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Empirical Analysis of Indirect Network Effects in the Market for Personal Digital Assistants

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Abstract. We present a framework to measure empirically the size of indirect network effects in high-technology markets with competing incompatible technology standards. These indirect network effects arise due to inter-dependence in demand for hardware and compatible software. By modeling the joint determination of hardware sales and software availability in the market, we are able to describe the nature of demand inter-dependence and to measure the size of the indirect network effects. We apply the model to price and sales data from the industry for personal digital assistants (PDAs) along with the availability of software titles compatible with each PDA hardware standard. Our empirical results indicate significant indirect network effects. By July 2002, the network effect explains roughly 22% of the log-odds ratio of the sales of all Palm O/S compatible PDA-s to Microsoft O/S compatible PDA-s, where the remaining 78% reflects price and model features. We also use our model estimates to study the growth of the installed bases of Palm and Microsoft PDA hardware, with and without the availability of compatible third party software. We find that lack of third party software negatively impacts the evolution of the installed hardware bases of both formats. These results suggest PDA hardware firms would benefit from investing resources in increasing the provision of software for their products. We then compare the benefits of investments in software with investments in the quality of hardware technology. This exercise helps disentangle the potential for incremental hardware sales due to hardware quality improvement from that of positive feedback due to market software provision.

Key words. high-technology products, indirect network effects, positive feedback, endogeneity

JEL Classification: C10, L10, M3, O32

1. Introduction

The role of indirect network effects is emerging as an important source of strategic advantage in the marketing of many high-tech products. Indirect network effects arise when the benefit from using a product increases with the use of a complementary set of compatible goods. For instance, demand for hardware and device technologies is often driven substantially by the variety of available complementary software applications. This inter-dependence in demand generates a feedback mechanism, or virtuous cycle. Higher demand for hardware stimulates software sales and profits, leading to a greater supply of software. Increased software availability, in turn, enhances the value of the hardware leading to subsequent adoption. Consequently, hardware demand is indirectly linked to the size of the installed base, generating a form of demand-side economies-of-scale. When firms offer competing incompatible technology standards exhibiting indirect network effects, we often observe "fights to the death" where a single standard emerges victorious (see Shapiro and Varian, 1999 for a thorough discussion of markets with network effects).[1] The ability to measure such indirect network effects is crucial to firms competing in such high-tech industries.

We develop a model that captures the inter-dependence between hardware and software demand in a competitive environment with differentiated technologies. From this model, we derive an econometric framework with which to measure empirically the size of indirect network effects. We model hardware demand as a nested logit demand system. Measurable product characteristics capture the differentiation amongst alternative devices, whereas the nesting structure captures differentiation amongst different hardware technology standards available in the market. Rather than model the indirect network effect in an ad hoc manner, we derive the effect of compatible software availability and variety on hardware demand by explicitly modeling consumer demand for software. We then derive the resulting equilibrium entry and software provision (i.e., supply) decisions of independent software vendors. Combining hardware demand and software supply, we obtain an equilibrium relationship between software variety and hardware sales. In equilibrium, the degree of software provision varies linearly with the (log of the) installed base of compatible hardware. The derived software supply and hardware demand equations form the basis of our econometric framework. This system enables us to measure the economic relationship between hardware sales and the hardware installed base—the network effect—empirically. Estimating the structural parameters of the software supply equation enables us to conduct policy experiments with which we can evaluate the relative importance of hardware attributes versus network effects in driving hardware sales.

An important feature of the estimation procedure is the control for the potential endogeneity of software variety on the hardware demand-side, and the hardware installed base on the software supply-side. In particular, software provision depends on total cumulative demand for hardware and, at the same time, total current demand for hardware depends on software availability. Since software variety and

1 For instance, Microsoft's bundling of its browser technology (IE) into its operating system (Windows) was deemed anti-competitive as it blocked the competing browser, Netscape, from generating a critical mass of users and hence, the development of complementary online applications and content (Bresnahan, 2002).

hardware sales are determined simultaneously, rather than sequentially in the market, we face a simultaneity problem that we handle using instrumental variables. Although we do not model hardware supply explicitly, we are careful to control for potential price endogeneity associated with strategic hardware pricing. On the hardware-demand side, we also control for the fact that market software availability could be correlated with unobserved product attributes that shift hardware demand but are not observed by the econometrician.

We fit the model described above to data for hardware and software in the US market for personal digital assistants (PDAs). In the PDA industry, indirect network effects arise as consumers derive benefits from the variety of software available for a particular hardware product.[2] The importance of this effect can be seen in the trade-press, which reports that the availability of third-party software is playing an increasingly important role in consumers' PDA purchase decisions:

> "[2001] was a great year for handhelds, which ultimately resulted in a blockbuster year for portable software," said Steve Koenig, senior software analyst, NPD Techworld. "Consumers discovered that handhelds have more functionality than storing a calendar and contacts. They have become a direct extension of the PC."

Similarly, Handango.com, the largest online reseller of handheld software, ran a repeat buyer survey and reported that 81.9% of repeat mobile [handheld] software buyers have installed six or more handheld applications and that 52.7% of repeat software buyers have installed 11 or more handheld applications on their devices. The study further reports the number of applications installed on the handheld device as the leading source of brand loyalty amongst a list of more than 20 factors.[3] Other statistics indicate that the average buyer in 2002 purchased 2.15 third-party applications from Handango.[4]

To quantify the relative importance of the PDA hardware and software markets, the market research firm NPD (2002) reports that retail revenues from PDA software sales more than doubled in 2001 to $27 million (versus $12 million in 2000). These revenues correspond to the sale of around 900,000 units of software sold through brick-and-mortar retail channels during 2001 (versus 225,000 units in 2000).[5] Unfortunately, comparable data are not available for online sales, which constitute a

2 To avoid confusion, note that when we say "software" we refer to compatible third-party software applications that PDA users buy subsequent to their purchase of the hardware. Thus, software applications that come bundled with the PDA operating system (O/S) at the time of purchase are excluded from this definition, as is the O/S itself.

3 "The Handango Yardstick", 3rd quarter, 2002, http://www.handango.com/pdf/HandangoYardstick3_2002.pdf

4 "Handango Compiles 2002 Software Stats", February 13 2003, http://www.palminfocenter.com/view_story.asp?ID = 5011

5 "Sales of Handheld Software Skyrocket", Scarlet Pruitt, IDG News Service, April 08 2002, http://www.pcworld.com/news/article/0,aid,93243,00.asp

large portion of total handheld software sales. Nevertheless, we obtain an approximation of the extent of online sales by noting that as of July 2002, there were 20,578,827 downloads of branded (non-shareware/freeware) PDA software on download.com, one of the largest providers of online software on the internet. If 50% of these downloads convert into purchases, we obtain roughly 11 million units of software sold across both channels. At the same time, the hardware installed base is 11.2 million at the end of July 2002, indicating that demand for PDA software from consumers is significant.

In addition to network effects, another interesting feature of the PDA industry is the standards war between the incompatible Palm and Microsoft O/S formats. If indirect network effects are indeed strong in this environment, then understanding the link to software could be crucial for success in the hardware market. Independent software providers have an incentive to create software compatible with the most profitable technology standard, which is directly related to the size of the installed base. The Palm Co. lists software availability as the third most important reason to choose the Palm O/S, after market leadership and hardware variety.[6] In its product design, the Palm Co. has a stated policy of balancing the need for standardizing the core design of the O/S, and of meeting diverse customer needs by encouraging the provision of third-party add-in software for the Palm O/S platform.[7] In fact, Palm actively encourages the development of third party software for its O/S through its PalmSource program.[8] The strategic management of hardware is becoming complex as manufacturers weigh the relative benefits of investing directly in the innovation of the hardware itself, as opposed to indirectly nurturing the network by investing in third-party software provision. Both Microsoft and Palm currently invest resources in third-party software provision. A critical issue for PDA manufacturers is thus the measurement of the degree of indirect network effects and, subsequently, the trade-offs between innovating the hardware and stimulating software creation. We measure these trade-offs using the model estimates.

Our analysis fits into a growing empirical literature devoted to measuring network effects in general for high-tech product markets. In some industries, direct network effects arise naturally when the technology enables networking amongst the installed base of users. Such direct network effects have been measured empirically in the market for ATM machines in the banking industry (Saloner and Shepard, 1995), FAX machines (Economides and Himmelberg, 1995) and computer spreadsheets (Gandal, 1994; Brynjolfsson and Kemerer, 1996). More directly related to our work is the empirical research devoted to indirect network effects arising from inter-dependent demands for technology and related applications. Such indirect network

6 "Top 10 reasons to choose the Palm O/S", http://www.palmsource.com/includes/top_ten_reasons_to_choose_palm_powered.pdf

7 "Why Palm O/S", Balancing standardization and diversity, slides 8 & 9, http://www.palmsource.com/palmos/Advantage/index_files/frame.htm

8 http://www.palmos.com/dev/programs/pdp/policies.html;Shim, R. and Sandeep Junnarkar, "Palm reaches out to developers", October 23 2001, http://news.com.com/2100-1040-274797.html

effects have been studied empirically in the context of VCRs and video movies (Ohashi, 2003; Park, 2002a), video games and video consoles (Shankar and Bayus, 2003), and CD/DVD players and CD/DVD titles (Gandal et al., 2000; Basu et al., 2003; Karaca-Mandic, 2003). Gupta et al. (1999) propose a conjoint-based approach to study indirect network effects and discuss several industries in which they expect their approach to be relevant, including PDAs. Unlike much of this previous research, we use data both for the hardware (PDAs) and the related applications (software). Furthermore, we model the equilibrium determination of software availability explicitly, which enables us to measure the indirect network effects structurally. This approach has several advantages over simply plugging the installed base as a variable into the hardware demand system. This latter approach could confound direct and indirect network effects. It could also capture spurious serial correlation in hardware demands. From the perspective of a hardware manager, the approach would not help understand the potential benefits from investing resources in increasing the provision of related software and applications. Finally, we find that accounting for the joint endogeneity of hardware sales and software availability has important implications for obtaining a valid unbiased measure of the network effects.

The rest of this paper is structured as follows. We first provide a brief description of the PDA industry and our data in Section 2. We present our model and derive the hardware sales and software provision equations that we employ in estimation in Section 3. In Section 4, we present the results from our estimations and discuss their significance. Section 5 provides discussion and applications of the results. Section 6 concludes.

