75 individuals per household. On the assumption that on average 1.5 individuals per household might adopt a CD player, our index would be approximately 472,000. Thus, rounding up, we take the size of the potential market to be $M = 500{,}000$. Our results, however, are robust to assuming that our potential market is just the number of households, $M = 300{,}000$. In Section 4 we confirm the robustness of our results to the value of M.

We now define the variables that we need to estimate the structural model developed in the previous section.

The series LINSTALLED BASE $= \log(Y_t)$ is the *natural log* of the cumulative CD player sales index.

The series LDPRICE $= \log(P_t - \delta P_{t+1})$.

The series LVARIETY $= \log(N_t)$ is the *natural log* of total compact disc availability.

The series LDFIXED $= \log(F_t - \delta F_{t+1})$.

In the following subsections, we report two sets of parameter estimates. We do not reject the constraint that $\alpha_1 = -\alpha_2$ (from the theory section) in either of these cases. Additionally, all of the coefficients have the expected and the same sign regardless of whether or not we employ the constraint. Since our results are robust to both the constrained and the unconstrained cases, we report the results without constraining $\alpha_1 = -\alpha_2$.

In an earlier version of the article, we estimated δ. Our estimates for δ fell in the range from .86 to .92. Here we use $\delta = .86$, and we discuss results for the case $\delta = .92$ in footnote 11.

□ **OLS estimation.** The two-equation system to be estimated consists of the consumer-adoption equation, (9), and the software-entry equation, (10). Two issues come up in estimating the coefficients of these equations. First, since the left-hand-side variables in both equations are cumulative variables, the error terms are likely to be autocorrelated. This issue is addressed by including AR(1) terms in the error structure.[9] Second, since VARIETY and SALES are endogenous, ordinary least-squares (OLS) estimates are biased (the same problem as in Section 2). This issue is addressed by using instruments.

We start out by reporting the results of OLS regressions with AR(1) terms; see Table 3. Table 3 shows that all of the coefficients have the expected sign, and that all of the estimates are statistically significant. In all cases, we use Newey-West standard errors that are robust to unknown serial correlation.

□ **Instrumental-variables estimation.** Since Y_t and N_t are endogenous, we now estimate each equation separately, using instrumental-variables (IV) estimation. It might appear more logical to *jointly* estimate the system, using generalized method of moments (GMM) or maximum likelihood. However, we have a limited number of observations (29), so instrumental-variables estimation on each equation separately is more appropriate here. The instruments we employ are LDFIXED, FIXED^2, LDPRICE, and

[9] We also examined AR(2) error terms. These did not have any appreciable effects on the results. See the end of the next subsection.

TABLE 3 **OLS Regressions with AR(1) error terms**

	Dependent Variable			
	Software-Entry Equation $\log(N_t)$		Consumer-Adoption Equation $\log(M - Y_t)$	
Independent Variables	Coefficient	t-statistic	Coefficient	t-statistic
CONSTANT (α_0)	3.92	5.51		
LDFIXED (α_1)	−.17	−2.26		
LINSTALLED BASE (α_2)	.62	8.15		
AR(1)	.54	8.67		
CONSTANT (β_0)			13.70	73.36
LDPRICE (β_1)			.049	4.08
LVARIETY (β_2)			−.048	−2.81
AR(1)			.81	14.49
	Adjusted R^2 = .993	DW = 1.18	Adjusted R^2 = .983	DW = 1.68
Number of observations	29		29	

PRICE². The first-stage regressions of the endogenous variables on the instruments have reasonably high R^2 values.

The results of this estimation are reported in Table 4. One noteworthy feature of the numbers in this table—compared with the numbers in Table 3—is that the (own) price effect is farther away from zero (.062 instead of .049 for the consumer-adoption equation), while the cross effect is closer to zero (−.033 instead of −.048 for the consumer-adoption equation). This is true both in the consumer-adoption equation and

TABLE 4 **IV Estimation**
Instruments: LDFIXED, FIXED², LDPRICE, PRICE²

	Dependent Variable			
	Software-Entry Equation $\log(N_t)$		Consumer-Adoption Equation $\log(M - Y_t)$	
Independent Variables	Coefficient	t-statistic	Coefficient	t-statistic
CONSTANT (α_0)	4.42	5.69		
LDFIXED (α_1)	−.26	−2.53		
LINSTALLED BASE (α_2)	.56	6.69		
AR(1)	.57	11.02		
CONSTANT (β_0)			13.58	181.54
LDPRICE (β_1)			.062	3.23
LVARIETY (β_2)			.033	−3.98
AR(1)			.76	15.18
	DW = 1.24		DW = 1.49	
Number of observations	29		29	

in the software-entry equation. As noted earlier, this is the consequence of the endogeneity bias in OLS estimation. In the next section we show that the theoretical direction of the bias is in accordance with what the two tables show.

