

Services and the Business Models of Product Firms: An Empirical Analysis of the Software Industry

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ABSTRACT

This article presents one of the first large-sample empirical analyses of the impact of services on the business models (i.e. the financial performance) of product firms. We build upon existing and recent literature in technology management, economics, and service operations in order to propose and test hypotheses regarding the relationship between level of service revenues and operating profitability. We test these hypotheses in a sample of approximately 500 pre-packaged software product firms (a dataset we collected for this purpose) using fixed-effects panel data and dynamic panel data (Arellano-Bond - GMM) econometric models methods. We find a non-linear relationship. Services initially are associated with lower profitability but at some point this relationship reverses. We estimate this inflection point to happen when services reach about half of total revenues, and discuss the theoretical reasons behind these results. We also discuss implications for managers in software and other industries as well as avenues for further research.

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MANAGERIAL RELEVANCE STATEMENT

In recent years, many technology companies that we usually think of as leading-edge product companies or systems providers, ranging from SAP and Oracle to IBM and Hewlett Packard, have seen increasing amounts of their sales coming from services. Is this shift toward services good or bad for product companies? Should product companies invest more in designing and delivering services or work harder to protect their products business? Do service revenues at the expense of product revenues hurt or help profitability? These are some of the questions we attempt to answer in this research, beginning with a careful statistical analysis of data from all software products companies publicly listed on U.S. stock exchanges between 1990 and 2006. We find that there is a more complex relationship between services and firm performance than previous researchers have assumed. Services in software product firms initially are associated with lower profitability, but at some point this relationship reverses and additional services appear to improve firm profitability. We estimate this “inflection point” to happen when services reach about half of a firm’s total revenues, though the point varies somewhat in different segments of the industry. Overall, our findings should inform managers who want a better understanding of how to balance the mix products and services in their offerings to customers.

1. INTRODUCTION

Many authors during the last several decades have noted the rising importance of services in the economy (e.g. Bell, 1973; Stanback, 1979). Indeed, services have become the largest, and often the fastest-growing sector in developed economies (Triplett and Bosworth, 2004), and service firms comprise a significant and growing fraction of the largest firms in the economy (Heskett, 1986). More recently, several authors have stressed the increasing importance of services in the business models of manufacturing firms and product firms in general (Quinn, 1992; Wise & Baumgartner, 1999). As their argument goes, some product firms (we can point to GE and IBM as prominent examples) have increasingly focused on services because services provide them with a more stable source of revenue than products; in addition, service revenues such as maintenance often outlast the life of the products themselves (Potts 1988; Quinn 1992). Some authors even have suggested that, in at least some industries, services can have higher margins than products, particularly during economic downturns (e.g. Anderson et al., 1997).

Much of the services literature also portrays the movement to more services in product industries as an almost inevitable process resulting from the passing of time and changes in the product industry conditions. The well-known examples of firms such as Cisco, Hewlett-Packard, Sun Microsystems, Dell, and EMC that have successfully placed more emphasis on services during the last decade have helped galvanize the idea that product firms are irreversibly moving toward services. IBM, arguably the best-known example, derives today more than half of its total revenues from services.

In this literature stream, the assumption – often a claim – is that services are “good” for product firms and firms should therefore welcome the increasing importance of services. In other words, a product firm’s performance and its level of services should have a positive and monotonic relationship. Some of the most recent research has explored “best practices” in the quest by product firms to integrate service activities into their product-driven routines (Oliva and Kallenberg, 2003; Reinartz and Ulaga, 2008). Wise and Baumgartner summarize the argument: “Downstream [services] markets... tend to have higher margins and to require fewer assets than product manufacturing. And because they tend to provide steady service-related revenue streams, they are often countercyclical. Clearly, in manufacturing today, the real money lies downstream, not in the production function” (1999, p. 134).

In this paper, we provide perhaps the first large-sample study of the impact of services on the profitability of product firms. By developing and testing specific hypotheses regarding the level of service revenues and the relationship to performance, we challenge the notion that additional services are “always good” (or always bad) for the business models of product firms. Our results strongly point to a nonlinear relationship between services and firm performance, after controlling for other predictors of performance. Services in our sample of software product firms initially are associated with lower profitability (in other words, additional services hurt profitability), but at some point this relationship reverses and additional services appear to improve firm profitability. The notion of an “inflection point” at which the impact of services on profitability changes is new to the literature and represents an important consideration that can inform future research. For the entire sample, we estimate this inflection point to

happen when services reach about half of a firm's total revenues. Also, the level at which the inflection point occurs seems to vary within sub-segments of the same industry.

Our study contributes to the literature on innovation and change in business models, particularly the relationship between service and product revenues. A broader concern is what determines firm performance as discussed in literatures ranging from technology management and innovation to strategy. Most of the prior literature we have reviewed either has ignored the impact of services on the business models of product firms or assumed a straightforward relationship with performance. The paucity of empirical studies on the importance of services in product firms, despite the fact that services may be an increasingly important component of the revenue mix of these firms, may be explained by the difficulties in obtaining reliable data. Most product firms do not break down revenues in a way that allows researchers to collect service revenue data. In order to explore these issues, we painstakingly assembled a dataset of close to 500 firms competing in the software products industry from 1990 to 2006, separating products and service revenues and costs. We then tested our hypotheses using GMM dynamic panel data methods (Arellano-Bond). Our results show that the services/performance relationship is important but more complex than what researchers have assumed so far.

The profitability of services seems to be related to economies of scale or scope in service design and production and to conditions and dynamics dictated by the stage of industry life cycle when services are offered. In addition, there may be important industry differences. For instance, several authors have noted that firms developing information-rich products such as software applications or videogames tend to have high product

margins and therefore weak incentives to switch to services (Shapiro & Varian, 1999; Cusumano, 2004)

2. SERVICES AND THE PERFORMANCE OF PRODUCT FIRMS

In the management literature, services generally have been considered as complements to a firm's product offerings -- intangible activities that are offered or sold after the sale of a product, such as product customization, maintenance, or training. In addition, the rise of services for product firms such as in manufacturing have often been thought to occur primarily in mature firms and industries where product prices decline as a result of "commoditization." In his widely cited 1986 paper, David Teece suggests that services "do not loom large" in the early stages of an industry (p. 251). Much of the subsequent literature regarding services in product firms seems to have followed Teece's dictum, assuming that services become important sources of revenue or profits mainly in mature product industries (e.g. Reinartz and Ulaga, 2008). At the same time, however, lifecycle theory -- largely developed based on manufacturing industries -- does not shed any additional light on the role of services for product firms. Indeed, the key papers in this stream of literature (Abernathy & Utterback, 1978; Anderson & Tushman, 1990; Klepper, 1996, 1997) contain almost no mention of services.

