Analyzing the Economies of Scale of Software as a Service Software Firms: A Stochastic Frontier Approach

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Abstract—**Software as a Service (SaaS) has been one of the fastest-growing delivery models in the software industry. The industry's trade press often considers economies of scale as the main benefit of SaaS firms, because information technology management and the associated resources are centralized at the SaaS vendors. However, centralized information technology management also requires the associated cost of expanding the firm's IT infrastructure to serve more customers. Intuitively, it is not necessary that the former effect must dominate the latter. Using public firm-level data from Compustat, this study attempts to analyze the economies of scale of SaaS firms relative to their traditional counterparts by using the stochastic frontier analysis (SFA) approach. Our empirical findings suggest SaaS firms have smaller economies of scale than traditional software firms. By utilizing the technical efficiency score obtained from SFA, we further examine the effects of R&D expense and advertising expense on technical efficiency. The analysis suggests that R&D expense, not the advertising expense, could be the cause of smaller economies of scale at SaaS firms.**

Index Terms—**Productivity analysis, R&D expense, software as a service (SaaS), software industry, stochastic frontier analysis (SFA).**

I. Introduction

We HAVE witnessed a sea of change in IT innovations for services management in the past decade [1]. One prominent innovation is the new software delivery model: Software as a Service (SaaS). In SaaS, software and the associated data are hosted centrally by the service providers, rather than being hosted in-house by the corporate clients. SaaS has been one of the fastest-growing segments in the industry since its inception, and is rapidly becoming an important consideration for enterprises of all types and sizes [2]. The most successful SaaS vendor, Salesforce.com, grew its revenue from $176.4 million in 2004 to $1.66 billion in 2010. Consistent growth in the revenue of SaaS vendors suggests that this new business model is not just a technology fad but rather an indication of where the software market is heading.

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A well-known property of the traditional software business is *economies of scale* [3]. Economies of scale exist when the average production cost decreases as the number of units produced increases [4]. Therefore, larger firms enjoy cost advantages with the presence of economies of scale. In the traditional software industry, the costs of replication and distribution are typically negligible after the significant cost incurred for the production of the "first copy" [3]. This leads to significant economies of scale[1]. The zero-variable-cost property usually curb competition and yield oligopolies [5], such as Microsoft, Oracle, and SAP.

In the SaaS era, economies of scale are also widely perceived as one of the key contributors to the fast adoption of the SaaS model, although for different reasons. Gartner defines "sharing resources and economies of scale" as one of the four components of SaaS [6], since the IT infrastructure is centralized on the vendor side and shared among all customers, which in turn leads to economies of scale (e.g., [7], [8]).The cost sharing and servers' load balancing are perceived as the main drivers of economies of scale in SaaS. For example, according to Salesforce.com, its multitenant architecture leads to massive economies of scale to optimize computing resources across all customers [9].

However, properties of the SaaS business models are frequently mentioned but rarely analyzed with rigor [10]. Although SaaS is recognized as a huge success of IT innovation, the widely accepted "economies of scale" have not been empirically tested in the literature. In theory, when the IT infrastructure is centralized at the SaaS vendors, the associated costs are shifted from the customers to the vendors. Accordingly, to provide more units of "computing services" and to serve more corporate customers, SaaS vendors may incur a variety of costs related to the units of computing services provided. The most straightforward cost items include electricity bills and the data communication costs of delivering SaaS. SaaS vendors may incur semivariable costs such as expanding their IT infrastructure in terms of installing more servers, procuring more storage devices, renting a larger space, as well as hiring more IT professionals. These IT infrastructure costs radically change the zero-variable-cost property in a unique way because infrastructure costs are neither purely fixed nor completely variable in nature [11][2]. In this way, there

[1]Adding to the supply-side economies of scale, a larger technology firm could outperform smaller competitors due to network effects as well.

[2]This infrastructure cost is not fixed because it depends on the number of buyers in a discontinuous fashion. Given a fixed number of servers, a SaaS firm can only serve a limited number of customers with satisfactory performance. In order to serve more customers, a SaaS firm needs to expand its "IT capacity."

are two countervailing effects regarding the economies of scale of SaaS firms, motivating us to further examine the overall effect by applying advanced productivity analysis to this new and promising software business model.

Therefore, the research objective of this study is to investigate the firm-level economies of scale of SaaS firms. Specifically, we are interested in the following questions.

1) Do SaaS firms exhibit economies of scale?
2) Are the economies of scale of SaaS firms larger or smaller than those of traditional software firms?
3) What are the major sources of (dis)economies of scale of SaaS firms?

We compiled an unbalanced panel dataset of 23 publicly listed SaaS firms and 480 publicly listed traditional software firms between 2002 and 2010. The firm-level measure of economies of scale is calculated by stochastic frontier analysis (SFA), one of the most advanced methods in productivity analysis. One main benefit of SFA over linear regression, which is widely used in the existing literature, is that SFA produces a technical efficiency (TE) score for each firm in each year. Consistent with the productivity literature, we use capital and labor as two input variables of the production function. The output variable is the economic value added [12]. The results show that SaaS firms exhibit diseconomies of scale, and at the same time, smaller economies of scale than traditional software firms. In addition, the analysis shows that R&D contributes more to TE growth than advertising, while more efficient SaaS firms tend to spend less on R&D but not less on advertising expenses. These findings indicate that diseconomies of scale may result from the decreasing return in R&D investment.

II. Theory and Hypotheses

A. *SaaS, Application Service Provider and On-Demand Computing*

SaaS is a relatively new software delivery business model. Compared with the traditional software delivery model, SaaS has three unique features. First, the SaaS model offers web-based access to business software applications, while the traditional model requires the software to be installed on customers' own machines. Second, in the SaaS model, multiple customers access the same application based on the shared IT infrastructure provided, without having to make additional investments for hardware, installation, and maintenance [13]. Third, customers pay a small recurring subscription fee based on usage, rather than a large, one-time software license, as in the traditional model (see Table I).

Two frequently used jargons similar to SaaS are application service provider (ASP) and on-demand computing. Around year 2000, ASP and SaaS were totally equivalent concepts [14], but after 2005, minor differences between them started to emerge. SaaS vendors typically self-develop and deliver a new software application based on a powerful shared computing infrastructure. In contrast, ASP is more like a third-party distributor of existing solutions. ASP vendors obtain authorization from the software developers and release the software to the end users as a service, using subscription-based pricing plans. The underlying IT infrastructure of ASP is often dedicated rather than shared.

IS researchers have examined various issues of the ASP business model. Walsh [15] provided an excellent overview of the technologies, economies, and strategies of ASP. Smith and Kumar [16] developed a theory of ASP adoption from the customer's perspective. Currie and Parikh [17] developed an integrative model to understand value creation in web services from a provider's perspective. Susarla *et al*. [18] empirically showed that expectations about ASP services had a significant impact on their performance evaluation. Cheng and Koehler [19] derived an optimal pricing policy for ASP vendors. Ma and Seidmann [20], [21] studied the profitability of ASP pricing. Susarla and Barua [22] studied the determinants of ASP survival.

