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## Article

# Survival of the fittest: The long-run productivity analysis of the listed information technology companies in the US stock market

Economics: The Open-Access, Open-Assessment Journal

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*Suggested Citation:* Qiao, Guangshun (2023) : Survival of the fittest: The long-run productivity analysis of the listed information technology companies in the US stock market, Economics: The Open-Access, Open-Assessment Journal, ISSN 1864-6042, De Gruyter, Berlin, Vol. 17, Iss. 1, pp. 1-11, <https://doi.org/10.1515/econ-2022-0035>

This Version is available at:

<https://hdl.handle.net/10419/306069>

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## Research Article

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# Survival of the Fittest: The Long-run Productivity Analysis of the Listed Information Technology Companies in the US Stock Market

<https://doi.org/10.1515/econ-2022-0035>

received March 10, 2022; accepted December 30, 2022

**Abstract:** This article tries to estimate the operating efficiency among 30 years (1989–2018) in the information technology (IT) industry, where technologies are everchanging. The balanced panel data model of Kneip et al. is extended to an unbalanced panel data model for more generic applications. The estimation results based on listed IT firms in the US stock market provide evidence that the law of the jungle is applicable to the IT industry. The industry survivors, which often obtain and maintain market power through merger and acquisition, create economic moats by setting high barriers to entry to defend against risk and uncertainty and dominate the capital-intensive and technology-intensive IT industry. At the same time, the estimation results also demonstrate that the global IT industry is highly sensitive to technological waves and business cycles. Though thriving start-ups and spin-offs stimulate innovation and generate a richer diversity, economies of scale are still essential for sustainable development in the IT industry.

**Keywords:** information technology industry, economies of scale, total factor productivity, factor model

## 1 Introduction

Information technology (IT), which produces deep-rooted and widespread changes in society, has long been one of the major forces that transform the global economy (Martin, 2017). Moore's law<sup>1</sup>, first observed by Gordon Moore in 1965, has guided the exponential growth in the global IT industry for over 50 years (Mack, 2011). On the one hand, the cost per

transistor, or in other words, the cost of computing power to the customer, falls dramatically, but on the other hand, the lithography tool cost to fabricate transistors, or in other words, the investment in manufacturing chips and components, soars (Thompson & Parthasarathy, 2006). Benefiting from the increasing capacity and decreasing cost of computing, applications powered by semiconductor chips, such as consumer electronics, artificial intelligence, machine learning, and advanced quantum computing, have been thriving in the past few decades. The rapid pace of evolution in the IT industry helped with expedite technological diversification. Niche companies, either start-ups or spin-offs that are more likely to possess the adjustments necessary to take advantage of new opportunities, flourished under such fast-paced innovations (Dosi & Nelson, 2010).

However, innovations are heavily dependent on research and development (R&D) investment and hence are capital-intensive and risky. Since the firm size is correlated with the ability to generate funds, start-ups are hampered by the constraint of financial and human resources to support continuous R&D activities, whereas the market dominants taking advantage of their large sizes reduce the risk associated with the prospective returns to innovation (Cohen, 2010). Therefore, in the IT industry, whether incumbent large companies which are benefitted from economies of scale or specified niche companies which are benefitted from economies of scope lead the trends of innovation and operate more efficiently remains a challenging empirical question.

According to the Schumpeterian theory of innovation, profits and operating efficiencies are generated either by reducing the overall cost of production or increasing the demand for products. Bartelsman et al. (2015), Kumbhakar et al. (2012), Siliverstovs (2016), and others examined the nonlinear relationship between R&D and productivity. Kumbhakar et al. (2012) and Siliverstovs (2016) pointed out that firms in high-tech sectors not only invest more

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<sup>1</sup> Moore's law is the observation that the number of transistors in a dense integrated circuit doubles about every 2 years.

in R&D but also achieve more productivity gains connected with research activities, while Bartelsman et al. (2015) emphasized the large heterogeneity in the returns of human capital. Ortega-Argilés et al. (2014) compared the productivity performance between Europe and the USA and found that firms in the USA are more efficient in translating their R&D investments into productivity both in sectors of manufacturing and services, and especially in high-tech related industries.

Many other factors might also affect productivity in the innovation-driving IT industry. Ding et al. (2016) examined the foreign competition effect on growth and innovation from a global point of view and argued that import competition stimulates domestic firms' productivity growth and R&D expenditure for firms and their industries closer to the worldwide frontier. Gopinath et al. (2017) focused on the impact of capital allocation and observed that misallocated capital flows would cause a decline in total factor productivity (TFP). Shu & Steinwender (2019) revealed interesting heterogeneities of trade liberalization to spur productivity and innovation at both the country level and the firm level. Lanfranchi & Grassi (2021) showed evidence that in a competitive market where new players are entering, industrial incumbents have to defend their market position by leveraging technology to improve their efficiencies. On the contribution of institutional factors to a firm's productivity, Agostino et al. (2020) argued that better local institutions can help firms, especially small and medium enterprises (SMEs), to reduce transaction cost and become more productive, while Añón Higón et al. (2022) found that higher governance quality can improve firms' operational efficiencies.

However, the productivity comparisons involved in the aforementioned empirical studies were either at the country level or across many industries or sectors but not dedicated to the IT industry. The roles and contributions of IT investments to IT-using industries have been widely discussed (e.g., Casolaro & Gobbi, 2007; Chen & Zhu, 2004; Sabherwal & Jeyaraj, 2015). But few empirical studies have evaluated the productivity performance of the IT industry, especially for the changes and trends in the long run. Yang et al. (2013) examined the entry barrier's difference between information and communication technology (ICT) and non-ICT industries, but their data mixed companies from both the manufacturing sector and the service sector, which are hardly comparable. Madudova et al. (2018) situated the process of economic sustainability in the ICT industry at marco-level.

This article aims to extend the literature on productivity analysis in the IT industry with a long-term perspective. We collect data from the IT industry in the Compustat

North America database over 30 years (1989–2018) for IT firms listed in the US stock market. The data include 510, 706, and 458 firms that have full observations in the 10 years periods: 1989–1998, 1999–2008, and 2009–2018, respectively. For the whole observing period of 30 years, an interesting finding is that there are 1,355 firms that have at least 10 years of continuous annual records, but only 112 firms that have continuous 30-years annual record. The phenomenon that a small number of corporations have survived and come to dominate the IT industry raises a debate of whether a winner takes all in the market (e.g., Chattergoon & Kerr, 2022; Inoue, 2019).