Recent research has attempted to fill this gap. Different types of services may in fact be offered at different periods of an industry and firm evolution; they may address different sets of needs; and respond to different firm strategies (Cusumano, Kahl and

Suarez, 2008). Services can indeed occur before (e.g. consulting services), during (e.g. financing) or after (e.g. maintenance) the purchase of the industry's product. Most scholars of industry evolution agree that industries reach a milestone point that changes "the resource conditions associated with competitive advantage" (Agarwal, Sarkar, and Echambadi, 2002, p. 976). This point divides the industry lifecycle into two clearly identifiable stages. Before the onset of maturity, product design changes rapidly, propelled by a growing number of new entrants who take advantage of the rapidly-changing technology to come up with different designs or entirely new technological approaches— the focus at this stage is on product features and performance. Processes tend to be flexible, with high manual content, and rely on general-purpose equipment (Utterback & Abernathy, 1975).

But in an early product industry, services can help firms reduce uncertainty about their technology and about customer needs. Services can act as important knowledge-transfer mechanisms between a firm and its potential customers and thus lower the latter's reluctance to adopt the new products. Technological uncertainty has been shown to reduce buyers' willingness to commit to product specific learning (Carpenter & Nakamoto, 1989). Cusumano, Kahl & Suarez (2008) argue that "Buyers are uncertain as to whether the industry as a whole may endure (that is, if some or all of the new products will indeed solve customer needs), uncertain regarding the performance differences between the competing designs and technologies, uncertain regarding the internal changes required to implement the new technology, and uncertain regarding which competing design will remain in the market. In order to resolve these

uncertainties, significant product-related knowledge needs to flow from the product firms to potential buyers” (p. 9).

In situations of high uncertainty, services can become a key mechanism to transfer product knowledge to new customers. For instance, Attewell (1992) documents the importance of services in the early mainframe computer industry. Specifically, he describes a “two-stage process” (p. 9) by which computer manufacturers first sold services to customers in order to overcome their reluctant attitude towards the new technology and be able to sell them the products in a second stage. In their detailed account of the computer industry, Fisher et. al. (1983) reach the same conclusion: “the provision of such support services by manufacturers greatly facilitated the marketing of their equipment to users by reducing the users’ risks in installing that new, unfamiliar, and expensive object, the computer” (p.172).

The implication is thus that services can help product firms overcome customer resistance during the high-uncertainty, high-risk period that characterizes an industry before the onset of maturity. By offering customized services to their buyers, product firms can gather valuable information about customer needs, educate customers about the benefits of their technology, and reduce customer’s reluctance to adopt. Note, however, that while services can help firms convince customers to try and learn about their products, services at this stage may not have a positive effect on firm profitability. Indeed, in uncertain or highly competitive markets, firms cannot generate much revenue from service activities as they bundle services with their product offerings in order to get new customers to try their products. Services may also not be profitable if the firm is relatively inexperienced and inefficient at providing services. Thus, given

the fast pace of technological change and the evolving needs and requirements of users during the early stage of an industry, the provision of services under these conditions can be strategically important but services can become costly to deliver.

Given unstable customer preferences, rapid technological change, and constant evolution in product design, the provision of services during the early stage often requires a high level of interaction with the customer – what the services literature labels “high-encounter” service situations (Mills, 1986; Skaggs and Huffman, 2003). In such situations, the service provider “will be required to secure and process copious amounts of information in order to address complex issues, and much of this information will be equivocal” (Mills, 1986). The services literature has long noted that the complexity of service operations increases substantially when high customer involvement is required. High-encounter service situations make the production of services complex and labor-intensive (Mills & Moberg, 1982). All of this tends to make the production of services expensive. At low levels of service production, and particularly during the complex and changing technology and demand environment that characterizes the early industry stage,

Hypothesis 1. (a) Services will negatively affect the profitability of product firms at low levels of service revenues; (b) This effect will be stronger during the period of higher technological or market uncertainty that characterizes the early phase of an industry lifecycle.

The negative effect of services on profitability need not persist over time, however. As postulated by lifecycle theory, when product industries evolve and the onset of maturity arrives, some firms will be selected out of the industry and concentration will increase (Utterback & Suarez, 1993). With a growing installed base of products in the market, the remaining firms will focus on improving profitability of products and services. This shift towards processes and increased efficiency fueled by growing economies of scale in products has been documented by many studies (Gort and Klepper, 1982; Anderson & Tushman, 1990).

A similar pattern can be observed for services. Indeed, a stream of studies has documented the existence of economies of scale in the production of services (Katrishen & Scordis, 1998; Murray & White, 1983). For instance, Dunning (1989) suggests that service firms achieve economies of scale through personnel specialization, financial management, and common governance. Changes in the demand side as industry evolves also contribute to increased economies of scale. More stable customer needs allow for the emergence of “blueprints” and “routines” for service production (Nelson & Winter, 1982). These increased efficiencies in turn may make it easier to port service production processes from one firm to another, as in the case of the commonly adopted good practices in software engineering that help software firms offer custom development or systems integration services in a cost-effective way (Humphrey 1989; Cusumano 1991; Upton and Fuller, 2005). Technological variation also tends to decrease as industries evolve, thus lowering the need for the complex and resource-intensive customized services that characterized the early stage. Aided by clearer and more stable customer requirements and technology, companies can write

more complete and specific service contracts, thus favoring arm-length relationships between service provider and customer, and therefore providing an additional boost to the service standardization (Mills, 1986).

Thus, for any given set of industry conditions, there is a point where additional services and appropriate attention to process improvement or automation can improve economies of scale or scope with the corresponding positive effect on firm performance. This is consistent with the traditional view that services become important to the financial performance of a product firm mainly during the mature industry stage. Indeed, some product industries experience extreme degrees of competition or commoditization. The effect of extreme competition or commoditization is particularly acute for firms in mature industries where little differentiation is possible (D'Aveni, 1994). In addition, “information goods,” with high costs for producing the first unit but very low marginal cost for the subsequent units, can also experience this form of severe competition. Prices for software products and other digital goods can and do fall to zero, such as in the case of free and open-source software, where many of the successful business models are based on the provision of services (e.g. RedHat). The result of these competitive dynamics is felt in the form of a sharp reduction in product prices and therefore on product profitability. Razor-thin product margins make it difficult for product firms to stay profitable if they focus solely on products. In situations like these, services can become an important source of revenues and even profits. Hypothesis 2 follows,

Hypothesis 2. (a) As the importance of service revenues grows for a product firm, there is a point when additional services will start to positively affect firm profitability. (b) This effect will be stronger during periods of reduced technological or market complexity and uncertainty that characterizes the mature phase of an industry lifecycle.

