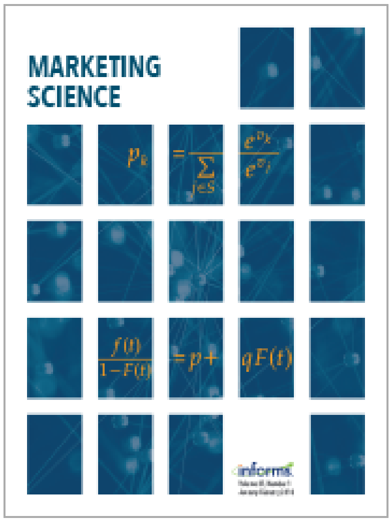

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New Product Diffusion Acceleration: Measurement and Analysis

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Abstract

It is a popular contention that products launched today diffuse faster than products launched in the past. However, the evidence of diffusion acceleration is rather scant, and the methodology used in previous studies has several weaknesses. Also, little is known about why such acceleration would have occurred. This study investigates changes in diffusion speed in the United States over a period of 74 years (1923–1996) using data on 31 electrical household durables. This study defines diffusion speed as the time it takes to go from one penetration level to a higher level, and it measures speed using the slope coefficient of the logistic diffusion model. This metric relates unambiguously both to speed as just defined and to the empirical growth rate, a measure of instantaneous penetration growth. The data are analyzed using a single-stage hierarchical modeling approach for all products simultaneously in which parameters capturing the adoption ceilings are estimated jointly with diffusion speed parameters. The variance in diffusion speed across and within products is represented separately but analyzed simultaneously.

The focus of this study is on description and explanation rather than forecasting or normative prescription. There are three main findings.

1. On average, there has been an increase in diffusion speed that is statistically significant and rather sizable. For the set of 31 consumer durables, the average value of the slope parameter in the logistic model's hazard function was roughly 0.48, increasing with 0.09 about every 10 years. It took an innovation reaching 5% household penetration in 1946 an estimated 13.8 years to go from 10% to 90% of its estimated maximum adoption ceiling. For an innovation reaching 5% penetration in 1980, that time would have been halved to 6.9 years. This corresponds to a compound growth rate in diffusion speed of roughly 2% between 1946 and 1980.

2. Economic conditions and demographic change are related to diffusion speed. Whether the innovation is an expensive item also has a sizable effect. Finally, products that required large investments in complementary infrastructure (radio, black and white television, color television, cellular telephone) and products for which multiple competing standards were available early on (PCs and VCRs) diffused faster than other products once 5% household penetration had been achieved.

3. Almost all the variance in diffusion speed among the products in this study can be explained by (1) the systematic increase in purchasing power and variations in the business cycle (unemployment), (2) demographic changes, and (3) the changing nature of the products studied (e.g., products with competing standards appear only late in the data set). After controlling for these factors, no systematic trend in diffusion speed remains unaccounted for.

These findings are of interest to researchers attempting to identify patterns of difference and similarity among the diffusion paths of many innovations, either by jointly modeling the diffusion of multiple products (as in this study) or by retrospective meta-analysis. The finding that purchasing power, demographics, and the nature of the products capture nearly all the variance is of particular interest. Specifically, one does not need to invoke unobserved changes in tastes and values, as some researchers have done, to account for long-term changes in the speed at which households adopt new products. The findings also suggest that new product diffusion modelers should attempt to control not only for marketing mix variables but also for broader environmental factors. The hierarchical model structure and the findings on the systematic variance in diffusion speed across products are also of interest to forecasting applications when very little or no data are available.

(*Diffusion*; *New Product Research*; *Empirical Generalizations*; *Hierarchical Models*; *Multilevel Analysis*)

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1. Introduction

Diffusion researchers try to identify patterns in how new products gain market acceptance that are generalizable across product categories, countries, and time. One theme that cuts across several studies is that diffusion may have accelerated. Many people believe that products launched today diffuse faster than products of older vintage. Although diffusion acceleration is often presented as a matter of fact in the business press, the evidence is actually far from compelling. While some studies report that more recently launched products diffuse faster than those of an older vintage within the same country (Clark et al. 1984, Olshavsky 1980), others find only mixed evidence (Kohli et al. 1999, Montgomery and Srinivasan 1994) or none at all (Bayus 1992, Fisher and Pry 1971, Mansfield 1961). Moreover, recent methodological research suggests that some of the evidence of diffusion acceleration may have been the result of estimation bias (Van den Bulte and Lilien 1997) and invalid inference (Edmonds and Meisel 1992).

In addition to the question of *whether* diffusion has accelerated, there is also the question of *what may cause* adoption of new products to accelerate over time. Diffusion research has mostly ignored potential antecedents of acceleration, limiting itself to some allusions to improved communication technology and more favorable attitudes towards technological change (e.g., Mansfield 1961). This study assesses to what extent basic economic and demographic conditions such as disposable income, unemployment, and the formation of new households are related to the speed of diffusion of consumer durables. Economic theory posits, and several empirical studies document, that these factors affect the demand of durable consumer products, including initial adoptions, and hence the products' diffusion (e.g., Bonus 1973, Olney 1991). This study includes a small number of products requiring a large complementary infrastructure or exhibiting competing standards early in their life, allowing it to shed some light on whether these factors retard innovation adoption, an issue for which economic theory provides no general result (Besen and Johnson 1986, Katz and Shapiro 1994). Empirical evidence on economic, demographic, and product effects on diffusion speed can help managers and analysts to use generalizable patterns across products to make forecasts when they have no or only very few data points to build on (cf. Gatignon et al. 1989). Because the early part of a durable product's life cycle consists primarily of first purchases (adoptions), explaining systematic variations in the rate of adoption also explains systematic variations in the early evolution of sales. This in turn may help us better understand whether, why, and under what conditions overall life cycles are getting shorter.

This study investigates changes in the diffusion speed over a period of 74 years (1923–1996) in the United States, using data on 31 electrical household durables. The two research questions are: (1) Has diffusion speed increased systematically over time? and (2) To what extent do changes in economic and demographic conditions and the greater prevalence of products requiring large investments in complementary infrastructure or exhibiting competing standards account for changes of diffusion speed over time? I first provide a definition and measure of diffusion speed. Next, I present an approach to model variations in diffusion speed among products and over time. I then describe the data and results. The paper concludes with a discussion of implications, research limitations, and opportunities for future research.

