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Abstract

This paper examines the importance of network effects in the Japanese market for word-processing software in the period between 1998 and 2001, using hedonic price and nested logit models. This was a period in which Microsoft Word had a large and steadily increasing share of the market. The presence of network effects was verified in the full regressions covering the entire period. Separate regressions for two consecutive years showed that network effects, as measured by the positive effect of the size of the user base on the product price or on the probability of the software group being chosen, were weak or insignificant in the beginning of the sample period. The paper discusses data and methodological issues, and possible reasons for these results, including the effects of switching costs.

Keywords: Network Effects, Software, Hedonics, Discrete Choice Model, Switching Costs.

JEL Classification Numbers: L86; L11; L13.

1. Introduction

The past decade has seen a rapid diffusion of word-processing software in Japan. As of March 2003, 63.3% of all ordinary households in Japan had at least one PC (Consumer Confidence Survey, Economic and Social Research Institute, Cabinet Office), and as of May 2000, 87.7% of all home PC users used word-processing software (Nikkei Newspaper). Justsystem's Ichitaro dominated the Japanese market for word-processing software until the mid-1990s, but Microsoft's Word overturned it around 1996-1997, and Word's market share has been increasing slowly but steadily since then.

A firm may be able to keep a high market share because its product displays a high cost-performance. It could also do so when there are network effects or switching costs.[1]

This paper examines whether network effects were at work in the Japanese market for word-processing software in the period between 1998 and 2001, and, if so, to what extent. It also discusses whether firms with small market shares can still attract consumers by providing superior products.

Empirical research measuring network effects in individual markets has been on the increase since the 1990s. Common methods for measuring network effects include hedonic pricing models, discrete choice models and vector auto-regressive (VAR) models.

Hedonic pricing models estimate how product prices are dependent on product characteristics. When there are incompatibilities between products

[1] Theoretical analysis of markets characterised by network effects was initiated by Rohlfs (1974), who dealt with a single-network set-up. There has been a big wave of theoretical literature on models with a multiple of networks starting from Katz and Shapiro (1985). Useful surveys of mainly theoretical literature include Katz and Shapiro (1994), Economides (1996), Shy (2001), Farrell and Klemperer (2001), and Gandal (2002).

where compatibility is in fact desired and if products with high market shares display high prices, controlling for product characteristics we may interpret this as evidence of network effects. Examples of this line of research include Brynjolfsson and Kemerer (1996) and Gandal (1994) who studied the US spreadsheet software market, Ohashi (2003a) who studied the US VCR market, and Asai and Tanaka (2003) who studied the Japanese PC market. Tanaka, Yasaki and Murakami (2003) discussed competition policy when both network effects and innovation are present and performed a hedonic analysis of the Japanese markets for spreadsheets and routers as well as word-processing software.

There is a growing literature measuring network effects in individual markets by directly modelling consumers' discrete choices. Nested logit (NL) is the common specification in these models. In NL models, consumers' choice alternatives are grouped together according to the correlation between utilities they would get from each choice. Consumers make two decisions, one regarding the choice of a group and the other regarding a particular alternative within this group. If consumers are more likely to choose products belonging to groups with high market shares, controlling for product prices and characteristics, we interpret that network effects are at work. NL models incorporate elements of hedonic pricing models in that product characteristics are included as control variables. Park (2003) and Ohashi (2003b) separately analysed the US VCR market using NL techniques. Rysman (2003) analysed indirect network externalities that arise between the number of advertisements and the number of consumers in the US market for Yellow Pages.

VAR models are used to test whether there is intertemporal correlation between two or more time series to investigate the presence or otherwise of positive feedback between them. Tanaka (2002) analysed network effects in the Japanese mobile phone market using both hedonic and VAR techniques, while Tanaka (2003) investigated the Japanese game software industry using VAR models.

This paper employs both hedonic pricing and NL models to test for the presence of network effects in the Japanese word-processing software market. As far as we are aware, this is the first attempt to measure network effects in word-processing software in any geographical market.

The rest of the paper is organised as follows. Section 2 briefly reviews the state of the word-processing software market in Japan, and section 3 explains how network effects may arise in that market. In section 4 we discuss the data we used and begin our empirical analysis of the Japanese word-processing software market between 1998 and 2000 or 2001. Section 5 explains the hedonic pricing technique and the results we obtained from them. Network effects seem to have been present when data from the three-year period between 1998 and 2000 are used, but when data from two consecutive years are grouped together and each group is estimated separately, network effects were found not to have been significant in the beginning. Similar results are obtained when lagged value of the network effect variable are used. Section 6 explains the NL technique and the results we obtained from them. Similar intertemporal patterns regarding observed network effects are obtained. Section 7 discusses various issues including data and methodological limitations, and the possibility that the presence of switching costs gave rise to such intertemporal patterns. Section 8 discusses how Microsoft was able to gain a dominant market position in the latter half of the

1990s. Using results from a questionnaire survey of users, we discuss in section 9 the possibility that technological progress slowed down since Microsoft secured a high and stable market share. Section 10 concludes our paper.

2. Overview of the Market

Word-processing software diffused rapidly among Japanese households as PCs themselves did in the 1990s. Figure 1 shows the volume and value of shipment of word-processing software in the Japanese market in flow terms since the late 1980s. Both volume and value of shipments increased rapidly throughout the 1990s. It should be noted that the word-processing component in Office-type integrated business software is included in the data. In such cases, the value is divided equally between its major components such as word-processing, spreadsheet and database.

Figure 2 shows how the domestic market shares of major word-processing software products by producers evolved between 1994 and 2000. Ichitaro had a market share of over 50% in the first half of the 1990s, but was overturned by Word in the latter half. In the late 1990s Word kept a high, stable and slowly increasing market share.[2]

Figure 3 shows how the list prices (or catalogue prices) of the most

[2] The data for 1994-1996 and those for 1997-2000 are taken from different sources, as it was not possible to collect a single time series that covers the entire period. The 1994-1997 data are taken from Business Computer News and are based on point-of-sale data at selected retailers. The 1997-2000 data are taken from the IT Basic Survey by Nikkei Market Access and are compiled from responses to questions on software usage in questionnaire surveys of PC users. Thus the 1994-1996 data are annual flow data and 1997-2000 data are stock data, and we cannot conclude from these figures alone that Microsoft traded places with Justsystem between 1996 and 1997. However, other available evidence also suggests that the share swap occurred in the latter half of the 1990s, probably around 1997.

recent versions of each major software product changed since 1991.[3] The price of both Ichitaro and Word stayed constant at 58,000 yen until 1995, but the situation changed drastically in 1996 when the list price of Ichitaro was lowered to 40,000 yen and that of Word to 15,000 yen. Prices were further reduced in 1997, Ichitaro to 20,000 yen and Word to 11,180 yen, and these prices remained the following year. A rapid market share reversal took place parallel to this. In 1999 the price of Word was raised to 18,800 yen. Strategic penetration pricing is often employed in industries with network effects or switching costs, and such pricing policies may have been used in this market from 1996 on.[4]

The fact that Microsoft was able to increase its market share in the late 1990s may have been because Word was less expensive than Ichitaro, controlling for product characteristics. It may also have been because Microsoft benefited more from network effects than did Justsystem because Microsoft had already acquired a larger market share. In the next section we briefly show why network effects are likely to be at work in the market for word-processing software. Subsequent sections discuss empirically whether network effects really were present in this market in the period between 1998 and 2000 or 2001.

3. Network Effects in Word-Processing Software Market

Network effects are said to be at work if the benefit accruing to each individual consumer from using a particular good or service is dependent on

[3] List prices are used because we were not able to obtain a similar time series for retail prices. However, available data suggests that retail prices followed a similar pattern of change.
[4] We will return to the issue of how Microsoft was able to gain dominance in section 8.

the number of other consumers who use compatible goods or services. There are two reasons why we think network effects may be present in the market for word-processing software.

