Serv Bus (2015) 9:137–160
DOI 10.1007/s11628-013-0221-y

THEORETICAL ARTICLE

Service quality and productivity in the U.S. airline industry: a service quality-adjusted DEA model

Kanghwa Choi · DonHee Lee · David L. Olson

Received: 10 September 2013 / Accepted: 25 November 2013 / Published online: 12 December 2013

Abstract The airline industry faces economic challenges making it paramount that they provide satisfactory service to customers relative to their expectations. This study uses a service quality-adjusted data envelopment analysis (SQ-adjusted DEA) to study US-based airline carrier operational efficiency. We found that airlines can overcome the traditional tradeoff between quality and productivity. Using SQ-adjusted DEA, we were able to find how airlines could set service levels in accordance with their strategic purpose or operational characteristics. Low-cost airlines were found to benefit by marginal improvements in service, often unexpected by their clientele. Network carriers, however, tended to have a harder time meeting service expectations. While there were short-term tradeoffs between service quality and productivity, in the long term a focus on service quality may help increase customer satisfaction, thus improving service productivity and overall organizational performance. SQ-adjusted DEA was found to be better suited to explore service productivity than the standard DEA.

Keywords SQ-adjusted DEA · Operational efficiency · Service quality · Service productivity · The US airline

K. Choi
Department of Management, Hansung University, 116 Samseongyoro, 16gil, Seongbuk-gu, Seoul, South Korea
e-mail: khchoi@hansung.ac.kr

D. Lee (✉)
College of Business Administration, Keimyung University, 1095, Dalgubeol-daero, Daegu, South Korea
e-mail: dhlee@kmu.ac.kr

D. L. Olson
Department of Management, 209 CBA University of Nebraska-Lincoln, Lincoln, NE 68588-0491, USA
e-mail: dolson3@unl.edu

1 Introduction

In 2011, the air transport industry increased at about double the rate of overall economic growth (Bhaskara 2012). In spite of its rapid expansion, the air transport industry has faced internal and external challenges, such as the ongoing global economic recession, the resulting financial crisis, and rising crude oil prices. In addition, the advent of low-cost carriers (LCCs) coupled with existing network carriers (NCs) has made the air transport market increasingly competitive. The increased competition, rising operational costs, and lower profit margins have led to a resurgence of mergers and acquisitions among airline companies. Given these rapid changes, airline companies have attempted to attain competitive advantage, improve their organizational effectiveness, and gain an edge by pursuing continuous innovation in their operations.

Service quality and productivity are factors that indicate the degree to which sustainable growth is possible in the airline industry (Davey et al. 2007; Parast and Fini 2010). Although improvements to both service quality and productivity would be ideal, there are inherent short-term tradeoffs between the two (Ferdows and De Meyer 1990; Safizadeh et al. 2000; Lapré and Scudder 2004; Calabrese 2012). For example, a service provider can increase productivity by reducing the firm's use of manpower, materials, or equipment but these strategies may result in poor product or service quality and decreased customer satisfaction. Conversely, to increase customer satisfaction, a service provider can customize its services, which inherently requires greater manpower and resources. This can lead to decline in productivity. Recently, many firms have attempted to increase long-term service productivity by improving quality and customer satisfaction, such as just-in-time approaches. This strategy, while potentially beneficial, often requires sacrificing short-term productivity.

Previous research on service quality in the airline industry has shown that there is a positive relationship between service quality and organizational performance (Lapré and Scudder 2004; Tsikriktsis 2007; Tiernan et al. 2008). Tsikriktsis and Heineke (2004) reported empirical results showing the impact of average and variation of service performance on customer dissatisfaction. However, the results of these studies do not account for the tradeoff between service quality and productivity. In particular, the methodologies employed in these studies demonstrate a violation of the original purpose of benchmarking. The incentive regulations generated by existing data envelopment analysis (DEA) methodologies determine best practices for increasing quantitative effectiveness, regardless of the quality of the service being delivered (Charnes et al. 1991; Scheraga 2004; Lin 2005; Tsikriktsis 2007; Parast and Fini 2010). However, DEA suffers from three key limitations. First, some studies have demonstrated that incentive regulations that incorporate only quantitative metrics for efficiency can cause reductions in quality and motivate reductions of expenditures (Lin 2005). Second, even those studies that explored both quality and efficiency suffered from methodological limitations, making their results difficult to interpret (Thanassoulis et al. 1995; Soteriou and Zenios 1999; Soteriou and Stavrinides 2000; Sherman and Zhu 2006; Bayraktar et al. 2012; Brissimis and Zervopoulos 2012).

This study investigates the operational efficiency of US-based airline carriers with a service quality-adjusted DEA (SQ-adjusted DEA). Five major carriers (based on volume) were selected, and compared with seven lower cost carriers, including two regional carriers and five carriers emphasizing lower costs. This methodology simultaneously considers service quality and productivity, and offers suggestions for improving operational efficiency. This study also suggests managerial strategies for improving service productivity through evaluation.

Given this focus, this study seeks to address three research questions. First, is it possible to measure airline service productivity with adjusted service quality while accounting for the inherent tradeoff between service productivity and quality? Second, how do the standard DEA and the SQ-adjusted DEA differ when applied to the case of US airline carriers? Third, what is the nature of the service quality–productivity tradeoff for NCs and LCCs, when US airlines are classified according to the size or the purpose of operations? This study investigates possible differences in service quality and productivity between major airlines focusing on high service quality and low-cost airlines.

The rest of this paper is organized as follows: Section 2 presents a review of literature related to service quality and service productivity. Section 3 describes a theoretical framework for SQ-adjusted DEA. Section 4 provides the results of data analysis. Section 5 presents a discussion of the results, including their implications for managers. Finally, Section 6 offers some concluding remarks, as well as the limitations of the study.

2 Literature review

2.1 Operational efficiency in the airline industry

Airline operational efficiency has been challenging due to the deregulation in 1978, an expansion of the market, and structural changes. Studies that specifically applied DEA in the airline industry have chiefly focused on measuring operational efficiency or presenting a comparative case study (Rhoades and Waguespack 2008). Good et al. (1993) explored the effect of the airline industry's privatization and deregulation on productivity and efficiency by comparing four European airlines and eight American airlines. That study showed that an increase in route density, particularly for those routes that were long distance or flown by a large airline, is positively associated with productivity.

2.2 Service quality in the airline industry

Service quality has become an essential component of organizational competitiveness, particularly for improving customer expectations and organizational performance in the service industry (Evans and Lindsay 2009). Typically, service quality is measured as the difference between what a consumer expects and what the consumer perceives that he/she received (Parasuraman et al. 1988). Many studies have measured service quality with Parasuraman et al.'s (1988) SERVQUAL model or Cronin and Taylor's (1992) SERVPERF model. In addition to these, airline carriers have used a variety of other measurement tools to measure the quality of the services they provide (Lapré and Scudder 2004; Tsikriktsis 2007; Tiernan et al. 2008). Specifically, many airline carriers have focused on service quality on the basis of consumers' perceptions of things like schedule and price (Headley and Bowen 1997; Tiernan et al. 2008; Gnanlet and Yayla-Kullu 2013). Airline carriers have also recognized that customer satisfaction and high service quality are key factors that affect customers' decisions to choose a given airline.

