

Researchers disagree about the critical drivers of success in and efficiency of high-tech markets. On the one hand, some researchers assert that high-tech markets are efficient with best-quality brands being dominant. On the other hand, many scholars suspect that network effects lead to perverse markets in which the dominant brands do not have the best quality. The authors develop scenarios about the relative importance of these effects and the efficiency of markets. Empirical analysis of historical data on 19 categories shows that though both quality and network effects affect market share flows, in general markets are 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 ones that are first to enter, dominate the market. Network effects enhance the positive effect of quality.

Keywords: network effects, tipping, path dependence, quality, high-tech products

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

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 potential 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 argue 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 over 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 need 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 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 (Moor-

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thy 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" (Liebowitz and Margolis 1999, p. 14). Their result not only contradicts the conclusions of many economists but also seems counter to the behavior of many users of products such as word processors, e-mail, and voice-over-Internet programs, who choose such products primarily on the basis of what their colleagues are doing rather than 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

Empirical studies in marketing have not yet tackled this issue sufficiently. These studies focus on proving the presence of network effects (Nair, Chintagunta, and Dube 2004), investigating the nature of network effects (Shankar and Bayus 2003), or analyzing the role of network effects in diffusion (Gupta, Jain, and Sawhney 1999). However, none have specifically examined the drivers of success of new high-tech products. In particular, no study has explicitly examined the relative importance of quality in relation to 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 has important implications for managerial strategies. Third, whether (as argued by many economists) network effects are strong enough to dominate and negate the role of quality, thus 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 be an interaction effect, such that network effects *enhance* the effect of quality? What does the empirical evidence show? The primary goal of this article is to answer these questions through empirical analyses.

¹This definition would correspond to the standard definition of efficiency in economics, for example, 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 because firms can produce it with superior technology at lower cost.

In the next section, we explore theoretically how quality and network effects may interact in markets. Then, we describe the method for collecting data to empirically test market response to quality versus network effects. Next, we analyze the data through 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. In the final section, we discuss the study's implications and limitations and provide directions for further 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 define quality as a composite of a brand's attributes, on each of which all consumers prefer more to less (Tellis and Wernerfelt 1987). Examples of such attributes are reliability, performance, convenience, and so forth. We conceptualize the network as the number of users of a brand.

Assume that brands in this market differ in initial market shares, primarily because of the time they enter the market, the brands' parentage, or some such extraneous factors. As a result, their network sizes would also be different; that is, the brand that enters first will have 100% 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? There are five important cases, depending on whether consumers in this market value neither 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 first explore the market outcomes that would emerge in each of these cases (Table 1 provides a summary of the five cases).

Case 1

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 high. In this case, consumers will pick randomly from the available brands in the market (adjusting for price differences). After a period equal to the repurchase cycle—for example, three years—every consumer will have bought or repurchased in the category at least once. Thus, over a period exceeding the repurchase cycle, after adjusting for price differences, if switching costs are not important, all brands have equal market shares regardless of the brand's real quality or initial market share. If switching costs are important, the brand that enters first will permanently dominate the market, regardless of the brand's network or quality. Thus, in either condition, the presence of network effects will not swamp consumers' responsiveness to quality.

Case 2

Assume that consumers value the network of users and not quality. In this case, consumers will poll their network

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

Table 1
SUMMARY OF THE FIVE THEORETICAL CASES

Case	Key Defining Conditions		Empirical Outcomes		Is Market Efficient?
	Do Consumers Value Network Effects?	Do Consumers Value Quality?			
1	No	No	If switching costs are important, first mover dominates the market.	If switching costs are not 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 than in Case 3.		Yes
5	No	Yes, some consumers	Best-quality brand dominates the market, albeit more slowly than in Case 4.		Yes

of coworkers (or coauthors) to find out the brand they are using. To minimize inconvenience and maximize utility, they will buy the same brand that their coworkers use. If all their coworkers do not use the same brand, they will adopt the one used by the highest proportion of their coworkers. This is a popularity-sensitive market, which is likely to have an outcome that depends on the starting point. Assuming that brands differ in network size because of the order of entry, parentage, or some preexisting factors other than quality, in each period, the brand with the larger network size will have a higher probability of being the most used by a consumer's coworkers and thus adopted by the network dependent consumers.³ The exact probability of this occurrence can be derived.⁴ As a result, over time, the brand with the largest network size as a result of initial conditions will dominate the whole market. If its quality were inferior to that of other brands in the market, after adjusting for prices, the market would be inefficient. Thus, in this case, the presence of network effects will swamp consumers' responsiveness to quality.