Similarly, on-demand computing service (a.k.a. utility computing) is a popular synonym of SaaS. Some SaaS firms, such as Omniture Inc., use an on-demand computing to describe their business model in their official annual reports. A few academic publications deal with on-demand computing or SaaS. Bhargava and Sundaresan [23] studied various pricing mechanisms for on-demand computing with demand uncertainty. Choudhary [13] contrasted SaaS and perpetual licensing. Xin and Levina [24] investigated the client-side determinants of SaaS model adoption. Fan *et al*. [25] examined short- and long-term competition between SaaS and traditional software providers. Recently, Chen and Wu [26] studied the impact of adopting on-demand services on market structure, firm profitability, and consumer welfare.

None of the above studies has examined the productivity of SaaS firms. However, there is a critical need to empirically measure the productivity of firms that adopt service innovations within service-oriented systems [27]. The present study contributes to the literature by bridging this gap and providing more empirical evidence on the economic properties of SaaS firms.

B. *Economies of Scale*

Although economies of scale of software development [28] and maintenance [29] have been investigated at the project level, economies of scale of SaaS firms have yet to be studied.

Trade magazine articles about SaaS generally cite economies of scale as one of the major benefits over the traditional software delivery model [6]–[8]. For example, some of them state that "*the sheer economies of scale achieved by public cloud providers will inevitably mean they dominate in future*" [7]. Economies of scale, if exist, are important to both SaaS vendors and customers for the following reasons. First, strong economies of scale would lead to a winner-takes-all situation. With this in mind, executives of SaaS vendors should adjust their strategies to build a larger customer base as soon as possible, even at the cost of a loss in the early stage. Second, from the perspective of investors or shareholders of SaaS firms, a winner-takes-all situation makes their investments riskier, because the target firm could either turn out to be a winner like Microsoft eventually or file bankruptcy in the long run. Last, clients of SaaS vendors should subscribe services from larger vendors even when the provided service is

The infrastructure cost is also not purely variable like material costs because the marginal cost of providing one more unit of IT service is still close to zero.

TABLE I
DIFFERENCES BETWEEN TWO SOFTWARE DELIVERY MODELS

	SaaS Delivery Model	Traditional Delivery Model
Installation	■ Vendors purchase the hardware. ■ Vendors install the software.	■ Customers purchase the hardware. ■ Customers install the software.
Maintenance	■ Customers do not need to have their own IT maintenance team.	■ Customers need to have their own IT maintenance team.
License/Fee	■ Subscription-based usage. ■ Customers pay small recurring fees.	■ Perpetual license. ■ Customers pay large fees at one time.

not the best fit for their business processes because smaller SaaS vendors will probably be forced out of the market, even if they offer better products.

However, we posit that the wisdom of crowds in the trade press may not be scientifically correct. In fact, as we will discuss in the next two paragraphs, two countervailing effects exist in the SaaS model with regard to economies of scale. One increases economies of scale, while the other decreases it. Therefore, SaaS firms may indeed have diseconomies of scale and smaller economies of scale than traditional software firms.

First, in the SaaS model, vendors provide applications based on a powerful server farm, a large data center, and a professional IT management team at their sites. The large fixed costs of the centralized IT infrastructure are indirectly shared among all customers [30]. This cost-sharing feature is the main source of economies of scale as mentioned in industry media articles. Furthermore, a shared IT infrastructure provides another source of economies of scale due to an increase in the utilization rate of computing resources resulting from load balancing. Studies have shown that the traditional software delivery model leads to overbuilding of IT assets: the utilization rate of the computing power of servers is around 10% to 35%, while that of desktop computers is only 5% [31]. In the SaaS delivery model, because multiple firms operate on the same infrastructure, the underutilization of processing power and storage can be alleviated. In sum, the infrastructure cost sharing and CPU time-sharing features increase the economies of scale of SaaS vendors and buyers as a group.

Second, however, when the IT infrastructure and staff are centralized at SaaS vendors, all costs then shift from the customers to the vendors. After this shift, the cost structure of SaaS vendors may depend on the amount of computing services provided and the number of corporate customers served. If the SaaS vendors outsource hosting to third-party firms, such as Amazon Web Services, all infrastructure costs become "variable" because of the on-demand pricing (per-unit usage pricing) plans of the hosting vendors. If the SaaS vendors host the IT infrastructure, the "direct variable cost" includes electricity bills and the data communication costs of Internet connection. In theory, the infrastructure costs themselves are also "semi-variable" by nature. The centralized infrastructure imposes a capacity constraint on SaaS firms: there is a limit on the CPU processing power, memory, and storage space. Within the capacity constraint, the variable and marginal costs are zero. However, to serve more customers beyond the capacity limit, SaaS vendors have to install more servers, rent a larger space, and hire more IT workers [32]. The marginal cost of IT infrastructure is nonzero at the capacity limit when the vendor acquires additional capacity. Theoretically, this unique cost structure has been shown to be equivalent to a constant variable cost [11]. In accounting, "cost of revenue" is closest to variable cost conceptually. Accounting practice also treats infrastructure costs as one type of variable cost. We observe that almost all of the SaaS firms in our sample mentioned "hosting our application suite" as one major component of the cost of revenue in the annual reports. SaaS vendors also include depreciation, amortization, and maintenance of infrastructure in "cost of revenue." For example, the third-largest SaaS vendor, Constant Contact, explicitly stated in its annual report.

"... *The expenses related to our hosted software applications are affected by the number of customers who subscribe to our products and the complexity and redundancy of our software applications and hosting infrastructure. We expect cost of revenue to increase in absolute dollars as we expect to increase our number of customers ....*"

Therefore, unlike traditional software firms, SaaS firms have significant costs that depend on the amount of computing services provided. Besides, the higher utilization rate achieved by the centralized infrastructure may also be offset by energy inefficiency due to unmanageably huge data centers. A *large* energy-inefficient data center is likely to attract negative attention from environmentalists and the media, damaging the corporate image.

"*A single data center can take more power than a medium-size town... However, on average, these data centers were using only 6% to 12% of the electricity powering their servers to perform computations."—The New York Times [33]*[3].

Considering these two effects together, we hypothesize that the economies of scale for SaaS firms will first increase before decreasing (as illustrated in Fig. 1). The reason is that, the average cost from the first effect will converge to zero as long as the firm size keeps growing. Consequently, the total average cost of SaaS firms will be dominated by the second effect (i.e., the variable-cost effect). Theoretically, all firms should operate at the most cost-efficient level, assuming they have enough resources to operate at any production level [34]. In practice, SaaS firms may operate at a size larger than the most cost-efficient level because of the moral hazard and agency problems of

[3]We do not intend to argue that all large data centers are inefficient but this report provides one piece of evidence that poorly managed large data centers could be inefficient. A large data center owned by famous companies is more likely to catch the attention of the media than small data centers. This is a potential cause of diseconomies of scale as well.

