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When does the majority become a majority? Empirical analysis of the time at which main market adopters purchase the bulk of our sales

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Abstract

The idea of a dual-market structure in the early stages of a product's life cycle has become one of the most widely accepted ideas among new product marketing practitioners in the past decade. Concepts such as "Early Market/Main Market" and "Visionaries/Pragmatists" have entered the lexicon of high-tech executives to express the notion that the market for new products is composed of early and main markets with a discontinuity in the diffusion process in between them. Moreover, these concepts have been at least partially tested and verified in the marketing academic literature in the past few years.

We extend this branch of research by investigating the timing issues in dual-market cases. We define Change-of-Dominance Time (CD-Time) as *the number of years it takes main market adopters to outnumber early market adopters*. We empirically investigate this timing issue on a comprehensive data set of new product sales in the consumer electronics industry. We find that regarding explanatory determinants of CD-Time, external influence, such as advertising, to the early market is the most important explanatory variable.

We examine the relationship between CD-Time and other early product life cycle phenomena: Takeoff, Saddle, and Rogers' size of adopter categories. We found relatively high correlations between these phenomena and CD-Time.

The answer to the question "When does the majority become a majority?" is indeed "at 16%"! In a dual-market setting, the average time at which the main market outnumbers the early market is when 16% of the

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market has already adopted the product. In terms of time, in 75% of the cases the majority becomes a majority in 5 to 10 years.

Keywords: Chasm; Innovation diffusion; Saddle; Timing

1. Introduction

The idea of a dual-market structure in the early stages of product life cycle has become one of the most widely accepted ideas among new product marketing practitioners in the past decade. Concepts such as "Early Market/Main Market" or "Visionaries/Pragmatists" have entered the lexicon of high-tech executives to express the notion that the market for new products is composed of early and main markets with a discontinuity in the diffusion process in between them (see for example Refs. [1,2]). The basis of Moore's [3] approach is the premise that the early market adopters differ so widely from the main market adopters that without a significant change in marketing strategy, including product offering, the new product has a good chance of failing.

Moreover, the concepts of dual markets and the difference between early and main markets have been tested and verified in the marketing academic literature in the past few years. For example, it has been demonstrated that given a dual-market structure, major changes should be implemented in the way new product marketing strategy is carried out ([4,5]). Tanny and Derzko [6] extended the Bass model [7] both theoretically and empirically, to allow for two distinct segments of Innovators and Main Market consumers. More recently, the chasm phenomenon, defined as a pattern of sales in which an initial peak is followed by a trough of considerable depth and duration, and eventually followed by sales levels that exceed the initial peak, was recently verified empirically ([8–12]).

We extend this branch of research by assuming that the dual market exists, and investigating the timing issues that arise in such cases. When the dual market exists, the market is segmented into early and main market adopters. Our interest is in examining the time it takes the main market adopters to outnumber the early market adopters.

The issue of the timing of the metamorphosis from the early market to the main market is of key managerial concern because it usually requires major changes in marketing strategies. The main market differs from the early market by its size, nature, demographics, product component expectations, customer price sensitivity, and key benefits derived from the product ([13,14]).

To be able to deploy strategies, practitioners need to understand timing issues of dual-market new products in general and to be able to foresee or at least to recognize the time at which dominance passes from the early adopters to the mainstream. Thus, marketing strategies and tactics should be changed when approaching the early or main market, respectively. The time of this in-between stage is also related to other early product life cycle changes and considerations such as resources and R&D planning, entry issues, competitor behavior, and dominant design ([15,16]).

In order to perform the analyses of the timing issues, we define *Change-of-Dominance Time* (CD-Time) as *the number of years it takes the main market adopters to outnumber the early market adopters*. Thus, CD-Time is the core of a process in which the dominance of the early market diminishes and the dominance of the main market is established. The case can be illustrated with the

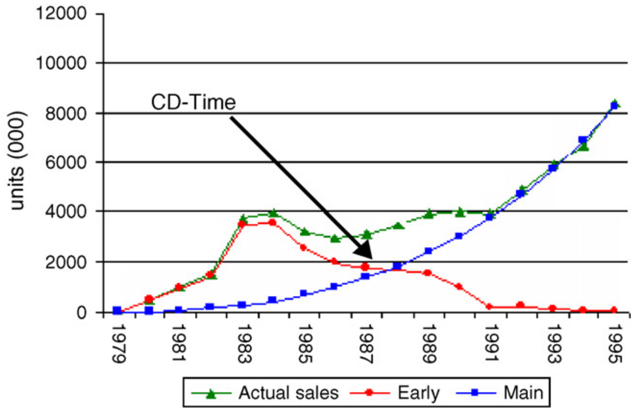

Fig. 1. Annual sales split to early and main market of PCs in the US.

help of Fig. 1, which describes the first 17 years after the introduction of personal computers in the US. By looking at a suggested split of early market and main market adopters, one can determine the first time the main market adopters outnumber the early ones–i.e., the Change-of-Dominance Time–as occurring during 1988.

