Multigeneration Innovation Diffusion: The Impact of Intergeneration Time

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This research focuses on the diffusion patterns of the adjacent generations of technology and its relation to the time that elapses between them (intergeneration time). The authors analyze 45 new technologies in 15 industries and find that the adoption curves systematically vary across generations from 2 years for dynamic random-access memory (DRAM) chips to more than 30 years for steelmaking. The longer the intergeneration time, the slower the adoption of the subsequent technology. Even though once the adoption begins imitation is greater for subsequent technologies, the slow initial innovation rate, driven by resistance to upgrading, retards adoption. The authors also demonstrate that predictions based on intergeneration time plus average patterns are more accurate than data-based predictions early in life cycles when such predictions are most crucial. Improved early predictions can provide advantages in terms of both making go versus no-go decisions and planning marketing and production.

Advancing technology seems an inevitable force. Regardless of the pace of change, the result almost always allows people to perform an existing function or satisfy an ongoing need differently and better than before. For people who forecast technological change and substitution in general and managers in industries in which technologies are periodically upgraded in particular, there is a continuing need for simple and accurate forecasting models.

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While the advent of newer technology provides customers an opportunity to switch from earlier generations to the later one, most customers do not adopt new technology immediately. Moreover, some customers who would otherwise have adopted the earlier product instead adopt the later one, and still others who would not adopt the old product may adopt the new one, raising total market potential. In addition, the sales of the earlier technology may continue to grow for some time after the newer one is introduced. In this article, we are interested in the relative speed of diffusion of a new technology compared with the old one and the impact of the time that elapses between the introduction of two adjacent technologies (hereafter "intergeneration time") on the subsequent diffusion.

The speed of adoption of new products has been the focus of numerous studies (e.g., Kumar, Ganesh, and Echambadi 1998). This article thus focuses on a particular aspect of diffusion, the time before product sales begin to rise. Golder and Tellis (1997) described the time to take off for new products (i.e., the time from when sales begin until sales begin to increase rapidly) and found it to be substantial. Kohli, Lehmann, and Pae (1999) examined the time delay between product invention and substantial sales and found it helped predict the shape of the diffusion patterns. In a related article, Datar, Jordan, Kekre, Rajiv, and Srinivasan (1996) demonstrated that extensive customer input post–concept development can slow time to market. Of course, speed to market and the related concept of first to market are no guarantee of success (Bayus 1997). This article differs from previous studies by concentrating on successive technologies in general and the time between them in particular, with a focus on early prediction of product diffusion. Given the cost of launching a new-generation technology, predicting subsequent adoption is an important task for managers. We demonstrate a way to improve the accuracy of such predictions even after sales data become unavailable.

We initially focus on describing intergeneration time per se: how long it tends to be. We then examine whether intergeneration time has any effect on the adoption curve of the new technology. Assuming some relationship exists, the length of the intergeneration period that is both known to and potentially a decision variable of managers may help predict the shape of the adoption curves of next-generation technologies. In the extreme, using intergeneration time makes it feasible to help forecast the diffusion curve of new-generation technology before actual sales occur.

This article proceeds as follows. First, it discusses technological substitution and diffusion models and their applications. Next, the procedure for measuring intergeneration time is explained. Then, the intergeneration times for 30 subsequent technologies are reported and related to the diffusion curves after the new technology is introduced. Finally, intergeneration time is used to forecast the diffusion curves of next-generation technologies.

TECHNOLOGICAL SUBSTITUTION AND DIFFUSION MODELS

Forecasting diffusion patterns is crucial for planning operations and marketing programs. Many cumulative adoption curves follow the general S-shaped pattern, and first-time purchase is well modeled by the Bass (1969) model. It assumes the adoption curve follows the model:

$$\mathrm{S}(t) = [p + q\,(\mathrm{F}(t) / m)]\,[m - \mathrm{F}(t)], \tag{1}$$

where

$\mathrm{S}(t)$ = sales in the period t,
$\mathrm{F}(t)$ = cumulative adoption up to time t, and
m = saturation level (market potential).

The coefficient p is called the coefficient of innovation and represents the fraction of unmet potential customers that adopt in each period. Similarly, q is called the coefficient of imitation since its effect increases as more people adopt, thus representing effects such as word of mouth.

