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Estimating the demand responses for different sizes of air passenger groups

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This paper investigates the sensitivity of demand for air travel by singleton passengers, couples, and families. It examines how the demand for air travel by these groups is potentially different. In this study, a compound Poisson structure of the demand of different passenger groups is considered, and aggregate demand observations and maximum likelihood procedures are used to decompound the processes and estimate demand sensitivity of each group of customers to price, time, season, and the economic cycle. The methodology is applied to Canadian market data and the results indicate there are significant differences among the different groups of customers.

1. Introduction

The airline industry has turned price differentiation into a highly refined skill as it sets prices for different market segments and varies these prices against select criteria on a continuous basis (Su, 2007; Mantin and Koo, 2009). This practice, called yield management, is now also applied in pricing hotels, rental cars, concert tickets, and in other markets where there are a number of market segments with differing demand elasticities. There is also intertemporal price discrimination. For example, as the departure date approaches, airfares generally rise but not at the same rate across all fare classes. Such yield management requires highly detailed data as well as sophisticated forecasting systems and measures of customer responsiveness to changes in prices.

The price sensitivity of passengers with differing trip purposes (i.e. business, leisure, visiting-friends and relatives) has been examined in both the economics and yield management literature. One can find hundreds of papers related to price sensitivity of different classes of customers and different routes. Summaries of these papers are published in (Oum et al., 1992; Gillen and Morrison, 2007). Although there is anecdotal evidence that price sensitivity differs as the size of the travel group increases, there has not been a systematic rigorous investigation of whether and by how much price elasticities may differ among singletons, couples and larger groups of travellers.[2] Additionally, there is the challenge of how such differences in price sensitivity would be revealed. In the case of, for example, business versus leisure travel, airlines can identify which passenger fits into which group; last minute bookings, short trips, time of flight, choice of destination are all possible means of discriminating.

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[2] Some demand models have included a variable for the size of the group in the estimation equation. For example, Alperovich and Machnes (1994) reported they have included family size in the regression models but they did not discuss it since their coefficient was insignificant.

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Booking data, unless one has access to actual records with the firm (i.e. airline, hotel, car rental, etc.), does not provide information on group size. Perhaps if the time of purchase and seat choice could be observed, one could make a judgment that three seats purchased at one time for the same flight is a group of three traveling together, but it may not necessarily be true. There is also nothing to reveal whether the group of three is more or less price sensitive than a couple for example.[3] An airline will observe the booking curve for a given flight and adjust fares depending on the degree to which the booking curve is deviating from the forecasted booking behaviour. The research questions we ask in this paper are: are differences in the price sensitivity contingent on the size of the group traveling together, and second, how can demand functions for different sizes of purchasing (in our case passenger) groups be estimated when only aggregated data are available. The answer, we argue can be found in the properties of integer numbers.

A key requirement for a successful revenue management system is accurate demand information including measures of the sensitivity of demand to changes in prices, service and other factors affecting demand. For example, when purchasing tickets, singletons behave differently from couples, or other groups of customers due to the simple fact that there are fewer constraints. Knowing how different groups of customers are affected by different demand variables can equip airlines with the information to effectively price differentiate among different groups of customers. As an example, they can provide special pricing packages in special seasons to families with 1 or 2 children in order to motivate them to travel more or to travel to select destinations.

Davis (1994) showed American airlines generated over $1.4 billion over the course of three years due to successfully applying revenue management techniques. This resulted in a sizable $891 million in net profit. Such a tremendous increase in profit undoubtedly justifies the airlines decision to be among the first industries to apply sophisticated mathematical and operations research pricing tools. The results of this paper suggest that significant-in cases near 10 times-differences in price sensitivity among different groups of customers can potentially be translated into an opportunity for airlines to reap more profit by considering the size of the travel group in both price differentiation and yield management.[4] As an example, based on the data used here, the airline could increase profit by giving discounts to larger groups in times of economic downturn while maintaining the price charged to singletons. Currently, pricing assumes all passengers are singletons, and an average elasticity is used in price setting which results in fare adjustments for all passengers regardless of group size.

One of the properties that is used extensively in this paper is the property of integer number and count data. Section 2 provides an introduction to count data models and describes their role and importance in developing the models used in the estimations. Section 3 describes the specifications of the data, the empirical research question that this data is used to address, and why compound Poisson processes and decompounding techniques are the most appropriate models among all possible candidates. An important contribution of this paper is the econometric method used in the estimation. Section 4 describes the development of the method and why it is appropriate for both the research question asked and the type of data available. Section 5 reports the empirical results, provides methods to use the results of the models to compute the elasticities and marginal effects, and illustrates how the results can be used in developing pricing and other revenue strategies. A summary is provided in Section 6.

2. Count data

2.1. Poisson distributions

Data counted in the form of integer numbers are referred to as count data. Usually count data are non-negative numbers; for instance, the number of days individuals are absent from work are considered as count data. Upon reflection, a significant proportion of data used in the operations management and transportation literature are count data; number of people in a queue, number of available seats on a particular flight, the inventory level, etc. are all count data. In general, anything that can be counted as discrete entities can be regarded as count data.

The Poisson distribution is commonly used to represent the distributions of count data. This distribution has the feature that if the expected number of occurrences in a predefined interval is $\lambda > 0$, then based on the Poisson distribution the probability of exactly k occurrences is computed by:

$$f(Y = k; \lambda) = \frac{\lambda^k e^{-\lambda}}{k!} \tag{1}$$

An interesting, but restrictive characteristic of Poisson distributions is that their mean and variance are both λ. This property allows us to fully identify the whole distribution by knowing the expected number of occurrences.[5] Another attribute of Poisson distributions is regularity when time intervals are changed. If an interval which is t times the original time interval is considered, the number of k occurrences resulting from such a time interval change can easily be computed as a Poisson process with parameter λt:

$$f(Y = k; \lambda, t) = \frac{(\lambda t)^k e^{-\lambda t}}{k!} \tag{2}$$

[3] Airlines do offer special pricing to larger groups but these are generally groups of nine or more.
[4] In general, spatial discrimination adopted by competing firms may put firms in a Prisoner's Dilemma (see Thisse and Vives, 1988).
[5] However, such a property restricts us from using Poisson distributions for data that exhibits a significant difference between the mean and variance.