2. PDA industry and data

PDA-s are a good example of a high-technology durable that has been rapidly adopted by the US population in the 1990s.[9] Due to wide differentiation, consumer adoption of PDA-s involves consideration of a broad range of attributes. Key factors include the operating system (O/S), brand, random access memory (RAM), processor clock speed, screen size, resolution, memory configurations, expansion capabilities, form factor,[10] and availability of third party software. Of these, choosing the operating system is probably the most important decision. Currently, the Palm and Microsoft (MS) O/S are the two dominant standards in

9 For an interesting history of PDA-s and their development, see Bayus et al. (1997).

10 The form factors available currently include tablets and clamshells. Tablets are smaller, personal organizers typically entailing touch-screen/pen input. Clamshells are smaller versions of notebooks, with larger displays, and typically allowing both keyboard and pen input.

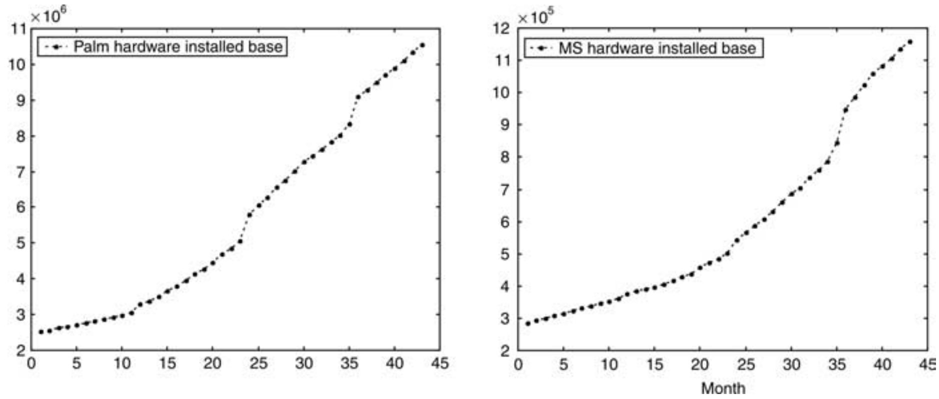

Figure 1. Evolution of Palm and MS O/S hardware installed base.

the industry.[11] Competition in the market is intense, with both the O/S standards and the brands compatible with each of the standards competing with each other for consumer adoption.

2.1. Hardware data

Our hardware data consists of SKU-level monthly sales and prices of all PDA models sold through the retail channel in the United States from January 1999 to July 2002. These data are collected by NPD Techworld using point-of-sale scanners linked to over 80% of the consumer-electronics retail ACV in the United States. After removing models corresponding to brands with insignificant overall market-shares (<1%), the data contained 2068 model-month observations of 132 different models across 43 months. These correspond to six brands, viz., Casio, Compaq, Handspring, Hewlett-Packard (HP), Palm and Sony.[12] Of these Casio, Compaq and HP run on the MS O/S, and Handspring, Palm and Sony run on the Palm O/S.

Figure 1 shows the evolution of the installed bases of the Palm and MS O/S PDA-s during the sample time-frame. As is evident, Palm O/S PDA-s have a large share of

11 Other O/S in the market viz. Symbian, a joint venture set up by Psion, Ericsson, Nokia, Matsushita and Motorola meant mainly for wireless phones, and Linux—have had very low market shares to date. See, Gartner Dataquest: Mary Hubley and Federica Troni, "PDA Operating Systems: Perspective", March 7 2002.

12 Compaq and HP merged in July 2002 to form Compaq-HP. Nevertheless, for the period of our data, they remained separate companies and hence we treat them as separate brands.

Table 1. Sample descriptive statistics.

Brand	Model-months	Share (%)	Total unit sales	Std. dev. of unit sales	Average price	Std. dev. in prices	Average no. of models/month	Total no. of models
Casio	317	1.72	152,792	2426.19	\$278.22	\$193.50	7.37	19
Compaq	352	4.41	392,204	10,850.54	\$375.52	\$217.23	8.19	33
Handspring	318	16.34	1,452,520	34,721.94	\$201.40	\$88.87	10.97	17
HP	378	3.44	305,773	7038.27	\$428.76	\$253.38	8.79	24
Palm	564	67.97	6,043,055	106,866.88	\$206.85	\$135.30	13.12	24
Sony	139	6.12	544,383	19,775.18	\$279.56	\$124.90	6.04	15
Total	2074	100.00	8,890,727					

the retail market and continue to remain dominant in the market to the end.[13] Sales of both O/S formats show exponential growth—a key characteristic of network good markets. Brand-level descriptive statistics are presented in Table 1. Overall, Palm O/S PDA-s—Handspring, Palm and Sony—have a combined share of 90.43% of the total unit sales in the data during the 43 month period.

Detailed attribute data for each of the 132 models were manually collected from online sources and trade publications, and cross-checked with manufacturer model descriptions for consistency. Table 2 presents a description of the attributes.[14]

2.2. *Software data*

To model the effects of software availability on hardware sales, we need to develop a measure of the benefit provided by compatible third party software applications to PDA owners in their use of the PDA. An ideal measure would be an index of utility that consumers obtain from use of compatible software in each period. To estimate such an index, we would need data on sales, prices, and "quality" of software. These data are unavailable to us. On the other hand, summarizing the benefit by collecting data on all software titles available in the market for each O/S is not feasible either, due to the large number of third-party applications currently available for PDA-s.

13 A potential reason why Palm O/S PDA-s have a large share in the data is that the retail sales data that we use does not include corporate purchases that are skewed more toward MS O/S compatible PDA-s. Nevertheless, Gartner (Todd Kort, Gartner DataQuest, "2001 PDA Forecast Scenarios: 3Q01 Update", October 9 2001) estimates that to date, at least 70% of all PDA-s sold are purchased through retail resellers, indicating that this is still a consumer-driven market. Hence, we expect the size of this bias to be small. Nevertheless, our results are subject to this caveat.

14 A hedonic regression of (log) model prices on brand fixed effects and model attributes had a R^2 of 0.676. An appendix with a history of the PDA industry, detailed descriptive statistics of model attributes and results from the hedonic price regression is available on request from the authors.

Table 2. PDA model attributes and descriptions.

Attribute	Description	Range in data
Form	Binary variable taking value 1 if the model is of a Tablet form-factor, and 0 if it is of a Clamshell form-factor	0–1
Clock-Speed	Processor speed of the model in Mhz	16–206
Area	Face area of the model, measured as length of model X breadth of the model, in sq-inches	11.16–91.38
Weight	Weight of the model (without case) in ounces	3.6–47.2
Color	Binary variable taking a value 1 if the model has a color display and 0 otherwise	0–1
Eslots	Number of expansion slots available in the model	0–3
Modem	Binary variable taking a value 1 if the model has a built-in modem and 0 otherwise	0–1
Lithium	Binary variable taking a value 1 if the model has built-in lithium batteries and 0 otherwise	0–1
RAM	RAM available in the model in mega-bytes	0.128–64

For this reason, we follow the approach adopted in previous literature (cf. Gandal et al., 2000) and develop an alterative index of software availability.

We collected data on all software available at download.com compatible with the Palm and MS O/S. The download.com website has information on when a particular software title was uploaded to their database, and the total number of downloads of that software title to date. From these data, we created an index of availability by counting only those software titles that were purchased by consumers (PDA shareware/freeware are thus excluded) and downloaded at least once a day (roughly 80% of the total titles). This serves as an estimate of the availability of "important" software of both formats.[15] The plot of software available for both the Palm and MS O/S is presented in Figure 2. The plot indicates that consistent with our expectation, more software is available for the Palm O/S than for the MS O/S in the marketplace. Both curves show exponential growth of software variety. From an alternate source, we also obtained data on the total number of software titles available (across both formats) at a major outlet for software titles for PDA-s since 1999. The pattern of software available from this dataset also looks very similar to the download.com data, which we construe as face validity for our software index.

15 Download.com offers more than 200,000 freeware and shareware titles on its website and currently facilitates an estimated 150,000 software downloads every day. The CNET network, which owns download.com, has agreements in place with around 20 Internet Service Providers to make download.com the default software downloading service on the Web browsers they are distributing to their customers (http://www.cnet.com/aboutcnet/0-13613-7-850335.html). For these reasons, trial-versions of most newly released software are made available at the website by software vendors hoping to entice users to buy their products. Thus, we consider the availability of software there as a reasonable representation of market software variety.

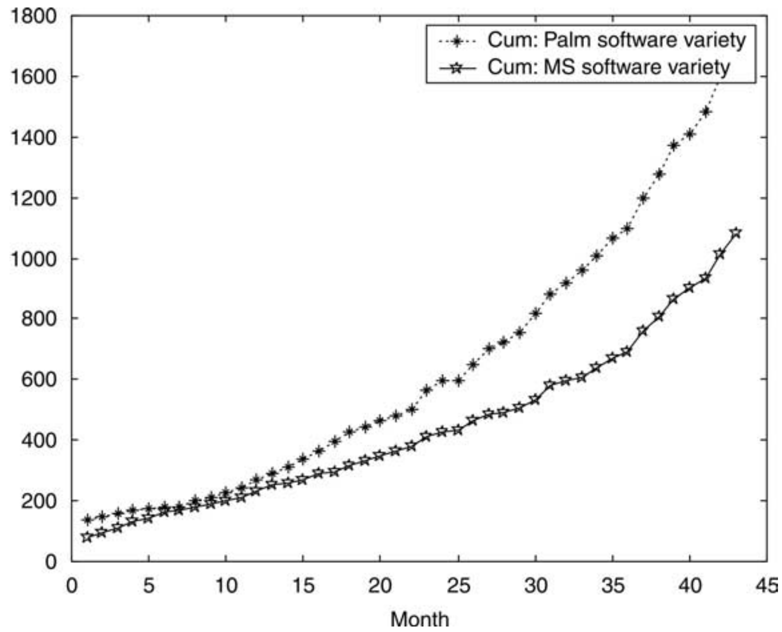

Figure 2. Evolution of Palm and MS O/S software stock.

A comprehensive analysis of firm entry and pricing decisions in the PDA software sector would require additional data such as the fixed costs of software development and software prices in each time-period. These data are unavailable. Manually collecting software price data is not feasible due to the large number of software titles available in the market, and due to the fact that historical price data are extremely difficult to obtain. These data limitations on the software side require us to make simplifying assumptions in modeling the software entry and pricing decisions of firms. The model frameworks for the hardware and software markets and the assumptions employed are presented in the next section. Our goal is to develop a simple model that captures the key features of complementary network good markets while recognizing the limitations of our data.

3. Model formulation

We first provide a brief overview of the model and a discussion of some of our main assumptions. In the following subsections, we provide formal details and derivations of hardware demand and software provision.