2. Defining and Measuring Diffusion Speed

Everyday language conceives of speed as a rate of movement, i.e., a ratio of distance divided by time of travel (e.g., 70 miles per hour). Equivalently, one can define speed as the reciprocal of that ratio, i.e., the amount of time it takes to travel a particular distance. In the realm of diffusion, the relevant distance metric is the difference between two penetration levels. Hence, a simple definition of diffusion speed is the amount of time it takes to go from one penetration level (e.g., 0% or 10%) to a higher level (e.g., 90% or 100%) (Fisher and Pry 1971, Grübler 1990).

Researchers typically measure diffusion speed by first estimating a specific diffusion model, and then using one or more of the parameter estimates as an indicator of diffusion speed. Studies in economics and the history of technology have typically used the logistic model,

$$x(t) = \beta F(t-1)[M - X(t-1)], \quad (1)$$

where

$X(t)$ = the cumulative number of adopters by time t,

$x(t) = X(t) - X(t-1)$,

M = the number of eventual adopters,

$F(t) = X(t)/M$.

The β parameter has a direct relationship to diffusion speed as defined above: the time to go from a penetration level P_1 to penetration P_2 equals $\beta^{-1}\ln\{(1-P_1)P_2/[(1-P_2)P_1]\}$.[1] For instance, the time to go from 10% to 90% of the ceiling M, i.e., $t_{90\%} - t_{10\%}$, equals $4.39/\beta$ in a logistic diffusion process (Mansfield 1961, Fisher and Pry 1971). Furthermore, $1/\beta$ also equals the logistic's Gini coefficient, i.e., the expected waiting time of a random potential adopter at a random point in time (Trajtenberg and Yitzhaki 1989).

The definition and the measure just offered conceive of speed as an aggregate or average property of the entire diffusion process over all adopters. Such a measure makes it hard to relate diffusion speed to various explanatory variables that vary over time, such as changes in purchasing power. Some researchers therefore propose to also use measures of instantaneous growth, that is, to measure growth in penetration at every point in time for which one has data. One possibility is to use the local slope of the diffusion curve, defined as $f(t) = dF(t)/dt$ and operationalized as $x(t)/M$. Trajtenberg and Yitzhaki (1989) use the empirical hazard rate, defined as $h(t) = f(t)/[1 - F(t-1)]$ and operationalized as $x(t)/[M - X(t-1)]$, while Dixon (1980) suggests using the empirical growth rate, defined as $g(t) = f(t)/F(t-1)$ and operationalized as $x(t)/X(t-1)$. An appealing property of the logistic distribution is that its parameter β, which has an unambiguous interpretation as an aggregate measure of speed, also has a unique relationship to the empirical growth rate as a measure of instantaneous gain in penetration (e.g., Dixon 1980):

$$x(t) = \beta F(t-1)[M - X(t-1)] = \beta \frac{X(t-1)}{M}[M - X(t-1)], \quad (2)$$

$$\frac{x(t)}{X(t-1)} = \beta\left[1 - \frac{X(t-1)}{M}\right] = \beta + \gamma X(t-1), \quad (3)$$

where $\gamma = -\beta/M$. This reparametrization relates the *instantaneous* rate of growth to the logistic model's rate parameter, the most accepted *aggregate* measure of speed.

3. Modeling Variations in Speed

Most analyses of diffusion acceleration use a two-step approach. The first step consists of estimating a diffusion model for each of a number of innovations. In the second step, estimates of parameters in the model's hazard function or some transformation thereof (e.g., β, $4.39/\beta$) are regressed on the innovations' vintage. The latter is typically operationalized as the time the innovation was introduced, the time it achieved a particular penetration level, or—when such information is not available—simply the time at which one's observations start. If the value of the parameters increases with vintage, the analyst interprets this as evidence of diffusion acceleration. Table 1 reviews how previous studies have operationalized speed and vintage.

While the two-step approach has dominated cross-product and cross-country diffusion research, a number of disadvantages have been identified over time. These are:

1. The first-stage parameter estimates are likely to be biased if one does not use enough data points in the estimation (Van den Bulte and Lilien 1997).

2. The second-stage analysis is sensitive to whether and how one controls for the uncertainty in the parameter estimates (Edmonds and Meisel 1992, Montgomery and Srinivasan 1994).

3. The approach provides only limited explanatory insights when important covariates vary not only across but also within innovations (cf. Diggle et al. 1995).

4. The analysis in separate steps is inefficient (Diggle et al. 1995, Gatignon et al. 1989).

[1]This formula follows from the continuous-time form of the logistic model. That model can be expressed as $\ln\{F(t)/(1-F(t))\} = c + \beta t$. Writing this for $F(t_1) = P_1$ and $F(t_2) = P_2$ (with $t_1 < t_2$), we have $\ln\{P_1/(1-P_1)\} = c + \beta t_1$ and $\ln\{P_2/(1-P_2)\} = c + \beta t_2$. Subtracting the former expression from the latter, we have $\ln\{(1-P_1)P_2/[(1-P_2)P_1]\} = \beta[t_2 - t_1]$.

Table 1 Studies Reporting Analyses of Diffusion Acceleration[a]

Innovations	Data	Measure	Association with	Control Variables	Conclusion	Comment
1. 14 industrial materials	Usage	$t_{90\%} - t_{10\%}$	τ	None	"Little correlation"	
2. 12 industrial durable goods and processes	Penetration (1890–1958)	β	Introduction time	Profitability, Investment required, Adopting industry	No significant acceleration	Low power ($df = 5$)
3. 30 consumer durables	Sales (1922–1990)	$p + q$, t^*, β	Start of data series	Price, Price trend, Estimated ceiling	No significant acceleration	Data likely to include replacements
4. 61 consumer durables	Not reported (1922–?)	β, τ	Not specified	Price, Price trend, "Efficiency" v. other products	Mixed: β decreases but τ does not significantly	
5. 32 consumer durables	Sales (1922–1992)	p, q, t^*	Start of "substantial sales data"	None	Mixed: q increases and t^* decreases, but p decreases too[b]	Data likely to include replacements
6. 265 miscellaneous innovations	Not reported (1800–1979)	$\bar{\beta}$(t) (Average β of innovations diffusing in year t)	Year	None	Acceleration[c] (no formal test)	Visual evidence only
7. 7 consumer durables	Sales (1925–1980)	$p + q$	Start of data series	None	Acceleration (no formal test)	Data include replacements
8. 25 consumer durables	Penetration (1922–1977)	β	Start of data series	High v. low price	Acceleration (+ .0056/yr)	Right-censoring bias likely (Van den Bulte and Lilien 1997)

Sources: (1) Fisher and Pry 1971, (2) Mansfield 1961, (3) Bayus 1992, (4) Montgomery and Srinivasan 1994, (5) Kohli et al. 1999, (6) Grübler 1990, (7) Clark et al. 1984, (8) Olshavsky 1980.

