

Does Quality Win? Network Effects versus Quality in High-Tech Markets

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ABSTRACT

Researchers disagree about the critical drivers of success in and efficiency of high-tech markets. On the one hand, a few researchers assert that high-tech markets are efficient with best quality brands dominating. On the other hand, many authors suspect that network effects lead to perverse markets in which the dominant brands do not have the best quality. We develop scenarios about the relative importance of these effects and the efficiency of markets. Empirical analysis of historical data on 19 categories shows that while both quality and network effects affect market share flows, markets are generally efficient. In particular, market share leadership changes often, switches in share leadership closely follow switches in quality leadership, and the best quality brands, not the first to enter, dominate the market. Network effects enhance the positive effect of quality.

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

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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. Many authors have questioned 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, p108) 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 accidents." 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; Tellis and Johnson 2007). In particular, Liebowitz and Margolis (1995, 1996, 1999) cite several examples to argue that quality is the principal driver of market position. 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 seems counter to the behavior 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. We define an efficient market as one in which the best quality brand (after adjusting for prices) emerges with the largest market share. This definition is similar to that used by Hjorth-Andersen (1984), Kamakura, Ratchford, and Agrawal (1988), and Tellis and Fornell (1988).¹

¹ This definition would correspond to the standard definition of efficiency in economics, e.g., maximizing the sum of consumer and producer surplus under the following two assumptions. First, consumers prefer the better quality product even if it comes at a higher price because they freely chose the option that leaves them with higher surplus. Second, the higher quality product commands an equal or higher margin, either because consumers are willing to pay more or firms can produce it with superior technology at lower cost.

Empirical studies in marketing have not yet tackled this issue sufficiently. These studies either focus 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 of success of new high-tech products. In particular, no study has explicitly examined the relative importance of quality vis-à-vis network effects in a unified framework, tested on the same categories, while drawing implications about market efficiency in these markets. 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 managerial strategies. Third, whether, as argued by many economists, network effects are as strong as to dominate and negate the role of quality leading to market inefficiency has profound policy implications.

Does the presence of network effects really swamp consumers' responsiveness to quality as many expert economists claim? How do quality and network effects interact in contemporary markets? Could there perhaps be an interaction effect, where network effects may *enhance* the effect of quality? What does the empirical evidence show? The primary goal of this paper is to answer these questions via empirical analyses.

The next section explores theoretically how quality and network effects may interact in markets. Section 3 describes the method for collecting data to empirically test market response to quality versus network effects. Section 4 analyzes the data via graphical analysis of market share flows, categorical and logit analyses of switches in market leadership, hazard analysis of time for a small superior-quality brand to assume market leadership, and regression analysis of market

share flows. The final section discusses the study's implications, limitations, and directions for future research.

Theory of Competition on Quality and Network Effects

Consider a high-tech market in which brands may differ on two key dimensions: network effects and quality, after adjusting for price differences.² We can think of quality as a composite of a brand's attributes, on each of which consumers prefer more to less (Tellis and Wernerfelt 1987). Examples of such attributes are reliability, performance, convenience and so on. We can think of the network as the number of users of a brand.

Now assume brands in this market differ in *initial* market shares, primarily because of the time in which they enter this market, the brands' parentage, or some such extraneous factors. As a result, their network sizes would also be different – the brand that enters first will have a hundred percent market share and the entire user-base to itself before other brands enter. How would the year-to-year market shares of various brands in this market evolve in response to network effects and quality, and what would be their equilibrium market shares? We can think of five important cases, depending on whether consumers in this market value neither one of these dimensions (quality and network of users), either one of these dimensions, or both of these dimensions. To motivate and interpret the empirical analysis, we here explore what market outcomes would emerge in each of these cases (the five cases are summarized in Table 1).

[Place Table 1 about here]

Case 1

First, as a base case, suppose that consumers do not put an adequate value on quality or network size because the cost of information on quality or the network is very high. In that case, consumers would pick randomly from the available brands in the market (adjusting for price

differences). After a time period equal to the repurchase cycle, say three years, every consumer would have bought or repurchased in the category at least once. Thus, over a time period exceeding the repurchase cycle, after adjusting for price differences, if switching costs are not important, all brands have equal market shares irrespective of the brand's real quality or initial market share. If switching costs are important, then the brand which enters first would permanently dominate the market, irrespective of the brands' network or quality. Thus, in either condition, the presence of network effects will not swamp consumers' responsiveness to quality.

Case 2

Second, assume that consumers value the network of users and not quality. In this case, consumers would poll their network of co-workers (or co-authors) to find out what brand they are using. To minimize inconvenience and maximize utility, they would buy the same brand that their co-workers use. Further, if all of their co-workers do not use the same brand, they will adopt the one used by the highest proportion of their co-workers. This is a popularity-sensitive market, which is likely to have an outcome that depends on the starting point. Assuming brands differ in network size due to the order of entry, parentage, or some other pre-existing factors other than quality, then, in each period, the brand with the larger network size will stand a higher probability of being the one which is most used by a consumer's co-workers and thus adopted by the network dependent consumers.³ The exact probability of this occurrence can be derived⁴. As

² The empirical analysis controls for prices via an independent variable, for the cases for which price data are available

³ The case of exactly equal market shares of brands is almost never observed in practice, and even in theory it would be highly unstable or "tippy" (Stanley and Farrell 1994; Katz and Shapiro 1985). Hence it is not considered in detail.

⁴ For example, in a two-brand case, with brands A and B having market share a and b respectively, the probability of A being chosen is, the sum of the terms when a occurs more often than b plus half the terms when a occurs the same time as b , in the expansion of the binomial theorem $(a+b)^n = \sum_{k=0}^n \binom{n}{k} a^{n-k} b^k$, where n is the number of network members that a consumer samples and a occurs more than b when the power of a is greater than that of b , and a occurs the same as b when its power is the same as b in the terms of the binomial expansion.

a result, over time, the brand with the largest network size due to initial conditions will dominate the whole market. If its quality were inferior to that of other brands in the market, after adjusting for prices, then the market would be inefficient. Thus in this case, the presence of network effects will swamp consumers' response to quality.

Case 3

Third, assume that consumers value quality and not network effects. In this case, in every period, those consumers who decide to buy the product will compare brands on their quality and choose the one that has the better quality. Assuming the higher quality brand does not charge too high a price premium, this market will quickly converge on the best quality brand. Indeed, this convergence will occur within the time of the purchase cycle, typically one to three years for many high-tech products. In such a market, market shares will be strongly responsive to quality and not dependent on prior period's market share and the market would be efficient. Again, in this case, the presence of network effects will not swamp consumers' response to quality.

Case 4

Now suppose the market is segmented with some consumers valuing network effects while others valuing quality. What would the equilibrium market look like? The casual reader might conclude that this is a combination of Cases 2 and 3. So the net result would be a weighted average of those two cases, with the weights equal to the proportion of segments in the market. However, the answer is not that simple for the following reason. If the two types of consumers are dispersed randomly across the population, those consumers who value quality will decide to choose based on the quality of brands. Within the time of the purchase cycle, all these consumers will converge on the best quality brand in the market. Now, those consumers who rely on the network would poll their coworkers. Some of their coworkers would be quality conscious and

would have chosen the best brand in the market. At least some network-valuing consumers will find that a majority of their co-workers will be quality conscious. So they will also end up choosing the best quality brand in the market. In subsequent periods, network valuing consumers who poll these latter consumers will also be led to the best quality brand in the market. So, in every period, the proportion of consumers who choose the best quality brand in the market will increase. Thus, the whole market will converge towards the best quality brand, albeit slowly. This would be an efficient market: even though network effects are present, they are not so strong as to create an inefficient or perverse market as in Case 1 or 2, respectively.

Intuitively, the reader will appreciate that the market share of the best quality brand depends on a) the difference in quality among the brands, b) the proportion of quality valuing consumers to network-valuing consumers in the market, and c) the proportion of consumers informed about quality. In this case, the market is efficient. Once again, the presence of network effects will not swamp consumers' responsiveness to quality.

Case 5

How would the market dynamics change if consumers were of the following two types: some value quality highly and others buy randomly without regard to network size or quality. In other words, what would happen if the market were a combination of cases 1 and 3? The result would be similar to Case 4, except that the convergence to the best quality brand would occur more *slowly* than in Case 4. Why so? The reason is that when some consumers value the network of users, they also benefit or suffer from the good or bad choices of the network. Now if the remaining consumers all decide on quality, then some of the network dependent consumers will benefit from their good choices.

However, if the network dependent consumers were to buy randomly, they do not derive any benefit from the segment of quality-valuing consumers. Thus, a market of quality conscious

and network dependent consumers converges on the better quality brands faster than a market with quality conscious and random buyers. In other words, the presence of network dependent buyers instead of one that buys randomly enhances the efficiency of the market, *if the market also contains a segment of quality conscious consumers.*

Note that much of the economics literature describes only the deleterious effect of network effects as outlined in Case 2. However, our Case 5 points out the beneficial effect of network effects, where it enhances the role of quality due to the presence of a quality valuing segment. Tellis and Yin (2002) sketch a simple model to formally demonstrate this effect. This effect may be empirically estimated by an interaction effect of quality and network effects on market share.

Summary. The prior analysis shows that one cannot make an *a priori* case for whether network effects lead to inefficient markets or efficient markets. The outcome depends critically on how many and to what extent consumers value quality versus the network of other users versus buy randomly. How do markets really respond to quality versus network effects? Do network effects swamp, enhance, or have no impact on the role of quality on market share?

The next two sections describe an empirical study to answer these research questions. Other factors may also play a role in these markets: price, advertising, distribution, and market growth. From our experience with these markets, we think that these factors are not critical in assessing the role of network versus quality. Therefore, in the empirical analysis, we treat them as control variables as much as data enable us.

METHOD

This section describes the sampling, data collection and measure of quality.

Sampling

We choose personal computer products and services as the sampling frame since these products are supposed to have strong network effects. Thus they would favor the received wisdom of the superiority of network effects over those of quality. Within this class of products, we include the most important categories for which we could obtain data. We consider 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 consider high-end and low-end brands as constituting different product markets as shown in Table 2, column 1. On this basis, we collect data on 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 are characterized by two or three firms with one dominant brand.