First, documents written using word-processing software will generally be used by the writer herself, but generally also will be given to others to read and/or print out via diskettes, CD-ROMs, LANs and the Internet. The benefit to the writer will be greater the larger the number of other people who use software compatible with her own. Thus, direct network effects through exchange of files tend to be at work.[5]

Second, in complement to the above, when a consumer starts to use a software product she will benefit from help given by others around her who use similar software. Moreover, the more consumers use a particular software product the larger will be the demand for guidance on how to use it or how to do particular tasks using it, and the more manuals and magazine articles will likely be written. The presence of such texts will benefit consumers further. Thus, indirect network effects also may be at work.

4. Data Set

4.1 Data Source

GFK, a market research firm, compiles average retail price and volume figures for various IT products from point-of-sale (POS) data from approximately 3,000 selected retailers. Our data set comprises average retail price and volume for all word-processing software products sold at those

[5] The importance of file exchange is said to have increased dramatically with the advent of the Internet. Thus, it is conceivable that direct network effects were stronger in the period after 1995 than in the period before 1992, but investigating the validity of this hypothesis is beyond the scope of this paper.

retailers in the months of December 1998, December 1999, December 2000 and December 2001. We thus have monthly data from those four points in time, a year apart from each other. Henceforth, we use terminology whereby Word, Ichitaro, and other such software each comprises a *software group*, and different versions of software, products that run on different operating systems, and products sold under different discount programmes (e.g. student discounts and academic discounts) are treated as different *software products*.

Usage share data for each software group for each period come from the IT Basic Survey by Nikkei Market Access that we mentioned in section 2, and are based on replies (multiple) to a questionnaire survey of home PC users. Data on the number of ordinary households (Population Census: 1st October 1995, 1st October 2000), population estimates (Statistics Bureau, Ministry of Public Management, Home Affairs, Posts and Telecommunications, 1st October each year), PC penetration rate in ordinary households (Consumer Confidence Survey, Economic and Social Research Institute, Cabinet Office, end of March each year), and word-processing software usage rate among home PC users (Nikkei Newspapers: May 1998, May 1999, June 2000; Nomura Research Institute: March 1997, March 1999) are used in calculating the number of users for each software group.

4.2 Sample Selection

We restricted ourselves to stand-alone products, so integrated business software is not included. The sale of products falling under software groups other than Word and Ichitaro was extremely low throughout the period, so data for these are excluded. English-language versions, products for primary school students (e.g. Ichitaro Smile), Java-based products (e.g. Ichitaro ARK), and other products for which characteristics were hard to determine were also excluded.

During the course of these years, the majority of PC users used Windows PCs. Also, the sale of products given academic discounts was much lower than that of products not given such discounts. Macintosh versions of word-processing software would not normally be an alternative for Windows users, and non-academic users cannot get academic discounts legitimately. Thus, Macintosh versions and academic discount versions were also excluded from our data set.

The above streamlining gives us a sample size of 76, and the composition of the sample is shown in Table 1. It should be noted that data on the same software product is treated as a different data point if they come from different points in time.

4.3 Variables

4.3.1 Product Characteristics

One of the hardest tasks we faced was that of identifying the variables that represent product characteristics. Word-processing software had acquired numerous functional abilities by the late 1990s, and counting them all up would lead to insufficient degrees of freedom in the analysis. Specifying all product characteristics and evaluating each product with respect to these characteristics would be extremely hard in any case for the following reasons. First, many characteristics cannot easily be reduced to a numeric scale or even to a dummy variable (e.g. cleverness of Kana-Kanji transformation function). Second, not all product characteristics are written out in a comparable form in catalogues or on websites. Third, by the late

1990s, PC magazines and trade journals had stopped carrying articles that compare different software products in depth.

Many products characteristics are common to all or most products, and these effectively go out of consideration when a consumer decides which product to purchase. For instance, by this period all products allowed pictures to be imported into document files at specified locations. These functions do not differentiate products. In our analysis we focused on those functions that were either emphasized by the producer in advertisements and manuals or featured heavily in magazine articles and guidebooks when the products went on sale. These functions are the ability to store multiple clippings (*D_MULTIPLECLIPS*), the presence of a working window (*D_WORKINGWINDOW*), and worksheets to which files made by other software can be imported and saved as one file in the same way a number of Excel sheets can be saved as one file (*D_WORKSHEET*), as well as those additional functions that are not an integral part of the word-processing software but are nevertheless used normally in conjunction with the software. Such additional functions include Kana-Kanji transformation (*D_JP*) and voice recognition (hardware and software) (*D_VOICE*).[6] Considering that consumers take into account information obtained from advertisements, manuals and guidebooks, it seems natural to think that the availability or otherwise of these functions influence their decisions.

We have also included a variable representing Lite versions of software, which supposedly provide a faster response to typing by concentrating on basic functions and shedding as many additional features as

[6] We made extensive use of catalogues and websites of Microsoft and Justsystem, press releases and news reports, and instruction books on Word and Ichitaro.

possible (*D_LITE*).

4.3.2 Network Effects

Either usage market share (*SHARE*) or the number of users of each software group in each period may be taken to represent network effects. We have not been able to obtain information on the latter, so we calculated it in the following manner.

First, we assumed that the average number of people in each ordinary household changed linearly over time, and calculated this number for the 1st of April of each year from the numbers for 1995 and 2000 and the population statistics for each year. From these and the data on PC penetration rate, the number of households with PCs was calculated. We think in terms of the number of households, not persons, regarding software usage in what follows.[7]

We then calculated the number of households that had word-processing software from the number of households with PCs and the word-processing software usage rate among PC users. The usage rate data for 1998, 1999, and 2000 are available from Nikkei, and those for 1997 and 1999 from Nomura Research Institute. The number of households with PCs was accordingly calculated in two incomplete time series, which were interconnected by multiplying a constant to the Nomura-based series so that the 1999 figures are equal.[8]

The number of households that have products under each software

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[7] This is to ensure consistency with the PC penetration data. We are assuming that the household PC adoption rate and the PC adoption rate of individual users are the same, and that the same proportion of home PC users as households with PCs uses word-processing software.

[8] We took the Nikkei data as the base simply because they contain more data points. Qualitatively the same results are obtained if we used the NRI data

group, or the group's installed base, is calculated by multiplying the number of households with word-processing software at all with the market share of the software group. Natural logarithm of the installed base figures (*LIB*) are used in the analysis.[9]

4.3.3 Market Share of Software Groups and Individual Software Product in Sales

For the NL analysis, we need data on the share of households that purchased a product from each software group and the share of those that did not buy any among all households that potentially might have bought one each period. We also need data on the sale share of each software product within the software group.

We first construct an index that measures the potential market size. Demand for word-processing software in each period is composed of demand by households that had not had word-processing software and renewal demand by those who had, and the potential market size has to encompass both. The number of households that might have purchased software new is equal to the number of households that have PCs but not word-processing software.[10] The number of households that might have renewed their software

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as the base.

[9] It is also possible to derive the number of households with products of a given software group directly from the PC adoption rate and the market share data for each software group. However, the NL analysis below assumes that each household (or individual) either uses Word, Ichitaro, or neither, thus excluding the possibility that it uses both. Thus we divided households that possess word-processing software into those that possess Word and those that possess Ichitaro. We were unable to obtain data on software groups other than Word and Ichitaro, but it can be safely assumed that the market shares of these were very small. (The simple sum of the market shares of Word and Ichitaro was 96.0%, 92.8%, 101.0% and 95.1% respectively for 1997-2000.)

[10] This is assuming that ownership and usage coincide.

is equal to the number of households for which the software they had had depreciated in value during that time period. It is hard to ascertain the real depreciation period of any particular product, but results from informal surveys suggests that the period is several years. According to the present Japanese taxation and accounting rules, PCs have a depreciation period of four years. Software should have a comparable depreciation period, and we assume that a quarter of those households that had word-processing software in the previous period are potential buyers of a software product.[11] Market size was calculated as the sum of the number of households that are potential new buyers and the sum of potential renewal buyers.