[a] β is the parameter in the logistic model: $x(t) = \beta F(t-1)\,[M - X(t-1)]$.

p and q are parameters from the Bass (1969) model: $x(t) = [p + q\,F(t-1)]\,[M - X(t-1)]$.

τ is the inflection point of the cumulative penetration curve in the logistic model, which also satisfies $E[X(\tau)] = M/2$, and t^* is the inflection point of the cumulative penetration curve in the Bass model, $t^* = (p + q)^{-1}\ln(q/p)$.

[b] In a second analysis, Kohli et al. regressed p and q on incubation time (time between invention and launch), launch year (i.e., first year with substantial sales data), two dummies distinguishing major appliances, consumer electronics and housewares, and two-way interactions among the variables. The main effect of launch year was not significant. Launch year × electronics and Launch year × incubation time were negatively associated with p, and Launch year × incubation time was positively associated with q.

[c] Grübler found that the average β had an upward trend, be it with a Kondratieff-like cycle around the trend (1990, p. 269). Hence, even though his discussion emphasizes the cycle rather than the trend and concludes that "no *general* acceleration tendency of diffusion rates over time has been observed in our data samples" (emphasis added), his results do suggest an acceleration trend (see his Figure 5.2, p. 269).

This study uses a single-stage approach in which all innovations are pooled and their key diffusion parameters are constrained to vary according to some parametric distribution. I apply this approach to the reparametrized logistic model (Equation 3). Let i denote an innovation. Also, allow the number of eventual adopters to vary across both innovations and time, but impose that the number varies over time proportionately to the size of the total population (e.g., Bayus 1992, Parker 1992). In other words, let $M_i(t) = \alpha_i M(t)$, where α_i is the fractional ceiling and $M(t)$ is the size of the total population. We then have the basic model structure:

$$\frac{x_i(t)}{X_i(t-1)} = \beta_i + \gamma_i \frac{X_i(t-1)}{M(t)} + u_{it}, \qquad (4)$$

with

$$u_{it} = \rho_i u_{i,t-1} + \epsilon_{it},\ E(u_{i0}) = 0,$$
$$\epsilon_{it} \text{ i.i.d. N}(0, \sigma_{ii}), \text{ and } \gamma_i = -\beta_i/\alpha_i.$$

The errors are allowed to follow a first-order autoregressive structure within products and to differ in variance and serial autocorrelation across products. I model the between-innovation variance in diffusion speed by allowing β_i to vary across innovations according to a random component U_{bi} i.i.d. $N(0, \tau_b)$:

$$\beta_i = \beta_0 + U_{bi} \quad U_{bi} \text{ i.i.d. N}(0, \tau_b), \tag{5}$$

where β_0 is the mean value of β_i. I estimate the γ_i parameters capturing the unknown penetration ceilings as fixed effects, i.e., without imposing any parametric constraint on their distribution.

The main question is whether the diffusion speed parameters β_i vary not only randomly but also as a function of covariates such as vintage. This can be modeled by expanding the last equation with the covariates of interest. In case a covariate, denoted Z_{kit}, varies over time, I average it over the innovation's observed diffusion history, resulting in a time-invariant covariate $\bar{Z}_{ki+}$. To preserve the interpretation of β_0 as a mean, the time-invariant covariates are centered over all innovations by subtracting $\bar{\bar{Z}}_{k++} = (1/I)\Sigma_i\bar{Z}_{ki+}$, resulting in the following expression:

$$\beta_i = \beta_0 + \sum_k \phi_k\, (\bar{Z}_{ki+} - \bar{\bar{Z}}_{k++}) + U_{bi}. \tag{6}$$

Similarly, I model within-innovation variance, i.e., deviations from the logistic diffusion process, by adding time-varying covariates, again mean-centered to preserve the interpretation of β_0:

$$\frac{x_i(t)}{X_i(t-1)} = \beta_i + \gamma_i \frac{X_i(t-1)}{M(t)} + \sum_k \delta_{ki}(Z_{kit} - \bar{Z}_{ki+}) + u_{it}. \tag{7}$$

As with β_i, the within-innovation effects δ_{ki} are allowed to vary across innovations randomly:

$$\delta_{ki} = \delta_k + U_{ki} \quad U_{ki} \text{ i.i.d. N}(0, \tau_k).$$

I estimate the model using residual maximum likelihood (Laird and Ware 1982). I impose $Cov(U_{bi}, U_{ki}) = Cov(U_{ki}, U_{k'i}) = 0$. This is necessary to obtain convergence in this study, but still allows U_{bi} and hence β_i to vary with γ_i, which is important because $\gamma_i = -\beta_i/\alpha_i$. As always in this type of model, U_{bi} and U_{ki} are assumed independent of ϵ_{it}.

4. Data

4.1. Research Setting

The setting for this study was selected using four criteria. First, to reduce the danger of unaccounted heterogeneity, I limit the scope of the study to a single country and to products that are qualitatively similar in potential adopters and usage situations (Olshavsky 1980). Second, to avoid confounding adoptions with repeat purchases, I require penetration or adoption data rather than sales data to be available.[2] Third, data have to be available over a sufficiently large number of years for many products. The criterion stems from the desire to disentangle time-varying period effects affecting all diffusion processes (e.g., periods of economic expansion and contraction) from time-invariant vintage effects, which is not possible when year of observation does not vary sufficiently from product vintage. Fourth, to avoid this same problem, I also require that a great majority of years have observations for multiple products of different vintage.

Electrically powered household durable goods in the United States are the only type of innovations identified to meet these considerations, and for which data were available. As in most diffusion studies, the data are at the product category level rather than the brand or model level. I analyze 31 consumer durables marketed in the United States in the 1923–1996 period.

[2]Penetration data are often generated through surveys (sometimes expert judgment), whereas sales data are often obtained from a near census of factory shipments or retail sales. Hence, penetration data are likely to have more random measurement error (on a percentage basis) than sales data, and may hence result in larger confidence intervals of the parameter estimates, though the estimates themselves should remain consistent. Parameter estimates obtained from sales data may have higher reliability, but only if they do not include significant levels of replacement sales or multiple purchases. Diffusion models applied to consumer durables can be grossly misspecified when the time series exceeds 5 to 10 years of sales data (Parker and Neelamegham 1997). Confounding adoptions with repeat purchases should result in systematically time-varying parameter estimates, and hence invalid measures of speed (Putsis 1998). The use of penetration rather than sales data might underlie this study's coming to different conclusions than earlier work mentioned in Table 1.

