Does Growth Accelerate Across Technology Generations?

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Abstract

Academic literature on growth acceleration of new products presents a paradox. On the one hand, the diffusion literature concludes that more recent markets show faster diffusion than older markets. In contrast, technology generation literature argues that growth rate, at least as measured by diffusion parameters, remains constant across generations. We resolve the paradox by testing whether growth acceleration occurs across technology generations, controlling for the passage of time. We check acceleration across 39 distinct technology generations in 12 product markets. The results show that intergeneration acceleration occurs in time to takeoff, but not in the growth parameters, i.e., newer generations of a product enjoy a shorter left tail but a similar overall growth process. More importantly, the paradox is resolved by examining whether this acceleration in time to takeoff is mostly driven by technology vintage, i.e., passage of time or technology generation, i.e., generational shifts. We show that the acceleration in time to takeoff is due to passage of time and not to generational shifts. Thus, time indeed is a factor that accelerates early growth, but generational shifts do not. This result holds also when controlling the effects of market vintage, the market being business-to-business or business-to-consumer, and the technology being a process technology or a product technology.

Keywords:

diffusion, acceleration, technology generations, takeoff.

1. Introduction

Despite the obvious interest in acceleration of the diffusion of innovations among practitioners as well as marketing academics, the academic literature on the subject presents a curious paradox. On the one hand, the diffusion acceleration literature compares the rate of growth across markets or product categories over time. By and large, these studies conclude that more recent markets show faster diffusion than older markets (Agarwal and Bayus 2002; Chandrasekaran and Tellis 2008; Kohli, Lehmann and Pae 1999[1]; Van den Bulte 2000 and 2002; Van den Bulte and Stremersch 2004 and 2008). Exceptions to this generalized finding are rare (Bayus 1994) and contested on the grounds of estimation bias and invalid inference (Van den Bulte 2004). On the other side of the argument, the technology generation literature either treats diffusion parameters as constant across generations or else show that the difference in the explanatory power - if one assumes they do change - is minimal or nonexistent. Thus the constancy of growth across generations is a key element of several studies across multiple product categories (Bass and Bass 2001, 2004; Kim, Chang and Shocker 2000; Mahajan and Muller 1996; Norton and Bass 1987, 1992). Exceptions to these consistent findings are not only rare (Pae and Lehmann 2003; Danaher, Hardie and Putsis 2001), but contested as well (Van den Bulte 2004).

This paper attempts to resolve the paradox by testing whether growth acceleration occurs across technology generations, controlling for the passage of time. We check acceleration across 39 distinct technology generations in 12 product markets. The results show that intergeneration acceleration occurs in time to takeoff, but not in the growth parameters, i.e., newer generations of a product enjoy a shorter left tail but similar overall growth process.

[1]Measuring acceleration could be achieved from Kohli, Lehmann and Pae (1999) by regressing the Bass coefficients against time of introduction to find positive relationships, the internal coefficient q being significant.

More importantly, the paradox is resolved by examining whether this acceleration in time to takeoff is mostly driven by technology vintage, i.e., passage of time or technology generation, i.e., generational shifts. We show that the acceleration in time to takeoff is due to passage of time and not to generational shifts. Thus time indeed is a factor that accelerates early growth, but generational shifts do not significantly do so.

2. Terminology

We use the following terms that require careful definition up-front.

Technology generation - A technology generation is a set of product brands and models similar in customer-perceived functionality characteristics (Bass and Bass 2001). To understand this concept better, we may refer to the market definition framework of Abell (1980), along three dimensions: technology, customer and function. On the technology dimension, a new technology generation may be characterized, as compared to the previous generation, not only by the use of a novel technology (e.g. digital television versus electronic color television), but also by a novel application of an existing technology (e.g. electronic color television versus electronic Black & White television), or a novel performance level of an existing technology (e.g. successive PC generations). The new generation typically offers a significant improvement in performance or benefits over the previous generation. On the customer dimension, a new technology generation may be used by existing customers (cannibalization or migration), but it may also significantly expand the market to new customers (Islam and Meade 1997). On the function dimension, a new technology generation performs a function similar to the old technology (e.g. DVD versus VCR). If that is not the case, it is not a new technology generation in an existing market, but the birth of a new market (e.g. radio versus TV). If we consider video game consoles as an example, then on the basis of this definition of technology generation, we can say that 16 bit video game consoles are third generation consoles.

Technology vintage - Technology vintage is the year in which the first model of the new technology was introduced commercially. This definition implies, for example that the vintage of the 16 bit video game console is 1989. Note that some researchers refer to vintage as the year at which the innovation reached 5% penetration rather than the launch year (Van den Bulte 2000). The disadvantage of the latter approach for the study of early growth is that it ignores the considerable differences between the growth rates of different products at these early stages: While some reach 5% rather fast (e.g. cellular phones), others have long left tails (e.g. fax machines).

