Estimating Dynamic Demand for Airlines

Diego, Escobari

The University of Texas - Pan American

18 April 2014

Estimating Dynamic Demand for Airlines*

(*Economics Letters*, Forthcoming)

Diego Escobari†

April 18, 2014

Abstract

This paper uses an original panel dataset with posted prices and sales to estimate a dynamic demand. We find that consumers become more price sensitive as time to departure nears which is consistent with having lower valuations. This result provides empirical support to a key theoretical implication in Deneckere and Peck [Deneckere, R., Peck, J., 2012. Dynamic competition with random demand and costless search: A theory of price posting. Econometrica 80, 1185-1247] — high-valuation consumers purchase earlier. We also find that the number of active consumers increases closer to departure.

Keywords: Dynamic demand, Consumers' valuations, Advance purchases, Airlines

JEL Classifications: C23, L93, R41

*I thank Paan Jindapon and an anonymous referee for helpful comments. Stephanie C. Reynolds provided outstanding assistance with the data.

†Department of Economics & Finance, The University of Texas - Pan American, Edinburg, TX 78539, Phone: (956) 665-3366, Fax: (956) 665-5020, Email: escobarida@utpa.edu., URL: http://faculty.utpa.edu/escobarida

1 Introduction

The demand for airline tickets is dynamic because tickets are offered in advance and consumers can delay their decision to purchase. Beliefs about future prices and sales are important as multiple sales periods give consumers intertemporal substitution possibilities and give firms intertemporal arbitrage opportunities (see Deneckere and Peck (2012)). Key features in the market for airline tickets make the problem interesting. On the demand side consumers have unit demands, can optimize the timing of their purchase (with potential delaying costs), and may be uncertain about their travel plans. On the supply side sellers post prices under aggregate demand uncertainty, capacity is costly and needs to be set in advance, and unsold seats expire after departure.

In this paper we use an original dataset to estimate a dynamic demand and analyze how valuations change as the departure date nears. This is an important question because existing theoretical literature assumes either that valuations are constant across periods (e.g., Gale and Holmes (1993), Gallego and van Ryzin (1994)), finds that they are increasing over time (e.g., Dana (1998)), or finds that high-valuation consumers purchase earlier.[1] Dana (1998) explains that lower-valuation consumers have incentives to buy in advance because the presence of high-valuation types (with more uncertain demands) increase the price they expect to pay in the spot market. Deneckere and Peck (2012) explain that high-valuation consumers purchase early and low-valuation consumers postpone their purchase decisions to exploit the option to refuse to buy in the future if the sale price exceed their valuation.

We find strong empirical support that consumers' purchasing behavior changes as the departure date nears. When consumers are viewed as making instantaneous decisions we find that valuations decrease as departure date nears. A dynamic demand interpretation of our estimates is consistent with the implication in Deneckere and Peck (2012) that high-valuation consumers purchase earlier. Our dynamic panel estimates are consistent with agents behaving dynamically and are robust to different assumptions on the endogeneity of prices and the selection of the instrument list. We also find that the number of active

[1] Zhao and Zheng (2000) present a theory with reservation prices that can be increasing, constant or decreasing over time.

consumers increases closer to departure.

2 Related Literature

Our findings are important to other industries in which consumers face intertemporal substitution possibilities, for example, during advance sales for hotel rooms, car rentals, and entertainment and sporting events. Studying demand dynamics is also important in models for storable goods (e.g., Nevo and Hendel (2013)), durable goods (e.g., Chevalier and Kashyap (2011)), new products (e.g., Stokey (1979)), habit persistence (e.g., Baltagi and Levin (1986)), and when sales are concentrated during particular season, e.g. fashion apparel or the Christmas season. Consistent with our results, Bitran and Mondschein (1997) argues that early buyers of fashion goods are willing to pay more. Two additional related studies on demand estimation includes Vulcano et al. (2010) who estimate a discrete choice model with Poisson arrivals for airline revenue management, and DHaultfœuille et al. (2013) who focus on the French railroad industry to estimate a structural model of demand in the presence of revenue management.