4.2. Diffusion Data

The diffusion data consist of annual observations between 1922 and 1996 on the ownership of 31 consumer durables by electrically wired households in the United States. I calculate ownership levels by multiplying the number of electrically wired households $M(t)$ by the percentage of such households owning the product category $PEN_i(t)$. Hence,

$$X_i(t) = PEN_i(t) \times M(t). \tag{8}$$

This study uses adoption rather than penetration data because the latter can be affected by population growth, resulting in measurement artifacts. Specifically, computing the empirical growth rate directly from penetration data underestimates the speed of diffusion in years of strong population growth. One obvious case is a year when no households adopt, but the population grows, such that $X_i(t) = X_i(t-1)$ but $PEN_i(t) < PEN_i(t-1)$. In that situation, using adoption data generates a growth rate of zero, while using penetration percentages directly generates a negative value.

For the period 1922–1979, the main sources for the penetration data are the trade publications *Merchandising* and *Merchandising Week*. For 1985–1996, the main data source is the annual *Product Saturation Survey* by Industrial Marketing Research (Clarendon Hills, IL). This survey's sample includes 10,000 households, with a response rate of 65%–80%, drawn from Market Facts panel members. The sample is drawn in December of each year and the questionnaire is mailed in early January to capture end-of-year ownership levels. The sample is drawn in population proportions regarding age, income, and region of the country, although no post-survey weighting is done to further ensure representativeness. For a few products in some years, data come from the *Statistical Abstract of the United States* (VCRs 1980–1995, Home PCs 1981–1988) and the Electronic Industries Association's *Electronic Market Data Book* (telephone answering devices 1983–1984). Penetration data for radios were calculated from data in the *Historical Statistics of the United States* (1975). The data on the number of electrically wired households between 1922 and 1979 are from *Merchandising* and *Merchandising Week*.[3] From 1980 onward, I assume 100% electrification and use the total number of households (Bureau of the Census, Current Population Survey). The data retained for analysis do not contain any observations for 1980, so the growth rates are not artificially affected by switching from one data source to another.

4.3. Vintage

Vintage is operationalized as the year in which an innovation achieved 5% household penetration rather than as its launch year (cf. Grübler 1990). There are two reasons for this. First, researchers often disagree on the year in which an innovation was launched. Microwave ovens, for instance, have been stated to have been launched in the United States in 1955 (Kohli et al. 1999), 1957 (Bayus 1992), and 1966 (Golder and Tellis 1997). Using the year that an innovation achieved 5% penetration as its vintage is not subject to such ambiguities. Second, the year that 5% penetration was first achieved is known for more product categories than the year of launch.

4.4. Control Variables

This study uses data on four variables previously documented to be associated with households' adoption or purchase of new durables: disposable income per household, unemployment, household formation rate, and price (e.g., Haldar and Rao 1998, Olney 1991, Parker 1992). The growth in electrification is also controlled for, since there may have been a correlation early in the 20th century between households' decisions to electrify their house and to adopt electric goods.

Disposable income per household is expressed in constant 1982 dollars. For 1922–1928, I use the estimates published by Olney (1991). For 1929–1996, I use the disposable personal income in current dollars per household (U.S. Department of Commerce 1997) and deflate it using the consumer price index (CPI, All Urban Consumers, All items, 1982–1984 = 100). Data on the civilian unemployment rate are from the *Historical Statistics of the United States* and the *Economic Report of the President 1997*. I computed the household formation

[3] I replaced the 24,556 value reported for 1932 by 20,556 because the values for 1931 and 1933 were both about 20,000. The replacement brings the implied level of electrification from 80% to 67%, a value corresponding to official statistics for 1931, 1932, and 1933.

rate as the growth rate in the number of households (*Historical Statistics of the United States;* Bureau of the Census, Current Population Survey). The electrification growth rate is the growth rate in the proportion of total households that were electrically wired. Finally, for a majority of products and years, data on the average selling price were also collected or computed from *Merchandising, Merchandising Week, Dealerscope Merchandising,* and the *Statistical Abstract of the United States.* I converted these prices into constant 1982 dollars using the price index mentioned above.

For the within-innovation analysis, I transformed the dollar prices into relative prices by dividing each price p_{it} by innovation i's average. This transformation implies that consumers respond to price changes in percentage rather than absolute terms.

To allow for more skew in the diffusion path than predicted by the logistic model, within-innovation duration dependence is also modeled. Duration is operationalized as the time lapsed since the product reached 5% penetration.

Some products included in this study required large investments in complementary infrastructure to be commercially viable or had multiple standards competing early on in the U.S. market. For such products, even innovative consumers may postpone adoption until the supporting infrastructure is sufficiently well developed or the uncertainty on the dominant standard has been resolved (Besen and Johnson 1986, Katz and Shapiro 1994). Why buy a color TV set, for instance, if your local station does not have color equipment or carries only very little programming content in color? Once the infrastructure is in place and the standard is set, however, the products may be quite appealing and interest may rapidly translate into actual adoptions. Such behavior results in a stronger positive feedback or "snowball effect" in the product's grow path, i.e., a more pronounced S shape of the diffusion curve $F(t)$. In the logistic model, this implies a larger β parameter. Still, the effect of standards incompatibility need not be very important. If, say, VCRs are very appealing to consumers, consumers may expect the total market to be large enough to support mutually incompatible standards. Or consumers may expect to enjoy their VCRs so much that they accept the risk of ending up with an obsolete machine two years after purchase. When intrinsic utility is high, consumers may not delay their adoption and diffusion may be rapid very early on, even in the presence of incompatible standards (Besen and Johnson 1986). To account for such differential effects, I use two dummy variables: whether the product category required large complementary infrastructure (1 for radio, black and white TV, color TV, and cellular telephone; 0 for others) and whether the product category had multiple competing standards (1 for VCR and PC; 0 for others). Note that compatibility issues often stem from the requirement to use complements with the focal product. VCRs and PCs are no different. To separate the effect of competing standards from the mere need for easily available complementary software, which theory does not suggest should affect diffusion speed, I use a separate dummy for CD players.[4]

Appendix A lists all the variables and the model equation incorporating all covariates. Estimation is facilitated when the covariates do not differ too much in their variance. I therefore rescaled the data, as indicated in the Appendix. The $M(t)$ values in the ratio $X_i(t-1)/M(t)$ appearing in Equations (4) and (7) were transformed into $[M(t) + M(t-1)]/2$. Using $M(t)$ assumes that the entire growth in the population from $M(t-1)$ to $M(t)$ happens on January 1. Using the average assumes that growth is uniform over the year, which is more defensible.