[Place Table 2 about here]

Data Collection

The limited availability of suitable data has been the major hurdle in empirical research in the past. Despite an extensive effort, we do not have complete success in collecting the data we need. We collect the majority of the market share data from IDC (International Data Corporation) and partly from Dataquest. However, even these firms do not have complete or adequate data on a number of categories. In those instances where the data are not available from any syndicated source, we collect data from archival sources following rules suggested by Golder (2000).

Measures

This section describes the measure for the key variable, quality, plus the measures for the other variables used in the analysis.

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 similar measures 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* are not evaluating the quality of computer products in the past, we resort to ratings and reviews in 3 most respected and widely circulated computer magazines: *PC Magazine*, *PC/Computing*, and *PC World*. For the three Mac product categories in our sample, word processor, spread sheet and DTP, we collect quality data from the leading magazine for Mac computers and software, viz. *Macworld*. We consider reviews for each of our brands for each year in the sample. However, since many of the magazines publish reviews without numerical ratings, we use a content analysis of reviews to arrive at numerical ratings.

For the content analysis we first develop a set of terms that reviewers often use to describe these products. We then group these terms into five levels expressing increasing quality on a 9-point scale ranging from 2 to 10 (see Appendix A). We then utilize two independent trained 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 arrive at the quality ratings of each brand for each year by averaging the ratings generated by the two independent raters. When reviews are missing for any years, we use the previous year's ratings to fill in the missing values.

Measure for other variables. Other key variables in our analysis are network size, price and growth rate. In creating a measure for network effects, we estimate that the repurchase cycle for all of these markets is about 3 years. This estimate is based on personal experience, interviews with some senior IT managers, and interviews with some consumers. Both indicate that software is typically upgraded or repurchased at least within three years. So, we measure network size using the accumulated market share of a brand in the past 3 years.

This measure differs from past work that measures network size by using the entire installed base of brands (e.g., Brynjolfsson and Kemerer 1996). We do not think that the entire installed base of a brand is an appropriate measure for its network size, especially for quickly evolving high-tech products. We believe that time of adoption or recency of purchase of the product matters for these products. Due to frequent repurchases and upgrades, the brands actually in use are the ones bought relatively recently (say in last three years). Hence, consumers would care about the more recent and thus more relevant network size of the brand rather than the total units of the brand ever sold (Liebowitz and Margolis 1999). Under the assumption that for such products, the average repurchase time is about 3 years, we use the accumulated market size of the past 3 years as the relevant network size for the brand under consideration. For the empirical analysis, we also repeat the analysis with taking the network as accumulated market size of the past 4 or 5 years. The results remain substantially similar.

We collect price data from the same sources as for the quality data, namely, from the three leading PC computer magazines, i.e., *PC Magazine*, *PC/Computing* and *PC World*, and one Mac computer magazine, i.e., *Macworld*. The price data are scattered around each issue of magazines in primarily two types of sources, the articles/features and the ads. We hire two graduate students to undertake this painstaking effort in locating all relevant pricing data for the brands that are included in our sample. We then compile all the price data into meaningful format by brands. For multiple entries in the price data for the same brands in the same year, we take the average of the multiple pricing data. If there are missing data in a specific year, we take the price of the previous year as the price for that year.

Collecting category growth data also required a considerable effort. We first search for all the available IDC reports on the product categories that are included in our sample. Within IDC reports, there are sometimes multiple unit sales data for the same product categories with overlapping time periods. To deal with the multiple data series, we adopt the data series that has the most complete data, then use the alternative data series only to fill in gaps in the first data series. When the two data series are of equal length, we take the average of the two series and come up with the final unit sales data for that product category. In addition to actual data, the firm has estimated data for the most recent years. To construct an accurate and consistent data series for all product categories, we first use actual data as much as we can. For more recent years where the actual data are not available, we use the estimated data. Once the unit sales data are collected, we compute annual growth rates for the category.

ANALYSIS AND RESULTS

We conduct several different analyses to address the research questions: 1) simple graphical analysis of market share flows, 2) categorical analysis of switches in market share and quality, 3) logit analysis of switches in market share, 4) hazard analysis of market-share

leadership, and 5) regression analysis of market share flows. The purpose for each of these analyses is stated at the start of the analysis. Table 3 summarizes the purpose and results of these analyses.

[Place Table 3 about here]

Graphical Analysis of Market Share Flows

To visually appreciate the dynamics of quality and market share in these markets, we graphically plot the market share and quality flows of all brands in each market for which we have data. In the interest of parsimony, we present detailed results for only 3 markets (spreadsheet, personal finance and word processor) for illustrative purpose. Similar graphs for other markets are in Appendix B.

[Place Figure 1 about here]

Spreadsheet market. Figure 1-A presents the graphical analysis of market share and quality in the spreadsheet market. Lotus has been the unquestioned market leader in both market share and quality since 1983. In 1987, Excel is launched for the PC market. Initially Excel's quality is inferior to Lotus' quality. However, two years later, in 1989, Excel's quality rating surpasses that of Lotus. Soon after, Excel's market share increases sharply with a corresponding decline in Lotus' market share. In 1993, Excel surpasses Lotus in market share and becomes the market leader. Excel's quality is superior to Lotus' quality subsequently. Correspondingly, Excel's market share does not fall below Lotus' market share for the time period for which we have data. So we can conclude that even though Lotus is an established brand with a large network of users, once Excel enters the market, it grows from zero and surpasses Lotus' position due to its superior quality. Moreover, the time it takes for Excel to overtake Lotus in market share is 4 years after that it overtakes Lotus on quality. This time period is probably a little longer than the repurchase cycle, which we estimate to be 3 years.

In this market, the time taken to crown a new yet superior market leader is 4 years, only slightly longer than the expected 3 year repurchase cycle. Thus, this case suggests that consumers in the spreadsheet market care about both quality and the network of users. Also, the ability to switch may have been facilitated by the fact that manufacturers enable one program to read files prepared by the other programs. So, overall, the spreadsheet market is efficient, resembling Cases 4 or 5 described in the theory section, but not Cases 1, 2 or 3.

Personal finance market. In the personal finance market, the early quality leader is Managing Your Money, which is introduced in early 1980s. It is also an early market share leader. Quicken enters the market in 1986. In 1988, it is rated higher in quality to Managing Your Money. Note how its market share begins to rise right away (see Figure 1-B). In 1990, Quicken's market share surpasses that of Managing Your Money and it becomes the market leader. While Managing Your Money does briefly increase in quality in 1992, that improvement does not last. Quicken manages to sustain its market leadership ever since because its quality remains superior to Managing Your Money for most of the time. Despite distribution and operating power of Microsoft's, Quicken maintains undisputable leadership in quality over Money, and thus, in market share until 1997, for which time period we have data..

Microsoft Money enters in 1991. However, its quality is consistently inferior to Quicken's quality. As a result, its market share never surpasses Quicken's market share. This market has two important lessons for us. First, quality appears to be the primary driver of market share flows. Second, Microsoft's brands do not always have the highest quality in the market. Consequently, the market shares of Microsoft's brands are also not the highest, despite the advantages of its brand name, distribution leverage and network effects stemming from its

windows platform and other complementary products. Indeed, when the quality of Microsoft's brand lies below that of competitors, so does its market share.

In sum, the market share leadership of Quicken swiftly (within 2 years) follows its quality leadership. Thus, this case suggests that consumers primarily care about quality and the market is efficient. This result makes intuitive sense because network effects are supposedly the lightest in the personal finance market due to the fact that users rarely have the need to share and exchange files. These results suggest a market similar to Case 3 in the theory section, but not Cases 1, 2, or 4.

Word processor market (PC). In the word processor market, the early leader is WordStar, which dominates the market for a number of years. However, from 1984, WordStar's quality begins a sharp and irreversible decline (see Figure 1-C). WordPerfect surpasses WordStar in quality in 1985 and its market share rises following its quality rise. However, the market share switch between WordPerfect and WordStar does not occur until 4 years later, i.e., 1989.

WordPerfect's market share keeps rising and maintains its market leadership until 1993 when it is surpassed by Microsoft Word. Microsoft Word's quality rating surpasses that of WordPerfect in 1991 and sustains its leadership since then. In contrast, WordPerfect's quality is consistently inferior to that of Microsoft Word after 1991 and its market share steadily declines over the same time period.

This market resembles Cases 3 or 4 in the theory section, but not Cases 1 or 2. The market dynamics played out between WordStar and WordPerfect appears to support Case 4, in which the market takes 4 years to settle down on a new yet superior brand, longer than expected for a perfectly efficient market. However, the competition between Word and WordPerfect appears to be in favor of Case 3, namely, the market takes only 2 years to crown the new leader

after its quality excels. Overall speaking, the word processor market, which is possibly the most network effects driven, still appears to be efficient.

Other markets. The market dynamics in the Mac word processor market, web browser market, desktop publishing market (both Mac, PC high-end and low-end markets), ISP market, presentation graphics market, project management market, operating system market (both PC and Network markets), image management market and database software market also indicate more or less the same pattern. That is, the market shares of brands appear to rise following the rise in their level of quality. This graphical analysis suggests that most switches in quality leadership are related to and precede switches in market leadership. So, quality seems to play an important role in influencing market dynamics. Moreover, these simple graphical analyses do not indicate these markets are perverse. That is, there is no evidence that early market share leaders dominate the market for long or do so if they lose their quality edge for most markets we analyze. We provide similar graphs for other categories in Appendix B and now summarize the patterns of market share and quality flows in all 19 markets with the following categorical analysis of switches in quality and market share.

Categorical Analysis of Switches in Quality and Market Share

We next attempt to test the generalizability of key findings of the graphical analyses by a categorical analysis of the relationship of the switches in market share and quality. By the term switch, we mean that between any *pair of brands* in a market, the subdominant brand's market share or quality exceeds that of the dominant brand (note that this dominant brand may not be the overall market leader). Thus, we are restricting the word "switch" narrowly to mean switch from being sub-dominant to being dominant in either market share or quality between only that one pair of brands in the market. Under the assumption of strong (and ever-increasing) network effects, the dominant brand will stay dominant so that market leadership will not change (Case

2). So, a simple indication for the presence of strong network effects and a perverse market is the absence of changes in market leadership. If there are changes, we examine to what extent they correlate with changes in quality.