It is not appropriate to calculate the size of the user base by summing up sales figures for each product from the POS data. This is because the sale of Word products is underrepresented in our data set, which does not include data on pre-installed software products or integrated business software products. We therefore assumed, as above, that the sale of products under each software group is equal to the number of households that have software of this group during this period less three quarters of the number in the previous period.

From the potential market size and sale volume of each software group thus calculated, we calculated further the sale share of each software group and the share of those households that did not purchase any software (i.e. chose the outside option), s_0, as the residual.

Dividing the share of each software group proportionally to the sale figures from the POS data gave us the sale share of each software product, s_j.

[11] The depreciation period for ordinary software is five years according to taxation and accounting rules, but we employed four years based on the observation that consumers tend to buy new software when they buy new PCs.

4.3.4 List of Variables

Table 2 lists the variables used in the analysis.

5. Hedonic Pricing Model

5.1 Methodology

When network effects are at work and there is little or no compatibility between products of different software groups, consumers make their purchase decisions based not only on price and product characteristics but also on the number of users who use products of the same product group. A firm with a larger user base can thus charge higher prices for products of similar quality. A positive correlation between the size of the user base and price, controlling for product characteristics, therefore indicates the presence of network effects. We thus ran regressions with product price as the dependent variable and variables representing product characteristics and the size of the user base (either the logarithm of the number of users of the software or the market share) as independent variables, and tested whether the user base variable has a statistically significant positive coefficient.

5.2 Base Model

We first used the logarithm of the current number of households that have software of the same group as the size of the user base. This number is derived from past sales, so there is a potential simultaneity bias between this and individual product prices. However, in our analysis the data on individual software products were monthly and taken in December, while the market share data and user base size data calculated from them were taken in

March-June of the same year, so the correlation between the error term and dependent variable probably is not strong. It is worth noting that when a consumer makes purchase decisions she can easily obtain price information of available software products, but up-to-date information on the size of user bases is hard to obtain and it is reasonable to assume that lagged data on user bases enter into her consideration. Our model is consistent with this assumption.

Our POS data come from the period between 1998 and 2001, and the user base data between 1997 and 2000. We therefore estimated the hedonic price equation for the three-year period between 1998 and 2000. Case 1 of table 3 reports the result. We excluded the functional variable *D-WORKINGWINDOW* at this stage because no software product available in this period had this function. We also ran regressions with data from two consecutive years to discover intertemporal patterns, and cases 2 and 3 of table 3 show the results.[12]

We then excluded the functional variable that was not statistically significant throughout the period, namely *D_WORKSHEET*, and estimated the hedonic equations again, and the results are reported as case 4-6 in table 3. In what follows we take the three-year estimation shown in case 4 of table 3 as our base model

The network effect variable has a statistically significant coefficient in the full three-year regressions, so we can conclude that network effects were at work in this market overall.[13] In our base model (case 4), the coefficient of the

[12] Single year estimations were not carried out due to lack of sufficient degrees of freedom.

[13] In chapter 3 of Tanaka, Yasaki and Murakami (2003), we were unable to verify the presence of network effects. The contrast underlines the importance of the newly employed functional variables, detailed data on which

network effect variable (logarithm of the number of households with software of the particular group) is 2098.48. This implies that multiplying the size of the user base by *e*, the base of natural logarithm, is consistent with a 2098-yen price rise. This translates to a 1% increase in the size of the user base corresponding to a 21-yen price increase. Our calculations show that the user base of Word was 3.030 times as large as that of Ichitaro as of 2000. This is consistent with the price of a Word product 2326 yen higher than that of an Ichitaro product with equivalent characteristics.

This price differential, however, is not something that could have been overcome by technological progress. The estimated coefficient of *D_MULTIPLECLIPS*, for instance, is 7265.46 and is significant. This suggests that the firm with the smaller user base can still overcome this difference and attract consumers if it can develop and embody into its products a new function that consumers value, assuming that its competitor does not change its actions. In practice, however, a new function that one vendor embodies in its products is often imitated by the other in the next version of its products. Therefore, to surmount the price difference the smaller firm needs continuously to develop new functions valued by consumers.

The estimated coefficients for the year dummies *D_99* and *D_00* are both negative and statistically significant. The values are -2522.28 and -3320.12 respectively, suggesting that the price of products with equivalent measurable characteristics decreased over time, though the rate of decrease slowed.

Comparison between cases 5 and 6 allows us to see intertemporal changes. The coefficient of the network effect variable was statistically

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we have since obtained.

significant in the 1999-2000 regression but was not in the 1998-1999 regression. This is discussed later.

We employ the functional variables used in the base model in what follows.

5.3 Robustness

To check the extent to which results from our base model are dependent on the particular specifications of the model we carried out weighted least squares (WLS) estimations, estimations using market share instead of the logarithm of the number of households as the network effect variable and estimations using lagged values of the network effect variable. We first outline why we consider this exercise to be of value.

The sale figures from each period differ greatly from one software product to another. It is quite conceivable that for software products with very low sale figures, the average retail price was heavily influenced by local circumstances of the particular retailers that happen to have sold them. WLS, with the sale figure for that period used as weights, was used to counter this problem.

The network effect variable is expected to be a function of the size of the user base, but economic theory does not specify its functional form. In empirical analyses of network effects, installed base share is often employed as the network effect variable because the data are relatively easy to obtain.[14] We follow previous studies here in using market share instead of the logarithm of the user base. This has an added advantage that the data are

[14] Brynjolfsson and Kemerer (1996), for example, used the installed base share as the network effect variable in their analysis of the US spreadsheet market.

less likely to be contaminated by errors.

The results from these estimations are reported in table 4. The network effect variable had a statistically significant effect on price in all cases, supporting the results from our base model. In the OLS regression with share data, the coefficient of the share variable is 4708.15, so a 1% point share increase corresponds to a 47.1-yen price rise. The difference in the market shares of Word and Ichitaro was 47.9% points in 2000. Thus, a Word product was on average 2255 yen more expensive than a functionally equivalent Ichitaro product.

WLS estimates tended to have more explanatory powers than OLS estimates, and explanatory variables tended to be more significant, underlining the possibility that data for software products with low sale volumes were influenced by local circumstances of the particular retailers.

We then estimated hedonic price equations using one-year lagged values of the logarithm of the user base size as the network effect variable. The simultaneity problem should be even less of a concern than in the base model. As we have explained, it takes time for consumers to obtain data on the size of the user base (actual figures of share), so the share data taken into consideration when consumers make purchase decisions are lagged by a certain period. The actual length of this certain period is a matter for another empirical investigation. Here we use one-year lagged values and compare the results with those from our base model.

Using one-year lags of the network effect variable also allows us to analyse intertemporal changes over the four-year period between 1998 and 2001. Estimates using data from all four years, three consecutive years, and two consecutive years are reported in table 5. The variable

D_WORKINGWINDOW was found not to be statistically significant in preliminary estimates, so it was dropped from the estimation.

The network effect variable was not found to be statistically significant in the 1998-1999 two-year regression, but was significant in 1999-2000 and 2000-2001. Estimates for three-year regressions show a similar pattern. The network effect variable was not a significant determinant of the product price in the regression with data from 1998-2000.[15] It was, however, a significant variable in the regression with data from 1999-2001.

From this and the results from 5.2 above, we can say that network effect, as measured by the positive effect of the size of the user base on product price, was found not to be at work in the beginning of the sample period but was at work towards its end.

6. Nested Logit Model

Next, we test for the presence of network effects in the Japanese word-processing software market by modelling consumer choice directly using NL models.

6.1 Methodology

Discrete choice models such as logit allows us to model situations in which individual decision-makers chose one option from available alternatives. Our data set includes sale figure of each software product. Because sale figures represent aggregated results of individual purchase decisions by individual households, a logit model based on sale shares of individual

[15] This is consistent with our finding in chapter 3 of Tanaka, Yasaki and Murakami (2003).

software products may be used to test whether network effects had a significant bearing on consumer utility.

