Network Effects, Quality and the Success of New High-Tech Products

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ABSTRACT

Researchers disagree about the critical drivers of success in high-tech markets and whether high-tech markets are efficient. Many authors suspect that network effects play a big role leading to perverse markets in which the dominant brands do not have the best quality. At the same time, few researchers assert that high-tech markets are efficient with best quality brands dominating. We develop a model to reconcile these conflicting positions. Our model shows that whether the market is perverse or efficient depends critically on consumer information about quality and consumers reliance on the network of users. As such, efficiency cannot be asserted a *priori*. Empirical analysis of 19 categories shows that 1) both quality and network effects are strong and 2) markets are generally efficient, though 3) while network effects are stronger than those of quality, they lie in a range in which they enhance the effect of quality.

Keywords: Network Effects, Path Dependence, Quality, New High-Tech Products

INTRODUCTION

Microsoft Windows. Microsoft Word. Oracle relational databases. These high-tech innovations have survived numerous challenges and dominate their respective categories. Their market domination grants them enormous advantages while drawing intense scrutiny as potentially illegal monopolists. Researchers and analysts have debated whether domination is the well-deserved reward of superior quality or the illegal rents from monopoly power and whether the market is efficient under such domination.

On the one hand, several authors state that network effects may play an important and perverse role (Church and Gandal 1992, 1993; Farrell and Saloner 1985, 1986; Katz and Shapiro 1985, 1986, 1992, 1994). *Network effects* refer to the increase in a consumer's utility from a product when the number of other users of that product increases. Many economists fear that such effects may lead to consumer inertia, lock-in, or path dependence that favors established inferior products to newer superior ones. For example, Besen and Farrell (1994, p. 118) state, "The coexistence of incompatible products may be unstable, with a single winning standard dominating the market. In these circumstances, victory needs not go to the better or cheaper product: an inferior product may be able to defeat a superior one if it is widely expected to do so." Katz and Shapiro (1994, p.108) observe, "Markets may tend to get locked-in to obsolete standards or technologies" even though superior quality alternatives may become available. Krugman (1994, p. 223) doubts that "markets invariably lead the economy to a unique best solution." Instead he asserts that "the outcome of market competition often depends crucially on historical accident." Arthur (1989, p.116) concludes, "A technology that by chance gains an early lead in adoption may eventually corner the market of potential adopters, with the other technologies becoming locked out" even though the latter are superior.

On the other hand, several studies emphasize the importance of quality in driving a product's success in the marketplace. For example, studies show that product quality exerts a significant positive influence on market share (Jacobson and Aaker 1985, 1987; Kordupleski, Rust and Zahorik 1993; Phillips, Chang, and Buzzell 1983), return-on-investment (Buzzell, Gale and Sultan 1975; Phillips, Chang and Buzzell 1983), premium prices charged (Moorthy 1984, 1988; Phillips, Chang and Buzzell 1983; Tellis and Wernerfelt 1987; Zhao 2000), advertising (Tellis and Fornell 1988; Zhao 2000), perception of quality (Hellofs and Jacobson 1999), and stock market return (Aaker and Jacobson 1994). In particular, Liebowitz and Margolis (1990, 1994, 1995, 1999) cite several examples to argue that quality is the principal driver of market position, *even in the realm of high-tech products*. Indeed, they assert, "The very heart of our argument is that network effects do not protect market participants from competition" (1999, p.14). Their result not only contradicts the conclusions of many economists, but flies in the face of many users of products such as word processors, email, and voice-over-internet programs, who choose such products based primarily on what their colleagues are doing rather than on an independent assessment of quality.

Thus the literature is divided about the role of quality and network effects in the success of high-tech products and whether such markets are efficient. Empirical studies in marketing have not yet tackled this issue sufficiently. These studies either focused on proving the presence of network effects (Nair, Chintagunta and Dube 2004), on investigating the nature of network effects (Shankar and Bayus 2003), or on analyzing the role of network effects in diffusion (Gupta, Jain and Sawhney 1999). However, none of them have specifically examined the drivers for success of new high-tech products. In particular, no study has explicitly examined the relative importance of quality vis-à-vis network effects using a single econometric model, tested on the same categories, while drawing implications about market efficiency in these markets. This is the goal of this paper. This issue is important for several reasons. First, new high-tech products are being introduced with increasing frequency and in many ways are shaping the modern economy and people's lifestyle. Second, whether these markets are driven by quality or network effects have important implications for strategy and public policy. Third, whether as argued by many economists, network effects can be so strong as to dominate and negate the role of quality leading to market inefficiency, has profound policy implications.

We develop a model of market-share flow based on utility maximization of heterogeneous consumers. The model allows for quality and network effects *occurring simultaneously*. Which of these two effects dominate depends crucially on the proportion of "informed" consumers and the extent of consumers' reliance on network effects. We show that under certain conditions network effects can *overwhelm* the effect of quality rendering the market perverse. In other conditions network effects can *enhance* the role of quality, rendering the market more efficient than it would have been in its absence. We also collect data across 19 categories to test which of these plausible scenarios actually occurs. We find that network effects are relatively stronger than the effects of quality. However, network effects are not so excessive as to cause markets to be perverse. In fact, the effects are within the range in which they enhance the effect of quality.

The rest of the paper is organized as follows: The second section describes the theoretical model. The third section presents our sample, data collection procedure and some exploratory analyses. The fourth section presents the econometric model and discusses the key empirical results. The final section discusses the study's implications, limitations, and directions for future research.

A MODEL OF QUALITY AND NETWORK EFFECTS

We model a market in which consumers derive utility from the purchase of a brand based on their assessment of its quality and the size of its network of users relative to that of other brands. Consumers may rely on size of the network for two reasons. First, they value the benefit from using the same brand as other consumers do. For example, users of Microsoft Word get more value from buying the brand the more other consumers use it instead of a rival brand such as WordPerfect. We refer to this as the network effect. Second, they interpret the number of other consumers of a brand as an assurance of its superiority to other brands in the market. We refer to this as the confidence network effect. In the rest of the paper, we do not distinguish between these two effects. Also, for the rest of this paper, we investigate brand-level network effect and not product category level network effects.

We capture the size of the network by the number of units of a brand in the market in current and past periods. We refer to this as the installed base. Because for many high-tech products, models change approximately every three years, it seems more reasonable to compute the network size by the number of units of a brand sold in the last three years, rather than in all the prior period. This metric is consistent with Liebowitz and Margolis (1999). Our empirical analysis also provides some justification for this three-year assumption. We assume that in each period, a group of consumers, normalized to one, enters the market to buy the product.[1] The set of competing brands is indexed by i ($i \in \mathrm{I}$). In the current model, we do not distinguish between new consumers and those who repurchase. However, we examined an extended model in which two groups are differentiated by their switching cost (see the Appendix 2).

[1] A growing market can be incorporated in the analysis but ignoring it only strengthens the network effect, and hence goes in the favor of the null hypothesis.

We measure quality with the variable Q, which takes strictly positive values and ranges from 2 to 10 in our empirical application. For algebraic convenience, we do not model price differences. As such our measure of quality may be considered as quality per dollar that the brand charges. Past research indicates that *not all* consumers are informed about quality of even mature, frequently purchased products (e.g., Tellis and Wernerfelt 1987). In the interest of parsimony and without loss of generality, we assume there are two types (or segments) of consumers. Some consumers are experts, knowledgeable about the product, and well-informed on the literature, especially about product reviews in periodicals and on the Internet. We refer to these consumers as informed. The other segment (whom we call uninformed hereafter) are not so informed, either because they are novices, non-experts, or too busy or uninterested to read up about the changing products. Because for high tech products, new brands keep entering the market while all brands are constantly changing and improving quality, information about quality gets obsolete quickly. So we assume that even when consumers repurchase, they need to "get informed" about quality all over again or choose to be uninformed. We operationalize the existence of these segments by assuming that a proportion θ of the entire market of consumers is informed consumers, while a complimentary proportion $(1-\theta)$ is uninformed. The parameter θ could vary from 0 to 1, thus allowing for the market to range from being fully uninformed to being fully informed. In our empirical analysis we estimate the parameter. Because we do not have sufficiently refined data for estimating a time-varying parameter, we assume θ to be constant over the period of estimation. We also explore the variation of θ over various sub-markets through three split sample analyses.