[Place Table 4 about here]

As Table 4 indicates, there exist fairly frequent changes in market leadership, which rarely rests with a single brand. The average duration of market leadership ranges from 5.5 years in operating systems to as short as 2 years in web browser. Across all categories examined in this exercise, the average duration for market leadership is only 3.8 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 also Table 2 in Golder and Tellis 1993).

In order to get a better idea of the relationship between quality switches and market share switches in these markets, we identify all switches in quality and market share in the product categories in our sample. As described in Table 4, we find that in 17 of the 19 markets, at least one switch in market share leadership occurs during an average period of 9.3 years sampled for these markets. Further, in 10 of these markets, there are multiple switches in market share. Overall, we count a total of 34 switches in market share across all the markets. Thus, as the graphical analysis also shows, market shares are in a state of constant flux. This observation does not support the existence of simple markets where consumers care only about network or randomly choose products ignoring network as well as quality.

[Place Table 5 about here]

Why is this happening? Table 5 presents an analysis for one of the causes of market share switches. Of the total 34 switches in share, 18% are related to a switch in quality the same year,

50% are related with a switch in quality in prior years, 20% are related to the sub-dominant brand already having a superior quality to the dominant brand. So, in total, 88% of the switches are related to the switches or superiority in quality of the sub-dominant brands, but only about 12% have no relationships to quality. In contrast, when there is no switch in share, we see that mostly quality of the inferior brand stays inferior.

So, overall, these results provide strong evidence that a superior quality or a switch in quality of a subdominant brand results in a switch in market share over the dominant brand. These results provide further support against Cases 1 and 2 and support for either Cases 3 or 4.

Our theory suggests that whether a subdominant brand becomes a market leader within or beyond the time of the repurchase cycle is an important determinant of the efficiency of the market. We use 3 years as the frame of reference, because for all these categories, our research indicates that the repurchase cycle is approximately 3 years. For web browser, Internet service provider, image management software, presentation graphics, and personal finance, it takes less than the 3-year repurchase cycle for a sub-dominant brand to become the new market leader after its quality excels that of the dominant brand (i.e., Case 3 is supported), while for word processor, spreadsheet, desktop publishing and network operating systems, the time to attain market leadership runs longer, e.g., 4 to 5 years (i.e., Case 4 is supported). These results demonstrate that the markets for the 1st group of products are highly efficient, so that superior products quickly gain market leadership once their quality dominates that of the rivals. The markets for the 2nd group of products are efficient, albeit markets settle down on superior brands more slowly than the repurchase cycle.

The case of the PC operating system seems a notable anomaly. This product category supposedly exhibits strong network effects, but a superior Windows quickly replaces DOS two

years after its quality surpasses that of DOS. One reason for this result is that the quality of Windows is so much better than that of DOS. Sufficient quality gap overwhelms the power of network effects. It again proves that quality rules in these markets and network effects cannot protect the incumbent leaders from competition. However, this advantage may have been facilitated by the backward compatibility of Windows to DOS.

These results make intuitive sense because the first group of products is generally believed to exhibit weaker network effects whereas the second group of products is much more influenced by network effects due to their intrinsic communication- or sharing-oriented nature. These results further support Case 4 indicating that network effects do slow down the process of superior brands taking over the market, but do not make the markets perverse.

Logit Analysis of Market Share Switches

To further investigate the role played by quality in driving market dynamics, we conduct a logit analysis of market share switches as a function of quality switches. For this analysis, we track quality and market share between every brand-pair for *every year* in all markets. For each year, between any two brands, we count whether or not a switch in market share and quality takes place, as defined above. We only consider up-switches (from inferior quality or low-share brand to superior quality or high-share brand) and exclude down-switches (from a higher to a lower position) to avoid double counting. We first define two dummy variables as below:

$MS(s)_{i,t} = 1$ 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 can analyze the relationship between market share switch and quality switch using the logit model (Maddala 1983, page 22):

$$(1) \quad P[MS(s)_{i,t} = 1] = \frac{\exp[\alpha + \beta_1 Q(s)_{i,t} + \sum_{k=1toK} \beta_{(k+1)} Q(s)_{i,t-k}]}{(1 + \exp[\alpha + \beta_1 Q(s)_{i,t} + \sum_{k=1toK} \beta_{(k+1)} Q(s)_{i,t-k}])}$$

We identify 34 switches in market share and 37 switches in quality. We estimate the model in Equation 1 using likelihood maximization techniques. We test a lag in a switch in quality (k in Equation 1 above) up to 4 periods, because rarely does a switch in market share occur beyond 4 years from a switch in quality. However, third and fourth lags are never significant.

[Place Table 6 about here]

The results of the logit analysis for K = 3 are in Table 6A. The Logit estimates indicate that a switch in quality has no significant current effect on the probability of a switch in market share. However, a switch in quality in the prior two periods has a relatively large effect on the switch in market share. This result is consistent with the result from the categorical analysis. We obtain a correct positive hit rate at 55%. These results do not support Cases 1 or 2 but support Cases 3 or 4. The results indicate that markets are responsive to quality, as evidence by prior switches in quality significantly increasing the probability of a market share switch in the immediate subsequent years.

However, this analysis does not explicitly model the time for market share switch and also does not take into account the *difference* in quality, difference in network effects, or other category-level factors. For example, we need to control for a category being more or less inertial in terms of market-share dynamics. For this purpose, we carry out a Hazard Analysis of time to market share leadership next.

Hazard Analysis of Time to Market Share Leadership

For this analysis, we once again use the measures for switches in share and quality defined for the logit analysis. To explicitly analyze the relative role of quality and network differences, and also in order to account for category level differences in inertia, we define additional variables as below:

$Time_{it}$ = number of years since there was a quality-switch in favor of brand i .

QG_{it} = quality gap in favor of brand i at year t , measured as the difference in quality rating of brand i over the quality rating of the other brand in the pair.

NR_{it} = ratio of networks, measured as network size of the brand i in period t over the network size of the other brand in the pair.

$Lead_Dur$ = average duration of the market-share leader in the category the pair of brands belong to (last column in Table 4).

In order to utilize the richness of our analysis in view of several time-varying independent variables (quality and network gaps), we model the market-share switch (i.e., the event $MS(s)_{i,t} = 1$) as a discrete time hazard function of the independent variables of interest. Each product i , for all included brand-pairs, has T_i observations, one per year of risk. The hazard h_{it} for brand i in period t is the probability that brand i , within a pair switches in market share to lead, given that it has not done so before, i.e., $h_{it} = P[MS(s)_{i,t} = 1 / MS(s)_{i,(t-n) \forall n \geq 1} = 0]$:

$$(2) \quad h_{it} = \frac{1}{(1 + \exp - [\alpha_t + \beta_1 QG_{it} + \beta_2 NR_{it} + Lead_Dur_i])}$$

In Equation 2, the hazard of the market share switch occurring at time t , is expressed as a function of the baseline hazard term α_t as well as the three variables of interest. We consider the baseline hazard term as a polynomial function of time: $\alpha_t = \alpha_1 + \alpha_2 Time_{it} + \alpha_3 Time_{it}^2$. In each period when the event occurs, the observation contributes h_{it} to the likelihood function, and it

contributes $(1-h_{it})$ to the likelihood function in all other time periods. Therefore, the likelihood function for the model is:

$$(3) \quad L = \prod_i \prod_t (h_{it})^{MS(s)_{it}=1} (1-h_{it})^{MS(s)_{it}=0}$$

As shown in Singer and Willet (1993), this likelihood is equivalent to that of time-varying logistic regression of a market share switch occurring any year. Hence we use PROC LOGISTICT in SAS to obtain the maximum likelihood estimates of the parameters in Equation 2.

The estimated parameters are in Table 6B. The results show that, except for the network ratio, all variables are statistically significant in the model. The results indicate that time for market leadership by the smaller share brand is affected positively and significantly by the improvement in quality of the smaller share brand over the larger share brand. The leadership duration variable has a negative and significant effect on the probability of market-share switch indicating that more inertial or slow moving markets take a longer time for a switch in market leadership. The last row in the table gives a point-estimate of odds ratio for each variable. It indicates that the quality-gap variable has the highest odds in influencing the probability of a market share switch. Thus, the difference in quality plays a much more important and significant role in influencing the switch in share than does the difference in network size.

Figure 2 graphically illustrates these results. The X-axis represents time since the smaller share brand improves in quality over the larger share brand. The Y-axis indicates the probability of market share leadership. We have two graphs, one for each level of quality gap. For either level of quality gap, the probability of market share leadership peaks about year 3 since the switch in quality, confirming the descriptive analysis above. However, the probability of such a

switch is much higher when the gap in quality (of the lower share brand over the high share brand) is higher.

[Place Figure 2 about here]

These estimates provide some evidence in answering our research question about relative importance of network and quality in favor of a stronger effect for quality. However, the analysis does not control for other marketing variables. To do so, we carry out a regression analysis of market share flows.

Regression Analysis of Market Share Flows

To ascertain the effect of quality and network effects on market share after controlling for other marketing variables, we estimate the following general relationship:

$$(4) \quad Sh_{i,t} = \alpha + \beta_1 N_{i,t} + \beta_2 Q_{i,t} + \sum_{m \in M} \beta_m Cov_{.m} + \varepsilon_{i,t}$$

Where, t is a subscript for time, i is a subscript for brand, α and the β_m are coefficients to be estimated, Sh is market Share, N is network size, Q is quality, and M is a set of covariates indexed by m , including an interaction term of quality x network size. Potentially relevant other covariates that are factors outside our focus are relative price, advertising, channel support of the brand and growth rate of the category. The error terms (ε) are assumed to be IID normal. In the interest of parsimony, we run pooled regressions across the 19 product markets in our dataset. We report a regression for which we have data on our key variables of interest: market size, quality and network effects. We also report a pooled regression of only nine categories for which, we have reasonably good data on two of the important covariates, relative price of the brand (P_t) and growth rate of the category (G_t). We are not able to get good data on advertising or channel support, therefore we do not include them in our regression analysis. We also run a model with fixed effects for each category but it has only marginally better fit than the one

without fixed effects. Moreover, only two category effects are significant while none of the other parameters are materially affected. Similarly, incorporating random effects for Year and Category in all our reported regressions also does not materially change the parameters of most interest, those associated with network and quality. For this reason, we elect to report the results from a model without fixed or random effects.