Unfortunately, the ability to fit such curves based on sparse data (e.g., 3-4 periods) is limited. This has led to efforts to forecast adoption patterns early in the life cycle based on past patterns (Sultan, Farley, and Lehmann 1990) and the lag between product development and the beginning of substantial sales (Golder and Tellis 1997; Kohli et al. 1999). While promising, these methods do not take into account the essential fact that most new technologies represent upgrades of previous ones and hence are technology generations rather than stand-alone innovations.

Most technological changes can be described as a substitution of one material, process, or product for another. Each subsequent technology, if successful, tends to follow an S-shaped curve: it starts slowly due to initial resistance; then proceeds more rapidly as the competition between the new and the old technology grows keener and the new technology gains an upper hand over the old one; and finally, as the new technology becomes widespread, the pace of growth slows down.

That substitution tends to take the form of an S-shaped curve and is generally supported empirically (Bewley and Fiebig 1988; Blackman 1971, 1972; Dixon 1980; Fisher and Pry 1971; Mansfield 1961; Stern, Ayres, and Shapanka 1975). Several reviews of research in multigeneration technological forecasting exist (Machnic 1980; Sharif and Kabir 1976; Sharif and Ramanathan 1982; Silverman 1981).

One simple forecasting method is based on product substitution analysis. It relies on the fact that most new technologies are replacements of old technologies. One useful approach to forecasting product substitution was proposed by Fisher and Pry (1971). In marketing, Norton and Bass (1987) were among the first to develop a multigeneration diffusion and substitution model for high-technology industries. Recently, Islam and Meade (1997) and Mahajan and Muller (1996) focused respectively on a single company's product in a single industry and successive generations of IBM computers, and Kim, Chang, and Shocker (1999) modeled intercategory multigeneration diffusion in information technology.

In Norton and Bass's (1987) model, sales of three successive generations of product have the following form. Sales of Generation 1 product at time t are a function of its potential before the Generation 2 product arrives. After the Generation 2 product is introduced, the potential of the Generation 1 product is reduced by the sales of the second-generation product. Similarly, sales of the Generation 2 product are a function of both its potential and sales of the first-generation product before the Generation 3 product arrives. Once the third-generation product is introduced, sales of the second-generation product face a reduced potential due to that captured by the third-generation product.

In general, a new generation appears before its predecessor has been fully diffused to its potential customers. Each successive generation's sales consist of customers switching from the earlier generation; customers who would have adopted the earlier product but, instead, adopt the later one; and customers who would only adopt the new (and presumably superior) technology. A key assumption of the Norton and Bass model is that the coefficients of innovation and imitation, p and q, are constant as successive generations are introduced. In this article, we show that p and q change systematically across generations.

MULTIGENERATION DIFFUSION AND INTERGENERATION TIME: RESEARCH HYPOTHESES

Old technology seldom vanishes quietly, and competition between old and new generations of technology is often fierce (Foster 1986). New technologies are typically disparaged when introduced since they frequently lack the design finesse of established products, are expensive, and are often based on assumptions yet to be proved in the market. Resistance by users of the old technology is also severe because of switching costs, the learning required, and general incompatibility (Norton and Bass 1992).

The substitution process normally follows an S-shaped curve. Sales initially grow slowly, reflecting the fact that during the first few years, a new technology must overcome the resistance of customers loyal to old technologies, performance bugs in early models, production diseconomies due to smaller scale of production, training the workforce to adopt new processing equipment and methods, and so on (Dixon 1980; Shanklin and Ryans 1987). These factors slow acceptance of a new technology and, combined with the fact that subsequent generations typically do not solve new problems, result in a smaller coefficient of innovation for the new technology (p_{new}), compared with the coefficient of innovation for the older (prior generation) technology (p_{old}).

Hypothesis 1: The coefficient of innovation for a new-generation technology (p_{new}) will be lower than for the old-generation technology (p_{old}).

The rate of new-technology adoption increases sharply as the fruits of new technology become accepted, processes improve, economies of scale are achieved, and the "learning period" for customers comes to an end. Learning should generally be faster for subsequent generations of technology. After overcoming initial resistance, the adoption curve of new technology is likely to proceed more rapidly, consistent with research suggesting the coefficient of imitation may be increasing over time (Jeuland 1994) and that the coefficients of innovation and imitation are negatively correlated (Bayus 1992). Therefore, it is expected that the coefficient of imitation for new technology (q_{new}) will be larger.