On the demand side, consumers adopt a PDA system consisting of two components: hardware and software. In each period, potential consumers either purchase one unit of the hardware technology or choose not to purchase in the category. Hardware is treated as a differentiated product, and extant hardware technologies are incompatible with each other. Consumers who purchase the hardware also purchase compatible software from the set of available software titles. We assume that consumers who make a hardware purchase subsequently exit the potential market for hardware; but could continue to purchase software of the selected standard in future periods.

Over time, we observe newer and better products appearing in the market. While we capture such hardware innovations through the changing product attribute levels in our data, we do not model new hardware introduction decisions explicitly. We do model the changing availability of software over time, whereby increases in the installed base of hardware induce more software firms to enter the market over time, resulting in more software variety.

In modeling the software industry, we incorporate several features of our data. First, we assume there are a large number of independent software vendors whose software products for a given technology standard are differentiated, albeit closely related substitutes.[16] We do not consider vertically integrated software firms because, based on our reading of the trade press, we believe that third party software vendors provide most handheld software titles available for users.[17] We also assume software vendors have common knowledge about software costs and demand, and there is free entry into the industry.[18] We first solve for the profit-maximizing price of a representative firm. We then search for a symmetric price equilibrium. To solve for the corresponding equilibrium number of firms, we use the free-entry condition, which implies zero profits in equilibrium. The derived equilibrium number of software titles is found to depend on the installed base of the hardware in each period. This equilibrium relationship forms our software provision equation in the empirical model.

As noted above, we lack data on fixed and marginal costs of software provision. We assume that each software firm produces a software product with a constant marginal cost and a fixed cost that is common to all firms producing software for a given hardware technology. Since software is an information good, with marginal costs close to zero (Shapiro and Varian, 1999), we do not expect the constant

16 Palm (http://www.palm.com/about/corporate/timeline.html) claims over 140,000 developers for its standard in 2001.

17 Software that are produced by the parent companies—Palm and Microsoft—typically come bundled with the PDA hardware O/S, and hence are excluded from our definition of "software", as is the O/S itself. Software provided directly by the hardware companies are mainly accessory drivers, desktop and O/S updates and patches (for example, see http://www.palmone.com/us/software/), which we consider as "fixes" for the O/S, rather than functional utilities that drive the indirect network effect. We thank one of our referees for alerting us to this issue.

18 In the literature, such an industry is referred to as being "monopolistically competitive", to capture the idea that the industry is perfectly competitive all respects, expect for the fact that the products are only close, not perfect substitutes, which gives each firm some monopoly power over its own product. See Dixit and Stiglitz (1977) and Spence (1976) and the references cited therein.

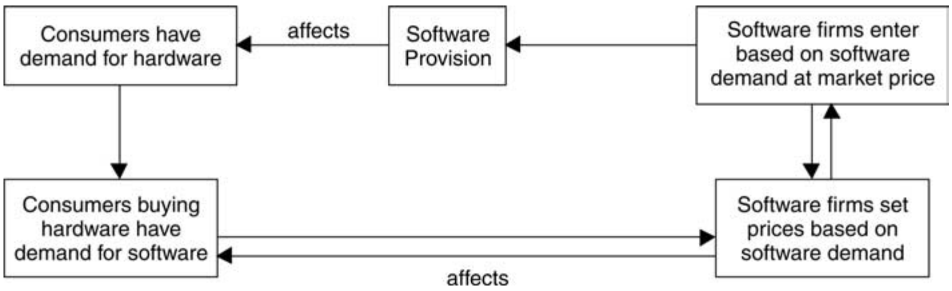

Figure 3. Interdependencies in the model.

marginal cost assumption to be problematic. Unlike similar two-sided markets, such as video games, PDA hardware manufacturers do not charge royalty fees to software providers and, hence, marginal costs do not reflect these types of side-payments. The fixed costs in the PDA software industry consist mainly of software development costs and set-up fees like office space rents and license charges. The uniform fixed cost assumption implies that software vendors supporting a given technology face roughly comparable man-hours of software development, which form a significant portion of software fixed costs. However, we cannot rule out differences in fixed costs reflecting the amount of software development support that hardware firms might provide to independent software vendors wishing to develop software for their technology.[19] To control for these differences, we include time and technology-specific fixed-effects in the software provision equation.

In each period, consumers purchase some units of the available models of the hardware product. Consumers who purchase the hardware then purchase complementary compatible software. Software firms enter the market. All software firms then sell their software to consumers who have adopted compatible hardware. By assumption, all these moves occur simultaneously. Figure 3 captures the various interrelationships and summarizes the modeling framework graphically.

The rest of this section is organized as follows. We first describe consumer preferences for hardware and software in the next subsection. We derive a demand equation for hardware sales from this model in Section 3.2. We then present the profit function for a representative software firm. By adding a free-entry condition, we develop an equation for market software provision in Section 3.3. Finally, in Section 3.4, we describe the procedure for estimating the hardware demand equation and the software provision equation.

19 For instance, Palm provides development and logistic support for third party software vendors who wish to develop software for the Palm O/S, through its software-support website at http://www.handango.com/.

3.1. Consumer preferences

The consumer's decision process is as follows. In a given time-period t, each consumer makes a discrete choice from among $J_t + 1$ hardware alternatives available to him in that time-period. Here, $j \in (1, \ldots, J_t)$ indexes the hardware models available in the market at time t, and $j = 0$ corresponds to the decision not to purchase PDA hardware. If the consumer chooses to purchase a model, he then purchases complementary software from among the set of compatible software titles available in the market. We implicitly assume that consumers behave myopically at the time of the hardware decision. In choosing a system type, they only consider current software availability and not the net present value of future software purchases. Note, once a consumer selects the hardware, he effectively commits to a system, or technology standard. In future periods, he could continue to purchase software compatible with this system.

Suppose consumer i considers purchasing hardware model j in time-period t. Let model j be compatible with technology $f \in (1, \ldots, \Im)$.[20] Let p_{jt} denote the price of model j at time t, N_{ft} represent the stock of software available for technology f at time t and let Y_{ft} represent the installed base of hardware for technology f at time t. Let y_{it} represent consumer i's income in time t and let z_{it} represent the outside good, a numeraire capturing the consumption of non-PDA system goods. At the time of the system adoption decision, we assume that the utility a consumer derives from a given PDA system of hardware and software is additively separable in the benefit from the hardware and the software. Denote by V_{ijt}^{HW} the consumer's benefit from hardware model j and by U_{ijft}^{SW} the consumer's benefit from the compatible software. Thus, the consumer's utility from adopting the hardware/software system, $j - f$, at time t, U_{ijft}, is:

$$U_{ijft} = V_{ijt}^{HW} + U_{ijft}^{SW}\left(x_{i1ft}, \ldots, x_{iN_{ft}ft}, z_{it}\right), \tag{1}$$

where $x_{ikft}, k = 1, \ldots, N_{ft}$ denotes the demand for software good k compatible with hardware technology f.

To derive the indirect utility of system $j - f$ we first derive the consumer's indirect utility from use of compatible software conditional on purchase of a hardware product in time t. Suppose the consumer has purchased model j (compatible with technology f). Letting ρ_{kft} denote the price of software k in time t, his demand for

20 We assume that no new technologies are introduced in the periods under consideration. That is, $\Im$ is the same for all time periods. Of course, the number of models of each hardware technology in the market varies over time.

compatible software for model j, $(x^*_{i1ft}, \ldots, x^*_{iN_{ft}ft})$, is the solution to:

$$\begin{aligned}&\max_{x_{i1ft},\ldots,x_{iN_{ft}ft}} U^{SW}_{ijft}\left(x_{i1ft}, \ldots, x_{iN_{ft}ft}, z_{it}\right)\\ &\text{st} \sum_{k=1}^{N_{ft}} \rho_{kft} x_{ikft} + z_{it} = y_{it} - p_{jt}.\end{aligned} \tag{2}$$

We assume that U^{SW}_{ijft} is additively separable in the software and in the outside good. We model consumer preferences for software using a modified CES utility function (e.g. Spence, 1976; Dixit and Stiglitz, 1977; Church and Gandal, 1992; Chou and Shy, 1990; Park, 2002b). The CES formulation helps us capture consumers' preference for software variety, so that consumers prefer more software titles to less. An alternative popular model would be the discrete choice model, such as the multinomial logit demand system (e.g. Anderson et al., 1989) whereby consumers would be assumed to purchase a single unit of one of the software titles. In contrast, the CES model enables us to capture consumers' preferences for software variety. Thus, we assume:

$$U^{SW}_{ijft}\left(x_{i1ft}, \ldots, x_{iN_{ft}ft}, z_{it}\right) = v\left(Q_{ift}\right) + z_{it}, \tag{3}$$

where, $Q_{ift} = (\sum_{k=1}^{N_{ft}} (x_{ikft})^{1/\beta})^{\beta}$ is a quantity index, and $v(Q_{ift}) = (Q_{ift})^{1/\alpha\beta}$, $\alpha \geq 1, \beta > 1$ is an increasing and concave function of Q_{ift}. The parameter β relaxes the perfect substitutability of the model so that consumers can purchase positive quantities of each of the software titles available. Given the above functional form, the consumer's optimal demand for software k, x^*_{ikft} is:

$$x^*_{ikft} = \left(\alpha\beta \mathrm{P}_{ft}\right)^{\alpha\beta/(1-\alpha\beta)} \left(\frac{\mathrm{P}_{ft}}{\rho_{kft}}\right)^{\beta/\beta-1}, \tag{4a}$$

where, $\mathrm{P}_{ft} = (\sum_{k=1}^{N_{ft}} (\rho_{kft})^{1/(1-\beta)})^{1-\beta}$ is a price index for the software.[21] By allowing for $v(\cdot)$, we introduce decreasing marginal returns from software variety into the CES utility. Further, we get the property that the optimal demand of software, x^*_{ikft} (equation (4a)), is decreasing in the variety of software. Therefore, as more software titles are provided in the market due to increases in the hardware installed base, the per-consumer demand for software decreases, thus allowing more hardware sales to result in more software titles in the market in equilibrium. In essence, $v(\cdot)$ drives the indirect network effect in the model.