Case 3

Assume that consumers value quality and not network effects. In this case, in every period, consumers who decide to buy the product will compare brands on their quality and choose the one that has the better quality. Assuming that 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 the prior period's market share, and the market would be effi-

cient. Again, in this case, the presence of network effects will not swamp consumers' responsiveness to quality.

Case 4

Suppose that the market is segmented, with some consumers valuing network effects and 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 who value quality will decide to choose on the basis of the quality of brands. Within the time of the purchase cycle, all these consumers will converge on the best-quality brand in the market. Consumers who rely on the network will poll their coworkers. Some of their coworkers will be quality conscious and will have chosen the best brand in the market. At least some network-valuing consumers will find that a majority of their coworkers are 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 toward the best-quality brand, albeit slowly. This will lead to an efficient market; that is, although network effects are present, they are not strong enough to create an inefficient or perverse market, as in Cases 1 or 2, respectively.

The market share of the best-quality brand depends on (1) the difference in quality among the brands, (2) the proportion of quality-valuing consumers to network-valuing consumers in the market, and (3) the proportion of consumers informed about quality. In this case, the market is efficient. 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

³The 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" (Besen and Farrell 1994; Katz and Shapiro 1985). Thus, we do not consider it in detail here.

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

the best-quality brand would occur more slowly than in Case 4 because when some consumers value the network of users, they also benefit or suffer from the good or bad choices of the network. If the remaining consumers all decide on quality, some of the network-dependent consumers will benefit from their good choices.

However, if the network-dependent consumers were to buy randomly, they would not derive any benefit from the segment of quality-valuing consumers. Thus, a market of quality-conscious and network-dependent consumers would converge 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 those who buy 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, Case 5 points out the beneficial effect of network effects, enhancing the role of quality as a result of the presence of a quality-valuing segment. Tellis and Yin (2005) sketch a simple model to demonstrate this effect formally. This effect can be empirically estimated by an interaction effect of quality and network effects on market share.

Summary

The prior analysis shows that an a priori case cannot be made 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?

In the next two sections, we describe an empirical study to answer these research questions. Other factors may also

play a role in these markets, such as price, advertising, distribution, and market growth. However, from our experience with these markets, we believe 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 the data enable us.

METHOD

Sampling

We choose personal computer products and services as the sampling frame because 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 treat different platforms, such as PC and Mac, as different product markets. However, we treat the two PC operating platforms, DOS and Windows, which emerged sequentially, as one market. We also treat high-end and low-end brands as different product markets (see Table 2, Column 1). On this basis, we collect data on 19 product markets. Because of limitations in the availability of data, this sample is heavily weighed toward software products rather than hardware and services. Most of the product markets are characterized by two or three firms with one dominant brand.

Data Collection

The limited availability of suitable data has been the major hurdle in empirical research in the past, and despite an extensive effort, we did not have complete success in collecting the data we needed. We collected the majority of the market share data from International Data Corporation (IDC) and some from Dataquest. However, even these firms do not have complete or adequate data on several categories. When the data were not available from any syndi-

Table 2
SAMPLE DESCRIPTION

Categories	Platform	Number of Brands	Period	Highest Quality	Lowest Quality	Approximate Price Level	Average Growth Rate
Operating systems	PC	3	1986–1996	10	1.5	N.A.	19%
	Network	3	1994–1998	10	4	N.A.	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)	Windows	2	1990–1995	10	4	N.A.	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)	Windows	3	1991–1994	10	4	N.A.	2%
Image management (low end)	Windows	3	1991–1994	10	5	N.A.	–1%
Databases	PC	3	1992–1998	10	4	N.A.	27%
Personal finance	DOS + Windows	3	1987–1997	10	4	59	47%
Web browsers	Windows	3	1994–1999	10	5	14	74%
Internet service providers	Windows	3	1991–1998	10	5	23	35%
Microprocessors	PC	2	1982–1999	10	4	N.A.	71%

Notes: N.A. = not available.

cated source, we collected data from archival sources, in line with Golder's (2000) suggested rules.