On the one hand, the average lifespan of an S&P 500 company went down from 60 years in the 1950s to under 20 years nowadays, while the 5-year survival rate of all US establishments was roughly 50% (Mauboussin et al., 2017). Furthermore, the survival time of innovative enterprises, which involve heavily in high-risk radical innovation activities, is significantly lower than that of the non-innovative ones (e.g., Boyer & Blazy, 2014; Buddelmeyer et al., 2010). On the other hand, the market position of the incumbents has also changed dramatically in the past few decades. In the annals of the IT industry, cutting-edge technology had upgraded from personal computer in the 1980s and the World Wide Web in the 1990s to multimedia and smartphone applications in the twenty-first century. The leading companies in the IT industry have updated constantly, from IBM in the 1980s and Microsoft in the 1990s to HP<sup>2</sup> in the 2000s and Apple in the 2010s. Few companies in the highly competitive IT industry could ride one wave of technology to its fullest and then change course quickly enough to catch another big one. We plan to take a long-term perspective (1989–2018) and follow the productivity frontier analysis approach to further dig out the shift in operational efficiency in the IT industry.

The productivity frontier analysis, which provides a convenient and comparable standard, is a popular approach for performance evaluation. In the literature on productivity and efficiency analysis in the IT industry, Chou et al. (2012) and Shu & Lee (2003) selected the stochastic frontier analysis (SFA) approach to examine cross-country performance worldwide, but their investigations use aggregated country-level data, not reflecting firm-level heterogeneities. Mathur (2007) chose data envelopment analysis (DEA) to examine India's IT industry, but the measurement based on the Malmquist index was more suitable for balanced panel applications. Gökgöz and Güvercin (2018) and Halkos &

<sup>2</sup> HP Inc. (NYSE: HPQ), an American company that develops personal computers, printers, and related supplies, was formerly known as Hewlett-Packard.

Tzeremes (2007) used the DEA approach to study TFP changes worldwide, but their works restricted the survey to the top 50–60 companies in the global IT industry. This article aims to evaluate the operating efficiencies in the IT industry with a firm-level perspective, dedicated to IT firms listed in the US stock market.

This article also chooses a novel semiparametric SFA approach, which bridges the DEA and SFA approaches to overcome some of the estimation errors. The tradeoff between the DEA approach and the SFA approach is a vexing problem for performance evaluation. The DEA approach, introduced by Banker et al. (1984), Charnes et al. (1978), and Deprins et al. (1984), has not only the advantage of being nonparametric but also the disadvantage of not allowing for statistical noise. In contrast, the SFA approach, proposed independently by Aigner et al. (1977), Battese & Corra (1977), and Meeusen & van Den Broeck (1977), has the attraction of allowing for both an inefficiency term and an error term and also has the drawback of requiring *a priori* parametric functional form of the frontier and the inefficiency distribution. Semiparametric models have come a long way to bridge the gap between the deterministic DEA approach and the econometric SFA approach. Fan et al. (1996), Kuosmanen & Kortelainen (2012), etc., suggested the nonparametric stochastic frontier approach, but their estimation retains a homoscedasticity assumption of the stochastic terms. Park & Simar (1994) and Park et al. (1998) analyzed the semiparametric stochastic frontier model for dealing with panel data, but their approach assumed time-invariant firm-specific technical inefficiency. Kneip et al. (2012) proposed a general and flexible semiparametric model by allowing for a time-varying firm-level inefficiency term and using factor models for estimation.

This article mainly follows the Kneip et al.'s (2012) approach to measure the long-term trends of TFP in the IT industry. Unfortunately, the Kneip et al. (2012) approach was based on balanced panel data, limiting its applications. In the real world, especially in the highly competitive IT industry, unbalanced panel data are unavoidable. On the one hand, continuous innovations in the IT industry accelerated market diversification, reduced entry barriers, and gave birth and growth to industry start-ups. However, the operating records of these niche companies were often unobservable until they grew up to a certain extent, for example, after the company had gone public. Since the lifespan of more than half of US establishments is less than 5 years, the destination of most of the niche companies in the IT industry was either bankrupt or taken over. On the other hand, the market incumbents were benefited by high capital investment thresholds. Hence,

they would have continuous business records that could be traced back for over decades. In order to match the econometric model with the reality in the IT industry to improve the estimation accuracy, this article extends the Kneip et al.'s (2012) approach to unbalanced panel data applications.

The estimation results indicate that the industry survivors, taking advantage of the economies of scale, have relatively higher technical efficiencies in the IT industry. At the same time, the estimation results also imply that the IT industry is highly sensitive to technological waves and global business cycles. Diversified preferences and rising demands and expectations from customers have stimulated continuous technological innovation of new products and services in the IT industry, leveraging companies to concentrate on a specific area in the IT industry to enhance their differentiating competitive advantages. The diversity of products and applications, either at firm-level or industry-level, has generated huge heterogeneities in the IT industry. These heterogeneities twisting to the ups and downs in the global economic cycle have generated high uncertainty of commercial success in the IT industry. Most of the industry survivors that operate with less uncertainty and more steady growth are capital-intensive large-scale companies in the IT industry, which are benefitted by the economics of scale by and large.

The rest of the article is organized as follows. Section 2 introduces the Kneip et al.'s (2012) model and extends the model to unbalanced panel data applications. Section 3 describes the dataset and defines the variables for this research. Section 4 gives the estimation results with a comparison for both balanced panel and unbalanced panel models. Section 5 provides a summary.