The *I* firms in the product market engage in monopolistic competition with differentiated products. We do not endogenize firm behavior in our analysis. We also do not explicitly model price differentials because in these markets firms usually compete on product quality at very similar price points, at least in the initial years. Moreover, firms try and offer the best quality product they can, so quality can also be taken as exogenous to the analysis of market share flow. We derive the market-share flow of these brands in two steps. The first step specifies the utility derived by the individual consumers. The second step develops the probability of purchasing different brands and then reinterprets those as the expected market share of different brands.

Step I: Individual Utility of Segments

We model the utility consumers derive in choosing a brand as probabilistic, comprising of a deterministic part and a random component (McFadden 1973). In our model and empirical application, the deterministic part of the utility is a linear function of both quality and network effects for all consumers. We model it as follows. Consistent with our concept of measuring the network size, we assume that the size of brand *i*'s network N_{it}, in any given period *t*, is the sum of its market shares in the last three periods. We capture consumers' reliance on the network by the parameter γ, which takes on only non-negative values. When γ is 0, consumers do not care about the size of the network. Thus, consumer utility for brand *i* is the parameter γ times the network size N_{it}. We assume that the quality portion of consumer utility for a brand *i* is captured by parameter, β, times the quality, Q_i, of the brand *i*. Both β and Q_i take on only non-negative values. β can be termed as consumer responsiveness to quality. By this specification, if β is 0, consumers are indifferent to quality, while its importance increases in β.

While both segments have consumers who care about quality and network, we allow the uninformed consumers to put relatively greater weight on network size. This may happen because uninformed consumers may transfer some of their quality weight on the network. We achieve this potential transfer in a parsimonious manner by introducing another parameter, a multiplier, k on the quality weight β only for the uninformed. The multiplier takes non-negative values equal to or lower than 1, i.e., $k \in (0,1]$ for the uninformed consumers, while it is 1 for the informed consumers. By this specification, k can be also considered as the extent to which the uninformed consider the network as a signal of quality. If k is 1 for the uninformed consumers, then their weight on quality is the same as that of the informed, and they use the network only for the real benefits it provides to them. If k is zero for the uninformed, then they are guided only by the network size of respective brands, which they use for benefits and as a signal of quality. We let the value of k be empirically determined. As such, we allow for a greater dispersion in consumer response than by assuming that k is either 1 or 0.[2]

Based on these assumptions, we can represent the deterministic portion of utility derived by informed consumer j at time t for the brand i in the market as:

(1) $$U_{ijt}^{IN} = (\beta Q_{it} + \gamma N_{it})$$

As mentioned before, N_{it} is given by the sum of market shares in the three immediately preceding periods, i.e., $N_{it} = m_{i(t-1)} + m_{i(t-2)} + m_{i(t-3)}$. utility of uninformed consumer l, for brand i, in time period t is given analogously by:

(2) $$U_{ilt}^{UN} = (k \beta Q_{it} + \gamma N_{it})$$

In Appendix 2, we explore a more general model that distinguishes the utilities of consumers who are repurchasing and those who are new to the categories by tracking the switching cost. Since we don't have all the data that are required to empirically test the impact of switching cost, we pursued numerical simulation only for that model.

[2] One could achieve the same effect by having a similar multiplier for the network effect parameter of the informed segment instead. However, since only relative weights on quality and network are different across the two segments, we could not have two multipliers.

Step II: Purchase Probabilities and Market Shares of Different Brands

We assume that the unobserved random portion of a consumer's utility independently and identically follows a type I extreme-value (Gumbel) distribution, which leads to the following probability of buying brand *i* at time *t* for the informed consumer *j* (Maddala 1983; McFadden 1973):

(3) $$Prob.(\text{choice} = i \mid Q_{it}, N_{it}) = \frac{e^{U_{ijt}^{IN}}}{\sum_{i \in I} e^{U_{ijt}^{IN}}}$$

In an analogous manner, the probability of buying brand *i* at time *t* for non-expert consumer l is:

(4) $$Prob.(\text{choice} = i \mid Q_{it}, N_{it}) = \frac{e^{U_{ilt}^{UN}}}{\sum_{i \in I} e^{U_{ilt}^{UN}}}$$

Since all informed or uninformed consumers are homogeneous in terms of their brand choice within their respective segments, we can re-interpret Equations (3) and (4) as the market share equations for brand *i* in the informed or uninformed segments respectively. Thus, the market shares for brand *i* (for all $i \in I$, the set of all brands in the market) within the informed and uninformed segments are respectively:

$$m_{it}^{IN} = \frac{e^{U_{ijt}^{IN}}}{\sum_{i \in I} e^{U_{ijt}^{IN}}} \text{ and } m_{it}^{UN} = \frac{e^{U_{ilt}^{UN}}}{\sum_{i \in I} e^{U_{ilt}^{UN}}}$$

Applying the segment weights, θ and (1-θ) respectively for the two segments of consumers, we finally get the following market share flow equation for the entire market. This equation links a brand's market share in any period to its current period quality, its network size, the distribution of informed consumers in the market, and their weights on quality and the network.

$$m_{it} = \theta \frac{e^{(\beta Q_{it} + \gamma(m_{i(t-3)} + m_{i(t-2)} + m_{i(t-1)}))}}{\sum_{i \in I} e^{(\beta Q_{it} + \gamma(m_{i(t-3)} + m_{i(t-2)} + m_{i(t-1)}))}} + (1-\theta) \frac{e^{(k\beta Q_{it} + \gamma(m_{i(t-3)} + m_{i(t-2)} + m_{i(t-1)}))}}{\sum_{i \in I} e^{(k\beta Q_{it} + \gamma(m_{i(t-3)} + m_{i(t-2)} + m_{i(t-1)}))}} \tag{5}$$

Equation (5) is an expression for the flow of market shares. It does not represent the equilibrium distribution of market shares. The equilibrium occurs when the right hand side of Equation 5 for some time period, t, is the same as that for $(t+1)$. Because of the complexity of Equation 5, we could not derive a simple expression for the solution of this condition. So, we simulate how market shares flow from period to period, for certain values of our parameters that are representative of those we estimated in the real market. The equilibrium is the point at which the market share reaches an asymptote.

Simulation of Market Dynamics

We explore the theoretical implications of the above equations on derived market shares in successive periods in a market with only two brands. So we conduct the numerical simulation in order to characterize the impact of three key parameters, θ, β, and γ on evolution of such markets. Recall, a critical issue in networks effects is whether a market can converge on a later entrant with superior quality instead of hanging on to an early entrant with inferior quality. So, we are particularly interested in the relative impact of network size and quality on market share flows and market efficiency, *when the later brand enters with superior quality*. So, for the purpose of simulation only, we assume that in the first period an incumbent firm offers the only brand and captures the entire market while in later periods, a late entrant comes with superior quality. Thus, the incumbent has a network size advantage but the entrant has a quality advantage. Quality is constantly improving in high-tech markets. Thus, as our data and indeed even casual observation suggest, high-tech markets are replete with examples of new brands entering late with superior quality.

We call the case when the brand with superior quality ends up with a lower market share *perverse* market. We call the reverse situation, where a high quality entrant overcomes the initial disadvantage in network size and obtains a larger market share in equilibrium as *efficient*. We also measure the *efficiency* in the market by the equilibrium market share of the high quality brand, which can range from 0 to 1. We now present two key propositions that relate to the existence of perverse or efficient markets and the extent of efficiency.

Proposition 1:
Unless consumers' reliance on the network size is excessive (i.e., $\gamma > \gamma^*$), the market is efficient, with better quality brands getting a bigger market share, even if they enter late.

The results of simulation that support this proposition are in Panel A of Table 1.

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Insert Table 1 here
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For the purpose of this simulation, based on our subsequent empirical analysis, we set the value of k to be relatively low at 0.05, implying that uninformed customers place a very low weight on quality. Again based on subsequent empirical analysis, we assume the incumbent's quality rating (Q_1) is 7 and the entrant's quality rating (Q_2) is 9. This assumption is consistent with many high-tech markets and our empirical data, in which new brands are constantly being introduced with superior quality. We assume that in the first period, only the incumbent is in the market and captures all of it. The better-quality new brand enters in the second period. The market share then flows from period to period as dictated by Equation (5). As firms compete in the market every period, they gradually move towards a steady-state equilibrium.[3].

[3] We say that a stable state has been achieved when market-shares in successive periods do not vary by more than 0.001 percentage points. This was typically achieved in less than thirty periods.