Metrics have been developed by two groups of researchers. In 1991, the Aviation Institute at the University of Nebraska-Omaha developed the airline quality rating (AQR) scale as "an objective method for assessing airline quality on combined multiple performance criteria" (Bowen and Headley 2012). As of 1993, the AQR scale provided a weighted average of 19 factors that influence customers' perceptions of an airline's quality. These factors included: the average age of the airline's fleet, the number of aircrafts owned by the airline, the extent to which the airline's flights were on time, the load factor, pilot deviations, the number of accidents an airline suffered, frequent flier awards, flight problems, overbooking, mishandled baggage, fares, refunds, customer service, ticketing/boarding, advertising, credit, financial stability, average seat-mile cost, and a miscellaneous category (Headley and Bowen 1997). To calculate quality scores for airlines, we consider AQR scores from four areas (on-time performance, involuntary boarding denial, reports of mishandled baggage, and consumer complaints).

Although the AQR model is widely used as a tool to measure service quality within the airline industry, some scholars identified its inherent limitations. Rhoades and Waguespack (1999) indicated that in the weighted average formula, there are negative influences (e.g., load factor) on the financial performance of airline carriers. Despite arguments to the contrary, we believe AQR to be a valid instrument for measuring airline service quality. Therefore, in this study, we utilize AQR scores of US-based airlines between 2008 and 2011 as data.

2.3 Service quality and productivity

Since the goal of a service firm is to cultivate customer satisfaction through the delivery of a high-quality experience, a low-quality service indicates a service failure, which can lead to customer defection. As such, a firm's service quality should be incorporated into any measure of that firm's productivity (Calabrese 2012).

Although service quality and productivity are often considered conceptually distinct, many studies (in addition to those referenced above) have assumed that there exists a relationship between them (Lapré and Scudder 2004; Frei 2006; Calabrese 2012). Therefore, in this study, we explore service productivity and quality, and explain the outputs from the two (see Fig. 1). To comprehensively explore the distinct and interrelated natures of service productivity and quality, productivity must be observed from the perspective of both the firm and the customer (Parasuraman 2010a, b). From the perspective of the firm, an increase in service resources can yield an improvement in service quality. From the perspective of the consumer, an increase in service quality indicates improved results. These dual perspectives of service productivity through service quality can be identified (Parasuraman 2010a, b).

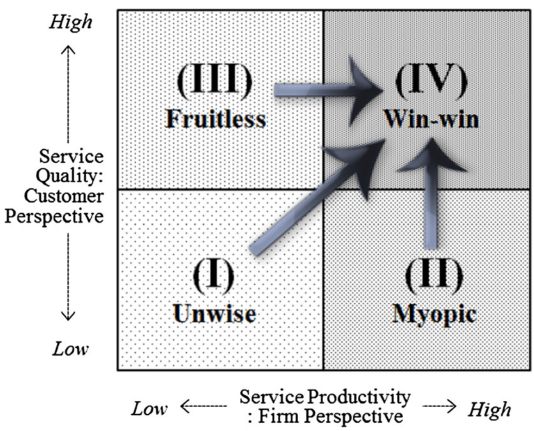
Although it is possible to examine service productivity and quality in conjunction with each other, there exist relationships among service resource inputs, service quality, and service output. Increased service resource inputs may improve a customer's perceptions of service quality but improved perceptions of service quality may not necessarily increase service output. Given this, there are four possible scenarios related to resource inputs, service quality, and service output. These scenarios are illustrated in Fig. 1 and described in the following sections.

2.3.1 Quadrant I: the unwise scenario

$$\Delta\ \mathit{Input}\ (\uparrow\uparrow\uparrow) \rightarrow^{+} \Delta\ \mathit{Service\ Quality}\ (\uparrow\uparrow) \rightarrow^{+} \Delta\ \mathit{Output}\ (\uparrow)$$

In Quadrant I, service resource inputs are relatively ineffective with respect to service productivity and quality. A service firm must distribute resource inputs on the basis of customers' needs, expectations, technical maturity, and ability to handle the service provided. However, firms in this quadrant inefficiently increase service resource inputs due to a lack of knowledge regarding customers' preferences. As a result, this scenario is referred to as "unwise."Service quality begins from the comparison of service by what the customer thinks they should receive and what the customer actually received. Customers have expectations about the quality of the services they are provided. In short, most customers feel that a company must provide the best service possible. However, firms that do not efficiently distribute resource inputs to improve service quality risk causing gaps between the service quality expectations and the actual quality of the service that is delivered (Parasuraman 2010a). This situation poses a constant threat to firms, as it is very difficult to continuously provide a high-quality service.

Fig. 1 Excelling in the marketplace through service quality and productivity



2.3.2 Quadrant II: the myopic scenario

$$\Delta\ \textit{Input}\ (\Uparrow\Uparrow) \rightarrow^{+} \Delta\ \textit{Service Quality}\ (\Uparrow) \rightarrow^{+} \Delta\ \textit{Output}\ (\Uparrow\Uparrow\Uparrow)$$

In Quadrant II, consumer perceptions of service quality are low relative to the amount of resource inputs provided by the firm. Despite low perceptions of service quality, high levels of output are nonetheless experienced. For example, consider a hotel that develops a device that allows a guest to control all the electronic equipment in a room as a means to improve service quality. Although this may improve the customer's experience, he/she may be unfamiliar with its use, resulting in customer dissatisfaction. Nevertheless, the hotel will likely increase its productivity through the implementation of the device. This scenario is referred to as "myopic."In the Myopic Scenario, service productivity may increase in the short term. However, customer complaints will gradually multiply, resulting in customers' reduced intention to purchase the services. Taken together, these conditions will eventually decrease service productivity. If the company tends to overemphasize service productivity, then service quality will suffer. As a result, service quality improvement strategies are needed in conjunction with strategies that focus on service productivity.

2.3.3 Quadrant III: the fruitless scenario

$$\Delta\ \textit{Input}\ (\Uparrow\Uparrow) \rightarrow^{+} \Delta\ \textit{Service Quality}\ (\Uparrow\Uparrow\Uparrow) \rightarrow^{+} \Delta\ \textit{Output}\ (\Uparrow)$$

In Quadrant III, service quality is relatively high as a result of increased levels of service resource inputs, but service productivity is relatively low. This scenario, which demonstrates the traditional tradeoff relationship between service quality and productivity, is called the "fruitless" scenario. This scenario occurs when improvements in service quality do not generate customers' purchase intentions. This, in turn, results in low organizational performance for the firm. In the Fruitless Scenario, there exists no significant, positive relationship between service quality, customer satisfaction, or organizational performance.In the Fruitless Scenario, efforts to improve service quality through resource inputs cause short-term decrease in productivity resulting from high initial expenses. However, the strategy can ultimately produce long-term benefits to organizational performance through improvements in service quality and subsequent customer satisfaction (Grönroos and Ojasalo 2004; Parasuraman 2010a, b). Therefore, an increase in service resource inputs may contribute to the improvement of service productivity in the long term. Given these relationships, the Fruitless Scenario requires a measurement of service productivity that accounts for service quality. A firm may risk a decrease in service productivity in the short term if the firm excessively pursues a service-oriented strategy. As such, firms must establish a strategy that considers both service productivity and quality.

2.3.4 Quadrant IV: the win–win scenario

$$\Delta\ Input\ (\uparrow) \rightarrow^{+} \Delta\ Service\ Quality\ (\uparrow\uparrow) \rightarrow^{+} \Delta\ Output\ (\uparrow\uparrow\uparrow)$$

In Quadrant IV, service resource inputs are sufficiently high to improve service quality, which allows gains in service outputs. As a result of the increased service inputs dedicated to both service quality and productivity, and the resulting financial gains earned by the firm, this is called a “win–win” scenario.According to previous studies (Nachum 1999; Grönroos and Ojasalo 2004; Parasuraman 2010b), a firm’s dedication of resources (e.g., human resources and material) to increase service quality leads to customer satisfaction, subsequent purchase intention, and overall improved organizational performance. Given this, the win–win scenario represents the optimal strategy for the firm.