Measures

Measure of quality. We define quality as a composite of attributes, on each of which all 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). Although 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*, do not evaluate the quality of computer products in the past, we resorted to ratings and reviews in three of the 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 desktop publishing—we collected quality data from the leading magazine for Mac computers and software—*Macworld*. We consider reviews for each of our brands for each year in the sample. However, because 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 that express increasing quality on a nine-point scale ranging from 2 to 10 (see Web Appendix A at <http://www.marketingpower.com/jmrapril09>). We then used 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 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.

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 these markets is approximately three years. This estimate is based on personal experience, as well as interviews with senior information technology managers and consumers, both of whom indicate that software is typically upgraded or repurchased at least within three years. Thus, we measure network size using the accumulated market share of a brand in the last three years.

This measure differs from prior work that measures network size by using the entire installed base of brands (e.g., Brynjolfsson and Kemerer 1996). We do not believe that the entire installed base of a brand is an appropriate measure for its network size, especially for quickly evolving high-tech products. Rather, time of adoption or recency of

purchase of the product matters for these products. Because of frequent repurchases and upgrades, the brands actually in use are those bought relatively recently (e.g., in the last three years). Thus, 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 approximately three years, we use the accumulated market size of the last three years as the relevant network size for the brand under consideration. For the empirical analysis, we also repeat the analysis, taking the network as accumulated market size of the last four or five years. The results remain substantially similar.

We collected price data from the same sources as 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 the magazines in primarily two types of sources: the articles/features and the advertisements. We hired two graduate students to undertake this painstaking effort in locating all relevant pricing data for the brands included in our sample. We then compiled all the price data into a meaningful format by brands. For multiple entries of the price data for the same brands in the same year, we take the average of the multiple entries. 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 searched for all the available IDC reports on the product categories included in our sample. Within IDC reports, there are sometimes multiple unit sales data for the same product categories with overlapping periods. To deal with the multiple data series, we adopted the data series that had the most complete data and then used the alternative data series to fill in gaps in the first data series. When the two data series were of equal length, we took the average of the two series to determine the final unit sales data for that product category. In addition to actual data, the firm had estimated data for the most recent years. To construct an accurate and consistent data series for all product categories, we first used actual data as much as possible. For more recent years for which the actual data were not available, we used the estimated data. After the unit sales data were collected, we computed 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. We state the purpose of each analysis at the beginning of its respective section. Table 3 summarizes the purpose and results of these analyses.

Graphical Analysis of Market Share Flows

To visually appreciate the dynamics of quality and market share in these markets, we graphically plot the market

Table 3
SUMMARY OF THE EMPIRICAL TESTS

<i>Test</i>	<i>Type of Empirical Analysis</i>	<i>Rationale</i>	<i>Key Findings</i>
1	Graphical analysis of market share flows	Provides visualization of graphics.	•The hypothesized five 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.	•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.	•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 (1) the effect of quality versus market share and (2) the time for these effects to occur.	•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 test of (1) the effect of quality versus network (2) after controlling for other marketing variables.	•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.	•Evidence for quality Granger-causing market share, but no evidence for market share Granger-causing quality ratings.

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 three markets (spreadsheet, personal finance, and word processor) for illustrative purposes. Similar graphs for other markets appear in Web Appendix B (<http://www.marketingpower.com/jmrApril09>).

Spreadsheet market. Figure 1, Panel A, presents the graphical analysis of market share and quality in the spreadsheet market. Lotus was the unquestioned market leader in both market share and quality since 1983. In 1987, Excel was launched in the PC market. Initially, Excel's quality was inferior to Lotus's quality. However, two years later, in 1989, Excel's quality rating surpassed that of Lotus. Soon after, Excel's market share increased sharply with a corresponding decline in Lotus's market share. In 1993, Excel surpassed Lotus in market share and became the market leader. Subsequently, Excel's quality became superior to Lotus's quality. Correspondingly, Excel's market share did not fall below Lotus's market share for the period for which we have data. We can conclude that even though Lotus was an established brand with a large network of users, when Excel entered the market, it grew from zero and surpassed Lotus's position because of its superior quality. Moreover, it took Excel four years from the time it overtook Lotus in quality to also surpass Lotus in market share. This period is probably a little longer than the repurchase cycle, which we estimate to be three years.