3. DATA, VARIABLES AND MODEL

3.1 Research Setting and Data Collection Process

We collected data from a sample of publicly traded firms in the pre-packaged software products industry over the time period of 1990-2006. Pre-packaged software (SIC code 7372, NAICS 51121) includes firms that sell discrete programs consisting of software code that, when executed on a hardware platform, performs a certain task, such as to automate a business process or display streaming video. Despite the fact that software is considered an intangible product, software products share many characteristics of physical products. Not only software does often come in a physical medium (box and CD) but, more importantly, as with tangible goods, software products embody a bundle of standardized features or “service characteristics” (Gallouj & Weinstein, 1997, p.542) that are usually provided to all customers.

Data was collected mainly from the Compustat and Mergent databases. Compustat provides business segment information, but software product firms often do not report product and service revenues as separate business segments. Software firms do, however, typically break out product and service revenues in their 10-K annual reports to

the U.S. Securities and Exchange Commission. We therefore used the Mergent Database to capture revenue and financial information from the 10-K reports.

We identified pre-packaged software firms as those listed in Compustat-Mergent under the pre-packaged software SIC code 7372 in 2002. Our sample includes firms who were acquired and went out of business prior to 2002. In addition, we identified public pre-packaged software firms that were included in the Software 500 list (www.softwaremag.com) during the years 2000-2003 and had not been captured by Compustat-Mergent. This resulted in a total of 464 firms identified. For each firm, we tried to collect data for the 1990-2006 period. Since Mergent goes back only 15 years, we conducted additional 10-K analysis to complete the dataset as much as possible. This additional step was also necessary because of other limitations with Mergent; for instance, this database does not capture firms that existed in 1990 but ceased to be listed before 1997 (such is the case of Lotus, acquired by IBM in 1995). We identified 51 such firms. Since data for these firms are not captured electronically, we collected 10-K information for as many of these firms as possible using microfilm records. This increased the total sample to 485 firms.

Despite our efforts, we found that not all firms break out products and service revenues in their 10-K reports. Some firms may be “pure product” firms, as in the case of most video games producers as well as Microsoft and Adobe for most of their histories. Others firms simply break out their revenue in other ways, without labeling them as products or services. We therefore took one further step. We carefully studied each firm’s business description in the 10-Ks to determine if, from their own description, we could safely assign their revenue categories to products or services. We only proceeded

when the description was obvious or unequivocal. Service revenues are typically associated with maintenance agreements, training, implementation, custom development, and post-implementation technical support.

Figure 1 shows that services have become increasingly important in the business models or revenue mix of software product firms. The importance of services, on average for the whole sample, has steadily increased from around 30% in 1990 to more than 50% in 2006. In other words, the majority of today's revenues in SIC code 7372 "software products," corresponds not to products but to services. (We also estimate that maintenance is approximately 55 to 60 percent of these service revenues for firms breaking out maintenance from other services.)

3.2 Estimation Models and Variables

We use an Arellano-Bower (1995)/Blundell-Bond (1998) dynamic panel estimation (also known as "system GMM," or generalized method of moments) to determine the impact of services on firm profitability. GMM models present important advantages over fixed-effects models, and are particularly well suited for datasets like ours, with a relatively short time-series dimension and a large cross-sectional dimension (small T, large N). For instance, the Arellano-Bower/Blundell-Bond estimation can deal with situations where the dependent variable partly depends on its own past realizations, situations where the predictors are not strictly exogenous (i.e. they could be correlated with past or current realizations of the error), and situations where heteroskedasticity or autocorrelation within individuals (but not across them) is suspected. All of these issues are not unusual in small T, large N datasets and could be present in our sample. We use the routine XTABOND2 in STATA version 10 to obtain the estimations below, and

follow an estimation procedure similar to that described in Roodman (2006). Despite the above, given the widespread use of fixed-effects models the literature, we provide in Appendix 1 a fixed-effects estimation. The fixed-effects results are largely consistent with our dynamic panel estimation results.

A dynamic panel data approach is also better suited to the purpose of this paper than the variance decomposition analysis used by other authors in the determinants of profitability literature. For instance, Schmalensee (1985), Rumelt (1991) and McGahan and Porter (1997) use a variance component model to look at the relative importance of industry, time, corporate, and business-unit effects on the variation of profitability among firms. A dynamic panel estimation like the one we use here examines the residual variation in firm performance that remains unexplained in a variance decomposition analysis, and it can thus be considered complementary to the variance component estimation literature (Goddard et al., 2005).

Our GMM model can be written as follows:

$$\ln\text{profit}_{i,t} = \beta_0 + \beta_1\text{servp}_{i,t} + \beta_2\text{servp}_{i,t}^2 + \beta_4\ln\text{sales}_{i,t} + \beta_5\text{maturityall}_{i,t} + \beta_6\text{servp}_{i,t} \cdot \text{maturityall}_{i,t} + \beta_7\text{mktsharecat}_{i,t} + \sum_{j=\text{year}} \theta_j \text{yeardum}_{j,i,t} + \alpha \ln\text{profit}_{i,t-1} + \eta_i + \nu_{i,t} \quad (1)$$

where,

lnprofit_{i,t} (our dependent variable) is the natural log of firm i's operating margin in year t. Operating margin is calculated as a firm's operating income divided by total sales, and thus cannot take values greater than 1 but can take large negative numbers (for instance, startups may have large negative operative incomes in relation to their small or even nil sales during the first years). This implies a potential non-normality situation with our

dependent variable, as the operating margin measure is capped at 1 on the right. We therefore proceeded to eliminate outliers with operating income of -3 or lower – that is, those with losses greater than 300% of sales. Eliminating outliers is a common procedure in determinants of profitability analysis (see for instance Goddard, Tavakoli and Wilson, 2005). Moreover, the outliers we eliminate represent less than 0.1% of the total data points in our sample, and thus their elimination should be no source of concern. In order to use a log transformation, we follow the standard procedure of adding a constant so that the lower bound in our transformed variable is non-negative, 1 in our case.

lnprofit_{i,t-1} is defined as the natural logarithm of a lagged expression of our dependent variable. It captures the speed at which external forces that cause firms to have above- or below-average profitability dissipate over time. This variable, therefore, captures the concern coming from the “persistence of profits” stream of literature (Bain, 1956; Weiss, 1974).

servp_{i,t} is the percentage of firm *i*'s revenues in year *t* that corresponds to services.