To choose the optimal service type from the perspectives of both the firm and the customer, firms must identify the characteristics of its customers that influence their preferences. The redistribution of resources is a critical issue when a firm considers which operational strategy to pursue. As such, firms must consider consumers’ expectations in making resource investment decisions.

To develop methods by which a “win–win” strategy can be realized, this study identifies conceptual problems in previous studies that utilized the standard DEA model to gauge service productivity. In addition, this study provides an alternative to the standard DEA model whereby service productivity is measured in conjunction with service quality. This alternative method, the SQ-adjusted DEA, is explicated in the following section.

3 Theoretical framework: SQ-adjusted DEA

Generally, service productivity is defined as a measure of how effectively resource inputs are converted into outputs. As such, high levels of productivity result from the use of small amounts of resources to maximize performance. Stated simply, service productivity is the ratio of outputs (e.g., high product quality and customer satisfaction) to inputs (e.g., raw materials and manpower). Using the DEA method without considering quality aspects to perform an analysis of organizational efficiency can result in managerial problems (Thanassoulis et al. 1995; Lin 2005). There is not an automatic conflict among objectives. For instance, Toyota’s lean management approach seeks to improve both quality and productivity simultaneously. Nonetheless, airlines face a number of factors where improvement on one factor can lead to detriment of another.

For example, if a decision-marking unit (DMU) uses resources to improve the quality of its goods or services rather than increase its output, the DMU can be considered efficient on the basis of quality-related criteria, but inefficient with respect to quantitative output (Schmenner 1986). In contrast, another DMU may utilize its resources to improve the firm’s productive capacity rather than the quality of its products. In this case, that firm will be judged as efficient with respect to quantitative output but inefficient with respect to quality. The latter case represents a situation in which the original purpose for benchmarking is violated.

There are two types of models that analyze organizational efficiency using quality *attributes*. The first type of model adds desirable output attributes into output variables. The other type of model is referred to as a "negative DEA" which adds undesirable output attributes into the model on the basis of the DMU's choices. Consequently, the efficiency is higher when desirable output attributes using DEA with larger desirable output attributes and smaller undesirable output attributes.

Thanassoulis et al. (1995) added two output variables in their study of DEA on perinatal medical treatment in the UK. These output variables included patients' perceptions of the quality of health service and survival rate of babies at risk (as a proxy measure for the quality of prenatal medical outcomes). Prior (2006) analyzed the model by adding the level of nosocomial infections as a negative outcome. Prior's (2006) study proposed that positive quality attributes are considered to be desirable inputs and that negative quality attributes are considered to be strongly desirable disposable inputs. Finally, in their study on power transmission networks in the UK, Giannakis et al. (2005) incorporated a number of interruptions and customer time loss due to those interruptions in their model.

Despite the number of studies that incorporated various inputs into their model, a question remains. Although quality attributes have been reasonably selected in past research, the inclusion of too much quality attributes as inputs can inflate estimates of organizational efficiency, providing a skewed representation of the firm's true operational effectiveness. Though useful for understanding how a number of inputs and outputs relate, results derived from the attribute approach to gauging efficiency are difficult to interpret given that quantitative scores are not considered. The second type of model for evaluating organizational efficiency redresses this shortcoming.

Rouse et al. (2002) utilized quality *score* indices to evaluate efficiency. Soteriou and Zenios (1999) and Soteriou and Stavrinides (2000) analyzed DEA with a single indicator for service quality that was recognized by internal and external customers. In their studies, the model stipulates that input variables are quantitatively conceptualized but output variables are not. As a result, increases in inputs but not outputs are relative to the DMU. Hence, this model may be useful for explaining efficiency in terms of the size of the DMU. By using output variables that relate only to service quality, this model violates the DEA's assumption that the DMU is a productive unit that converts input into output. For example, in their study related to international airline carriers' service performance, Rouse et al. (2002) conceptualized delivery performance, total hours charged, and time spent on capital improvements as quantitative outputs. In addition to these quantitative output measures, this model also included an output variable based on a quality score index. They argued that the inclusion of the quality score index provided a more balanced evaluation of organizational performance. However, this model has an issue that the DMU with lower service quality is considered as a target of benchmarking.

Sherman and Zhu (2006) treated quality and efficiency as independent factors for organizational efficiency and, respectively, represented them on the x- and y-axis of a graph. This approach was applied to banking services (Sherman and Zhu 2009). In their study, they considered DMUs that produced high-quality and high-productivity services (HQ-HP) as benchmarks, and excluded low-quality and high-productivity firms (LQ-HP) on the basis of the reference group. They suggested the use of a multi-stage DEA model called quality-adjusted DEA (Q-DEA), which incorporates service quality into an algorithm by controlling for the influence of LQ-HP. Despite its strengths, this model has a limitation in that it is reliant on low-quality DMU. As such, it may be difficult to identify benchmarks if DMUs are in the LQ-HP quadrant. Brissimis and Zervopoulos (2012) proposed a modified version of the DEA which is inherently quality-driven (MQE-DEA) to address the limitations encountered by Sherman and Zhu (2006). The MQE-DEA establishes target values for endogenous and exogenous inputs. In this way, the MQE-DEA model provides estimates for feasible short- and long-term optimization solutions for the process by which goods and services are produced.

This study further extends the quality-adjusted DEA model. As a result of the quality-adjusted DEA model's extensive use in the public sector, such as the education (Färe et al. 2006; Khan et al. 2008) and healthcare industries (Chang et al. 2011), it has become clear that the value of the model's output that can be increased to a degree that is proportional to the level of service quality the model means to evaluate. Given this, our new model is called the SQ-adjusted DEA.

Depending on the cost associated with improving the quality of a service, DMUs that deliver services of higher quality produce higher service outcomes and DMUs with lower service quality produce lower service outcomes. This generated a new variable by multiplying the service output by the service quality index. In addition, service quality as conceptualized with quality criteria generates a new variable through the conversion of a service quality index (Färe et al. 2006; Chang et al. 2011).

Empirical research by Fixler and Zieschang (1992) developed a "multifactor productivity index" for commercial banks. In their model, the "Fisher input-oriented multifactor productivity index" is calculated as $P_x^F(x^0, x^1, a^0, a^1, y^0, y^1) = B \times P_x{}^{ccd}$ through multiplication of "the characteristics conditional productivity index" of Caves et al. (1982), $P_x{}^{ccd}$, and quality adjustment factor B. Friesner (2003) defined the service output of a healthcare provider as a quality-adjusted output (Y_i). Y_i was computed by multiplying the total number of patients in the hospital (X_i) by the quality of the service provided (q_i). Färe et al. (2006) and Chang et al. (2011) suggested that the quality-augmented Malmquist productivity change index (QMI) is computed by multiplying relative efficiency change (EC), technical change (TC), and quality change (QC).