In this market, the time taken to crown a new, superior market leader was 4 years, only slightly longer than the expected three-year repurchase cycle. Thus, this case suggests that consumers in the spreadsheet market care about both quality and the network of users. In addition, the abil-

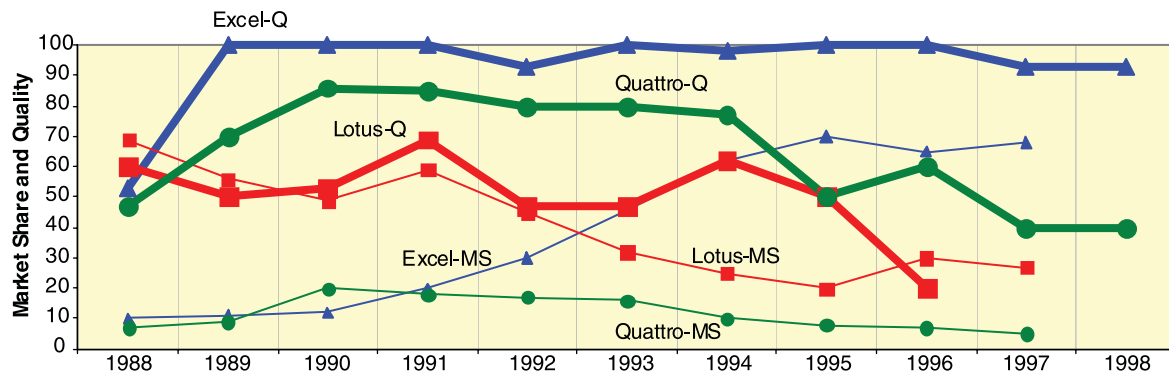
ity to switch may have been facilitated by manufacturers enabling one program to read files prepared by the other programs. Thus, overall, the spreadsheet market is efficient, resembling the previously described Case 4 or 5, but not Cases 1, 2, and 3.

Personal finance market. In the personal finance market, the early quality leader was Managing Your Money, which was introduced in the early 1980s. It was also an early market share leader. Quicken entered the market in 1986. In 1988, it was rated higher in quality than Managing Your Money. Note how its market share began to rise right away (see Figure 1, Panel B). In 1990, Quicken's market share surpassed that of Managing Your Money, and it became the market leader. Although Managing Your Money briefly increased in quality in 1992, the improvement did not last. Quicken managed to sustain its market leadership ever since because its quality remained superior to Managing Your Money for most of the period.

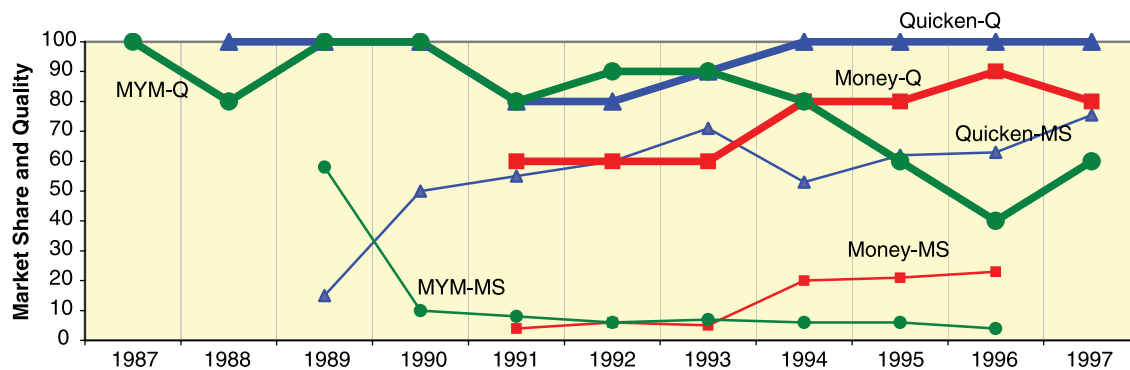
Despite the distribution and operating power of Microsoft, Quicken maintained undisputable leadership in quality over Microsoft Money, and thus in market share, until 1997 (the period for which we have data). Microsoft Money entered in 1991. However, its quality was consistently inferior to Quicken's quality. As a result, its market share never surpassed Quicken's market share. This market provides two important lessons. 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 not the highest, despite the advantages of its brand name, distribution leverage, and network effects stemming from its Windows platform and other comple-