Takeoff - After introduction, the sales evolution of any generation undergoes a typical pattern, which is marked by an introduction period in which sales linger at low levels, and at a certain point in time, it breaks into rapid growth, often marked by extremely high growth rates, such as 300-400%. We call this point takeoff, following Golder and Tellis (1997), Stremersch et al. (2007), Tellis, Stremersch and Yin (2003), and Van Everdingen, Fok and Stremersch (2009). Takeoff is often regarded as the point at which the life cycle of a new product makes a transition from the introduction stage to the growth stage (Golder and Tellis 1997, 2004). For example, the takeoff of the 16 bit video game console occurred in 1990.

3. Data

As we explained in the introduction, we test for acceleration across a comprehensive dataset. This dataset includes generational sales data on a large number of product markets. The type of product markets we sample are quite typical for research on multi-generation diffusion (e.g. Bass and Bass 2004 and 2001; Pae and Lehmann 2003). The data sources we used to obtain these data were Bass (2004), Christensen (1993), Consumer Electronics Association (CEA), the Digital

Entertainment Group, Disktrend Inc., Kovac (1969), the NPD group, Phister (1979), and the U.S. Statistical Abstract. Also, fellow academics, such as Frank Bass, Portia Bass, Donald Lehmann and Jae Pae graciously contributed to our sample in providing us with data. As one can see from Table 1, we have data on 39 generations in 12 product markets. We identified the technology generation and technology vintage, using the historical method (Golder 2000) with frequent cross-checking of references. With respect to intergeneration time, interestingly, we do not find any evidence that intergeneration launch times are decreasing, which is a wide-held belief (Kueste, Montaguti and Robertson 1998; Sood and Tellis 2005). In our dataset, we find that the intergeneration times are actually increasing in five markets (television, video game console, personal computer, rigid disk drive and steel making). For two markets (IBM GP computer and tire cord), there is no clear and consistent pattern. For the other five markets (audio system, flexible disk drive, home entertainment, oil cracking, optical disk drive), we are unable to tell as we only have data on two generations.

4. Time to takeoff across Technology Generations

We identify the time at which takeoff occurs for each of the technology generations in each market, with the heuristic developed by Tellis, Stremersch and Yin (2003) and study whether acceleration occurs in time to takeoff across technology generations. The values of the threshold function from Tellis, Stremersch and Yin (2003) are given in Appendix A and we refer the reader to the original paper for more detail on its implementation. The threshold function varies from 600% at 0.1% market penetration to 25% as of 3.5% market penetration. The last two columns of Table 1 report takeoff year and time to takeoff. It demonstrates acceleration in time to takeoff in 9 out of 12 product markets (audio system, flexible disk drive, home entertainment, oil cracking, optical disk drive, steel making, television, tire cord, and video game console), while we find a constant time to takeoff in two markets (IBM GP computers and PC generations) and an inconsistent pattern in the case of rigid disk drive. This finding provides support for acceleration in time to takeoff across technology generations.

To further support the results, we generate additional metrics in Table 2 that reports three statistics. We report these statistics for all generations in our data, from generation 1 (G1) to generation 9 (G9), even though statistics on generations 4 to 9 are relatively less reliable due to the small number of product markets with more than 3 generations. The first statistic in Table 2 is the average time to takeoff for a generation, which is the average across all markets of the generation's time to takeoff. We find that this average declines from 7.33 for generation G1, over 5.58 for G2, to 2.86 for G3.

As markets may strongly diverge in average time to takeoff, we also correct for the product market, by developing a second statistic - the average lag/lead in time to takeoff (Tellis, Stremersch and Yin 2003). This statistic is calculated by first averaging time to takeoff across all generations for each market, and then subtracting this average from the time to takeoff of each generation for each market. The average of these lags and leads across all markets is the second statistic in Table 2. The results for this second statistic imply that on average, the time to takeoff of the first generation lags the average generation in a market by almost two years. The time to takeoff of the second generation is very close to the time to takeoff of the average generation, while the time to takeoff of the third generation leads the time to takeoff of the average generation by more than three years. A third statistic is the average reduction in time to takeoff in percentage terms across generations. This statistic is calculated by first taking the percentage change in time to takeoff from one generation to the next, for each product market and for each generation. These percentage changes are then averaged across all markets per generation. We see that time to takeoff declines consistently across generations 2, 3 and 4.

Table 2 also contains the evolution in time to takeoff across three time periods, for products which were introduced before 1940 (WWII), between 1940 and 1980, and after 1980. We find acceleration in time to takeoff over time (in line with the findings of Chandrasekaran and Tellis 2008).

5. Diffusion Parameters across Technology Generations

We use a technological substitution model to estimate the acceleration in diffusion parameters. Related models are the ones developed by Norton and Bass (1987) and Mahajan and Muller (1996). Unfortunately, these models are not suitable for our data since they assume that after the second generation entry, the first generation either entirely stops (Norton and Bass 1987), or is considerably constrained (Mahajan and Muller 1996) in the acquisition of new customers, a situation which does not match the pattern in our data. When applied to our data, these models failed to converge or yielded poor fits. We thus had to construct a new model, much along the lines of Mahajan and Muller (1996), but with a more precise specification of the substitution process. The model is described in Appendix B.