4.5. Selecting Observations for Analysis

Penetration data very early and very late in a diffusion process may have rather large percentage errors stemming from small random shocks and measurement errors (Dixon 1980, Olshavsky 1980), so I exclude observations with less than 5% or more than 95% household penetration. The 1942–1945 period when the United

[4]Though this little "pseudomanipulation check" shows the desired result (see below), the dummy coding scheme does not allow one to assess whether products requiring large complementary infrastructure or having competing standards diffused faster *because* of these characteristics, or because of other unaccounted for but coincident (and hence, confounded) factors. Higher than average intrinsic utility or product appeal may be one such factor. A reviewer advanced several alternative explanations, including that radio, black and white TV, and color TV are all substitutes or successive generations, and that cell phones might be considered a substitute for CB radio.

States was a war economy is deleted as well (e.g., Olshavsky 1980). Finally, I limit the time series of each product to a maximum of 20 observations to avoid the data set from being very unbalanced and dominated by long series of old-vintage products.

Hence, the data series for each product starts with the year in which it first reached 5% household penetration, and ends 20 years later, when the household penetration reached 95%, or with the last year for which penetration data were available (whichever happened first). Table 2 lists the products and years used, as well as the penetration level observed in the last year (Data Set 1, $N = 457$). It also reports those products and years for which price data were available (Data Set 2, $N = 353$).

5. Results

Table 3 reports the results for Data Set 1. Each column presents the estimates from a different model. The first model contains no covariates and simply computes the mean diffusion speed and the population variance around the mean. The second model has vintage as its only covariate allowed to affect β_i. The third model has all covariates except average disposable income (i.e., averaged over each innovation's data series), which is included only in the fourth model. I estimate the "covariate" model both with and without mean disposable income because that variable is very highly correlated with vintage ($r = 0.98$), which may create collinearity artifacts.

The first key result is from Model 1: Diffusion speed differs quite a bit across innovation. The mean of β_i is 0.529, but the standard deviation is no less than 0.228 (the square root of 0.052). The 90% interval for β_i is between 0.155 and 0.903. Put differently, the 90% confidence interval for the time to go from 10% to 90% of ultimate penetration (i.e., $4.39/\beta$) is 5 to 28 years.

The second key result is from Model 2: Diffusion speed significantly increases with vintage. That is, diffusion has accelerated. The extent of acceleration is considerable. The mean value for β_i in Model 2 is 0.477, while the vintage coefficient indicates that it increases by 0.930 per 100 years. The mean vintage year in Data Set 1 is 1963. Hence, the results suggest that the expected value for β reached two-thirds of its 1963 value, i.e., 0.318, in 1946 and four-thirds of its 1963 value, i.e. 0.636, in 1980. This in turn suggests that it took about 34 years for diffusion speed to double after 1946. This corresponds to a compound growth rate of 2% per year.

The third result is that the changing nature of products and economic and demographic conditions significantly affected diffusion speed (Models 3 and 4). Innovations with competing standards and innovations requiring large investments in complementary infrastructure diffused faster than other products once 5% household penetration was achieved. CD players, merely requiring standardized and widely available software, did not. This result is similar to that by Golder and Tellis (1997), who found no association between time to takeoff and the need for a complementary product, though Golder and Tellis did not parcel out products with competing standards from those requiring a complementary product. High unemployment was associated with slower diffusion. Penetration gains were harder to achieve in a quickly growing population, but were higher when the proportion of households that live in electrically wired dwellings grew fast. After controlling for these variables, disposable income per household did not affect the diffusion speed across innovations over and above mere vintage. Income and unemployment, however, were the only variables to have a significant impact on within-innovation diffusion speed beyond what a logistic model accounts for.

The fourth and perhaps most important finding is that the significant association between vintage and diffusion speed vanishes once one controls for the presence of competing standards and infrastructure requirement, unemployment, household formation, and electrification.

The final finding of interest is the pattern in the population variance in diffusion speed, var(U_b), across models. Controlling for the nature of the product, economic conditions, and demographic trends, both between and within innovations, decreases the population variance in diffusion speed from 0.052 in Model 1 to only 0.004 in Models 3 and 4. In other words, 92% of the variation in diffusion speed across products can be attributed to changes in the nature of products and in economic and demographic conditions.

Table 2 Products and Years Included in the Data[a]

Product	Year in Which Household Penetration Reached 5%	Launch Year[a]	Data Set 1 Max. Obs. Pen.	Data Set 1 Years	Data Set 2 Years
1. Coffeemaker	1922[b]	—	36.2%	1923–25, 1932–41	1925, 1932–41
2. Radio	1924	1920	89.8	1924–32	—
3. Refrigerator	1928	1918 (1913)	71.2	1928–41, 1946–47	1928–41, 1946–47
4. Ranges	1931	(1919)	21.0	1931–41, 1946–50	1931–41, 1946–50
5. Water heater	1947	—	26.7	1947–66	1947–66
6. Freezer	1949	1939 (1929)	28.5	1949–68	1949–68
7. Black and white television	1949	1939 (1939)	94.1	1949–64	1949–64
8. Bedcover	1950	1936	47.5	1950–69	1950–69
9. Clothes dryer	1953	1936 (1939)	51.0	1953–72	1953–72
10. Room air conditioner	1955	1929 (1933)	51.6	1955–74	1955–74
11. Blender	1955	1938 (1946)	43.8	1955–74	1955–74
12. Food disposer	1955	1935 (1935)	37.2	1955–74	1955–74
13. Dishwasher	1957	1900 (1912)	39.6	1957–76	1957–76
14. Built-in ranges	1959	—	19.8	1959–78	1959–78
15. Can opener	1961	1956 (1957)	63.6	1961–79	1961–79
16. Color television	1964	1954 (1954)	89.8	1965–79	1965–79
17. Hairdryer	1973	—	79.6	1973–79, 1986–92	1973–79
18. Auto drip coffeemaker	1974	—	76.6	1974–79, 1988–92	—
19. Curling iron	1974	—	82.0	1974–79, 1988–90	—
20. Slow cookers	1974	1972	58.7	1974–79, 1986–93	—
21. Toaster oven	1974	—	38.2	1974–79, 1986–93	—
22. Microwave oven	1976	1966 (1955)	90.1	1976–79, 1986–95	1976–79, 1986–94
23. Hand-held massager	1977	—	23.1	1977–79, 1990–96	—
24. Food processor	1979	1973 (1971)	40.6	1979, 1986–96	—
25. VCR	1983	1972 (1975)	81.0	1983–95	1983–84, 1986–95
26. Home PC	1983	(1975)	39.3	1983–96	1986–96
27. Telephone answering device	1984	1972	67.7	1984–96	1984–96
28. Power leaf blower (gas + electric)	1986	—	24.2	1986–96	—
29. CD player	1987	1983 (1983)	30.6	1987–96	1987–96
30. Camcorder	1988	1984	26.9	1988–96	1988–96
31. Cellular telephone	1990	1983 (1983)	27.8	1990–96	1990–96