Figure 1
SHARE AND QUALITY FLOWS

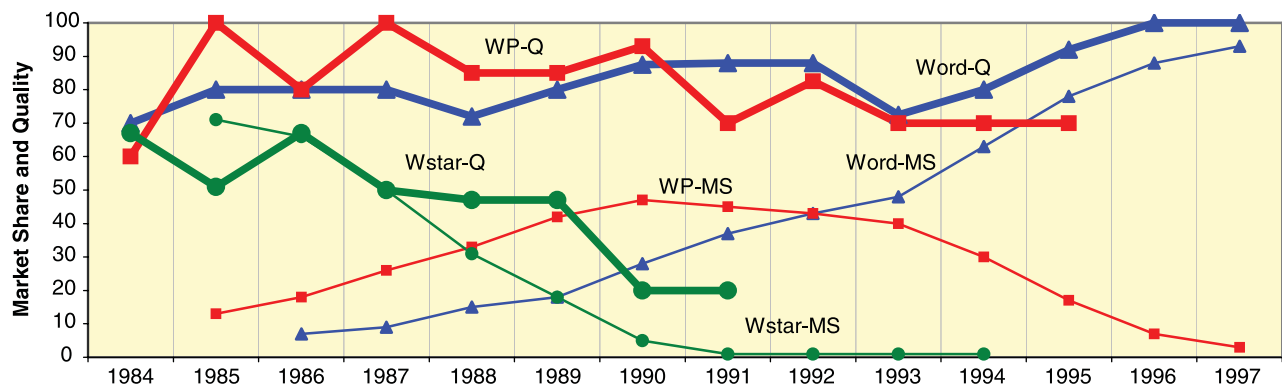
A: The Spreadsheet Market: PC



B: The Personal Finance Software Market



C: The Word Processor Market



Notes: Q = quality, MS = market share, MYM = Manage Your Money, Wstar = WordStar, and WP = WordPerfect.

mentary products. Indeed, when the quality of Microsoft's brand lies below that of competitors, so does its market share.

In summary, the market share leadership of Quicken swiftly (within two years) followed 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 since users rarely have the need to share and exchange files. These results suggest a market similar to Case 3, but not Cases 1, 2, and 4.

Word processor market (PC). In the word processor market, the early leader was WordStar, which dominated the

market for several years. However, from 1984, WordStar's quality began a sharp and irreversible decline (see Figure 1, Panel C). WordPerfect surpassed WordStar in quality in 1985, and its market share rose following its quality rise. However, the market share switch between WordPerfect and WordStar did not occur until four years later (i.e., 1989). WordPerfect's market share kept rising, and it maintained its market leadership until 1993, when it was surpassed by Microsoft Word. Microsoft Word's quality rating surpassed that of WordPerfect in 1991 and has sustained its leadership since then. In contrast, WordPerfect's quality was consistently inferior to that of Microsoft Word after 1991, and its market share steadily declined over the same period.

This market resembles Cases 3 and 4, but not Cases 1 and 2. The market dynamics played out between WordStar and WordPerfect appear to support Case 4, in which the market took four years to settle down on a new but superior brand, which is longer than expected for a perfectly efficient market. However, the competition between Word and WordPerfect appears to be in favor of Case 3; that is, the market took only two years to crown the new leader after its quality excelled. Overall, the word processor market, which is possibly the most driven by network effects, still appears to be efficient.

Other markets. The market dynamics in the Mac word processor market, Web browser market, desktop publishing market (both Mac and PC high-end and low-end markets), Internet service provider 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. Thus, quality seems to play an important role in influencing market dynamics. Moreover, these simple graphical analyses do not indicate that these markets are perverse. That is, for most markets we analyze, there is no evidence that early market share leaders dominate the market for long or do so if they lose their quality edge. We provide similar graphs for other categories in Web Appendix B (<http://www.marketingpower.com/jmrapril09>) 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

Next, we attempt to test the generalizability of key findings of the graphical analyses by conducting 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 restrict the word "switch" to mean a switch from being subdominant 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). Thus, 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 the extent to which they are correlated with changes in quality.

As Table 4 indicates, there are fairly frequent changes in market leadership, which rarely rests with a single brand. The average duration of market leadership ranges from 5.5 years for operating systems to as short as 2 years for Web browsers. Across all categories we examined, the average duration for market leadership is only 3.8 years. In contrast, consider that Coke has maintained market leadership for more than 100 years. Other leading brands in various traditional markets have been able to sustain their market dominance for extraordinarily long periods (see Golder and Telis 1993, Table 2).