Hypothesis 2: The coefficient of imitation for new-generation technology (q_{new}) will be larger than for the old-generation technology (q_{old}).

Intergeneration time may vary for a number of reasons related to both producers and consumers. On the producer side, a number of factors are relevant. Generally, the larger the improvement, the more time and effort are required for development. A radical (or discontinuous) innovation generally needs a longer lead time for feasibility assessment and market acceptance (Moore 1994; Sharif and Kabir 1976). This is particularly true when the basic technology changes between product generations. Major changes in technology require substantial educational and marketing efforts, so really new products will tend to be introduced infrequently, that is, with longer intergeneration times. Since really new products often take years to become popular, this suggests longer intergeneration time will be correlated with slower initial adoption (i.e., lower p_{new} values). Furthermore, as intergeneration time grows longer, the older technology and the pool of the old technology users will become larger and more entrenched and at least initial resistance to adopting the new technology stronger.

On the other hand, products with longer intergeneration times may both have greater advantages over the previous generation and be more sensitive to the presence of other users (i.e., have larger q_{new} values) since the benefits often depend on the number of other users, that is, network externalities (Katz and Shapiro 1985, 1994), and the risks are reduced by observing other users.

On the basis of a study of successive generations of IBM products, Mahajan and Muller (1996) found that early introduction of new technology speeds up the adoption by capturing old-technology demand, but delayed introduction of new technology slows adoption. This is consistent with results in the incubation time (i.e., time delay between product invention and product introduction) study of Kohli et al. (1999), in which as incubation time becomes longer, market adoption becomes slower.

Finally, intergeneration (release) time is a managerial decision that may be related to replacement cycle (a consumer decision), which determines adoption. Hence, managers may delay introduction when they expect slow replacement. Taken together, these factors suggest the following:

Hypothesis 3a: The longer the intergeneration time, the smaller the coefficient of innovation for new-generation technology (p_{new}).

Hypothesis 3b: The longer the intergeneration time, the larger the coefficient of imitation for new-generation technology (q_{new}).

Of course, each technology generation has a number of unique factors such as its relative advantage, compatibility, and risk with respect to the previous generation, the number and efforts of competitors, and economic conditions. For reasons of parsimony and limited sample size as well as lack of such data, we do not explicitly consider these variables. As a consequence, the noise (error) in our data is greater, which makes it more difficult to find a significant impact of intergeneration time.

DATA

Data were collected on 45 technologies in 15 industries, which produced 30 subsequent technologies (Table 1). All these technologies have previously been studied in the context of the technological substitution. The 30 pairs of old and new technologies can be categorized as consumer and industrial technologies. Consumer product technologies (products sold direct to consumers) include detergents, televisions, recording instruments, recording software, and personal computers. Tire cord material, steelmaking technology, oil-cracking technology, aircraft engines, semiconductor products (DRAM, or dynamic random-access memory), floppy drives, hard disk drives, mainframe computers, and beer and soft drink cans are classified here as industrial (business-to-business) technologies since they are sold primarily to business that then incorporate them in products for their customers. Previous work (Sultan et al. 1990) found that industrial products were adopted more rapidly than consumer products so we include this factor in our analysis. However, this classification is somewhat imperfect. Computers are dual products (i.e., have both consumer and industrial applications), and cans require direct consumer acceptance. So we merely report the results for interest's sake.

RESULTS

Basic Analysis

Diffusion parameters were estimated separately for each of the 30 technology pairs using nonlinear least squares (Mahajan, Mason, and Srinivasan 1986; Srinivasan and Mason 1986). Table 2 shows the means of intergeneration time and the diffusion parameters. Across adjacent competing technologies, the coefficient of innovation for the new technology is smaller. The difference in p and q values between generations is related to their absolute values. As an example, steelmaking technology has much smaller values (average p and q values across generations are .0003 and .0906, respectively) than DRAM chips (average p and q values across generations are .0034 and .9418, respectively) that are related to industry-specific effects. We assess changes across generations by taking the ratio between new and old generations in order to remove industry-specific effects and have a measure that is interpretable in terms of percentage changes.