In order to check for acceleration, two methods are possible. The first is to estimate the set of equations with different parameters p_i and q_i for each generation i, and the second is to assume a uniform acceleration rate, that is to define an acceleration rate δ, which is identical for q and p, and does not change over generations, that is, $p_i = (1+\delta)p_{i-1}$ and $q_i = (1+\delta)q_{i-1}$ for each generation i. We report the results of the latter method, as using uniform acceleration significantly reduces the number of parameters, and enables an explicit, straightforward acceleration analysis. This is especially relevant for products with many generations. We also used the former method, allowing different diffusion parameters across generations and our results are highly consistent.

To assess the reliability of the model, we performed a series of simulations where we generated data with our model, estimated the parameters and observed whether our model returned the correct parameters. Simulations were done on 300 sets of parameters, selected randomly from all the possible combinations. For all the simulations, the model estimated the correct parameters, i.e., the difference between the estimated parameters and the original ones were not significant.

For each product, we applied the appropriate version of the Equation set (2) of Appendix B according to the number of generations and estimated the parameters. One should note that some of the data is sales data that obscure the substitution process of the upgraders – since upgraders may repeat purchase each generation, in which case they would be re-counted in each generation's sales figures. In order to retrieve the adoption data from the sales data, we used the method of Tellis, Stremersch and Yin (2003). The p and q estimates have face validity and remain within the typical range, previously reported for diffusion parameters (average p is 0.024, average q is 0.3). The estimates for the market potential seem also coherent with market reality and industry expectations. The adjusted R-squared measures are reasonable, except in two cases (the first generations in the audio system market and in the rigid disk drive market) in which the generational data covered a short time window.

Table 3 shows that the acceleration parameter δ is non significant, for all product categories, except steel making. That is, we observe no acceleration in the diffusion parameters across a wide range of product markets. This result holds also for the non-uniform acceleration specification, in which p_i and q_i are estimated freely for both generations.

6. The Effects of Vintage and Generation - Theory

This section explores reasons as to why acceleration in time to takeoff may occur over technology generations, and tie these reasons either to the succession of generations (technology generation) or to the passing of time (technology vintage).

6.1. Technology generation

We discuss two main sources related to generational shifts that can contribute to takeoff acceleration. The first factor is the presence of competing standards. The second factor is the efforts required from consumers to adopt and use the new product due to the need for change in their usage behaviors and habits.

Competing standards – The first generation in a product market often is plagued by standard battles, while subsequent generations may not face such standard battles. Good examples in our data are the standard wars fought in the first generation markets for tape deck and the VCR. In contrast, the second generation in these markets – CD and DVD – did not face such battles, as Sony and Philips allied on a common standard before its commercial launch. Since the presence of competing standards slows down early speed, one may expect time to takeoff to be relatively long in the first generation (8 years for the tape deck and 5 years for the VCR), but not in the second generation (only 1 year in case of CD player and DVD player).

Adoption efforts of consumers - Earlier generations may require a more dramatic change in behavior from consumers as they may be more novel. VCR opened up new experiences, such as recording, time shifting and the viewing of rental movies, while DVD did not open up major new experiences. Kohli, Lehmann and Pae (1999) have shown that products that require a dramatic change in behavior have longer incubation times. Their conceptualization of incubation time, as the period between the time when the product is ready for launch and the time of substantial sales, is akin to the concept of time to takeoff. Consumers that enter this market later often are able to learn faster thanks to the behaviors of others that they can imitate.

6.2. Technology vintage

We discuss two main reasons that may contribute to takeoff acceleration across generation vintage: increasing affordability and better communication and information channels.

Increasing affordability – Golder and Tellis (1997) show that around takeoff new products cross a price level that makes them more affordable. Such price declines may be caused by learning effects on the supplier side. This may be especially so for the products we study here, which Parker (1992) would refer to as “necessity” products, because their markets are long lived and show high ultimate penetration levels. Parker also showed that in such “necessity” markets, early market growth will be sensitive to price declines. One should note that the price of the previous generation might also decline around the time of introduction of the new generation and this might have an effect on the diffusion of the latter as well.

Suppliers’ learning rates may also increase over time. The longer their experience in the market, the stronger the learning they have undergone. For instance, the DVD player was introduced in 1997 at a price of $500 on average, and dropped already to $250 by 1999. The dominant manufacturers – Sony, Philips and Panasonic – were typically manufacturers with a long-lasting experience in the VCR market. In contrast, the VCR initially was priced at approximately $600, increased in price over 1975 ($675) and 1976 ($714), and eventually dropped temporarily to $564 in 1977, the year the VCR took off (nominal prices; source: The Consumer Electronics Association). VCR was also a very new application for the companies that manufactured it. In sum, the DVD decreased much faster in price than the VCR did, probably because of faster learning among manufacturers. In addition, consumers’ purchasing power has also grown considerably over time (Van den Bulte 2000), which may make more recent technology generations affordable to all faster than old technology generations.