Given 29 observations and two right-hand-side variables (excluding the constant term), the value of the Dubin Watson (DW) statistic for the consumer-adoption equation in Table 4 falls in the middle of the indeterminate range. When we estimated the consumer-adoption equation including both AR(1) and AR(2) terms, the value of the parameter estimates remained essentially unchanged ($\hat{\beta}_1 = .074$ and $\hat{\beta}_2 = -.034$), while the AR(2) term was totally insignificant and the DW statistic was again 1.49. This suggests that the AR(1) term does adequately control for autocorrelation in the error term of the consumer-adoption equation.

In the case of the software-entry equation, the DW statistic is indeed borderline. When we added an AR(2) term to the error structure, the coefficient estimates changed only slightly. In the case of OLS with AR(1) and AR(2) terms, we get estimate values of $\hat{\alpha}_1 = -.078$ and $\hat{\alpha}_2 = .64$; in the case of IV, using the instruments of Table 4, we get estimate values of $\hat{\alpha}_1 = -.20$ and $\hat{\alpha}_2 = .58$. The estimates are again consistent with the theoretical direction of the OLS bias. With both AR(1) and AR(2) terms, the DW statistic was 2.32 (2.25) in the OLS (IV) case.

We also added quarterly variables to the consumer-adoption equation (Table 4), resulting in little change to the estimates of the other coefficients ($\hat{\beta}_1 = .066$ and $\hat{\beta}_2 = -.032$). Furthermore, the quarterly dummy variables are completely insignificant. In our theoretical model, the dependent variable in the consumer-adoption equation is a function of cumulative sales rather than the per-period sales. It is therefore not surprising that quarterly dummies are not significant as explanatory variables.

□ **Direction of OLS bias.** Let us now show that the comparison between Tables 3 and 4 makes sense. One way to check this is to examine the direction of the bias under OLS estimation. Rather than including the derivations,[10] we spell out the intuition as follows.

First consider the consumer adoption equation. From (9), when $\epsilon_{1,t}$ increases, Y_t decreases and, from (10), N_t increases in Y_t. Hence $\log(N_t)$ and $\epsilon_{1,t}$ are negatively correlated. Since β_2 (the coefficient on variety) is negative, the OLS estimate of β_2 is biased away from zero. Likewise, it can be shown that the OLS estimate of β_1 (the price effect) is biased toward zero.

Now consider the software-entry equation. From (10), when $\epsilon_{2,t}$ increases, N_t increases. This leads to an increase in Y_t. Hence $\log(Y_t)$ and $\epsilon_{2,t}$ are positively correlated. Since α_2 (the installed-base coefficient) is positive, the OLS estimate of α_2 is biased away from zero. It can also be shown that the OLS estimate of α_1—the fixed-cost coefficient—is biased toward zero.

In summary, the OLS estimates of the cross coefficients are biased away from zero, while the OLS estimates of the own coefficients are biased toward zero. Our results in Tables 3 and 4 are consistent with the theoretical direction of the OLS bias. This suggests that the instruments are working properly.

□ **Interpretation and application of results.** As stated in the Introduction, an overriding concern for firms introducing new system technologies is to ensure that the technology is widely adopted, with an eye toward creating a de facto standard. This concern drives a variety of firm strategies. Many firms introducing new systems discount or give away the "hardware" portion in order to ensure future sales of hardware:

[10] The formal derivations of the direction of the OLS bias are available from the authors upon request.

vertically integrated firms may also discount hardware in order to stimulate software sales. On the other hand, hardware firms may stimulate hardware sales by vertically integrating into software production in order to ensure a greater variety of software.