The average values for the coefficient of innovation for new and old technology are .0045 and .0063, respectively, and the ratio is significantly different from 1 (t = 3.31, $p < 0.01$), and a paired t-test is also significant (t = –2.70, $p < .01$), supporting Hypothesis 1. Furthermore, the average coefficient of imitation for new technology becomes larger (.4618 vs. .4282). This pattern clearly is evident for seven industries (airplane, beer can, soft drink can, detergent, TV, recorder hardware, and recorder software) and generally true for three others (tire cord, steel, and PC). However, there is no real pattern for two industries (mainframe and hard drive) and for three, opposite patterns emerge (floppy drivers, oil cracking, and some generations in the DRAM case). The average ratio is significantly different from 1 ($t = 2.77$, $p < 0.01$), supporting Hypothesis 2, but a paired t-test is not ($t = 1.13$, $p > .10$), which is largely due to the impact of DRAM results.[1] As a consequence, this revealed only mixed support.

Intergeneration time has a mean of 11.4 and a median of 10 years, with 8.7 years of standard deviation. DRAM chips (4K vs. 16K) and mainframe computers (Generation 3 vs. Generation 4) had the shortest intergeneration time (2 years), and steelmaking technology (open-hearth vs. electric furnace) had the longest intergeneration time (more than 30 years). The distribution of intergeneration time is given below.

Intergeneration Time	*Number of Technology Pairs*
Up to 5 years	12 (40%)
6-10 years	4 (13%)
11-15 years	6 (20%)
16-20 years	3 (10%)
21+ years	5 (17%)

Overall, intergeneration time is related with p and q in an opposite direction; as intergeneration time becomes longer, p decreases, while q increases between generations. While the average time to peak sales increases between old and new generations (from 19.3 to 21.4 years), the net increase is not significant ($t = .43$).

The coefficient of innovation is significantly smaller ($p < .05$) for new versus old technologies for both industrial (.0042 vs. .0057) and consumer technologies (.0057 vs. .0078). In addition, for consumer technologies, the coefficient of imitation is significantly larger for new versus old technologies (.4749 vs. .3746).

The Relation of Intergeneration Time to Diffusion

Several significant correlations exist. Not surprisingly, p and q are highly correlated across subsequent generations (.8 and .9, respectively). Furthermore, there is more variance across industries than within. Thus, the assumption of constant p and q (from Norton and Bass 1987) may

TABLE 1
Description of Technology and Diffusion Parameters

		Market Year	*Coefficient Innovate*	*Coefficient Imitate*	*Data Year*	*Data Source*
DRAM	4K	1974	0.0059	1.1200	1974-1985	Dataquest
	16K	1976	0.0027	0.8698	1976-1985	
	64K	1979	0.0027	1.2760	1979-1994	
	256K	1982	0.0039	0.7985	1982-1994	
	1M	1985	0.0039	0.7384	1985-1994	
	4M	1988	0.0014	0.8483	1988-1994	
Mainframe	G1	1970	0.0230	0.5494	1974-1988	Computer Industry Forecast
	G2	1978	0.0138	0.6411	1978-1988	
	G3	1982	0.0102	0.6495	1982-1990	
	G4	1984	0.0089	0.6094	1984-1990	
Floppy drive	5.25 inch	1979	0.0057	0.4724	1979-1991	Computer Industry Forecast
	3.5 inch	1983	0.0038	0.4111	1983-1993	
Hard drive	5.25 inch	1983	0.0092	0.7263	1983-1991	Computer Industry Forecast
	3.5 inch	1986	0.0112	0.7262	1986-1991	
Oil cracking	Thermal	1913	0.0053	0.1083	1913-1966	*Oil & Gas Journal*
	Catalytic	1938	0.0025	0.0864	1938-1992	
	Hydro	1960	0.0012	0.0774	1961-1992	
Tire cord	Cotton	1910	0.0053	0.1134	1910-1955	Merino (1990)
	Rayon	1938	0.0052	0.2039	1938-1970	
	Nylon	1947	0.0024	0.1658	1947-1980	
	Polyester	1962	0.0063	0.1728	1962-1990	
	Steel	1972	0.0047	0.2038	1972-1992	
Steel	Bessemer	1856	0.0006	0.0857	1856-1960	*Statistical Abstract*
	Open hearth	1868	0.0002	0.0700	1868-1970	
	Electric	1900	0.00001	0.1160	1900-1970	
Airplane	Piston	1936	0.0072	0.1721	1941-1977	International Air Transport Association
	Turbine	1953	0.0017	0.1857	1956-1985	
Beer can	Metal	1936	0.0024	0.1880	1941-1978	Demler (1980)
	Aluminum	1961	0.0007	0.3043	1961-1978	
Soft drink can	Metal	1953	0.0010	0.3046	1953-1978	Demler (1980)
	Aluminum	1966	0.0004	0.4040	1967-1978	
Personal computer	8080/86	1979	0.0150	0.5543	1979-1991	Computer Industry Forecast
	80286	1983	0.0126	0.6441	1984-1992	Computer Industry Almanac
	80386	1988	0.0192	1.0100	1988-1994	
	80486	1991	0.0160	0.9996	1991-1994	
Detergent	Natural	1915	0.0017	0.1505	1915-1970	*Chemical Economy Handbook*
	Synthetic	1927	0.0002	0.1721	1927-1970	
Television	Black-and-white	1939	0.0069	0.1125	1940-1975	*Statistical Abstract*
	Color	1954	0.0012	0.1476	1954-1987	
Recorder (hardware)	Turntable	1950	0.0133	0.0991	1950-1978	*Statistical Abstract*
	Tape deck	1964	0.0016	0.2256	1964-1988	
	CD player	1983	0.0007	0.3190	1983-1994	
Recorder (software)	LP	1954	0.0004	0.2685	1954-1992	Universal Almanac
	Tape	1964	0.0002	0.3069	1964-1994	
	CD	1983	0.0001	0.4500	1983-1994	