[a]Sources: Golder and Tellis (1997) and, for values between brackets, Kohli et al. (1999).

[b]This value is assumed. Because the household penetration was 5.2% in 1922, 6.1% in 1923, and 8.6% in 1924, it seems defensible to assume the penetration in 1921 was below 5.0%.

Note: This study excludes some consumer durables analyzed in previous diffusion studies (e.g., calculators, vacuum cleaners, steam irons) because the year in which they reached 5% household penetration is unknown, the adopting population are not households but individuals, or the available data series are shorter than 7 data points, resulting in estimation problems.

The results for Data Set 2, incorporating price, are similar (Table 4) so I focus only on the differences. Innovations having a low price diffused faster than those taxing households' purchasing power more heavily (Models 3 and 4). Average disposable income has a negative effect, which the large change in the vintage effect between Models 3 and 4 suggests is a collinearity artifact. This might also explain why after controlling for both price and income, the effects of household formation and electrification growth are not statistically significant anymore. For the remainder, the analysis on Data Set 2 leads to the same results: Diffusion speed

Table 3 Analysis of Diffusion Speed for Data Set 1

	Mean Only (1)	Mean + Vintage (2)	Without Income (3)	With Income (4)
Mean speed (β_0)	0.529[c]	0.477[c]	0.562[c]	0.550[c]
	(0.056)	(0.046)	(0.042)	(0.045)
Between-product effects				
Vintage (ϕ_1)		0.930[c]	−0.003	−1.088
		(0.270)	(0.727)	(1.610)
SW, Competing standards (ϕ_2)			0.706[a]	0.726[a]
			(0.282)	(0.285)
SW, No competing standards (ϕ_3)			0.294	0.340
			(0.326)	(0.336)
Infrastructure (ϕ_4)			0.868[b]	0.842[b]
			(0.283)	(0.281)
Average unemployment rate (ϕ_5)			−0.639[a]	−0.501
			(0.260)	(0.289)
Average disposable income per household (ϕ_6)				0.348
				(0.436)
Average household formation rate (ϕ_7)			−6.182[a]	−6.276[a]
			(2.830)	(2.827)
Average electrification growth rate (ϕ_8)			2.076[b]	1.902[a]
			(0.801)	(0.821)
Within-product effects				
Duration (δ_1)			1.370[a]	1.232
			(0.647)	(0.650)
Unemployment rate (δ_2)			−0.043[a]	−0.043[a]
			(0.020)	(0.020)
Disposable income per household (δ_3)			0.125[a]	0.126[a]
			(0.055)	(0.056)
Household formation rate (δ_4)			0.111	0.114
			(0.079)	(0.080)
Electrification growth rate (δ_5)			0.005	0.006
			(0.041)	(0.041)
Var(U_b)	0.052	0.030	0.004	0.004
Var(U_1)			4.789	4.548
Var(U_2)			0	0
Var(U_3)			0	0
Var(U_4)			0.044	0.046
Var(U_5)			0.008	0.008
Res. Log Likelihood	437.14	439.63	467.34	467.67

[a]$p < 0.05$; [b]$p < 0.01$; [c]$p < 0.001$

Standard errors are shown between brackets. Significance levels are from two-sided Wald tests. Likelihood ratio tests must not be used because the residual likelihood function corrects for the loss of degrees of freedom due to estimating fixed effects (including the coefficients of explanatory variables).

increased with vintage, but differences in the nature of the product, price, and economic and demographic conditions can account for these changes. The latter effects can account for the entire population variance in diffusion speed. The lack of a significant price effect on within-product variation is troublesome, and may be due to collinearity with other regressors (e.g., the correlation between price and disposable income is −0.74). When reestimating Models 3 and 4 without controlling for any other within-product variation but

Table 4 Analysis of Diffusion Speed for Data Set 2

	Mean Only (1)	Mean + Vintage (2)	Without Income (3)	With Income (4)
Mean speed (β_0)	0.513[b]	0.360[b]	0.663[b]	0.669[b]
	(0.060)	(0.029)	(0.054)	(0.051)
Between-product effects				
Vintage (ϕ_1)		1.068[b]	−0.488	8.388[a]
		(0.171)	(0.938)	(3.464)
SW, Competing standards (ϕ_2)			0.548[b]	0.650[b]
			(0.152)	(0.150)
SW, No competing standards (ϕ_3)			0.135	0.218
			(0.308)	(0.319)
Infrastructure (ϕ_4)			1.562[b]	1.314[b]
			(0.302)	(0.301)
Average unemployment rate (ϕ_5)			−1.230[b]	−0.703[a]
			(0.231)	(0.303)
Average disposable income per household (ϕ_6)				−2.671[a]
				(1.161)
Average household formation rate (ϕ_7)			−6.576[a]	5.001
			(3.155)	(4.545)
Average electrification growth rate (ϕ_8)			9.216[b]	3.081
			(1.811)	(3.465)
Average Price (ϕ_9)			−0.514[b]	−0.429[b]
			(0.075)	(0.075)
Within-product effects				
Duration (δ_1)			1.122	0.943
			(0.660)	(0.642)
Unemployment rate (δ_2)			−0.029	−0.029
			(0.023)	(0.023)
Disposable income per household (δ_3)			0.145[a]	0.147[a]
			(0.060)	(0.061)
Household formation rate (δ_4)			0.105	0.098
			(0.082)	(0.083)
Electrification growth rate (δ_5)			0.015	0.013
			(0.041)	(0.041)
Price (δ_6)			−0.032	−0.022
			(0.056)	(0.055)
Var(U_b)	0.051	0.005	0	0
Var(U_1)			3.001	2.594
Var(U_2)			0	0
Var(U_3)			0.009	0.011
Var(U_4)			0.049	0.049
Var(U_5)			0.008	0.008
Var(U_6)			0.030	0.029
Res. Log Likelihood	411.51	417.57	438.00	439.38

[a] $p < 0.05$; [b] $p < 0.001$

price (as in most other diffusion studies), the price coefficient switches to -0.067 in both models (both $p < 0.05$).