The value in Column 3 in Panel A of Table 1 is the maximum γ that still leads to an efficient outcome, i.e., when the high quality entrant ends up with a higher market share than the low quality brand. This result is in the graph of the efficiency frontier in Panel A of Figure 1.

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Insert Figure 1 here

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The figure shows how market efficiency depends on consumers' responsiveness to quality (β) versus their reliance on network (γ). The curve is in β-γ space. The efficiency frontier is the locus of the points for each level of quality responsiveness (β) that represents the maximum level of network effect (γ) which still results in an efficient outcome. Points above the frontier represent situations where perverse outcome prevails but points below the curve signify efficiency.

Note that even when consumer response to quality is very high, the presence of strong network effects may still lead to a perverse market, e.g., there always exists a region for perverse market outcomes (i.e., for any $\gamma > \gamma^*$). However, our subsequent empirical analysis shows that such inefficient outcomes are unlikely in the real world. On the contrary, the subsequent empirical analysis shows frequent changes in market leadership, in which superior products replace inferior incumbents.

Proposition 2:
When consumers' reliance on network effect is moderate, the market is *more efficient* than it would have been without any network effects.

An even more important result emerging from the simulation of market share flows is that uninformed consumers' reliance on network effects makes the market more efficient than it would have been in the absence of such network effects. We present the supporting numerical simulation results in Panel B of Table 1.

For instance, given $\beta = 2$, compare the cases where $\gamma = 1$ and 0.5. When $\gamma = 1$ (i. e., reliance on the network is moderate), the superior quality entrant brand can take over almost the entire market, e.g., $ms_2^* = 0.95$. In the case when $\gamma = 0.5$ (i.e., reliance in the network is comparatively low), the superior quality brand can obtain only 73% of the market. Therefore, the market can be more efficient when network effects are strong, within this range of values. The extended model incorporating switching cost described in Appendix 2 shows that except for an extreme level of switching cost, our basic propositions hold.

Why does this happen? The intuition for the result is that the uninformed consumers benefit from relying on other consumers, some of whom are informed. The informed consumers are aware of quality and can discriminate the better quality brands. Thus, they constitute a core of good choices in favor of the better quality brands. In the presence of network effects, because the uniformed consumers rely on the network of users, some of whom are informed, in each period, more of the uninformed consumers choose the better quality brand. As this process carries on and the network refreshes itself periodically, the market converges on the better quality brand. Thus the informed provides a positive externality to the uninformed. In other words, moderate network effect in fact makes the market more efficient. Interestingly enough, it does not take a very large segment of informed consumer to achieve this result. For example, the above specific simulation shows that only 20% of the market is informed, within parameter values obtained from our empirical analysis.

To better appreciate these relationships, we plot the relationship of the equilibrium market share of a late entering but better quality brand against network effects (γ) in Panel B of Figure 1.

In this figure, the values for θ and β are 0.2 and 2.25 respectively, corresponding to estimates from the empirical analysis.[4] The graph shows how at low levels, stronger network effects (γ) lead to an increase in the market share of this superior quality brand. However, as γ increases above about 1.6, the market gets increasingly perverse and the superior quality brand ends up with lower equilibrium market share. We can also see that:

1) For the values of θ, q_1, and q_2 assumed above, the positive externality occurs when $\gamma <$ approximately 1.6. In such a scenario, the uninformed consumers rely enough on the market that they can benefit from the informed consumers, but are not so reliant that popular brands grow and dominate the market even though they are of inferior quality, as discussed in Proposition 1.

2) When γ is relatively small, there always exists a segment of inferior brands. Superior quality brands cannot take over the entire market. However, as γ increases from 0 to γ^* (=1.6 in this case), the better brand obtains an increasingly larger share in equilibrium than the inferior early entrant and eventually takes over the entire market.

Summary

The prior analysis shows that one cannot make an a priori case for whether network effects lead to perverse markets as asserted by many economists, or to greater market efficiency. The outcome depends critically on the number of informed consumers and their reliance on quality versus the network of other users. Thus empirical analysis is essential to determine the role of quality and networks in high-tech markets. Our empirical analysis is a test of Equation 5. Its purposes are: to first examine the relative impact of network effect vs. quality in driving market share; second, to investigate whether the network effect is within the range where the market is still efficient; and third to examine whether markets are generally efficient or perverse.

[4] Once again, these values are consistent with our pooled empirical estimate of the parameters.

DESIGN FOR EMPIRICAL ANALYSIS

This section describes the sampling, data collection, measure of quality and some exploratory empirical analysis of the data.

Sampling

We chose personal computer products and services as the sampling population since they are supposed to have strong network effects. Thus they would favor the null hypothesis of the superiority of network effects over those of quality. Within this class of products, we included the most important categories for which we could obtain data. We considered different platforms, such as PC and Mac, as different product markets. However, we treat the two PC operating platforms, DOS and Windows, which emerge sequentially, as representing one market. We considered high-end and low-end brands as constituting different product markets as shown in Table 2, column 1.

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On this basis, we collected data on a total of 19 product markets. Due to limitations in the availability of data, this sample is heavily weighed towards software products relative to hardware and services. Most of the product markets were characterized by two or three firms with one dominant brand.

Data Collection

The limited availability of suitable data for this study has been the major hurdle in the empirical analysis. We collected the majority of the market share data from IDC (International Data Corporation) and partly from Dataquest. However, even these firms did not have complete or adequate data on a number of categories. In those instances where the data were not available from any syndicated source, we collected from archival sources following rules suggested by Golder (2000).

Measure of Quality

We define quality as a composite of attributes of which consumers prefer more to less. Thus, reliability, speed, high resolution, ease-of-use, and so on, are common dimensions of quality in our product categories. Our quality measure is based on the ratings or reviews of experts. Numerous marketing studies have used such a measure of quality (e.g., Archibald, Haulman and Moody 1983; Ratchford 1980; Tellis and Wernerfelt 1987). While incongruity between dimensions could create a problem, authors have shown that this situation is uncommon and rarely creates a problem (Curry and Faulds 1986; Kopalle and Hoffman 1992).

Because established consumer magazines such as *Consumer Reports* did not evaluate the quality of computer products in the past, we resorted to ratings and reviews in 3 most respected and widely circulated computer magazines: *PC Magazine, PC/Computing, and PC World.* We considered reviews for each of our brands, for each year in the sample. However, since many of the magazines published reviews without numerical ratings, we used a content analysis of reviews to arrive at numerical ratings.

For the content analysis we first developed a set of terms that reviewers often use to describe these products. We then grouped these terms into five levels expressing increasing quality, on a 5-point scale ranging from 2 to 10 (see Appendix 1). We then trained two independent raters to content analyze each review in each magazine for each brand in our sample, and to transform it into a numerical score based on the prevalence of such terms in the review.

The coefficient of reliability between the raters was 87%, which is above the normally accepted level of 85% (Kassarjian 1977). We arrived at the quality ratings of each brand for each year by averaging the ratings generated by the two independent raters. When reviews were missing for any years, we used the previous year's ratings to fill in the missing values.

Exploratory Empirical Analysis

We conducted two exploratory empirical analyses before the formal econometric analysis to get a feel for these markets. The first analysis is a simple graphical analysis of market share flows in two product categories: spreadsheet and the personal finance. The second is an analysis of switches in market leadership as a function of switches in quality using a simple logit model.

Graphical Analysis of Market Share Flows

Figure 2-A presents the results of such an analysis for the spreadsheet market.

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In this market, Lotus had been the unquestionable market leader in both market share and quality since 1983. In 1987, Excel was launched for the PC market. Two years later, in 1989, Excel's quality rating surpassed that of Lotus. Soon after, one can see a sharp increase in Excel's market share and a corresponding decline in Lotus' market share. By 1994, Excel became the market leader. Its quality has been rated superior to Lotus' ever since. Note how its market share did not fall below Lotus' market share (until 1997, for which time period we have data). So, even though Lotus was an established brand with an established network of users, Excel entered the market late, grew from 0 and surpassed Lotus' position due to its superior quality. This case suggests that market leadership is not permanent and quality plays a role in leadership changes and market share flows**.**

The market dynamics in five other markets including the personal finance software market, web browser market, high-end desktop publishing market, ISP market, and the word processor market also indicate the same pattern, namely, when a brand's quality improves, so does its corresponding market share (see Figure 2-B and Figure 3).