NOTE: All the diffusion parameters are estimated by the sales or productions data starting from the introduction of that technology. If the early sales data are not available, they are treated as missing data. DRAM = dynamic random-access memory.

not be far off from our correlation results. However, there are significant and systematic differences; as is obvious from Table 2, p decreases by 32% on average, and q increases by 18 percent in subsequent technologies. This suggests that initial demand may be reduced due to the existence of a substitute product but that once the newer technology begins to take over, it does so more rapidly. However, the ratio of the new to old coefficients of imitation is smaller when the coefficient of imitation of the old technology is higher.

As intergeneration time becomes longer, the coefficient of innovation for new technology becomes smaller compared with that of old technology. According to correlation analysis, the ratio of the coefficients of innovation between new and old technologies (p_{new} / p_{old}) is negatively correlated to intergeneration time ($r = -.32$, $p < .10$). By

TABLE 2
Mean Intergeneration Time and Diffusion Parameters

	IT	p_{Old}	p_{New}	p_{Ratio}	q_{Old}	q_{New}	q_{Ratio}
Industrial technologies (n = 21)	11.6 (9.7)[a]	0.0057 (0.0052)	0.0042 (0.0039)	0.7349[b] (0.5553)	0.4530 (0.3674)	0.4553 (0.3391)	1.0931 (0.3179)
Consumer technologies (n = 9)	11.3 (6.2)	0.0078 (0.0072)	0.0057 (0.0078)	0.5607[b] (0.4530)	0.3746 (0.3044)	0.4749 (0.3362)	1.3861[b] (0.3814)
Total (N = 30)	11.4 (8.7)	0.0063 (0.0058)	0.0045 (0.0052)	0.6827[b] (0.5252)	0.4282 (0.3464)	0.4618 (0.3329)	1.1810[b] (0.3584)

IT = intergeneration time.
p_{Old} = coefficient of innovation for old-generation technology.
p_{New} = coefficient of innovation for new-generation technology.
p_{Ratio} = ratio of coefficients of innovation (p_{New} / p_{Old}).
q_{Old} = coefficient of imitation for old-generation technology.
q_{New} = coefficient of imitation for new-generation technology.
q_{Ratio} = ratio of coefficients of imitation (q_{New} / q_{Old}).
a. Standard deviation.
b. From the *t*-test, the ratio is significantly different from 1 at $p < .05$.

contrast, as intergeneration time becomes longer, the coefficient of imitation for new technology becomes larger compared with that of old technology ($r = .44$, $p < .01$), consistent with Hypothesis 3b.