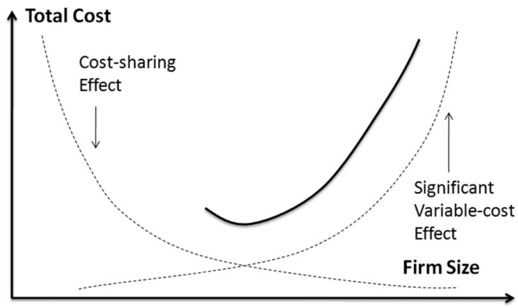

Fig. 1. Economies of scale from two effects.

executives, which usually keep the firm operating at a size larger than the optimal level [34]. For example, the CEO's overconfidence has been documented in the literature to explain why firms overpaid to acquire smaller firms to accelerate company growth [35], [36]. To sum up, we propose that SaaS firms may have the solid cost curve illustrated in Fig. 1. We hypothesize that

H1a: The production function of SaaS firms has diseconomies of scale.

H1b: The production function of SaaS firms has smaller economies of scale than those of traditional software firms.

C. Productivity Analysis

We expect that the productivity contribution (output elasticity) of capital in the SaaS firms' production function is larger than that of the traditional software firms' production function. This is because traditional software firms use capital or fixed assets mainly for R&D or administrative purposes, whereas a large part of the fixed assets (e.g., data centers) of SaaS firms are used to deliver SaaS services to their customers. If there are more customers, SaaS firms need to increase capital proportionally. Therefore, at SaaS firms, a large portion of the fixed assets costs may be directly accrued into the final service pricing formula. As a consequence, percentage increases in capital is highly correlated with the percentage changes in value-added. In contrast, fixed assets in traditional software firms are not that related to the output (value-added). Take computing equipment as an example of fixed assets. Computers at traditional software firms have lower utilization rate than those at SaaS firms as discussed because more computing equipment at SaaS firms are shared among multiple users or clients. Therefore, we hypothesize that

H2: The output elasticity of capital is higher in SaaS firms than in traditional software firms.

Meanwhile, IT service firms need to employ both technical and client-facing personnel [37], [38]. Prior studies have supported the existence of learning curves in software development and have highlighted its importance in the knowledge production processes [39]. SaaS firms will not be able to leverage prior techniques and experience as much as traditional software firms do. In other words, SaaS firms enjoy less learning-by-doing effect. For example, the scaling problem of SaaS services, in terms of data center expansion and operation optimization, is a common challenge to the employees of SaaS firms [40]. Lacking the required techniques and experiences would result in slow responses to service requests and customer dissatisfaction, which eventually leads to lower labor productivity and may require more R&D investment to get it fixed.

At the same time, since SaaS firms are responsible for the IT management of their customers, they will have to recruit more non-R&D IT professionals than their traditional competitors. Further, customer acceptance is relatively low for SaaS firms. Facing competition from non-SaaS incumbent competitors, many new SaaS vendors struggle to understand the key messages to put forth and how to articulate the value of their SaaS offering [41]. For example, Gartner observed that sales representatives from SaaS vendors have more difficulties in convincing customers about the reliability and security of SaaS services [41]. Moreover, many enterprises have substantial sunk cost in legacy software systems. Thereby, the switching costs are high, creating another barrier to migrate to SaaS products [9]. As a result, the sales team at SaaS firms needs to work harder to persuade and lure customers from their traditional counterparts, indicating that the marketing return on investment (ROI) of SaaS firms will be lower relative to traditional software firms. Therefore, we hypothesize that

H3: The output elasticity of labor is lower in SaaS firms than in traditional software firms.

Further, in research-intensive industries such as the SaaS industry, firms are forced by continual investment in R&D to introduce upgraded products for survival. R&D investment is broadly defined as investment in new knowledge that improves the production efficiency or the product quality. Extensive empirical studies have proven the benefits and necessity of R&D investment. For example, Lichtenberg and Siegel [42] found that R&D investments pay off significantly by improving productivity. However, R&D investment is likely to have decreasing marginal return in the absence of real technical innovation [43], meaning that high productivity firms may have less incentive to invest intensively because the return to further investment is low.

Typically, most of the functionality provided by SaaS firms is similar to existineg on-premise enterprise software. SaaS firms typically use R&D investments to migrate from old software architecture to the modern one with incremental changes such as adding new features, enhancing functionalities, and improving user interface [9], but not to conduct disruptive, breakthrough innovation. Therefore, the ROI of R&D may reach plateau earlier than their traditional counterparts. A larger proportion of the R&D expenses of SaaS firms are invested to overcome key technical issues for scaling of the provided service [40]. After building up the required capabilities, efficient SaaS firms may no longer need as many R&D investments as before. Besides, SaaS firms provide all customers with services based on one version because of multitenancy [13], while traditional software firms have to support and maintain dozens of old versions. As a result, leading traditional software firms may be required to undertake more R&D investments than SaaS firms for maintenance of legacy systems. Therefore, we hypothesize that, *H4:* Relative to traditional software companies, SaaS firms with higher productivity tend to spend less in R&D investments.

III. Method and Model

A. Production Function

A production function describes the mathematical relationship between the input factors and the output of a firm, an industry, or an entire economy. Typically, the input factors consist of capital, labor, and other tangible or intangible assets. Due to its mathematical properties, the Cobb–Douglas function is one of the most widely adopted production functions, which satisfies all textbook assumptions. The most frequently used Cobb–Douglas production function with two inputs, capital (*K*) and labor (*L*), and one output (*Y*) is given by

$$Y_{it} = A_t \mathrm{K}_{it}^{\beta_K} L_{it}^{\beta_L}, \tag{1}$$

where Y_{it} denotes the output of the *i*th firm at the *t*th period. Here, *A* is a scale factor defined as the total factor productivity in the literature, K_{it} and L_{it} represent the capital input and labor input of the *i*th firm at the *t*th period. After taking the logarithms, it follows that:

$$\ln(Y_{it}) = \ln(A_t) + \beta_K \ln(K_{it}) + \beta_L \ln(L_{it}). \tag{2}$$

There are three useful properties. First, this functional form fits the linear regression estimation approach. Second, in this expression, β_K and β_L represent the output elasticities of capital and labor, respectively, which measure the percentage change in output after a one-percent increase in the corresponding input. For example, the output elasticity of capital, β_K, represents the percentage increase in output provided by a 1% increase in capital. Third, the sum of β_K and β_L can be defined as the economies of scale. To illustrate this, if sum of β_K and β_L equals *X* and all inputs in (1) are multiplied by *N*, the output will increase by N^X in (1). Consequently, output increases more than *N* times if and only if $X > 1$. In this study, we define economies of scale as follows. *A production function exhibits economies of scale if its output increases more than N times when all inputs increase N times.*

The literature on IT productivity has examined this logarithm expression by various regression methodologies. Since the seminal work of Brynjolfsson and Hitt [12], Information Systems researchers have used similar approaches to study IT productivity [44]–[53].

Our study is unique, in that, we focus on contrasting the productivity of SaaS and non-SaaS software firms, whereas the majority of the literature focuses on the productivity of IT capital and IT labor, relative to non-IT capital and labor.