There is a long tradition in marketing of estimating multiplicative models for analyzing market share, and their performance vis-à-vis other competing specifications have been established to be comparable or superior (Brodie and Kluyver 1984, Ghosh, Neslin and Shoemaker 1984; Tellis 1988). Thus we also use the multiplicative model, given below in a log-form as Equation 5 below:

$$(5) \quad \ln(Sh_{i,t}) = \alpha + \beta_1 \ln(N_{i,t}) + \beta_2 \ln(Q_{i,t}) + \beta_3 \ln(P_{i,t}) + \beta_4 G_t + \varepsilon_{i,t}$$

In this equation, natural-logs of all variables have been taken, except for the growth variable (G_t). This is because growth could take both positive and negative values and it may be taken purely as a covariate. The results are in Panel A of Table 7. (The results from a log-linear model and a purely linear model are similar, but these models have less desirable properties). To better control for unobserved excluded exogenous variables and to explore causality, we also present later a first-difference regression model version of the relationship of interest in Equation (4) and also a Granger test of causality.

Looking at the estimated parameters, the category growth rate does not affect the relationship significantly. The effect of relative price of the brand is significant but has an unexpected positive sign. One probable reason is that data aggregation (annual level) and pooling (cross-section x time series) positively bias estimates of the effect of price on market share (Tellis 1988; Tellis and Franses 2006). However, importantly, both network and quality have a

significant and positive effect on market share of the brand on both the reported regressions. Thus, these results support Case 4 indicating both network and quality to be important determinants of market share. Importantly, the interaction effect of quality x network is positive and significant in the regression run on all 19 product categories, supporting Case 5 in the theory section. Following the logic of Case 5, this interaction effect suggests that network effects enhance the efficiency of the market, evident in the positive response (main effect) of market share to quality.

As mentioned before, we are unable to obtain data for some potentially important variables, which can lead to omitted variable bias. We can control for the role of omitted exogenous variables which do not change from year to year (e.g., distribution and management talent) by estimating a model in first differences of all included variables. Such a model also has two other advantages. First, it captures flow better than does a regular regression model because each observation reflects a change in values from the previous time period. Second, it represents a more rigorous test of causality because each observation reflects whether a change in quality is related to a change in market share. The model of first differences takes the following form:

$$(6) \quad (Sh_{i,t} - Sh_{i,t-1}) = \alpha + \beta_1(N_{i,t} - N_{i,t-1}) + \beta_2(Q_{i,t} - Q_{i,t-1}) + \beta_3P_{i,t} + \beta_4G_t + \varepsilon_{i,t}$$

The results of estimating Equation 6 are in Panel B of Table 7.⁵ The variables P and G are the control variables, i.e., relative price of the brand and growth rate of the category, whenever available. Note the only variables with significant effects on market share are quality and network (both variables measured as first differences). The t-values are high indicating that these effects are strong and substantially different from chance. On the strength of higher t-

⁵ As suggested by a reviewer, we also estimated a first-difference model after taking the natural-logs of the variable. The results are similar, except that the network effects are even weaker and sometime insignificant. We choose to present this model because we believe that in a first difference model, taking logs first is not essential.

values alone, we can see that quality influences market share more than network size. Neither growth rate nor relative price has any significant impact on market share in this model. These results also support Cases 3 or 4 and not Cases 1 or 2.

Our final analysis is motivated by the following argument. Because quality is obtained from published reviews, one could argue that critics who write the reviews are influenced by sales of products. That is, market share or changes in market share affect quality levels rather than the other way around. One way to address the direction of causality in time series data is by using the approach proposed by Granger (1969) and popularized by Sims (1972).

Testing causality in the Granger sense requires one to test whether lagged information on a variable X provides any statistically significant information about a variable Y in the presence of lagged values of Y. If so, then X is supposed to be Granger-causing Y. One particularly simple approach to test for Granger causality uses the autoregressive specification of a bivariate vector auto-regression. This assumes a particular autoregressive lag length p, and then estimates restricted and unrestricted regressions of the following type by ordinary least squares (OLS):

$$(7) \quad Y_t = \alpha + \sum_{i=1}^p \beta_i Y_{t-i} + \sum_{i=1}^p \gamma_i X_{t-i} + \varepsilon_t$$

The above equation with all free parameters gives the unrestricted version of the regression, while the restricted version has all the $\gamma_i = 0$. Besides simply looking at the estimated parameters of the lagged variables, formally testing for the Granger causality is equivalent to testing the restriction on parameters in the regressions. Support for the null hypothesis (all the $\gamma_i = 0$) implies no evidence of Granger causality. The F statistic for testing the null hypothesis can be calculated as:

$$(8) \quad F_{(p, T-2p-1)} = \frac{(ESS_0 - ESS_1) / p}{ESS_1 / (T - 2p - 1)},$$

where ESS_0 and ESS_1 are the error sums of squares of the null and unrestricted models respectively, p is number of lags in the model and T is the number of observations or the length of time-series. We report the two unrestricted regression estimates, one with market share as the dependent variable and the other with quality as the dependent variable in Table 8. In both estimations, only the first lags of quality and market-share variables are included besides the intercept terms since higher order lags of the two variables are not significant. Both quality and market share lags are significant in the market share regression but only the quality lag is significant in the quality equation. In Table 8, we also report the values of the calculated F-statistics and the critical F-values. Based on the parameters and the F-tests, we reject the null hypothesis in the first case and fail to reject it in the second case. Therefore we conclude that there is evidence of quality rating Granger-causing market shares but not vice-versa.

[Place Table 8 about here]

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, several authors suggest that such markets could be perverse with the inferior quality brand having the highest market share. 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 develop a theoretical model which integrates both network and quality effects. We then carry out a variety of descriptive and empirical analyses utilizing a dataset about hardware and software products that we put together for 1980s and 1990s. 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:

- Market leadership changes frequently and market leaders hold sway for an average of a mere 3.8 years.
- Change in market leadership is generally associated with a change in quality the same year or a few years earlier.
- Both network effects and quality are factors in determining market share, but quality seems more important.
- Even in the presence of network effects, the market is not inefficient.
- The presence of network effects *enhances* the efficiency of the market that derives from a quality conscious segment of consumers. This interaction effect of quality and network effect supports this conclusion while Case 5 helps to interpret it.

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 myth of pioneering advantage, which has been dispelled by prior research (Golder and Tellis 1993; Tellis and Golder 1996, 2001; Shankar, Carpenter and Krishnamurthy 1998). The current inquiry suggests that superior quality

appears to be a very important driver of success and path dependence is not that important. 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 superior product that has a small user network. This study shows that switches in quality consistently result in switches in market share, albeit with a lag of some years. Network effects may delay but do not prevent superior brands taking over the market. On the contrary, 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, we argue that network effects, under certain circumstances, can make the market more efficient. If sufficient consumers care about quality, then network effects enhance the role of quality, because other consumers also benefit from the choices of quality-conscious ones. Consequently, the entire market settles on the better products 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. Some might argue that the best way to create a strong network of users is through quality. While it is true these two variables are related, we think the causality if any, proceeds in the opposite direction. A strong network enhances the impact of quality.

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 drives the success of these high-tech giants, even though 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 unnecessary.

LIMITATIONS AND FUTURE RESEARCH

This study has several limitations, which could be addressed by future research.

First, we do not account for advertising and do not adequately account for price. These omissions are due to data availability. For the cases we do have price, this variable is not significant and has the wrong sign, either because it is not important or the data are aggregated at the annual level.

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..

Third, we do not account for bundling of new products that may enable one firm (e.g., Microsoft) to promote the adoption of its products by pre-installing it on computers. However,

the failure of Microsoft Money to dominate Quicken shows that even such bundling power fails to swamp the effect of quality.

Fourth, the dominance of one supplier in some of these markets may discourage innovation and prevent better quality brands from emerging. While recent years have seen fewer changes in some of these markets, innovation in software is still vibrant as witnessed by introduction of numerous products including the rise of some entirely new brands (e.g., Google, YouTube, MySpace).

Fifth, the replacement cycle might depend on quality in that consumers may not see the need to change products if their quality is still good. If this were indeed true, it would result in quality having an even stronger impact on equilibrium market share than estimated here.

Sixth, the entire analysis is limited by the cross section of categories studied, predominantly from the software market. However, many of these are supposed to show strong network effects.

Seventh, our modeling does not provide a full game theoretic analysis of firm strategies about price, quality and compatibility. Nevertheless, our simple model development yields some important insights and provides a good basis for some interesting empirical analyses about comparing the role of network effects and quality in determining the success of a new high-tech product.

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Table 1
Summary of the Five Theoretical Cases

Case	Key Defining Conditions		Empirical Outcomes	Is Market Efficient
	Do consumers value <i>network effects</i>	Do consumers value <i>quality</i>		
1	No	No	If switching costs are important - first mover dominates the market If switching costs are <i>not</i> important - all brands have equal market shares	No
2	Yes	No	First mover dominates the market	No
3	No	Yes	Best quality brand dominates the market	Yes
4	Yes, some consumers	Yes, some consumers	Best quality brand dominates the market albeit more slowly – compared to <i>case 3</i>	Yes
5	No	Yes, some consumers	Best quality brand dominates the market albeit more slowly – compared to <i>case 4</i>	Yes

Table 2
Sample Description

<i>Categories</i>	<i>Platform</i>	<i># of Brands</i>	<i>Time Period</i>	<i>Highest Quality</i>	<i>Lowest Quality</i>	<i>Approx Price Level</i>	<i>Ave. Growth Rate</i>
Operating systems	PC	3	1986-1996	10	1.5	NA	19%
	Network	3	1994-1998	10	4	NA	23%
Word processors	PC	3	1984-1997	10	2	240	19%
	Mac	2	1986-1997	10	7.1	205	6%
Spreadsheets	PC	3	1985-1998	10	2	244	26%
	Mac	3	1988-1997	10	6.7	255	18%
Project management (High-end)	Win	2	1990-1995	10	4	NA	6%
Project management (Low-end)	Win	3	1990-1994	10	3	494	35%
Desktop publishing (High-end)	PC	3	1987-1996	10	7	519	12%
Desktop publishing (Low-end)	PC	3	1990-1996	10	4	105	24%
Desktop publishing (High-end)	Mac	3	1988-1996	10	4	525	16%
Presentation graphics	PC	3	1986-1997	10	6	297	37%
Image management (High-end)	Win	3	1991-1994	10	4	NA	2%
Image management (Low-end)	Win	3	1991-1994	10	5	NA	-1%
Databases	PC	3	1992-1998	10	4	NA	27%
Personal finance	D+W	3	1987-1997	10	4	59	47%
Web browsers	Win	3	1994-1999	10	5	14	74%
Internet service providers	Win	3	1991-1998	10	5	23	35%
Microprocessors	PC	2	1982-1999	10	4	NA	71%

NA: Not available.