Using Intergeneration Time to Predict the Adoption of Next-Generation Technology

Intergeneration time is significantly related to the diffusion parameters. To demonstrate this further, we estimated the impact of intergeneration time on the ratio of the diffusion parameters:

$$p_{\text{new}} / p_{\text{old}} = \alpha_0 + \alpha_1 \,\text{LN}(IT) + \alpha_2\, IND + \alpha_3\, MUL, \tag{2}$$

$$q_{\text{new}} / q_{\text{old}} = \beta_0 + \beta_1 \,\text{LN}(IT) + \beta_2\, IND + \beta_3\, MUL, \tag{3}$$

$$m_{\text{new}} / m_{\text{old}} = \gamma_0 + \gamma_1 \,\text{LN}(IT) + \gamma_2\, IND + \gamma_3\, MUL, \tag{4}$$

where

P_{old} = coefficient of innovation for old technology
p_{new} = coefficient of innovation for new technology
q_{old} = coefficient of imitation for old technology
q_{new} = coefficient of imitation for new technology
m_{old} = market potential for old technology
m_{new} = market potential for new technology
LN(*IT*) = log of intergeneration time
IND = dummy variable = 1 for industrial technologies
MUL = dummy variable = 1 for technologies that consist of three or more generations

We used the logarithm of intergeneration time to reduce the impact of large outliers (e.g., steel technology) and because we expect decreasing marginal impact (i.e., the impact of going from 1 to 100 years should not be 10 times the impact of going from 1 to 10 years).

The regression results (Table 3) show that intergeneration time is negatively related to the coefficient of innovation of new technology and positively related to the coefficient of imitation of new technology. Thus, despite the imperfect nature of the measure of intergeneration time, it may aid prediction of the eventual adoption pattern. Furthermore, intergeneration time is negatively related to market size (m). Market size for new technology decreases as intergeneration time becomes longer for multigeneration technologies.

To see whether intergeneration time helps predict sales, we estimated sales 1, 2, and 3 years in the future for all 30 technology pairs. We did this using 5 years of data to forecast years 6, 7, and 8 and 6 years of data to forecast years 7, 8, and 9, then average the results. We compared these results to six alternatives that use combinations of the average p and q values from previous generations (.0045 and .4618), intergeneration time, and the p and q values from the previous generation with the data. Note that both the average p and q values were from previous generations, and p and q values predicted using intergeneration time forecasted as well as the data, reinforcing the unreliability of early data-based forecasts. Six forecasting methods shown in Table 4 are the following: (1) data-only forecast using the Bass model, (2) a forecast using average p and q values and the Bass model, (3) a forecast that combines data and average p and q, (4) intergeneration time predicted p and q based on Table 3, (5) data and p and q predicted by intergeneration time, and (6) forecast based on the p and q values for the previous generation. To forecast errors for Methods (3) and (5), we used the Goldberger-Theil mixed-estimation method. This method (Johnston 1972) produces a weighted combination of the prior (here the average or predicted p and q) and Bass model estimates based on the given data (here the first 5 years, then the first 6 years). The weights are proportional to the inverse of the variances of the two estimates. The percentage forecast

TABLE 3
Regression Results Predicting Parameter Ratios Between New and Old Technology

	P		*Q*		*M*	
Constant	1.08**	(2.16)[a]	1.06***	(4.42)	1.99***	(5.68)
LN(IT)	–0.19*	(–1.73)	0.16**	(2.50)	–.24**	(–2.25)
IND	0.14	(0.73)	–0.27*	(–1.98)	0.43**	(2.17)
MUL	0.26	(1.20)	0.03	(0.21)	–0.29*	(–1.78)
R^2	.12		.33		.35	

P = ratio of the coefficient of innovation between new and old technologies.
Q = ratio of the coefficient of imitation between new and old technologies.
M = market potential ratio between new and old technologies.
LN(IT) = Log of intergeneration time.
IND = industrial technologies dummy variable.
MUL = dummy variable for technologies that consist of three or more generations (e.g., dynamic random-access memory or DRAM, PCs).
a. *t*-statistics.
*$p < .10$. **$p < .05$. ***$p < .01$.

errors are 31.2, 29.8, 26.8, 24.4, 23.4, and 25.5, respectively. Including intergeneration time as prior improves prediction over data alone as the mean absolute percentage error dropping indicates from 31.2 to 23.4, a 25 percent reduction. Thus, not only does knowledge of intergeneration time improve forecasts when no data exist but intergeneration time improves predictions even when considerable sales data for a new technology are available. Interestingly, actual data add relatively little to a forecast based on average *p*s and *q*s adjusted for intergeneration time, reducing error only from 24.4 to 23.4 percent, a modest 4.1 percent reduction. Furthermore, both forecasts using intergeneration time are slightly better than ones based on the previous generation's parameters.

As an example, consider 16-megabyte DRAM. Specifically, we estimated the diffusion curve based on intergeneration time without sales data. Figure 1 demonstrates the predictive potential of intergeneration time.