B. Stochastic Frontier Approach

In practice, given the same inputs, different firms may deliver different amounts of output. This deviation could result from random error (noise) or from the differences in production efficiency of the target firms. In economics, a production frontier is defined as the maximum output that can be achieved given certain inputs by the most efficient production technology at that scale of inputs. In other words, production frontier describes the production function of the most efficient firms of different sizes. Economists also use production functions to describe the mathematical properties of the production frontier.

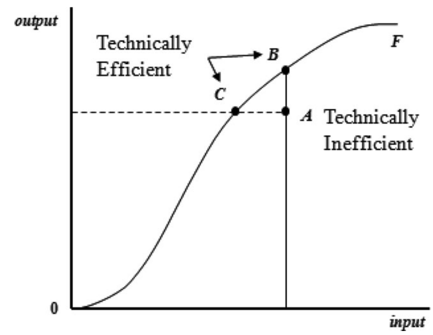

Fig. 2. Production Frontier and TE.

Designed to estimate the production frontier, SFA was developed independently by Aigner *et al*. [54], and Meeusen and Van den Broeck [55]. If we ignore the random error, firms operate either on or beneath the frontier according to SFA (see Fig. 2). They cannot operate above the frontier. Therefore, the shortage of output between the production frontier and a firm's actual output will be attributed to production inefficiency (line AB).

Formally, a Cobb–Douglas production frontier estimated by SFA is given as

$$\ln(Y_{it}) = \beta_0 + \beta_K \ln(K_{it}) + \beta_L \ln(L_{it}) + V_{it} - U_{it} \tag{3}$$

where V_{it} is a random variable that accounts for measurement error and other random factors. It is assumed to be normally distributed with variance σ_v and can be either positive or negative. Here, U_{it} is a *nonnegative* random variable with variance σ_u. It is assumed to be independently distributed and represents production loss due to firm-specific technical inefficiency. Thus, it is not less than zero. More details about the definitions of parameters can be found in the works of Battese and Coelli [56] and Greene [57].

In empirical productivity analysis, there are three major approaches for estimating the production frontier: linear regression, SFA, and data envelopment analysis (DEA). The most common approach used in the IS literature is linear regression. In this case, (3) without U_{it} is estimated by various panel-data econometrics methods and all deviations from the Cobb–Douglas function are considered as "noise." Therefore, one advantage of SFA over the linear regression approach is that it separates the deviations into random errors and the firm-specific inefficiency (U_{it}). With the consideration of U_{it}, SFA can provide more accurate estimation results regarding the production frontier. In contrast, DEA uses the convex hull of all data samples to estimate the production frontier. In other words, DEA assumes that all observed deviations from the production frontier are considered as firm-specific inefficiency. Readers can refer to the work of Banker *et al*. [58] for more details.

Using (3), the TE score for the *i*th firm at time *t* is

$$\mathrm{TE}_{it} = \frac{Y_{it}}{\max[Y_{it}]} = \exp(-U_{it}). \tag{4}$$

The TE score is an important measure of a firm's productivity performance. It gauges the percentage of output for the target firm divided by that of the most efficient firm. Therefore, TE is a percentage and is smaller when the target firm is less efficient.

There are few studies that use SFA in the IS literature, in sharp contrast to SFA's popularity in the economics literature. Lin and Shao [59] use SFA to investigate the business value of IT at the firm level. Shao and Lin [60] found strong statistical evidence to confirm that IT exerts a significant favorable impact on TE and, in turn, gives rise to the productivity growth. Li *et al.* [61] used a stochastic frontier production function to measure the capability for each software firm in each time period by calculating their TE.

C. Stochastic Production Frontier

We follow the standard procedure in the literature to conduct a two-stage SFA. In the first stage, we apply SFA with the Cobb–Douglas production function to estimate the production frontier and the TE of each software firm in each year. In the second stage, we conduct regression analysis using TE as the dependent variable. The independent variables are R&D expenses and advertising expenses (e.g., [61]).

The equation for SFA is specified as follows:

$$\begin{aligned}\ln(\mathrm{Y}_{it}) = {} & \beta_0 + \beta_K \ln(K_{it}) + \beta_L \ln(L_{it}) \\ & + \sum_{t=2002}^{2009} \beta_t \mathrm{Year}_t + V_{it} - U_{it}\end{aligned} \tag{5}$$

where Y_{it} is the economic value added of firm *i* in year *t*; K_{it} and L_{it} are the capital and labor of firm *i* in year *t*; and Year_t is a set of year dummies. Equation (5) is estimated for SaaS and traditional software firms separately. We also estimate (5) by OLS as robustness checks

$$\begin{aligned}\ln(\mathrm{Y}_{it}) = {} & \beta_0 + \beta_K \ln(K_{it}) + \beta_L \ln(L_{it}) \\ & + \sum_{t=2002}^{2009} \beta_t \mathrm{Year}_t + V_{it}.\end{aligned} \tag{6}$$

1) TE Model: In the second stage, potential causes such as R&D investment and advertising expense are included to regress upon the TE scores [61]. Formally, we estimate the following models:

$$\begin{aligned}&\text{Efficiency Model I: } \mathrm{TE}_{it} = \delta_0 + \delta_1(\mathrm{RD}_{it}) \\ &+ \delta_2(\mathrm{AD}_{it}) + \delta_3(\mathrm{FSIZE}_{it}) + \sum_{t=2002}^{2009} \beta_t \mathrm{Year} + \varepsilon_{it}\end{aligned} \tag{7a}$$

$$\begin{aligned}&\text{Efficiency Model II: } \mathrm{TEG}_{it} = \delta_0 + \delta_1(\mathrm{RD}_{i,t-1}) + \delta_2(\mathrm{AD}_{it}) \\ &+ \delta_3(\mathrm{FSIZE}_{it}) + \sum_{t=2002}^{2009} \beta_t \mathrm{Year} + \varepsilon_{it}\end{aligned} \tag{7b}$$

where TE_{it} is the TE score obtained from (5); TEG_{it} is the growth of TE score defined as $(\mathrm{TE}_{i,t+1} - \mathrm{TE}_{it})/\mathrm{TE}_{it}$; $\mathrm{RD}_{i,t}$ is the R&D investment of firm *i* in year *t*; AD_{it} is the advertising expense of firm *i* in year *t*; and FSIZE_{it} is the firm size of firm *i* in year *t*, and ε_{it} is the error term. Firm size and year dummies are used as control variables in the literature and are included in our second-stage analysis [61], [62].

The results of (7a) shed light on the strategies of efficiency leaders in the software industry. Specifically, it shows whether an efficient software firm spends more on R&D and advertising expenses in the same year. In contrast, (7b) examines: when a firm spends more on R&D or advertising, how does efficiency score change in the next year? We use $\mathrm{RD}_{i,t-1}$ because R&D activities typically have impacts in the future years [63].