There is important variation in our data when it comes to the percentage of sales that corresponds to services. To explore possible non-linear effects of services on performance derived from our two hypotheses, we considered not only the main effect of services as percentage of revenues, but also a quadratic effect, **servp2**.

maturitycat_{i,t} captures the level maturity along the industry lifecycle, at any given year. To determine the onset of maturity in the software industry we looked at the evolution in the number of firms in the industry and by industry category. An abundant body of literature has shown that the point at which the total number of firms peaks corresponds to the emergence of a major change in industry dynamics that leads to the “shakeout” that

announces the onset of maturity (e.g. Agarwal, Sarkar & Echambadi, 2002; Utterback & Suarez, 1993).

Figure 2 plots the number of active software product firms per year from our dataset. The software industry follows the expected pattern with the number of firms first increasing and then decreasing, and the onset of maturity can be considered starting around 1998. Indeed, when plotted independently (not shown in Figure 2), 5 out of the 7 product categories peak in 1998 before starting to see a decrease in the number of firms in the category -- and the other two peak within a year from 1998. Using the total number of active firms in each category per year (**densitycat_t**), we then calculated our maturity variable as $(1/\text{densitycat}_t) \times 100$ for $t > 1998$, and $(-1) \times (1/\text{densitycat}_t) \times 100$ for $t \leq 1998$. Thus **maturitycat** takes positive and increasing values after 1998, but negative and decreasing values as one move further back in time from 1998.¹ The interaction term **servp x maturitycat** captures differences that may exist in the effect of services on profitability depending on the stage in the industry life cycle.

In addition to the above, the following control variables are used:

mktsharecat_{i,t} is firm *i*'s market share in year *t* in the product category where firm *i* reported the majority of their business. This variable follows from the structure-conduct-performance paradigm (Bain, 1956), which maintains that firm profitability is mainly due to firms' market power and the resulting industry structural conditions. Following industry practices, we divided our sample of software companies into seven product categories: business applications, business intelligence, multimedia, databases, operating systems, networking, and "others." The category "games" was excluded from our

¹ We tried other specifications of maturity such as using a dummy variable = 1 for observations starting in 1998. However, our current specification seems to capture more of the variance. The sign of the maturity coefficient in our estimations remains the same independent of the specification used, which is reassuring.

analysis due to the fact that almost all game-producing companies have no service revenue.

lnsales_{*i,t*} is the natural logarithm of firm *i*'s sales in year *t*, and is included here (as done in many studies) as a proxy for firm size and resources.

yeardum is a set of year dummy variables to capture the effect of time. The inclusion of year dummies is a prudent step in fixed effects (and GMM) models, because the estimates of the coefficients standard errors assume no correlation across firms in the idiosyncratic disturbances. Time dummies make this assumption more likely to hold.

η_{*i*} is a set of individual firm effects (fixed effects) that captures all cross-sectional variation in operating income.

v_{*i,t*} is an error term capturing the idiosyncratic shocks.

Table 1 presents descriptive statistics for all variables and the corresponding correlation matrix. The table suggests no collinearity problems in our data.

4. RESULTS

Table 2 presents the results of the dynamic panel estimations. Model I includes variables capturing the structure-conduct-performance effect (MKTSHARECAT), the effect of firm size and resources (LNSALES), the percentage of total revenues coming from services (SERVP, our proposed predictor), and the lagged dependent variable term (L.LNPROFIT). Firm size has long been associated with the possession of key resources that help firms compete in the market, such as brand recognition, R&D capabilities, and

access to distribution channels (Dierickx & Cool, 1989; Schoenecker and Cooper, 1998). In our sample, firm size shows the expected positive effect on firm performance – i.e. larger firms tend to be associated with higher operating income. The effect is also highly significant. The market share variable, however, shows a negative coefficient that remains unchanged in all models we run. This is not consistent with the conventional structure-conduct-performance paradigm in that, in our sample, greater market power as measured by larger market share is associated with lower firm performance. The negative sign could indicate some peculiarities of the software product industry we study; for instance, software product firms may have to “buy” market share at the expense of profits given the industry’ strong network effects and high fixed-to-marginal cost ratio. It is also worth noting that there has been considerable debate in the firm performance literature as to the extent of the effect – if any --of market share on performance (Schmalensee, 1985; McGahan & Porter, 1997).

The lagged dependent variable (L.LNPROFIT) has an expected positive sign, and is highly significant. A significant and positive coefficient for the lagged dependent variable indicates that past realizations of a firm’s performance can partly explain current realizations, lending support to the “persistence of profits” argument. Our proposed service predictor, SERVP, is not significant, suggesting in principle no relationship between a firms’ percentage of services in total revenue and performance. However, in order to test Hypotheses 1(a) and (2) properly, Model II adds a square service term, SERVP2. The inclusion of a square term boosts both the size and the significance of the SERVP coefficient. Both SERVP and SERVP2 achieve significance in Model II, thus

lending strong support for a non-linear relationship. Moreover, the negative sign for the main effect and positive sign for the square term lend support to Hypotheses 1(a) and 2(a).

In order to test Hypotheses 1(b) and 2(b), Model III in Table 2 adds the industry lifecycle variable (MATURITYCAT), and its interaction with the service main effect variable (I.SERVPMATURITYCAT). Neither the maturity variable nor its interaction term is significant, which leaves Hypotheses 1(b) and 2(b) unsupported in our sample. The coefficients and significance of all other variables remain largely unchanged.

Given that the inclusion of a lagged dependent variable is a key feature of GMM models, we conducted several robustness tests for the inclusion of this variable. For instance, as suggested in Bond (2002) and Roodman (2007), we calculated theoretical upper and lower bounds for the coefficient of the lagged dependent variable. The upper bound is given by running a simple OLS regression, whose results are shown in Model VII in Table 3. With OLS, the lagged dependent variable will be correlated with the error, thus biasing the estimate upward. In our case, this OLS regression provides a coefficient for the lagged dependent variable of 0.426 – higher than the GMM coefficient of 0.314 shown in Model IV. The lower bound is given by the coefficient of the lagged dependent variable in a “within” or fixed effects (FE) regression, as it can be shown that this estimator has a downward bias in situations of dynamic behavior (Roodman, 2006). In our case, the FE regression is shown in Model VI in Table 3. The coefficient for the lagged dependent variable is 0.168 – lower than that resulting from the GMM model. Our GMM coefficient for the lagged dependent variable falls, therefore, within the expected bounds.