One could have also investigated the time at which sales reach the first slowdown, or saddle. The reasons we chose the first approach is that the dual market is the main effect, the saddle being only a

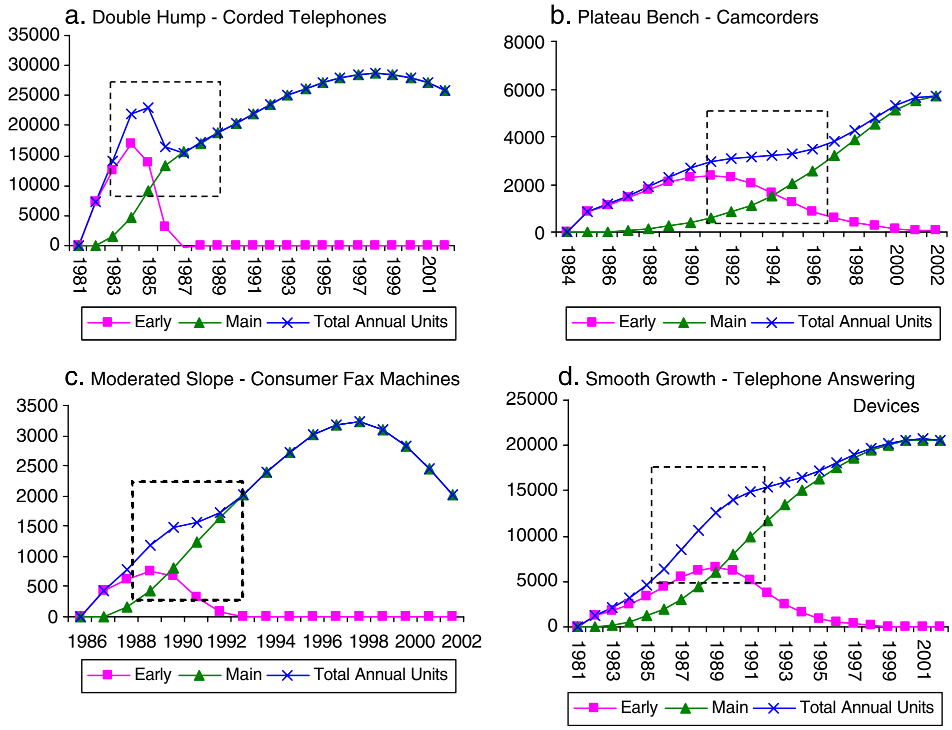

Fig. 2. The changing dominance stage—shapes of a dual market (thousands of units).

manifestation of this main effect. Another reason is that there are many cases in which a dual market exists, yet a slowdown in sales is not observed. In addition, to be used in our study, a saddle occurrence needs to be recognized and a specific year should be identified to represent it, which might have resulted in an increased validity problem. Thus, a dual-market event is a more general and widespread occurrence than the saddle phenomenon.

We named the period in which the dominance shifts from Early to Main Market as the *Changing Dominance Stage*. The growth pattern of the cumulative number of adopters in this stage can roughly characterized by four basic shapes. Fig. 2 describes these basic shapes where in three of them, the gap between the two markets can be visibly detected at the aggregated sales level, and in the fourth, the gap is not notable. In this fourth shape, the existence of a dual-market structure is possible and can have an important influence on the players in the market. The four shapes represent theoretical shapes of dual-market structure, which we named Double Hump, Plateau Bench, Moderated Slope, and Smooth Growth. In Fig. 2 we demonstrate these four basic shapes by plotting four representative diffusion processes with their split into early market and main market based on a model we will describe later.

2. A dual-market model

Diffusion theory generally supports the idea of opinion leadership by adopters in early stages of the diffusion process. In contrast, recent publications suggest that regarding high-tech products, not only are innovators not opinion leaders, but they do not have personal influence at all over later adopters [3]. Moore builds on Rogers' [17] normal diffusion curve and his division into adopter categories along the curve, to explain how new products spread in the market. However, Moore sees a discontinuity in the process, in that the social process of contagion is broken at some point, because the later adopters, or *mainstream market*, refuse to rely for information on the earlier adopters, or *early market*.