For a better idea of the relationship between quality switches and market share switches in these markets, we identify all switches in the product categories in our sample. As we describe in Table 4, in 17 of the 19 markets, at least one switch in market share leadership occurred during an average period of 9.3 years for these markets. Furthermore, in 10 of these markets, there were multiple switches in market share. Overall, there were 34 switches in market share across all the markets. Thus, as the graphical analysis shows, market shares are in a state of constant flux. This observation does not support the existence of simple markets in which consumers care only about networks or randomly choose products and ignore both network and quality.

Why does this happen? Table 5 presents an analysis for one of the causes of market share switches. Of the 34 switches in share, 18% are related to a switch in quality the same year, 50% are related to a switch in quality in prior years, and 20% are related to the subdominant brand already having a superior quality to the dominant brand. Thus, 88% of the switches are related to switches in or superiority of quality of the subdominant brands; only approximately 12% have no relationship to quality. In contrast, when there is no switch in share, in general, quality of the inferior brand stays inferior.

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 for either Case 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 three years as the frame of reference because for all these categories, our research indicates that the repurchase cycle is approximately three years. For Web browsers, Internet service providers, image management software, presentation graphics, and personal finance, it takes less than the three-year repurchase cycle for a subdominant brand to become the new market leader after its quality excels that of the dominant brand (i.e., in support of Case 3). For word processors, spreadsheets, desktop publishing, and network operating systems, the

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 because of 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
Project management (high end)	2	1	No initial data on quality switch because of data censoring	6	Primavera → Project Workbench	3
Project management (low end)	0	1	No quality switch because of 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 because of data censoring	7	N.A.	N.A.
Average years taken to market leadership			2.2		Average duration of market share leadership	3.8

Notes: N.A. = not available.

Table 5
CATEGORICAL ANALYSIS OF SWITCHES IN MARKET SHARE AND QUALITY

A: 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%)
B: 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 Unsustained Quality Advantage	Potential Data Censoring	
Number of cases (%)	8 (44%)	6 (33%)	4 (22%)	

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

time to attain market leadership is longer (i.e., four to five years) (i.e., in support of Case 4). These results demonstrate that the markets for the first group of products are highly efficient, such that superior products quickly gain market leadership when their quality dominates that of rivals. The markets for the second group of products are efficient,

though markets settle 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 the superior Windows quickly replaced DOS two years after its quality surpassed that of DOS. A 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. Again, it 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, in general, the first group of products is believed to exhibit weaker network effects, while the second group of products is much more influenced by network effects because of their sharing- or intrinsic communication-oriented nature. These results further support Case 4, indicating that network effects 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 of 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 a switch in market share and quality took place, as defined previously. We consider only “up-switches” (from an inferior quality or low-share brand to a 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 follows:

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

We can analyze the relationship between market share switch and quality switch using the following logit model (Maddala 1983, p. 22):

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

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) up to four periods because rarely does a switch in market share occur beyond four years from a switch in quality. However, third and fourth lags are never significant.

The results of the logit analysis for $K = 3$ appear in Table 6, Panel A. 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 and 2 but support Cases 3 and 4. The results indicate that markets are responsive to quality, as evidenced 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 does not account for the differ-

ence 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.

Hazard Analysis of Time to Market Share Leadership

For this analysis, we 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 to account for category-level differences in inertia, we define the following additional variables:

- $Time_{it}$ = 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 brand i in period t over the network size of the other brand in the pair; and
- $Lead_Dur$ = average duration of the market share leader in the category to which the pair of brands belong (last column in Table 4).

To use 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—that is, $h_{it} = P[MS(s)_{i,t} = 1 / MS(s)_{i(t-n)} \forall n \geq 1 = 0]$:

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

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 and the three variables of interest. We consider the baseline hazard term a polynomial function of time: $\alpha_t = \alpha_1 + \alpha_2 Time_{it} + \alpha_3 Time_{it}^2$. In each period when the

Table 6
ANALYSIS OF MARKET SHARE SWITCHES

A: Logit Analysis of Market Share Leadership Switches					
Independent Variables	Coefficients	SE	Wald Statistic		
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%				
N		540			
B: Discrete Time Hazard Analysis of Time to Market Share Leadership					
	Time	Time ²	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

* $p < .005$.

event occurs, the observation contributes h_{it} to the likelihood function, and it contributes $(1 - h_{it})$ to the likelihood function in all other periods. Therefore, the likelihood function for the model is as follows:

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

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

The estimated parameters appear in Table 6, Panel B. The results show that, except for the network ratio, all variables are statistically significant in the model. The results indicate that the 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 the difference in network size.