Table 3
Summary of the Empirical Tests

Test	Type of Empirical Analysis	Rationales	Key Findings
1	Graphical analysis of market share flows	Provides visualization of graphics	<ul style="list-style-type: none"> • The hypothesized 5 cases have adequate face validity • Quality plays a critical role in driving market share flows • Early market share leaders do not dominate the market for long • Markets are efficient in general
2	Categorical analysis of switches in share and quality leadership	Provides summary of the key findings of the graphical analyses	<ul style="list-style-type: none"> • Changes in market leadership are frequent. The average duration of market leadership is only 3.8 years • 88% of switches in market shares are related to switches in or superiority of quality • Markets are efficient in general
3	Logit analysis of market share switches	Provides formal tests of the role of quality in market dynamics	<ul style="list-style-type: none"> • A switch in quality in the prior two periods has a relatively large effect on the switch in market share • Markets are generally efficient
4	Hazard analysis of time to market share leadership	Provides a formal test of a) the effect of quality versus market share and b) the time for these effects to occur	<ul style="list-style-type: none"> • Time for market leadership by the smaller share brand is affected positively and significantly by the improvement in quality of the smaller share brand over the larger share brand • The quality gap variable has the highest odds in influencing the probability of a market share switch
5	Regression analysis of market share flows	Provides a formal tests of a) the effect of quality versus network b) after controlling for other marketing variables	<ul style="list-style-type: none"> • Both network and quality have a significant and positive effect on market share of the brand • Network effects enhance the efficiency of the market
6	Test of Granger causality	Tests whether quality causes market share or high market share products end up getting better quality ratings	<ul style="list-style-type: none"> • Evidence for quality Granger-causing market share but no evidence for market share Granger-causing quality ratings

Table 4
Switches in Quality, Market Shares and Market Share Leadership

Markets	Switches in Quality	Switches in Market Share	Years Taken to Become Market Leader After Quality Switch	Total Years	Switches in Market Share Leadership	Duration of Market Share Leadership
Word Processor	3	3	4	14	WordStar – WordPerfect – Word	4.7
Spreadsheet	2	2	4	14	Lotus – Excel	7
Internet Service Provider	2	3	1	8	Prodigy – CompuServe – AOL	4.2
Personal Finance	4	2	2	11	Managing Your Money – Quicken	5.5
Web Browser	1	3	1	6	Mosaic – Netscape – Explorer	2
Desktop Publishing(Mac)	1	1	4	9	PageMaker – QuarkExpress	4.5
Desktop Publishing(High-end)	5	3	0	10	Ventura – PageMaker – QuarkExpress	3.3
Desktop Publishing(Low-end)	0	3	No quality switch due to data censoring	7	First Pub – Express Pub – MS Publisher	2.3
Presentation Graphics	3	3	1	12	Freelance – Harvard – PowerPoint	4
Operating Systems(PC)	6	1	2	11	DOS – Windows	5.5
Operating Systems(Network)	1	1	5	5	NetWare – Windows NT	2.5
Word Processor(Mac)	1	1	1	12	MacWord – MacWrite	6

Markets	Switches in Quality	Switches in Market Share	Years Taken to Become Market Leader After Quality Switch	Total Years	Switches in Market Share Leadership	Duration of Market Share Leadership
Project Management(High -end)	2	1	No initial data on quality switch due to data censoring	6	Primavera – Project Workbench	3
Project Management(Low-end)	0	1	No quality switch due to data censoring	5	Timeline – MS Project	2.5
Image Management(High -end)	3	2	1	4	PicturePub – PhotoStyler	2
Image Management(Low-end)	4	3	0	4	PhotoFinish – PaintBrush	2
Database	4	1	No clear leader due to data censoring	7	NA	NA
Average Years Taken to Market Leadership			2.2		Average Duration of Market Share Leadership	3.8

Table 5
Categorical Analysis of Switches in Market Share and Quality

Cases when Market Share Switch Occurred (N=34)				
	Classification of Causes for Switch in Market Share			
	Current Switch in Quality	Recent Switch in Quality	Lower Share Brand had Better Quality	None
Number (%) of Cases	6 (18%)	17 (50%)	7 (20%)	4 (12%)
Cases when Market-Share Switch Did Not Occur (N=18)				
	Classification of Causes for No Switch in Market Share Despite an Observed Switch in Quality			
	Brand Becoming Higher Quality Already Has Bigger Market Share	Small Brands / Very Brief and Un-sustained Quality Advantage	Potential Data Censoring	
Number (%) of Cases	8(44%)	6 (33%)	4 (22%)	

Note: There are total 52 cases in the sample where there is at least one switch either in quality or in market share.

Table 6
Analysis of Market Share Switches

Panel A: Logit Analysis of Market-share Leadership Switches

Independent Variables	Coefficients	Std. Error	Wald Stat.
Quality switch (t)	-.08	.75	.01
Quality switch (t-1)	1.41 **	.38	13.48
Quality switch (t-2)	1.21 **	.44	7.66
Quality switch (t-3)	.44	.56	.61
Correct Prediction	54.5%		
<i>N</i>	540		

** p-value < 0.005

Panel B: Discrete Time Hazard Analysis of Time to Market-Share Leadership

	Time	Time²	Quality Gap	Network Ratio	Leadership Duration
Parameter Estimate	.85	-.15	.31	-.22	-.44
Wald-Statistic (χ^2)	7.92	4.22	5.74	1.50	6.32
p-value	.01	.04	.01	.22	.01
Odds Ratio	2.35	.86	1.37	.79	.64

Table 7
Linear Regression Analysis Results

Panel A: Log-log Regression

	(Equation 5) Dep. Variable: $\ln(Sh_{i,t})$			
	Sample of 9 Categories with All Variables N = 204 Adj. R ² : 0.60		All Categories with only Market Share and Quality Variables N = 479 Adj. R ² : 0.96	
Variable	Estimated Parameter	t-value	Estimated Parameter	t-value
Intercept	-3.87**	-8.48	-3.13**	-45.71
Network: $\ln(N_{it})$.48*	2.30	.03**	2.74
Quality: $\ln(Q_{it})$	1.49**	7.73	1.47**	44.90
Interaction: $\ln(Q_{it}) * \ln(N_{it})$.05	.44	.47**	80.81
Relative Price: $\ln(P_{it})$.45*	2.24	-	-
Category Growth (G_t)	.11	.66	-	-

Panel B: Regression of First Differences

	(Equation 6) Dep. Variable: $(Sh_{i,t} - Sh_{i,t-1})$			
	Sample of 9 Categories with All Variables N = 204 Adj. R ² : 0.29		All Categories with Only Market share and Quality Variables N = 478 Adj. R ² : 0.17	
Variable	Estimated Parameter	t-value	Estimated Parameter	t-value
Intercept	-.04	-1.33	.001	.18
Network: $(N_{it} - N_{it-1})$.09**	3.65	.077**	4.69
Quality: $(Q_{it} - Q_{it-1})$.05**	7.57	.041**	8.22
Relative Price: (P_{it})	.10	1.27	-	-
Category Growth (G_t)	.027	1.14	-	-

* Significant at 5% level ** Significant at 1% level

Table 8
Test of Granger Causality

	Market Share Equation Dep. Variable: M_{it} N = 479 Adj. R^2 : 0.63		Quality Equation Dep. Variable: Q_{it} N = 479 Adj. R^2 : 0.70	
	Error SS: 11.43 Error DF 476 F-Statistic for Granger Test: 12.90** Critical $F_{1,476}$ for 1% = 6.69		Error SS: 807.68 Error DF 476 F-Statistic for Granger Test: 0.03 Critical $F_{1,476}$ for 5% = 3.86	
Variable	Estimated Parameter	t-value	Estimated Parameter	t-value
Intercept	-.04	-1.32	1.48**	6.63
LagShare (M_{it-1})	.76**	19.71	-.04	-.16
LagQuality (Q_{it-1})	.014**	4.87	.80**	27.44