To check the robustness of these results, I performed several additional analyses reported here only briefly:

- Evidence of acceleration may be an artifact when (1) more recent innovations have shorter series, (2) shorter series lead to lower penetration ceiling estimates, and (3) lower ceilings lead to higher q or β estimates (Van den Bulte and Lilien 1997). The data do exhibit the first characteristic (cf. Table 2), but two analyses found no evidence that this study's results are affected by systematically underestimating the maximum penetration ceiling α captured in γ.
- The decision not to code competing standards for cellular telephones can be questioned. Re-estimating Models 3 and 4 for both data sets after recoding the dummy to 1 barely changed the point estimates and did not change any of the significance tests or substantive insights.
- For the 22 products for which launch year is reported in Table 2, I expanded (at a reviewer's request) all four models in Table 3 with a covariate measuring the time between launch and the year that 5% was achieved. "Time-to-5%" was significantly negatively associated with β (overall diffusion speed) in Models 1, 2, and 4. This suggests that products taking a long time to reach 5% household penetration also have a lower overall diffusion speed. The effect was small, though. While the mean time-to-5% was 12.5 years, extending it by not less than 10 years decreased β with only 0.10 in Model 1, 0.07 in Model 2, 0.02 in Model 3, and 0.03 in Model 4. Overall, estimates of other covariates' effect were not meaningfully affected.
- Finally, I also conducted a "traditional" two-stage analysis for all 31 products using 3 different ways to incorporate the precision of the first-stage estimates. I found no effect using OLS, significant deceleration using WLS (with $1/\text{Var}(\hat{\beta})$ as weights), and significant acceleration using White's heteroscedasticity-consistent variance estimates. In short, different methods produced very different results, illustrating one of the four disadvantages of the two-stage approach (cf. Edmonds and Meisel 1992).

6. Discussion

This study offers two insights as to whether, how much, and why diffusion speed has changed for consumer durables in the United States between 1923 and 1996. The results indicate a rather sizable and statistically significant increase in diffusion speed. Perhaps more importantly, the results indicate that diffusion acceleration can be accounted for by economic and demographic conditions and changes in the nature of the products studied.

6.1. Substantive Implications

The results have implications for managers worried about an acceleration trap of ever-shortening windows to recoup their investments. On one hand, acceleration does exist and is rather sizable. On the other hand, changes in diffusion speed are a function of broad macro-economic and demographic forces and product characteristics (price, standards, complementary infrastructure), all factors that business analysts have ample experience dealing with. Products that had competing standards early in their life cycle and required complementary infrastructure diffused markedly faster than other products after 5% household penetration was achieved. This empirically supports the idea that such products face stronger nonlinearities in market demand (though rival explanations are not excluded, cf. Footnote 4). In such businesses, the results suggest, managers face not only large investments up-front, uncertain pay-offs, and expectedly a longer time to takeoff, but also a much faster market penetration (and hence payback) once the new product category takes off. This makes the need for a careful consideration of causal factors driving (1) the probability and timing of takeoff and (2) the speed after takeoff even more pressing. However, incorporating these causal factors into forecasts for new products is a problem when data are scant or even nonexistent. In such situations, hierarchical models that pool information across multiple products are useful (e.g., Gatignon et al. 1989).

Diffusion researchers trying to identify patterns in how new products gain market acceptance that are generalizable across product categories and time will note how well differences in purchasing power, demographics, and the nature of the products account for the variance around the mean. Systematic differences in these antecedents are likely to underlie several earlier findings. For instance, this study's results may explain the finding by Kohli et al. (1999) that consumer electronics had a higher coefficient of imitation (q in the Bass 1969 model) than did appliances and housewares: (1) electronic products were typically launched later and hence benefited from higher disposable income; (2) the majority of the appliances and housewares analyzed by Kohli et al. diffused throughout the 1930s, a period of high unemployment; and (3) some of their electronic products required large complementary infrastructure and had competing standards early on. The results should also be of particular interest to current debates on the emergence and evolution of consumer markets (e.g., Brewer and Porter 1993). Specifically, this study supports Weatherill's (1988) thesis that one does not need to invoke changes in tastes and values to account for long-term changes in the ownership of durable goods.

6.2. Limitations and Implications for Research

This study has several limitations, some of which suggest opportunities for further research. The empirical findings span a wide time horizon, but are limited to electric household durables within the United States. Additional research could investigate different products, another country, or variance among multiple countries (Dekimpe et al. 1998, Kumar et al. 1998). The single-stage approach is particularly promising for multinational studies of products that evolve only slowly and of countries with different cultural, economic, and sociodemographic characteristics that change considerably over time. Efficient estimation and jointly modeling the variance across and within products and/or countries are especially important in such situations.

The set of control variables is obviously incomplete, stemming from the need to analyze many products diffusing over a long period. Studies of more recent products might be able to control for product performance, distribution, and marketing communication, all variables likely to vary both across products and over time. Still, collecting such detailed data may be feasible only for studies focusing on different models or brands within a single product market rather than broad multicategory studies such as this one. The evidence on the importance of product standardization and complementary infrastructure investments suggests that investigating how supply-side dynamics affect market acceptance could be a fruitful research venue. Focusing on only one or a very few product markets may allow researchers to measure standardization, infrastructure, and other supply-side factors more directly and satisfactorily than in this study. Although I do not expect strong substitution or complementarity effects to have existed among the products investigated, the error structure used in this study does not allow one to investigate patterns of contemporaneous error correlations among products. Such models are not yet available for use with both unbalanced and missing data. Another opportunity exists in using nonlinear hierarchical modeling to identify the ceiling levels α_i directly, and to explicitly model variations in ceilings as a function of explanatory variables in a single-stage analysis. This new set of statistical models will also allow one to extend the analysis from the logistic to the Bass model. The logistic specification enables one to capture diffusion speed through a single parameter, β. The Bass (1969) model, on the other hand, allows one to identify whether specific antecedents operate on the probability to adopt directly (captured through p) or through endogenous feedback (captured through q). Making this distinction may help us better understand why such products as radio, television, VCRs, and cellular telephones diffused faster than average after they achieved 5% penetration. Was it indeed because of stronger nonlinearities resulting from infrastructure and standards, as suggested earlier, or did these products happen to address hitherto unanswered customer needs (cf. Footnote 4)?