Figure 2 illustrates these results. The x-axis represents the 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 curves, one for each level of quality gap. For either level of quality gap, the probability of market share leadership peaks at about the third year since the switch in quality, confirming our descriptive analysis. However, the probability of such a switch is much higher when the gap in quality (of the lower-share brand over the higher-share brand) is higher.

These estimates provide some evidence in answering our research question about the 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:

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

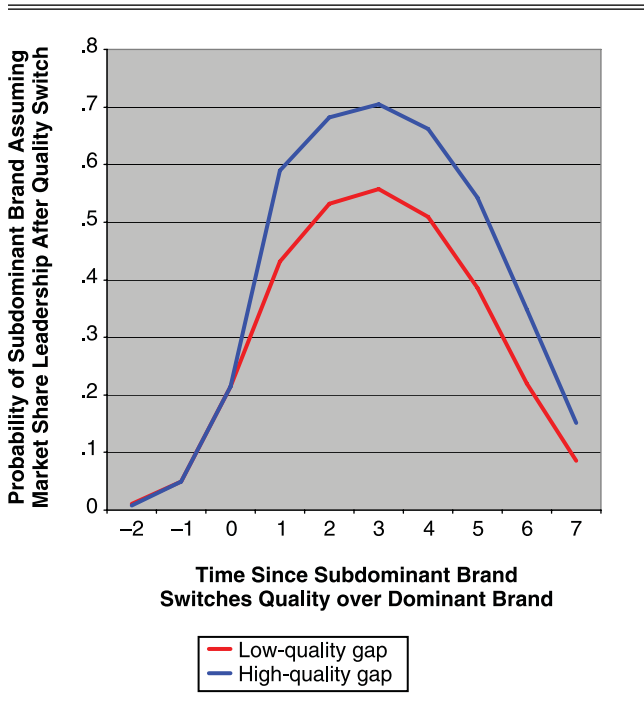
where t is a subscript for time, i is a subscript for brand, α and β_m are coefficients to be estimated, Sh is market share, N is network size, Q is quality, and M is a set of covariates (Cov) indexed by m , including an interaction term of quality $\times$ network size. Other potentially relevant covariates 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 i.i.d. normal. In the interest of parsimony, we run pooled regressions across the 19 product markets in our data set. 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 do not have good data on advertising or channel support and therefore 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 model without fixed effects. Moreover, only two category effects are significant, and none of the other parameters are materially affected. Similarly, incorporating random effects for year and category in all our reported regressions does not materially change the parameters of interest (i.e., 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 in relation to other competing specifications has been established to be comparable or superior (Brodie and De Kluyver 1984; Ghosh, Neslin, and Shoemaker 1984; Tellis 1988). Thus, we also use the following multiplicative model in a log-log form:

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

In this equation, natural logs of all variables have been taken, except for the growth variable (G_t). This is because

Figure 2
PROBABILITY OF SUBDOMINANT BRAND ASSUMING MARKET SHARE LEADERSHIP FOLLOWING A QUALITY SWITCH OVER DOMINANT BRAND



growth could take both positive and negative values, and it may be taken purely as a covariate. The results appear in Table 7, Panel A. (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 subsequently present a first-difference regression model version of the relationship of interest in Equation 4 and a Granger test of causality.

If we consider 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. A probable reason is that data aggregation (annual level) and pooling (cross-section $\times$ 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 that both network and quality are important determinants of market share. The interaction effect of

quality $\times$ network is positive and significant in the regression run on all 19 product categories, in support of Case 5. If we follow the logic of Case 5, this interaction effect suggests that network effects enhance the efficiency of the market, as evidenced by the positive response (main effect) of market share to quality.

As mentioned previously, we were 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 has two additional advantages. First, it captures flow better than 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 appear in Table 7, Panel B.⁵ The variables P and G are the control variables—that is, relative price of the brand and growth rate of the category, whenever this information is available. Note that the only variables with significant effects on market share are quality and network (both variables are 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 -values alone, it is apparent 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 and 4, but not Cases 1 and 2.