GMM models can potentially generate too many instruments, which in turn can overfit endogenous variables and bias coefficient estimates. This potential problem arises by the fact that GMM models generate instrument sets in numbers that grow quadratically in T (time). In order to test that this was not a serious issue in our case, we followed a procedure described in Roodman (2007) that in essence consists of reducing the number of instruments in order to observe possible changes in parameter significance. Models III, IV and V in Table 3 show the results of a same model (Model III, from Table 2) at different levels of instrument count: in Model III, GMM is allowed to create instruments with no restrictions (421 instruments created); Models IV and V impose restrictions on the number of instruments (223 and 187 instruments created, respectively). We restrict the number of instruments by using the “laglimits” sub-command in STATA’s XTABOND2 routine). As it can be seen in the table, the magnitude and significance levels of the coefficients for all variables remain fairly unchanged as the number of instruments decreases – an indication that our GMM model is appropriate (in addition, note that the GMM coefficients’ sign and significance is consistent with those of the fixed-effects estimation shown in Appendix 1).

In short, we find a nonlinear effect of services on firm profitability: more service revenues relative to product revenues tend to hurt profitability up to some point where this relationship changes direction and more services start to be associated with higher profitability. We can calculate that “inflection point,” i.e. the effect of a change in the relative importance of services on firm performance, by calculating the following semi-elasticity:

$$\frac{\partial \ln profit_{i,t}}{\partial servp_{i,t}} = \beta_1 + \beta_2 servp_{i,t}$$

The inflection point in this expression is that point where the slope of a curve depicting the effect of services on performance changes its sign. Using the coefficients for **SERV**P and **SERV**P2 in Model IV we can estimate the inflection point to be at **SERV**P= 48%. That is, for the whole sample and using the GMM estimations, at low levels of services and up to a level where services represent 48% of sales, an increase in services can actually harm firm profitability. When services reach 48% of sales, their effect on profits turns positive – additional services will tend to increase profitability.

We run additional models to test for the effect of additional variables, not reported in the tables here. For instance, we tested for the specific effect of R&D expenditures by creating a “share of industry R&D” variable, which did not turn out significant. We also tried different specifications for the “industry maturity” variable, including an “onset of maturity” dummy variable that took the value of 0 for data points before 1998 and 1 otherwise – these failed to achieve significance, same as with the MATURITYCAT variable used here. We also tried to separate the effect of specific types of services on performance, particularly product maintenance, by creating a variable measuring the percentage of service revenues corresponding to product maintenance. The rationale for doing this was case evidence suggesting that maintenance is often a stable, high-margin service activity. However, this exercise reduced the sample considerably given that relatively few firms break out the service revenue in its different components. As a result, the maintenance variable did not turn out significant.

4. DISCUSSION

Based primarily on anecdotal and case evidence, many authors in the last decade have heralded the rising importance of services and assumed that product firms should or could emphasize services more than in the past as their business models evolve. At least in the software products industry, our data does indicate a rise in the importance of services with regard to total firm sales over time, as shown in Figure 1. However, our study raises a word of caution as to the effect of services on firm performance. The literature on service operations has suggested that services can be a more stable and profitable source of revenue than products (Anderson et al., 1997; Wise & Baumgartner, 1999). Literature specific to software products, however, has suggested that services in most cases generate lower profits than products (because digital products can have up to 99% gross margins) and can therefore hurt the profitability of product firms, unless those firms find their product sales or prices decreasing and have no alternative but to emphasize services (Cusumano, 2004, 2007, 2008).

We also find that the impact of services on profitability is not a simple linear relationship. For software product firms, services first tend to lower profitability, but at higher levels of service revenues this relationship turns positive, with more services increasing firm profits. As noted earlier, we calculate this “inflection point” to be around 48% for our entire sample of publicly listed software products firms using a GMM estimation model.

Our results cannot be fully explained by the existing theoretical treatment of services. Services so far have been considered complements to products that play a role mainly in the mature stage of an industry (Teece, 1986). Our data shows that services

play a role even in the early industry stage. An interesting question then arises: Why would product firms invest in the early development and provision of services when these have a negative effect on profitability? This situation seems to defy traditional economic theory and common business sense, and suggests that we need more theoretical work on why product firms offer services. For instance, product firms may invest in service production early on because services are an important vehicle to learn about the market, transfer product knowledge to customers, and reduce early customer's reluctance to adopt new products or technology (Cusumano, Kahl and Suarez, 2008). In other words, services may play a key role in the diffusion of new products (Attewell, 1992). Therefore, the provision of early services may be positively associated with the survival of product firms (despite the fact that their impact on profitability is negative.) Indeed, this is an intriguing hypothesis that we defer to future research, as our data is not suitable to a survival analysis given that it only relates to public firms.

Our results should also be interpreted with caution due to the nature of the industry we have studied. Software products are information-intensive goods with a peculiar cost structure (Shapiro & Varian, 1999). Replicating an information good is a trivial expense. As noted earlier, gross margins on the products business (that is, sales minus direct expenses for producing and delivering the product – but not including R&D, or sales and marketing and general administrative expenses) can be extremely high. At the same time, we must note that large R&D, sales, and marketing expenses may erode much of these potential profits and, because of the same marginal cost characteristics, price competition can get extremely fierce in bad times. In addition, given the unrelenting pace of change in computers, the software product industry may not lend itself very

neatly to the traditional phases of industry evolution (despite the fact that Figure 2 shows a pattern similar to that seen in other industries).

In spite of these caveats, there may be more similarities than differences between software products and other product industries. For instance, many products industries are governed by high fixed costs that generate competitive dynamics that are not too different from that of software products. Also, many products industries experience “de-maturity” trends or important changes in innovation dynamics even during their mature stage. Thus, although we cannot claim strong external validity from a single-industry study, we believe that our results will probably hold in at least some other industrial contexts. Obviously, further empirical research in other product industries will help sort out these issues.