21 The derivation is available from the authors upon request.

Given the symmetric demands for software in (4a), and an assumption that all third party software vendors face identical costs, there exists a symmetric equilibrium in which all software firms charge the same price, ρ (see Section 3.3). With identical software prices, the demand for software becomes:

$$x^*_{ikft} = (\alpha\beta\rho)^{\alpha\beta/(1-\alpha\beta)}\left(N_{ft}\right)^{\beta(\alpha-1)/(1-\alpha\beta)}. \tag{4b}$$

Substituting for x^*_{ikft} into the budget constraint in (2), we can derive the consumer's indirect utility from use of software, V^{SW}_{ijft} as:

$$V^{SW}_{ijft} = y_{it} - p_{jt} + \gamma\left(N_{ft}\right)^{\delta}, \tag{5}$$

where, $\gamma = (\rho\alpha\beta)^{1/(1-\alpha\beta)}(1-(\alpha\beta)^{-1})$ and $\delta = (\beta-1)/(\alpha\beta-1)$. The restriction that $\alpha \geq 1, \beta > 1$ implies that $0 < \delta \leq 1$. Given (5), the consumer's indirect utility from purchasing the hardware/software system, $j-f$, at time t, V_{ijft}, is:

$$V_{ijft} = V^{HW}_{ijt} + y_{it} - p_{jt} + \gamma(N_{ft})^{\delta}. \tag{6}$$

After accounting for the software provision equilibrium, the consumer's utility from purchasing a hardware model depends on the stand-alone benefit from the model, his income, the price of the hardware and a power function of the variety of compatible software available in the market for that hardware technology. In the next subsection, we derive the corresponding hardware demand system.

3.2. Hardware demand

Let model j compatible with technology f be marketed under the brand name b, $b\varepsilon(1,\ldots,\mathrm{B})$. We assume that V^{HW}_{ijt} has the following form:

$$V^{HW}_{ijt} = \alpha_{ib} + \overline{Z}_{jt}\theta + \xi_{jt} + \zeta_{ift} + (1-\sigma)\varepsilon_{ijt},$$

where, α_{ib} is consumer i's intrinsic preference for brand b (with which model j is associated), $\overline{Z}_{jt}$ is a $(1 \times R)$ vector of observed attributes associated with model j, θ is a $(R \times 1)$ vector of parameters associated with these attributes and ξ_{jt} is an error term representing unobserved (to the econometrician) attributes associated with model j in time period t. In the PDA context, we think of the ξ_{jt} terms as capturing the effect of omitted cosmetic features (like model color, "sleekness") and potentially changing mean consumer tastes for these features for which we are unable to control using our observed attribute variables. ε_{ijt} is an i.i.d. extreme value random error term representing idiosyncratic tastes of consumer i for model j in time t. ζ_{ift} is an error component for models compatible with technology f, whose distribution depends on σ such that $\zeta_{ift} + (1-\sigma)\varepsilon_{ijt}$ is also an extreme value random variable. Substituting this specification of hardware utility into (6), we obtain the following expression for overall PDA conditional indirect utility from model j:

$$V_{ijft} = y_{it} - p_{jt} + \gamma\left(N_{ft}\right)^{\delta} + \alpha_{ib} + \overline{Z}_{jt}\theta + \xi_{jt} + \zeta_{ift} + (1-\sigma)\varepsilon_{ijt}. \tag{7}$$

This takes the form of a familiar nested logit with $\Im + 1$ nests corresponding to the various technologies available and nesting parameter σ. Note the outside good $(j = 0)$ forms the only member of nest 0.[22]

To further allow for unobserved heterogeneity in tastes for brands, we assume that the intrinsic brand preferences have the following normal distribution in the population:

$$\alpha_{ib} \sim N\left(\overline{\alpha}_b, \sigma_b^2\right).$$

We can write the unconditional probability, q_{jt}, that a consumer chooses model j in time-period t as:

$$q_{jt} = \int_{-\infty}^{\infty} \frac{\mathrm{e}^{(\overline{\delta}_{jt}+\mu_{ib})/(1-\sigma)}}{D_{ift}^{\sigma}\left(\sum_{f=0}^{\Im} D_{ift}^{(1-\sigma)}\right)} \phi(\omega)\partial\omega. \tag{8a}$$

As is the convention in the literature, we have simplified the notation inside the exponentiated terms to reflect a component that is common across consumers, $\overline{\delta}_{jt}$, and a component that is consumer-specific, μ_{ib}. Thus, in the above equation, $\overline{\delta}_{jt} = \overline{\alpha}_b - \vartheta p_{jt} + \gamma(N_{ft})^{\delta} + \overline{Z}_{jt}\theta + \xi_{jt}$ is the common component of the utility for model j in time-period t,[23] and $\mu_{ib} = \sigma_b\omega_{ib}$ is the individual-specific component. σ is the within-nest correlation parameter of the nested-logit; D_{ift} is a nest-specific term with $D_{ift} = \sum_{j=1}^{J_f} \mathrm{e}^{(\overline{\delta}_{jt}+\mu_{ib})/(1-\sigma)}$ and $D_{i0t} = 1$; and $\phi(\cdot)$ is the pdf of a standard multivariate normal.

The random effects (or heterogeneity) in (8a) are important for our model as they allow for flexible substitution patterns between hardware models within and across formats. For instance, the brand intercepts control for the mean impact of brand name on shares. The deviations from the mean brand taste, the error component $\sigma_b\omega_{ib}$, captures the correlation in utilities of models with same brand name. Similarly, the format nests control for correlation in utilities of models with same

22 For more details on this formulation see Berry (1994 pp. 252–253) and Cardell (1997).

23 ϑ is implicitly the inverse of the scale parameter of the extreme value distribution, and all other parameters are implicitly scaled down by the scale parameter.

format, and the no-purchase nest controls for non-IIA switching between inside and outside goods. Finally, the observed product characteristics control for mean differences in shares of models net of brand and technology format. We do not however control for the changing willingness-to-pay of PDA adopters over time. Modeling these demand dynamics (cf. Song and Chintagunta, 2003) is beyond the scope of the paper, and also requires access to further demographic data.

Let M_t denote the potential market in time-period t. Given the total market size denoted as $\overline{M}$, we calculate M_t, the potential market for hardware in month t as $M_t = \overline{M} -$ cumulative PDA unit sales till month t. This reflects the idea that we treat potential consumers as first-time buyers of the hardware, who drop out of the market after purchase.[24]

The expected demand, Q_{jt}, for model j in time-period t is then:

$$Q_{jt} = q_{jt} M_t, \tag{8b}$$

(8a) and (8b) together represent the hardware demand equation. In fitting this demand system to PDA sales data, we need to be careful to control for the potential endogeneity of hardware prices and software variety. Although we do not model hardware pricing explicitly, if hardware firms set prices strategically and account for the unobserved (to the econometrician) product features ξ_{jt} each period, prices will be correlated with the error term (see Berry, 1994 for a further discussion of this issue). The endogeneity of software variety reflects the simultaneity of software provision and hardware sales in the industry. In the estimation section below, we explain how we control for both these sources of endogeneity using instrumental variables.

We now present the software model and the implied software provision equation.

3.3. *Software provision*

Let Y_{ft} represent the installed base of hardware for technology f at time t. Consider the software firm producing software k compatible with hardware technology f in time-period t. Let its fixed cost be F_{ft}, and its marginal cost be c. Its profit, π_{kft}, is:

$$\pi_{kft} = (\rho_{kft} - c) \sum_{i=1}^{Y_{ft}} x^*_{ikft} - F_{ft}, \tag{9}$$

where, x^*_{ikft} is the demand for software k from a consumer who has bought a model

24 Replacement sales are ignored—the bias is expected to be small given that our data are for the initial years of this relatively new category, where most retail purchases are made by first-time buyers.

of hardware technology f given in equation (4a). The first-order condition for price for the firm implies that each software firm sets the price of software such that its marginal revenue equals its marginal cost. To obtain the marginal revenue function for the firm, we first derive the price elasticity of demand for software. The price elasticity of demand faced by firm k in time t, η_{kft}, is $-\partial \ln x^*_{ikft}/\partial \ln \rho_{kft}$, where, x^*_{ikft} is the consumer's demand for software k given in (4a).

From (4a) we see that the price affects the demand for software both directly and indirectly through its effects on P_{ft}, the price index. As in common in the literature, we assume that due to the large number of software titles available in the market, the indirect effect of price on P_{ft} is negligible and can be ignored.[25] With this assumption, the price elasticity of software demand, η_{kft}, is obtained as $\beta/(\beta-1)$. Therefore, the marginal revenue of the software firm is $\rho_{kft}(1-\eta_{kft})/\eta_{kft} = \rho_{kft}/\beta$. Equating this to the marginal cost, c, the optimal price is $\rho_{kft} = \rho = \beta c$. Thus, with the symmetric demand functions in (4a) and identical marginal costs, in equilibrium all software firms charge the same price, ρ.

With free entry, each firm will earn zero (economic) profits. Substituting for ρ and for x^*_{ikft} from (4b) into the profit function in (9) and setting equal to zero, we obtain,

$$\pi^{\text{free-entry}}_{kft} = (\beta c - c)\, Y_{ft}(\alpha\beta\rho)^{\alpha\beta/(1-\alpha\beta)}(N_{ft})^{\beta(\alpha-1)/(1-\alpha\beta)} - F_{ft} = 0.$$

Taking logs and rearranging, we get the equilibrium software provision equation:

$$\ln(N_{ft}) = \kappa_{ft} + \varphi \ln(Y_{ft}) + \upsilon_{ft}, \tag{10}$$

where, $\kappa_{ft} = (\alpha\beta-1)/\beta(\alpha-1)\ln[c(\beta-1)/F_{ft}(\alpha\beta^2 c)^{\alpha\beta/(1-\alpha\beta)}]$, $\varphi = (\alpha\beta-1)/\beta(\alpha-1)$ and υ_{ft} is an additive mean zero error term. The software provision equation is thus a loglinear equation in software variety and hardware installed base. When fitting equation (10) to data, we will need to account for the endogeneity of the hardware installed base, which is determined simultaneously by the availability of software.

3.4. *Model estimation*

We now describe the empirical procedure we use to estimate the parameters of the model derived in the previous section. The equations to be estimated are:

25 This is a standard assumption in the literature on monopolistic competition. See Dixit and Stiglitz (1977) and Church and Gandal (1992), and more recently Park (2002b).

- The hardware demand equation (8a and 8b):

$$Q_{jt} = M_t \int_{-\infty}^{\infty} \frac{e^{(\overline{\delta}_{jt}+\mu_{ib})/(1-\sigma)}}{D_{ift}^{\sigma}\left(\sum_{f=0}^{\Im} D_{ift}^{(1-\sigma)}\right)} \phi(\omega)\partial\omega,$$

and,
- The software provision equation (10):

$$\ln(N_{ft}) = \kappa_{ft} + \varphi \ln(Y_{ft}) + \upsilon_{ft}.$$

We conduct estimation in two steps. First, we fit the hardware demand equation to recover consumer taste parameters. Then, we fit the software provision equation to recover the parameters describing the relationship between software availability and hardware installed base. The fact that we do not estimate hardware and software demand jointly could lead to inefficient estimates if the respective error terms ξ_{jt} and υ_{ft} are correlated. Differences in the dimensionality of these two error terms would complicate joint estimation. Furthermore, we found no evidence of correlation between these two error terms based on the estimates we report below. A second source of efficiency loss comes from the potential estimation of the common parameters, α and β, across equations. In the current context, we are not specifically interested in these parameters, but rather in the net effect of software variety on hardware demand (γ and δ) and the effect of the hardware installed base on software provision (φ). Hence, we carry-out estimation of these two equations sequentially.