Moore's explanation for this phenomenon centers on the difference between adopters in the early market, especially that of the group preceding the chasm ("visionaries") vs. the group that adopts after the chasm, or the main market ("pragmatists"). Early market adopters are more interested in the new technology itself and the way they can use it as a window of opportunity for their company and themselves. They are influenced by people with the same interest in technology across other industries, and agree to purchase products that may be costly and may not be complete in terms of support, compatibility with existing infrastructure, and reliability.

The pragmatists are not especially interested in the technology itself, and are not willing to "bet on the outcome". They expect to get a functional solution that is reasonably priced and already reliable and effective. Because of the difference between the solutions they demand compared to those demanded by the visionaries, pragmatists tend to be influenced only by other pragmatists. Thus, adoptions of new products can "fall into a chasm" between the visionaries and the pragmatists, causing the product to fail to enter the main market.

A diffusion-based theory of dual markets will thus build on a partial communication break as follows: Like others ([3,5,6,8,12]), we assume that there are two major groups of adopters: early market and main market. If we consider the well-known classification of Rogers [17], then the common interpretation of this split is that the first two adopter categories of Innovators and Early Adopters constitute the early market, and the Early Majority and Late Majority constitute the main market. In contrast to Moore, building on diffusion theory, we allow for some degree of communications between the early market and the main one, and let the data decide regarding its size and effect.

Let the index i (innovators) denote the early market segment, and index m (majority) denote the main market. Let N_i be the market potential of the early market, and N_m the market potential of the main market. The parameters p and q are the coefficients of external influence and of internal influence, where p_i and q_i represent these coefficients for the early market, and the parameters p_m and q_m are the coefficients of external influence and of internal influence for the main market. The cross-market communication between the early market and the main market is denoted by q_{im}. Let $I(t)$ be the number of adopters out of the early market population, and $M(t)$ the number of adopters out of the main market population.

The adoption process in the early market progresses through a Bass process as follows:

$$\frac{\mathrm{d}I(t)}{\mathrm{d}t} = \left(p_i + q_i\frac{I(t)}{N_i}\right)(N_i - I(t)). \tag{1}$$

In the main market segment, word-of-mouth activity is broken down into its two components: word-of-mouth activity among the main market population (q_m), and cross-market communications between the early market and the main market (q_{im}):

$$\frac{\mathrm{d}M(t)}{\mathrm{d}t} = \left(p_m + q_m\frac{M(t)}{N_i + N_m} + q_{im}\frac{I(t)}{N_i + N_m}\right)(N_m - M(t)). \tag{2}$$

One should note that Bass [7] is a special case of this equation when there is only one market, i.e., $M(t)=0$. Similarly, the two-stage model by Tanny and Derzko [6] is a special case of Eqs. (1) and (2) when $p_m=0$ and $q_{im}=q_m$. The relationship to the two-stage model by Mahajan and Muller [5] is more complex, as the latter has a non-uniform influence parameter δ and an additional multiplicative advertising term in the equation governing the main market. However, the dynamics of the two models coincide if $\delta=0$ and if in Eqs. (1) and (2) $q_i=p_m=q_{im}=0$.

3. Empirical analyses of timing in dual markets

Our empirical analysis is based on a comprehensive data set of new product sales made available by the Electronic Industries Alliance, a major source of data on new product growth. The original data from the Electronic Market Data Book contains US sales through 2002, and includes 62 innovations, primarily in the consumer electronics industry. By eliminating all cases that contained less than 12 points of data or that did not contain data on per-unit sales, we were left with a sample of 35 valid cases.

The type of analysis we use raises problems similar to those of classical diffusion modeling, namely the need to examine multi-parameter models with few data points. As the model has seven parameters, the estimation could be unstable. We therefore reduced the number of parameters to five by assuming that $p_m=0$ and estimating N_m from external sources, namely from the actual sales data. In order to verify that the N_m estimation does not strongly reflect on the other parameters, we estimated N_m, together with the other parameters (six-parameter Non-Linear regression), and verified that the results are similar to the previous ones (five-parameter Non-Linear regression). Similarly we checked that if we do estimate the parameter p_m, its value is close to zero and insignificant.