Better communication and information channels - Communication and information channels have improved over time. Extensive use of these channels may be required to educate and inform potential customers about the benefits of a new technology (Agarwal and Bayus 2002). More informed consumers may adopt an innovation faster than consumers that are less informed. Therefore, improvements in communication and information channels may shorten time to takeoff over generation vintage.

7. The Effects of Vintage and Generation – Empirical Evidence

Our theoretical review above provided reasons for possible influence of both technology vintage, and technology generations on takeoff acceleration over generations. We now show that although there is *theoretical* support for the impact of both factors, *empirical* analysis indicates that it is only the vintage that has a significant influence on the time to takeoff.

We estimate a discrete-time proportional hazard model (Allison 1982; Cox 1972). The model describes the takeoff probability at each point in time, as a function of vintage and generation, as well as other influences we aim to control. Given that our model does not contain time-varying covariates and is to be estimated on sparse data, we opt for a simple model structure and a parsimonious set of predictors. The model structure is Cox's proportional hazard model estimated by the semi-parametric estimator developed by Han and Hausman (1990) – see Appendix C. Unlike the estimator developed by Cox (1972 and 1975) that conditions the baseline hazard function out of the estimation procedure, the Han and Hausman estimator treats the logarithm of the integrated baseline hazard as constants in each period and estimates them along with the parameters β. The Han and Hausman specification is flexibly parametric in the sense that the baseline hazard is nonparametric, while the effect of the covariates takes a particular (linear) form. This estimator has two main important advantages. First, this estimator is a discrete time specification, while Cox's estimator is a continuous time estimator. Second, Cox's estimator is problematic in the case of many ties. Our data are discrete time and it contains many ties.

We include six covariates in the independent vector of the proportional hazard model (see correlation matrix in Appendix D):

a) technology vintage - TECHVIN; b) technology generation – TECHGEN; c) two dummies - MARVIN1 and MARVIN2- that control for the vintage of the market – the vintage of the first generation within the market – whether pre-WWI or whether between WWI and WWII, with post-WWII as a base; d) two dummies - B2B and PROC - to control for the type of technology market under consideration – whether a business-to-business market (B2B = 1) or business-to-consumer market (B2B = 0) and whether a process market (PROC = 1) or a product market (PROC = 0).

To evaluate robustness, we specify multiple models (see Table 4). The first three models regress time to takeoff separately on technology vintage (TECHVIN) in Model 1, technology generation (TECHGEN) in Model 2, and the control variables of market vintage (MARVIN1 and MARVIN2) and the type of technology market (B2B and PROCESS), in Model 3. Model 4 regresses time to takeoff on technology vintage and technology generation, while Model 5 specifies the full model. We find that the results are robust for technology vintage, but not for technology generation. The estimates for the other variables we included (MARVIN1, MARVIN2, B2B, PROC) are more significant when included on their own, as compared to when TECHVIN and TECHGEN are included. Thus, we can conclude that technology vintage captures a large part of the variation in the effect of these other variables.

The full model (model 5) shows consistently that the higher the technology vintage ($\beta_{TECHVIN}$ = -.09, $p < 0.01$), the shorter the time to takeoff. The higher the technology generation, the shorter the time to takeoff, but this effect is statistically not significant ($\beta_{TECHGEN}$ = -.38; $p > 0.10$). The only model in which technology generation has a statistically significant effect on time to takeoff is model 2 ($\beta_{TECHGEN}$ = -.53; $p < 0.01$), in which technology generation is included as the sole predictor. Results of model 4 and 5 show, however, that the variance captured by technology generation in model 2, is in part due to the passing of time (technology vintage), rather than generational shifts.

The effects of market vintage are marginally significant when included in the full model ($\beta_{MARVIN1}$ = 3.71; $p < 0.10$; $\beta_{MARVIN2}$ = 2.59; $p < 0.10$), while strongly significant in model 3 ($\beta_{MARVIN1}$ = 5.75; $p < 0.01$; $\beta_{MARVIN2}$ = 4.05; $p < 0.01$). Thus, technology generations in markets that originated before WWI take longer to take off than technology generations in markets that originated after WWII. Technology generations in markets that originated between WWI and WWII also take longer to take off than technology generations in markets that originated after WWII, but to a lesser extent. The effects of B2B (whether a product is business-to-business or business-to-consumer) and PROC (whether it concerns a process or a tangible product) are not significant at the 0.10 level in the full model, while when regressed without TECHVIN and TECHGEN, B2B products have a marginally longer time to takeoff.

We evaluate the fit of the model in several ways. From comparing the maximized value of the log-likelihood function, we learn that it is mostly technology vintage that explains the variation in time to takeoff, rather than any other variable in the model. The χ^2–statistic is significant in all models. We also present the likelihood ratio index. The likelihood ratio index (0.34 for the full model) is high, as compared to prior work on explaining takeoff. Golder and Tellis (1997) reported an LRI of 0.31 (though they referred to it as U^2) while Tellis, Stremersch and Yin (2003) reported an LRI of 0.18 for the full model.