There is a large empirical literature on airlines that uses fares collected from websites with nearly all of the work focused on explaining pricing decisions. McAfee and te Velde (2007) considers price dynamics, Mantin and Koo (2009) and Alderighi (2010) explain fare dispersion, and Bilotkach et al. (2010) document different pricing strategies among competitions. Bilotkach and Rupp (2011) test for differences across online distributors of travel services, while Malighetti et al. (2009) and Alderighi et al. (2012) study pricing strategies of low-cost airlines. Moreover, Alderighi et al. (2012) as well as Escobari (2009) find evidence that airlines respond to remaining capacity. Escobari (2012) finds evidence that airlines learn about the aggregate demand and adjust prices depending on demand expectations. More recently, Lazarev (2013) includes dynamic consumers to estimate the welfare effects of intertemporal price discrimination in U.S. monopoly markets, while Escobari et al. (2013) find evidence of dynamic price discrimination based on the time of the day purchase. Williams (2013) disentangles the interactions between the arrival pattern of consumer types and remaining capacity to find that dynamic price adjustment is important to secure seats for high-valuing consumers who arrive close to departure. Siegert and Ulbricht (2014) find that the increase of prices towards the scheduled travel date is decreasing in competition and that the sensitivity to competition increases with the heterogeneity of consumers.

There is also a large literature in airlines aimed at estimating demand, but it uses more aggregate data. Ito and Lee (2005) assess the impact of September 11 terrorist attacks on airline demand while Lederman (2007) at the effect of enhancements of loyalty programs on airline domestic demand. On the theoretical side most of the modeling of airline demand comes from the operations research perspective. Yan and Tseng (2002) present a passenger demand model for airline flight scheduling and fleet routing while Brons et al. (2002) work on meta-analysis to analyze passengers' price elasticities of demand. Wei and Hansen (2005) analyze the impact of aircraft size and seat availability on airlines' demand, and Bieger et al. (2007) look at the drivers of growth in demand for air travel.

3 Data

This paper uses an original panel dataset of prices and seat inventories obtained from the online travel agency Expedia.com for 228 U.S. domestic flights that departed on Thursday, June 22, 2006. Each cross-sectional unit is a non-stop, one-way flight observed every three days for 35 dates between 103 days and 1 day to departure. Unlike similar datasets (e.g., Stavins (2001)), the advantage in this dataset is that we observe the inventory of seats at each date. Escobari (2009) and Alderighi et al. (2012) also observe inventory levels.

The construction of the data focuses on one-way non-stop flights to define a single inventory at each posted fare. Moreover, having only one-way flights is helpful to control for price differences associated with round-trip tickets (e.g., Saturday-night stayover), and non-stop flights helps to control for price variation that arises from more sophisticated itineraries. Economy-class tickets control for the fare class, and by selecting the least expensive price, we control for the existence of more expensive refundable tickets. The carriers in the sample are American, Alaska, Continental, Delta, United, and US Airways.[2]

[2]For more details on the dataset see Escobari (2012).

4 Dynamic Demand

The dynamic demand has the following specification:

$$\text{S}_{\text{ALES}ijt} = \alpha\text{S}_{\text{ALES}ij,t-1} + \beta\text{D}_{\text{AY}t} + (\gamma + \delta\text{D}_{\text{AY}t}) \cdot \text{F}_{\text{ARE}ijt} + \nu_{ij} + \varepsilon_{ijt}, \tag{1}$$

where the subscript i refers to the flight, j to the route, and t to time. The variable SALES_{ijt} captures sales during period t and it is obtained as the difference between beginning-of-period and end-of-period available seats, relative to the aircraft size times 100 (i.e., $\text{SALES}_{ijt} = 1$ means that one seat was sold in a 100-seat aircraft during period t). DAY_t is the number of days prior to departure and FARE_{ijt} is the posted fare.[3] Equation 1 is consistent with the theoretical model in Deneckere and Peck (2012), where each period firms start posting prices, then consumers arrive in random order, observe posted prices and decide whether to purchase.