For every product, we ran four runs with four discrete sets of starting values, thus ensuring that the results converge to the same final estimation. For every product, we then checked whether:

1. The estimated model represents a dual-market structure based on the fit of the model (adj. $R^2 > 0.80$).
2. The estimated parameters are in a reasonable range ($p_i < 0.25$; $p_i / q_m < 1$).
3. Early market precedes main market.
4. The estimated per-unit sales in the period we are interested in are close to the actual sales.
5. The estimations are stable.

Of the 35 products we studied, 26−or about 75%−have a dual-market structure. The parameters of the 26 estimations are summarized in Table 1.

First, observe that q_i is always larger than q_{im}. Moreover, q_i is at least double that of q_{im} in 77% of the cases. This result is consistent with the dual-market approach that claims that there is a partial communication break between early market and main market groups ([3,12]). Communication within the early market adopters (q_i=0.62 on average) is wider than that within the main market (q_m=0.31 on average). This result is significant at a confidence level of more then 0.99 and holds true in most

Table 1
Dual-market parameter estimation, CD-time, and adoption at CD-time

	Product category	p_i	q_i	q_m	q_{im}	N_i	Adj. R^2 (%)	CD-time	Adoption at CD-time (%)
1	Remote control units	0.030	0.45	0.58	0.04	131072	98	10	24
2	PC monitors	0.056	0.38	0.23	0.07	8124	97	9	9
3	Audio cassettes	0.185	0.29	0.22	0.27	1317	96	5	23
4	Video cassettes	0.053	0.83	0.17	0.30	719	96	6	12
5	Camcorders	0.051	0.39	0.25	0.09	15634	96	9	17
6	Color TVs	0.000	0.95	0.11	0.25	15921	99	15	3
7	Compact audio systems	0.162	0.06	0.29	0.04	19789	91	8	12
8	Corded telephones	0.135	1.00	0.15	0.25	53266	86	5	12
9	Cordless telephones	0.054	1.10	0.22	0.26	11821	97	6	13
10	DBS systems	0.000	1.39	0.39	0.25	5163	98	12	10
11	Fax machines	0.145	0.75	0.31	0.39	2881	95	4	10
12	Laserdisc players	0.220	0.19	0.71	0.17	339	98	4	16
13	LCD color TVs	0.041	0.51	0.15	0.22	989	99	7	10
14	LCD monochrome TVs	0.051	0.82	0.14	0.28	1775	97	6	20
15	Monochrome TVs	0.031	0.59	0.07	0.23	24242	80	8	10
16	PC printers	0.054	0.51	0.26	0.06	13477	99	9	4
17	Personal computers	0.056	0.59	0.25	0.08	16030	97	8	8
18	Personal word processors	0.093	0.40	0.23	0.29	9038	98	6	24
19	Portable CD equipment	0.010	0.70	0.82	0.06	66424	100	10	31
20	Portable tape/radio-tape players	0.077	0.47	0.25	0.29	44998	96	6	21
21	Projection TVs	0.131	0.31	0.42	0.07	1627	96	7	15
22	Rack audio systems	0.012	1.33	0.27	0.32	4489	97	7	32
23	Telephone answering devices	0.025	0.44	0.15	0.21	52778	99	9	12
24	Total CD players	0.003	0.59	0.75	0.04	123209	100	14	33
25	VCR decks	0.001	0.69	0.27	0.08	54721	94	16	21
26	VCR decks with stereo	0.168	0.27	0.47	0.10	8062	97	6	9
Average		0.071	0.62	0.31	0.18	26458	96	8.2	15.8

of the individual cases. Thus we can expect that word-of-mouth intensity within the early market would be higher than that in the main market. One should also observe that not only is the fit high, but it is higher than that of the Bass model, especially with regard to the early stages of the product life cycle. The Bass model yields an average Adjusted R^2 of 86.6% where our dual-market model has an average of 95.9%. Moreover, during the most important early years after introduction, the dual-market model remains in about the same level of fit of 95.8.% (adj. R^2 in first years up to the CD-Time) while Bass model R^2 declines to 41.4% in average. By using the dual approach the MAD (mean absolute deviation between prediction and actual sales) is reduced by 65% in the years prior to the CD-Time.

CD-Time is a result of our estimation, which is based on the estimated annual unit sales to the early market and to the main market. The first year wherein main market sales outnumber those of the early market minus the year of introduction is the CD-Time (see Fig. 1). In terms of our model, CD-Time is *the first time where* $\mathrm{d}I(t)/\mathrm{d}t \le \mathrm{d}M(t)/\mathrm{d}t$. CD-Time values range from 4 years to 16 years following the introduction of the product. The median CD-Time is found to be 7.5 years. CD-Time for more than 75% of the products fell into the range of 5 to 10 years. Note that the average adoption at CD-Time is 16%, which is surprisingly similar to the theoretical size of Rogers' [17] Innovators and Early Adopters categories (further investigation into the size issue will be conducted in Section 4.3).