Following in respective traditions of these conceptualizations, the SQ-adjusted DEA computes service productivity by multiplying service output by a service quality index (SQI) that is converted into a ratio scale such that it ranges from 0 to 1. Specifically, the SQ-adjusted DEA in this study is calculated as:

$$\begin{aligned}&\text{Service Quality} - \text{adjusted Output}\\&= \text{Quantity of Output} \times \text{Service Quality Index}\\&(\text{if}, 0 < \text{Service Quality Index} \leq 1)\end{aligned}$$

The SQ-adjusted CCR Model (output-oriented) used in this study is calculated as:

$$\begin{aligned}\phi^{k*} &= \max_{\theta,\lambda,s-,s+} \phi^k + \varepsilon\left(\sum_{m=1}^{M} s_m^- + \sum_{n=1}^{N} s_m^+\right)\\ s.t. x_m^k &\geq \sum_{j=1}^{J} x_m^j \lambda^j + s_m^- \quad (m = 1, 2, \cdots, M);\\ \phi^k y_n^k &\leq \sum_{j=1}^{J} Q_n^j y_n^j \lambda^j - s_n^+ \quad (n = 1, 2, \cdots, N);\\ \lambda^j &\geq 0,\ 0 < Q_n^j \leq 1 \quad (j = 1, 2, \cdots, J)\end{aligned}$$

The SQI that represents service quality is computed by standardizing the measured score of service quality such that it ranges from 0 to 1 (i.e., service quality score = 100, SQI = 1). When the service quality index score is less than 1 (i.e., 0 < service quality score ≤ 100, 0 < service quality index ≤ 1), output decreases proportionally with the SQI score. This model indicates that service quality is inversely and proportionally related to the distance from the origin.

4 From theory to empirics

In this study, we develop assessment criteria for service productivity in the airline industry and analyze the service productivity of 12 American airline carriers using the SQ-adjusted DEA. In addition, we use the SQ-adjusted DEA to identify differences between NCs and LCCs.

Given that we utilize a novel approach for measuring efficiency, this study significantly deviates from previous research in three key ways. First, we utilize the SQ-adjusted DEA to consider measurement items for service quality. Second, we compare the standard DEA and the SQ-adjusted DEA in terms of calculation efficiency. Finally, we employ longitudinal data from 2008 to 2011.

4.1 Data collection

Data for this study were acquired from the US Department of Transportation's monthly Air Travel Consumer Report and the Bureau of Transportation Statistics. From these sources, we collected data from 12 US-based airlines over a four-year period, from 2008 to 2011. These airlines included AirTran Airways (FL), Alaska Airlines (AS), American Airlines (AA), American Eagle (MQ), Delta Air Lines (DL), Frontier Airlines (F9), Hawaiian Airlines (HA), JetBlue Airways (B6), SkyWest Airlines (OO), Southwest Airlines (WN), United Airlines (UA), and US Airways (US). In addition, SQI scores, which are announced annually by AQR, were used as proxy variables for the measurement of service quality.

Table 1 Descriptive statistics for inputs and outputs

		2008	2009	2010	2011
Total number of employees	Arithmetic mean	24,987	24,744	27,221	27,691
	Standard deviation	22,961.12	22,371.49	26,625.49	26,580.12
	Maximum	75,074	71,450	82,424	81,853
	Minimum	3,707	3,844	4,023	4,314
Available seat miles (ASM)	Arithmetic mean	60,710,001	57,117,210	64,109,455	60,167,768
	Standard deviation	56,746,984.76	52,381,540.10	63,488,681.21	58,517,270.67
	Maximum	163,384,378	151,587,373	195,540,168	182,400,046
	Minimum	9,490,183	9,694,579	10,125,903	10,812,158
Revenue passenger miles (RPM)	Arithmetic mean	48,200,846	45,944,952	52,826,528	49,782,051
	Standard deviation	45,649,222.10	42,517,181.84	52,918,647.10	48,517,446.28
	Maximum	131,663,198	122,304,104	164,152,874	151,750,839
	Minimum	7,383,756	7,146,149	7,985,814	8,335,335
Operating revenue	Arithmetic mean	8,701,899	7,495,356	9,531,576	10,554,623
	Standard deviation	8,633,479.01	7,216,181.73	10,199,111.87	11,099,107.75
	Maximum	23,696,100	19,898,245	31,893,702	35,271,378
	Minimum	1,211,733	1,113,397	1,312,221	1,651,121
Service quality index	Arithmetic mean	0.63	0.58	0.66	0.67
	Standard deviation	0.24	0.20	0.21	0.22
	Maximum	0.94	0.84	0.91	0.90
	Minimum	0.08	0.09	0.08	0.07

To measure service productivity for each respective airline, we treated total number of employees and available seat miles (ASM) as input variables, and revenue passenger miles (RPM) and operating revenue as outcome measures. Since the airline industry is labor-intensive, our incorporation of the total number of employees into the model as an input variable was intended to reflect the degree of interaction that a particular airline carrier's employees may have with customers. The inclusion of ASM as an input variable and RPM as an outcome measure is well-established in the literature on DEA analyses of the airline industry (Barbot et al. 2008; Barros and Peypoch 2009; Merkert and Hensher 2011). Further, we treated operating revenue as an outcome measure because it is particularly sensitive to, and thus, highly indicative of, changes in service quality (see Table 1).

As discussed above, we used Bowen and Headley's (1991) AQR to assess functional service quality in the airline industry. Based on a report by the US

Table 2 The definition & formulation of AQR (*Source* Airline Quality Rating Reports)

Factor	Weight	Description
On-time performance (OT)	+8.63	Regularly published data regarding on-time arrival performance is obtained from the U.S. Department of Transportation's Air Travel Consumer Report. According to the DOT, a flight is counted "on time" if it is operated within 15 min of the scheduled time shown in the carriers' Computerized Reservations Systems. The AQR calculations use the percentage of flights arriving on time for each airline for each month
Mishandled baggage reports (MB)	−7.92	Regularly published data regarding consumer reports to the carriers of mishandled baggage can be obtained from the U.S. Department of Transportation's Air Travel Consumer Report. According to the DOT, a mishandled bag includes claims for lost, damaged, delayed, or pilfered baggage. Data are reported by carriers as to the rate of mishandled baggage reports per 1,000 passengers and for the industry. The AQR ratio is based on the total number of reports each carrier received from passengers concerning lost, damaged, delayed, or pilfered baggage per 1,000 passengers served
Involuntary denied boardings (DB)	−8.03	This criterion includes involuntary denied boardings. Data regarding denied boardings can be obtained from the U.S. Department of Transportation's Air Travel Consumer Report. Data include the number of passengers who hold confirmed reservations and are involuntarily denied boarding on a flight that is oversold. These figures include only passengers whose oversold flight departs without them onboard. The AQR uses the ratio of involuntary denied boardings per 10,000 passengers boarded by month
Consumer complaints (CC)	−7.17	The criteria of consumer complaints are made up of 12 specific complaint categories monitored by the U. S. Department of Transportation and reported monthly in the Air Travel Consumer Report. Consumers can file complaints with the DOT in writing, by telephone, via e-mail, or in person. The AQR uses complaints about the various categories as part of the larger customer complaint criteria and calculates the consumer complaint ratio on the number of complaints received per 100,000 passengers flown for each airline

$\mathrm{AQR} = \frac{8.63\times \mathrm{OT} - 7.92\times \mathrm{MB} - 8.03\times \mathrm{DB} - 7.17\times \mathrm{CC}}{8.63+7.92+8.03+7.17}$

Department of Transportation (DOT), the primary role of the AQR is to establish the respective importance of four factors that could influence consumers' perceptions of airline quality, and then determine each airline's service quality through a weighted average calculation that incorporates those factors.