FARE_{ijt} is potentially endogenous in the sense that it can be correlated with $\nu_{ij} + \varepsilon_{ijt}$. By taking first differences of Equation 1 we eliminate the time-invariant effect ν_{ij}. We allow for different assumptions about the contemporaneous correlation between FARE_{ijt} and the demand shock ε_{ijt}. If FARE_{ijt} is predetermined, then ε_{ijt} is a true demand shock for the carrier and the econometrician. Hence carriers set prices after observing previous demand realizations (including demand shocks), but do not observe contemporaneous or future demand shocks. Modeling FARE_{ijt} as endogenous additionally allows for contemporaneous correlation between FARE_{ijt} and ε_{ijt}.

The estimation uses the methods in Arellano and Bond (1991) and Blundell and Bond (1998) to obtain consistent estimates of $(\alpha, \beta, \gamma, \delta)$. A detailed discussion of these methods is presented in Baltagi (2013). The difference estimator uses moments $E(\Delta\varepsilon_{ijt}\text{Z})$, while the system estimator additionally uses moments $E[(\nu_{ij} + \varepsilon_{ijt})\text{W}]$. Under predetermined FARE_{ijt}, the vector of instruments Z includes lags of FARE_{ijt} and lags of $\text{SALES}_{ij,t-1}$, while W includes $\Delta\text{SALES}_{ij,t-1}$, ΔFARE_{ijt} and the lags of both. Treating FARE_{ijt} as potentially endogenous invalidates FARE_{ijt} and ΔFARE_{ijt} as instruments, but their lags are still valid. Equation 1 extends Escobari (2012) by allowing the slope of the demand to change with days to departure (DAY_t).

[3] The sample means and standard deviations of these variables are: $\hat{\mu}_{\text{SALES}}$=1.716, $\hat{\sigma}_{\text{SALES}} = 4.345$, $\hat{\mu}_{\text{DAY}} = 52$, $\hat{\sigma}_{\text{DAY}} = 30.30$, $\hat{\mu}_{\text{FARE}} = 291.2$, and $\hat{\sigma}_{\text{FARE}} = 171.8$.

Weak exogeneity or endogeneity of $\textsc{Fare}_{ijt}$ means that the price at t is uncorrelated with future demand shocks. It does not prevent sellers and buyers from forming beliefs about future sales and prices. Arellano and Bond (1991) explain that short-run dynamics will compound influences from expectation formations and decision processes. Weak exogeneity and endogeneity are consistent with rational expectation models in which sellers and buyers use Equation 1 to form expectations. However, variance in who buys when arises due to heterogeneous arrival rates and private information such as individual demand uncertainty, valuation and heterogeneity in beliefs formation.

5 Empirical Results

To guide the interpretation of the results we start with a simple dynamic demand framework, but we will then follow the intuition behind the more general dynamic demand model in Deneckere and Peck (2012). In the simple dynamic demand model airline seats are homogeneous and we have N_t active consumers at each time t prior to departure. Reservation values are uniformly distributed $[0,\bar{v}_t]$, with $\bar{v}_t$ denoting the highest valuation for a seat. Therefore, the demand at each day prior to departure can be written as $\textsc{Sales}_t = N_t - (N_t/\bar{v}_t) \cdot \textsc{Fare}_t$. Using this demand function along with Equation 1 we have that $N_t = c + \beta\textsc{Day}_t$ and $\bar{v}_t = -(c + \beta\textsc{Day}_t)/(\gamma + \delta\textsc{Day}_t)$, where $c = \alpha\textsc{Sales}_{t-1} + \nu$. Notice that we assume $\varepsilon_t = 0$ $\forall t$ and to simplify the notation we dropped the subscripts ij. This simple structure allows us to test if the number of active consumers increases as the date of departure approaches ($\beta < 0$) and if valuations decrease as the departure date nears ($\beta\gamma/c\delta < 1$).[4]

The estimation results are presented in Table 1. $\textsc{Fare}_{ijt}$ is treated as weakly exogenous in columns 1 through 4 and as endogenous in columns 5 and 6. All system GMM specifications pass both identification tests: there is no serial correlation in ε_{ijt} and the Sargan test validates the instrument lists. The negative and statistically significant coefficient on $\textsc{Day}_t$ across all specifications indicates that the number of active consumers N_t increases as the departure date approaches — using the point estimates in the last column we find that N_t increases from 3.47 at $\textsc{Day}_t = 35$ to 5.59 at $\textsc{Day}_t = 7$.[5] In addition, we have a

[4]The condition $\beta\gamma/c\delta < 1$ is obtained from $\partial\bar{v}_t/\partial\textsc{Day}_t > 0$.

