Transportation Research Part B 96 (2017) 113–125

Contents lists available at ScienceDirect

Transportation Research Part B

journal homepage: www.elsevier.com/locate/trb

# Modeling technical and service efficiency

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ARTICLE INFO

*Article history:*
Received 7 September 2015
Revised 17 November 2016
Accepted 18 November 2016
Available online 3 December 2016

*Keywords:*
Service efficiency
Technical efficiency
Output distance function
U.S. airlines
Bayesian analysis
Markov chain Monte Carlo

ABSTRACT

Previous research on service failures, often measured by customer complaints, has not examined how organizations can measure or monitor their service efficiency. In this article, we introduce a new model that is suitable for measuring both service efficiency and technical efficiency when both bad outputs (i.e. service complaints) and good outputs (i.e. passenger trips and flights) are present. We develop our model with an output distance function, using Bayesian methods of inference organized around Markov chain Monte Carlo (MCMC). We illustrate our model with an application in the U.S. airline industry, an industry sector beset with service failures affecting both revenues and costs. We present the service inefficiency results of various US airlines and discuss the determinants of bad outputs in this industry. We also test whether our results are in line with market expectations by comparing the service efficiency estimates against the “American Customer Satisfaction Index” data.



## 1. Introduction

Service failures (i.e. the delivery of the service that did not meet a benchmark standard) are, at times, a considerable problem in the airline industry. However, even the best service companies with the tightest quality control procedures, experience occasional errors in their service delivery. In contrast to the manufacturing sector, the labor-intensive nature of many services makes them prone to variability in the service outcome (Berry, 1980). The simultaneous production and consumption of services also increases the chance of service errors due to the lack of opportunity for quality inspections prior to delivery (Hess et al., 2003).

There is ample evidence of the negative downstream consequences of service failures on various outcomes (Gursoy et al., 2005). For example, service failures influence consumers' future choices (Truitt and Haynes, 1994; Ostrowski et al., 1993; Bejou and Palmer, 1998; Suzuki et al., 2001), lead to enhanced negative word of mouth (Richins, 1983), lower satisfaction, and higher customer turnover (Parasuraman et al., 1988; Keaveney, 1995). Inevitably, as service failures have an unfavorable impact on firm profitability, there is a continuous need for managers to minimize the risk of these service failures.

Such an effort would be easier if managers had a clear understanding of how to measure what we call the “service efficiency” of their company. Any service operation has the potential to produce undesirable outcomes (e.g. service failures),

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http://dx.doi.org/10.1016/j.trb.2016.11.010
0191-2615/

that are attached to the desirable outputs/services (e.g. passenger trips, flights). The challenge is how to measure service efficiency given the unique characteristics of the service industry. The current literature proposes several methods to deal with undesirable outputs, but these were mainly in manufacturing or agricultural contexts. The characteristics of service industries needs to be reflected in any statistical approach designed to deal with undesirable outcomes. Typically the modeling of bad outputs is confined to manufacturing (for example $CO_2$ emissions) or agriculture contexts (sulfur emissions). Most decision-making units in such industries have emissions that increase in proportion with production but they do not directly compete in the market through their bad outputs. As an example, steel firms produce emissions along with steel, but the amount of emissions does not influence the market for steel. In the service context, the negative outputs are different. Bad outcomes can play an important differentiating role by influencing future purchases or the credibility of the firm.

Importantly, the treatment of bad outputs is also different in the service industry. For example, bad outputs in services are not completely outside management control. There is also conflicting evidence on whether service complaints always increase with higher production; larger hotels, for instance, do not always have larger number of service complaints. In addition, while it is common in manufacturing to aggregate bad outputs as they are simply a by-product of firm outputs (Fernandez et al., 2002), in services the situation is different. Different types of customer complaints can be driven by different factors, and not only necessarily outputs. In the airline context reasons that lead to complaints on customer service are not necessarily the same factors that lead to complaints on flight problems and neither may be related to outputs. For example, the service literature discusses several circumstances that can increase or decrease the number of complaints, ranging from associated inputs to quality performance and other related indicators (Tsaur et al., 2002; Babbar and Koufteros, 2008; Grainer et al., 2014).