Further research could also look at the nuances coming from differences in the role of services within an industry. If the type and role of services depends on the level of uncertainty and complexity of the technology, as discussed earlier, we should see differences within industries where distinctive segments can be identified. Appendix 2 presents some basic results by industry segment using our dataset. These results should be considered exploratory since the number of firms in several categories is quite small (this is particularly important for GMM models, and thus Appendix 2 is based on a fixed-effects estimation, where the inflection point for the entire sample is 58% compared to 48% in the GMM model). A quick look at the results for the largest segments (these achieve significant coefficients for SERVP and SERVP2) suggests that there may be interesting differences within an industry. For instance, the largest segment, business applications, shows an inflection point of 64%, larger than the overall sample average

and much larger than that of the second-largest category, networking software products (inflection point of 49%). In another category, operating systems, services start to show a positive impact on profitability when they represent as low as 31 percent of revenues (although this result is significant only at the 10 percent level). A better understanding of these intra-industry differences can be important for firms competing or planning to compete in multiple industry segments.

Overall, we believe our findings have important implications for managers who want a better understanding of the relationship between business models or financial performance and the decisions made in R&D as well as operations that influence the mix and delivery of product and service offerings. Many product firms do not pay enough attention to developing and offering new services and the impact that services can have on their performance and long-term survival. As we described, services can be key to the success of a new product or technology even if they hurt profitability in the short term. Product firms need to weigh the immediate negative effect on profitability from starting a significant service offering versus the higher future probability brought about by the early investment in services.

Anecdotal evidence suggests that most product firms, far from strategically managing their service transitions, simply focus on products and tend to let the importance of services gradually rise as an unintended consequence of their failure to keep product revenues or margins up. Dell Computers' late push towards services in the mid-2000s may be a good example of this. A successful product company for many years, Dell did not pay much attention to services until their product business started to falter. Despite their predominant position in hardware, catching up with companies like

IBM and Hewlett-Packard, which have emphasized services for a number of years, has not been easy for Dell.

Building up service capabilities within a product organization seems to be a slow, difficult and error-prone process. The difficulty arises from the fact that service capabilities can be considered a manifestation of “dynamic capabilities” insofar as they help firms understand and shape the market. Eisenhardt and Martin (2000) define dynamic capabilities as “identifiable and specific routines... that use resources to match and even create market change” and “organizational and strategic routines by which firms achieve new resource configurations as markets emerge, collide, split, evolve and die” (p. 1107), while Teece (2007) defines them as the capabilities for “sensing” and “seizing” opportunities and threats. By their own nature, service capabilities may help firms transfer knowledge back and forth from the market and the organization – a vital capability during periods of uncertainty.

However, building effective service capabilities requires laying down the organizational “microfoundations” (Teece, 2007) that feed and support them. These organizational processes relate to ways in which firms collect and process the information gathered from customers, develop hypotheses about what they find, and synthesize the learning – none of which can be done overnight. A better understanding of the financial and organizational importance of services should help firms design better and timelier service strategies.

It is likely that services will continue to be important for product companies and may also bring them into conflict with services partners as these companies compete for the same services “pie.” This is especially true for the software products industry but

also other technology companies that face increasing global competition and difficult economic conditions. For example, during the last couple of years, a new business model has emerged called “software as a service” (SaaS). In this model, firms such as Salesforce.com do not license pre-packaged software products at high fees and then sell expensive services such as maintenance and basic technical support separately. Instead, they “rent” the software product with these basic services for reduced monthly or periodic or usage-based fees. Professional services, such as to customize the product or provide training to customers, are still usually sold separately or provided by partners but minimized in this new pricing and delivery model. In addition, the software product itself (the lines of code) usually does not reside any longer in the customer premises or computers, but stays with the service provider. Even the most product-oriented software companies, such as Microsoft, have reacted to this new trend and, as of 2008, have started to release SaaS offerings to the market (Dubey and Wagle, 2007; Cusumano, 2007, 2008).

It is too early to determine the effect of this new trend on the financial performance of software product firms or their partners in the IT services business, but SaaS seems to trade off the boom and bust of large, one-time product revenues for the longer-term stability of smoother and recurring (albeit smaller) service revenues. It is an important development for the software business and will make it harder in the future to distinguish product revenues from service revenues such as basic technical support and maintenance. Other product companies such as Apple or Nokia may well find that they also can make more money in the future by selling new types of automated services such as digital content subscriptions rather than traditional hardware products such as music

players or cell phones, although analysis of these broader trends we also leave to future research.

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Figure 1. The Revenue Contribution of Services in the Software Products Industry*