The AQR uses the following four factors to determine an airline's service quality: on-time arrival (OT), mishandled baggage (MB), involuntary denied boarding (DB), and 12 types of customer complaint. In addition, a constant value in the denominator represents the relative importance of each factor (see Table 2).

4.2 Calculation of service quality index (SQI)

Since SQ-adjusted DEA is calculated by multiplying the service output by SQI, existing AQR scores must be converted to a standardized SQI value that falls somewhere between 0 and 1. An SQI value of 1 indicates a service quality score of 100 (i.e., perfect output). When an airline's SQI value is less than 1, output decreases proportionally with it.

Upper bound (f) and lower bound (f) are computed with *f (upper bound) = max OT + min (MB, DB, CC)* and *f (lower bound) = min OT + max (MB, DB, CC)*, respectively. The upper and lower bound values are calculated by a range of setting of years. Additionally, the AQR score for each DMU is converted to its corresponding value between 0 and 1, and the converted score is further transformed to an SQI score. For example, the ranges of SQI scores for each airline are depicted in Fig. 2. Each DMU is marked with its respective upper and lower bound. The numbers in parentheses are the SQI scores for each respective airline carrier.

4.3 Results of SQ-adjusted DEA on US airlines

The chief goals of this study are to analyze differences between the standard DEA and the SQ-adjusted DEA, and examine airline efficiency using the SQ-adjusted DEA on 12 US airlines consisting of NCs and LCCs. This section reports the results of the analyses we conducted to achieve these goals.

First, the average AQR score for all the LCCs, FL, F9, HA, B6, OO, and WN, except MQ, was 0.73. MQ not used to calculate average AQR because its score was an outlier (too low). The average AQR score for NCs was 0.63. Among the LCCs, FL, MQ, HA, UA, and US were shown to be efficient prior to quality adjustment. Of these airlines, only FL and HA remained efficient after quality adjustments. There were no efficient NCs after quality adjustments were made.

As stated above, LCCs provide cheaper fares than those offered by other airlines. Because of decreased revenue associated with these lower fares, LCCs have largely adopted an approach that provides minimal services to reduce operating costs. For example, many LCCs have eliminated VIP lounges at airports, reduced the number

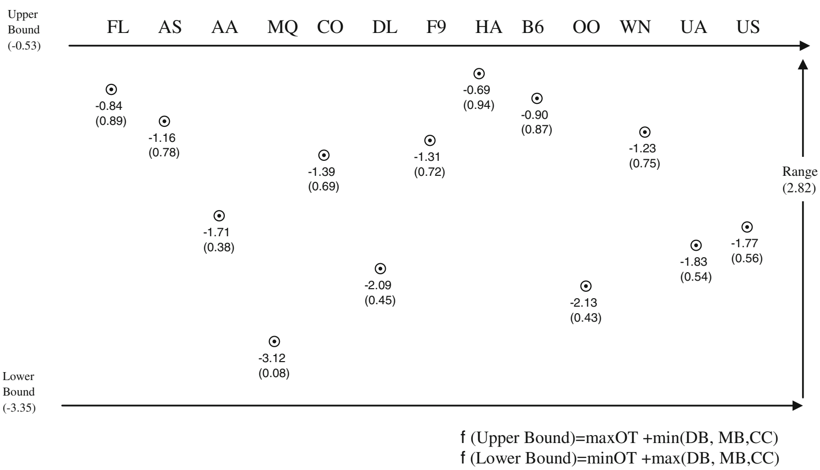


Fig. 2 The change of service quality index from AQL score in 2008 year

of flight attendants to their legal minimum per flight, and done away with first- and business-class flight options. Nevertheless, the fact that the AQR scores for LCCs are higher than those for NCs suggests that the NCs suffer operational problems while the LCCs are operationally efficient. Since customers who use NCs typically have high expectations about the quality of the airline service they are to receive, the gap between expected and actual service quality can be significant.

On the contrary, passengers who use LCCs typically expect a low level of service quality. Therefore, small improvements can translate to perceptions of high service quality among passengers. To exploit this, LCCs have recently begun to provide a number of services to customers that they had previously not offered. These improvements have resulted in higher perceptions of service quality among passengers and an increase in service productivity. These results, as well as those for the NCs, are shown in Table 3.

The analyses also demonstrated that among LCCs, MQ is the most efficient airline. Regardless of its service quality, MQ generates high levels of service productivity. In contrast, WN is perceived well in terms of service quality but service productivity is low. Taken together, MQ and WN demonstrate the long-established negative correlation between service quality and service productivity.

FL and HA demonstrated high levels of service quality and productivity. In contrast, OO was shown to have lower levels of service productivity and service quality. In contrast to the relationships depicted above, the mutually positive relationships for service productivity and quality associated with FL and HA, in conjunction with the mutually negative relationships for service productivity and quality associated with OO collectively demonstrated a positive correlation between service productivity and quality. B6 was shown to have service quality and productivity levels that were relatively close to the average. As a consequence, it is difficult to interpret the relationship between service quality and service productivity for that airline carrier.

Finally, among the NCs, DL, UA, and US showed higher levels of service productivity and lower levels of service quality in 2008 and 2009. Additionally, AS demonstrated relatively better service productivity associated with higher levels of service quality. As such, UA, US, and AS illustrated the existence of a tradeoff between service quality and service productivity. Like OO, however, AA was characterized as low service quality and productivity, thus providing evidence against the presence of an inherent tradeoff.

4.4 Mann–Whitney test between NC and LCC

The respective efficiencies of the individual airline carriers may be attributable to the group for which they were assigned. This seems common sense, as different levels of efficiency were expected for NCs and LCCs. Therefore, to compare LCCs and NCs on the basis of their collective efficiencies, we employed a Mann–Whitney test to analyze the differences between the two groups. The Mann–Whitney test is used to empirically examine differences between two groups when one (or both) group(s) are either non-normally distributed or comprised fewer than 30 observations.

Table 3 The results of U.S. airline standard DEA and SQ-adjusted DEA

Carrier	DMU	Year	Standard DEA				SQ-adjusted output DEA				AQL score		Score variation
			Efficiency	Excessive input		Reference	Efficiency	Excessive input		Reference			
				Input 1	Input 2			Input 1	Input 2				
LCC	AirTran (FL)	2008	1.000	0	0	FL	1.000	0	0	FL	0.89	◎	
		2009	1.000	0	0	FL	1.000	0	0	FL	0.82	o	
		2010	1.000	0	0	FL	1.000	0	0	FL	0.91	◎	
		2011	1.000	0	0	FL	1.000	0	0	FL	0.90	◎	
	American Eagle (MQ)	2008	1.000	0	0	MQ	0.144	9,391	8,874,077	HA	0.08	▼	0.856
		2009	1.000	0	0	MQ	0.169	9,163	8,157,396	HA	0.09	▼	0.832
		2010	1.000	0	0	MQ	0.130	9,756	9,393,304	US	0.08	▼	0.870
		2011	0.982	5,724	207,888	US	0.098	10,567	10,090,093	DL	0.07	▼	0.884
	Frontier (F9)	2008	0.990	194	114,771	HA	0.759	1,280	2,895,395	HA	0.72	o	0.231
		2009	0.966	1,684	354,775	HA	0.722	2,706	2,930,625	HA	0.63	▼	0.244
		2010	0.977	1,283	253,955	HA	0.704	2,479	3,263,374	HA	0.63	▼	0.273
		2011	1.000	0	0	F9	0.951	1,222	533,722	FL,HA	0.79	o	0.049
	Hawaiian (HA)	2008	1.000	0	0	HA	1.000	0	0	HA	0.94	◎	
		2009	1.000	0	0	HA	1.000	0	0	HA	0.84	o	
		2010	1.000	0	0	HA	1.000	0	0	HA	0.87	◎	
		2011	0.996	18	45,451	FL,AS	1.000	0	0	HA	0.85	◎	−0.004
	JetBlue (B6)	2008	0.989	134	365,266	FL,DL	0.934	788	2,155,456	FL,HA	0.87	◎	0.055
		2009	0.963	464	1,205,544	FL,HA	0.893	1,346	3,497,491	FL,HA	0.78	o	0.071
		2010	0.977	299	801,081	FL,HA	0.911	1,159	3,110,226	FL,HA	0.83	o	0.066
		2011	0.968	454	1,097,101	AS,F9	0.957	2,028	1,449,251	FL,HA	0.85	◎	0.010

