PRODUCTIVITY DIFFERENCES AND CATCH-UP EFFECTS AMONG SOFTWARE AS A SERVICE FIRMS: A STOCHASTIC FRONTIER APPROACH

Research-in-Progress

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Abstract

Since its inception, SaaS market has been one of the fastest growing segments in the software industry. It is fast becoming a serious consideration for enterprises of all types and sizes. This paper attempts to measure the productivity of SaaS firms by adopting a stochastic frontier approach. We define a two-stage empirical model to examine the catch-up effects among SaaS firms, as well as the performance differences between SaaS firms and traditional software firms. In the first stage, a stochastic frontier model is specified to derive technical efficiency scores and measure SaaS firms’ productivity. In the second stage, the efficiency scores and their growth rate are treated as dependent variables and regressed on firm-level explanatory variables to identify the source of the catch-up effects. In these two stages, traditional software firms serve as a benchmark. The findings of our study may shed light on the SaaS business model.

Keywords: Software-as-a-service, on-demand computing, stochastic frontier analysis, technical efficiency, R&D, catch-up effects
Introduction

“SaaS has proved it is not a ‘fad.’ Thus, CIOs and IT managers must urgently involve themselves in SaaS acquisition and management”

——Gartner (2009)

Software as a Service (SaaS) is a relatively new business model of software delivery. It is fast becoming a serious consideration for enterprises of all types and sizes (Gartner 2009). In recent years, SaaS has been proven to be a booming industry. Recently, International Data Corporation (IDC) states that in 2009, worldwide SaaS software generated $13.1 billion in revenue. Moreover, they forecast that revenue will be $40.5 billion in total by 2014, representing a 25.3% compound annual growth rate. By 2014, about 34% of all new business software purchases will be consumed via SaaS, and SaaS delivery will constitute about 14.5% of worldwide software spending across all primary markets. In that case, understanding the drivers of the sales productivity growth of SaaS firms can shed light on how to make the SaaS business more efficient and help make the SaaS “cake” bigger.

The growth prospect between SaaS and non-SaaS software business differs significantly. Consider an example, Salesforce.com, which delivers customer relationship management (CRM) solutions to business over the Internet, is enjoying dramatic growth. From 2004 to 2009, its revenue grew from $176.4 million to $1.3 billion, at an annual growth rate of 49.2%. SaaS is and will continue to be a big portion of the business software industry. This motivates our research questions: first, behind skyrocketed sales of SaaS, are there any differences in productivity growth between SaaS firms and traditional software firms? Second, if yes, what are the causes of these differences? Answers to these questions could shed more light on the business model and help practitioners to improve the performance of SaaS firms.

The econometric model used in this paper is Stochastic Frontier Analysis (SFA) for productivity analysis in economics. SFA has been widely adopted in several disciplines. One main benefit of this approach is that it produces an estimated efficiency score of each firm in each year. Given these estimated efficiency scores, we can further investigate the drivers of the sales productivity differences among SaaS firms, as well as the differences between SaaS firms and traditional software firms. To the best of our knowledge, no other study has used SFA to examine the productivity of SaaS firms. This paper is the first attempt to provide additional insights into the dynamics of performance differences of SaaS firms through a panel regression model.

The standard output variable of SFA is economic value-added (defined as “sales” minus “cost of goods sold” in our analysis). Consistent with the SFA literature, we use capital (total fixed assets) and labor (total number of employees) as the input variables of the production function. This study is implemented in two stages. In the first stage, we use a stochastic frontier model to construct a production frontier of all SaaS firms (and later for traditional software firms) and estimate each firm’s technical efficiency score. In the second stage, those estimated technical efficiency scores and the growth of efficiency scores are treated as dependent variables and are regressed upon the firm-level explanatory variables to examine the source of technical efficiency by fixed-effect panel regression models.

Understanding the dynamics and the drivers of the sales productivity growth of SaaS firms will not only contribute to the productivity studies of SaaS, but also help SaaS practitioners identify the sources of efficiency, and eventually find out a way to improve their firms’ technical efficiency. For example, if research and development (R&D) investments could be proved to be a main source of technical efficiency for SaaS firms, then implication for placing more investments in R&D could be made. These mentioned contributions will also be helpful to the policy decision makers.

The current paper is organized as follows: Section 2 discusses the related literature, and Section 3 presents the hypotheses while Section 4 specifies the empirical model. Section 5 reports the data source and the relevant variables, with Section 6 concluding the paper.