## 2 The Model

The seminal work of Solow (1957) provides a measure of productivity growth that is usually referred to as the Solow residual or TFP. For a production technology with one output and  $p$  inputs, the output distance function is given as follows:

$$\frac{Y}{\prod_j^p X_j^{\beta_j}} \leq 1, \quad (2.1)$$

where  $\beta_j$  is the weight of input  $X_j$ . By taking log transformation in equation (2.1), a stochastic frontier model can be derived as follows:

$$\ln Y = \sum_j \beta_j \ln X_j - u_i(t) + \varepsilon_{it}, \quad (2.2)$$

where  $u_i(t)$  is the nonnegative firm-specific inefficiency term, and  $\varepsilon_{it}$  is the adding statistical noise term. Traditional parametric SFA approaches, such as Battese & Coelli (1992), Cornwell et al. (1990), Greene (2005), and Kumbhakar (1997) are based on the maximum likelihood estimation (MLE) technique, which needs ex-ante functional form assumptions.

Kneip & Sickles (2011) introduce an alternative approach to decompose the TFP into exogenous technical change and endogenous efficiency change by modifying (2.2) as follows:

$$y_{it} = \beta_0(t) + \sum_{j=1}^p x_{itj} \beta_j + v_i(t) + \varepsilon_{it}, \quad (2.3)$$

$$i = 1, \dots, N, \quad t = 1, \dots, T,$$

where  $y_{it} = [\ln Y]_{it}$ ,  $x_{itj} = [\ln X_j]_{it}$ ,  $\beta_0(t) = \frac{1}{N} \sum_{i=1}^N u_i(t)$ , and  $v_i(t) = -\beta_0(t) - u_i(t)$ . Note that  $\sum_{i=1}^N v_i(t) = 0$  by construction. Hence, the sources of TFP growth are split into an external technical change term  $\beta_0(t)$  due to an exogenous long-term trend and an internal technical efficiency (TE) term  $v_i(t)$  due to endogenous productivity performance. Taking the advantage of panel data, the exogenous term  $\beta_0(t)$  in equation (2.3) can be eliminated trivially by centering the variables. In detail, we define  $y_{it}^* = y_{it} - \frac{1}{N} \sum_{i=1}^N y_{it}$ ,  $x_{itj}^* = x_{itj} - \frac{1}{N} \sum_{i=1}^N x_{itj}$ , and  $\varepsilon_{it}^* = \varepsilon_{it} - \frac{1}{N} \sum_{i=1}^N \varepsilon_{it}$ . Hence, the model in equation (2.3) is simplified to

$$y_{it}^* = \sum_{j=1}^p x_{itj}^* \beta_j + v_i(t) + \varepsilon_{it}^*. \quad (2.4)$$

As the TE term  $v_i(t)$  in equation (2.4) is unobservable, we recommend estimating the model semiparametrically. More specifically, we can use cubic splines and factor models to estimate (2.4) without extra functional restrictions on the TE term  $v_i(t)$ . By using cubic splines, the estimation of equation (2.4) is to optimize

$$\sum_{i=1}^N \sum_{t=1}^T \frac{1}{T} (y_{it}^* - \sum_{j=1}^p \beta_j x_{itj}^* - \vartheta_i(t))^2 + \sum_{i=1}^N \kappa \int_1^T \frac{1}{T} (\vartheta_i''(s))^2 ds, \quad (2.5)$$

where  $\vartheta_i(t)$  denotes a nonparametric approximation of  $v_i(t)$ , and  $\vartheta_i''(t)$  denotes the second derivative of  $\vartheta_i(t)$ . To further simplify the notation, the objective function (2.5) can be written in matrix form as follows:

$$S(\beta, \zeta) = \sum_{i=1}^N (\|Y_i - X_i \beta - Z \zeta_i\|^2 + \kappa \zeta_i^T R \zeta_i), \quad (2.6)$$

where  $Y_i = (y_{i1}^*, \dots, y_{iT}^*)^T$ ,  $X_i$  is a  $T \times P$  matrix with elements  $X_{itj}^*$ ,  $Z$  and  $R$  are  $T \times T$  matrices to be decided by cubic splines,  $\zeta_i = (\zeta_{i1}, \dots, \zeta_{iT})^T$ , and  $\kappa$  is a preselected parameter to control the smoothness of  $\vartheta_i(t)$ . Hence, the estimators of  $\beta$  and  $\zeta_i$  in equation (2.6) can be expressed explicitly as follows:

$$\hat{\beta} = \left( \sum_{i=1}^n X_i^T (I - Z_k) X_i \right)^{-1} \left( \sum_{i=1}^n X_i^T (I - Z_k) Y_i \right), \quad (2.7)$$

$$\hat{\zeta}_i = (Z^T Z + \kappa R)^{-1} Z^T (Y_i - X_i \hat{\beta}),$$

where  $Z_k = Z(Z^T Z + \kappa R)^{-1} Z^T$ . Based on the results in equation (2.7), the estimator of  $v_i$  can be written as  $\hat{v}_i = Z_k (Y_i - X_i \hat{\beta})$ .

Furthermore, the unknown structure of  $\hat{v}_i(t)$  can be derived by factor models as follows:

$$\hat{v}_i(t) = \sum_{l=1}^D \lambda_{il} f_l(t), \quad (2.8)$$

where  $D$  is the number of unknown factors,  $f_l(t)$  is one of the unknown factors, and  $\lambda_{il}$  is the corresponding individual loading. Using principal component analysis (PCA) with suitable normalization conditions, the factor  $f_l(t)$  and loading  $\lambda_{il}$  in equation (2.8) can be expressed as follows:

$$\hat{f}_l(t) = \sqrt{T} \gamma_{lt},$$

$$\hat{\lambda}_{il} = \frac{1}{T} \hat{f}_l^T (Y_i - \bar{Y} - (X_i - \bar{X}) \hat{\beta}), \quad (2.9)$$

where  $\gamma_l$  is the  $l$ th eigenvector of the covariance matrix  $\Sigma = \frac{1}{N} \sum_{i=1}^N \hat{v}_i \hat{v}_i^T$ ,  $\gamma_{lt}$  is the  $t$ th element of the eigenvector  $\gamma_l$ , and  $\hat{f}_l^T = (\hat{f}_l(1), \dots, \hat{f}_l(T))^T$ . In practice, applications with missing observations are common. As discussed in the introduction, the average lifespan of an S&P 500 company is less than 20 years, and the lifespan for a firm in the IT industry is even shorter. For a study of firms in the IT industry for 30 years (1989–2018), the dataset is commonly an unbalanced panel. Therefore, the balanced panel data model in equations (2.4)–(2.6) needs to be modified into an unbalanced panel data model.