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Insert Figure 3 here
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This exploratory analysis suggests that a switch in quality leadership is related to and precedes a switch in market leadership, So quality seems to play a in important role in influencing market dynamics. Moreover, these simple graphical analyses do not indicate these markets are perverse either. We have also performed such analyses on all other product categories that we have data, and none of these markets turned out to be perverse.

Logit Model of Switches in Leadership

To further investigate the role played by quality in driving market dynamics, we conducted another exploratory empirical analysis which looks for a link between switches in quality and corresponding switches in market share for any pair of brands. Under the assumption of strong (and ever-increasing) network effects, the dominant brand will stay dominant so that market leadership will not switch. So, a simple indication for the presence of strong network effects and a perverse market is the absence of switches in market leadership. If there are changes, we examine to what extent they correlate with changes in quality.

We record such switches as follows. A switch in quality leadership in year t is coded as 1, if one brand becomes superior to all others in quality in year t, given that it was not the quality leader in year t-1. We use an analogous rule for switches in market share leadership. We only consider up-switches and exclude down-switches to avoid double counting. We analyze this relationship with a logit model as follows:

(6) $$P[MS(s)_{i,t}] = \frac{1}{1 + \exp[\beta_1 Q(s)_{i,t} + \beta_2 Q(s)_{i,t-1} + \beta_3 Q(s)_{i,t-2} + \beta_4 Q(s)_{i,t-3}]}$$

Where,

P[.] = the probability of the event

$MS(s)_{i,t}$ = 1 for switch in market share leadership of brand i at time t, and 0 otherwise

$Q(s)_{i,t}$ = 1 if there is a switch in quality leadership of brand i at time t , and 0 otherwise

We test the effect of 1 to 3 lags of quality, because rarely a switch in market share occurs more than 4 years after the switch in quality.

We identified 32 switches in market share and 33 switches in quality in our entire dataset of all the products categories. Table 3 presents the switches by market.

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This table clearly indicates that a fairly frequent switch in market leadership occurs within a relatively short period of time. Market leadership rarely rests with a single brand and keeps switching from brand to brand. On average, market leadership changes every 4.9 years. In contrast, consider that Coke has maintained market leadership for over 100 years. A larger number of other leading brands in various traditional markets have been able to sustain their market dominance for extraordinarily long periods of time (see Table 2 in Golder and Tellis 1993).

The result of logit analysis of this data is in Table 4. The Logit estimates indicate that a switch in quality has a significant but relatively small current effect on the probability of a switch in market share leadership and a relatively large effect at the first lag. Its effect subsequently decays but is effective for 3 periods. This result provides some validity for our assumption in the theoretical model that installed base of the network should be computed on sales or market share of the last 3 periods. The U^2 is 0.28 with a correct positive hit rate at 89.4%. These results clearly support the view that quality is an important driver for market share dynamics. Perhaps because some consumers are informed, markets are not perverse, and respond to quality. Because the direction of causality is apparent in this analysis, we did not find it necessary to carry out a Granger test of causality.

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However, this analysis also does not explicitly account for the effect of network effects, does not compare this effect with that of quality, and does not estimate the proportion of informed consumers in the market. The subsequent econometric estimation of Equation 5 can achieve these goals.

ECONOMETRIC ANALYSIS

Our main analysis of the drivers of market share consists of an econometric estimation of the parameters in the market share flow equation expressed as equation (5). Since equation (5) is a nonlinear function, we adopt the Nonlinear Least Squares (NLS) approach and use SAS-NLP procedure for estimating that equation, which is based on the Gauss-Newton iterative methods. We first report the estimation result of pooled analysis, where all the nineteen products and all the years are stacked to generate one estimate. Table 5 shows other results of this estimation.

****
Insert Table 5 here
****

The estimate of θ is 0.19. This implies that about 19% of the population is informed. We can assess the external validity of this fraction from our knowledge of magazine circulation, penetration of computers products, and the number of households in the US. For this purpose, we assume that informed consumers become so primarily by reading computers magazines. For about the median time period of our data, we came up with the following rough estimates for these variables. The total number of subscribers of the three major computers magazines is about 3 million. The households in the US are approximately 90 million. The penetration of computers in these households is approximately 30%. We also assume many more consumers read these magazines at work or in libraries that subscribe to them. So the actual number of informed consumers is larger than the number of magazine subscribers. Combining these figures, gives an estimate of the fraction of informed at 20%, close to the number we obtained from the model.

Furthermore, both estimates of the network effect and the quality effect are significant, indicating that both factors play important role in determining market leadership. In terms of the relative importance of these two factors, the parameter estimate of β is 2.28 and that of γ is 0.90. We may not be able to directly assess their relative importance based on these parameter estimates because they are not standardized. Due to the non-linear nature of the estimation, we are not able to obtain standardized coefficients. Therefore, our comparison of the relative impact of network effect vs. quality is based on partial and marginal R^2. Green (2003) suggests that while R^2 is not bound between 0 and 1 in non-linear regression models, it is nonetheless a useful metric of how the model fits the data. The full model with both network and quality variables has an R^2 of 0.76 which indicates a good fit to the data. The market-share model with quality alone has an R^2 of 0.48 and the model with network size variable alone has an R^2 of 0.62. Thus the effect of the network seems larger than that of quality. The marginal R^2 of the network effect in the pooled sample is 0.28 and that of quality is 0.14. Thus, based on this statistic again the network effect seems larger than the quality effect. So we conclude for the markets we sample, the network effect plays a more important role than quality in driving market dynamics.

However, our simulation suggests that the threshold value for network effect is 1.6 above which the market is perverse. The estimated value for the network effect is 0.9, substantially lower than the threshold value. It indicates that the market is not perverse even though network effect is stronger than quality effect. Moreover, the estimated value is within the region in which the network value *enhances the effect of the quality.*

Taken together, these results mean that since θ is greater than 0, at least some consumers are informed. Second, the network effect is stronger than the quality effect, even though the latter is also important. Third, the network effect is not so excessive that the market is perverse. These estimates are very robust and insensitive to different initial values. This result provides quite compelling evidence that high-tech markets are efficient and are strongly responsive to both the network size and quality of brands.[5]

In order to enhance the validity of our findings, we also conducted separate estimations on the following three subcategories based on their information structures: 1) collaborative products vs. non-collaborative products; 2) office suite products vs. non-office suite products; 3) product categories with Microsoft brands vs. categories without Microsoft brands. Results are in Table 6.

****
Insert Table 6
****

We split the sample based on our preconception of the strength of network effect in each sub-market. We want to investigate in network dominated segments, whether the network effect is excessive, whether quality still has an important role to play, and whether the market is perverse. The detailed rationales for these subcategories are as follows.

[5] The value of k parameter is close to 0.05, i.e., the data is consistent with even uninformed consumers putting non-zero weight on quality but that they give relatively much more importance to the network size than their informed counterparts.

1) Collaborative vs. Non-Collaborative Products

Collaborative products, such as word processor, spreadsheet, PowerPoint, database, and desktop publishing, are those for which users work together with others on collaborative projects. As such, network effects would be stronger for collaborative product than non-collaborative projects. Word-processors are the best examples to describe the collaborative products in our sample. Even though translators now exists for converting from one brand of a word-processor to another, subtle features may be lost, such as fonts, equations, or tracking of changes. So, users derive more utility from a brand as more users adopt it. So, we expect that consumers' reliance on the network size is stronger for collaborative products than for non-collaborative products.

Several findings emerge from the empirical analysis of this split sample: first, both network size and quality play a significant role in driving market leadership in this sub-market. Second, the network effect is stronger than the quality effect for both submarkets based on their marginal R^2. Third, the estimate of the network effect is much lower than the threshold value γ^*, i.e., 1.79. So, the market is not perverse. Fourth, network effects are stronger in the collaborative submarket than in the non-collaborative submarkets (0.29 vs. 0.23) as we expected.

2) Office Suites vs. Non-office Suite Products

Office suites are products such as word processing, spreadsheet programs, or presentation programs that are currently packaged as an integrated bundle or suite. Some analysts argue that a suite provides consumers with an indirect network benefit because consumers derive some utility by buying all products that belong to an integrated bundle. We therefore investigate the impact of quality versus network effect in products bundled as suites relative to those products not bundled in suites. We refer to these groupings of products as submarkets.