Sales and marketing expenses are included because they typically account for the single largest expense of software firms. For software firms, these costs are typically as high as 50% of the total revenue. There is ample evidence in the literature that suggests a positive relationship between advertising expense and firm performance [64]. Because the SaaS business model is new and the target market segment is small and medium firms [65], even large SaaS vendors may need to invest a significant amount of capital to educate potential corporate buyers, build brand awareness, and create new sales leads. For example, although Salesforce.com expected its revenue to rise in 2012, its overall profitability remains in the red due to increased sales and marketing costs. In its 2012 annual report, Salesforce.com stated "*we expect marketing and sales costs, which were 52% of our total revenues for fiscal year 2012 and 48% for the same period a year ago, to continue to represent a substantial portion of total revenues in the future as we seek to add and manage more paying subscribers, and build greater brand awareness*" [9].

IV. Data and Variables

The list of sample SaaS firms (full list in the appendix) was obtained from industry reports of the Software Equity Group[4], a consulting company. Traditional software firms are defined as publicly listed firms with NAICS code of 511210 (the software publisher) excluding SaaS firms. By this definition, we are forced to leave out some famous firms, such as IBM and Amazon, part of whose businesses are based on the SaaS model. In other words, our definition of SaaS is relatively strict, those firms are SaaS-only firms. Firms that have some SaaS products are still categorized as traditional software firms.

Financial data was obtained from Compustat database. Observations with missing values were dropped. The final dataset comprises an unbalanced panel of 23 publicly listed SaaS firms and 480 publicly listed traditional software firms from 2002 to 2010 with 135 and 2315 observations, respectively. The beginning year is 2002, because the first two pure-SaaS firms went public in 2002. The ending sample year is 2010, the most recent year with complete Compustat data. We are unable to analyze private SaaS firms due to data unavailability.

[4]http://www.softwareequity.com/research_annual_reports.aspx

A. Dependent Variable: The standard output measure used in the literature is economic value added, defined as the additional value of the final product over the cost of input materials used to produce it from the previous stage of production [12], [47], [66]. We use the same definition from the literature [47]: output, i.e., value added, is operationalized as the total annual sales minus the cost of goods sold (COGS) with total sales deflated by producer price index (PPI) in the software industry and COGS deflated by PPI for intermediate goods.

B. Independent Variables: In the first stage of SFA, "capital" is operationalized as "total fixed assets," while "labor" is operationalized as "the number of employees." Both variables are standard input factors commonly used in the productivity literature.

In the second stage, we define R&D intensity as the R&D expense divided by total revenue. We define the advertising intensity as the advertising expense divided by total revenue. Firm size is operationalized as the natural logarithm of total asset. Following the literature [45], [67], all variables are deflated to measure the real but not nominal values. A summary of the construction process and deflator for key variables is provided in Table II. The deflated descriptive statistics are reported in Table III.

V. Analysis and Discussions

A. SFA for Economies of Scale: The estimation results of SFA in the first stage are summarized in Table IV. The analysis is applied to the SaaS group and the traditional group separately, since they may have different production functions, as well as different frontiers. Main productivity coefficients (β_K and β_L) are significant at the 1% level for both SaaS and traditional software firms.

Based on Table IV, we can calculate the economies of scale of the two groups, defined as *the sum of the beta coefficients of the two input factors*. Consistent with H1, the sum of these two beta coefficients of SaaS firms is smaller than one (0.889 versus 1), and smaller than that of the traditional software firms (0.889 versus 0.964). From the formal tests (Wald tests of joint significance) [68], [69] reported in Table V, we conclude that SaaS firms exhibit diseconomies of scale and smaller economies of scale than traditional software firms. Therefore, *Hypothesis 1a and 1b are both supported*.

As robustness checks, we also estimate the Cobb–Douglas production function by four commonly used linear regressions: (1) fixed-effect (FE) panel regression, (2) random-effect (RE) panel regression (RE), (3) panel linear regression with panel-corrected standard errors (PCSEs), and (4) panel linear regression with AR1 errors (AR1). Results are reported in Table VI. The sum of these two input factors is consistently smaller in SaaS firms than in traditional software firms in all cases except the FE model. However, β_K of SaaS firms in the FE model is not significant and hence is not comparable.[5] Therefore, H1 is also supported in the robustness checks.

Considering that R&D activity is important in the production of software firms, we also included R&D investment (measured as absolute amount, differs from Table II) as an input of production function to check the robustness of our baseline analysis. Results are reported in Table VII. The sum of β_K, β_L, and β_{RD} is smaller for SaaS firms, relative to traditional firms (except the FE model, in which β_K is not significant). In Tables VI and VII, β_K of SaaS firms is consistently larger than that of traditional firms, while β_L of SaaS firms is consistently smaller. Further, the contribution of R&D in SaaS firms is consistently smaller except the FE model.

B. Output Elasticities of Input Factors: This section examines H2 and H3. Recall that β_K and β_L indicate the marginal contribution to productivity of the input factors. Specifically, they measure the percentage change in the output once the input is increased by one percent, i.e., the output elasticity of that input factor. Results of the Wald Test are reported in Table VIII.

1) *Capital Productivity:* SaaS firms have an insignificantly larger coefficient than that of traditional software firms (p value is 0.1934). This test is inconclusive due to the small sample size of SaaS firms. However, this result[6] is consistent with the conjecture that capital of traditional software firms contributes less to its output, because fixed assets in traditional software firms, such as computers or buildings, are mainly used to support R&D and back office operations. In contrast, a significant proportion of the fixed assets of SaaS firms are directly used for delivering SaaS services (e.g., data centers). The productivity difference is also economically significant[7]: the productivity of the capital at SaaS firms is 1.44 times (0.217 divided by 0.151) larger than that of traditional software firms. For every 1% increase in capital, there is a 0.217% and 0.151% increase in economic value added for SaaS firms and traditional software firms, respectively. In dollar amount, every $1 investment in capital contributes to $1.207 and $0.835 (i.e., marginal products) value-added in SaaS firms and traditional software firms, respectively[8]. *Hypothesis 2 is partly supported*.
2) *Labor Productivity:* Our results suggest that the output elasticity for employees in SaaS firms is much lower than that in traditional software firms. Specifically, a 1% increase in employees leads to a 0.672% and 0.813% increase in value added for SaaS firms and traditional software firms, respectively. This difference is both

[5]Indeed, Ackerberg *et al.* [70] pointed out that fixed-effect panel estimations usually resulted in unreasonably low estimate of capital coefficient for firm production function.

[6]Although the result of the coefficient of capital in Table 8 is only significant at a 20% significance level, Tables VI and VII [Models (2)–(4)] do show that the coefficient of capital of SaaS firms is significantly larger than that of traditional software firms. The robustness checks in Tables VI and VII actually support H2. Therefore, we conclude that H2 is partly supported.

[7]A coefficient is economically significant when it has a significant influence on the amount of the dependent variable. A statistically significant but economically insignificant coefficient does not really influence the amount of the dependent variable.