[5]To obtain c we use the regression constant for ν (because the regression constant is usually interpreted

downward sloping demand — at the sample mean of Day_t, a one dollar increase in fares decreases sales by 0.155 seats in a 100-seat aircraft.

[Table 1, here.]

The estimates in the last column show that the highest valuation for an airline seat at 35 days to departure is \$934.8 while it is \$774.5 at 7 days to departure. Both of these figures are statistically significant as shown by the small p-values associated with the null that the population parameters are equal to zero. Smaller estimates of $\bar{v}$ closer to departure are also found across all system GMM specifications under different assumptions on the contemporaneous correlation between Fare_{ijt} and ε_{ijt}, and with different lags in the instrument vectors Z and W. When looking at the condition to have decreasing valuations we have that the estimates of $\beta\gamma/c\delta$ are 0.843 and 0.871 at 35 and 7 days to departure respectively. The p-values associated with the null of $\beta\gamma/c\delta < 1$ indicate that at a 10% significance level we reject the null of decreasing valuations at 7 days to departure, but we fail to reject the null at 35 days to departure.[6]

Note that this simple dynamic demand structure assumes that 1) valuations at time t are uniformly distributed, 2) only $\bar{v}_t$ changes with t, not the lower bound or the shape of the distribution, and 3) consumers purchase immediately and vanish otherwise. Assumptions one and two help define a linear demand that rotates clockwise as $\bar{v}_t$ increases. The specification of a linear demand implies that changes in the demand intercept $\bar{v}$ as time to departure declines are identified by changes in the slope of the demand as time to departure declines. While the demand estimation allows consumers to behave dynamically, assumption three and the identification of $\bar{v}$ comes from a simple demand specification where consumers cannot choose when to purchase. Our estimates cannot distinguish between consumers with low valuations arriving late and those with low valuations postponing their purchase decisions.

A more general dynamic demand interpretation follows from Deneckere and Peck (2012)'s model in which consumers can choose when to purchase. Our results can also be interpreted

as the average value of the fixed effects) and lagged fitted values for Sales_{t-1}, obtained assuming that all previous shocks ε_t are zero. The regression constant affects N_t and $\bar{v}_t$ via c.

[6] If we restrict N_t to be constant (i.e., $\beta = 0$), the condition for decreasing valuations is simply $\delta > 0$, which is also supported by the estimation results.

as showing that consumers wait if time to departure is high but not if time to departure is low. That is, if consumers with the same distribution of valuations arrive in random order, the option to wait makes early consumers (particularly those with low valuations) less sensitive to price. Then as time goes by the distribution of remaining consumers will become more skewed towards lower valuations. As the option of waiting declines these consumers will start to act more price sensitive, consistent with our results.

6 Conclusion

Our results support the claim that consumers' purchasing behavior changes as the departure date nears. When we view consumers as making instantaneous decisions, the evidence suggests that they become more price sensitive as the time to departure draws closer which is consistent with having lower valuations. High-valuation consumers buying earlier is consistent with one key prediction in Deneckere and Peck (2012). Our result can be interpreted as evidence that airline travelers sort themselves efficiently in equilibrium with low valuation types postponing their purchase decisions and even deciding not to buy if prices closer to departure are higher than their valuation. Deneckere and Peck (2012) explain that this implies that rationing arises endogenously in equilibrium. While their model predicts that markets clear, airline markets still show underutilized capacity that perhaps arises due to high aggregate demand uncertainty, price stickiness, or slow or incomplete aggregate demand learning.

References

Alderighi, M., 2010. Fare dispersions in airline markets: A quantitative assessment of theoretical explanations. *Journal of Air Transport Management* 16, 144-150.

Alderighi, M., M. Nicolini, and C.A. Piga, 2012. Combined Effects of Load Factors and Booking Time on Fares: Insights from the Yield Management of a Low-Cost Airline. FEEM Working Paper.