1 http://www.idc.com/research/viewdocsynopsis.jsp?containerId=223628
Theoretical Background

Production Function

A production function is a function that specifies the output of a firm, an industry, or an entire economy for all combination of inputs. The inputs used in production process are called factors of production. Typically the inputs consist of capital, labor and others. The economic theory of production places certain technical constraints on the choice of functional form, such as quasi-concavity and monotonicity (Varian 1992). Perhaps the simplest functional form that relates inputs to outputs and is consistent with these constrains is the Cobb-Douglas specification, variants of which have been used since 1896 (Berndt 1991). While this approach is not the only method used for conducting productivity analysis, it is by far the most common functional form used for estimating production functions, calculating the elasticities and marginal products of inputs (Hitt and Brynjolfsson 1996), and remains the standard for studies (Brynjolfsson and Hitt 1996).

The Cobb-Douglas production function with two inputs, capital (K) and labor (L), and one output (Y) can be specified as:

\[ Y_i = A_i K_i^{\beta_K} L_i^{\beta_L} \]  

Where \( Y_i \) denotes the output of the \( i-th \) firm at the \( t-th \) period. \( A \) is a scale factor defined as total factor productivity in the literature. \( K_i \) and \( L_i \) represent the capital input and labor input of the \( i-th \) firm at the \( t-th \) period. After taking the logarithms and adding an error term, we had the following estimating equation:

\[ \ln(Y_i) = \ln(A_i) + \beta_K \ln(K_i) + \beta_L \ln(L_i) + V_i \]  

In this specification, \( \beta_K \) and \( \beta_L \) represent the output elasticities of capital and labor, which measure the percentage change in output after a one-percent increase in the corresponding input. For example, the output elasticity of capital, \( \beta_K \), represents the percentage increase in output provided by a 1% increase in capital. \( V_i \) serves as the error term.

Extant literature on IT productivity has examined this logarithm expression by various regression methodologies (Black and Lynch 1996; Dewan and Kraemer 2000; Hitt et al. 2002). This approach is closely related to a literature on the impact of R&D investments on productivity, as well as to a literature on the productivity of information technology investments (Tambe and Hitt 2010). By adopting this approach, Brynjolfsson and Hitt (1996) documented how IS spending had made a substantial and statistically significant contribution to firm output; Kudyba and Diwan (2002) re-examined the productivity paradox with updated data; Aral et al. (2006) found that firms that successfully implement IT, react by investing in more IT; Cheng and Nault (2007) estimated the effects of IT investments made upstream on downstream productivity; Mitt and Nault (2009) studied the indirect impact of IT on the production function at the industry level.

Stochastic Frontier Approach

The stochastic frontier production function was developed independently by Aigner, Lovell, and Schmidt (1977), and Meeusen and Van den Broeck (1977). Battese and Coelli (1995) defined a stochastic frontier production function for panel data on firms.

\[ Y_i = \exp(x_i \beta + V_i - U_i) \]  

Where \( Y_i \) denotes the output of the \( i-th \) firm (\( i = 1, ..., N \)) at the \( t-th \) period (\( t = 1, ..., N \)). \( x_i \) is a \((1 \times k)\) vector of known functions of inputs of production and other explanatory variables associated with the \( i-th \) firm at the \( t-th \) period. \( \beta \) is a \((k \times 1)\) vector of coefficients to be estimated. \( V_i \) is a random variable that accounts for measurement error and other random factors. \( U_i \) is a non-negative random variable. It is assumed to be to be independently distributed and represents production loss due to firm-specific technical inefficiency. Thus, it is always
greater than or equal to zero. More details about the definitions of parameters could be found in Battese and Coelli (1995). Equation (3a) could also be rewritten as below,

\[ Y_i = f(x_i, t; \beta) \exp(-U_i) \]  

(3b)

Where, \( f(\cdot) \) is the deterministic kernel of a stochastic production frontier with technology parameter vector \( \beta \) to be estimated. For stochastic frontier production function, the generalized Cobb-Douglas functional form is one of the most frequently used specifications. According to Battese and Coelli (1995), the stochastic frontier production function can be estimated below by adopting Cobb-Douglas function,

\[ \ln(Y_i) = \beta_0 + \beta_k \ln(K_i) + \beta_L \ln(L_i) + V_i - U_i \]  

(3c)

The real advantage of frontier estimation, however, is that it permits the estimation of firm-specific inefficiency (Caudill et al. 1995). The main difference between stochastic frontier model and others is that it attributes part of the deviations to technical inefficiency (\( U_i \)) and part of the deviations to random noise (\( V_i \)). In other words, stochastic frontier approach takes both inefficiency and random noise into account while others do not. It is then generally believed that stochastic frontier is a better approach to measure productive efficiency than deterministic frontier (Schmidt 1985).