3.4.1. Hardware demand equation. Using the demand system in (8a) and (8b), we can write the expected market share for hardware model j at time t, $\hat{s}_{jt}$, by dividing through by the total potential market size, M_t:

$$\hat{s}_{jt} = \int_{-\infty}^{\infty} \frac{e^{(\overline{\delta}_{jt}+\mu_{ib})/(1-\sigma)}}{D_{ift}^{\sigma}\left(\sum_{f=0}^{\Im} D_{ift}^{(1-\sigma)}\right)} \phi(\omega)\partial\omega. \tag{11}$$

In (11) above, denote the parameters that enter $\overline{\delta}_{jt}$ linearly as Δ, and let $\Theta = (\Delta, \delta, \sigma, \{\sigma_b\}_{b=1}^{B})$ represent the vector of all the parameters to be estimated. Define the stacked matrix of variables corresponding to the linear parameters Δ as $X_{jt}(\Theta)$. Note that $X_{jt}(\Theta)$ depends on Θ since one of the variables in it is the power function of software variety, $(N_{ft})^{\delta}$. In the empirical specification, $X_{jt}(\Theta)$ thus includes brand-intercepts (not brand-model intercepts as there are several), prices, the power function of software variety, form, speed, area, weight, color, eslots, modem, lithium and holiday.

A concern with estimating (11) via non-linear least squares is the potential correlation between the unobserved product characteristics, ξ_{jt}, and the observed hardware prices and software availability. Analogous to Berry (1994), we first invert (11) to recover the vector $\overline{\delta}_{jt}(\Theta)$ based on which we set up the criterion for estimating the model parameters. Since the inverse does not have a simple analytic form, we use a modified version of the contraction-mapping proposed by BLP (1995).[26] Intuitively, we calibrate values of $\overline{\delta}_{jt}(\Theta)$ that exactly fit the predicted shares in (11), $\hat{s}_{jt}$, to the observed shares in the data. The advantage of using $\overline{\delta}_{jt}(\Theta)$ for estimation is that the corresponding prediction error, $\overline{\delta}_{jt}(\Theta) - X_{jt}(\Theta)\Delta$, is the unobserved attribute, $\xi_{jt}(\Theta)$. The fact that $\xi_{jt}(\Theta)$ enters $\overline{\delta}_{jt}(\Theta) = X_{jt}(\Theta)\Delta + \xi_{jt}$ linearly facilitates the use of a standard instrumental variables procedure. Note that if we ignored heterogeneity, then the system could be inverted analytically in logarithms and we could estimate the model using standard instrumental variables regression (Berry, 1994; Besanko et al., 1998).

We now provide a brief informal discussion of identification in the model. The linear parameters Δ are identified from variation in model market shares due to variations in X_{jt}. Deviations from IIA-type inter-brand substitution patterns help us identify the $\{\sigma_b\}_{b=1}^{B}$ parameters. To see the identification of σ, denote the within format share of model j as $\hat{s}_{j|f,t}$, and note that:

$$\frac{\partial \hat{s}_{jt}}{\partial \overline{\delta}_{jt}} = \frac{1}{(1-\sigma)} \hat{s}_{jt}[1 - \sigma \hat{s}_{j|f,t} - (1-\sigma)\hat{s}_{jt}].$$

As σ approaches zero, only the model market share, and not the within-format share affects the derivative. Thus, the nesting parameter σ is identified by the relationship between the model market shares and within-format shares in the data.

We now set up the estimation procedure to estimate the system $\overline{\delta}_{jt}(\Theta) = X_{jt}(\Theta)\Delta + \xi_{jt}$. Note that we evaluate the integrals in (11) via Monte Carlo simulation and, hence, we simulate the expression $\overline{\delta}_{jt}(\Theta)$. Estimation is conducted using the method of simulated moments (Pakes and Pollard, 1989). We use moments implied by $\overline{\delta}_{jt} = X_{jt}\Delta + \xi_{jt}$ to construct orthogonality conditions. Technically, we can construct orthogonality conditions using any set of covariates, Z_{jt}, that are mean-independent of $\xi_{jt}(\Theta)$. Since prices and software provision are expected to be correlated with ξ_{jt}, we construct a vector of instruments that are mean independent of ξ_{jt} such that $E[Z'_{jt}\xi_{jt} \mid Z_{jt}] = 0$. As suggested by Berry (1994), we use functions of observable product attributes as instruments for prices, and the sum of characteristics of all models compatible with a given technology as instruments for the within-nest share. From the software provision equation (10), we see that market software variety depends on current hardware sales (through the installed base).

26 Since we have a nested logit model, we modify the contraction mapping to invert for the weighted mean utility: $\tilde{\delta}_{jt}(\Theta) = \overline{\delta}_{jt}(\Theta)/(1-\sigma)$, from which we recover $\overline{\delta}_{jt}(\Theta)$.

Hence observable hardware product attributes are valid instruments for market software variety. Thus, the set of instruments that we used are squared terms and interactions of own RAM, speed, weight and area, number of models of the hardware technology available in the market.[27] The validity of these instruments requires us to assume the attributes are uncorrelated with the error term. For instance, we must assume hardware firms do not set PDA observed attributes and the unobserved characteristic jointly. This identifying assumption has been made in the extant literature (e.g., BLP, 1995), and is partially motivated by the difficulty in obtaining better instruments.

For estimation, we use the sample analog of the moment conditions: $\hat{M}(Z,\Theta) = 1/JT\sum_{j=1}^{J}\sum_{t=1}^{T_j} Z_{jt}\xi_{jt}$, where J is the number of unique models in the data, and $T = \sum_{j=1}^{J} T_j$. The model parameters, Θ, are estimated by minimizing the GMM objective function $\hat{M}(Z,\Theta)\hat{W}\hat{M}(Z,\Theta)'$. We also allow for serial dependence in ξ_{jt}, and assume that $E[\xi_{jt}\xi_{kt}] = \Omega_{|t-k|} \geq 0$, where $\Omega_{|t-k|}$ is a finite scalar. For estimation, an estimate of the efficient weighting matrix, $\hat{W}$, robust to serial dependence is computed as:

$$\hat{W} = \sum_{j=1}^{J} \sum_{k=-(T_j-1)}^{T_j-1} \frac{1}{T_j}\lambda_T(k) \sum_{t=1}^{T_j-|k|} (z_{jt}\xi_{jt})(z_{j,t+k}\xi_{j,t+k})',$$

where, $\lambda_T(k)$ is the Bartlet weighting function defined as:

$$\lambda_T(k) = \left| \begin{array}{ll} 1 - \dfrac{|k|}{L_T}, & |k| < L_T, \\ 0 & \text{otherwise.} \end{array} \right.$$

Finally, to calculate the market shares, s_{jt}, we need to choose values for the hardware installed base in the first month of our data (January 1999), Y_{f0}, and for $\overline{M}$, the total market size for hardware in the United States. IDC reports that at the end of 1998, the Palm O/S installed base stood at 2.5 million units compared to the MS O/S installed base of 282,000 units. We use these as the initial values to compute the hardware installed base series for the Palm and MS O/S PDA-s. A study released by Palm pegs the size of the total US market for handheld devices at 63 million; however, this includes both projected first-time and replacement purchases.[28] Therefore, we experiment with various values for the total market size including 65 million, 30 million and 20 million. The results are robust across these values.

27 The first-stage R^2 values for the regressions of the endogenous variables on the instruments were as follows: prices (0.5785), software variety (0.8027), and within-nest share (0.3827).

28 Maritz: "Thompson Lightstone US only segmentation study", March 2002, http://news.cnet.com/investor/news/newsitem/0–9900–1028–20844730–0.html.

3.4.2. Software provision equation. We use the reduced-form of the equilibrium number of software firms, derived in Section 3.3, as the basis for our software provision regression:

$$\ln(N_{ft}) = \kappa_{ft} + \varphi \ln(Y_{ft}) + \upsilon_{ft}.$$

The software provision equation is a log-linear regression with an endogenous explanatory variable (the installed base) which we estimate using two-stage least squares. We use the sum of characteristics of all models compatible with a given technology format—number of models, and sum of RAM, speed, weight and area of models of the technology format—as instruments.[29] We assume κ_{ft} in (10) to be composed of a format-specific term and a time-period specific term. Thus, for the software provision equation, we estimate a constant, 42 time-period fixed effects, a Palm O/S fixed effect and the coefficient on hardware installed base.

4. Results

4.1. *Hardware demand*

We now report the results from three models specifications to assess some of the structure we impose. Our first model consists of an OLS regression based on the log-linearization of (11). Here, in addition to ignoring heterogeneity in tastes (no brand random effects), we also implicitly assume that software variety enters the demand system linearly. Implicitly, we set $\delta = 1$ (or $\alpha = 1$ in the CES demand model). Parameter estimates for this hardware demand model are presented in the first two columns of Table 3. In the third and fourth columns, we introduce the non-linear effect of software provision on the mean utility ($\delta \in (0, 1)$) and control for the endogeneity of prices, software availability, and within-nest share. We estimate this model by GMM. Finally, the fifth and sixth columns report the results of our main model, which also incorporates unobserved heterogeneity, and which we estimate using the method of simulated moments procedure described previously.

Looking at the OLS results in Table 3, we note that all the parameter results make sense intuitively. The fixed effects are all negative due to the large share of the outside good. The effect of price is negative and significant.[30] Software variety has a positive and significant effect on hardware sales—preliminary evidence for a complementary network effect. The positive coefficient on form indicates that on average consumers prefer the tablet form factor for PDA-s to the clamshell form-

29 The first-stage R^2 value for the regression of the (log of the) installed base on the instruments was 0.9253.

30 In all specifications we use real-prices obtained by deflating model prices by the CPI. Thus all prices are in 100s of January 1999 dollars.

Table 3. Results for estimation of hardware demand equation with linear and power specifications for software variety.