As seen in Table 1, the variance of CD-Time is relatively wide, and thus we turn next to the determinants of this variable. One could presumably obtain an analytical solution for CD-Time. This, however, is infeasible given the complexity of the equations. Obtaining an analytical solution for CD-Time also precludes us from empirically finding the antecedents of this important variable. We estimated a log-linear model and omitted the variables that were non-significant to come up with the following:

$$\text{CD-Time} = -2.2 - 1.34\,\log(p_i) - 2.2\,\log(q_{im}) - 0.99\,\log(q_m). \tag{3}$$

The adjusted R-Square is 95.5%. The standardized coefficients are: -0.846 for Log (p_i), -0.549 for Log (q_{im}), and -0.186 for Log (q_m). In a stepwise regression, the order of entry of the variables to the regression is that the first is Log (p_i) which explains 74% of the variance, while second comes Log (q_{im}), which contributes an additional 15% of variance explanation. Lastly, Log (q_m) added another 6% of the variance. The negative sign of the coefficients implies that a decrease in these parameters contributes to longer CD-Time. Also note from the standardized coefficient that the strongest influence is that of p_i. These results are consistent with Table 1 regarding the direction of the

Table 2
Jackknife results

CD-time	3	4–5	6–7	8–9	10–12	13–16	Total
4–5	1	3					4
6–7		3	5	1			9
8–9				7			7
10–12					2	1	3
13–16						3	3
Total	1	6	5	8	2	4	26

— Average residual = 0.01 years; average absolute residual = 0.61. Seventy-seven percent correct estimations.
— For only three products, the estimations are more than 1 year away from calculated CD-time.

Table 3
CD-time product group

CD-time (years)	Group no.	No. of cases	Parameter	Mean	Standard deviation	Consumer electronics
4–5	I	4	p_i	0.172	0.039	Audio cassettes, corded telephones, fax machines, laserdisc players
			q_i	0.56	0.39	
			q_m	0.35	0.25	
			q_{im}	0.27	0.09	
			N_i/N_m	14.2%	7.3%	
6–7	II	10	p_i	0.076	0.048	Video cassettes, cordless telephones, LCD color TVs, LCD monochrome TVs, personal word processors, portable tape/radio-tape players, projection TVs, rack audio systems, VCR decks with stereo
			q_i	0.67	0.37	
			q_m	0.26	0.12	
			q_{im}	0.24	0.09	
			N_i/N_m	14.4%	8.1%	
8–9	III	6	p_i	0.062	0.046	PC monitors, camcorders, compact audio systems, monochrome TVs, PC printers, personal computers, telephone answering devices
			q_i	0.43	0.18	
			q_m	0.21	0.08	
			q_{im}	0.11	0.08	
			N_i/N_m	9.7%	4.2%	
10+	IV	6	p_i	0.007	0.012	Remote control units, color TVs, DBS systems, portable CD equipment, total CD players, VCR decks
			q_i	0.8	0.34	
			q_m	0.49	0.28	
			q_{im}	0.12	0.11	
			N_i/N_m	19.7%	13.7%	
Total		26				

influence. When predicting CD-Time using Eq. (3), and rounding the results, one gets accurate predictions for 13 products. An additional 12 products have one year of difference between observed and predicted CD-Time, and only one product (VCR) had a predicted CD-Time that was 2 years away from the observed one.

In order to validate the model, we estimated the CD-Time model coefficients using 25 products, and used this model to estimate the CD-Time of the 26th product. We compare this predicted CD-

Table 4
CD-time — confusion matrix

	Group		Predicted group membership			
			I	II	III	IV
Original group membership	Count	I	4	0	0	0
		II	0	8	1	0
		III	0	1	6	0
		IV	0	0	1	5
	Percent	I	100.0	0	0	0
		II	0	88.9	11.1	0
		III	0	14.3	85.7	0
		IV	0	0	16.7	83.3

Ninety-two point three percent of original grouped cases correctly classified.

Time to the observed ones for all 26 products to calculate the Jackknife Adjusted R-Square. The Jackknife procedure results in an Adjusted R-Square of 93.1%, implying that the fit of this procedure is quite high, and that the Jackknife results are similar to the regular linear regression. Both a difference of only 2.4% in the Adjusted R-Square and the high fit suggest a quite reasonable validation of the model. Table 2 shows the classification to CD-Time group by using Jackknife procedure. We also classified the 26 products to groups by their CD-Time value, and calculated the parameter means and standard deviations. Table 3 shows the results.