Arellano, M. and S. Bond, 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies* 58, 277-297.

Bieger, T., A. Wittmer, and C. Laesser, 2007. What is driving the continued growth in demand for air travel? Customer value of air transport. *Journal of Air Transport Management* 13, 31-36.

Bitran, G.R. and S.V. Mondschein, 1997. Periodic pricing of seasonal product in retailing. *Management Science* 43, 64-79.

Baltagi, B.H., 2013. *Econometrics Analysis of Panel Data*. 5th ed. Chichester, UK: Wiley.

Baltagi, B.H. and D. Levin, 1986. Estimating dynamic demand for cigarettes using panel data: The effects of bootlegging, taxation and advertising reconsidered. *Review of Economics and Statistics* 68, 148-155.

Bilotkach, B., Y. Gorodnichenkob, and O. Talavera, 2010. Are airlines' price-setting strategies different? *Journal of Air Transport Management* 16, 1-6.

Bilotkach, V. and N. Rupp, 2011. A guide to booking airline tickets online. in James Peoples (ed.) *Pricing Behavior and Non-Price Characteristics in the Airline Industry* (Advances in Airline Economics, Volume 3), Emerald Group Publishing Limited, 83-105.

Blundell, R.W. and S. Bond, 1998. Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics* 87, 115-143.

Brons, M., E. Pels, P. Nijkamp, and P. Rietveld, 2002. Price elasticities of demand for passenger air travel: a meta-analysis. *Journal of Air Transport Management* 8, 165-175.

Chevalier, J.A. and A.K. Kashyap, 2011. Best prices. NBER working paper 16680. Cambridge, MA.

DHaultfœuille X., P. Février, and L. Wilner, 2013. Demand estimation in the presence of revenue management. Working Paper.

Dana, Jr. J., 1998. Advance-purchase discounts and price discrimination in competitive markets. *Journal of Political Economy* 106, 395-422.

Deneckere, R. and J. Peck, 2011. Dynamic competition with random demand and costless search: A theory of price posting. *Econometrica* 80, 1185-1247.

Escobari, D., 2009. Systematic peak-load pricing, congestion premia and demand diverting: Empirical evidence. *Economics Letters* 103, 59-61.

Escobari, D., 2012. Dynamic pricing, advance sales, and aggregate demand learning in airlines. *Journal of Industrial Economics* 60, 697-724.

Escobari, D. and P. Jindapon, 2014. Price discrimination through refund contracts in airlines. *International Journal of Industrial Organization*, 34, pp. 1-8.

Escobari, D., N. Rupp., and J. Meskey, 2013. Dynamic price discrimination in airlines. Working Paper.

Gale, I. and T. Holmes, 1993. Advance-purchase discounts and monopoly allocation of capacity. *American Economic Review* 83, 135-146.

Gallego, G. and G.J. van Ryzin, 1994. Optimal dynamic pricing of inventories with stochastic demand over finite horizons. *Management Science* 40, 999-1020.

Ito, H. and D. Lee, 2005. Assessing the impact of the September 11 terrorist attacks on U.S. airline demand. *Journal of Economics and Business* 57, 75-96.

Lazarev, J., 2013. The welfare effects of intertemporal price discrimination: An empirical analysis of airline pricing in U.S. mononoly markets. Working Paper.

Lederman, M., 2007. Do enhancements to loyalty programs affect demand? The impact of international frequent flyer partnerships on domestic airline demand. *RAND Journal of Economics* 38, 1134-1158.

Malighetti, P., S. Paleari, and R. Redondi, 2009. Pricing strategies of low-cost airlines: The Ryanair case study. *Journal of Air Transport Management* 15, 195-203.

Mantin, B. and B. Koo, 2009. Dynamic price dispersion in airline markets. *Transportation Research Part E* 45, 1020-1029.

McAfee, R. P. and V. te Velde, 2007. Dynamic pricing in the airline industry. In Hendershott T. J. (ed.), Handbook of Economics and Information Systems, Vol. 1, (Elsevier Science, New York, New York, U.S.A.).

Nevo, A. and I. Hendel, 2013. Intertemporal price discrimination in storable goods markets. *American Economic Review* 103, 2722-2751.