Given these strategies, a natural question is which strategy, or which combination of strategies, a firm should choose. In other words, one would like to compare the effectiveness of strategies that directly subsidize consumers (by lowering the price of hardware) versus strategies that increase software variety (by vertically integrating into software production). We can do this by computing the elasticity of adoption with respect to prices and with respect to variety. From the consumer-adoption equation, (9), the elasticity of hardware adoption with respect to the variety of software is $\epsilon_{Y_t,N_t} = (\partial Y_t/\partial N_t)(N_t/Y_t) = [-\beta_2(M - Y_t)]/Y_t$, while the elasticity of hardware adoption with respect to a permanent price cut is

$$\epsilon_{Y_t,P_t-\delta P_{t+1}} = \frac{\partial Y_t}{\partial(P_t - \delta P_{t+1})}\frac{P_t - \delta P_{t+1}}{Y_t} = \frac{-\beta_1(M - Y_t)}{Y_t}.$$

While these elasticities depend on time, their ratio, β_2/β_1, does not. Hence, it is convenient to capture the relative effectiveness of price cuts versus software provision by the absolute value of the ratio $-\beta_2/\beta_1$.

Using the parameters estimates from Table 4, we can see that $(-\beta_2/\beta_1)$ is approximately .54. This suggests that a 10% increase in CD titles would have as large an effect as a 5% price cut.[11]

□ **Robustness of results.** We now examine the robustness of our estimates of parameters of the consumer-adoption equation to alternative specifications.

We estimated the model using a potential market size of $M = 300{,}000$. In this case, both the price and variety effects nearly double in absolute value. The estimate of the price parameter (β_1) is .11 (a t-statistic of 3.26), while the estimate of the variety parameter (β_2) is $-.057$ (a t-statistic of -3.78). The estimate of the ratio $(-\beta_2/\beta_1)$ remains essentially unchanged at .52.

We also examined an alternative set of instruments for the consumer-adoption equation. In the alternative case, we employed just LDFIXED as an instrument. In this case, the pricing equation is exactly identified. The coefficient estimates are essentially identical to those reported in Table 4. In particular, the parameter estimate for β_1 is .059 (t-statistic 2.86), while the parameter estimate for β_2 is $-.033$ (t-statistic -5.43).[12] The ratio, $-\beta_2/\beta_1$, is .56.

We also estimated equation (9) in first differences. Using IV estimation with LDFIXED − LDFIXED(−1) as an instrument for LVARIETY − LVARIETY(−1), the parameter estimate for β_1 is .0014 (t-statistic .66), while the parameter estimate for β_2 is $-.0067$ (t-statistic -2.36). This suggests that the price effect may be relatively less important[13] and the variety effect may be relatively more important.

□ **An alternative dependent variable for the consumer-adoption equation.** Finally, since the left-hand-side variable $\log(M - Y_t)$ is perhaps a little unintuitive, we

[11] Of course, when we use $\delta = .92$ rather than $\delta = .86$, the estimate of the price parameter is smaller (although still statistically significant), while the estimate of the variety parameter is more negative. In this case, the ratio of the variety to the price parameter increases to 1.5.

[12] The only major difference is that the DW statistic (1.17) is much lower in this regression.

[13] Because of our perfect-competition assumption, our price indices only control for changes in the cost of producing CD players and not for changes in consumer valuations of the technological improvements, which could be an omitted variable.

reestimated the consumer-adoption equation using $\log(Y_t)$ as the dependent variable. Using the same instruments as in Table 4, both the price and the variety parameters are statistically significant: The estimate of the price parameter is $-.60$ (t-statistic of -3.68), while the estimate of the variety parameter is 1.40 (t-statistic of 16.33). Note, of course, that the signs are reversed, since the sign of Y_t changes on the left-hand side of the equation. These estimates are virtually unchanged when using LDFIXED as the lone instrument. The significance of both the price and the variety parameters suggests that the presence of feedback is robust to alternative specifications of the consumer-adoption equation.

5. The effect of compatibility

■ Assume that it had been possible to make CD players compatible with LPs, and that the IV parameter estimates in Table 4 describe the true diffusion process. Using simulations, we examine how compatibility could have accelerated the adoption process. We find that if the amount of variety had grown by 100% between the first and the second quarter of 1985 (due to compatibility),[14] the "predicted" installed base of CDs in the first quarter of 1991 would have been as large as the actual installed base in the third quarter of 1992 (the last period for which we have data).

We performed this counterfactual by calculating an index of hardware installed base for the second quarter of 1985, Y_2. We do this for the second quarter (instead of the first) because we need Y_1 and N_1 to calculate Y_2. If we let the amount of variety grow (artificially) by 100% between the first and the second quarters of 1985, the predicted hardware installed base for the second quarter of 1985 is approximately the same as the actual installed base in the fourth quarter of 1986; thus, the diffusion process would have been shortened by 1.5 years. Hence, in such a case, we would reach the actual installed base achieved in the third quarter of 1992 by the first quarter of 1991.