Evaluated on any criterion, technology vintage explains the most variance in time to takeoff. To test the sensitivity of our results, we also tested alternative models. A model in which we first took the natural logarithm of technology generation and technology vintage, shows a fit that is very similar to the fit of model 5, presented above. Moreover, the effects we find are very similar as well. We can also think of alternative ways of specifying the technology generation variable. For instance, one could expect the technology generations after generation 3 to be non-informative, or even worse, given that they are based on very few markets, sensitive to biases. Therefore, an alternative operationalization would be a generation variable in three categories, namely generation 1 (=1), generation 2 (=2) and generation 3 or higher (=3). This alternative coding produced very similar results. The only difference was that the PROC dummy turned marginally significant in the full model. One may also be concerned about the categorical nature of our technology generation variable. An alternative would be a dummy coding. Thus, we could include two dummies in equations (1) and (2), one for generation 2 and one for generation 3 and higher, thus using generation 1 as the base. However, such analysis also produces findings similar to those presented in Table 4. The only difference was that the PROC dummy turned marginally significant in the full model. To check to what extent our estimation is affected by sample composition, we also deleted one product market at a time and re-estimated all models. There were no sign reversals on any of the coefficients and very few significance changes.

Another robustness test is to assess the degree to which our results are sensitive to the measurement method for takeoff. To do so, we used an alternative method suggested by Agarwal and Bayus (2002). This method uses discriminant analysis, identifying time intervals to be preor post-takeoff, based on the mean growth rate. We were able to identify takeoff with this method for all, but four technology generations (G4 of IBM GP computers, G9 of PC, G1 and G3 of Steel making). The reason for not being able to identify takeoff in these four cases, using this alternate method, is that it works well on long and smooth sales patterns, but becomes less robust in case of short or unstable sales patterns. Using this alternate method, we arrive at very similar conclusions as based on our own method. Out of the 35 generations for which takeoff could be measured by both methods, 31 show identical time to takeoff. For the remaining four (G1 of Audio systems, G1 of Oil cracking, G2 of Optical disk drives, and G2 of Rigid disk drives), takeoff differences are of one year (1962, 1946, 1998, 1986, respectively). Also, the hazard analysis provides consistent results.

8. Conclusions and Discussion

We have shown that the acceleration in time to takeoff is due to passage of time and not to generational shifts. Thus, time indeed is a factor that accelerates early growth, but generational shifts do not. This result holds also when controlling the effects of market vintage, the market being business-to-business or business-to-consumer, and the technology being a process technology or a product technology. We also show that intergeneration acceleration occurs in time to takeoff, but not in the growth parameters, i.e., newer generations of a product enjoy a shorter left tail but similar overall growth process.

Our results are relevant to marketing executives. First, acceleration in the time to takeoff across generations allows companies to achieve a faster return on their investment, as the new generation will show sizeable sales earlier than the previous generation. On the other hand, it also implies that companies who bring next-generation innovations to market need to tool up manufacturing and marketing resources at an ever-increasing pace. Such acceleration may generate an enormous barrier to entry. In fact, this is exactly what Christensen (1997) argues, since successive technology generations by definition are sustaining innovations (Christensen and Cape 1998).

Second, our results provide managers with clear metrics as to when to pull the plug on a new technology generation. Pulling the plug on a new technology is an important decision, with tremendous implications (Foster, Golder and Tellis 2004, Garber et al 2004). Our consistent finding that time to takeoff shortens over generations implies that if a new technology generation takes longer to take off than the previous generation it is a signal that the technology may be a commercial failure, even at the danger of being leapfrogged by consumers. In this situation, management should seriously consider withdrawing support from that technology and put more resources in the future technology generation to speed up its release and/or acceptance.

A third managerial implication deals with the forecasting of multigenerational growth. Many managerial concerns, if not most, have to do with the very early stages of the product life cycle where little or no data exist. To predict adoption patterns, managers can use an analogy in terms of a product with similar attributes or market characteristics so that the parameters of the mixed influence model (Bass 1969) can be imputed (Ofek 2005). One obvious analogy one can draw is prior technology generations (Bass and Bass 2001 and 2004). Our research shows that such an approach is useful, as often diffusion parameters do not change over generations. However, since time to takeoff does show acceleration across technology generations, using such an analogy method for time to takeoff forecasting is not straightforward, especially if substantial time has passed between the generations.