** Significant at 1% level

Figure 1-A: Share and Quality Flows in Spreadsheet Market

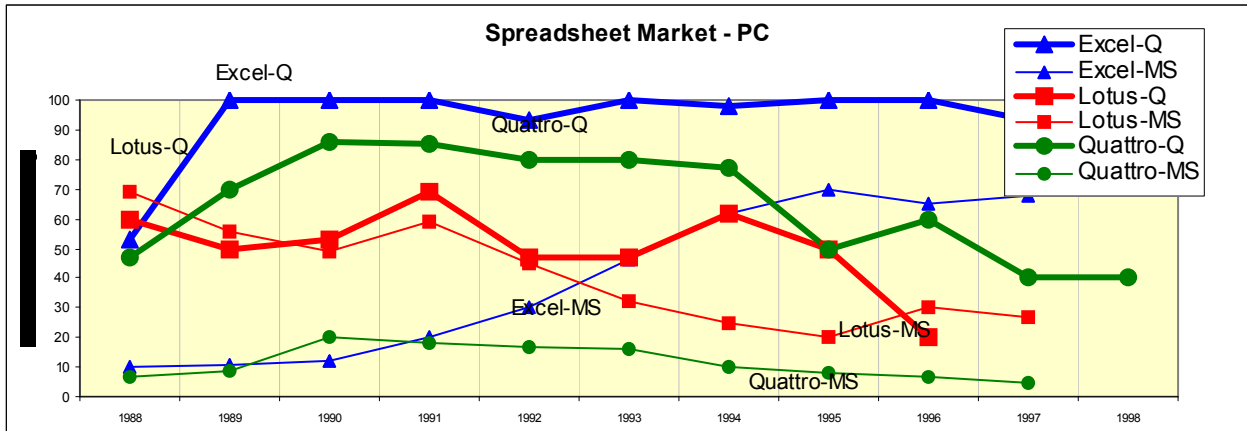


Figure 1-B: Share and Quality Flows in Personal Finance Software Market

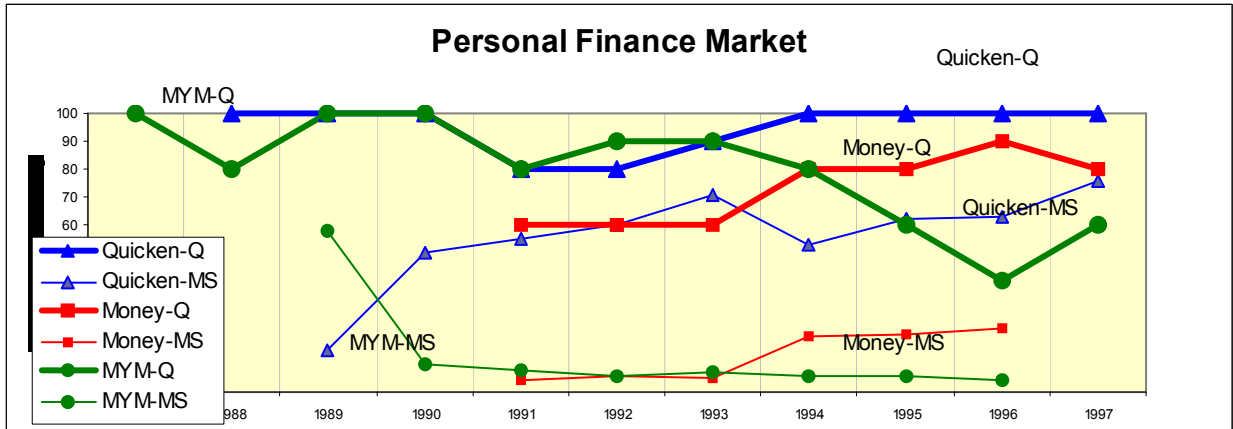


Figure 1-C: Share and Quality Flows in Word processor Market

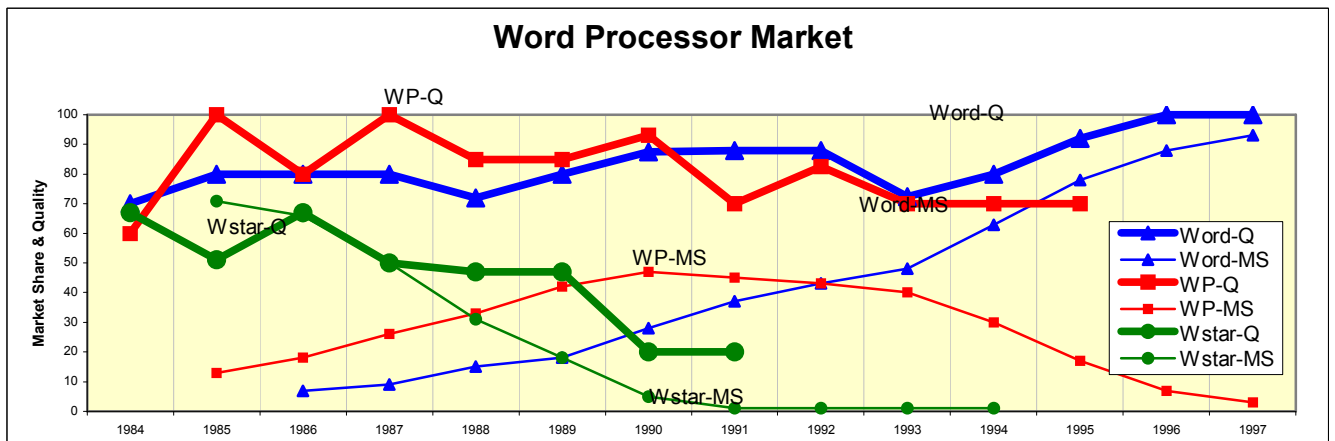
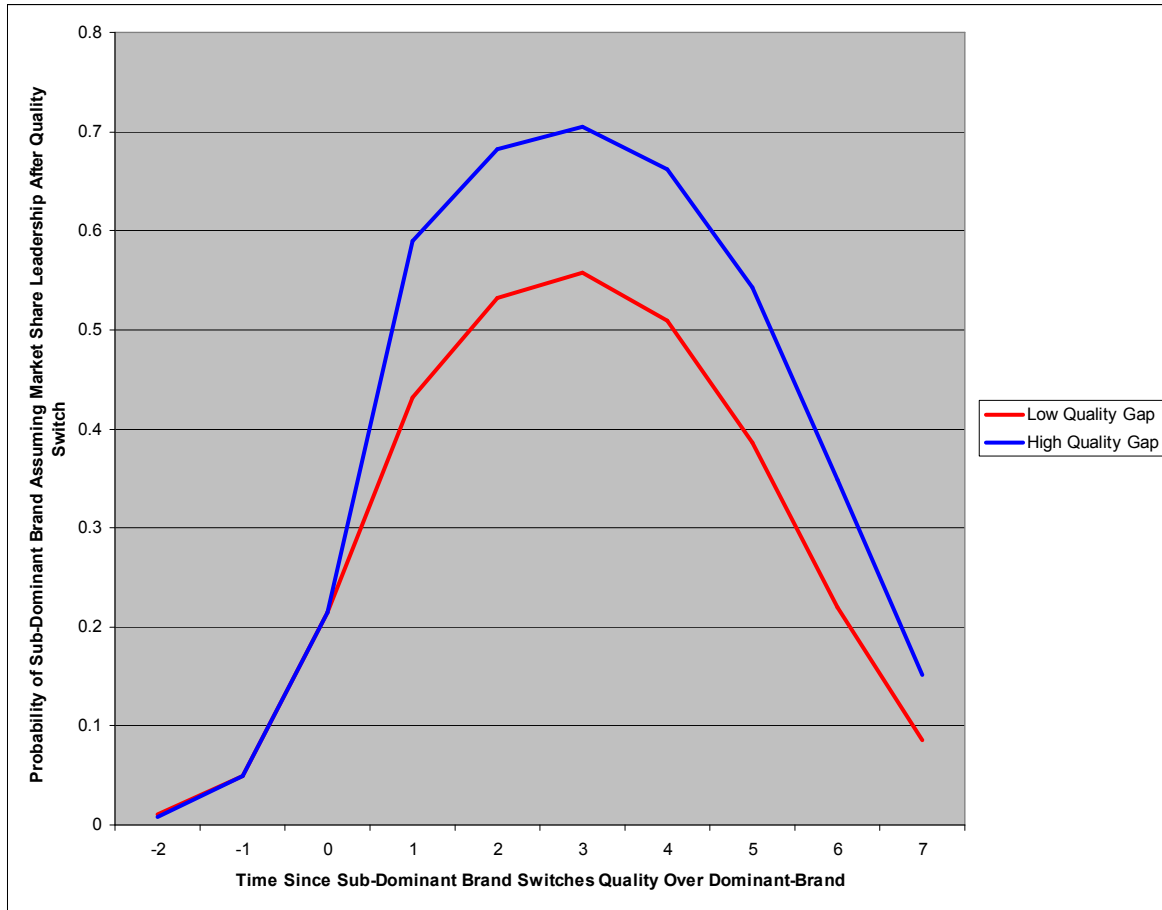


Figure 2: Probability of Sub-Dominant Brand Assuming Market-Share Leadership Following a Quality Switch over Dominant Brand



Appendix A

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 B Supplementary Graphical Analyses