Results enable us to draw four conclusions: First, both network and quality are important factors in both submarkets. Second, in both submarkets, the network effects are stronger than the quality effect as measured by marginal R^2. Third, neither market is perverse because the network effects are lower than their respective critical values, γ^*. Fourth, consistent with our expectation, the network effects are stronger in the suits submarkets than in the non-suites submarket (0.32 vs. 0.25).

3) Categories with Microsoft's Brands vs. Categories without Microsoft's Brands

Microsoft has been the dominant market leader for most product categories where it has a presence. Some analysts claim that this dominance is due to Microsoft's advantage in the operating system, which it leverages to makes its other software the first one of choice for consumers. Therefore, in markets where Microsoft's products compete, consumers are more likely to be influenced by some "Microsoft's network" than in other categories.

We carry out a split sample analysis contrasting estimates in all markets in which Microsoft compete versus those in which it does not compete. The estimates between these two split sample analyses are similar, leading to the following four observations. First, in both samples, network and quality are important factors in driving market dynamics. Second, the network effects are stronger than quality in both samples. Third, neither sample of markets is perverse in the presence of strong network effect. Fourth, network effects are stronger in the submarket where Microsoft has a strong presence than in the submarket where Microsoft is absent (0.29 vs. 0.25).

DISCUSSION

Research in economics emphasizes the prominent role of network effects in driving market dominance of high-tech products by a single leading brand. As such, researchers suggest that such markets could be perverse with the inferior quality brand having the highest market share. Yet, a few authors claim that markets for high-tech products are quite efficient with the best quality brands always having the highest market share.

We developed a theoretical model which integrates these rival positions by showing that the efficiency of markets depends on the reliance of consumers in the network versus their demand for and information about product quality. We then carry out an empirical analysis to estimate the parameters of the models and assess the efficiency of markets. The next three subsections present the summary results, implications, and limitations of our study.

Summary of Results

Our major results can be summarized as follows:

Theoretical results:

- When the informed customers segment is small, and consumer reliance on the network is excessive (i.e., γ exceeds certain critical values), the market could end up perverse. In such markets, an inferior quality brand can be the market share leader or even the dominant brand.
- When a significant number of customers are informed and consumers' tendency of following network effect is moderate, the market is more efficient than it would have been without any network effects.

Exploratory empirical results:

- Market leadership changes frequently and market leaders hold sway for an average of a mere 4.9 years.
- Change in market leadership is generally associated with a change in quality the same year or a few years earlier.

Econometric results:

- Both network and quality are important factors in all markets and submarkets.
- The network plays a stronger role than does quality in all markets.
- Network effects are indeed stronger in some submarkets where we expect consumers benefit more from such networks than they do in other markets.
- Even in the presence of strong network effects, the market is not perverse in general or in any of the sub-segment.
- The estimate of the network effect lies in the region that it enhances the role of quality.

Implications

Our results have some important implications for business strategy and public policy.

Is “Rush to Market” a Right Mantra to Follow?

As previously discussed, high-tech firms spend enormous resources in rushing new products to market in an attempt to outpace their respective competitors. However, the undeniable truth is that many new products fail. One of the major reasons of these failures is the premature product launch undertaken by many high-tech managers who rush to market, encouraged by the popular myths of path dependence and pioneering advantage. The current inquiry suggests that superior quality appears to be a very important driver of success. Thus firms may need to put a premium on quality rather than on speed to market.

Are Network Effects a Reliable Shield for Existing Leaders?

Were the theory of network effects as strong as some claim, existing market leaders should be persistent winners because consumers will not adopt a new product that has a small user network, as the network effects theory implies. This study shows that switches in quality leadership consistently result in switches in market leadership, albeit with a lag of up to three years. Thus, even established market leaders, though they enjoy a large network of users, are vulnerable to threats from new entrants that introduce superior alternatives. A network is not a reliable shield on which an existing leader can rely. Constant quality enhancement is an effective way for existing leaders to defend their current positions.

Are Network Effects the Devil Responsible for Perverse Equilibria?

Network effects have been blamed as the devil that causes market inefficiency, e.g., an inferior product or standard can dominate the market simply because of its large network size. However, our analysis indicates that network effects, under certain circumstances, can make the market more efficient. If sufficient consumers are informed, and consumer reliance on network is moderate, then network effects enhance the role of quality, because uninformed consumers benefit from the decisions of informed ones. Consequently, the entire market settles on the better product more quickly and at a higher level than it would have in the absence of network effects. In this case, network effects speed the transfer of information from the informed to the uninformed.

Should Government Substitute For the Invisible Hand?

In the networked world, as a prominent economist states, "markets cannot be relied on to get things right"(Krugman 1994, p.235). Such thinking implies that government intervention seems to be a legitimate way to rescue the market in which the so-called "invisible hand" malfunctions. Therefore, governments should investigate and control firms' efforts to make standards or establish networks. The cases by the Federal and State governments against Microsoft are at least partly motivated by this argument.

This study shows that quality plays an important role in driving the success of these high-tech giants, even though strong network effects are present. It seems that markets do settle on the best option while remaining open to better ones. Therefore, high-tech markets are reasonably efficient and rational. Government intervention, which is intended to assume the role of the "invisible hand" in high-tech markets, may be costly and counterproductive.

Limitations and Future Research

This research has several limitations, which could be addressed by future research. First, we do not take other marketing variables into full consideration. The apparent omission is again due to data availability. This omission may be justified to some extent by the fact that consumers tend to be less influenced by price, advertising, and other promotional activities in high-tech markets due to the comparative pricing of brands that differ primarily on quality.

Second, we do not account for distributors, especially retailers. Now, as long as the retailers do not have brands of their own, they would not be able to exploit network effects differently from the manufacturer brands. This is the situation for most of our categories, which involve software products and microprocessors. Thus, exclusion of distributors in this model is not a serious problem. However, extensions of the model to markets in which retailers do exploit network effects different from manufacturers would be interesting.

Third, our empirical data was unable to account separately for switching costs. To the extent these costs are prevalent and we do not account for them, the network effects we estimate will be on the low side. However, our extended model shows that except for an extreme level of switching cost, our basic propositions still hold. Fourth, our modeling does not take into account game theoretic strategies that firms could adopt when choosing the level of quality. Nevertheless, our simple model yields some important insights and provides a good background for the econometric analysis.

Table 1

Panel A: Existence of Perverse or Efficient Markets

Size of Informed Segment (θ)	Quality Parameter (β)	Critical Value of Network Effect Parameter for Efficient Market (γ^*)
0.1	0.25	0.756
0.1	0.50	0.829
0.1	1.0	0.958
0.1	2.0	1.154
0.1	5.0	1.263
0.2	0.25	0.803
0.2	0.50	0.912
0.2	1.0	1.135
0.2	2.0	1.563
0.2	5.0	1.822

Note: The other parameters for the simulation are: $Q_1 = 7$, $Q_2 = 9$, and $k = 0.05$

Panel B: Efficiency and the Network Effect

		Reliance on Network (γ)			
		0	0.5	1	2
Responsiveness to Quality (β)	0	0.50	0.50	0.07	0.003
	0.5	0.54	0.65	0.11	0.003
	1	0.58	0.71	0.95	0.006
	2	0.60	0.73	0.95	0.04
	5	0.60	0.74	0.96	0.23

Note: The reported numbers in this panel are our measure of efficiency in the market, i.e., the equilibrium market share of high quality late entrant that enters the market with a quality advantage but a network disadvantage. The other parameters for the simulation are, $Q_1 = 7$, $Q_2 = 9$, $\theta = 0.2$ and $k = 0$.

