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Estimating flight-level price elasticities using online airline data: A first step toward integrating pricing, demand, and revenue optimization

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ABSTRACT

We estimate flight-level price elasticities using a database of online prices and seat map displays. In contrast to market-level and route-level elasticities reported in the literature, flight-level elasticities can forecast responses in demand due to day-to-day price fluctuations. Knowing how elasticities vary by flight and booking characteristics and in response to competitors' pricing actions allows airlines to design better promotions. It also allows policy makers the ability to evaluate the impacts of proposed tax increases or time-of-day congestion pricing policies. Our elasticity results show how airlines can design optimal promotions by considering not only which departure dates should be targeted, but also which days of the week customers should be allowed to purchase. Additionally, we show how elasticities can be used by carriers to strategically match a subset of their competitors' sale fares. Methodologically, we use an approach that corrects for price endogeneity; failure to do so results in biased estimates and incorrect pricing recommendations. Using an instrumental variable approach to address this problem we find a set of valid instruments that can be used in future studies of air travel demand. We conclude by describing how our approach contributes to the literature, by offering an approach to estimate flight-level demand elasticities that the research community needs as an input to more advanced optimization models that integrate demand forecasting, price optimization, and revenue optimization models.

1. Introduction and motivation

Within the airline industry, there is growing interest in understanding how prices influence demand. As strange as this may seem, current airline revenue management (RM) systems do not forecast demand as a function of price. Instead, these systems forecast demand for a particular booking class. To generate booking class forecasts, all prices sold in the market (which can exceed more than a hundred for a single flight) are mapped into a smaller – and more manageable – number of booking classes. RM systems optimize revenue by using information about the historical demand and average fares associated with each booking class.

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These RM systems worked well in the era after deregulation because fare restrictions (such as advance purchase, minimum stay, and Saturday night stay requirements) made it relatively straight-forward to segment customers and map them to distinct booking classes with monotonically-increasing average fares. However, these systems are currently struggling because the market today is fundamentally different than it was after deregulation when these first-generation RM systems were built. Overall, the market has become more competitive. The Internet has become a more significant distribution channel and low cost carriers (LCC) have increased market penetration. For example, in 2012, U.S. business and leisure travelers are estimated to have spent $85.7 billion online for airline tickets (Harteveldt, 2012). In 2009 Southwest Airlines was the largest U.S. domestic carrier, carrying over 101 million passengers; 81% of these passengers made their bookings via www.southwest.com (Southwest Airlines, 2009, 2010).

These factors have increased price and flight transparency making it easier for consumers to compare prices across multiple competitors and tailor travel plans to take advantage of lower fares. Airlines have responded to this increased competition by investing in automated price response systems. These systems help airlines identify when competitors have introduced new fares into the market, and provide recommendations as to how to respond to these changes (*e.g.*, match the fares of United, or price fares $50 higher than Spirit). This automation is essential, as there is no way to manually manage the process. To put this in perspective, at any given time, there are more than 100 million fares in the world (ATPCo, 2013b). On a given day, there may be more than one million fare changes (Vinod, 2010). In the U.S., domestic fares are updated through the Airline Tariff Publishing Company (ATPCo) up to four times a day and international fares can be updated hourly (ATPCo, 2013a). Clearly, with such a dynamic environment, it is challenging for airlines to maintain accurate inputs into their RM systems and map customer bookings and their associated fares into smaller sets of booking classes with monotonically-increasing average fares. However, as noted by Vinod (2010), "although frequently overlooked, addressing the fare class misalignment problem is *mandatory* for revenue management to produce positive results."

These and other challenges have spurred interest in developing the next generation of RM systems that better represent how customers make decisions in today's online environments. The development of these choice-based RM systems requires information about the prices (or choices) viewed by customers at the time of booking – both on the carrier of interest and, potentially, across several different competitors. The ultimate goal of these new RM systems is to forecast demand as a function of price and maximize revenue by jointly determining what prices to offer in the market, as well as how many seats to sell at each price. In turn, this means that airlines will need to develop methods for estimating demand elasticities that take into account day-to-day fluctuations in prices.

The majority of extant work has estimated air travel demand elasticities at a high level of data aggregation, typically at the market or route level. This is due to researchers only having access to highly aggregated datasets, most notably the U.S. Department of Transportation's Origin and Destination Survey Databank 1A/1B, which provides a 10% sample of route-level prices over an entire quarter. Although these measures are useful for such things as forecasting the impacts of mergers, the entry of a low cost carrier into a market, or the imposition of system-wide fuel surcharges and passenger taxes, they provide limited insight on how to design promotions and when (and how) to respond to competitors' fare changes. Moreover, these more aggregate measures provide limited insights into questions that policy makers need to address, such as the potential impact of time-of-day congestion pricing. To fully answer these types of questions, researchers need flight-level price elasticities that can be used to forecast responses in demand due to day-to-day fluctuations in prices.

In this paper, we show how flight-level price elasticities can be estimated using publically-available online data. Importantly, we use an instrumental variable approach to correct for price endogeneity. This is critical since failure to correct for endogeneity in these types of models leads to biased estimates and incorrect pricing recommendations. Our results indicate that price elasticities vary as a function of advance booking, departure day of week, departure time of day, booking day of week, and promotional sales dates of a competitor. We use these elasticities to show how they can be used to support airline pricing decisions.

The remaining sections are organized as follows. Section 2 describes the data and discusses potential sources of selection bias. Section 3 presents our methodology, with a particular focus on how we addressed missing data and price endogeneity. Empirical results are presented in Section 4 while robustness and study limitations are discussed in Section 5. We provide specific examples of how our results can help support airline pricing decisions in Section 6. We conclude by highlighting how our model contributes to the literature by offering an approach to estimate flight-level demand elasticities that will allow the research community to move one step closer toward its ultimate goal of developing advanced optimization models that integrate demand forecasting, price optimization, and revenue optimization models.[1]

2. Data

This section describes the data and variables used in the study.[2] It highlights information about the data that is relevant for interpreting results. For additional information on the pricing data, readers are referred to Mumbower and Garrow (2014) and to other papers that have used this data for pricing and revenue management applications (*e.g.*, Newman et al., 2013; Mumbower et al., 2013).

[1] Because airlines do not store information about the prices actually paid by consumers within their RM systems, airlines would need to use data sources such as the ones we use in this study to develop prototypes that will help them justify multi-million dollar investments required for them to store and access data required to successfully implement choice-based RM systems.

[2] The pricing data is available upon request and is described more fully in Mumbower and Garrow (2014).