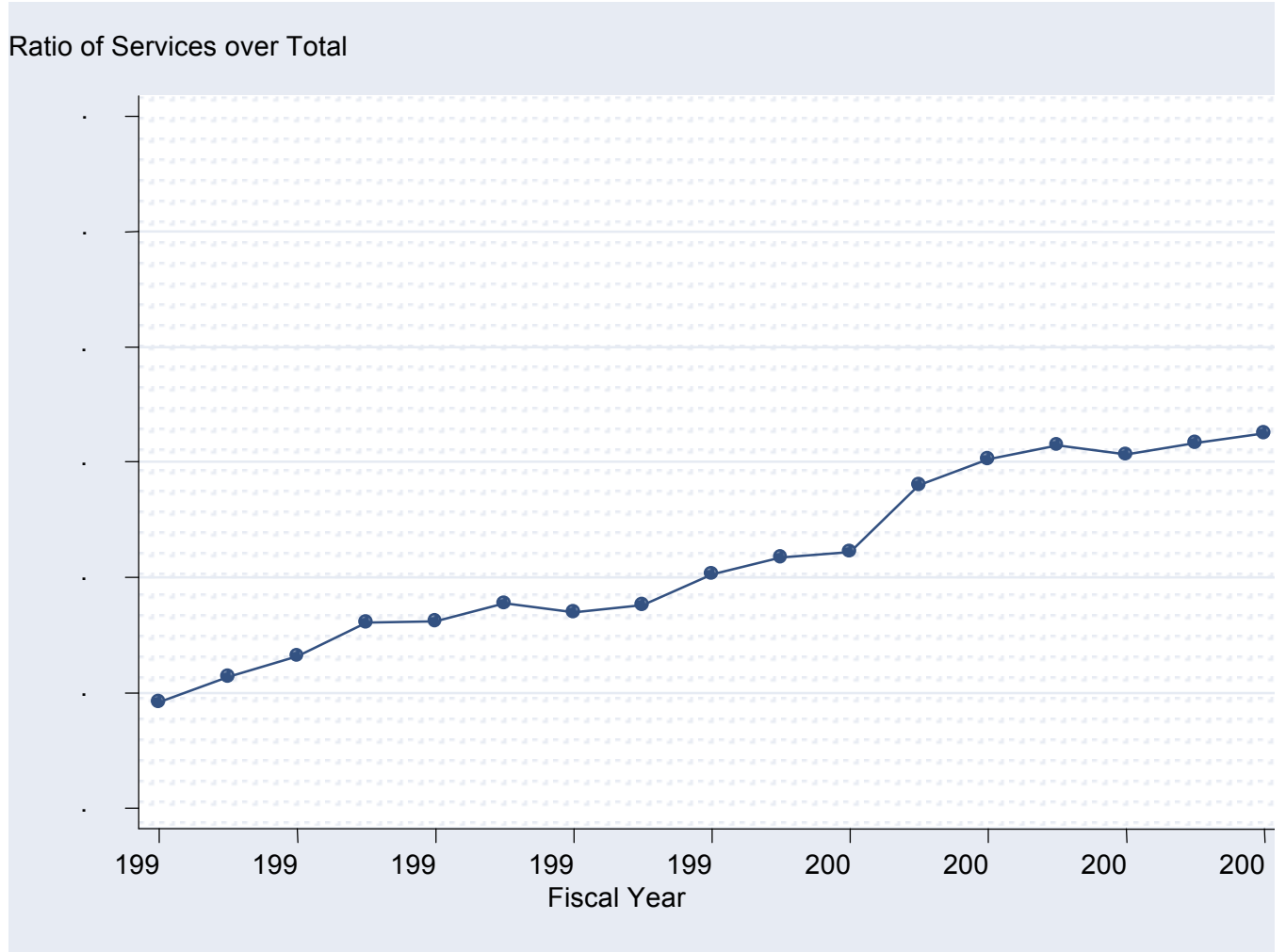


Figure 2. Total Number of Firms in the Software Products Industry*

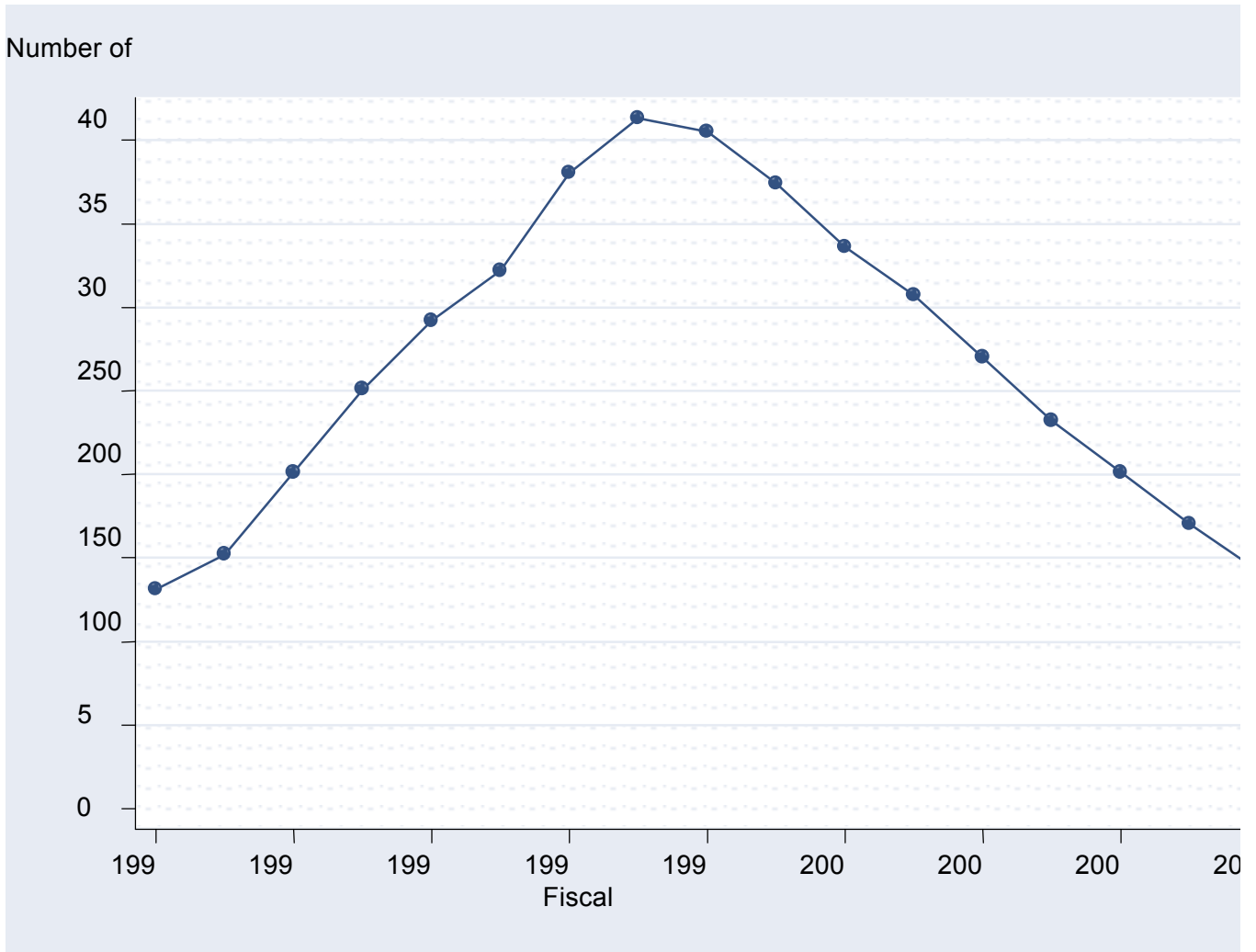


Table 1. Descriptive Statistics and Correlation Matrix

Variable	Mean	Std. Dev.	Min Value	Max Value	1	2	3	4	5	6	7
1. Inprofit	1.73	0.20	0.00	1.94	1						
2. servp	0.42	0.24	0.00	1.00	-0.002	1					
3. servp2	0.23	0.23	0.00	1.00	-0.016	0.950	1				
4. Insales	10.56	1.93	1.16	17.61	0.394	0.079	0.035	1			
5. maturityall	-0.02	0.40	-0.76	0.70	-0.039	0.260	0.233	0.278	1		
6. mktsharecat	0.03	0.08	0.00	0.92	0.139	-0.084	-0.056	0.539	0.020	1	
7. density	59.88	38.76	0	138	-0.095	0.223	0.187	-0.101	-0.057	-0.219	1

Table 2. Results of GMM Dynamic Panel Data Estimations

	GMM Models		
	Model I	Model II	Model III
Lagged lnprofit	0.300*** (0.087)	0.316*** (0.087)	0.314*** (0.080)
Lnsales	0.062*** (0.015)	0.053*** (0.013)	0.055*** (0.012)
Mktsharecat	-1.303* (0.583)	-1.002* (0.426)	-1.049* (0.420)
Servp	-0.047 (0.059)	-0.237 [†] (0.128)	-0.246 [†] (0.130)
Servp2		0.248* (0.118)	0.256* (0.118)
Maturitycat			0.003 (0.006)
Interaction servp –maturitycat			0.002 (0.009)
Year Dummies	YES	YES	YES
Number of Observations	2,890	2,890	2,890
Number of Groups	389	389	389
Number of Instruments	286	421	421
F-Statistic (d. of freedom)	12.81*** (19, 388)	16.02*** (20, 388)	14.74*** (22, 388)
Difference-in-Hansen test (P- Value)	27.63 (p= 0.590)	13.21 (p= 1.000)	11.21 (p= 1.000)

Standard errors are in parentheses, except where indicated.