In order to distinguish the notation between the balanced panel data model and the unbalanced panel data model, we introduce additional variables of  $N_t$ ,  $T_i$ , and  $I_{it}$ , where  $N_t$  represents the number of observations in period  $t$ ,  $T_i$  represents the sum of years with observations, and  $I_{it}$  is a dummy variable that  $I_{it} = 1$  if  $i$  is observed in period  $t$ , and  $I_{it} = 0$  if  $i$  is not observed in period  $t$ . Then the unbalanced panel data model is modified from equation (2.4) to

$$y_{it}^{**} = \sum_{j=1}^P \beta_j x_{itj}^{**} + v_i(t) + \varepsilon_{it}^{**}, \quad (2.10)$$

where  $y_{it}^{**} = y_{it} - \frac{1}{N_t}(\sum_{i=1}^N y_{it} I_{it})$ ,  $x_{itj}^{**} = x_{itj} - \frac{1}{N_t}(\sum_{i=1}^N x_{itj} I_{it})$ , and  $\tilde{\varepsilon}_t = \frac{1}{N_t}(\sum_{i=1}^N \varepsilon_{it} I_{it})$ . Note that  $N_t = \sum_{i=1}^N I_{it}$  and  $T_i = \sum_{t=1}^T I_{it}$ .

The estimation procedures for the unbalanced panel model are similar to what has been done for the balanced panel model above. In detail, the objective function in equation (2.10) can be reformulated in matrix form as follows:

$$\tilde{S}(\beta, \zeta) = \sum_{i=1}^N (\|\tilde{Y}_i - \beta \tilde{X}_i - Z_i \zeta_i\|^2 + \kappa_i \zeta_i^T R_i \zeta_i), \quad (2.11)$$

where  $\tilde{Y}_i = (y_{i1}^{**}, \dots, y_{iT}^{**})^T$ ,  $\tilde{X}_i$  is a  $T \times P$  matrix with elements  $X_{itj}^{**}$ ,  $Z_i$  and  $R_i$  are  $T \times T$  matrices, and  $\kappa_i$  is the smoothing parameter to control the smoothness of  $\vartheta_i(t)$ . The estimators of  $\beta$  and  $\zeta_i$  are obtained by optimizing  $\tilde{S}(\beta, \zeta)$  in equation (2.11) as follows:

$$\begin{aligned} \tilde{\beta} &= \left( \sum_{i=1}^N \tilde{X}_i^T (I - \tilde{Z}_i) \tilde{X}_i \right)^{-1} \left( \sum_{i=1}^N \tilde{X}_i^T (I - \tilde{Z}_i) \tilde{Y}_i \right), \\ \tilde{\zeta}_i &= (Z_i^T Z_i + \kappa_i R_i)^{-1} Z_i^T (\tilde{Y}_i - \tilde{X}_i \tilde{\beta}). \end{aligned} \quad (2.12)$$

It is straightforward from (2.12) that  $\tilde{v}_i = \tilde{Z}_i (\tilde{Y}_i - \tilde{X}_i \tilde{\beta})$ , where  $\tilde{Z}_i = Z_i (Z_i^T Z_i + \kappa_i R_i)^{-1} Z_i^T$ . The main difference between (2.7) and (2.12) is that in a balanced panel, both  $Z_k$  and  $\kappa$  are constant for all firms, but in an unbalanced panel, the parameters  $Z_i$  and  $\kappa_i$  are specific for each individual firm  $i$ . To further study the unknown structure of  $v_i(t)$  in unbalanced panel model, we follow the functional PCA approach of Paul & Peng (2009) to derive the unknown heterogenous term  $v_i(t)$  as follows:

$$\tilde{v}_i(t) = \lambda_i^T F_t + \xi_{it}, \quad (2.13)$$

where  $F_t$  can be presented by basis functions as  $F_t^T \approx (\phi_1(t), \dots, \phi_M(t))B$ , that  $\{\phi_j\}_{j \leq M}$  is a set of orthonormal basis functions and  $B$  is an orthonormal coefficient matrix. Note that  $B^T B = I$ . If suppose  $\lambda_i \stackrel{iid}{\sim} N(0, \Sigma_\lambda)$  and  $\xi_{it} \stackrel{iid}{\sim} N(0, \sigma^2)$ , the time-varying inefficiency term  $\tilde{v}_i(t)$  in (2.13) can be identified by MLE.

### 3 The Data

The data are collected from the IT industry in the Compustat North America database, covering IT firms listed in the US stock market over 30 years (1989–2018). The US equity markets have long been the largest and most liquid in the world, continuously attracting technology companies to

raise equity capital from public investors. Since 30 years include many ups and downs of the technological waves of innovation in the IT industry, we further split the sample by each of the 10 years to compare operational efficiencies between the mid-term and the long-term. Hence, in a balanced panel data point of view, the data include 510, 706, and 458 firms, which have full observations in the 10 years periods: 1989–1998, 1999–2008, and 2009–2018, respectively. Meanwhile, in the whole sample period of 30 years, there are 112 firms that have continuous 30 years' annual data, while in an unbalanced panel data point of view, the data include 1,355 firms that have at least 10 years of continuous annual records in the 30 years 1989–2018.

We specify one output (revenue ( $REV_{it}$ )) and  $p = 3$  inputs (direct production cost ( $PRO_{it}$ ); overhead cost, measured by the sales and marketing expenditure ( $OVE_{it}$ ); and capital investment, measured by property, plant, and equipment ( $PPE_{it}$ )). Table 1 gives summary statistics for the variables in each of the 10 years of balanced panels, and in 30 years of balanced and unbalanced panels. All the values in Table 1 are in log-form, with units in thousand dollars for the original data before the log transformation.