[8]The calculation is derived by the following procedure for an average SaaS firm. In Table III, the average value added is $e^{4.081}$ and the average capital is $e^{2.365}$. So 1% increase in capital is equivalent to 0.01 * $e^{2.365}$ increase in capital, which produces 0.22% * $e^{4.081}$ value added. Dividing 0.22% * $e^{4.081}$ by 0.01 * $e^{2.365}$ leads to 1.207. The number for traditional software firms can be derived by the same procedure.

TABLE II
DATA CONSTRUCTION PROCEDURE AND DEFLATORS[9]

Variable	Notation	Measurement Construction Process	Deflator
Value Added (Output)	Y	Total sales (revt) minus cost of goods Sold (cogs), converted to constant 2002 dollars	PPI for software (NAICS code = 511210) (Bureau of Labor Statistics 2010)
Capital	K	Total assets (at) minus (total current assets (act) and intangible asset (intan)), converted to 2002 dollars	PPI for Intermediate Materials, Supplies and Components (Bureau of Labor Statistics 2010)
Labor	L	Total number of employees (emp)	N/A
R&D investments	RD	R&D expense (xrd) divided by total sales (sale)	PPI for Intermediate Materials, Supplies and Components (Bureau of Labor Statistics 2010)
Advertising	AD	Advertising expense (xad) divided by total sales (sale)	PPI for Intermediate Materials, Supplies and Components (Bureau of Labor Statistics 2010)
Firm size	FSIZE	Natural logarithm of total assets (at)	PPI for Intermediate Materials, Supplies and Components (Bureau of Labor Statistics 2010)

TABLE III
DESCRIPTIVE STATISTICS

	SaaS firms					Traditional software firms				
Variable	N	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max
Value-Added (ln)	135	4.185	0.960	1.845	7.345	2315	3.683	2.131	−5.298	10.968
Capital (ln)	135	2.448	1.253	−0.372	6.921	2315	1.973	2.435	−7.269	9.764
Labor (ln)	135	−0.662	0.816	−2.847	1.669	2315	−1.102	1.812	−6.908	4.682
R&D	130	0.160	0.085	0.033	0.488	2190	0.302	1.372	0	39.102
Advertising	115	0.036	0.059	0.000	0.368	1401	0.033	0.177	−0.036	6.091
Firm Size	135	4.782	1.134	1.988	8.134	2315	4.3943	2.281	−4.304	11.472
TE*	135	0.715	0.164	0.323	0.959	2315	0.509	0.216	0.002	0.969

,*TE is generated from SFA in Table IV.

TABLE IV
ESTIMATION RESULTS OF SFA[10]

	SaaS firms			Traditional software firms		
Independent Variable	Coefficient	Std. Err.	*P*-value	Coefficient	Std. Err.	*P*-value
β_K	0.217***	0.051	0.000	0.151***	0.014	0.000
β_L	0.672***	0.073	0.000	0.813***	0.019	0.000

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ All intercept estimates are omitted for brevity.

statistically and economically significant. Labor productivity at SaaS firms is only 82.66% of that of traditional software firms (0.672% versus 0.813%). In dollar amount, one additional employee leads to \$77 131 and \$97 317 in value added of SaaS firms and traditional software firms, respectively. In that case, the labor productivity of SaaS firms is 79.26% of that of traditional software firms. *Hypothesis 3 is supported*.

C. Do Efficient Firms Invest More in R&D or Advertising?: Fig. 3 depicts the scatter plots of TE scores over years for SaaS and traditional software firms. The differences in performance among SaaS firms have been shrinking, while the average TE scores of traditional software firms have been decreasing recently. One possibility is that the surge of interests in SaaS and cloud computing has shifted market share from traditional software firms to SaaS firms. In Sections V-C and V-D, we will examine the correlation among TE score, R&D expenses, and advertising expenses.

We estimate (7a) by five models. The results are reported in Table IX. Model 1 is estimated using FE panel regression; Model 2 is estimated by FE-R standard errors; and Model 3 is estimated by the RE model. Based on Model 3, Model 4 is estimated without advertising expense and Model 5 is estimated without R&D investment.

1) SaaS Firms: The results in Table IX suggest that R&D intensity is negatively correlated with TE, whereas advertising expense is uncorrelated with TE in the same year. In other words,

[9]Names after variables in the parentheses are the variable names in Compustat.

[10]Year dummies are included in the estimation but not reported in the Table for brevity. All the following estimations in this study include year dummies. The year dummies of both groups in Table IV have been increasing in recent years, indicating that the total factor productivity has been growing in the software industry.

TABLE V
WALD TEST FOR ECONOMIES OF SCALE IN SAAS FIRMS

Null hypothesis (H_0)	χ^2	P-value	Conclusion
(SaaS) $\beta_K + \beta_L >= 1$	7.01	0.0081	H_0 is rejected at 1% confidence level.
(SaaS) $\beta_K + \beta_L >= 0.964$	3.20	0.0734	H_0 is rejected at 10% confidence level.

TABLE VI
ESTIMATION RESULTS OF FE LINEAR REGRESSIONS

	SaaS Firms				Traditional Software Firms			
	(1) FE	(2) RE	(3) PCSE	(4) AR1	(1) FE	(2) RE	(3) PCSE	(4) AR1
β_K	0.061	0.252***	0.399***	0.289***	0.083***	0.139***	0.217***	0.205***
	(0.058)	(0.051)	(0.047)	(0.053)	(0.016)	(0.015)	(0.022)	(0.028)
β_L	0.750***	0.611***	0.452***	0.566***	0.611***	0.809***	0.830***	0.821***
	(0.114)	(0.083)	(0.078)	(0.102)	(0.027)	(0.022)	(0.031)	(0.041)
$\beta_K + \beta_L$	0.811	0.863	0.851	0.855	0.694	0.948	1.047	1.027
Overall R^2	0.822	0.879	0.890	0.799	0.877	0.883	0.885	0.803

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ All intercept estimates are omitted for brevity.

TABLE VII
ROBUSTNESS CHECK WITH R&D INCLUDED AS AN INPUT

	SaaS Firms				Traditional Software Firms			
	(1) FE	(2) RE	(3) PCSE	(4) AR1	(1) FE	(2) RE	(3) PCSE	(4) AR1
β_K	0.079	0.184***	0.329***	0.214***	0.059***	0.093***	0.124***	0.130***
	(0.054)	(0.048)	(0.045)	(0.043)	(0.016)	(0.015)	(0.019)	(0.024)
β_L	0.375**	0.453***	0.418***	0.450***	0.440***	0.599***	0.605***	0.633***
	(0.147)	(0.085)	(0.071)	(0.085)	(0.031)	(0.025)	(0.032)	(0.044)
$\beta_{R\&D}$	0.398***	0.311***	0.157***	0.279***	0.247***	0.319***	0.349***	0.310***
	(0.095)	(0.065)	(0.050)	(0.056)	(0.025)	(0.021)	(0.020)	(0.027)
$\beta_K + \beta_L + \beta_{R\&D}$	0.852	0.948	0.904	0.943	0.746	1.011	1.078	1.073
Overall R^2	0.844	0.889	0.902	0.869	0.909	0.912	0.913	0.912

Standard errors in parentheses*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ All intercept estimates are omitted for brevity.