	OLS—linear software variety[1]		GMM—power software variety		GMM with random coefficients on brand intercepts—power software variety[2]	
Variable	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic
Casio	−8.209	−135.545	−8.574	−17.198	−9.334	−5.152
Compaq	−8.307	−138.155	−8.657	−17.419	−9.534	−4.945
Handspring	−6.131	−90.764	−6.454	−9.344	−7.205	−4.021
HP	−8.203	−126.474	−8.548	−17.028	−9.339	−5.147
Palm	−6.162	−99.083	−6.501	−10.494	−7.219	−3.120
Sony	−6.282	−87.507	−6.661	−10.879	−7.346	−3.510
Price/CPI	−0.025	−3.890	−0.019	−2.350	−0.037	−2.837
Log(Software variety/100)	0.956	47.718				
(Software variety/100)$^{\delta}$			0.904	4.916	1.077	3.149
δ			0.498	3.185	0.394	3.105
σ	0.988	314.794	0.810	62.777	0.967	16.102
Form	0.070	1.710	0.009	1.124	0.119	1.277
RAM	0.004	3.536	0.004	3.159	0.005	2.116
Clock-Speed	0.002	6.023	0.003	5.624	0.003	4.117
Area	0.018	3.043	0.017	2.056	0.031	3.990
Weight	−0.040	−3.647	−0.035	−2.183	−0.059	−3.001
Color	0.052	1.547	0.045	2.172	0.077	1.855
Eslots	0.010	0.518	0.058	1.934	0.007	2.008
Modem	0.042	1.538	−0.007	−0.220	0.058	0.390
Lithium	−0.026	−0.989	−0.050	−1.391	0.014	0.302
Holiday	0.765	33.921	0.810	18.696	0.805	12.925
N			2068			
R^2	0.9885					
Obj. Function value			65.7649		78.7532	

For all models, potential market each period is computed as 20M-cumulative PDA units sold till that period.
[1]Dependant variable is $\log(s_{jt}/s_{0t})$.
[2]Standard errors are robust to heteroscedasticity and unknown serial correlation. Standard deviation of brand-intercepts estimated, but not reported.

factor. As expected, the RAM and processor clock-speed have a significant positive effect on hardware sales. Consumers prefer larger face area to lesser area and prefer lighter models to heavier ones on average. PDA-s with color displays are preferred to ones with monochrome displays. The benefit from hardware is also increasing in the number of expansion slots available and in the availability of a built-in modem and lithium batteries. As expected, the holiday effect is significant indicating that seasonality plays an important role in determining PDA sales. Overall these results are in line with what we would expect a priori. The R^2 for the regression is high mainly because the within-nest share closely predicts the market share of the models. This also suggests that within a nest, hardware models are perceived by consumers as being fairly similar. Testing this model against 2SLS (not reported) gave a Hausman test statistic of 64.123. Comparing this to the critical value of $\chi^2(3) = 7.81$ strongly rejects the OLS model, indicating that controlling for endogeneity is important.

We now present the results for the non-linear model, which controls for endogeneity (columns 3 and 4 in Table 3). We see that after using instruments, the effect of software variety is positive and significant, indicating that a higher software variety results in higher hardware sales for that technology. The estimated value of δ close to 0.5 indicates that the marginal benefit of software variety for consumers is decreasing. The total effect of software variety has also increased after using instruments. This indicates that ignoring the endogeneity of software variety can lead to misleading inferences about its effect on hardware demand. The within-nest coefficient σ is close to 1 and significant indicating that models within a given nest—that is those compatible with a given technology format—are perceived as being fairly homogenous by consumers. The effect of the other observable attributes remain fairly the same as in the OLS case. The coefficients on modem and lithium have changed sign, but are insignificant.

Columns five and six presents the estimates of the full model in which we allow for both decreasing marginal benefits from software variety and unobserved heterogeneity in brand valuations. The pattern of results from this random-coefficients specification is similar to that from the previous two specifications: software variety is positive and significant; price is negative and significant; σ is close to 1; the attribute-effects are of the expected sign. The Hansen J-statistic for this model is 0.0399 ($= 82.4395/2068$)—the corresponding critical value at the 95% confidence level, $\chi^2(34 - 26)$ is 15.51, indicating that our over-identifying restrictions are not rejected. In contrast to the previous two specifications, this model allows for very flexible brand- and format-substitution patterns. For this reason, in the remaining discussion, we focus on the results from this model.

4.2. *Software provision*

Here we present the 2SLS results for estimation of the software provision equation. We check whether the data are consistent with a higher installed base of hardware resulting in higher software variety for that technology in the market. Table 4 presents the results (the constant and the time-period and format specific fixed effects are suppressed). Controlling for time-period and format fixed effects, the effect of hardware installed base is positive and significant, indicating that the data are consistent with a hardware feedback effect.[31]

31 We did not find evidence of serial correlation on the software provision side. A regression of the software innovations on lagged residuals $\upsilon_{ft} = r\upsilon_{f,t-1} + \tau_{ft}$, gave an estimate of -0.0241 for r with a t-statistic of -0.2193 and an R^2 of 0.0085.

Table 4. Results for 2SLS estimation of software provision equation.

	Without Instruments—OLS		With Instruments—2SLS	
Variable	Parameter	*t*-statistic	Parameter	*t*-statistic
Log(Installed Base/100,000)	0.787	5.234	0.613	3.457
N	43			
R^2	0.9833			
Obj. Function value			50.1356	

Dependant variable is $\log(N_{ft})$; constant, Palm O/S and time-period dummies estimated, but not reported.

To summarize our results at this point, we find evidence for positive feedback from software variety on hardware sales and from hardware installed base on software variety. The results support the anecdotal evidence for complementary network effects in the market for PDA-s. As we see, this effect is fairly robust across model specifications. The implications of these results are that software availability drives adoption of PDA-s, and that brand-managers of PDA products could increase the rate of adoption of their models by encouraging market provision of third-party compatible software. We return to this issue in the subsequent section.

We now discuss the application and implications of these results.

5. Application and implications of results

5.1. *Quantifying the network effect*

Given the above results, an immediate question that arises for PDA brand-managers is the assessment of the relative importance of the network effect versus the price-quality effect in driving PDA sales. If the availability of third-party software is indeed very important relative to price-quality effects, then the firm should invest resources in increasing the provision of third-party software for its models, say through vertical integration into software or by providing infrastructure and development support to third party software vendors.[32] Alternatively, if software availability is not very important relative to price-quality effects in determining sales,

32 For example, Palm already offers a free basic program to third-party developers that provides core services such as software development kits, product images, limited access to source code, and access to prerelease tools and information. It also offers an advanced plan, which costs $495 per year, that provides direct technical support, a quarterly CD with the latest development tools and technology, and help with marketing (for details see http://www.palmos.com/dev/programs/pdp/policies.html and/or Shim, R. and Sandeep Junnarkar, "Palm reaches out to developers", October 23 2001, http://news.com.com/2100–1040–274797.html).

the firm is better off investing resources in improving its price-quality advantage. One way to determine this tradeoff is to look at the percentage of the relative sales of the Palm O/S vs. MS O/S PDA-s explained by the network effect as opposed to the price-quality difference between the models of these two formats.[33] From the nested logit formulation, for a given draw α_{rb} from the distribution of brand valuations, the following relationship holds (see Ohashi, 2003; Park, 2002a):

$$\log\left(\frac{s^r_{\text{Palm},\,t}}{s^r_{MS,\,t}}\right) = (1-\sigma)\left[\log\left(\sum_{j\in\text{Palm}} \mathrm{e}^{(\alpha_{rb}-\vartheta p_{jt}+\overline{Z}_{jt}\theta+\xi_{jt})/(1-\sigma)}\right) - \log\left(\sum_{j\in MS} \mathrm{e}^{(\alpha_{rb}-\vartheta p_{jt}+\overline{Z}_{jt}\theta+\xi_{jt})/(1-\sigma)}\right)\right] + \gamma\left(N^{\delta}_{\text{Palm},\,t} - N^{\delta}_{MS,\,t}\right). \tag{12}$$

The first term on the right-hand side of (12) can be thought of as the price-quality advantage of all Palm O/S PDA-s over all MS O/S PDA-s, and the second term as the network advantage. The mean percentage of the log relative sales of Palm O/S vs. MS O/S PDA-s explained by the network advantage in each period is therefore $1/R\sum_{r=1}^{R}\gamma(N^{\delta}_{\text{Palm},t} - N^{\delta}_{MS,t})/\log(s^r_{\text{Palm},t}/s^r_{MS,t}) * 100$ where R is the number of draws from the distribution of brand valuations. Figure 4 presents the plot of this term over the time-period of our data. Looking at Figure 4 we see that consistent with our expectations, the effect of the network advantage is increasing over time, reflecting the faster growth of Palm software variety compared to that of the MS format. We find that by month 43 (July 2002) price and model features explains around 78% of the (log) relative sales of Palm O/S compatible PDA-s over all MS O/S compatible PDA-s. The network advantage factor explains the remaining 22%. Given that this is still a growing category, this effect could become even larger over time.

Previous literature has used the decomposition in (12) to measure the size of network effects. Ohashi (2003) and Park (2002a) compute a measure analogous to (12) in a nested logit model without heterogeneity. However, while we measure indirect network effects using our index of software availability, Park (2002a) uses time-period and format specific fixed effects to identify network effects, while Ohashi (2003) relies on the effect of past hardware installed base on current hardware sales to identify the same. A potential concern in the use of format specific fixed effects is the confound between network effects and quality differences across models of the technology formats in each period. Similarly, the use of past installed base as an explanatory variable for current hardware sales

33 To avoid confusion, we will refer to the Palm Operating System format as "Palm O/S" and to the Palm PDA Company as "Palm Co."

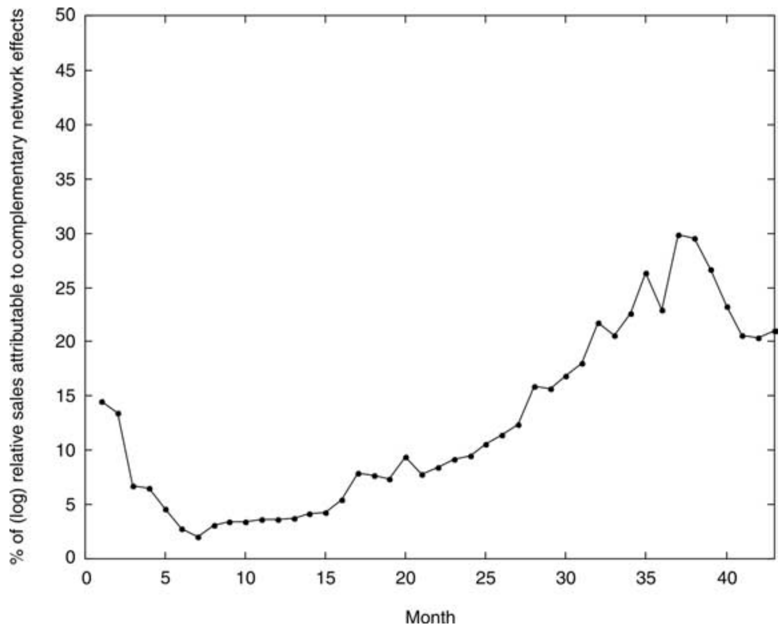

Figure 4. Percentage of log relative shares of Palm O/S vs. MS O/S explained by network advantage factor.

could potentially overstate the network advantage effects by confounding direct network effects, market phenomena like herding (Banerjee, 1992; Bikhchandani et al., 1998), and possible signaling effects of past market share on consumer adoption decisions (Caminal and Vives, 1996), with the feedback effects of complementary software.