The drastic difference between the number of firms in different periods in Table 1 is rooted in the feature that the IT industry is both technology and capital-intensive. As a technology-intensive industry, the IT industry is driven by continuous innovations that reduce entry barriers and give birth and growth to the start-ups. Unfortunately, the operating records to the start-up companies are often unobservable until these companies grow up to a certain extent. As a capital-intensive industry, the IT industry is dominated by industry giants, which take advantage of capital investment to set up economic moats and minimize competition. One frequently used strategy by the incumbents to maintain and intensify their market power is to scale up by mergers and acquisitions (M&A). This is why the industry survivors are so few in the IT industry that many of the SMEs have already been integrated into industry giants before they grow into formidable competitors.

### 4 Estimation and inference

In order to derive consistent estimation in equations (2.6) and (2.11), Bada & Liebl (2014) propose to use a parameter iteration algorithm together with generalized cross-validation (GCV). The iteration algorithm starts with certain

Table 1: Descriptive statistics

	Min	Q1	Median	Mean	Q3	Max	N	Unique firm
Balanced panel								
1989–1998								
REV	3.81	9.56	10.88	11.02	12.33	18.26	5,100	510
PRO	2.20	8.89	10.23	10.38	11.68	17.82	5,100	510
OVE	1.39	8.46	9.67	9.88	11.12	17.15	5,100	510
PPE	3.43	8.28	9.63	9.83	11.20	18.04	5,100	510
1999–2008								
REV	3.78	10.41	11.72	11.85	13.16	18.59	7,060	706
PRO	1.61	9.61	10.98	11.10	12.44	18.29	7,060	706
OVE	5.64	9.62	10.77	10.89	11.97	17.21	7,060	706
PPE	3.26	9.12	10.50	10.66	11.98	18.22	7,060	706
2009–2018								
REV	3.87	10.93	12.71	12.65	14.27	19.40	4,580	458
PRO	1.95	10.17	11.90	11.87	13.47	18.85	4,580	458
OVE	6.67	9.99	11.53	11.51	12.89	17.43	4,580	458
PPE	3.66	9.71	11.41	11.43	13.18	18.55	4,580	458
1989–2018								
REV	7.08	10.62	12.44	12.63	14.55	19.40	3,360	112
PRO	3.53	10.04	11.83	11.96	13.68	18.85	3,360	112
OVE	6.23	9.40	11.13	11.35	13.18	17.43	3,360	112
PPE	5.45	9.57	11.40	11.55	13.40	18.55	3,360	112
Unbalanced panel								
1989–2018								
REV	0.69	10.13	11.53	11.67	13.09	19.40	24,188	1,355
PRO	1.39	9.33	10.79	10.92	12.36	18.85	24,188	1,355
OVE	1.39	9.29	10.52	10.65	11.88	17.43	24,188	1,355
PPE	0.69	8.73	10.25	10.42	11.87	18.55	24,188	1,355

Note. All the values are in log-form.  $N = n(\text{firms}) \times T(\text{years})$  in the balanced panel.  $N = n(\text{firms}) \times T(\text{years})$  excludes the missing observations in the unbalanced panel. REV represents the output variable of revenue. PRO represents the input variable of direct production cost. OVE represents the input variable of overhead cost. PPE represents the input variable of capital investment in property, plant and equipment.

initial values of  $\beta$ , defined as  $\hat{\beta}_{ob}$  in the balanced panel model and  $\hat{\beta}_{ou}$  in the unbalanced panel model, then iterates until the estimates of  $\beta$  converge at certain  $\hat{\beta}_b$  and  $\hat{\beta}_u$  in the balanced panel and unbalanced panel models, respectively. The initial values of  $\hat{\beta}_{ob}$  and  $\hat{\beta}_{ou}$  are derived by

$$\begin{aligned}\hat{\beta}_{ob} &= \left( \sum_{i=1}^N X_i^T (I - G_b G_b^T) X_i \right)^{-1} \left( \sum_{i=1}^N X_i^T (I - G_b G_b^T) Y_i \right), \\ \hat{\beta}_{ou} &= \left( \sum_{i=1}^N \tilde{X}_i^T (I - G_u G_u^T) \tilde{X}_i \right)^{-1} \left( \sum_{i=1}^N \tilde{X}_i^T (I - G_u G_u^T) \tilde{Y}_i \right),\end{aligned}\quad (4.1)$$

where  $G_b$  and  $G_u$  are  $T \times D$  matrices of the eigenvectors corresponding to the first  $D$  eigenvalues of the augmented covariance matrices  $\Gamma_b$  and  $\Gamma_u$ , which are defined as follows:

$$\begin{aligned}\Gamma_b &= \frac{1}{NT} \sum_{i=1}^N (Y_i, X_i)(Y_i^T, X_i^T)^T, \\ \Gamma_u &= \frac{1}{NT} \sum_{i=1}^N (\tilde{Y}_i, \tilde{X}_i)(\tilde{Y}_i^T, \tilde{X}_i^T)^T.\end{aligned}\quad (4.2)$$

Though there are many methods to estimate the optimal dimension  $D$ , a convenient approximation of the suitable dimension  $D$  is given by  $D = \min\{\sqrt{N}, \sqrt{T}\}$ . Thereafter, we optimize (2.6) and (2.11) with respect to  $\zeta_i$  to obtain

$$\begin{aligned}\hat{\zeta}_{ib} &= (Z^T Z + \kappa R)^{-1} Z^T (Y_i - X_i \hat{\beta}_b), \\ \hat{\zeta}_{iu} &= (Z_i^T Z_i + \kappa_i R_i)^{-1} Z_i^T (\tilde{Y}_i - \tilde{X}_i \hat{\beta}_u),\end{aligned}\quad (4.3)$$

where  $\hat{\zeta}_{ib}$  and  $\hat{\zeta}_{iu}$  are estimates of  $\zeta_i$  in the balanced and unbalanced panel models, respectively. Using the results in equation (4.3), we can optimize equations (2.6) and (2.11) with respect to  $\beta$  to obtain

$$\begin{aligned}\hat{\beta}_b &= \left( \sum_{i=1}^N X_i^T X_i \right)^{-1} \left( \sum_{i=1}^N X_i^T (Y_i - Z_i \hat{\zeta}_{ib}) \right), \\ \hat{\beta}_u &= \left( \sum_{i=1}^N \tilde{X}_i^T \tilde{X}_i \right)^{-1} \left( \sum_{i=1}^N \tilde{X}_i^T (\tilde{Y}_i - Z_i \hat{\zeta}_{iu}) \right),\end{aligned}\quad (4.4)$$