Table 1: 39 Generations in 12 Product Markets

Market	Geographic Scope	Generation	Years in Sample	Technology Vintage	Inter-generation Time	Takeoff Year	Time to takeoff
Audio system	U.S.	Tape deck	1956-2004	1953	N/A	1961	8
	U.S.	CD player	1983-2004	1983	30	1984	1
Flexible disk drive	World	5.25”	1976-1998	1976	N/A	1981	5
	World	3.5”	1981-1998	1981	5	1984	3
Home entertainment	U.S.	VCR	1974-2004	1972	N/A	1977	5
	U.S.	DVD	1997-2004	1997	25	1998	1
IBM GP computer	U.S.	701, 650, 702, 704, 705, 709	1955-1975	1955	N/A	1956	1
	U.S.	1620, 1401, 1410, 1440, 1460, 7090, 7070, 7074, 704x, 7010	1959-1978	1959	4	1960	1
	U.S.	360, 1130, 1800	1965-1978	1965	6	1966	1
	U.S.	370, system 3, system 7	1970-1978	1970	5	1972	1
Oil cracking	U.S.	Catalytic cracking	1941-1992	1938	N/A	1945	7
	U.S.	Hydro cracking	1963-1994	1962	24	1966	4
Optical disk drive	World	CD-ROM	1985-2002	1985	N/A	1990	5
	World	DVD-ROM	1996-2002	1996	11	1997	1
Personal computer	U.S.	Desktop PC kits	1975-1979	1975	N/A	1976	1
	U.S.	Manufactured PC	1977-1982	1977	2	1978	1
	U.S.	Application software home computer	1979-1985	1979	2	1980	1
	U.S.	IBM PC compatible	1982-1988	1982	3	1983	1
	U.S.	Hard drive home computer	1984-1991	1984	2	1985	1
	U.S.	32-Bits desktop	1987-1994	1987	3	1988	1
	U.S.	Windows PC	1990-1997	1990	3	1991	1
	U.S.	Multimedia PC	1994-2000	1993	3	1994	1

	U.S.	Internet PC	1997-2000	1997	3	1998	1
Rigid disk drive	World	5.25”	1980-1998	1980	N/A	1982	2
	World	3.5”	1983-1998	1983	3	1987	4
	World	2.5”	1988-1998	1988	5	1990	2
Steel making	U.S.	Open hearth	1869-1991	1868	N/A	1905	37
	U.S.	Electric furnace	1909-1999	1905	37	1941	36
	U.S.	Basic oxygen	1955-1999	1954	49	1963	9
Television	U.S.	Electronic black & white	1946-2004	1939	N/A	1947	8
	U.S.	Electronic color	1954-2004	1954	15	1962	8
	U.S.	Digital	1998-2004	1998	44	1999	1
Tire cord	U.S.	Cotton	1910-1955	1910	N/A	1918	8
	U.S.	Rayon	1938-1979	1938	28	1944	6
	U.S.	Nylon	1947-1979	1947	9	1953	6
	U.S.	Polyester	1962-1979	1962	15	1966	4
Video game console	U.S.	16 bit machines	1989-2004	1989	N/A	1990	1
	U.S.	32-64 bit machines	1993-2004	1993	4	1994	1
	U.S.	128 bit machines	1999-2004	1999	6	1999	0

# markets with accelerating time to takeoff	9/12
# markets with constant time to takeoff	2/12
# markets with inconsistent time to takeoff across generations	1/12

Table 2: Summary Statistics on Time to takeoff

	G1	G2	G3	G4	G5-G9
Avg. Time to takeoff (yrs.)	7.33	5.58	2.86	2.00	1.00
Avg. Lag (+)/Lead(-) in Time to takeoff	1.97	0.22	-3.48	-0.67	0.00
Average % Reduction in Time to takeoff	N/A	-22.13%	-30.36%	-11.11%	0.00%
Number of Markets	12	12	7	3	2

	Before 1940	Between 1940 and 1980	1980 or later
Avg. Time to takeoff (yrs.)	17	3.73	1.55

Table 3: Diffusion Parameters across Technology Generations

Industry	*p*	*q*	δ	m_1 (000)	m_2 (000)	m_3 (000)	m_4 (000)	Adj. R^2 G1	Adj. R^2 G2	Adj. R^2 G3	Adj. R^2 G4
Audio system	.014	.142*	.536	62,415*	268,690*			.03	.71		
	(.008)	(.059)	(0.700)	(9,188)	(20,745)						
Flexible disk drive	.007*	.291*	.000	50.9*	482.9*			.40	.95		
	(.003)	(.029)	(.000)	(5.7)	(50.2)						
Home entertainment	.008*	.165*	2.021	124,700*	150,000†			.57	.91		
	(.003)	(.068)	(2.116)	(48,655)	(N/A)						
IBM GP computers	.110*	.365*	.000	2.9*	16.4*	31.6*	43.9*	.74	.79	.81	.53
	(.010)	(.042)	(.000)	(0.15)	(0.56)	(0.75)	(1.1)				
Oil cracking	.011*	.078*	.000	98.7*	60†			.59	.26		
	(.002)	(.010)	(.000)	(4.7)	(N/A)						
Optical disk drive	.013*	.724*	.195	310.5*	270†			.94	.90		
	(.005)	(.058)	(.156)	(15.7)	(N/A)						
Personal computer	.059*	.315*	.000	725.5*	7,259*	57,990*		.42	.29	.60	
	(.017)	(.117)	(.000)	(138.4)	(940)	(7,257)					
Rigid disk drive	.004*	.427*	.000	20.8*	443.7*			.09	.98		
	(.002)	(.021)	(.000)	(2.9)	(19.6)						
Steel making	.002*	.063*	1.027*	2,227*	1,571*			.58	.57		
	(.001)	(.009)	(.468)	(230)	(131)						
Television	0.011*	.126*	.000	54,801*	120,510*			.32	.52		
	(.004)	(.015)	(.000)	(5,616)	(7,184)						
Tire cord	.012*	.175*	.000	0.199*	0.373*	0.618*	0.646*	.23	.33	.23	.02
	(.005)	(.025)	(.000)	(0.025)	(0.061)	(0.078)	(0.094)				
Video game console	.042*	.726*	.170	32,708*	48,109*	52,954*		.81	.81	.93	
	(.009)	(.077)	(.083)	(746)	(945)	(3,010)					