Logit analysis using share data was initiated by Berry (1994), and empirical analyses of specific markets are emerging. The analysis in this section is one application of this methodology, which is briefly explained below.

In each period, each household in the market either buys one unit of one of the products or none at all. Household *i* chooses product *j* to maximize its indirect utility represented by

$$u_{ij} = b_0 + \sum_k x_{jk} b_k + x_j - a\, p_j + g\, N_g + e_{ij},$$

where x_j represents observable characteristics of product *j*, x_j its characteristics unobservable to the investigator ($E(x_j) = 0$ is assumed), p_j its price, and N_g network effect variable when product *j* belongs to product group g.

Writing $d_j = b_0 + \sum_k x_{jk} b_k + x_j - a\, p_j + g\, N_g$, the above indirect utility can be rewritten as $u_{ij} = d_j + e_{ij}$, where the average utility consumers derive from purchasing product *j* is d_j, which is normalised so that the average utility from the outside option (of not purchasing any of the products) is zero.

In simple logit models, the market share of product *j* is given by $s_j = e^{d_i} \big/ \sum_j e^{d_i}$, but this presupposes that there is no correlation among the utilities a household obtains from different options. In the word-processing software market, however, if network effects are at work a household that wishes to buy a Word product, even if that particular product is not available, would likely choose another Word product and not an Ichitaro product. When we think that there may be correlation between utilities arising from some of the options, NL specifications may be employed.

Letting s_g represent the market share of product group g (group share), $s_{j/g}$ the share of product j within group g (within-group share), in NL models the market share of product j is given by $s_j = s_g s_{j/g}$, where

$$s_g = \frac{\left[\sum_{j\in g} e^{d_j/(1-s)}\right]^{1-s}}{\sum_g \left[\sum_{j\in g} e^{d_j/(1-s)}\right]^{1-s}}, \text{ and}$$

$$s_{j/g} = \frac{e^{d_j/(1-s)}}{\sum_{k\in g} e^{d_k/(1-s)}}.$$

Here, s is a measure of the degree of correlation between the utilities arising from different options within the same group, with $0 \le s \le 1$ provided that households are maximizing the indirect utility given above.[16] If $s = 0$ there is no within-group correlation of utilities and the NL model reduces to a simple logit model. If $s = 1$ the correlation is perfect.

Letting s_0 represent the share of the outside option, using $d_0 = 0$, we have

$$s_0 = \frac{1}{\sum_g \left[\sum_{j\in g} e^{d_j/(1-s)}\right]^{1-s}}.$$

Note that $s_0 + \sum_j s_j = 1$ holds.

Taking logarithms of the product share and outside option share,

$$\ln(s_j) - \ln(s_0) = \frac{d_j}{1-s} - s \ln\left[\sum_{k\in g} e^{d_k/(1-s)}\right].$$

From the logarithms of the group share and the outside option share we obtain

[16] The reader is referred to Cardell (1997) for more in-depth discussions.

$$\ln(s_g) - \ln(s_0) = (1 - s)\ln\left[\sum_{k \in g} e^{d_k/(1-s)}\right].$$

Eliminating the terms involving $\ln\left[\sum_{k \in g} e^{d_k/(1-s)}\right]$ from these expressions, we can easily derive

$$\ln(s_j) - \ln(s_0) = d_j + s \ln(s_{j/g}) .$$

Substituting for the average utility d_j, we arrive at

$$\ln(s_j) - \ln(s_0) = b_0 + \sum_k x_{jk} b_k - a p_j + gN_g + s \ln(s_{j/g}) + x_j .$$

This is our equation to be estimated.

The logarithm of the number of households with products of particular software groups is used as the network effect variable.

We use the same variables as in the case of hedonic analysis to represent functional characteristics. The right-hand side of the estimation equation involves the within-group share of the product under consideration and its average real retail price, giving rise to a simultaneity problem. Thus, for each functional variable we calculated the average value of the functional variable over all software products of the same product group sold that period except itself, and used this as its instrumental variable. The instrumental variable thus defined is expected to be negatively correlated with the product's within-group share, and with the product price.

6.2 Estimation Results

The result using the entire sample from 1998-2000 is reported as case 1 in table 6. The estimated coefficient of the network effect variable is positive and significant at 1% level, indicating the presence of network effects.[17]

The estimated coefficients of the functional variables are positive. If consumers are behaving rationally--if two products are sold at the same price and network effects operate equally on them--the product with better functions is likely to be chosen and the positive sign contradicts this.

One possible reason behind such a result is that, as in the case of hedonic analysis, the price and quantity data of products with very low sale figures were influenced by the circumstances specific to the particular retailers that sold them. For example, they might have sold them in clearance sales organized to save on inventory costs. To eliminate this effect, we carried out estimates excluding data for products with sale figures of less than three in that period according to POS data, and the result is reported as case 2 in table 6.[18]

As before, the estimated coefficient of the network effect variable is significant, indicating the presence of network effects. Here, the coefficients of all characteristics variables are statistically significant and have expected signs. The estimated coefficient of the average real price is negative and statistically significant. The estimated coefficients of year dummies are negative, indicating that the sale of a product declines over time if its price remains the same as new and functionally better products are introduced into the market.

As explained above, the user base for Word was 3.030 times as large as that for Ichitaro as of 2000. Using the estimate for case 2 it is easy to

[17] See also discussions in section 7.4.
[18] Similar results are obtained if installed base shares are used in place of the logarithm of the size of the installed base. The results are available from the authors upon request.

calculate that a 3.030-fold difference in the size of the user base corresponds to a difference of 2.747 in the dependent variable. This difference cannot be overturned even with the adoption of three functions *D_MULTIPLECLIPS*, *D_JP*, and *D_VOICE* (the sum of the estimated coefficients of these variables is 2.554). This is in contrast with the results from our hedonic price model, where the price difference arising from network effects can be overturned by the adoption of new functions. We will return to this point in section7.4.

The estimated coefficient of s is 0.955 and significant at 1% level, indicating the appropriateness of the NL specification.

We then conducted analyses with data from two consecutive years, and obtained results reported as cases 3 and 4 in table 6. The coefficient of the network effect variable is positive and significant in 1998-1999 and 1999-2000, but the estimated coefficient in the former is less than half that of the latter.

7. Discussion

We have shown that in the Japanese word-processing software market, network effects were weak or unobservable in the beginning of the sample period between 1998 and 2001, but were clearly at work in later stages.

This section discusses the limitations of our empirical analysis and the possibility that these results were obtained despite network effects being present throughout the sample period.

7.1 Limitations with the Data

It should be noted at the outset that the data we used were constrained in the following senses.

(i) The data only include stand-alone products and do not include integrated business software products.

(ii) The data only include products that were sold at retailers and do not include those that were pre-installed in PCs.

(iii) The data only include products that were sold at retailers and do not include those that were sold to firms by wholesalers.

(iv) The data cover the period between 1998 and 2001, which is a period after the fierce struggle between Microsoft and Justsystem for dominance in the market.

(v) The data used were monthly but taken only from four different points in time, as discussed below.

Hedonic price models are appropriate when the movement in market shares is not drastic, so (iv) is not a problem but rather a condition for appropriate analysis. Regarding (v), the sales figures may vary greatly from month to month, but product characteristics are invariant and prices move only gradually. In our analysis we used price information from the POS data, but user base and share data were taken from other sources so this is unlikely to be a cause of a problem for our hedonic analysis. In contrast, the results from our NL analysis, where we used volume figures from POS data to calculate sales shares of products, should be treated with some caution.

A very high proportion of word-processing software is sold as part of integrated business software in recent years, and is often pre-installed in PCs. Business users also account for a large proportion of word-processing software users. Thus, (i), (ii) and (iii) all imply that the market we analysed is only a part of Japan's word-processing software market. If the valuation placed on a software product with certain characteristics differs greatly between users of stand-alone software and integrated software or pre-installed software, or between users at home and users in firms, then the results of our analysis reflect these biases. In what direction would these biases work?