Table 2

Description of Sample

Categories	*Platform*	*# of Brands*	*Ave. Quality*	*Ave. Price*	*Ave. MS*
Operating systems	PC	3	6.4	113	0.33
	Network	3	6.9	2914	0.27
Word processors	PC	3	6.6	237	0.29
	Mac	2	8.7	406	0.39
Spreadsheets	PC	3	6.9	125	0.30
	Mac	3	8.2	393	0.29
Project Software (High-end)	Win	2	6.2	4750	0.17
Project Software (Low-end)	Win	3	6.6	607	0.28
Desktop publishing (High-end)	PC	3	8.2	486	0.32
Desktop publishing (Low-end)	PC	3	6.9	100	0.27
Desktop publishing (Low-end)	Mac	3	7.6	NA	0.32
Graphics	PC	3	8.0	487	0.28
Image editing (High-end)	Win	3	7.5	672	0.31
Image editing (Low-end)	Win	3	7.1	387	0.27
Databases	PC	3	7.7	485	0.34
Personal finance	D+W	3	8.2	40	0.26
Web browsers	W	3	7.8	42.2	0.28
ISPs	Win	3	7.1	NA	0.31
Microprocessors	PC	2	8.1	NA	0.45

Table 3

Switches in Market Leadership

Markets	Number of Switches	Time (in years)	Years Per Switch	Market Leaders
Spreadsheets	3	20	6.7	VisiCalc – Lotus – Excel
Web Browsers	3	7	2.3	Mosaic – Netscape – Internet Explorer
Databases	3	17	5.7	dBASE – Paradox – MS Access
Business Graphics	3	12	4	Freelance - Harvard Graphics – PowerPoint
Word Processors	3	19	6.3	WordStar – WordPerfect - Word
Desktop Publishing	3	14	4.7	FrameMaker – PageMaker - QuarkXpress
Operating Systems	3	24	8	CP/M – DOS – Windows
Personal Finance	3	13	4.3	MS Money – Dollars & Sense - Quicken
Internet Service Providers	3	8	2.7	Prodigy – CompuServe – AOL
Project Management	1	7	7	TimeLine - Microsoft Project
Image Enhancement	2	9	4.5	PicturePublisher –PhotoStyler - PhotoShop

Part of this table is adopted from Evans, Nichols and Reddy (1999)

Table 4

Logit Analysis of Leadership Switches

Dependent variable: switch in market share

Independent Variables	Coefficients	Std. Error	Wald
Quality switch (t)	1.58*	0.70	5.13
Quality switch (t-1)	3.38**	0.57	34.9
Quality switch (t-2)	2.22**	0.64	11.9
Quality switch (t-3)	1.17	0.45	1.82
Correct Prediction (cut value=0.5)	89.4%		
U^2	0.28		
N	301		

** < 0.005
* < 0.05

Table 5

Estimates of Market Share Response Model (Equation 5)

For the Overall Market

	Parameter	Estimate (non-standardized)	Std. Error	t-statistic	Marginal R^2
Reliance on Network	γ	0.90	0.05	18.88	0.28
Responsiveness to Quality	β	2.28	1.05	2.17	0.14
% of Informed Consumer	θ	0.19	***	***	
Quality Multiplier for Uninformed	k	0.048	***	***	
		No. of Observations = 534	R^2 = 0.76		

Note: The last two parameters are bound between 0 and 1. As such, they were estimated after an exponential re-parameterization. Both the parameters were statistically significant at 5% level.

Table 6

Split-Sample Estimation Results

Parameter (non-standardized)	Collaborative	Marginal R^2	Non-collaborative	Marginal R^2	Office	Marginal R^2	Non-Office	Marginal R^2	Microsoft	Marginal R^2	Non-Microsoft	Marginal R^2
γ (network)	0.98	0.29	0.79	0.23	1.10	0.32	0.81	0.25	0.93	0.29	0.80	0.25
β(quality)	1.34	0.17	1.93	0.12	4.23	0.12	1.63	0.16	2.22	0.14	2.92	0.16
θ(informed)	0.22		0.25		0.18		0.21		0.20		0.14	
γ^*	1.79		1.36		1.51		1.58		1.49		1.62	

Note: All estimated parameters are statistically significant at 5% level or below.