TABLE VIII
WALD TEST FOR COMPARING ELASTICITIES

Null hypothesis (H_0)	χ^2	***P*-value**	**Conclusion**
(SaaS) $\beta_K <= 0.151$	1.69	0.1934	H2 is partly supported
(SaaS) $\beta_L >= 0.813$	3.72	0.0537	H3 is supported

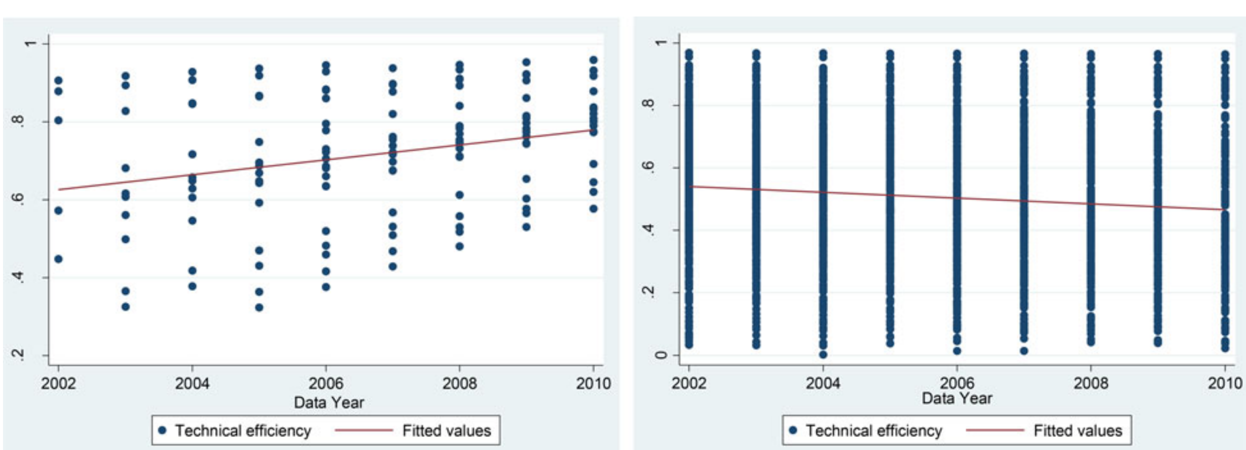

Fig. 3. TE over years of SaaS firms (left) and Traditional Software firms (right).

TABLE IX
ESTIMATION RESULTS OF EFFICIENCY MODEL I

	SaaS Firms					Traditional Software Firms				
	(1) FE	(2) FE-R	(3) RE	(4) RE	(5) RE	(1) FE	(2) FE-R	(3) RE	(4) RE	(5) RE
δ_1	-0.430^{***}	-0.430^{**}	-0.417^{***}	-0.475^{***}		0.006^{***}	0.006^{***}	0.006^{***}	0.003^{***}	
(R&D)	(0.085)	(0.187)	(0.089)	(0.076)		(0.001)	(0.002)	(0.002)	(0.001)	
δ_2	-0.115	-0.115	-0.008		-0.412^{**}	0.021^{***}	0.021	0.021^{***}		0.018^{***}
(Advertising)	(0.215)	(0.266)	(0.211)		(0.208)	(0.007)	(0.014)	(0.007)		(0.007)
δ_3	-0.004	-0.004	0.004	-0.003	0.005	0.001^{***}	0.001^{**}	0.001^{***}	0.001^{***}	0.001^{***}
(Firm Size)	(0.007)	(0.010)	(0.008)	(0.006)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	110	110	110	130	115	1349	1349	1349	2190	1401
Within R^2[11]	0.881	0.881	0.880	0.889	0.844	0.909	0.909	0.909	0.926	0.910
Overall R^2	0.065	0.065	0.097	0.093	0.058	0.039	0.039	0.041	0.036	0.039

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ All intercept estimates are omitted for brevity.

more efficient SaaS firms spend less on R&D investment, while keeping the advertising investment at a consistent level. Even with a small sample of SaaS firms, we can show that this result is significant at the 1% level. The absolute value is also quite large: a 4.17% increase in TE score is correlated with a 10% decrease in R&D intensity.

At the same time, it is also possible that the negative correlation is caused by laggard firms spending more on R&D. To rule out this possibility, we run the same regressions on two subsamples of SaaS firms: 1) laggard firm in around bottom 30% TE; and 2) leading firm in around top 30% TE. The results are shown in Table X. The negative correlation of R&D is not caused by laggard firms but leading firms. Therefore, *Hypothesis 4 is supported*.

Meanwhile, changes in R&D expense typically result from changes in R&D headcounts, stock-based compensation to R&D staffs, or third-party consulting fees. It is intuitive that a firm with high TE may have better performance and bestows larger stock-based compensation to its R&D staffs, which contradicts our finding. With this in mind, the observed negative correlation between TE and R&D suggests that leading SaaS firms either recruit fewer R&D employees or spend less on third-party consulting fees.

Interestingly, advertising expense does not exhibit a similar pattern (Table IX), which provides one falsification test. In other words, results from the advertising expense suggest that the negative correlation between R&D and TE does not appear in all types of expenses.[11]

2) Traditional Software Firms: Results in Table IX show that efficient traditional software firms spend more on both R&D and advertising. This finding is statistically significant but with very small absolute values. It provides a good robustness check that our finding of SaaS firms is not a property of all software firms.

Overall, the results support our previous findings about the diseconomies of scale of SaaS firms. Leading traditional firms spend more on both R&D and advertising, whereas leading SaaS firms spend significantly less on R&D. Since R&D and advertising are the two most important expenses, reducing investment in R&D implies that SaaS firms expect a lower return for developing new products relative to their traditional counterparts. This is consistent with the decreasing return in R&D. Our results seem to suggest that one potential cause of the diseconomies of scale of SaaS firms could be the decreasing return in R&D.

D. How do R&D or Advertising Expenses Affect TE?

Equation (7b) is estimated by the same five models in Section V-C. There are two differences: the dependent variable is the growth of TE score and the R&D expense is from the previous year. We investigate how R&D and advertising contribute to the productivity growth. The results are summarized in Table XI.

1) SaaS Firms: Table XI shows that R&D investment is positively correlated with TE growth, whereas advertising expense does not have significant impacts. Interestingly, these two coefficients have similar absolute values. In other words, our results imply that the absolute values of "*productivity* ROI" for R&D and adverting are similar, while the ROI for R&D is less volatile than for advertising. This finding is also economically significant: a 1% increase in R&D intensity is associated with a 0.123% increase in TE for the following year. This shows that R&D investment does pay off in terms of improving TE and confirms that R&D indeed exhibited decreasing return. The reason is that efficient SaaS firms should spend more on R&D accordingly. And, if they do not spend more on R&D, it is very likely that R&D exhibited decreasing return.

2) Traditional Software Firms: The coefficients in our results are statistically significant yet economically insignificant. It again provides a falsification check that our findings are applicable on SaaS firms, but not all software firms.