![Figure 1. Production Frontier and Technical Efficiency](image)

Production theory suggests the economic process of transforming different inputs (resources) into outputs. The input-output transformation process can be described by a production frontier, which tells the maximum output that can be achieved given certain inputs. Firms in a certain industry operate either on the frontier, or beneath the frontier (Lin 2009)(see Figure 1). Thus, the difference between the production frontier and a firm’s actual output is referred to as technical inefficiency (line AB), while the shifts in the frontier itself is called technical change.

The technical efficiency of production for the \( i\text{-th} \) firm at the \( t\text{-th} \) observation is defined by equation (4),

\[ TE_i = \exp(-U_i) \]  

(4)

Technical efficiency is an important and useful economic measure of firms’ performance. It simply means that firms get the most production from available resources. If firms cannot attain the most production, it is said that they are technically inefficient. Technical efficiency (especially those derived from Stochastic Frontier) has not been widely used in the study of IT value in the past. It was recently utilized by Lin and Shao (2000) to empirically investigate the business value of IT at the firm level in the MIS literature. Shao and Lin (2002) found strong statistical evidence to confirm that IT exerts a significant favorable impact on technical efficiency and in turn, gives rise to the productivity growth.

Technical change is a measure of shifts in the production frontier as defined in (5). At a given point in time, the production frontier is determined by the most productive firm. Technical change shifts the production frontier up (\( TC > 0 \)), leaves it unchanged (\( TC = 0 \)), or shifts it down (\( TC < 0 \)).

\[ TC = \partial \ln f(x, t; \beta) / \partial t \]  

(5)

Moreover, Kumbhakar et al. (1991) and Battese and Coelli (1995) suggested that determining the factors responsible for inefficiency is an essential component of efficiency analysis. Similarly, identifying the sources of efficiency not only contributes to a better understanding of the productivity, but also provides direction to improve technical efficiency. Therefore, in the second stage, we will investigate the sources of
efficiency of SaaS firms. Before formally introducing the empirical model, more explanations on SaaS and catch-up effects are outlined first in the next section.

**Hypotheses Development**

**Technical Change of SaaS firms**

With SaaS, customers contract to use an application hosted by a third party, rather than buying a software license and installing the application on its own machines in the conventional software delivery model (McKinsey 2007). We first highlight three unique features of SaaS (Huang and Wang 2009). First, the SaaS model offers web-based access to business software applications while traditional model requires software installed on customers’ own machines. Therefore, fixed costs such as capital expenditures shifted from clients to SaaS vendors, and the economies of scale of SaaS may be constrained due to the difficulty to manage a huge server farm or MIS staff team. Second, in the SaaS model, multiple customers access the same application based on a shared IT infrastructure provided. The shared infrastructure and MIS staff leads to the load-balancing effect and economies of scale. Third, customers pay a small, recurring subscription fee based on usage rather than a large, one-time software licenses in the traditional model.

Because of the three features, with the advent of SaaS delivery model, enterprise software is no longer just for large firms. Before the SaaS firms come to market, enterprise software was typically bought by large enterprises that could afford to purchase the software licenses, the requisite hardware, and the costly installation and customization services. Demirkan et al. (2010) point out: customers in small and mid-sized market segments lack the wherewithal to make the level of IT investments that is typical of large organizations, but would be receptive to a service that would allow them to get the benefits of ERP software and be charged on an ongoing basis. Similar statements could also be found in Susarla et al. (2009). With SaaS, the same application can be offered to both small and large customers.

Due to the market expansion effect, SaaS revenue is predicted to grow at just over five times the growth rate of traditional packaged software. Starting in one segment does not preclude a SaaS firm from entering any other. This is in direct contrast to traditional software, where firms that start in the low end of the market have difficulty selling to large organizations because of limited functionality and scalability. In other words, SaaS firms have a larger size of the total available market than traditional software firms.

An example is Salesforce.com, which first appealed to small and mid-sized companies and later large companies became comfortable with and thus interested in its services. To achieve this market expansion, Salesforce.com added a direct sales team to target large enterprise.