*: significant at the 95% level; †: external estimate

Table 4: Technology Vintage Accelerates Time to takeoff

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Parameter Estimates					
Technology Vintage	-.11***			-.10***	-.09***
(TECHVIN)	(.01)			(.02)	(.02)
Technology Generation		-.53***		-.30	-0.38
(TECHGEN)		(.18)		(.21)	(.23)
Pre-WWI Market			5.75***		3.71*
(MARVIN1)			(1.87)		(1.98)
Between WWI & WWII			4.05***		2.59*
(MARVIN2)			(1.33)		(1.38)
B2B Technology			1.56*		0.62
(B2B)			(.87)		(.98)
Process Technology			-2.14		-2.62
(PROC)			(1.80)		(1.79)
Fit Statistics					
Log-Likelihood (LL)	-48.35	-65.31	-55.81	-47.50	-45.73
Chi-squared (χ^2)	42.2***	8.3***	27.3***	43.9***	47.4***
Likelihood Ratio Index	0.30	0.06	0.20	0.32	0.34
N	39	39	39	39	39

*: p < 0.10; **: p < 0.05; ***: p < 0.01 (two-sided tests).

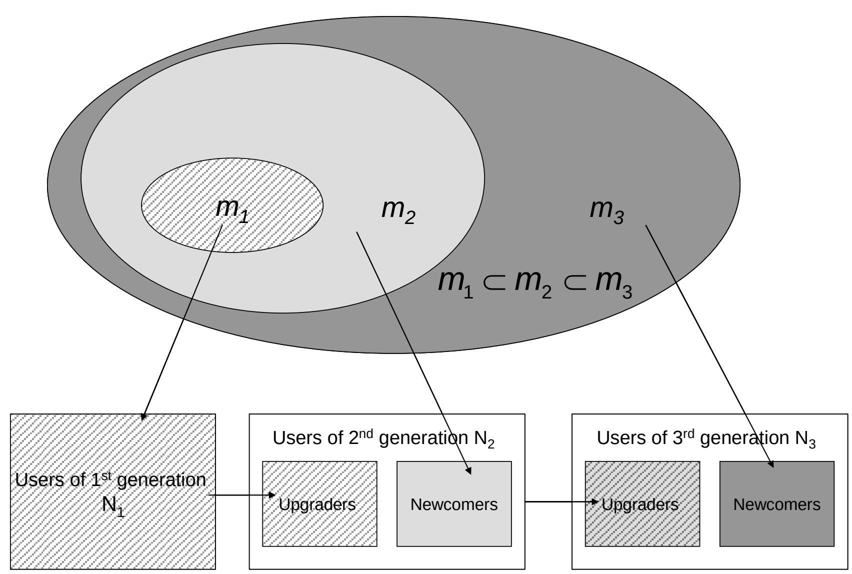
Appendix A: Values of the Takeoff Threshold Function

Market Penetration	Sales Growth Threshold	Market Penetration	Sales Growth Threshold
0.1%	600%	2.1%	39%
0.2%	475%	2.2%	38%
0.3%	375%	2.3%	37%
0.4%	300%	2.4%	36%
0.5%	240%	2.5%	35%
0.6%	190%	2.6%	34%
0.7%	150%	2.7%	33%
0.8%	110%	2.8%	32%
0.9%	75%	2.9%	31%
1%	50%	3%	30%
1.1%	49%	3.1%	29%
1.2%	48%	3.2%	28%
1.3%	47%	3.3%	27%
1.4%	46%	3.4%	26%
1.5%	45%	3.5%	25%
1.6%	44%	…	25%
1.7%	43%	…	25%
1.8%	42%		
1.9%	41%		
2%	40%		

Appendix B: Our Technological Substitution Model

The model we present goes much along the lines of Mahajan and Muller (1996), but with a more precise specification of the substitution process – see Figure 1.