Figure 1 – Panel A

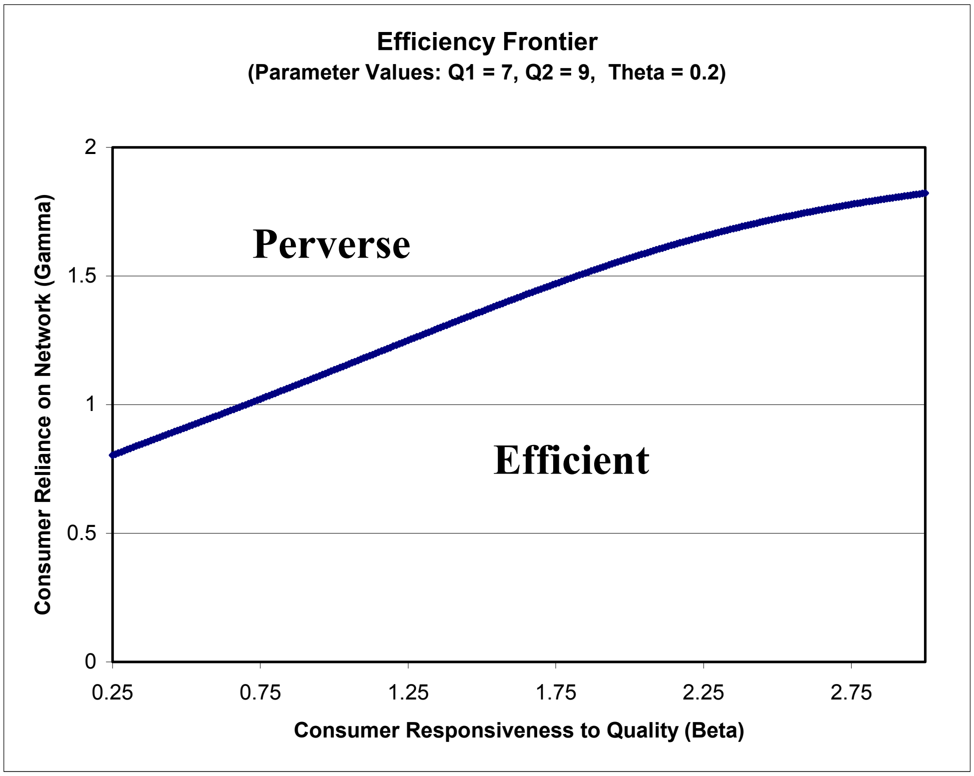


Figure 1 – Panel B

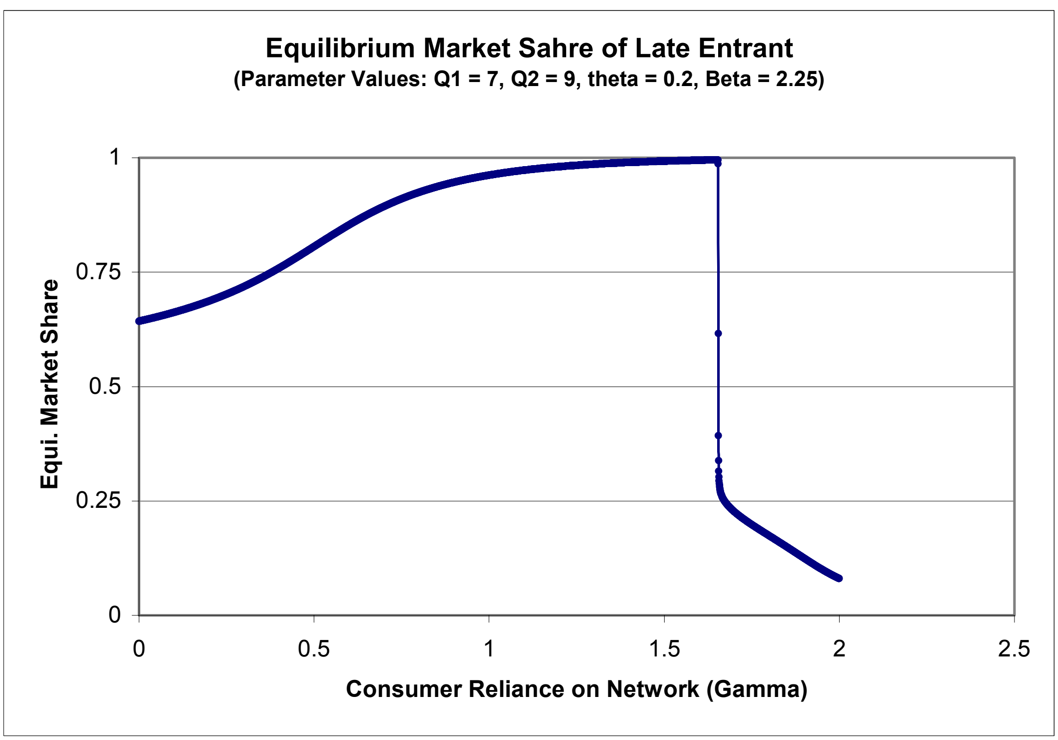


Figure 2–A

Market Share and Quality Flows in Spreadsheet Market

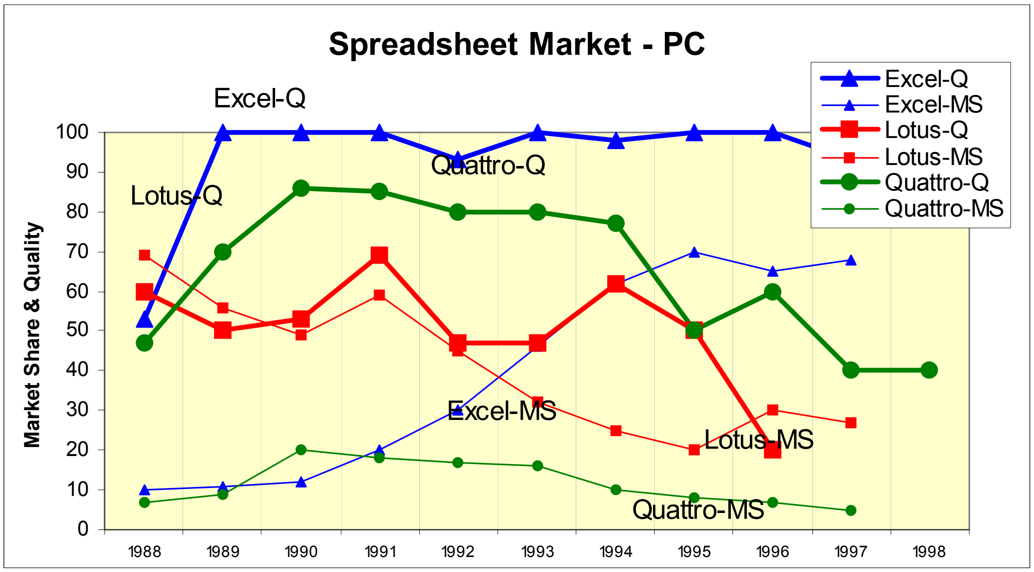


Figure 2–B
Market Share and Quality Flows in Personal Finance Software Market

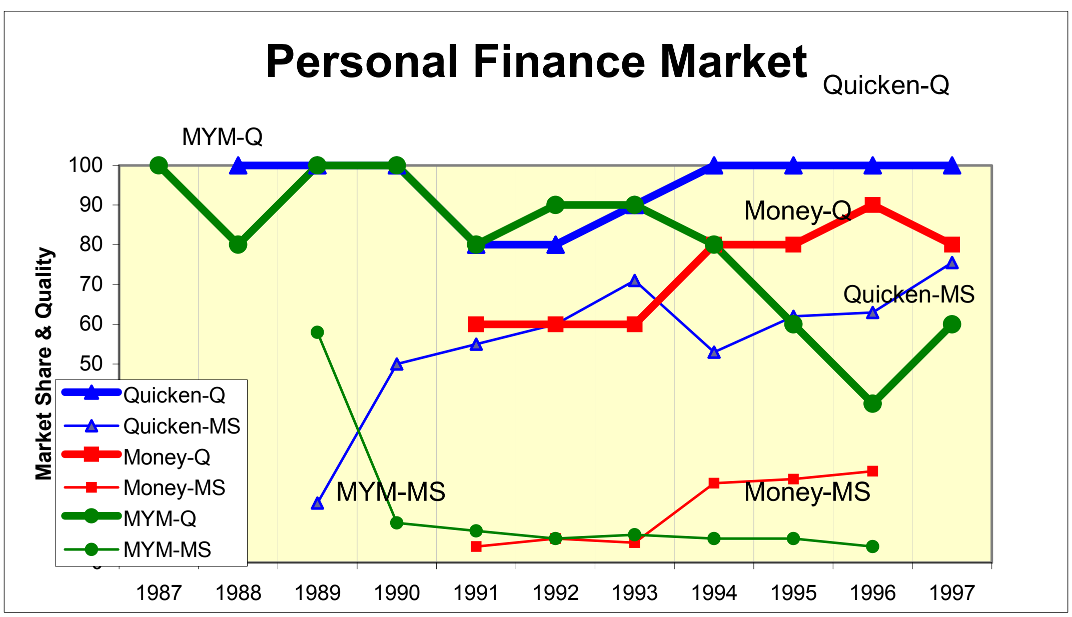
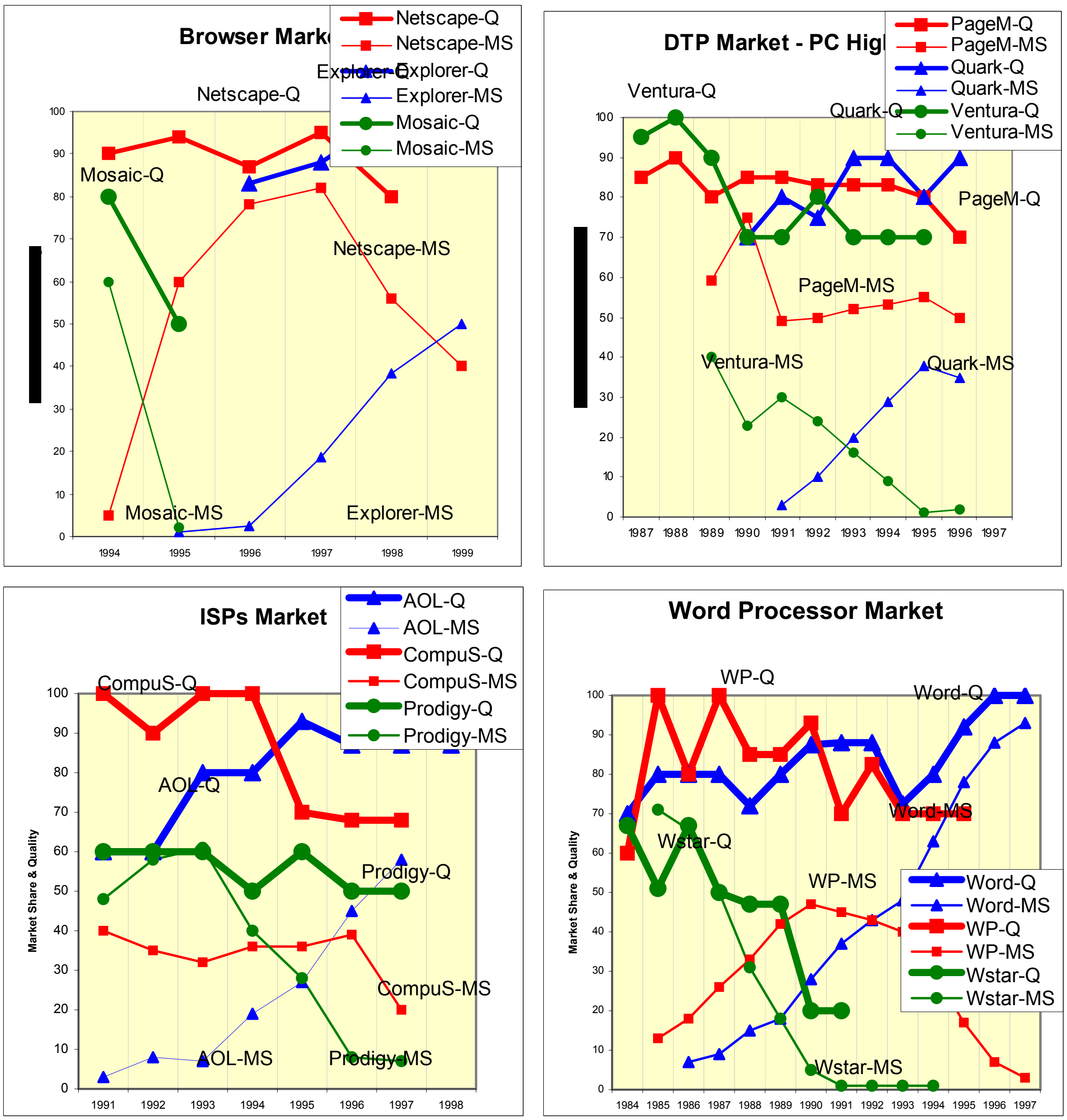


Figure 3
Market Share and Quality Flows in Four Software Markets



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Appendix 1

Quality Scale for Content Analysis

The outline for quantifying review information is given as follows:

1) **Excellent – 10: A market leader that offers exceptional performance**
    - It is considered the most powerful product available today
    - This product is the big winner
    - Editor's Choice
    - This product is excellent
    - This product could be one of those milestones that change the way we use computers
    - It is unquestionably the most powerful product you can buy
    - It is miles ahead of the competition
    - The product stands at the top
    - It is the very best product of the year
    - This product has a very good chance of establishing a new standard
    - It is one of the products that does everything right
    - It is clearly the most richly endowed product that you can purchase
    - It is an outstanding performer for its wealth of features and flexibility

2) **Good – 8: Excels in many areas; a good buy**
    - This product is an attractive alternative
    - This product is a good choice
    - This product is a serious threat to the current standard
    - It is an impressive product
    - It is a richer product than its principal competitors

3) **Acceptable – 6: Average for its class; a justifiable purchase**
    - The product is well thought out, but there are still a few problems with it
    - It is an economical and elegant program. Is it a right product for you? As usual, it depends
    - It is a popular choice. However, it may not make you happy
    - It is a strong competitor to its rival. However, its major weakness is….