We conjecture that the explosive sales growth can be translated into productivity growth as the SaaS market gradually matures. In other words, the sales production frontier of SaaS firms should shift upwards faster than that of traditional software firms. There are two considerations. First, R&D productivity increases: as SaaS advances, technologies become more mature. Thus the value-added of their products increases, which then leads to the increase of productivity. Second, marketing productivity increases: as SaaS becomes more mature, corporate buyers become more aware of the benefits of SaaS software. Therefore, SaaS vendors do not need to spend large expenses to educate their customers and promote the products. We then hypothesize that,

**H1: SaaS firms have a bigger technical change than traditional software firms in the same period.**

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4 http://www.hyperoffice.com/saas-reviews-for-smbs/
**Competition and Catch-Up Effects among SaaS firms**

Due to the nascence of SaaS, it is natural to observe differences in technical efficiency among SaaS firms. We define leaders and followers as firms with higher and lower technical efficiency scores, respectively. Therefore, catch-up effects are defined as: the followers gradually improve their technical efficiency to the level of those leaders, and could be measured by technical efficiency (Kumar and Russell 2002).

Leaders typically enjoy some first-mover advantages in R&D and innovation. However, when the leaders do not have strong enough first-mover advantages and sustainable competitive advantages, it will be easier for the followers to catch up simply by mimicking leader’s strategies and operations. Several authors have documented the existence of the imitation of other followers and the catch-up effects (Bernstein and Nadiri 1988; Jaffe 1986; Romer 1990). Chung and Alcácer (2002) found that technical laggards seek knowledge to catch up with other firms at the production frontier, while leaders do not. It is common that the leading firm firstly promotes technical or business model innovation (e.g. SaaS) and the followers later catch up by also adopting the innovation.

In certain industries, firms compete by innovation in perpetual races without clear finishing lines. Examples of such market structures are found in disk drive (Lerner 1997) and semiconductor (Gruber 1994) industries. Hörner (2004) models such races as a multiple round game with an infinite time horizon. He found that, firms would invest in R&D under two distinct circumstances: (1) while sufficiently ahead, to outstrip their lagging rival and secure a durable leadership; (2) while behind, to regain leadership and prevent the situation from worsening to the point where their leading rival outstrips them. The finding indicates that catch-up effects will be stronger if firms’ differences in technical efficiency are smaller. SaaS firms can be generally considered under the latter situation in Hörner’s model, while traditional software firms under the former situation. Because in the traditional software industry, Microsoft, Oracle, and SAP have established their dominance in all market segments whereas only Salesforce.com just started to emerge as a leader in the HR and CRM segment among SaaS firms.

In general, in the innovation competition, if there is decreasing return of R&D investment, followers will eventually catch up with the leading firms (Eeckhout and Jovanovic 2002). However, a follower’s potential for growth weakens as its productivity level converges towards that of the leader (Abramovitz 1986). In the stochastic frontier context, this means that all firms will eventually fall on the efficient frontier with 100% efficiency score and zero variance in the ideal case. From the abovementioned literature, we hypothesize that,

- **H2a:** Average SaaS firms’ technical efficiency scores increases over recent years.
- **H2b:** Average SaaS firms’ technical efficiency scores is greater than that of traditional software firms in the same period.
- **H2c:** Variance of SaaS firms’ technical efficiency scores decreases over recent years.

H2a postulates that the SaaS followers on average catch up with the leaders. H2B postulates that SaaS firms exhibit stronger catch-up effects than traditional software firms. H3c provides another angle of catch-up effect. If the variance of technical efficiency decreases, it implies that the technical efficiency of firms becomes more similar, which is equivalent to that followers gradually catch-up with leaders.

**R&D as the Source of Catch-up Effects**

What is the driver behind the catch-up effects? In other words, what drives the followers of SaaS firms to move closer to the production frontier? Our study hypothesizes that R&D investments should be the key. R&D has long been seen as an important source of knowledge generation and productivity improvement (Shell 1966). In research-intensive industries (e.g. SaaS), firms invest in R&D not only to gain immediate profit by selling better products, but also to maintain the level of their R&D technology or Knowledge (Aoki 1991).