E. Robustness Check on Two Industries That Produce Noninformation Goods: Considering that software firms produce information goods, it is critical to know whether decreasing return of R&D also influence scale economies of the industries that produce noninformation goods. We tested two industries: "electronic computers industry (ECI)" (NAICS 334111) and "computer storage devices (CSDs)" (NAICS 334112) between 2002 and 2010. The sample includes 296 observations for 57 firms. We applied the same method by first running SFA and next regressing R&D intensity on the generated TE scores. The results of SFA are reported in Table XII. The economies of

[11]Within R^2 is the proportion of variability that is explained by the model within the group of each firm.

TABLE X
LAGGARD AND LEADING SAAS FIRMS

	(1) Laggard SaaS Firms	(2) Leading SaaS Firms
δ_1	−0.024	−0.152**
(R&D)	(0.041)	(0.061)
N	37	37

Standard errors in parentheses $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ All intercept estimates are omitted for brevity.

TABLE XI
ESTIMATION RESULTS OF EFFICIENCY MODEL II

	SaaS Firms					Traditional Software Firms				
	(1) FE	(2) FE-R	(3) RE	(4) RE	(5) RE	(1) FE	(2) FE-R	(3) RE	(4) RE	(5) RE
δ_1	0.125***	0.125**	0.123***	0.140***		0.0005***	0.0005	0.0005***	0.0001	
(R&D 1-yr lag)	(0.028)	(0.046)	(0.028)	(0.025)		(0.0001)	(0.0003)	(0.0001)	(0.0001)	
δ_2	0.143*	0.143	0.0812		0.203***	0.0003	0.0003	0.0003		0.0008
(Advertising)	(0.081)	(0.084)	(0.072)		(0.005)	(0.0006)	(0.0012)	(0.0006)		(0.0007)
δ_3	0.0024	0.0024	−0.0002	0.0006	−0.0013	0.0001***	0.0001	0.0001***	0.0001***	0.0000
(Firm Size)	(0.0028)	(0.0031)	(0.0028)	(0.0025)	(0.0028)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
N	92	92	92	108	96	1079	1079	1079	1706	1118
Within R^2	0.783	0.783	0.778	0.792	0.721	0.695	0.695	0.694	0.706	0.661
Overall R^2	0.034	0.034	0.073	0.101	0.026	0.056	0.056	0.064	0.054	0.028

Standard errors in parentheses $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ All intercept estimates are omitted for brevity.

TABLE XII
SFA RESULTS FOR ECI AND CSD

Independent Variable	Coefficient	Std. Err.	*P*-value
β_K	0.141***	0.033	0.000
β_L	0.840***	0.057	0.000

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ All intercept estimates are omitted for brevity.

TABLE XIII
SECOND STAGE ESTIMATION RESULTS OF ECI AND CSD

	(1) RE	(2) FE
δ_1	0.004	0.005
(R&D)	(0.007)	(0.007)

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All intercept estimates are omitted for brevity.

scale of ECI and CSD are significantly larger than that of SaaS firms by Wald Test. The results for (7a) are given in Table XIII. R&D is not significantly related to TE, indicating that our finding on SaaS firms, does not apply to these two industries that produce non-information goods. This, again as a falsification check, supports our findings.

VI. Conclusion

This study is the first attempt to use SFA to examine the economies of scale of SaaS firms as well as to contrast the productivity differences between SaaS firms and traditional software firms. Because SFA takes both inefficiency and random noise into account, it is generally considered as a better approach for productivity analysis. We first investigate the economies of scale of SaaS firms and then examine the potential sources of diseconomies of scale.

Our results demonstrate diseconomies of scale in SaaS firms. This finding results from the fact that SaaS firms simultaneously sell a software application and offer the associated IT infrastructure management service for corporate clients. Software application is well accepted as atypical example enjoying both supply- and demand-side economies of scale. However, the IT infrastructure management service does not have zero variable costs, which reduces the supply-side economies of scale. As a result, the production function of SaaS firms has smaller economies of scale than that of traditional software firms. Our productivity analysis suggests that the input factor of capital contributes more to the output of SaaS firm than to that of traditional software firms. At the same time, labor contributes significantly less to the output of SaaS firms, which may be due to the difficulty in scaling the centralized IT infrastructure. Our results also indicate that the diseconomies of scale may result from the decreasing return in R&D investment of SaaS firms.

There are several limitations to this study. First, similar to most firm-level studies in the literature, our analysis can be conducted only by using the historical financial data of publicly listed firms. Since private SaaS firms are usually smaller and have fewer resources than publicly listed SaaS firms, they may exhibit different properties from publicly listed SaaS firms. Second, we do not have detailed product-level data. Particularly, some firms provide both SaaS and traditional software products. These firms are categorized as traditional software firms in this study. With product-level data, we may be able to examine the productivity of SaaS versus traditional software production at a granular level. Third, our sample size of SaaS firms is

A1. List of SaaS Firms

Athenahealth Inc	Kenexa Corp	Rightnow Technologies Inc	Taleo Corp
Concur Technologies Inc	Kintera Inc	Salary.Com Inc	Ultimate Software Group Inc
Constant Contact Inc	Liveperson Inc	Salesforce.Com Inc	Visual Sciences Inc
Convio Inc	Medidata Solutions Inc	Soundbite Communications Inc	Vocus Inc
Dealertrack Holdings Inc	Netsuite Inc	SPS Commerce Inc	Webex Communications Inc
Demandtec Inc	Omniture Inc	Successfactors Inc	

relatively small because the SaaS market is still in a nascent and morphing phase. Researchers may observe more interesting results by conducting similar analysis with larger sample in the future. Finally, since we only have firm-level financial data, we focus on production from the viewpoint of SaaS firms. We cannot analyze IT service productivity by considering the corporate buyers of SaaS vendors along with the vendors themselves. In other words, we underestimate the benefits of productivity improvement by the SaaS delivery model. Some benefits of the SaaS model may be realized only on the buyers due to competition, as it was in the traditional software industry documented in the literature [71]. Therefore, our analysis does not suggest that SaaS is not a beneficial technology and service innovation. Our findings only suggest that SaaS firms do not exhibit economies of scale in their operational performance.

There exist several directions for future research. First, our study has identified significantly lower labor contribution at SaaS firms. It would be interesting to further study the productivity contribution of different types of employees (marketing versus R&D, IT versus non-IT). Second, many other features of the SaaS model are also worth studying, such as customization. On the client side, corporate buyers may require more customization as the SaaS market matures. However, the customization of service provided by SaaS firms may call for individualized design, whereas efficient production may call for more process standardization. This tradeoff remains unexplored in the productivity literature. Third, the impact of the centralized risks on the valuation of SaaS firms is another important issue. Since SaaS firms centralize the IT infrastructure, risks such as disruption or security problems also become centralized. For example, Salesforce.com had several outage events in the past, leaving thousands of businesses without access to their applications. These risks are not captured in the productivity analysis framework. Finally, SFA itself is a growing area in economics. Applying more advanced SFA tools to this dataset is another research direction.

Appendix

See Table A1.

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