An interesting question is whether we could still capture the impact of network effects simply by using an appropriate functional form for hardware installed base in the hardware demand equation. In our model, the equilibrium total number of software in the market is indeed related to the hardware installed base through the free entry condition. Hence, the model predicts that the installed base of hardware should always correlate positively with current demand since it contains information about software availability. Nevertheless, we claim that with indirect network effects, the use of auxiliary data on software variety is superior to using the hardware installed base as a covariate. In most high-technology categories like PDA-s where prices are falling over time and sales are rising over time, it is difficult to disentangle whether higher sales reflect lower prices versus network effects. The use of auxiliary software variety data resolves this issue.

The corresponding value to (12) for a model in which we use the installed base as a covariate to capture the network effect is around 68%. This suggests that using a

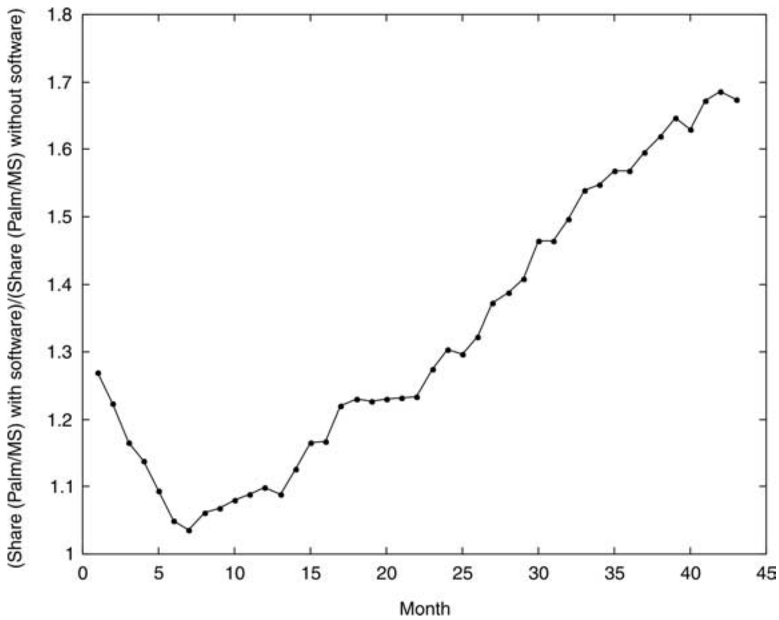

Figure 5. Relative shares of Palm O/S vs. MS O/S with software variety over relative shares of Palm O/S vs. MS O/S without software variety.

model with the installed base as a variable tends to overstate the extent of network effects in this category relative to our model. Further, this approach does not help us derive implications vis-à-vis the potential benefits on the hardware side from increasing market provision of software.

We further examine the importance of the network factor using another metric. For this, we first compute the relative shares of Palm and MS O/S compatible PDA-s in the data. We then simulate the total sales of Palm and MS O/S PDA-s that would occur without any compatible third-party software in the market (or equivalently when consumers do not value software variety at all). To do this, we set the effect of software variety in the hardware demand equation (11) to zero and simulate the growth of the installed base of the Palm and MS O/S formats using the parameter estimates in Table 3 (full model). We then compute the ratio of the relative sales of Palm O/S and MS O/S PDA-s with and without software availability. Figure 5 plots this metric over the time-period of our data. We see from Figure 5 that the relative sales of Palm O/S over the MS O/S format with software available in the market, relative to that without software available in the market, is increasing over time. By month 43, the relative sales of Palm O/S over MS O/S with software available in the market is almost double of that without software available in the market. It appears that the advantage enjoyed by the

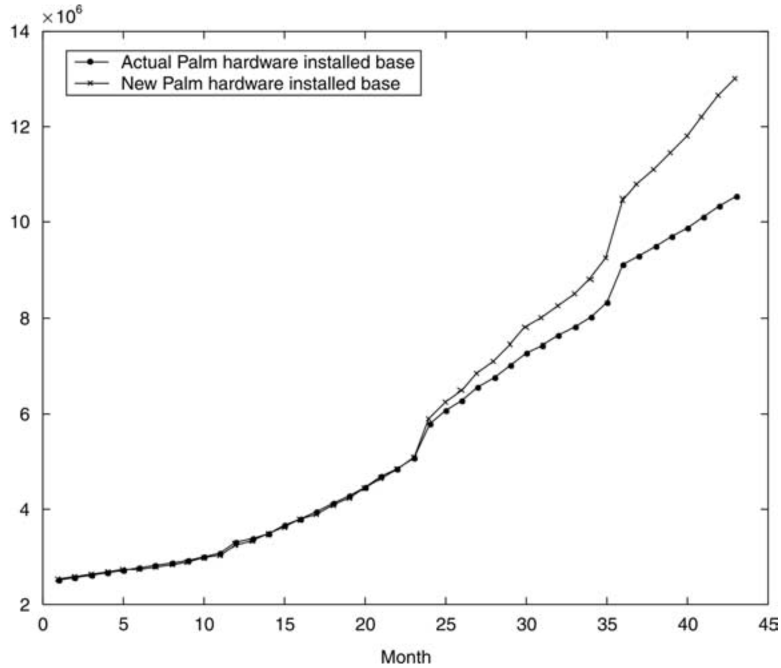

Figure 6. Evolution of Palm O/S installed base with no MS O/S software in market.

Palm O/S over the MS O/S in terms of the number of compatible third-party software available is significant. In particular, the availability of compatible software has helped the Palm O/S to almost double its hardware sales relative to the MS O/S.

We further examine the effect of software variety of one format on the hardware sales of the other using two more simulations. In the first, we simulate the growth of the Palm O/S hardware installed base setting all MS O/S compatible software in the market to zero. To do this, we start with the period 0 installed base of the Palm O/S and MS O/S and simulate the Palm O/S software variety in the market using the results from Table 4. We use the Palm O/S software variety in period 1 and the results from Table 3 to simulate the Palm O/S hardware sales in period 1, holding the MS O/S software variety to be zero. We proceed in this manner to obtain the Palm O/S hardware installed base over time, holding the MS O/S software variety at zero in all periods. Our attempt here is to examine the Palm O/S hardware growth if MS O/S products had no compatible third-party software on the market. Figure 6 plots the results for this simulation. Figure 7 plots the corresponding growth curves for the case where the Palm O/S software variety in each period is set to zero.

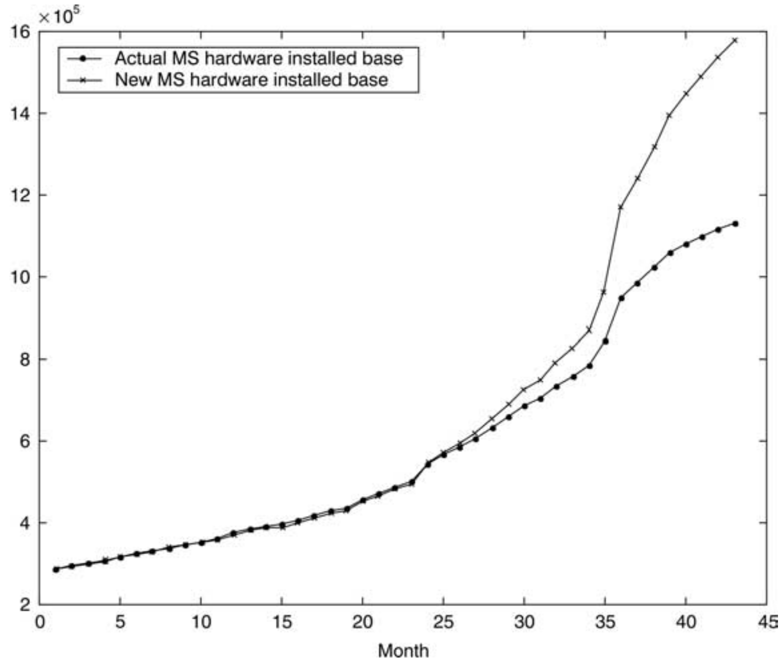

Figure 7. Evolution of MS O/S installed base with no Palm O/S software in market.

From Figures 6 and 7, we see that lack of rival third-party software in the market affects the growth of both formats. At the end of month 43, Palm O/S's gain from the unavailability of MS O/S-compatible software is about a 24% increase in its installed base, while MS O/S's gain from the unavailability of Palm O/S-compatible software is about a 38% increase in its installed base. MS O/S benefits more from the unavailability of the larger stock of Palm O/S-compatible software in the market, than does Palm O/S from the unavailability of the smaller stock of MS O/S-compatible software.

The above results indicate that third-party compatible software plays an important role in the growth of PDA sales in the United States. The results can be of potential use to both Palm O/S and MS O/S managers deciding on future strategy for their O/S standards. We focus on these below, taking the perspective of a Palm Co. hardware manager deciding on long-term strategies for his product.[34]

34 Recall that we refer to the Palm operating system format as "Palm O/S" and to the Palm PDA Company as "Palm Co."

5.2. Strategy for hardware managers

5.2.1. Improvement in hardware attributes. We take the perspective of a Palm Co. manager considering the trade-offs involved in improving the attributes of a Palm Co. PDA. Subject to design constraints, the manager faces the task of deciding the level of attributes in each model in the Palm Co. product line. The decision to improve the quality of a model by improving an attribute involves comparing the incremental revenues from the improvement against the costs of making the change. A critical input to this decision is the expected increase in Palm Co. sales that the improvement would generate. Additionally, since Palm Co. is the sponsor of the Palm O/S standard, the manager would also want to consider the effect of the improvement on the total installed base of the Palm O/S standard. Improving the quality of a model by enhancing an attribute has two effects. The first is a direct effect reflecting the value of enhancement in attributes; the second is an indirect effect reflecting the positive feedback from software availability. The direction of the direct and indirect effects is as follows:

- *Direct effect*: Due to improvement in an attribute that consumers value, sales of the model and thus of Palm Co. increase. Since other Palm O/S-compatible PDA-s are close substitutes of the model, the increase in sales of the enhanced model come mostly at the expense of the other Palm O/S-compatible PDA-s. Hence, sales of other Palm O/S-compatible PDA-s decrease. If the net effect of these two is positive (negative), the installed base of Palm increases (decreases).
- *Indirect effect*: The increase (decrease) in the installed base of Palm O/S encourages (discourages) further provision of Palm O/S-compatible third-party software in the market. The increase (decrease) in software further increases (decreases) sales of all Palm O/S PDA-s.