Table 3 continued

Carrier	DMU	Year	Standard DEA				SQ-adjusted output DEA				AQL score		Score variation
			Efficiency	Excessive input		Reference	Efficiency	Excessive input		Reference			
				Input 1	Input 2			Input 1	Input 2				
	SkyWest (OO)	2008	0.927	4,710	1,065,850	DL,HA	0.507	6,996	7,211,338	HA	0.43	▼	0.421
		2009	0.932	4,008	1,015,119	DL,HA	0.540	6,381	6,902,422	HA	0.48	▼	0.392
		2010	0.926	3,941	1,235,617	HA	0.663	5,690	5,637,347	HA	0.62	▼	0.263
		2011	0.917	3,459	1,298,957	F9	0.681	6,492	4,991,987	FL,HA	0.63	▼	0.236
	Southwest (WN)	2008	0.889	3,994	11,504,600	FL,DL	0.760	8,611	30,540,495	FL,HA	0.75	o	0.129
		2009	0.988	406	5,228,919	FL,UA	0.797	6,906	26,595,028	FL,HA	0.66	∆	0.191
		2010	0.974	907	3,535,145	FL,UA	0.866	4,731	13,195,861	FL,HA	0.72	o	0.108
		2011	0.951	1,884	4,718,472	AS,F9	0.801	8,117	18,955,948	FL,HA	0.72	o	0.149
Major	Alaska (AS)	2008	0.938	1,453	1,514,442	DL,HA	0.859	2,082	3,412,785	HA	0.78	o	0.079
		2009	0.955	668	1,033,591	DL,HA	0.680	3,690	7,387,311	HA	0.54	▼	0.275
		2010	0.980	189	481,311	FL,HA,UA	0.936	617	1,568,739	FL,HA	0.74	o	0.045
		2011	1.000	0	0	AS	1.000	0	0	AS	0.77	o	
	American (AA)	2008	0.978	13,766	3,530,604	DL,HA	0.700	30,397	49,007,743	HA	0.58	▼	0.278
		2009	0.970	10,042	4,551,331	DL,HA	0.740	26,961	39,385,224	HA	0.58	▼	0.230
		2010	0.966	12,238	5,195,585	HA,UA	0.800	18,780	30,691,561	HA,US	0.62	▼	0.167
		2011	0.959	8,301	5,797,967	F9,UA	0.715	27,667	40,287,904	DL,HA	0.59	▼	0.244
	Delta (DL)	2008	1.000	0	0	DL	0.630	17,877	49,894,817	HA	0.45	▼	0.371
		2009	1.000	0	0	DL	0.624	23,247	45,653,747	HA	0.43	▼	0.376
		2010	0.996	6,751	785,140	HA,UA	0.932	5,638	13,375,642	HA,US	0.65	∆	0.064
		2011	0.987	3,208	2,331,958	F9,UA	1.000	0	0	DL	0.77	o	−0.013

Table 3 continued

Carrier	DMU	Year	Standard DEA				SQ-adjusted output DEA				AQL score		Score variation
			Efficiency	Excessive input		Reference	Efficiency	Excessive input		Reference			
				Input 1	Input 2			Input 1	Input 2				
	United (UA)	2008	1.000	0	0	UA	0.728	13,210	42,695,036	HA	0.54	▼	0.272
		2009	1.000	0	0	UA	0.711	13,467	36,394,493	HA	0.53	▼	0.289
		2010	1.000	0	0	UA	0.918	3,804	9,798,788	FL,HA	0.61	▼	0.082
		2011	1.000	0	0	UA	0.685	14,626	33,655,131	AS,DL	0.51	▼	0.315
	US Airways (US)	2008	1.000	0	0	US	0.782	11,179	16,161,830	HA	0.56	▼	0.218
		2009	1.000	0	0	US	0.888	7,147	7,936,198	HA	0.60	▼	0.112
		2010	1.000	0	0	US	1.000	0	0	US	0.66	Δ	
		2011	1.000	0	0	US	0.856	6,785	9,601,685	DL	0.64	▼	0.144

⊙: AQL $\geq$ 0.85, o: 0.70 < AQL $\leq$ 0.85, Δ: 0.65 < AQL $\leq$ 0.70, ▼: AQL $\leq$ 0.65

As demonstrated by Table 4, between 2008 and 2011, the NCs and LCCs maintain nearly the same level of efficiency according to the standard DEA and the SQ-adjusted DEA. In the study, the Mann–Whitney test verifies this perceptible trend, as there is no overall significant difference between NCs and LCCs with respect to efficiency. However, when the analysis is isolated to 2010 and 2011, results of the SQ-adjusted DEA suggest that LCCs may be more efficient than NCs. Despite this possibility, the failure of the Mann–Whitney test to identify a statistically significant difference in the efficiency of the two groups makes it difficult to conclude that the respective efficiencies of the groups differ.

5 Managerial implications

Given the findings reported above, there are several implications of this study that may be important for understanding the airline industry and its operations. First, after quality adjustment, WN moved from Quadrant III (Fruitless Scenario) to Quadrant IV (win–win scenario). This indicates that DMUs do not exist in the Fruitless Scenario. By analyzing service productivity with SQ-adjusted DEA, this result illustrates that quality and productivity can both be attained. As service quality improves, customer satisfaction also improves, which leads to an increase in service productivity. Therefore, the results of this study suggest that organizations must develop strategic methods for improving service quality (and, as a result, service productivity) by leveraging inputs of service resources.

Second, the results show that the ways in which the airlines are evaluated with respect to service productivity differs as a function of the methodology employed (see Fig. 3). For example, the results show that after the quality adjustment, several DMUs' (DL, UA, and US) respective levels of service productivity were reduced. However, AA and AS, which initially suffered from low levels of service productivity, experienced a service productivity increase after adjustment. B6, OO, and WN also showed general increases in service productivity as a result of the SQ-adjusted DEA. On the other hand, MQ, which was considered to be an effective company among DMUs, was shown to be inefficient by the SQ-adjusted DEA. These results suggest that SQ-adjusted DEA generates a more comprehensive view of service productivity than had previously been possible through the standard DEA. As such, this study has shown that the SQ-adjusted DEA model is an effective tool for gauging service productivity through comparative evaluation among DMUs.