DISCUSSION AND CONCLUSIONS

This article has focused on a specific time-dependent aspect of multigeneration innovation diffusion. The results suggest that intergeneration time contains systematic variance that is related to the coefficients of innovation and imitation of the Bass (1969) model. The longer the intergeneration time, the smaller the coefficient of innovation and the larger the coefficient of imitation for new technology. This suggests that shortening intergeneration cycle time may not produce an equivalent decrease in time to substantial sales due to the negative relationship between intergeneration time and adoption by innovators.

Intergeneration time, as well as data for previous generations of this technology, therefore can help compensate for the lack of data points for new-generation technology. That is, intergeneration time can be used to refine predictions of new generations based on the pattern of past generations before there is actual sales data history. In addition, it improves predictions even after sales data become available. This is especially beneficial in short-cycle industries (e.g., 2-4 years) where the past generation's parameters are not yet able to be estimated accurately.

Of course, this study has limitations. Although a market economy relies on dynamic technical advancement of products, the role of the competitive environment and marketing strategy are largely ignored by the dominant diffusion of innovation paradigm (Gatignon and Robertson 1991). Therefore, it would be beneficial to also consider competition and strategy in technology advancement (i.e., the decision about when to introduce a new generation) and their relation to subsequent product diffusion. For example, it seems feasible and desirable to use intergeneration time to estimate and predict other aspects such as relative pricing of generations of technology (e.g., Speece and MacLachlan 1992).

More generally, our results are correlational. It may not be clear, for example, whether longer intergenerational time (a managerial decision) leads to lower coefficients of innovation (i.e., by allowing an existing technology to become more firmly established) or the knowledge that resistance to change is greater (a consumer characteristics) leads to delayed introduction of subsequent technologies by managers. Furthermore, the pace of technological development (and the impact of the level and nature of R&D spending) are not part of this analysis. Subsequent work should explore the process by which the results we demonstrate come about.

It is also worth noting that the products collected and analyzed were basically "successful" in each market and became widely adopted. According to Product Development and Management Association (PDMA) research on new-product development practices (Griffin 1997), around 40 percent of new-product development efforts failed. Furthermore, between one third (Booz, Allen & Hamilton, Inc. 1982) and as high as three fifths (Silk and Urban 1978) of product introductions are rated as failures. Whether our results apply to failed products is unknown.

Future work in this area has many other possible directions to pursue. One issue is the role of intergeneration time in the context of the international market introductions. Another fairly obvious direction for research is the development of explanations for the variance in intergeneration time. Further research should try to understand what goes on in the time between generations and to examine what, if anything, can be done to manipulate the length of intergeneration time (i.e., shrinking cycle time).

The main conceptual contribution of this article is the introduction of intergeneration time as a useful construct in understanding new product development and diffusion.