where  $\hat{\beta}_b$  and  $\hat{\beta}_u$  are estimates of  $\beta$  in the balanced and unbalanced panel data models, respectively. The smoothing parameters  $\kappa$  and  $\kappa_i$  are determined by the GCV criterion as follows:

$$\begin{aligned}\kappa &= \arg \min_{\kappa} \frac{1}{\frac{N}{T} \text{tr}(I - Z_{\kappa})^2} \sum_{i=1}^N \|(I - Z_{\kappa})(Y_i - X_i \hat{\beta}_b)\|^2, \\ \kappa_i &= \arg \min_{\kappa_i} \frac{T_i}{\text{tr}(I - \tilde{Z}_i)^2} \|(I - \tilde{Z}_i)(\tilde{Y}_i - \tilde{X}_i \hat{\beta}_u)\|^2.\end{aligned}\quad (4.5)$$

We can iterate from (4.3) to (4.5) until the estimates of  $\beta$  and  $\zeta$  converge.

Table 2 provides the estimates of  $\beta_{\text{PRO}}$ ,  $\beta_{\text{OVE}}$ , and  $\beta_{\text{PPE}}$  in both balanced and unbalanced panels. The variance of  $\beta_b$  and  $\beta_u$  are calculated by

$$\begin{aligned}\hat{\Sigma}_{\beta_b} &= \hat{\sigma}_b^2 \left( \sum_{i=1}^N X_i^T (I - Z_k Z_k^T) X_i \right)^{-1} \\ &\quad \times \left( \sum_{i=1}^N X_i^T (I - Z_k Z_k^T)^2 X_i \right) \left( \sum_{i=1}^N X_i^T (I - Z_k Z_k^T) X_i \right)^{-1}, \\ \hat{\Sigma}_{\beta_u} &= \hat{\sigma}_u^2 \left( \sum_{i=1}^N \tilde{X}_i^T (I - \tilde{Z}_i \tilde{Z}_i^T) \tilde{X}_i \right)^{-1} \\ &\quad \times \left( \sum_{i=1}^N \tilde{X}_i^T (I - \tilde{Z}_i \tilde{Z}_i^T)^2 \tilde{X}_i \right) \left( \sum_{i=1}^N \tilde{X}_i^T (I - \tilde{Z}_i \tilde{Z}_i^T) \tilde{X}_i \right)^{-1},\end{aligned}\quad (4.6)$$

**Table 2:** Estimates by various groups

Period	Intercept	$\beta_{\text{PRO}}$	$\beta_{\text{OVE}}$	$\beta_{\text{PPE}}$	$\hat{D}$
<b>Balanced panel</b>					
1989–1999	1.55*** (0.19)	0.71*** (0.01)	0.19*** (0.01)	0.02 (0.01)	2
1999–2008	1.56*** (0.21)	0.64*** (0.01)	0.28*** (0.02)	0.02 (0.01)	3
2009–2018	1.59*** (0.21)	0.57*** (0.01)	0.32*** (0.02)	0.05*** (0.01)	3
1989–2018	0.97*** (0.21)	0.57*** (0.01)	0.42*** (0.02)	0.00 (0.01)	5
<b>Unbalanced panel</b>					
1989–2018	0.69*** (0.18)	0.60*** (0.00)	0.32*** (0.01)	0.05*** (0.01)	4

*t* statistics in parentheses.

\* $p < 0.05$ , \*\* $p < 0.01$ , \*\*\* $p < 0.001$ .

where the estimators of  $\sigma_b^2$  and  $\sigma_u^2$  can be obtained by

$$\begin{aligned}\hat{\sigma}_b^2 &= \frac{\sum_{i=1}^N \|Y_i - X_i \hat{\beta}_b - \sum_{l=1}^D \hat{\lambda}_{il} \hat{f}_l\|^2}{\text{Degrees of freedom}}, \\ \hat{\sigma}_u^2 &= \frac{\sum_{i=1}^N \|\tilde{Y}_i - \tilde{X}_i \hat{\beta}_u - \tilde{v}_i(t)\|^2}{\text{Degrees of freedom}}.\end{aligned}\quad (4.7)$$