It has been documented that decreasing return in R&D is prevalent in the high-tech industry. In other words, high productivity firms may have less incentive to invest intensively because the return to further investment is low (Aw et al. 2007). Empirical evidences also confirmed this phenomenon. Cui and Mak (2002) found that in high R&D firms, firms with higher growth rate in assets tend to have lower R&D
intensity. Research has been also done and found that the great increase in R&D investments were associated with a stagnant or decreasing productivity growth rate, both at aggregate level (most OECD countries) and firm levels (Jones 2002; Klette and Kortum 2004). The implication of these studies lies in that, firms with a high productivity are likely to reduce their R&D investments since the marginal benefits are now not as attractive as they were.

We therefore believe that less technical efficient SaaS firms will tend to place more R&D investments to catch up with the more efficient ones, while the more technical efficient SaaS firms will tend to place less R&D investments, due to the decreasing return of R&D investments. Based on that, we hypothesize that,

\[ H_3: \text{R&D investments of SaaS firms are negatively associated with their technical efficiency scores in the same period.} \]

H3 is also related to R&D spillover in the literature. Spillover is defined as the scenario in which firms undertaking R&D investments are unable to completely appropriate all of the benefits from their R&D projects. Because the R&D investments by a firm not only improves its own product, but also reduces the R&D investments for competing firms to produce similar products. Arrow (1962) argues that knowledge spillovers are more important in highly R&D intensive industries. Therefore, it is reasonable to assume R&D spillover will become prominent in the SaaS industry, which is at the frontier of the software innovation. Jaffe (1989) and Acs et al. (1994) found that investment in R&D by private corporations and universities “spillover” for third-party firms to exploit it. R&D spillover effects may or may not support H3. At one hand, followers can spend less R&D to achieve the same results, which is against H3. On the other hand, Followers may spend more R&D than leaders because the original R&D may foster incremental or even leapfrog R&D activities. Moreover, if there is no more new R&D opportunities, leaders will reduce R&D investments whereas the followers need to spend re-engineering R&D to absorb the incoming spillovers. As a consequence, this may partially explains why catch-up effects can be created.

Lastly, what is the payoff of the R&D investments in this context? Many researchers have investigated the returns to R&D investments. Extensive empirical studies have been conducted in this domain. Jaffe (1986) studied 432 firms and found that R&D pays off as technological opportunity in an industry increases. Lichtenberg and Siegel (1991) found that in firms that formalize R&D, investments pay off significantly in improved productivity. Graves and Waddock (1994) documented the R&D payoffs in most industries. Ettlie (1998) confirmed R&D intensity was significantly associated with improvements in market share and agility in manufacturing.

The abovementioned evidences suggested that once followers of SaaS firms spend relatively larger R&D expense, it is highly possible these R&D investments would have positive payoffs according to literature. As long as the R&D investment does not exhibit increasing return to cumulative R&D investment, SaaS followers can catch up with the leaders over years. As a result, the technical efficiency scores would increase as time goes by. Therefore we hypothesize the driver behind this catch-up effect is:

\[ H_{4a}: \text{R&D investments of SaaS firms are positively correlated with the 1-year growth rate of technical efficiency scores.} \]

\[ H_{4b}: \text{R&D investments have greater influences on 1-year growth rate of SaaS firms than that of traditional software firms.} \]

H4b states that the influence of R&D on 1-year growth of traditional software firms is likely to be smaller. The reason is that conventional software business on average is relatively matured and if the R&D investment exhibits decreasing return, SaaS will have larger return to R&D investments.

**Empirical Model**

For empirical estimations, we perform a two-stage analysis on our data. In the first stage, we adopt Cobb-Douglas production function into the stochastic frontier model. This model is employed to construct a production frontier and estimate the technical efficiency scores of SaaS firms. Based on the estimation we can then calculate the mean, variance and 1-year growth rate of these scores, as well as technical change. In the second stage, an efficiency model is specified to examine the sources of technical efficiency for SaaS firms. In this stage, the technical efficiency scores and the 1-year growth rates of these efficiency scores are separately treated as dependent variables in the efficiency model.
In the first stage, we specify a stochastic frontier production function for the SaaS firms (and also for the traditional software firms) as shown in equation (6):

\[
\ln(Y_{it}) = \beta_0 + \beta_K \ln(K_{it}) + \beta_L \ln(L_{it}) + \theta_t + V_{it} - U_{it}
\]  

(6)

Where, \(Y_{it}\) is the economic value added of firm \(i\) in year \(t\); \(K_{it}\) is the capital of firm \(i\) in year \(t\); \(L_{it}\) is the labor of firm \(i\) in year \(t\); \(\theta_t\) is a set of year dummies. Equation (6) is based on equation (3c).