Third, when evaluating their own service productivity, rather than using a universal method for evaluation, service firms must use a method that is in accordance with the firm's purpose or operational characteristics. Consider, for example, the differences that emerged between the LCCs and NCs. Analysis of the LCCs demonstrated that there is no relationship between service quality and productivity. As a result, low-cost airlines are better suited to be evaluated by the standard DEA because of a more complex relationship between service equality and productivity. Further, LCCs attain competitive advantages through price competitiveness and cost reduction rather than service quality. In contrast, it would be more

Table 4 Mann–Whitney test between NC and LCC

Variables		NC			LCC			Mann–Whitney U	Z	*P* value (two-side)
		Average efficiency	Average rank	Rank sum	Average efficiency	Average rank	Rank sum			
Efficiency (2008)	Standard	0.971	7.10	35.50	0.983	6.07	42.50	14.50	−0.520	0.603
	SQ-adj.	0.729	5.80	29.00	0.740	7.00	49.00	14.00	−0.569	0.569
Efficiency (2009)	Standard	0.978	7.10	35.50	0.985	6.07	42.50	14.50	−0.520	0.603
	SQ-adj.	0.731	5.60	28.00	0.728	7.14	50.00	13.00	−0.732	0.464
Efficiency (2010)	Standard	0.979	7.00	35.00	0.988	6.14	43.00	15.00	−0.422	0.673
	SQ-adj.	0.753	7.80	39.00	0.917	5.57	39.00	11.00	−1.063	0.288
Efficiency (2011)	Standard	0.973	7.80	39.00	0.989	5.57	39.00	11.00	−1.095	0.274
	SQ-adj.	0.784	6.80	34.00	0.852	6.29	44.00	16.00	−0.248	0.804

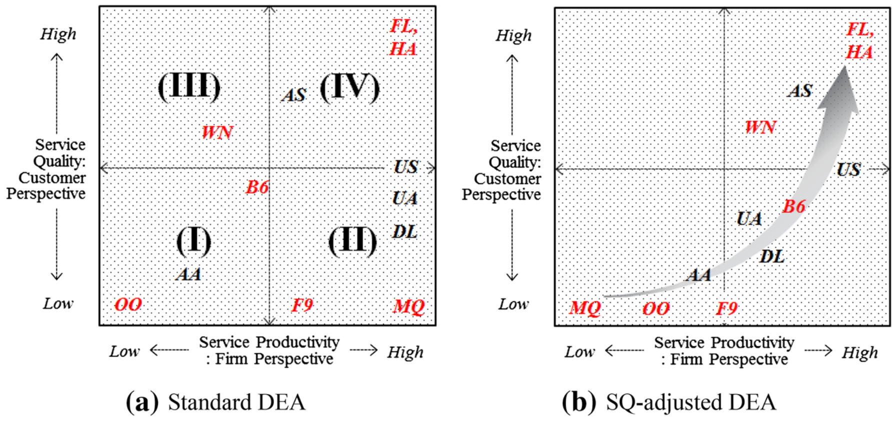


Fig. 3 The change of service productivity in U.S. airlines

appropriate to evaluate the service productivity of NCs with the SQ-adjusted DEA because NCs highlight the quality of their services to attain a competitive advantage.

Finally, the results of this study suggest that while service quality is an attractive quality element for LCCs, it is a required quality element in NCs (Kano et al. 1984). For LCCs, a high degree of service quality can provide satisfaction to customers whether it meets their expectations or not. For NCs, however, customers anticipate having their expectations met. Therefore, for NCs, increases in service quality may generate a relatively small increase in customer satisfaction, but a decrease in service quality results in large decrease in customer satisfaction. Consequently, service firms must strategically provide service quality that matches the firm's classification.

While customers who select NCs expect to receive the highest level of service quality, customers of LCCs are more motivated by the cost of the flight. Therefore, NCs must seek to improve service quality but LCCs can attain success through a strategic approach that forgoes service quality for the sake of lower airfares.

6 Conclusions

In response to the assertion that a measurement tool for service productivity that integrates service quality would be critically important for various service industries, this study proposed a model for evaluating the service productivity of airline carriers called the SQ-adjusted DEA. Relative to the standard DEA, the SQ-adjusted DEA places a greater emphasis on service quality as a factor that relates to service productivity.

As firms increasingly dedicate resources to improving service quality, they tend to focus on efficiency in the short term. However, in the long term, a focus on service quality may help to increase customer satisfaction, thus improving service productivity and overall organizational performance. However, because standard

DEA does not incorporate service quality into its calculations, it is limited in its ability to evaluate service productivity. In contrast, the SQ-adjusted DEA, which bases its calculations on service quality, is better suited to explore service productivity.

As mentioned above, firms that pursue an excessively quality-oriented strategy in the short term may risk decreasing their service productivity. Therefore, firms would do well to establish strategies that account for service productivity and quality. Doing so allows firms to pursue a "win–win" strategy that is characterized by a balance of service quality and productivity. The use of the SQ-adjusted DEA to measure service productivity may be especially useful for helping a firm to establish a strategy that can resolve balancing service quality and productivity.

Although the SQ-adjusted DEA model is clearly useful for firms that seek to develop optimal strategies for balancing quality with productivity, it can be a helpful tool for customers as well. Previous research has shown that improvements in service quality yields increased customer satisfaction (Grönroos and Ojasalo 2004; Parasuraman 2010a, b). In addition, increases in service output can be interpreted as increases in service productivity. Since the SQ-adjusted DEA model integrates these two concepts into one strategic measurement tool, it could be useful for customers that value service quality as a criterion with which to select an airline carrier.

According to Shmenner's service process matrix (1986), service firms are categorized into four areas on the basis of customization and labor intensity. According to the matrix, emphases on service quality or productivity are a function of the characteristics and operational tendencies of firms. The respective weights for service quality and productivity must be set on the basis of the stage of the life cycle in which the firm currently exists. Additionally, the weights must be set established as a function of a service quality (SQ)-focused strategy for NC customers and service productivity (SP)-focused strategy for LCC customers. This method of evaluation is contingent upon the careful identification of the strategic position or operational purpose of the firm. Given its incorporation of two evaluation indices (priority and weight), the SQ-adjusted DEA model may be useful for this type of integrated analysis.

Despite the contributions offered by this study, it does suffer from a few limitations. First, the AQR, which we used to measure airline service quality, is limited in its ability to sufficiently evaluate the nature or delivery of service quality. As such, service quality as evaluated by the AQR is likely different from service quality as perceived by customers (Gardner 2004). To remedy this issue, the development of a widely applicable service quality index that incorporates customer perceptions is required. For example, there are currently a number of tools that evaluate the service quality of airlines around the world. Some of these tools include the Airline of the year distinction by ATW, the World's 5-Star Airlines by *Skytrax*, and the Global Traveler Tested Awards by *Global Traveler*. Each of these measures of airline service quality incorporates some degree of customer perception. The use of these tools may assist in identifying critical factors related to service quality. These factors can then be applied to the SQ-adjusted DEA to more effectively measure service productivity.

Second, improved service quality does not necessarily lead to an immediate purchase. Generally, there is a time lag between customers' perceptions of the service quality and the purchase of that service. SQ-adjusted DEA does not account for this time lag. In this model, service productivity is calculated by multiplying SQI by service outcomes, both of which are measured during a fixed time period. Future studies can redress this shortcoming by incorporating variables that account for the time lag effect.

Third, because direct customer interaction is a critical component of service in the airline industry, all input and output variables in the SQ-adjusted DEA model relate to face-to-face interactions with customers. Since the SQ-adjusted DEA model does not account for other variables that might affect the quality of a service (e.g., available tonne-miles and passenger load factors), their respective influences on service quality and productivity cannot be inferred. A consideration of these variables in future research would produce a more comprehensive model for evaluating service quality.

Acknowledgments This Research was financially supported by Hansung University during sabbatical year (2013).