Figure B-1: Share and Quality Flows in Mac Word Processor Market

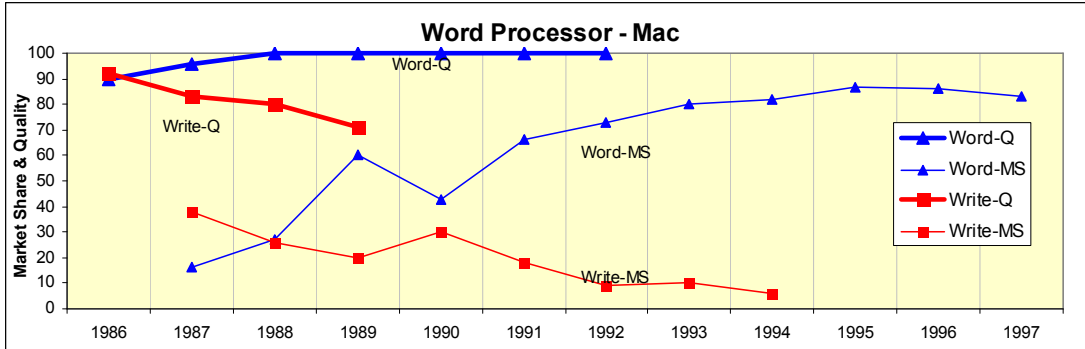


Figure B-2: Share and Quality Flows in Operating System Market

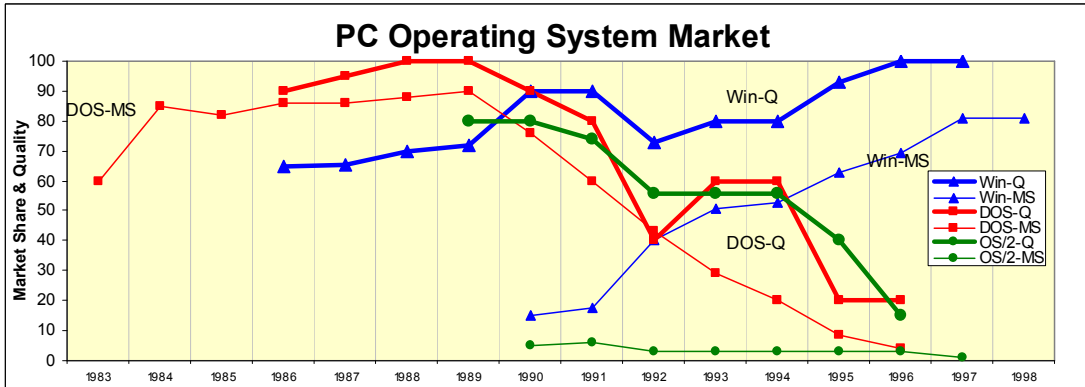


Figure B-3: Share and Quality Flows in Network Operating System Market

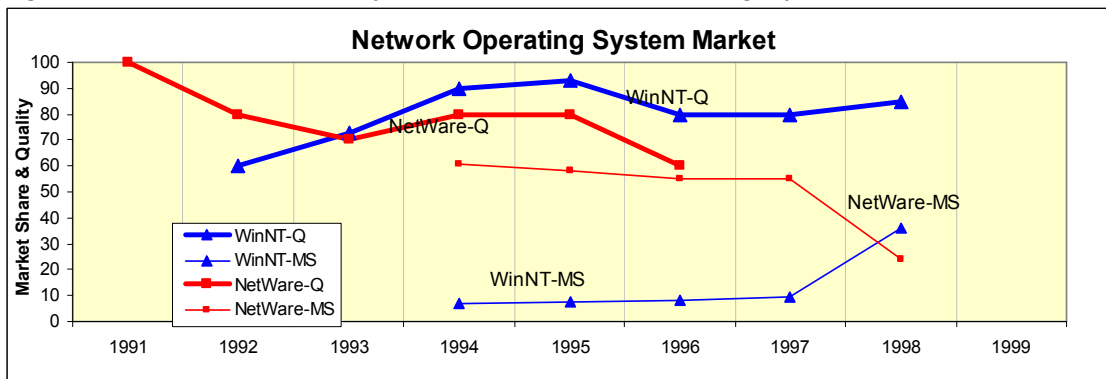


Figure B-4: Share and Quality Flows in Desktop Publishing PC Low End Market

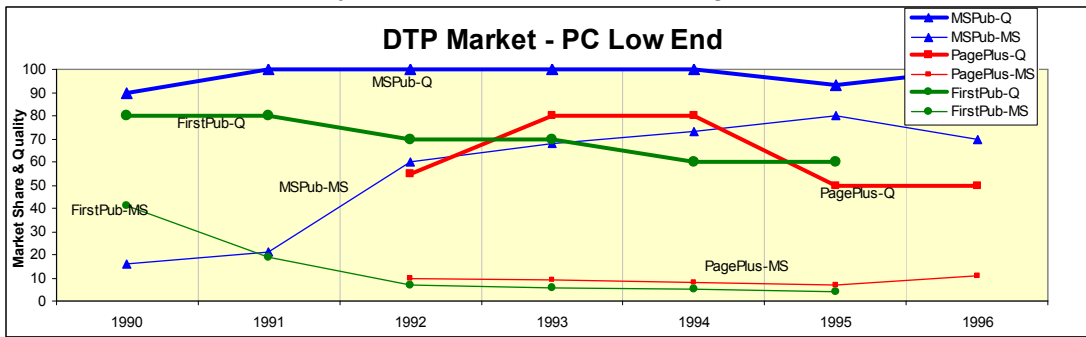


Figure B-5: Share and Quality Flows in Desktop Publishing PC High End Market

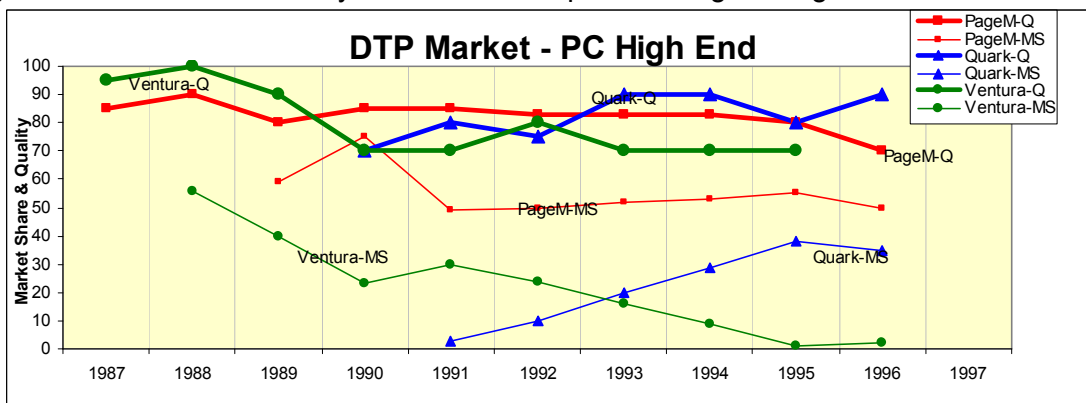


Figure B-6: Share and Quality Flows in Desktop Publishing Mac Market

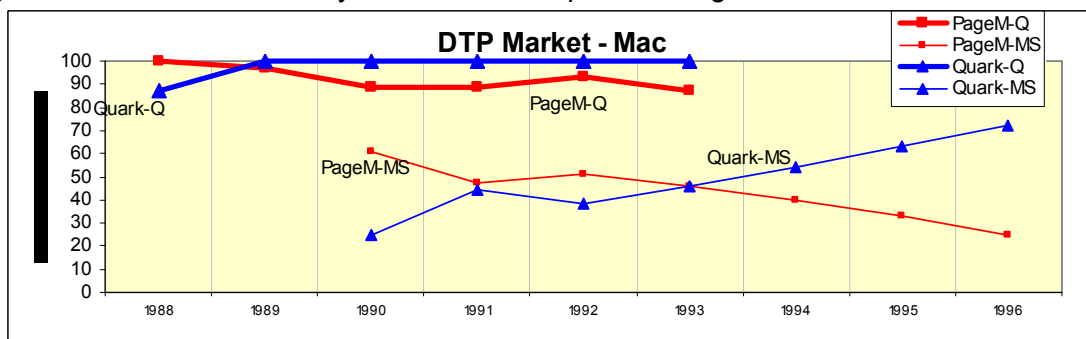


Figure B-7: Share and Quality Flows in ISP Market

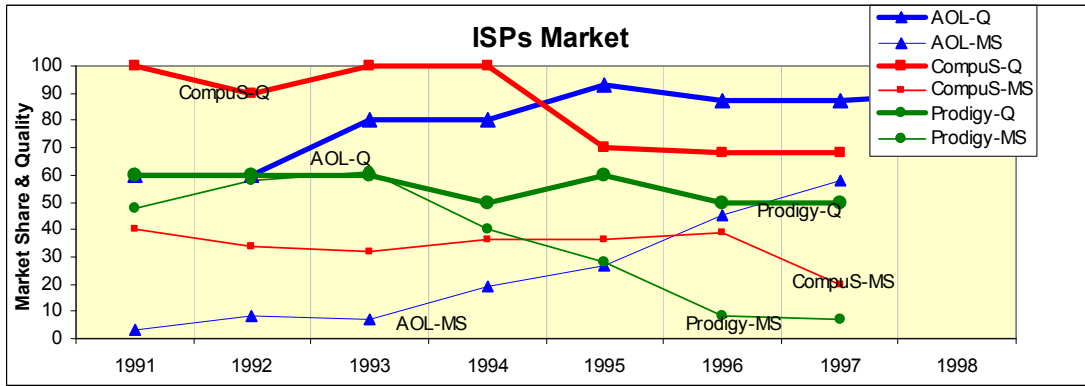


Figure B-8: Share and Quality Flows in Web Browser Market

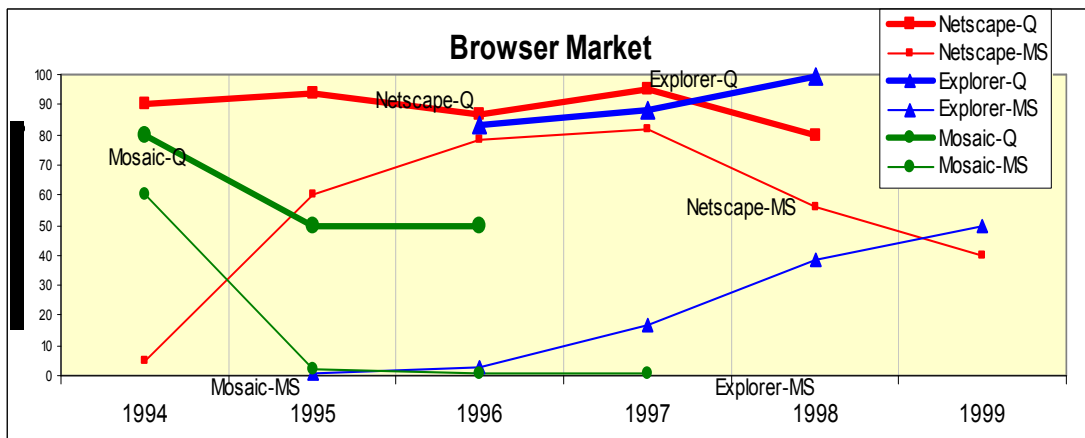