Our final analysis is motivated by the following argument: Because quality is obtained from published reviews, it could be argued 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. A 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 testing 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, X is supposed to Granger-cause Y . A particularly simple approach to test for Granger causality uses the autoregressive specification of a bivariate vector autoregression. This assumes a particular autoregressive lag length p and then estimates restricted and unrestricted regressions of the following type by ordinary least squares:

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

⁵As a reviewer suggested, 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 sometimes insignificant. We present this model because we believe that in a first-difference model, taking logs first is not essential.

Table 7
LINEAR REGRESSION ANALYSIS RESULTS

A: Log-Log Regression				
(Equation 5) Dependent Variable: $\ln(Sh_{i,t})$				
Variable	Estimated Parameter	t -Value	Estimated Parameter	t -Value
Intercept	−3.87**	−8.48	−3.13**	−45.71
Network:				
$\ln(N_{i,t})$	.48*	2.30	.03**	2.74
Quality:				
$\ln(Q_{i,t})$	1.49**	7.73	1.47**	44.90
Interaction:				
$\ln(Q_{i,t}) \times \ln(N_{i,t})$	.05	.44	.47**	80.81
Relative price:				
$\ln(P_{i,t})$	.45*	2.24	—	—
Category growth (G_t)	.11	.66	—	—
B: Regression of First Differences				
(Equation 6) Dependent Variable: $(Sh_{i,t} - Sh_{i,t-1})$				
Variable	Estimated Parameter	t -Value	Estimated Parameter	t -Value
Intercept	−.04	−1.33	.001	.18
Network:				
$(N_{i,t} - N_{i,t-1})$	.09**	3.65	.077**	4.69
Quality:				
$(Q_{i,t} - Q_{i,t-1})$	.05**	7.57	.041**	8.22
Relative price:				
$(P_{i,t})$	.10	1.27	—	—
Category growth (G_t)	.027	1.14	—	—

* $p < .05$.

** $p < .01$.

Equation 7 with all free parameters gives the unrestricted version of the regression, but in the restricted version, all $\gamma_i = 0$. Rather than simply considering 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 $\gamma_i = 0$) implies no evidence of Granger causality. The F-statistic for testing the null hypothesis can be calculated as follows:

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

where ESS_0 and ESS_1 are the error sums of squares of the null and unrestricted models respectively, p is the number of lags in the model, and T is the number of observations or the length of time series. In Table 8, 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 both estimations, other than the intercept terms, only the first lags of quality and market share variables are included because 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. On the basis of the parameters and the F-tests, we reject the null hypothesis in the first case but 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.

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 efficient, with the best-quality brands always having the highest market share.

We develop a theoretical model that integrates both network and quality effects. We then carry out a variety of

descriptive and empirical analyses using a data set of hardware and software products that we put together for the 1980s and 1990s.

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.
- In general, a change in market leadership is 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 is 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, and Case 5 helps interpret it.

Implications

Is “rush to market” the right mantra to follow? As we 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. A major reason for 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; Shankar, Carpenter, and Krishnamurthi 1998; Tellis and Golder 1996, 2001). The current inquiry suggests that superior quality is an 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? If the theory of network effects is as strong as some researchers 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 from 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., when an inferior product or standard dominates the market simply because of its large network size). However, we argue that, under certain circumstances, network effects can make the market more efficient. If enough consumers care about quality, 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

Table 8
TEST OF GRANGER CAUSALITY

Variable	Market Share Equation: Dependent Variable: M_{it} ($N = 479$, Adjusted $R^2 = .63$)		Quality Equation: Dependent Variable: Q_{it} ($N = 479$, Adjusted $R^2 = .70$)	
	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

* $p < .01$.

to the uninformed. Some researchers might argue that the best way to create a strong network of users is through quality. Although it is true that these two variables are related, we believe that 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 is 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 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 FURTHER RESEARCH

This study has several limitations, which could be addressed by further 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 for which we have price, this variable is not significant and has the wrong sign, either because it is not important or because the data are aggregated at the annual level.

Second, we do not account for distributors, especially retailers. 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 preinstalling 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. Although there have been fewer changes in some of these markets in recent years, innovation in software is still vibrant, as witnessed by the introduction of many products, including the rise of some entirely new brands (e.g., Google, YouTube, MySpace).

Fifth, the replacement cycle may depend on quality in that consumers might not feel 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 regarding price, quality, and compatibility. Nevertheless, our simple model develop-

ment yields some important insights and provides a good basis for empirical analyses that compare the role of network effects and quality in determining the success of a new high-tech product.

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