Regarding home users, direct network effects through file exchange are unlikely to be very different among stand-alone software buyers, integrated software buyers and pre-installed software buyers. On the other hand, PC novices are more likely to purchase integrated software that packages standard software and PCs with standard software pre-installed, and stand-alone products are more likely to be purchased by those who know precisely what they want to buy. This suggests that the indirect network effects, through the availability of instructors or books, may be weaker for stand-alone software buyers than for home users as a whole. Thus, in terms of (i) and (ii), our present analysis may be understating network effects.

Next, firm users are likely to experience larger direct network effects through the exchange of files than home users. On the other hand, a home user is more likely than a user at a firm to think it important to have someone available to help them in case of trouble, because a user at a firm is likely to have someone in charge of information technology. Indirect network effects therefore are likely to be stronger for home users. Because direct effects are likely to be the dominant, firm users are likely to experience a higher network effect overall. Thus, our present analysis may be understating network effects in terms of (iii) as well.

To summarise, (iv) and (v) do not pose problems for our analysis, while (i), (ii) and (iii) imply that our present analysis may be understating network effects.

7.2 Methodological Limitations

We have not been able to separate network effects from brand effects in either the hedonic price model or NL model. We may partly overcome this problem if we can obtain data for products by firms other than Microsoft and Justsystem, and if we conduct analyses with dummies representing Microsoft products.

Another defect with the methodologies used in our present study is that both hedonic price and NL models test the relationship between the equilibrium user base and price, and neither separates demand side effects from supply side effects, when network effects only operate on the demand side.

7.3 Strategic Pricing

Apart from the data and methodological limitations described above, the possibility may be raised that one reason why we observed little or no network effects in the beginning of our sample period is that Microsoft continued to set low prices strategically. However, as figure 2 indicates, Microsoft had obtained a high market share by this time, and it would be necessary to investigate whether Microsoft really did have an incentive to engage in this pricing strategy.

7.4 Switching Costs

Switching costs may be yet another reason why little or no network effects showed up towards the beginning of our sample period. When compatibility between different software groups is imperfect, a user who has accumulated documents written on word-processing software will incur switching costs when she decides to switch to a product of a different software group. If she cannot read her new software documents written on her old software, she will incur disutility directly. Converting file format involves time and effort, and figures, tables and styles planted on a document often cannot be converted accurately. These are all sources of switching costs.

Ichitaro had a large share of the word-processing software market until the mid-1990s, so it is conceivable that the average switching costs involved in a switch from Ichitaro to Word was larger than those involved in a switch in the opposite direction.

It can be easily shown that, in general, if the switching cost involved in a switch from format A to B is larger than that involved in a switch in the opposite direction, the price of A is set at a higher level than that of B, other things being equal.

Thus, the results from cases 5 and 6 in table 3 may be interpreted as follows. On the one hand, network effects were indeed at work in 1998-1999, and this had the effect that Word would be priced higher than Ichitaro. On the other hand, in this period the switching costs involved in switching from Word to Ichitaro were higher than those involved in a switch in the opposite direction, and this had the effect that Ichitaro would be priced higher. These two effects acting together largely cancelled each other out, so the estimated coefficient of the user base variable was weak or not statistically significant. In 1999-2000, Word had enjoyed a high market share for some time, and the average switching costs involved in switching from Ichitaro to Word were no longer larger than those involved in a change in the opposite direction, and the network effects appear without hindrance by asymmetric switching costs in estimated results.

Switching costs may also be used to provide one explanation for the difference between the results from our hedonic price and NL analyses regarding whether the adoption of key product features would have allowed Justsystem to overtake Microsoft's share. In the hedonic price analysis, the difference in the sizes of the user bases is reflected in the estimates only through network effects. In contrast, in the NL analysis the difference in the sizes of the user bases is reflected in the estimates through both network effects and switching costs. The presence of switching costs gives rise to the tendency for shares to be sticky, giving rise to a large estimated coefficient for the network effect variable, which in fact reflect both network effects and switching costs.

8. How was Microsoft able to Overturn Ichitaro's High Market Share?

Despite the fact that both network effects and switching costs tend to cause lock-in, Microsoft was able to topple Justsystem's dominance in the word-processing software market around 1997.

When there is large and asymmetric technological progress, this kind of change in places is possible even in the presence of network effects and switching costs. However, as we will see in section 9, there has unlikely been large and asymmetric technological progress in word-processing software since 1995. There are at least three reasons why Microsoft was able to trade places with Justsystem despite this.

First, it is claimed that Microsoft required PC manufacturers to pre-install Word in all PCs with pre-installed Excel (Microsoft).[19] Microsoft

[19] Japan's Fair Trade Commission found in its investigations of the Microsoft case (Heisei 10, Recommendation No. 21) that Microsoft entered into contracts

had already achieved dominance in the spreadsheet software, so network effects in the spreadsheet market meant that a new buyer of spreadsheet software was more likely to choose Excel over other alternatives. If Word was bundled with Excel and pre-installed on PCs, network effects in the spreadsheet market meant that a PC buyer who also was considering buying business software was likely to buy a PC with Word and Excel both pre-installed, and this helped the widespread adoption of Word.

Second, Microsoft was able to develop and sell the Windows 95-compatible version of Word promptly, but it took Justsystem a long time to develop a Windows 95-compatible version of Ichitaro. It is often reported that this fact, coupled with the fact that many PCs with Windows 95 pre-installed also had Word pre-installed, meant that Word diffused rapidly as Windows 95 PC sales grew rapidly.

Third, Microsoft strategically lowered the price of Word around 1996. As explained briefly in section 2, by lowering the prices of Word substantially Microsoft was able to create a price differential in excess of network effect disadvantage, and this was also a possible reason Microsoft was able to trade places with Justsystem.

9. Effects of Weakened Competition

When network effects or switching costs are present, fierce competition tends to take place in the beginning to attract customers, while competition tends to be weak once there is a large difference in market shares. As we have seen in section 2, Word had acquired a large section of the market by

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with PC manufacturers allowing the latter to pre-install Excel and Word, but refused requests that they be allowed to install Excel only. A concise overview of Japan's Microsoft case may be found in Chaen (2002).

1998 and has slowly but steadily increased its share since then, suggesting that competition has indeed become weak.

Weakening of competition arising from a firm's dominance has two harmful consequences, namely, high prices and slow technological progress. In terms of prices, our base model shows the year dummies have negative coefficients that increase in absolute terms with time. So prices have not stayed high, although the rate of price decrease has slowed.

To obtain an indication of how much technological progress took place, we conducted a questionnaire survey in December 2002, asking users to evaluate how much technological progress was made with the arrival of new versions of the software. We surveyed IT personnel in universities and large firms. 1179 firms, Internet service providers (ISPs) and universities were approached, and we obtained 771 responses (65.4% response rate). The list of firms comprises 649 firms listed on the first section of the Tokyo Stock Exchange whose non-consolidated total assets is no less than 100 billion yen (excluding banks and insurance firms), and all 207 member banks and firms of the Japanese Bankers Association, the Life Insurance Association of Japan and the General Insurance Association of Japan. The list of ISPs comprises 50 members of the New Media Development Association with no less than 10,000 subscribers and 51 randomly selected members of the Japan Internet Providers Association that have nation-wide operations. The list of universities comprises all 99 national universities and all 123 members of the Japan Association of Private Colleges and Universities. We asked respondents to reply in the capacity as personal PC users.

A number of new versions of both Word and Ichitaro were introduced. We asked respondents to evaluate each new version in terms of functional improvements in percentage over the previous version from the viewpoint of an ordinary user rather than as a technical specialist. We asked them not to comment on versions they had not used. The replies for two consecutive versions are summarised in figure 4 for Word and figure 5 for Ichitaro. The introduction dates for the new versions are stated in brackets.