Figure B-9: Share and Quality Flows in Presentation Software Market

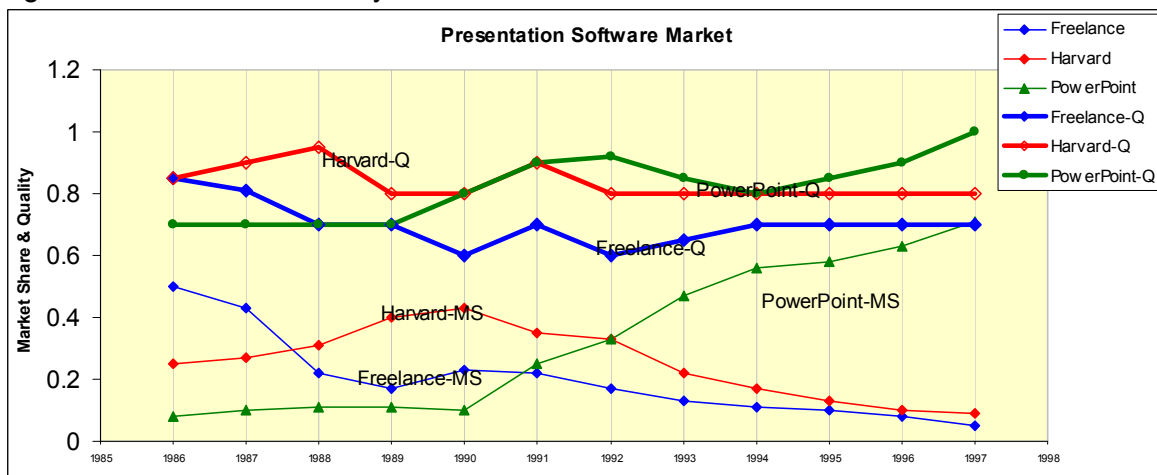


Figure B-10: Share and Quality Flows in Project Software Market – Low End

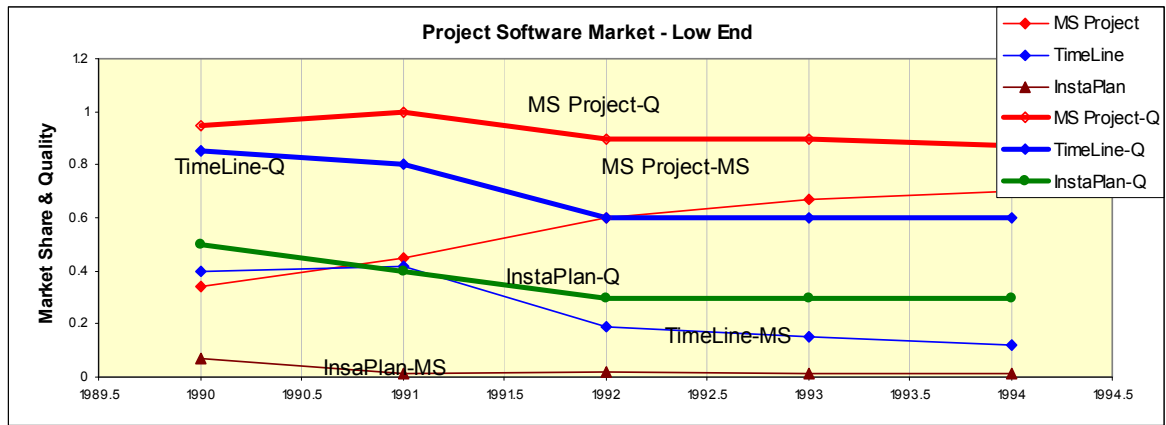


Figure B-11: Share and Quality Flows in Project Software Market – High End

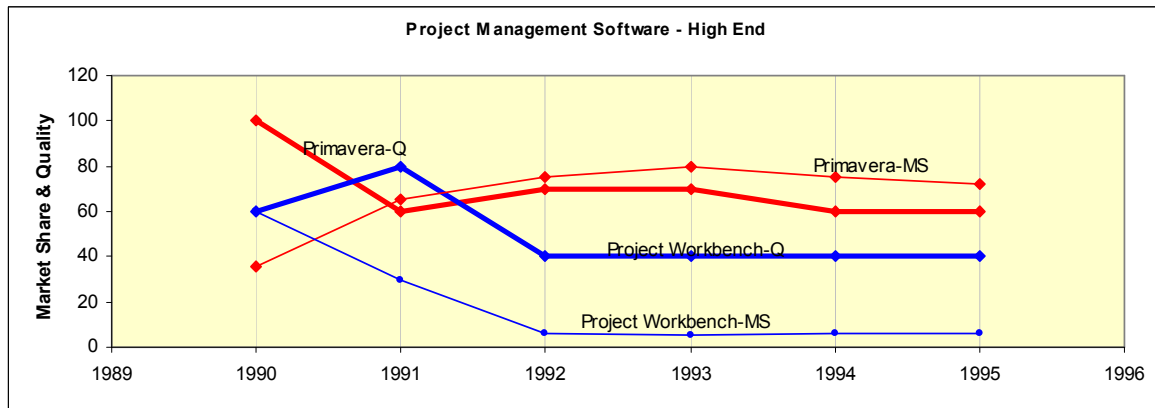


Figure B-12: Share and Quality Flows in Database Software Market

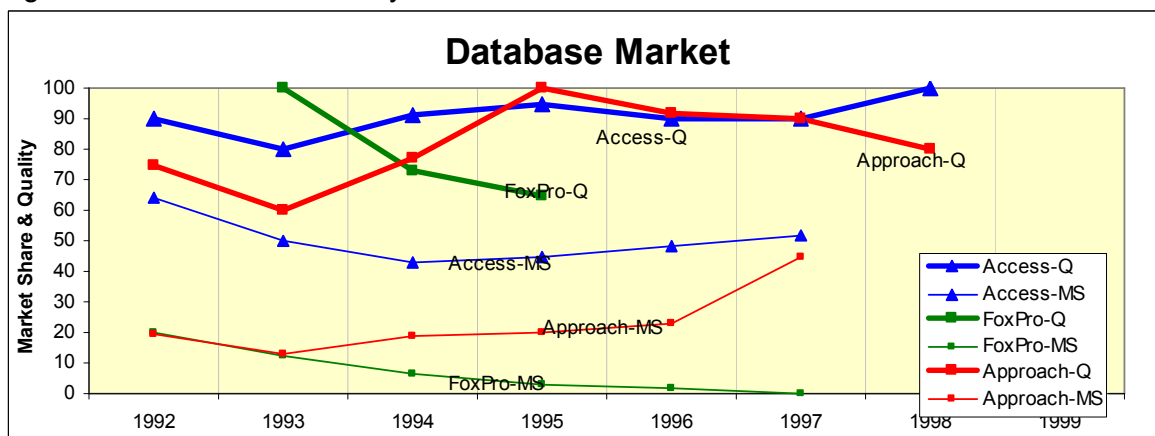


Figure B-13: Share and Quality Flows in Image Management Software Market – High End

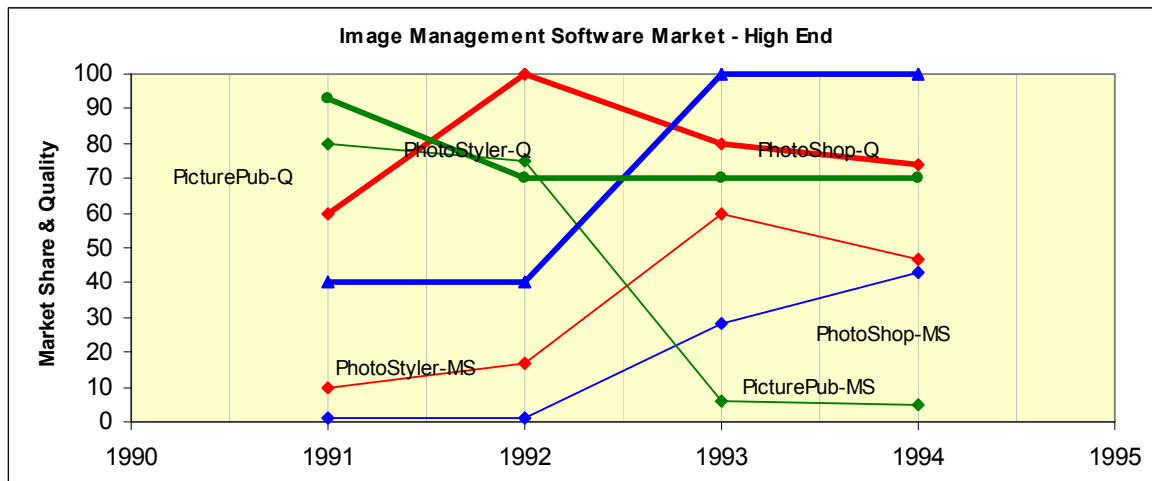


Figure B-14: Share and Quality Flows in Image Management Software Market – Low End

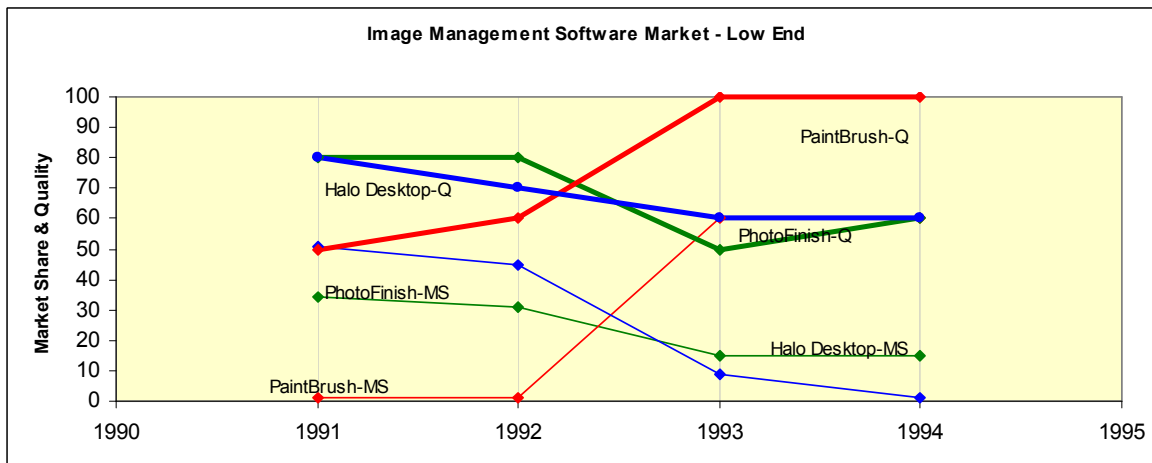


Figure B-15: Share and Quality Flows in Microprocessor Market

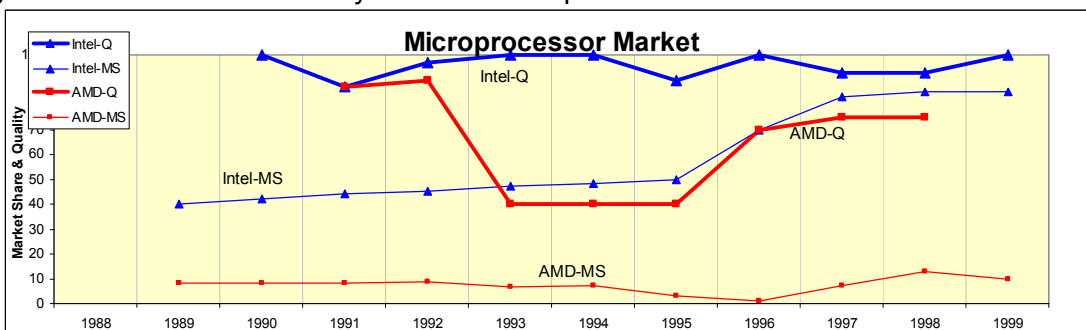


Figure B-16: Share and Quality Flows in Spreadsheet Market - Mac