In the second stage, the technical efficiency effects are assumed to be defined by equation (7a) and the 1-year growth of technical efficiency are assumed to be defined by equation (7b):

Efficiency Model I:

\[
TE_{it} = \delta_0 + \delta_1(RD_{it}) + \delta_2(AD_{it}) + \delta_3(FSIZE_{it}) + \delta_4(\text{COMPETE}_{it}) + \text{SEG} + \theta_t + \varepsilon_{it}
\]

(7a)

Efficiency Model II:

\[
TEG_{it} = \delta_0 + \delta_1(RD_{it}) + \delta_2(AD_{it}) + \delta_3(FSIZE_{it}) + \delta_4(\text{COMPETE}_{it}) + \text{SEG} + \theta_t + \varepsilon_{it}
\]

(7b)

Where, \(TE_{it}\) is the technical efficiency score obtained from model (6); \(TEG_{it}\) is the 1-year growth of technical efficiency score obtained from model (6); \(RD_{it}\) is the R&D investments of firm \(i\) in year \(t\); \(AD_{it}\) is the advertising expenses of firm \(i\) in year \(t\); \(FSIZE_{it}\) is the firm size of firm \(i\) in year \(t\); \(COMPETE_{it}\) indicates the market competition level for firm \(i\) in year \(t\); \(\text{SEG}\) is a set of dummies indicating market segment effects; \(\theta_t\) is a set of year dummies; \(\varepsilon_{it}\) is the error term. The two efficiency models are estimated by panel-data fixed effects.

In these two models, we also include advertising expenses as an alternative explanatory variable because marketing expenses and R&D expenses are two critical items on the income statements of enterprise software companies. Firm size is added as a control variable because of diseconomies of scale in SaaS (Huang and Wang 2009). Market competition level is also added as an explanatory variable to control the effects of firm competition on productivity growth. Besides, market segment effects are considered in our models as well, since software firms in different market segments (e.g., ERP, CRM) may also differ in productivity growth. Year dummy variables are included to control for the time trends and unobservable heterogeneity associated with years.

Data and Variables

The list of SaaS firms in our study is obtained from annual industry reports from the Software Equity Group. Later the list is used to retrieve annual financial data from COMPUSTAT.

Next, for each SaaS firm, we need to pick a counterpart in the conventional software industries. Note that software firms in different market segments are not well comparable. For example, Salesforce.com is in the market segment of customer relationship management (CRM) and is not well comparable to Oracle which provides licensing database and middleware software. It is imperative to select a traditional software firm in the same market segment with the matching SaaS firm. Within each segment, propensity score (Griliches 1984) is calculated to select the most similar traditional software firm in the same market segment by the financial data obtained from COMPUSTAT.

The standard output measure used in the literature is economic value added, which is 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 (Brynjolfsson and Hitt 1996; Dewan and Min 1997; Kudyba and Diwan 2002). The following measures are specified for the first stage estimation: (i) total fix assets (a typical measure of “capital” in the literature), and (ii) number of employees (a typical measure of “labor” in the literature). These two variables are standard inputs in the productivity analysis literature.

The following measures are specified for efficiency model estimations in the second stage: (i) R&D intensity (R&D investments normalized by sales, a typical measure of R&D investments in the literature),

\[\text{http://www.softwareequity.com/research_annual_reports.aspx}\]
and (ii) Advertising intensity (advertising expenses normalized by sales, a typical measure of advertising expense in the literature), and (iii) natural logarithm of firm’s total assets (a typical measure of firm size in the literature), and (iv) R&D investments normalized by average R&D investments in the same market segment (measure of market competition level). And all inputs must be measured as real rather than nominal quantities (Lieberman et al. 1990). This means proper deflation is needed.

**Conclusion**

This study is the first attempt to use SFA to examine the productivity differences and catch-up effects among SaaS firms. SFA takes both inefficiency and random noise into account and is a better approach for productivity analysis. We first investigate the catch-up effects among the SaaS firms and next investigate the sources of catch-up effects. Our work not only contributes to the productivity literature of SaaS, but also helps SaaS practitioners have a better understanding of the dynamics and drivers of the catch-up effects through a comparison to traditional software firms. Moreover, identifying the sources of catch-up effects could also shed light on SaaS business model and help improve SaaS firm performance.

**References**