We can see from these figures that functional improvements with the introduction of a new version have become smaller for both Word and Ichitaro. Of course, there is a problem involved in whether a user who responded to the survey in late 2002 or early 2003 could really remember and compare two consecutive versions from 1993 as well as she could evaluate versions that were around in 2002. Theoretically also, the lower size of innovation per upgrade may have been caused by the maturity of the product and not by weakened competition. Thus, we cannot conclusively claim that the figures show slowed technological progress as a result of one firm's dominance. However, the figures are suggestive of this possibility, and further investigations on the speed of technological progress and its determinants are warranted when designing policy prescriptions.

10. Conclusions

This paper tested whether network effects were at work in the Japanese market for word-processing software in the period between 1998 and 2000 (or 2001) using both hedonic price and NL models. The presence of network effects was verified in the full three-year regression for 1998-2000 (and in the full four-year regression for 1998-2001 using lagged values of the network effect variable). Regressions for two consecutive years showed that network effects, as measured by the positive effect of the size of the user base on the product price or on the probability of the software group being chosen, were verified for the latter part of the sample period but not in the beginning. We discussed data and methodological limitations, as well as the effect of switching costs and the possibility that Microsoft continued to set strategically low prices as possible causes for our results.

The paper also discussed possible reasons why Microsoft was able to overturn Ichitaro's dominance despite the tendency for lock-in in markets characterized by network effects and switching costs. It also suggested, using results from a questionnaire survey, the possibility that technological progress slowed after Microsoft achieved dominance.

Analysis of network effects using richer data, including those on integrated software and software pre-installed on PCs, would be an obvious direction for future research, as would be direct modelling of switching costs.

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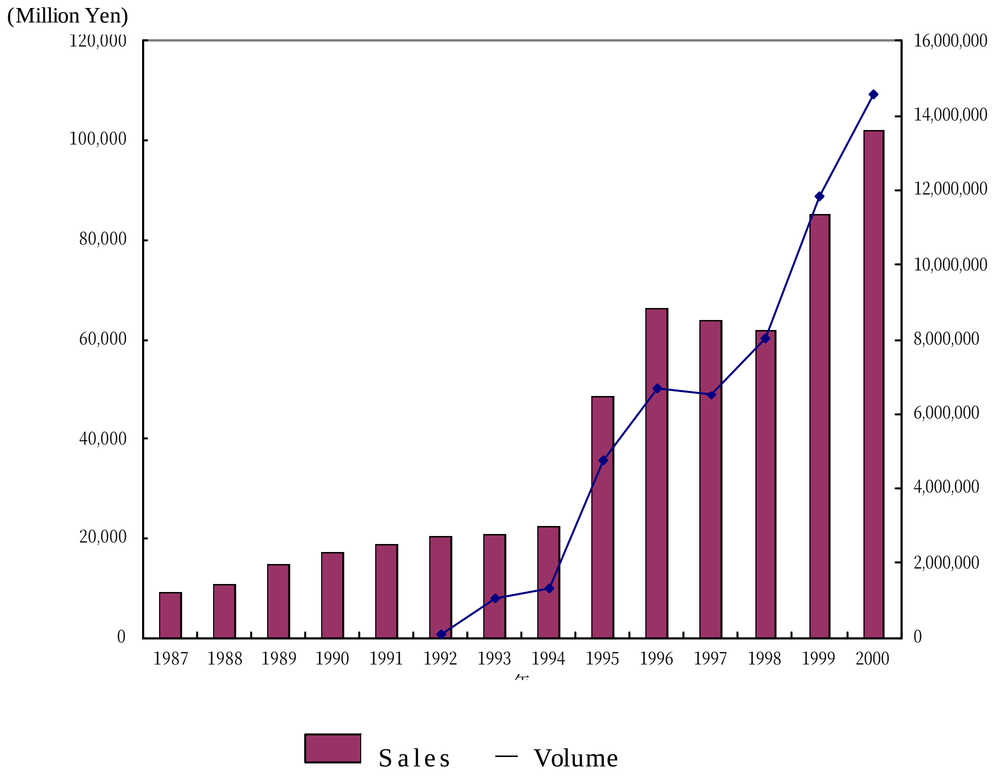
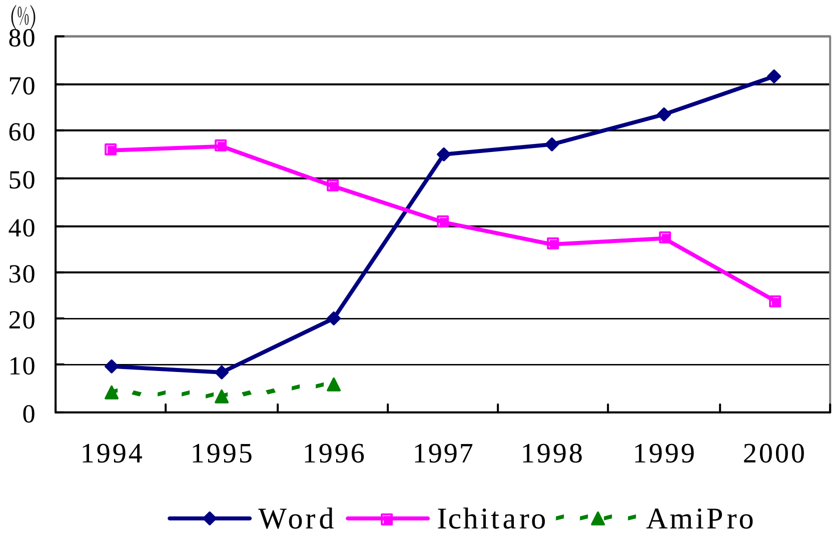
Figure 1 Size of the Japanese word-processing software market



Source: Japan Personal Computer Software Association

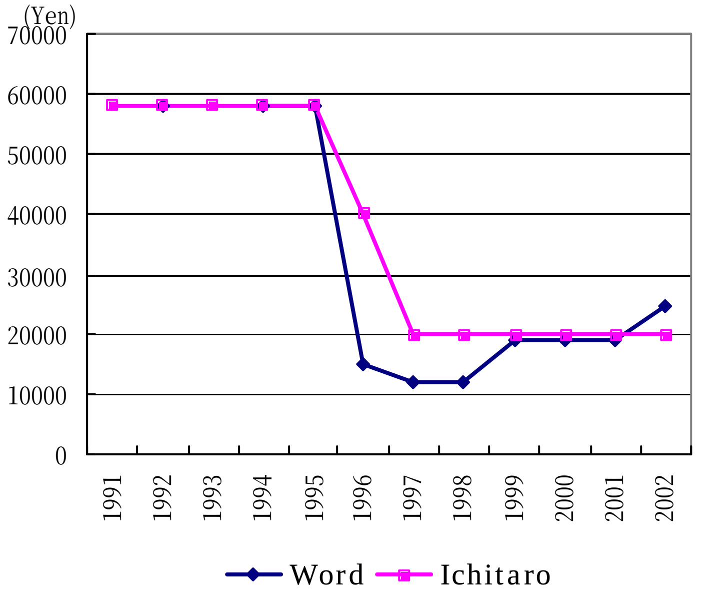
Note: Volume data available only since 1992.