While this counterfactual is purely a "thought experiment" for the CD system, it is of great relevance for other systems. A timely example is high-definition television (HDTV). Recently, the Federal Communications Commission (FCC) set down the guidelines for the new digital television (HDTV) standard. National Television System Committee (NTSC) televisions will be able to view new (HD) broadcasts with a "down-converter" box, which will provide a somewhat improved image. New HDTVs will be able to watch old NTSC programs if they have a second (analog) tuner built in. At the same time, the FCC has scheduled an end to NTSC broadcasts by the year 2006.[15] Therefore, the FCC has imposed (temporary) backward and forward compatibility of the hardware with the software. To what extent this will speed up diffusion can be determined by performing an analogous counterfactual on the TV market.

6. Conclusion

■ In addition to the business press and to the empirical literature we discussed in the Introduction, there is a long strand of theoretical literature discussing complementarities, coordination failures, and multiple equilibria. The basic argument in that literature—as applied to the diffusion of systems—is that the hardware-adoption decision of consumers depends on the variety of available software and, conversely, that the supply decision of software manufacturers depends on how many consumers have

[14] The actual increase in variety between these two periods was 35%.

[15] See "HDTV: How the Picture Looks Now," *Business Week*, May 26, 1997, p. 174 E2 and "Should You Roll Out the Welcome Mat for HDTV?" *The New York Times*, April 27, 1997, p. 3.

already adopted the hardware. Hence, the diffusion of such systems could be marked by bottlenecks in which one side of the market is awaiting the other before making its own commitments, i.e., there may be a "chicken and egg" problem.

The aim of this article was to provide an empirical counterpart to this literature, namely, to quantify the importance of complementarities for one particular system. As we argued, this can be useful for understanding the actual dynamics of the system, and to aid in the selection of strategies that might affect the dynamics.

Appendix

■ To derive a quality-adjusted price index for compact disc players, we employed quality and price data gathered by Horstmann and MacDonald for the 1983–1992 period. The data on price and product characteristics were gathered from an annual survey contained in the October issues of *Audio* magazine. Their dataset contains 1,700 observations. As sales data for each model were not available, we were unable to produce a "sales-weighted" quantity-adjusted price index. To avoid giving too much weight to models for which few sales could be expected, we restricted the set to compact disc players costing less than $1,000; this reduced the number of observations to 1,291.

The results of the hedonic price regression are in Table A1. We use all variables for which there were no missing observations; hence the following variables are used:

The variable Lsnratio is the log of the signal-to-noise ratio of the compact disc player; the higher this ratio, the less extraneous noise is introduced.

TABLE A1 Hedonic Price Regression
Dependent Variable: log(Nominal Price)

	Dependent Variable	
	log(Nominal Price)	
Independent Variables	Coefficient	Standard Error
CONSTANT	−3.10	.76
Lsnratio	1.66	.17
Losrate	.05	.0098
Lthd	−.067	.010
Lfrelo	.054	.013
Lweight	.71	.028
Light	1.50	0.71
Year 1984	−.37	.12
Year 1985	−.56	.12
Year 1986	−.59	.12
Year 1987	−.56	.12
Year 1988	−.58	.12
Year 1989	−.75	.12
Year 1990	−.86	.12
Year 1991	−.94	.12
Year 1992	−.96	.12
	Adjusted R^2 = .55	
Number of observations	1,291	

The variable Losrate is the log of the oversampling rate of the compact disc player; it gives an indication of how rigorously the player translates the digits contained on the disc into sound.

The variable Lthd is the log of the total harmonic distortion that the player introduces when reproducing music.

The variable Lfrelo gives the log of the lower limit of the frequency response of the compact disc player.[16]

Lweight is the log of the weight of the compact disc player.

Light is a dummy variable that takes on the value one if the CD player weighs less than 5 pounds. This provides a proxy for portable players as opposed to stereo components.

Finally, the year 19xx variables are the time dummy variables.

From the regression, all variables were significant, and all characteristics except Lfrelo had the correct sign. All of the time dummy variables had a negative sign. The hedonic price index was calculated by taking the exponentiated estimated coefficients on the time dummy variables.

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[16] A variable for the upper limit of the frequency response was not available in every year of the sample.

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