4) **Poor – 4: Out-of-date or substandard; positives offset by more negative features**
    - It is a product I would love to love, but can't
    - It has been outdistanced by its competitors
    - It looks dim beside its competition
    - In many ways, it still clings awkwardly to its past
    - It performs unsatisfactorily

5) **Unacceptable – 2: Missing necessary features; avoid**
    - It scored the lowest in overall satisfaction
    - It occupies the lowest spot
    - It is definitely bad
    - It is very poor
    - It performs quite sluggishly
    - Definitely avoid/do not buy

Appendix 2: Model with Switching Cost

Compared to the model in the paper, we now need to account for a proportion of consumers who are repeat buyers, i.e., existing users who are replacing their product. To accommodate this, we need to make the following two additional assumptions:

i). Every body who wants to upgrade does so after three periods.

ii) A proportion (p_t) of each year's market (for t > 3) consists of repeat customers.

For this model, we derive the market-share flow equation in three steps. The first step specifies the utility derived by the individual consumers.

Step I: Individual Utility

The deterministic portion of utility for the informed consumer *j,* for purchasing brand *i*, in time period *t* is given by:

(A1) $$U_{ijt}^{IN} = (\beta Q_{it} + \gamma N_{it} + \delta X_{it,j})$$

Like before, Q_{it} is true quality of brand *i*, N_{it} is the network size of brand *i* . The variable $X_{it,j}$ is an indicator variable that takes the value 1, if consumer *j* is considering replacing brand *i* in period *t*, and 0 otherwise. Reflecting the idea that the products have a replacement cycle of three years, N_{it} is given by the sum of market shares in the three immediately preceding periods, i.e., $N_{it} = m_{i(t-1)} + m_{i(t-2)} + m_{i(t-3)}$, β is the quality weight parameter, γ is the network weight parameter and δ is the switching cost parameter in determining the utility.

The utility of uninformed consumer l, for brand i, in time period t is given similarly by:

(A2) $U_{ilt}^{UN} = (k\beta Q_{it} + \gamma N_{it} + \delta X_{it,j})$ where $Q_{it}, N_{it}, X_{it,l}, \beta, \gamma$ and δ have the same meaning as those for the informed consumers in equation (1) above, and *k* is a multiplier for the quality weight parameter which takes non-negative values strictly lower than 1, i.e., $k \in (0,1]$.

Step II: Probability of purchasing different brands

Continuing to assume that the unobserved random portion of the utility is distributed iid type I extreme-value (Gumbel), leads to the following probability of buying brand *i* at time *t* for consumers belonging to the two segments respectively:

(A3) $$\Pr ob.(\text{choice} = i \mid Q_{it}, N_{it}, X_{it,j}) = \frac{e^{U_{ijt}^{IN}}}{\sum_{i \in I} e^{U_{ijt}^{IN}}}$$ and

(A4) $$\text{Prob.}(\text{choice} = i \mid Q_{it}, N_{it}, X_{it,l}) = \frac{e^{U_{ilt}^{UN}}}{\sum_{i \in I} e^{U_{ilt}^{UN}}}$$

Step III: Expected market-share of different brands

Unlike the model in the paper, now we cannot interpret the probabilities in (A3) and (A4) as market shares of the brands in the market since the consumers are differentiated within each segment with respect to a crucial characteristic, i.e., their existing brand that they are considering replacing, and therefore whether they face a switching cost or not in buying different brands. Thus, we need to aggregate the expected probability obtained in step II above separately for repeat customers, (denoted by subscript R) and fresh customers (denoted by subscript F) within the two segments of informed and uninformed customers and then add up the market shares for brands within each segment.

First note that for the first three periods, there are no repeat customers and hence all indicator variables $X_{it} = 0$ for all customers. Thus, the market share for these years is just like that in the model in the paper. Similarly, for the fresh customers in the market, that will continue to be the market share.

(A5) $$m_{Fit}^{IN} = \frac{e^{(\beta Q_{it} + \gamma N_{it})}}{\sum_{i \in I} (\beta Q_{it} + \gamma N_{it})}$$ and (A6) $$m_{Fit}^{UN} = \frac{e^{(k\beta Q_{it} + \gamma N_{it})}}{\sum_{i \in I} (k\beta Q_{it} + \gamma N_{it})}$$

The equation for repeat customers of informed segment is given by:

(A7) $$m_{Rit}^{IN} = m_{i(t-3)} * \frac{e^{(\beta Q_{it} + \gamma N_{it} + \delta)}}{\sum_{i \in I} e^{U_{ijt}^{IN}}} + \sum_{-i} m_{i(t-3)} * \frac{e^{(\beta Q_{it} + \gamma N_{it})}}{\sum_{i \in I} e^{U_{ijt}^{IN}}}$$

Note that market-share among the informed segment consists of two parts, the first part reflects the consumers who do not face a switching cost if they buy brand *i*, since they are the existing customers of brand *i*, having bought it three periods ago. The second part of the expression reflects the existing users of all other brands (other than *i*, denoted as *–i*). Each part is weighted by the market share of the brands three periods ago. This mirrors the underlying heterogeneity within the informed segment, which naturally forms because these customers face different utility trade-offs depending upon what brand they are existing customers of. The equation for segments is also very similar with similar interpretations, and is given below:

(A8) $$m_{Rit}^{UN} = m_{i(t-3)} * \frac{e^{(k\beta Q_{it} + \gamma N_{it} + \delta)}}{\sum_{i \in I} e^{U_{ilt}^{IN}}} + \sum_{-i} m_{i(t-3)}^{UN} * \frac{e^{(k\beta Q_{it} + \gamma N_{it})}}{\sum_{i \in I} e^{U_{ilt}^{IN}}}$$

Finally, the total market share in period t can be expressed as a weighted average of the market shares within the four segments weighted by, weighted by their respective proportions in the overall market. Thus, we have the general expression as the final market-share flow equation:

(A9) $m_{it} = (1 - p_t)[\theta * m_{Fit}^{IN} + (1 - \theta) * m_{Fit}^{UN}] + p_t[\theta * m_{Rit}^{IN} + (1 - \theta) * m_{Rit}^{UN}]$.

Since equilibrium of this model is also an analytically intractable expression, one would need to conduct numerical simulations to find equilibrium market share and its sensitivity to different parameters. This market share flow equation (A9) can be empirically estimated with data on quality, market share and proportion of repeat buyers in the market over a number of time periods. Since we do not have all the data to empirically estimate this model, we simulate the market as it unfolds for a wide range of new parameters and missing data (δ and p_t) respectively. A situation where δ or p_t is zero is equivalent to our base model in the paper since switching cost is applicable only to repeat buyers. In our simulations, we find that as far as market efficiency is concerned, unless the proportion of repeat buyers is very large in the initial years (to the order of 90% of the market or higher) and unless δ is simultaneously very high, both our propositions in the paper, i.e., (i) quality matters for market share and (ii) for a broad range of parameters, higher network effect actually enhances the efficiency in the market, remain valid. This is because as the effective network refreshes itself, high quality brand establishes a foothold and gets stronger as repeat purchases by these customers solidifies its position. The process does not get a chance only when in the initial years of competition, most customers are repeat customers whose switching cost prevents them from buying the higher quality product and thus the new product never takes a foothold.

Conclusion

This extended model shows that except for an extreme level of switching cost, our basic propositions hold.