TABLE 4
Percentage Error by Forecast Method

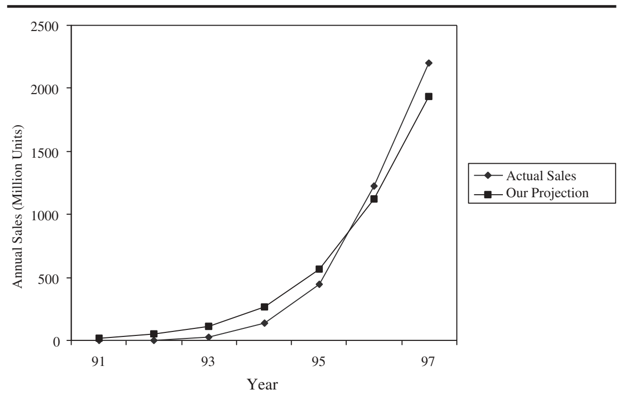
	Data Year	*A*	*B*	*C*	*D*	*E*	*F*
16K DRAM	1976-1985	21.5 [a]	23.3	21.1	18.1	17.6	19.1
64K DRAM	1979-1985	22.6	22.6	19.8	17.8	17.1	18.7
256K DRAM	1982-1994	25.5	23.4	19.4	18.5	16.6	18.9
1 mega DRAM	1985-1994	23.0	22.0	18.8	17.4	16.4	16.8
4 mega DRAM	1988-1994	24.2	23.5	20.9	17.7	16.6	20.0
PC-80286	1984-1992	31.7	30.7	25.4	22.8	21.2	22.4
PC-80386	1988-1994	30.0	28.1	23.8	21.9	21.4	22.3
PC-80486	1991-1997	31.1	30.3	26.7	24.8	23.0	24.2
Mainframe (G2)	1978-1988	31.5	29.9	27.2	25.0	24.0	26.1
Mainframe (G3)	1982-1990	29.2	29.2	25.1	22.8	22.6	24.2
Mainframe (G4)	1984-1990	29.9	28.8	24.9	23.3	23.5	23.6
Floppy drive (3.5 inch)	1983-1993	30.5	28.6	25.1	21.9	21.2	23.4
Hard drive (3.5 inch)	1986-1991	29.8	30.6	27.1	23.2	23.8	24.9
Oil cracking (catalytic)	1938-1992	38.9	39.2	32.9	30.5	30.9	32.8
Oil cracking (hydro)	1961-1992	33.5	31.0	26.8	24.1	22.0	27.1
Tire cord (rayon)	1938-1970	38.7	37.3	37.8	34.2	34.9	37.7
Tire cord (nylon)	1947-1980	36.5	33.6	31.8	27.1	25.6	29.9
Tire cord (polyester)	1962-1972	36.2	33.9	30.5	29.0	27.6	30.0
Tire cord (steel)	1972-1982	39.8	36.2	32.7	31.7	30.0	31.8
Steel (open hearth)	1868-1970	49.0	43.6	40.1	37.8	38.1	39.3
Steel (electric)	1900-1970	42.6	38.6	38.9	36.8	36.2	38.2
Airplane (turbine)	1956-1985	32.4	30.3	28.6	26.0	22.9	26.9
Beer can (aluminum)	1961-1978	32.2	31.4	26.0	23.9	24.1	24.8
Soft can (aluminum)	1967-1978	30.1	30.6	27.5	23.8	22.5	26.5
Detergent (synthetic)	1927-1970	35.5	33.6	31.7	30.5	28.1	30.2
Color television	1954-1987	32.0	30.3	28.3	24.8	22.0	27.2
Recorder (tape deck)	1964-1988	26.5	24.5	22.9	20.9	20.6	20.8
Recorder (CD player)	1983-1994	23.1	22.1	21.2	16.0	16.3	19.0
Recorder (tape)	1964-1994	24.8	25.3	22.0	20.8	20.0	20.6
Recorder (CD)	1983-1994	22.9	23.0	19.9	18.3	16.1	18.6
Average forecast error		31.2	29.8	26.8	24.4	23.4	25.5

A = data-only forecast.
B = average *p* and *q*.
C = data (A) + average *p* and *q* (B).
D = *p* and *q* prediction using intergeneration time.
E = data and intergeneration time.
F = *p* and *q* values for the previous generation.
a. The number is average of 3-year predicted sales level.

Specifically, intergeneration time is both an interesting dependent variable (i.e., how long it is and which other variables are systematically related to do it) and a useful independent variable for predicting the diffusion patterns that follow. Managers should examine what factors lead to slow initial adoption of subsequent generations. This would be of use to both incumbents who desire to slow adoption and outsiders who wish to accelerate it.

This line of research is clearly related to the question of optimal entry timing for a product line extension. Analytic findings of Wilson and Norton (1989) suggest that, for a monopolist operating under a long-term planning horizon, "now or never" is the optimal timing strategy: a monopolist should either introduce a successive generation of a product as soon as it is available or else delay its introduction indefinitely. Bayus (1997) suggested it is advantageous to be

FIGURE 1
Sales Forecast of 16-Megabyte DRAM Based on Intergeneration Time



NOTE: DRAM = dynamic random-access memory.

first to market if product generations are long and have stable margins and high sales as long as the product is high in performance. As intergeneration time becomes shorter, the adoption rate of the new product increases, but the cannibalization of the old product is likely to be larger. Thus, to make a sensible decision regarding introduction timing, the impact of intergeneration time on sales and profits of competing technologies needs to be considered. Based on our results, it seems that an optimal time other than immediately may exist.

NOTE

1. Paired *t*-tests are more powerful than independent tests. However, they still suffer from a certain problem, in that larger changes tend to occur for larger values (and produce larger absolute differences, but not ratios, which reduces the power of the test). Regarding the fact that the *p* and *q* values are estimates across industries, this makes the error (noise) larger and works against finding significant results.

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