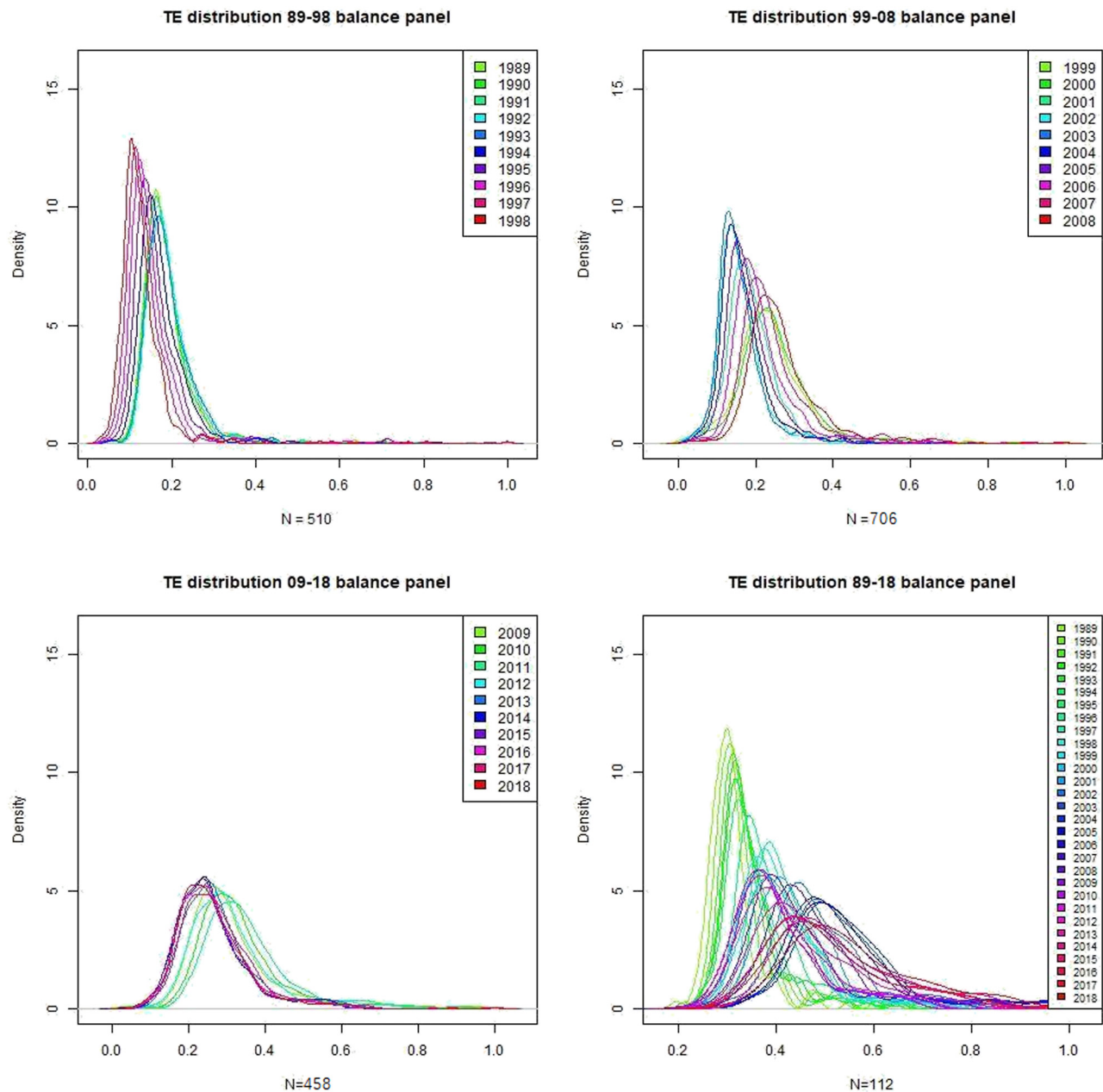
The estimates in Table 2 show that in the production function, the weights of direct production costs are about 60% or higher, and the weights of overhead are around 30%. However, the weights of property, plant, and equipment (PP&E) are 5% or less in the production function. Furthermore, the coefficients of  $\beta_{\text{PRO}}$  and  $\beta_{\text{OVE}}$  are statistically significant in every situation, but the coefficient of  $\beta_{\text{PPE}}$  is not statistically significant in more than half of the cases.

The trivial weights of PP&E in the production function may be caused by the popularity of the light-asset mode in the IT industry (e.g., Sarma & Sun, 2017; Wang et al., 2020). Since the capital expenditure (CAPEX) for manufacturing leading-edge products has become prohibitive for all but a few vendors in the IT industry, it creates high barriers to entry. In order to optimize the limited resource, many start-up and spin-off companies in the IT industry choose to specialize in R&D and direct their limited funding to human capital investment instead of fixed capital investment. On the contrary, the industry giants who can afford the burden of CAPEX may gain monopoly power and dominate the market through risky but profitable capital investment.

Once the time-varying individual effects are estimated, we follow the approach of Schmidt & Sickles (1984) to calculate TE for firm  $i$  at time  $t$  as follows:

$$\text{TE}_i(t) = e^{(v_i(t) - \max_{j=1, \dots, N} v_j(t))}. \quad (4.8)$$

Note that  $0 < \text{TE}_i(t) \leq 1$  by construction. Figures 1 and 2 plot the densities of estimated TE in the balanced and unbalanced panel models, respectively. In Figure 1, the densities of annual TE have only small shifts within each of the 10-year periods. The slight differences in the TE density curves are more likely affected by business cycles than structural changes driven by technological waves in the IT industry. Oppositely, also in Figure 1, the density curves of annual TE in the 30-year balanced panel change drastically. That is, the densities of annual TE for the surviving companies in the 30-year balanced panel have a steady trend shifting to the right. Such distinct structure changes of TE imply that the industry survivors gain market power as time passes so that they have relatively higher and closer TEs. As products and applications keep diversifying



**Figure 1:** Distribution of TE in the balanced panel.

through technological waves and evaluations, although no single company could maintain monopoly power and domain of the market in the long run, a few companies, such as Intel for semiconductor chips, Apple for smartphones, and Microsoft for desktop operating systems, may raise monopoly power at some level in one of the subsectors in the IT industry.

In Figure 2, we also observe apparent shifts of the density curves of TE in the 30-year unbalanced panel, but in a different way. In detail, the curves first shift to the left till around the end of the first decade of the 2000s, then shift

backward to the right in the 2010s. It is worth mentioning that the shifting trend of the density curves has a turning point during the 2008 financial crisis, which could hardly be a coincidence. Starting in the 1990s, the trend of globalization provided incentive to incumbents in the IT industry to intensify their market power through cross-border M&A activities. However, this M&A wave ended in the 2008 financial crisis (Junni & Teerikangas, 2019). After the great recession of 2008, with the gradual recovery of the global economy, another innovation wave led largely by the transition to mobile and the rise of data has accelerated the

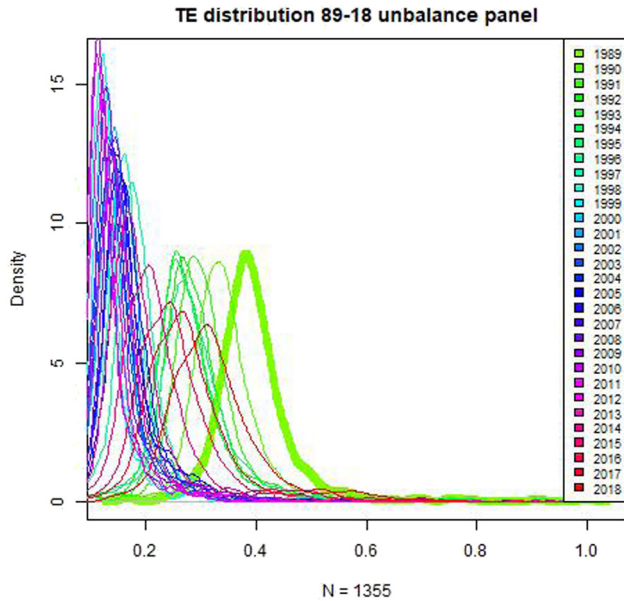


Figure 2: Distribution of TE in the unbalanced panel.

growth of artificial intelligence, e-commerce, and social media and radically changed our day-to-day lives. The flourished IT industry not only attracts more start-ups to enter the market but also pushes most firms into more challenging conditions. The intensified competition in the IT industry impels companies to improve their operations management and hence pushes the TE curves to shift to the right.