Figure 2 Market shares of the major word-processing software by producer in Japan



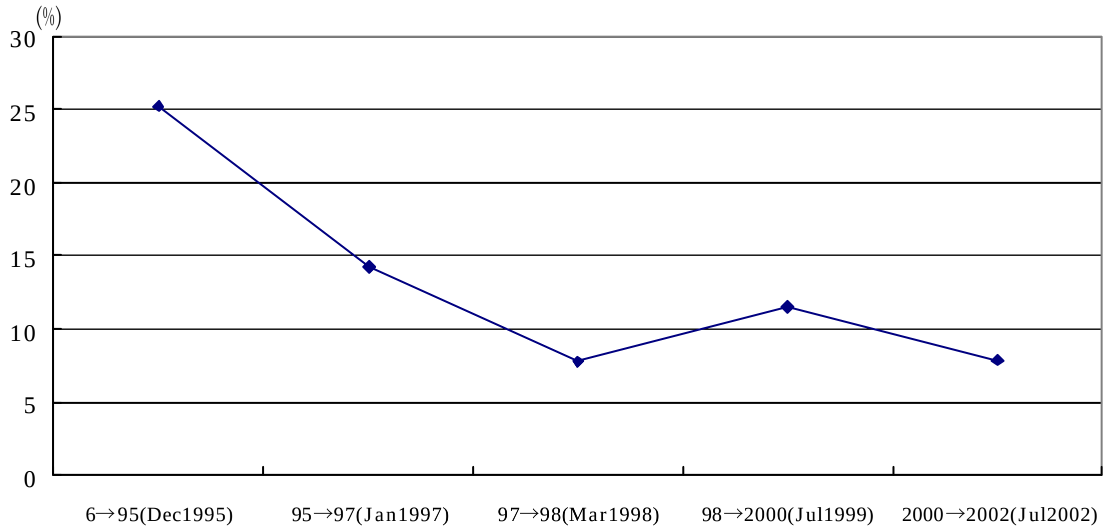
Source: Business Computer News (1994-1996), Nikkei Market Access (IT Basic Survey) (1997-2000)

Figure 3 List prices of major word-processing software products in Japan



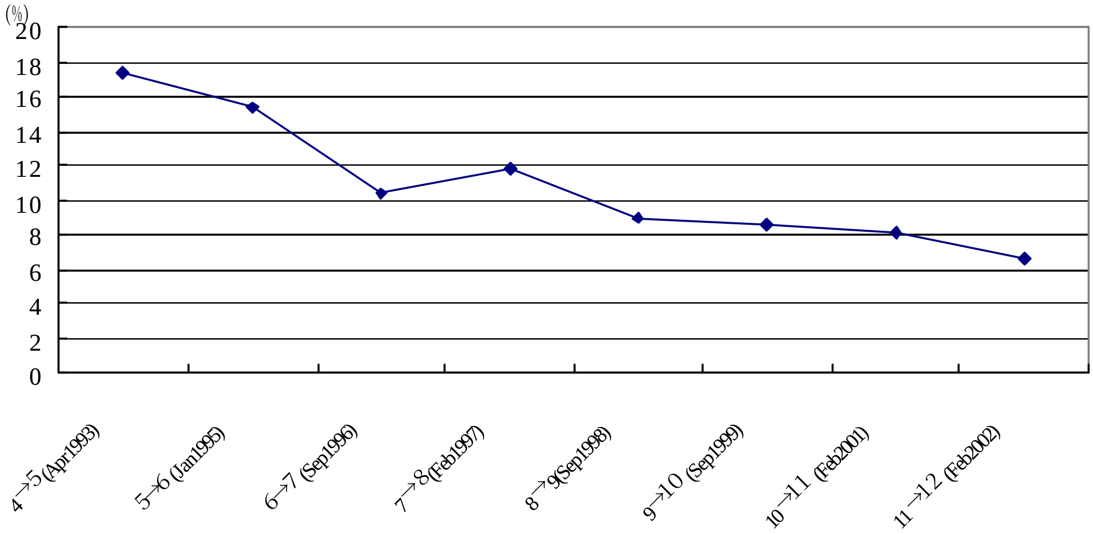
Source: Justsystem, Microsoft, and Nikkei Newspapers

Figure 4 Users' evaluation of function improvement of Word



Note: Time of sales is in parenthesis.

Figure 5 Users' evaluation of function improvement of Ichitaro



Note: Time of sales is in parenthesis.

Table1 Sample distribution by software group

	Word （Microsoft）	Ichitaro （Justsystem）	Total
1998	4	9	13
1999	10	13	23
2000	9	15	24
2001	8	8	16
Total	31	45	76

Table 2 Definition of variables

	variable	definition	notes
price	*AVG_RPRICE*	Average real retail price of each software product (yen)	Average nominal retail price is divided by quarterly GDP deflators under 93SNA standard
network effects	*SHARE*	User base share of each software group (one when all PC users use products falling under this group)	
	SHARE_L1	One-year lagged value of user base share of each software group (one when all PC users use products falling under this group)	
	LIB	Logarithm of user base size of each software group	
	LIB_L1	One-year lagged value of logarithm of user base size of each software group	
functions and options (dummy variables)	*D_MULTIPLECLIPS*	Multiple clippings (where the clipboard can store more than one clippings)	
	D_WORKINGWINDOW	Working window (where an auxiliary window appears by the side of the text window that helps editing)	Knowledge Window in Ichitaro
	D_WORKSHEET	Worksheet (where a multiple of documents including ones made on other software can be saved as a single file on the word-processing software)	
	D_JP	Has a Kana-Kanji transformation software component	MS-IME in Word, and ATOK in Ichitaro
	D_VOICE	Has a Voice recognition software unit and a microphone	
	D_LITE	Lite version	Ichitaro Lite
target market (dummy variables)	*D_UPGRADE*	Upgrade discount	
	D_SPOFFER_JS	Discount for users of products by the same firm	
	D_CUPGRADE	Discount for users of products by the same or competitor firm	
year (dummy variables)	*D_99*	1999 data	
	D_00	2000 data	
	D_01	2001 data	
sale share	s_j	Market share in sales (of individual products)	
	s_0	Market share of those who made no purchase	
	$s_{j/g}$	Within-group share in sales (of individual products)	

Note: Dummies take the value one when the data fits the description.

Table 3 Results of hedonic price estimates

	Case 1		Case 2		Case 3		Basic model Case 4		Case 5		Case 6	
Period	98-00		98-99		99-00		98-00		98-99		99-00	
Dependent var.	*AVG_RPRICE*		*AVG_RPRICE*		*AVG_RPRICE*		*AVG_RPRICE*		*AVG_RPRICE*		*AVG_RPRICE*	
	Est. Coeff.	T stats.	Est. Coeff.	T stats.	Est. Coeff.	T stats.	Est. Coeff.	T stats.	Est. Coeff.	T stats.	Est. Coeff.	T stats.
C	-35441.5	-1.69597 *	28146.0	.537349	-61773.3	-2.77740 ***	-22833.0	-1.27853	23835.6	.496000	-42327.8	-2.37359 **
LIB	2930.91	2.20326 **	-1166.59	-.348089	4302.51	3.10402 ***	2098.48	1.87290 *	-882.942	-.288366	3071.85	2.79031 ***
D_MULTIPLECLIPS	7057.67	7.50780 ***	5554.06	3.61100 ***	8789.41	8.60119 ***	7265.46	7.84920 ***	5539.48	3.67200 ***	9179.03	9.19245 ***
D_WORKSHEET	1478.83	1.15160	-463.879	-.231389	1993.43	1.42825						
D_JP	1354.73	1.29801	1377.16	.815950	1773.24	1.81280 *	1462.82	1.40262	1336.68	.811157	1838.30	1.85546 *
D_LITE	2455.63	1.92642 *	-229.000	-.112038	5173.67	3.64255 ***	1879.42	1.59774	-74.9895	-.039530	4268.70	3.31185 ***
D_VOICE	6651.44	4.09196 ***	6736.43	2.84749 ***	6818.37	3.67695 ***	6957.71	4.32448 ***	6638.67	2.90539 ***	7580.93	4.21020 ***
D_UPGRADE	-8528.19	-9.55487 ***	-7921.57	-5.81180 ***	-8700.50	-9.55276 ***	-8496.01	-9.49195 ***	-7918.83	-5.91874 ***	-8647.84	-9.37194 ***
D_SPOFFER_JS	-2147.66	-1.03121	-3766.21	-1.34238	-1294.91	-.519044	-3142.39	-1.65269	-3512.36	-1.38566	-3225.85	-1.51735
D_CUPGRADE	-4768.47	-4.48604 ***	-4513.95	-2.88404 ***	-5423.00	-4.40980 ***	-4569.12	-4.34223 ***	-4556.05	-2.98565 ***	-4977.47	-4.12678 ***
D_99	-3067.65	-2.91336 ***	-1262.27	-.802038			-2522.28	-2.67311 ***	-1442.94	-1.07572		
D_00	-4039.75	-3.49965 ***			-1130.83	-1.61745	-3320.12	-3.40951 ***			-934.024	-1.34393
No. observations	60		36		47		60		36		47	
R^2	.843913		.818859		.876237		.839600		.818471		.869224	
Adjusted R^2	.808143		.746403		.841858		.806865		.755635		.837414	
F statistic	23.5927		11.3014		25.4879		25.6486		13.0254		27.3252	