References

Barbot C, Costa Á, Sochirca E (2008) Airlines performance in the new market context: a comparative productivity and efficiency analysis. J Air Transp Manag 14:270–274

Barros CP, Peypoch N (2009) An evaluation of European airlines' operational performance. Int J Prod Econ 122(2):525–533

Bayraktar E, Tatoglu E, Turkyilmaz A, Delen D, Zaim S (2012) Measuring the efficiency of customer satisfaction and loyalty for mobile phone brands with DEA. Expert Syst Appl 39(1):99–106

Bhaskara V (2012) US air travelers face higher airfares in 2012. Aspire Aviation. http://www.aspireaviation.com/2012/01/05/us-airtravellers-face-higher-airfares-in-2012/. Accessed 9 Dec 2013

Bowen BD, Headley DE (2012) Airline quality rating report 2012. W. Frank Barton School of Business, Wichita, KS. www.aqr.aero

Brissimis NS, Zervopoulos DP (2012) Developing a step-by-step effectiveness assessment model for customer-oriented service organizations. Eur J Oper Res 223(1):226–233

Calabrese A (2012) Service productivity and service quality: a necessary trade-off? Int J Prod Econ 135(2):800–812

Caves DW, Christensen LR, Diewert WE (1982) The economic theory of index numbers and measurement of input, output, and productivity. Econometrica 50(6):1393–1414

Chang S, Hsiao H, Huang L, Chang H (2011) Taiwan quality indicator project and hospital productivity growth. Omega 39(1):14–22

Charnes A, Cooper WW, Thrall RM (1991) A structure for characterizing and classifying efficiency and inefficiency in data envelopment analysis. J Prod Anal 2(3):197–237

Cronin JJ, Taylor SA (1992) Measuring Service Quality: a Re-Examination and Extension. J Mark 56(3):55–68

Davey A, Heracleous L, Wirts J, Pangarkar N (2007) Flying high in a competitive industry. Serv Bus 1(2):177–179

Evans J, Lindsay W (2009) Managing for quality and performance excellence. South-Western Cengage Learning, Mason

Färe R, Grosskopf S, Forsund FR, Hayes K, Heshmati A (2006) Measurement of productivity and quality in non-marketable services: with application to schools. Qual Assur Educ 14(1):21–36

Ferdows K, De Meyer A (1990) Lasting improvements in manufacturing performance: in search of a new theory. J Oper Manag 9(2):168–184

Fixler D, Zieschang K (1992) Incorporating ancillary measures of process and quality change into a superlative productivity index. J Prod Anal 2(4):245–267
Frei FX (2006) Breaking the trade-off between efficiency and service. Harvard Bus Rev 88(11):93–101
Friesner LD (2003) An empirical examination of cost-adjusting in outpatient clinics. J Socio-Econ 31(6):745–759
Gardner ES (2004) Dimensional analysis of airline quality. Interfaces 34(4):272–279
Giannakis D, Jamasb T, Pollitt M (2005) Benchmarking and incentive regulation of quality of service: an application to the UK electricity distribution network. Energy Policy 33(17):2256–2271
Gnanlet A, Yayla-Kullu H (2013) Impact of national culture on the quality of information delivery in service. Serv Bus 2013:1–35
Good DH, Nadiri I, Roller L-H, Sickles RC (1993) Efficiency and productivity growth comparisons of European and U.S. air carriers: a first look at the data. J Prod Anal 4:115–125
Grönroos C, Ojasalo K (2004) Service productivity. Towards a conceptualization of the transformation of inputs into economic results in services. J Bus Res 57(4):414–423
Headley DE, Bowen BD (1997) International airline quality measurement. J Air Trans World Wide 2(1):55–63
Kano N, Seraku N, Takahashi F, Tsuji S (1984) Attractive quality and must-be quality. Hinshitsu 14:39–48
Khan MS, Mahapatra SS, Sreekumar NA (2008) Service quality evaluation of technical institutions using data envelopment analysis. Int J Prod Qual Manag 3(1):127–143
Lapré MA, Scudder GD (2004) Performance improvement paths in the U.S. airline industry: linking trade-offs to asset frontiers. Prod Oper Manag 13(2):53–71
Lin C (2005) Service quality and prospects for benchmarking: evidence from the Peru water sector. Util Policy 13(3):230–239
Merkert R, Hensher DA (2011) The impact of strategic management and fleet planning on airline efficiency: a random effects Tobit model based on DEA efficiency scores. Trans Res A 45:686–695
Nachum L (1999) The productivity of intangible factors of production: some measurement issues applied to Swedish consulting firms. J Serv Res 2:123–137
Parast MM, Fini EH (2010) The effect of productivity and quality on profitability in US airline industry: an empirical investigation. Manag Serv Qual 20(5):458–474
Parasuraman A (2010a) Service productivity, quality and innovation: implications for service-design practice and research. Int J Qual Serv Sci 2(3):277–286
Parasuraman A (2010b) Service quality and productivity: a synergistic perspective. Manag Serv Qual 12(1):6–9
Parasuraman A, Zeithaml VA, Berry LL (1988) SERVQUAL: a multiple item scale for measuring consumer perceptions of service quality. J Retail 64(1):12–40
Prior D (2006) Efficiency and total quality management in healthcare organization: a dynamic frontier approach. Ann Oper Res 145(1):281–299
Rhoades DL, Waguespack B (1999) Better safe than service? The relationship between service and safety quality in the US airline industry. Manag Serv Qual 9(6):396–400
Rhoades DL, Waguespack B (2008) Twenty years of service quality performance in the US airline industry. Manag Serv Qual 18(1):20–33
Rouse P, Puterill M, Ryan D (2002) Integrated performance measurement design: insights from an application in aircraft maintenance. Manag Account Res 13(2):229–248
Safizadeh MH, Ritzman LP, Mallick D (2000) Revisiting alternative theoretical paradigms in manufacturing strategy. Prod Oper Manag 9(2):111–127
Scheraga CA (2004) Operational efficiency versus financial mobility in the global airline industry: a data envelopment and Tobit analysis. Trans Res A 38(5):383–404
Schmenner WR (1986) How can service businesses survive and prosper. Sloan Manag Rev 27(3):21–32
Sherman HD, Zhu J (2006) Benchmarking with quality-adjusted DEA(Q-DEA) to seek lower cost high quality service: evidence from U.S. bank application. Ann Oper Res 145(1):301–319
Sherman HD, Zhu J (2009) Case study: improving branch profitability and service with data envelopment analysis. Bank Account Finance 22(3):15–24
Soteriou A, Stavrinides Y (2000) An internal customer service quality data envelopment analysis model for bank branches. Int J Bank Mark 18(5):246–252
Soteriou A, Zenios SA (1999) Operations, quality, and profitability in the provision of banking services. Manag Sci 45(9):1221–1238

Thanassoulis E, Boussoufiane A, Dyson RG (1995) Exploring output quality targets in the provision of perinatal care in England using data envelopment analysis. Eur J Oper Res 80(3):588–607

Tiernan S, Rhoades DL, Waguespack B (2008) An exploratory cross-country analysis of the disconnect between consumer perception and actual performance in the airline. Manag Serv Qual 18(3):212–224

Tsikriktsis N (2007) The effect of operational performance and focus on profitability: a longitudinal study of the U.S. airline industry. Manuf Serv Oper Manag 9(4):506–517

Tsikriktsis N, Heineke J (2004) The impact of process variation on customer dissatisfaction: evidence from the U.S. domestic airline industry. Decis Sci 35(1):129–141