If consumers value the attribute highly, then the gains for Palm Co. from the direct effect will be high. If the positive feedback from software is strong, then the gains from the indirect feedback effect will also be high. Additionally, the stronger the direct effect, the stronger will be the indirect effect, since positive feedback in the market implies that any increase in the Palm O/S installed base will be compounded through increased market software provision. Quantifying the extent of the direct and the indirect effects on his and competitors' sales will help the Palm Co. manager obtain a full picture of the effect of an improvement in an attribute. We undertake such an exercise below.

For our study, we consider the Palm V model manufactured by the Palm Co. The model was introduced into the US market in February 1999 (month 2 in our data), remained in the market until July 2002, and accounted for around 3% of the total PDA unit sales in the data. The model had 16 Mhz clock-speed, 14 square inches of monochrome display, and no expansion slots. Table 5 presents simulated sales figures from exogenously improving the Clock-speed, Color, Area and Eslots attributes of the model in February 1999 (the month of introduction) holding all

Table 5. Effect of exogenous changes in attributes of the Palm V model.

			Simulated–fixed software variety				Simulated–changing software variety			
			Installed base[1]		Unit sales[2]		Installed base[1]		Unit sales[2]	
Attribute	Actual value	New value	Palm O/S[3]	MS O/S	Palm Co.[4]	Other palm O/S compatibles	Palm O/S[3]	MS O/S	Palm Co.[4]	Other palm O/S compatibles
CLOCK-SPEED (Mhz.)	16	33	6.70	− 0.53	14.16	− 7.46	14.83	− 1.22	19.91	− 5.09
Color	0	1	18.18	− 1.42	38.81	− 20.63	39.99	− 3.28	54.29	− 14.30
Area (Sq. in.)	14	17	13.01	− 1.02	27.66	− 14.65	28.70	− 2.36	38.79	− 10.09
Eslots	0	2	3.36	− 0.26	7.06	− 3.71	3.18	− 0.26	4.25	− 1.07

All values in 1000s of units sold; The Palm V was introduced in February 1999, was available in the market until the end of the time period of the data (July 2002) and accounted for about 3% of the total PDA unit sales in the data.
[1]At the end of the last month in data (July 2002).
[2]Total over all months in data (January 1999–July 2002).
[3]All Palm O/S compatible PDA-s.
[4]All PDA-s manufactured by the Palm company.

other variables (including prices) fixed. For each attribute, we disentangle the direct and indirect effects of the improvement using two scenarios. In the first scenario, we fix the market software variety at the observed values in the data (direct effect), and in the second, we allow the market software variety to respond to changes in the hardware installed base (direct and indirect effect). For each, we compute the total installed bases of Palm and MS O/S PDA-s, and the unit sales of Palm Co. and other Palm O/S-compatible PDA-s at the end of July 2002. Hardware sales are simulated using the estimates in Table 3 (full model). Software variety is held fixed at the observed values in the data in the first scenario, and simulated using the estimates from Table 4 in the second. Thus the first scenario does not account for the incremental change in hardware sales due to the changed software provision in the market, while the second allows market software provision to respond to changes in hardware installed base, and thus allows for hardware sales to respond to changing market software variety.

We discuss the results from increasing the clock-speed (row 1 in Table 5). Holding software availability fixed, we find that increasing the clock-speed of the Palm V model from 16 to 33 MHz has increased the total sales of Palm Co. PDA-s by 14.16 thousand units at the end of July 2002. This is the direct effect of improvement in clock-speed. Sales of other Palm O/S-compatible PDA-s have dropped by 7.46 thousand units indicating strong substitution away from these products to the improved Palm Co. model. This is not surprising since we find from our estimation results that consumers perceived models within the same nest to be fairly similar (σ is close to 1). The installed base of Palm O/S standard has increased by 6.70 thousand units, while that of MS O/S has decreased by around 530 units. Looking at the results with changing software variety, we see that when the feedback effect is factored in, Palm Co. sales have increased by 19.91 thousand units. This is the sum of both the direct and the indirect effects. The difference—5.75 thousand units (19.91 – 14.16)—is what Palm Co. gained due to the positive feedback from increased software provision in the market. Further, we see that sales of other Palm O/S-compatible PDA-s have decreased less than before. The difference—2.37 thousand units (7.46 – 5.09)—is what other Palm O/S-compatible PDA-s gained due to the positive feedback from increased provision of Palm O/S-compatible software. The Palm O/S installed base has increased significantly (8.13 thousand units from the indirect effect alone), and the MS O/S installed base has decreased (by around 690 units from the indirect effect). Overall, the size of the market has increased due to the improvement in the attribute. Rows three to five presents the corresponding results for improvements in color, face area, and number of expansion slots. Providing a color interface in February 1999 is seen to be particularly effective especially since color display was not available in other Palm O/S PDA-s until January 2000.

As is seen from above, enhancing the attributes of hardware products in markets with positive feedback result in complex self-reinforcing effects that fuel further hardware sales. In such markets, the supply of compatible software can be a significant competitive advantage. Quantifying the extent of direct and indirect

Table 6. Additional Palm O/S-compatible software required in February 1999 to achieve equivalent unit sales from improvement in attributes of the Palm V model.

Attribute	Actual value	New value	Increase in Palm Co. unit sales from Jan. '99–July '02 due to improvement in attribute[1]	Additional Palm O/S-compatible software titles required in Feb. '99 to achieve equivalent Palm Co. unit sales[2]
Clock-Speed	16	33	19.91	83
Color	0	1	54.29	224
Area	14	17	38.79	161
Eslots	0	2	4.25	19

[1]In 1000s of units.
[2]Assumes that the Palm Co. provides these software titles over and above the available Palm O/S-compatible software titles in the market in February 1999 (the month in which Palm V was introduced).

effects, and understanding how incremental sales are be achieved can help managers in such markets make better and more improved decisions.

5.2.2. ***Equivalent software provision.*** From the above results, it is clear that the availability of compatible software in the market is of value in driving hardware sales. Thus, hardware manufacturers can achieve equivalent increases in sales by providing compatible software in the market, either through vertical integration into software or by providing infrastructure and development support to third party software vendors. To evaluate the trade-offs, managers need to be able to know the number of incremental software titles required in the market in a given period to achieve the same sales increase as an improvement in a specific attribute. We evaluate this trade-off for the four attribute-enhancements to the Palm V model presented in the previous section. Specifically, for each attribute, we use our model to evaluate the number of software titles that Palm Co. will have to provide in the market in February 1999 (the month of introduction of the Palm V model) to achieve the new Palm Co. sales in July 2002. In doing so, we account for decreasing marginal returns to software variety and for the positive feedback that occurs in the market in all subsequent periods in response to the increased software provision. Table 6 shows the results. We see that Palm Co. need to provide 224 more titles in the market in February 1999 to achieve the same unit sales that it would have achieved in July 2002, from providing a color display on Palm V. The corresponding numbers for the other attribute-improvements are: 161 for the increase in face area from 14 to 17 sq. inches; 83 for increasing the clock-speed from 16 to 33 MHz, and 19 for providing two expansion slots. Given access to the cost of software provision, the manager can use these results to evaluate the trade-offs involved in these strategies.

Finally, a caveat to the above simulation results is that they do not consider the price responses from the hardware providers to the policy changes. Implicitly, we assume that simulated prices are the same as actual prices. Thus, the results should be interpreted as illustrating the trade-offs inherent in innovating hardware versus providing software, rather than the formal full-equilibrium evaluation of a counterfactual scenario.

6. Conclusions

We present an econometric framework with which to measure empirically the size of indirect network effects in a competitive market with differentiated technologies. The indirect network effect arises through the inter-dependence between hardware and software demand and supply that we capture in our model. We empirically estimate the model using data on hardware/software in the market for PDA-s in the United States. In estimation, we control for the potential endogeneity of software variety on the hardware demand-side, and the hardware installed base on the software supply-side. Our estimated results provide evidence for significant network effects in this market.

To illustrate the strategic importance of nurturing the network, we use the model structure to analyze the growth of the installed bases of Palm and Microsoft, the two dominant PDA hardware technologies, with and without the availability of compatible third party software. We find that lack of third party software negatively impacts the evolution of the installed bases of both formats. These findings suggest PDA hardware firms would benefit from investing resources in increasing the provision of software for their products. We also use the model results to compute the incremental sales achieved from improving PDA attributes. Further, we decompose the incremental hardware sales into a component reflecting quality improvement via the attributes (the direct effect) and a component reflecting positive feedback due to increased software supply (the indirect effect). Finally, we compare the trade-offs of investments in product attributes versus investments in complementary software by measuring the impact of improving model attributes in terms of the equivalent number of software titles. These form important inputs to PDA hardware managers evaluating future strategies for their products.

A potential extension of the paper would be to incorporate the quality of software, rather than just the availability, into the model framework. Though straightforward, estimating such a model would require considerably more data on the software side. Modeling the supply of hardware to understand how hardware product introduction and pricing is related to software availability would also be a useful extension. We do not pursue this line of research in this paper because, (a) data on PDA model development costs, R&D expenditures and other information on innovation activity within hardware firms are unavailable, and (b) formally modeling the product introduction and pricing decisions of firms require the solution of a dynamic optimization problem which is beyond the scope of this paper. Further, this is outside of our current focus of measuring and understanding the implications of indirect network effects. Nevertheless, we are careful to control for potential price endogeneity associated with strategic hardware pricing within our estimation procedure. Another extension could be to account for the forward-looking behavior of consumers. Forward-looking consumers could potentially take future software availability into account in deciding on current hardware adoption. However, this issue likely to be of second-order importance for PDA-s since based on our reading of the trade-press and other consumer surveys, we do not expect PDA consumers to worry too much about future software-availability when purchasing hardware. However, for other categories like video-games, where the hardware (consoles) has no functional use without software (games), this effect might be important.

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