Figure 1: Technological Substitution Model in a three generation market



Assume that at time t, there are k technological generations which operate in the market. Each generation increases the market potential, from m_{i-1} to m_i. We make the following assumptions: After the entry of generation i, the older generation i-1 continues to acquire customers from m_{i-1}. Generation i acquires new adopters from m_i-m_{i-1}, and upgraders from m_{i-1}. The approximation we made here, that the newer generation does not acquire new adopters from the market potential of the previous generation is reasonable for our data, since the differences in market potential are large. *Upgraders* to generation i are customers of generation i-1 who switched to the newer generation i due to the marketing efforts and communication with generation i. We denote $Nu_{i-1,i}(t)$ as the cumulative number of customers who ever upgraded from generation $i-1$ to generation i, (some of them might have later upgraded further to newer generations, as illustrated in Figure 1) $dNu_{i-1,i}/dt = (p_i + q_i N_i / m_i)N_{i-1}$. For the simplicity of the model, we assume no leapfrogging (i.e. upgrading beyond the subsequent generation). We denote *Newcomers* to generation i as adopters of generation i who did not own a previous generation, and thus arrive from m_i-m_{i-1}. The number of newcomers acquired by generation i at time t is given by $dNc_i / dt = (p_i + q_i N_i / m_i)(m_i - m_{i-1} - N_i + Nu_{i-1,i} - Nu_{i,i+1})$. If $N_i(t)$ is the number of customers of generation i at time t, then, under the above assumptions the growth of each generation can be described as –

For the first generation:

(1.1) $$dN_1 / dt = (p_1 + q_1 N_1 / m_1)(m_1 - N_1 - Nu_{12}) - (p_2 + q_2 N_2 / m_2)N_1$$

For generations 1<i<k:

(1.2) $$\begin{aligned} dN_i / dt &= (p_i + q_i N_i / m_i)(m_i - m_{i-1} - N_i + Nu_{i-1,1} - Nu_{i,i+1}) + \\ &+ (p_i + q_i N_i / m_i)N_{i-1} - (p_{i+1} + q_{i+1} N_{i+1} / m_{i+1})N_i \end{aligned}$$

For the last generation (i=k):

(1.3) $$dN_k / dt = (p_k + q_k N_k / m_k)(m_k - m_{k-1} - N_k + Nu_{k-1,1}) + (p_k + q_k N_k / m_k)N_{k-1}$$

The upgraders:

(1.4) $$dNu_{i-1,i} / dt = (p_i + q_i N_i / m_i)N_{i-1}$$

To understand the logic behind the Equation set 1, one should regard the growth of a generation as a result of incoming and outgoing customer streams: Each of the intermediate generations has an incoming stream of newcomers, an inwards stream of upgraders from the previous generation, and an outgoing stream of upgraders to the next generation (with only outgoing upgraders for the first generation and only incoming upgraders for the last).

There are two ways to proceed with the issue of acceleration. The first is to estimate the above set of equations with the parameters pi and qi, and the second is to assume a uniform acceleration rate between generations, i.e., an acceleration that is identical for q and p, and is denoted by δ that is, $p_i = (1+\delta)p_{i-1}$ and $q_i = (1+\delta)q_{i-1}$. Using uniform acceleration significantly reduces the number of parameters, and enables an explicit, straightforward acceleration analysis. This is especially relevant for products with many generations.

Appendix C: The Discrete Time Proportional Hazard Model

Given observations of takeoff times at discrete periods $t = 0,1,2,\ldots T$, for product i, the hazard function, which is the takeoff rate at time τ conditional upon "survival" (in our case, the product not having taken off yet) to time τ, with $\lambda_0(\tau)$ being the baseline hazard for takeoff at time τ, is

$$\lambda_i(\tau) = \lim_{\Delta \to 0} \frac{prob[\tau < t_i < \tau + \Delta \mid t_i > \tau]}{\Delta} = \lambda_0(\tau) e^{-\beta \mathbf{x}_i} \tag{A1}$$

Where $\lambda_0(\tau)$ is specified in the log form of the integrated hazard as

$$\log \int_0^{t_i} \lambda_0(\tau) d\tau = X_i \beta + \varepsilon_i \tag{A2}$$

The vector X contains the variables which influence the takeoff (in our case the vintage, generation, and control variables), and their coefficients are denoted by β.

The error term ε takes an extreme value form.

Now let:

$$\log \int_0^{t} \lambda_0(\tau) d\tau = \delta_t \text{ , } t = 1, \ldots, T \tag{A3}$$

So the probability of takeoff in period t for product i is:

$$\int_{\delta_{t-1} - X_i \beta}^{\delta_t - X_i \beta} f(\varepsilon) d\varepsilon. \tag{A4}$$

The log-likelihood function takes the form:

$$\log L = \sum_i \sum_t y_{it} \log \int_{\delta_{t-1} - X_i \beta}^{\delta_t - X_i \beta} f(\varepsilon) d\varepsilon \tag{A5}$$

For with an extreme value distribution the likelihood function is of an ordered logit form. In this log-likelihood function, y_{it} is an indicator variable that takes on the values $y_{it} = 1$ if takeoff of product i occurs in period t, and $y_{it} = 0$, otherwise.

Appendix D: Correlation Matrix of Independent Variables

	Time to takeoff	**Technology Vintage**	**Technology Generation**	**Pre-WW1 Market**	**Between WW1 & WW2**	**B2B Technology**
Technology Vintage	-.83					
Technology Generation	-.40	.39				
Pre-WW1 Market	.64	-.70	-.09			
Between WW1 & WW2	.27	-.14	-.17	-.18		
B2B Technology	.36	-.44	-.32	.46	-.09	
Process Technology	.67	-.72	-.16	.85	.15	.53

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