We further ran a Discriminate Analysis to see if the dual-market parameters can be used to correctly classify products into the CD-Time groups, and what parameters are dominant in the classification. The Confusion Matrix is presented in Table 4. The result of the test of equality of groups' means shows that p_i is very significant (0.000) as a discriminator between the groups. The parameters q_m and q_{im} are significant at a level of about 5% (0.054 and 0.051, respectively). N_i/N_m and q_i are non-significant as discriminators. Thus, the dual-market parameters can be used to classify products into CD-Time groups. Note that the order of importance of the parameter is consistent with our previous analysis.

4. CD-time and other early PLC timing phenomena

Developing the model theoretically and examining it in the electronics market gave us fairly good results with regards to fit and forecasting ability. We next wish to examine the relationship between our dual-market model and other well-known phenomena in early stages of the product life cycle, namely takeoff, saddle, and Rogers' adopter categories. This examination, if positive, will reinforce our results by giving us an external validity test for our findings.

Table 5
CD-time and saddle timing

Product	Computed CD-time	Actual saddle (years)			Difference between CD-time and saddle minimum	Within saddle range
		Initial peak	Sales minimum	Sales recovery		
PC monitors	9	5	7	11	2	Yes
Audio cassettes	5	3	4	5	1	Yes
Video cassettes	6	5	6	8	0	Yes
Camcorders	9	6	8	9	1	Yes
Color TVs	15	15	17	19	−2	Yes
Compact audio systems	8	1	5	13	3	Yes
Corded telephones	5	3	7	12	−2	Yes
Cordless telephones	6	5	6	8	0	Yes
DBS systems	12	11	12	14	0	Yes
PC printers	9	5	7	11	2	Yes
Personal computers	8	5	7	11	1	Yes
Portable CD equipment	10	9	10	11	0	Yes
Projection TVs	7	3	6	7	1	Yes
Total CD players	14	13	14	15	0	Yes
VCR decks	16	13	16	19	0	Yes
VCR decks with stereo	6	2	3	6	3	Yes

4.1. CD-time and saddle

The saddle phenomenon as describes by Goldenberg et al. [12] and CD-Time are both based on a dual-market approach. Thus, it is of interest to compare the computed CD-Time to the saddle's start, minimum, and recovery years. One should note that this comparison is based on two differing approaches: The CD-Time is an imputed measure that is based on the dual-market model, while the saddle is an empirical construct that is based on actual annual unit sales.

Proposition 1. *When saddle exits, CD-Time will occur in between the first peak and rebound of sales.*

Table 5, which contains sixteen products out of our 26 that do have a visible saddle, describes CD-Time; saddle's beginning, minimum, and recovery years; the difference between CD-Time and minimum year of the saddle; and indication of whether the CD-Time is within the saddle period.

CD-Time always occurs during the span of years in which the saddle takes place. The closest saddle parameter to CD-Time is the year with minimum sales, where the average time span between them is less than eight months. Six out of the 16 products share the same year, and an additional four have a time difference of 1 year. The correlation between CD-Time and saddle minimum is 93%. In all but two cases, the saddle minimum precedes CD-Time. Note that this is not an obvious result, as the saddle is defined directly by the annual empirical noisy date. On the other hand, the CD-Time is a theoretically calculated time, based on the parameters of our smooth dual-market model. The fact that CD-Time occurs during saddle times shows that our model succeeded in grasping its fundamental empirical phenomenon.

4.2. CD-time and takeoff

A takeoff, as defined in Golder and Tellis [18] or Stremersch and Tellis [11], is a dramatic increase in sales, early in the history of the product. It is of interest to find out if CD-Time can be a predictor of the product takeoff, as the latter has obvious marketing and financial implications for the firm. The correlation between the first takeoff and CD-Time was found to be low (4.9%). In 70% of the cases the takeoff occurred in the second year after introduction (the first year in which takeoff is defined), and in only one case did the first takeoff occur after the slowdown years. In addition, our data indicate

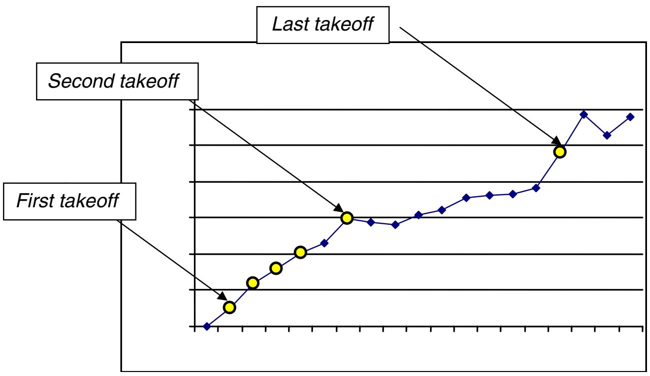

Fig. 3. Takeoffs during camcorder market growth.