Economic and demographic factors can affect diffusion speed markedly. Hence, diffusion models should control for these factors rather than only for marketing mix effects. The same applies to prelaunch forecasting based on meta-analyses or on product analogies. Analysts should use not only the similarity of the products but also economic and demographic conditions when matching their forecasting problem to previous cases for which parameter estimates are already available. To aid such applications and sharpen our empirical generalizations, it would be worthwhile to conduct meta-analyses and investigate whether parameter values obtained from simple models vary as a function of (changes in) economic and demographic conditions (e.g., is the Bass model's $\hat{q}$ related to the average (growth in) real income over the estimation period?)

The lack of reliable data on the actual time of launch and the use of a proxy for vintage is a limitation of this study. The exclusion of data points with less than 5% household penetration to estimate β, however, is much less so. The estimates can still be used to make statements about the diffusion speed prior to 5% penetration (assuming, of course, that the logistic is an appropriate representation of the entire diffusion process). The formula presented in §2 can be used to calculate the expected time between any two penetration levels greater than 0% and smaller than 100%; e.g., the expected time between 0.1% and 5% of the ceiling M is $3.96/\beta$. Such calculations are extrapolations, however. Researchers specifically interested in the very early parts of the diffusion process, rather than overall diffusion acceleration, should of course use data from the very left tail of the diffusion curve (e.g., Golder and Tellis 1997, Kohli et al. 1999).

Finally, the disappearance of acceleration once one controls for some basic contextual and product factors suggests we might benefit from more investigations on whether and under what conditions product life cycles tend to shorten (Bayus 1998, Greenstein and Wade 1998). Future studies may benefit from using a data analysis strategy similar to the one in the present study. Rather than first computing one overall index of PLC length for each product and then regressing that index against time of launch, one might consider developing a measure of year-by-year sales evolution, organizing the product-by-year observations in a panel, and analyzing the data using hierarchical modeling.[5]

Appendix A. Variable Definitions and Model Equation

$TIME_i(t)$ = YEAR/100

$PEN_i(t)$ = Proportion of electrically wired household having the product i

$HH6_i(t)$ = Number of households at midyear

$HH12_i(t)$ = Number of households at end year (December 31)

$HHE_i(t)$ = Number of electrically wired households at end year (December 31)

$UNEMP_i(t)$ = Unemployment rate (in 10%)

$DPI_i(t)$ = 1922–1928: Disposable income per household estimated by Olney (1991)
1929–1996: National disposable income divided by number households at midyear (in constant 1982 $10,000)

$PRICE_i(t)$ = price (in constant 1982 $1,000)

$T5_i$ = first year in which $PEN_i(t) \geq 0.05$ (divided by 100)

N_i = number of observations in final data set for product i

I = number of products in final data set

$X_i(t) = PEN_i(t) \times HHE_i(t)$

$Y_i(t) = [X_i(t) - (X_i(t-1)]/X_i(t-1)$

$LPEN_i(t) = X_i(t-1)/\{[(HHE_i(t) + HHE_i(t-1)]/2\}$

$ELEC_i(t) = HHE_i(t)/HH12_i(t)$

$HFR_i(t) = [HH6_i(t) - HH6_i(t-1)]/HH6_i(t-1)$ (multiplied by 10)

$EGR_i(t) = [ELEC_i(t) - ELEC_i(t-1)]/ELEC_i(t-1)$ (multiplied by 10)

$ATIME_i = \Sigma_i\, TIME_i(t)/N_i$

$AUNEMP_i = \Sigma_i\, UNEMP_i(t)/N_i$

$ADPI_i = \Sigma_i\, DPI_i(t)/N_i$

$AHFR_i = \Sigma_i\, HFR_i(t)/N_i$

$AEGR_i = \Sigma_i\, EGR_i(t)/N_i$

$APRICE_i = \Sigma_i\, PRICE_i(t)/N_i$

SW_CST_i = 1 for VCR and PC, 0 otherwise

SW_NOCST_i = 1 for CD players, 0 otherwise

$STRUC_i$ = 1 for radio, black and white TV, color TV, and cellular telephone, 0 otherwise

$MT5_i = T5_i - \Sigma_i\, T5_i/I$

$MUNEMP_i = AUNEMP_i - \Sigma_i\, AUNEMP_i/I$

$MDP_i = ADPI_i - \Sigma_i\, ADPI_i/I$

$MHFR_i = AHFR_i - \Sigma_i\, AHFR_i/I$

$MEGR_i = AEGR_i - \Sigma_i\, AEGR_i/I$

$MPRICE_i = [APRICE_i - \Sigma_i\, APRICE_i/I]/[\Sigma_i\, APRICE_i/I]$

$DUR_i(t) = TIME_i(t) - ATIME_i$

$CUNEMP_i(t) = UNEMP_i(t) - AUNEMP_i$

$CDPI_i(t) = DPI_i(t) - ADPI_i$

$CHFR_i(t) = HFR_i(t) - AHFR_i$

$CEGR_i(t) = EGR_i(t) - AEGR_i$

$CPRICE_i(t) = [PRICE_i(t) - APRICE_i]/APRICE_i$

$$Y_i(t) = \beta_0 + U_{bi} + \phi_1 MT5_i + \phi_2\, SW\_CST_i + \phi_3\, SW\_NOCST_i + \phi_4\, STRUC_i + \phi_5\, MUNEMP_i + \phi_6\, MDP_i + \phi_7\, MHFR_i + \phi_8\, MEGR_i + \phi_9\, MPRICE_i + (\delta_1 + U_{1i})\, DUR_i(t) + (\delta_2 + U_{2i})\, CUNEMP_i(t) + (\delta_3 + U_{3i})\, CDPI_i(t) + (\delta_4 + U_{4i})\, CHFR_i(t) + (\delta_5 + U_{5i})\, CEGR_i(t) + (\delta_6 + U_{6i})\, CPRICE_i(t) + \gamma_i\, LPEN_i(t) + u_{it} \text{ (where } u_{it} = \rho_i\, u_{i,t-1} + \epsilon_{it})$$

(Note: Estimates of γ_i and ρ_i are not reported in the paper because they are of no substantive interest)

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