*Significant at 10% level

** Significant at 5% level

*** Significant at 1% level

Table 4 Robustness check

Method of est.	WLS			OLS			WLS		
Dependent var.	*AVG_RPRICE*			*AVG_RPRICE*			*AVG_RPRICE*		
	Est. Coeff.	T stats.		Est. Coeff.	T stats.		Est. Coeff.	T stats.	
C	-22048.1	-3.26702	***	7247.64	3.33840	***	6196.56	6.44281	***
LIB	1977.75	4.66729	***						
SHARE				4708.15	1.83486	*	4560.05	4.87048	***
D_MULTIPLECLIPS	5025.62	12.3532	***	7289.52	7.80276	***	5066.50	12.5756	***
D_JP	3452.52	5.11424	***	1460.35	1.39447		3484.41	5.22759	***
D_LITE	-271.653	-.470169		1918.23	1.60623		-214.107	-.374197	
D_VOICE	6908.46	14.9973	***	6968.21	4.32217	***	6927.28	15.2332	***
D_UPGRADE	-9215.30	-37.8058	***	-8488.53	-9.47179	***	-9205.82	-38.2584	***
D_SPOFFER_JS	-3830.33	-6.34686	***	-3131.66	-1.64486		-3838.13	-6.44595	***
D_CUPGRADE	-5570.36	-18.7011	***	-4566.51	-4.33150	***	-5558.08	-18.9030	***
D_99	-635.196	-2.57786	**	-2284.70	-2.48907	**	-381.431	-1.66880	
D_00	-699.758	-2.32016	**	-2659.02	-2.86644	***	-79.0719	-.280441	
No. observations	60			60			60		
R^2	.984315			.839168			.984733		
Adjusted R^2	.981114			.806345			.981617		
F statistic	307.495			25.5666			316.049		

*Significant at 10% level
** Significant at 5% level
*** Significant at 1% level

Table 5 Results of hedonic price estimates (with the size of the user base as the network effect variable)

Period	98-01			98-00			99-01			98-99			99-00			00-01		
Dependent var.	*AVG_RPRICE*			*AVG_RPRICE*			*AVG_RPRICE*			*AVG_RPRICE*			*AVG_RPRICE*			*AVG_RPRICE*		
	Est. Coeff.	T stats.		Est. Coeff.	T stats.		Est. Coeff.	T stats.		Est. Coeff.	T stats.		Est. Coeff.	T stats.		Est. Coeff.	T stats.	
C	-36261.8	-1.99010	*	-40670.0	-1.26018		-54547.0	-2.89958	***	32446.1	.582567		-84801.8	-2.57233	**	-59261.1	-2.89184	***
LIB_L1	2991.39	2.53698	**	3334.01	1.58782		3897.25	3.27542	***	-1466.29	-.403449		5853.96	2.79648	***	4116.50	3.21545	***
D_MULTIPLECLIPS	7079.44	8.33664	***	7317.67	7.53612	***	8671.27	9.23360	***	5465.11	3.71502	***	9502.55	9.08712	***	8405.69	6.70898	***
D_JP	2125.23	2.46043	**	1370.61	1.29394		2361.87	2.80109	***	1261.68	.761737		1909.36	1.90739	*	2523.13	2.45315	**
D_LITE	2067.67	1.89876	*	1953.79	1.54344		4136.53	3.40394	***	-209.552	-.111962		4809.91	3.44342	***	4053.16	2.48715	**
D_VOICE	7015.66	4.87528	***	6972.84	4.27880	***	7542.06	4.74688	***	6601.74	2.89704	***	7757.69	4.28701	***	7559.68	3.91645	***
D_UPGRADE	-8709.52	-11.0613	***	-8427.03	-9.35011	***	-8816.32	-10.7767	***	-7909.76	-5.92647	***	-8615.46	-9.36667	***	-9293.56	-9.34465	***
D_SPOFFER_JS	-3172.44	-1.76330	*	-3091.84	-1.61071		-3168.36	-1.57149		-3526.41	-1.39305		-3129.28	-1.47267		-2071.19	-.691392	
D_CUPGRADE	-4191.19	-4.43261	***	-4581.06	-4.30245	***	-4204.80	-3.96323	***	-4575.34	-3.02552	**	-4945.73	-4.09725	***	-3939.06	-3.15173	***
D_99	-2858.76	-2.88880	***	-3215.31	-2.72203	***				-1141.11	-.669058							
D_00	-4028.99	-3.68627	***	-4502.95	-3.11449	***	-1413.24	-1.88273	*				-1815.03	-2.33204				
D_01	-3406.85	-2.55097	**				-1135.60	-1.17871								291.572	.339648	
No. observations	76			60			63			36			47			40		
R^2	.826930			.836529			.845547			.819024			.869325			.860135		
Adjusted R^2	.797184			.803167			.815844			.756378			.837539			.818176		
F statistic	27.7994			25.0747			28.4672			13.0739			27.3494			20.4992		

*Significant at 10% level
** Significant at 5% level
*** Significant at 1% level

Table 6 Results of NL estimates

	Case 1			Case 2			Case 3			Case 4		
Period	98-00			98-00			98-99			99-00		
Sample	All			Volume over 2			Volume over 2			Volume over 2		
Dependent var.	$\log(s_j)-\log(s_0)$			$\log(s_j)-\log(s_0)$			$\log(s_j)-\log(s_0)$			$\log(s_j)-\log(s_0)$		
	Est. Coeff.	T stats.		Est. Coeff.	T stats.		Est. Coeff.	T stats.		Est. Coeff.	T stats.	
C	-33.9253	-20.2340	***	-37.1437	-14.1159	***	-17.1445	-14.9531	***	-37.6988	-12.7573	***
$\log(s_{j/g})$	.960343	50.5392	***	.955370	26.9535	***	1.00827	145.761	***	.945992	22.1601	***
AVG_RPRICE	.00000230308	.042072		-.000129623	-2.34138	**	.0000106050	1.01395		-.000107016	-2.22826	**
LIB	2.20652	16.8381	***	2.47868	13.6227	***	1.13333	14.7757	***	2.46872	12.9332	***
D_MULTIPLECLIPS	.266614	.688499		1.19938	2.95418	***	-.126433	-1.57278		1.16122	2.65450	***
D_JP	.035038	.330477		.471185	2.49294	**	-.032991	-.743505		.415195	2.35388	**
D_LITE	.322258	2.59607	***	.472275	3.04272	***	-.067330	-1.82127	*	.545242	2.64215	***
D_VOICE	.094256	.241447		.883513	2.29430	**	-.085222	-1.07261		.751997	2.12320	**
D_UPGRADE	.044611	.094292		-1.18627	-2.37506	**	.081522	.897834		-1.04280	-2.29850	**
D_SPOFFER_JS	-.096722	-.471964		-.538438	-1.73259	*	.055591	1.00249		-.546773	-1.32474	
D_CUPGRADE	.051864	.200800		-.715460	-2.13153	**	.038162	.653389		-.593311	-1.89182	*
D_99	-.384216	-2.66370	***	-.424692	-3.42603	***	.00197146	.071308				
D_00	-1.51004	-8.25211	***	-1.71906	-10.1725	***				-1.28479	-11.6721	***
No. observations	60			41			26			31		
R^2	.997817			.995102			.999890			.995926		
Adjusted R^2	.997259			.993003			.999804			.993567		

*Significant at 10% level
** Significant at 5% level
*** Significant at 1% level