Table 6
CD-time, second and last takeoff

Product	CD-time	Second takeoff	Last takeoff
Remote controls	10	7	7
PC monitors	9	12	12
Camcorders	9	6	15
Color TV	15	9	18
Compact audio systems	8	9	15
Corded telephones	5	8	8
Cordless telephones	6	8	12
DBS satellite	12	13	15
Fax machines[a]	4	7	7
PC printers	9	13	16
Personal computers	8	13	13
Portable CD equipment	10	12	12
Total CD players[a]	14	7	16
VCR decks	16	7	26
VCR decks with stereo	6	5	14

[a] We used a relaxed threshold criterion of 20% instead of 25% annual growth.

that the first takeoff is often followed by a slowdown or even several slowdowns before it takes us to really high levels of sales. Thus, we will look at the relationship between CD-Time and (1) the second takeoff and (2) the last market takeoff.

Proposition 2. *When a Second Takeoff or Last Takeoff exists, its timing will be highly correlated with CD-Time and with a tendency to occur later.*

Fig. 3 illustrates various takeoffs in a product's life cycle. Takeoff can occur after any slowdown or moderated growth in sales. The dots represent all years that satisfy the Golder and Tellis threshold for takeoff. A Takeoff year is defined as the first year of a sequence of rapid growth in product sales. These takeoffs have important managerial implications and are quite common in new product growth [18,9].

We thus define the *Second Takeoff* as the first year that satisfies the Golder and Tellis [18] threshold criteria for takeoff that follows right *after* the first sequence of high growth ends. For the purpose of computing the Second Takeoff, we first had to find all years that satisfy the threshold for takeoff. We selected the first year of every sequence of growth and thus received the ith takeoff for $i=1.2...$ We ran this procedure on our 26 products' annual unit sales.

The *Last Takeoff* is defined as the last takeoff that occurs before the peak of sales. The only difference in the calculation procedure is the selection of the first year in the *last* growth sequence instead of the first year in the *second* growth sequence. Table 6 summarizes the results.

Fifteen products out of our 26 have more than one takeoff. The other 11 products fall into two groups: (1) do not have any year that satisfies the takeoff criteria (five products), and (2) have only one takeoff very early in PLC (six products). These 11 products have a cumulative unit sales graph that looks like Fig. 2b and d—Plateau Bench and Smooth Growth.

CD-Time occurs before the second takeoff in 60% of the cases and before the last takeoff in all cases. While correlation between CD-Time and second takeoff is low (11%), its correlation with the last takeoff is fairly high at 83%.

4.3. CD-time and Rogers' classification

In our dual-market model, the Early Market is related theoretically to Rogers' first two adopters' categories: Innovators and Early Adopters. If indeed this relationship exists, we should expect penetration at CD-Time to be about 16% according to Rogers' proportion. Mahajan et al. [19] suggest that adopters' category size can be calculated from the Bass model's inflection points. They calculated the size of Innovators and Early adopters from a variety of empirical product growth data and suggested a range of early market sizes.

Proposition 3. *Adoption at CD-Time will occur when 16% of the market has adopted the product. The range will be similar to the one reported by Mahajan, Muller, and Srivastava (1990).*

Table 1 shows the percentage of adopters at the year of CD-Time for all of our 26 products. On average, CD-Time occurs when 16% of the population has already adopted. This percentage is the same as Rogers' [17] for Innovators and Early Adopters. When we cut off 10% of the extreme lowest and of uppermost cases, the range of the population proportion in CD-Time is 8–27.5%. This is somewhat broader than the Mahajan et al. [19] range of 12.3–20.2%.

Altogether, all three propositions are supported by the empirical data. Thus CD-time and our dual-market model are closely related to other well-known models and phenomena in marketing. This examination also reinforces our results by giving an external validity test for our findings.