Figure 3 plots the average annual TEs in both balanced and unbalanced panels. Consistent with the findings shown in Figures 1 and 2, the curves in Figure 3 provide evidence that the industry survivors, which are often the capital-intensive large scale companies, take the advantage of their market power to defend against the threats from technological evolution, market uncertainty, and global economic ups and downs, have relatively higher average TEs. Figure 3 also demonstrates cyclic fluctuations of the average annual TEs, especially in the long run. In the 30-year balanced panel, the two wave troughs of the average annual TEs correspond to the periods of the dot-com crash in 2000 and the subprime mortgage crisis in 2008. Despite the market fluctuations by business cycles, the curve of average annual TEs in the 30-year balanced panel shows a steady upward trend, implying that the market incumbents keep gaining operating efficiencies in the long run. On the contrary, the curve of average annual TEs in the 30 years unbalanced panel shows a U-shaped trend (or a W-shaped trend, though a little bit vague) implying that the whole market is suffering and losing operating efficiencies during the hard times of the dot-com crash and the global financial crisis. Furthermore, it is not surprising that in Figure 3 the estimates of average TEs in the balanced panel are much higher than the estimates of average TEs in unbalanced panel, since the balanced panel is dominated by the survival market giants.

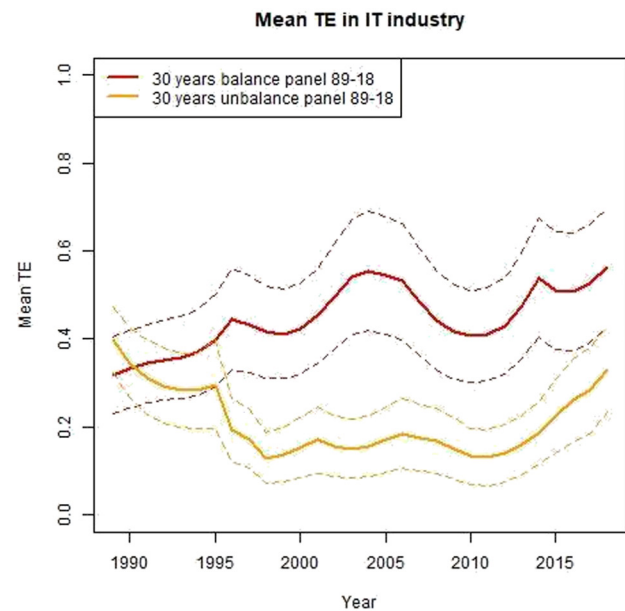
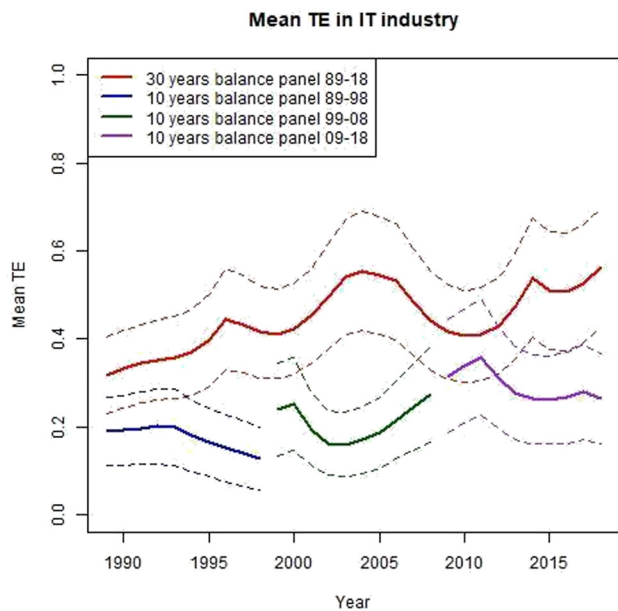


Figure 3: Mean TE in the IT industry.

## 5 Summary and conclusions

It is an intimidating subject to analyze the operating efficiency in the IT industry where technologies are ever-changing. This article chooses the data from listed IT firms in the US stock market to study the operating efficiency in the IT industry with a long-term perspective (1989–2018). The estimation results in this article provide evidence that the law of the jungle is applicable to the IT industry. Despite the market ups and downs either by technological evolutions or by business cycles, the industry survivors, which often obtain and maintain market power through M&A, dominate the highly competitive IT industry in the long run. As the development of internet technologies has helped to overcome the obstacles in border regions and facilitate a global product chain and supply chain in the IT industry, quite a number of the listed IT firms in the US stock market are multinational corporations with R&D centers, manufacturing sites, customers, and businesses all over the world. Hence, the estimation results based on listed IT firms in the US stock market are also applicable to a worldwide picture. In the capital-intensive and technology-intensive global IT industry, the incumbent market giants take advantage of high barriers to entry and create economic moats to defend against the threats and risks either from competition with new entrants in the global market or from the uncertainty of technological investments in R&D.

However, although the economies of scale are still essential in the IT industry, they are not the only driving forces for sustainable technology development. Diverse preferences and rising expectations from customers have stimulated continuous technological innovation of new products and services in the IT industry. More and more companies choose to concentrate on a specific subsector in the IT industry to differentiate and enhance their competitive advantages. The diversity of products and applications, either at the firm-level or industrial-level, has generated huge heterogeneities in the IT industry. Further studies of the operating efficiency in the IT industry could either focus on a more specific subindustry or develop more advanced econometric tools to control and monitor the impacts of heterogeneities. With the expansion of market scale and market scope, the flourishing and prosperity of the IT industry depend on the contributions of both innovative sparks from start-ups and continuous capital investments from market incumbents.

**Funding information:** This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

**Conflict of interest:** The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge, or beliefs) in the subject matter or materials discussed in this manuscript.

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