Complaints on customer service, for instance can be affected by training expenses on employees (input), the number of flights or passengers (output), or percentage of departure on times (quality performance indicator). Training expenses should improve the quality of employees and reduce the total complaints on customer service.[1] There is ample evidence that suggests investment in customer service training and in complaint management practices in particular is needed to enhance customer satisfaction (Grainer et al., 2014). Airline passengers are highly sensitive to the courtesy and responsiveness of the airline crew (Tsaur et al., 2002; Babbar and Koufteros, 2008). Quality performance indicators such as departure on time, may also reduce the conflict between passengers and the employees and reduce the number complaints. Previous research shows that on-time performance has a negative impact on customer complaints (e.g., Behn and Riley, 1999).

As mentioned while research is not clear on whether the number of complaints may necessarily increase with desirable outputs (e.g., number of flights), one can make the argument that large airlines may have more complex organizations and networks. They could have more delays but investing in technology, training and planning, they may have fewer delays and hence complaints than smaller carriers.[2] Hence, it is important to account for good outputs in modeling bad outputs in service. We also believe that technical inefficiency may also play a role here. While there is not much evidence in the literature on this, one would expect that technically inefficient firms pay less attention to technical details which should affect the overall quality and likely increases the number of complaints. Hence, it is also important to test for this hypothesis.

Motivated by the above, this paper introduces, for the first time, a model for measuring service efficiency that is separate from the traditional measure of technical efficiency.[3] We base our model on the following definition: a firm is said to be service efficient if given its inputs, the firm produces the least possible amount of undesirable outcomes (e.g. customer complaints). Whereas, a firm is technically efficient if given its inputs, undesirable outcomes, the firm produces the maximal amount of [good] output(s). This paper offers three important contributions to the transport and service related literature. First, we introduce a novel approach in terms of modeling the production of bad (or undesirable) outputs in service. Our novel feature is that we allow 'bad outputs' to be produced depending on selected inputs, selected outputs, technical inefficiency, quality performance and other related indicators. Importantly, in our approach we do not consider a general distance function of the form $D(x, y, b)=0$ where the underlying mechanism for generating the bad outputs is left unspecified and therefore they have to be treated formally as inputs; a fact that is empirically and theoretically unacceptable.

Second, we allow for the overproduction of bad outputs (i.e. service inefficiency) through introducing nonnegative error components separately for each of the bad equation. This is in line with our previous argument that these types of outputs in service delivery behave differently. For example, within the context of the dairy farm industry, Fernandez et al. (2002) used an output aggregator and treated the behavior of all bad outputs similarly. Third and finally, we allow for input endogeneity using a reduced-form equation where inputs depend on outputs and other variables. This would have the outcome of a standard cost minimization problem but in the absence of input prices we try to allow for a degree of firm-specific heterogeneity using dummy variables. Moreover, outputs are also treated as endogenous. Hence, we have a system

[1] In their seminal work, Bitner et al. (1990) collected 700 incidents from customers of airlines, hotels, and restaurants and found that the largest percentage of dissatisfactory encounters was related to employees' inability or unwillingness to respond in service failure situations.

[2] Fortune Magazine reported in September 2015 that American and Delta Airlines had surged ahead in customer satisfaction rankings by investing in their customer service infrastructure and training, with an emphasis on high-revenue business travelers.

[3] While several papers have measured the technical efficiency of airlines or airports (e.g. Assaf et al., 2014; Adler et al., 2013; Yan et al., 2009; Assaf, 2009; Martín and Voltes-Dorta, 2011; Barros, 2014) none has focused on differentiating between technical and service efficiency. Some have also accounted for undesirable outputs in the estimation of technical efficiency focusing mainly on the number of delays, but again these measured only technical efficiency (Pathomsiri et al., 2008; Yu et al., 2008; Ha et al., 2011).