5. Concluding comments

Early market adopters are of special importance to new product growth. Not only do they have a strong tendency to adopt early, but they also induce an overall faster growth process that originates from strong external influence (marketing efforts) as well as from strong internal communication between group members. What we found is that the external influence is crucial with respect to what really drives sales and profits: the speed at which the main market joins the adoption process. This finding can have a major implication for marketers in the early stages of product growth. By focusing the early years' marketing efforts such as advertising on potential adopters that constitute the early market, we can significantly contribute to overall adoption speed.

The understanding that the characteristics of its customers are changing, and particularly knowing the timing of this change, can help the firm to better allocate marketing efforts, change product design, and produce better forecasts. The findings that in 75% of the cases CD-Time is between 5 to 10 years after introduction, and that it occurs at about 16% penetration, are just two examples. Furthermore, the importance of the external coefficient p_i in explaining CD-Time is an additional attempt to influence it, for example by advertising directly to the early market.

While our work provides additional support for the dual-market phenomenon, and a first shot at the timing issues, many important questions are still left open such as finding empirical evidence for product and market factors that most differentiate early and main market adopters. Other unanswered issues relate to the factors that affect the depth of the communications break between the markets, the existence of more than two segments (early and main), and issues of forecasting the precise change of dominance of a specific product. Aggregate adoption data might not be sufficient for answering these questions, and more in-depth investigations, possibly across various time points, should be conducted.

It is clear that if the dual-market phenomenon is indeed widespread, then important changes should be made in the way that we teach and research the diffusion of innovations. This study is only a step in this direction.

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References

[1] S. Park, Y. Soo-Hyeon, Separating early adopters from the majority: the case of broadband Internet access in Korea, Technol. Forecast. Soc. Change 72 (2005) 301–325.
[2] J.J. Mohr, S. Sengupta, S. Slater, Marketing of High-Technology Products and Innovations, 2nd edition, Prentice Hall, New York, 2004.
[3] J. Moore, Crossing the Chasm, Harper Business, New York, 1991.
[4] R. Kohli, D.R. Lehmann, J. Pae, The extent and impact of incubation time in new product diffusion, J. Prod. Innov. Manag. 16 (1999) 134–144.
[5] V. Mahajan, E. Muller, When is it worthwhile targeting the majority instead of the innovators in a new product launch? J. Mark. Res. 36-4 (1998) 488–495.
[6] M.S. Tanny, N.A. Derzko, Innovators and imitators in innovation diffusion modeling, J. Forecast. 7 (1988) 225–234.
[7] F.M. Bass, A new product growth model for consumer durables, Manage. Sci. 13–5 (1969) 215–227.
[8] J. Goldenberg, B. Libai, E. Muller, R. Peres, "Blazing saddles: early market and main market in the product life cycle in the high-tech industry," Economic Quarterly (in press) (in Hebrew).
[9] P.N. Golder, G.J. Tellis, Growing, growing, gone: cascades, diffusion, and turning points in the product life cycle, Mark. Sci. 23 (2004) 207–218.
[10] D. Goswami, K. Karmeshu, Study of population heterogeneity in innovation diffusion model: estimation based on simulated annealing, Technol. Forecast. Soc. Change 71 (2004) 705–722.
[11] S. Stremersch, G.J. Tellis, Understanding and managing international growth of new products, Int. J. Res. Mark. 21 (4) (2004) 421–438.
[12] J. Goldenberg, B. Libai, E. Muller, Riding the saddle: how cross-market communication can create a major slump in sales, J. Mark. 66 (2002) 1–16.
[13] H. Gatingon, T.S. Robertson, A propositional inventory for new diffusion research, J. Consum. Res. 11 (1985) 849–867.
[14] D.F. Midgley, Innovation and New Product Marketing, John Wiley, New York, 1977.
[15] E. Montaguti, S. Kuester, T.S. Robertson, Entry strategy for radical product innovation: a conceptual model and propositional inventory, Int. J. Res. Mark. 19 (2002) 21–42.
[16] V. Shankar, G.S. Carpenter, L. Krishnamurthi, The advantages of entry in the growth stage of the product life cycle: an empirical analysis, J. Mark. Res. 36 (1999) 269–276.
[17] E.M. Rogers, Diffusion of Innovation, 4th Edition, The Free Press, New York, 1995.
[18] P.N. Golder, G.J. Tellis, Will it ever fly? Modeling the takeoff of really new consumer durables, Mark. Sci. 16 (1997) 256–270.
[19] V. Mahajan, E. Muller, R.K. Srivastava, Determination of adopter categories using innovation diffusion models, J. Mark. Res. 26 (1990) 37–50.

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