*** Significant at the 0.1% level, **Significant at the 1% level;

* Significant at the 5% level; [†] Significant at the 10% level.

Table 3. Robustness of GMM Dynamic Panel Data Estimations

	GMM Models			Fixed Effects	OLS
	Model III	Model IV	Model V	Model VI	Model VII
L.Inprofit	0.314*** (0.080)	0.320*** (0.087)	0.318*** (0.089)	0.168*** (0.016)	0.426*** (0.014)
Lnsales	0.055*** (0.012)	0.059*** (0.015)	0.065*** (0.016)	0.032*** (0.004)	0.022*** (0.002)
Mktsharecat	-1.049* (0.420)	-1.293* (0.573)	-1.460* (0.630)	-1.135 (0.092)	-0.148*** (0.035)
Servp	-0.246 [†] (0.130)	-0.304 [†] (0.163)	-0.333* (0.169)	-0.344*** (0.054)	-0.048 (0.033)
servp2	0.256* (0.118)	0.307* (0.150)	0.340* (0.158)	0.243*** (0.055)	0.026 (0.035)
Maturitycat	0.003 (0.006)	0.001 (0.010)	-0.003 (0.011)	0.000 (0.004)	-0.001 (0.002)
Interaction servp – maturitycat	0.002 (0.009)	-0.001 (0.011)	-0.005 (0.013)	-0.001 (0.004)	-0.001 (0.003)
Year Dummies	YES	YES	YES	YES	YES
Number of Observations	2,890	2,890	2,890	2,890	2,890
Number of Groups	389	389	389	389	
Number of Instruments	421	223	187		
F-Statistic (d. of freedom)	14.74*** (22, 388)	15.78*** (22, 388)	14.89*** (22, 388)		
Difference-in- Hansen test (P- Value)	11.21 (p= 1.000)	57.54 (p= 0.099)	66.32 (p= 0.021)		

Standard errors are in parentheses, except where indicated.

*** Significant at the 0.1% level, **Significant at the 1% level;

* Significant at the 5% level; [†] Significant at the 10% level.

Appendix 1. Fixed Effects Panel Data Estimations

The fixed effects transformation removes the firm-specific unobserved factors that may explain performance, by time-demeaning each explanatory variable. This method is widely used in panel data analysis (see, for instance, Wooldridge 2003), and it is often preferred over “random effects” models which assume that the unobserved firm-specific effects are uncorrelated with each explanatory variable in all time periods (hence, random effects models do not remove the unobserved firm-specific factor). We run the Hausman specification test to confirm that fixed effects is the preferred model in our case. The null hypothesis in the Hausman test is that the random effects model will be consistent and efficient. In our case, the Hausman test results in a Chi-square (21) value of 49.45 (p-value of 0.0004), suggesting that we should reject the null hypothesis and therefore that a fixed effects model is preferable. We use the routine XTREG in STATA 10.0, and our fixed effects model can be written as follows:

$$\ln \text{profi}_{i,t} = \beta_1 \text{servp}_{i,t} + \beta_2 \text{servp}_{i,t}^2 + \beta_4 \ln \text{sales}_{i,t} + \beta_5 \text{maturityall}_{i,t} + \beta_6 \text{servp}_{i,t} \cdot \text{maturityall}_{i,t} + \beta_7 \text{mktsharecat}_{i,t} + \sum_{j=\text{year}} \theta_j \text{yeardum}_{j,i,t} + \eta_i + \nu_{i,t}$$

The results of three fixed-models we fitted to our data are shown in the following table.

	Fixed Effect Models		
	Model A	Model B	Model C
lagged lnprofit			
lnsales	0.060*** (0.003)	0.063*** (0.003)	0.063*** (0.004)
mktsharecat	-0.307** (0.27)	-0.307** (0.104)	-0.299** (0.104)
Servp	-0.057** (0.021)	-0.294*** (0.059)	-0.297*** (0.059)
servp2		0.253*** (0.059)	0.257*** (0.060)
maturitycat			-0.001 (0.002)
Interaction servp - maturitycat			-0.002 (0.004)
Year Dummies	YES	YES	YES
Number of Observations	3,276	3,276	3,276
Number of Groups (firms)	394	394	394
R-Squared	0.217 (overall)	0.211 (overall)	0.2107 (overall)
F-Statistic	22.37*** (18, 3619)	22.31*** (20, 2862)	20.32*** (21, 2861)
Difference- in-Hansen test (P- Value)			

Standard errors are in parentheses, except when indicated.
*** Significant at the 0.1% level, **Significant at the 1% level; * Significant at the 5% level; † Significant at the 10% level.

Appendix 2. Coefficients of the Service Variables by Product Category and Estimation of the Respective Inflection Points (Fixed Effects)

	Coefficient	Significance	Inflection Point (%)	# Observations	# of Groups
All Sample (Model C, Appendix 1)					
SERVP	-0.297	***	58%	3,276	394
SERVP2	0.257	***			

Product Categories					
Business Applications					
SERVP	-0.4588	***	64%	1,291	151
SERVP2	0.3601	***			
Business Intelligence					
SERVP	-0.2115		45%	332	40
SERVP2	0.2363				
Multimedia					
SERVP	-0.0852		-50%	257	26
SERVP2	-0.0858				
Database					
SERVP	-0.3409	*	50%	188	19
SERVP2	0.3406				
Operating Systems					
SERVP	0.2004		31%	458	52
SERVP2	-0.3282	†			
Networking					
SERVP	-0.3723	**	49%	560	80
SERVP2	0.3824	**			
Other					
SERVP	-0.7212	**	60%	190	27
SERVP2	0.6005	**			