Siegert, C. and R. Ulbricht, 2014. Dynamic oligopoly pricing: Evidence from the airline industry. Working Paper.

Stokey, N.L., 1979. Intertemporal price discrimination. *Quarterly Journal of Economics* 93, 355-371.

Stavins, J., 2001. Price discrimination in the airline market: The effect of market concentration. *Review of Economics and Statistics* 83, 200-202.

Vulcano, G., G. van Ryzin, and W. Chaar, 2010. Choice-based revenue management: An empirical study of estimation and optimization. *Manufacturing & Service Operations Management* 12, 375-388.

Wei, W. and M. Hansen, 2005. Impact of aircraft size and seat availability on airlines demand and market share in duopoly markets. *Transportation Research Part E* 41, 315-327.

Williams, K.R., 2013. Dynamic Airline Pricing and Seat Availability. Working Paper.

Yan, S. and C-H. Tseng, 2002. A passenger demand model for airline flight scheduling and fleet routing. *Computers & Operations Research* 29, 1559-1581.

Zhao, W. and Y.S. Zheng, 2000. Optimal dynamic pricing for perishable assets with non-homogeneous demand. *Management Science* 46, 375-388.

Table 1: GMM Dynamic Demand Results

FARE treated as:	Weakly exogenous				Endogenous	
GMM Estimator:	Difference		System		System	
Instruments Z and W:	$t-2$	$t-3$	$t-2$	$t-3$	$t-2$	$t-3$
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
$\text{SALES}_{ij,t-1}$	-0.189*	-0.190*	-0.191*	-0.191*	-0.193*	-0.190*
	(0.0250)	(0.0256)	(0.0240)	(0.0251)	(0.0255)	(0.0261)
DAY_t	-0.0628*	-0.0649*	-0.0751*	-0.0800*	-0.0774*	-0.0831*
	(0.0125)	(0.0117)	(0.00892)	(0.00866)	(0.0102)	(0.00974)
$\text{FARE}_{ijt} \cdot 10^{-3}$	-16.51*	-17.33*	-7.142*	-7.727*	-7.343*	-8.091*
	(3.648)	(3.258)	(1.784)	(1.738)	(1.663)	(1.589)
$\text{DAY}_t \cdot \text{FARE}_{ijt} \cdot 10^{-3}$	0.0539	0.0533‡	0.107*	0.117*	0.113*	0.125*
	(0.0339)	(0.0316)	(0.0264)	(0.0264)	(0.0247)	(0.0236)
Constant	8.837*	9.267*	6.372*	6.679*	6.453*	6.827*
	(1.248)	(1.138)	(0.808)	(0.756)	(0.721)	(0.693)
At $\text{DAY}_t = 7$:						
$\bar{v}_t$	484.4	483.7	815.5	791.1	804.6	774.5
H_0: $\bar{v}_t = 0$	[0]	[0]	[0]	[0]	[0]	[0]
$\beta\gamma/c\delta$	2.332	2.438	0.871	0.876	0.862	0.871
H_0: $\beta\gamma/c\delta < 1$	[0.913]	[0.923]	[0.270]	[0.260]	[0.113]	[0.104]
At $\text{DAY}_t = 35$:						
$\bar{v}_t$	428.5	427.1	977.1	945.7	979.3	934.8
H_0: $\bar{v}_t = 0$	[0]	[0]	[0.0135]	[0.00773]	[0.000107]	[1.03e-05]
$\beta\gamma/c\delta$	2.274	2.377	0.842	0.847	0.834	0.843
H_0: $\beta\gamma/c\delta < 1$	[0.909]	[0.920]	[0.223]	[0.211]	[0.0668]	[0.0573]
Specification tests:						
Serial correlation[a]	-0.547	-0.543	-0.688	-0.666	-0.709	-0.624
	[0.584]	[0.587]	[0.491]	[0.506]	[0.478]	[0.532]
Sargan[b]	180.7	196.5	215.6	227.0	215.9	226.9
	[0.000830]	[0.0134]	[0.626]	[0.879]	[0.565]	[0.850]

Notes: The dependent variable is SALES_{ijt}. Figures in parentheses are the Windmeijer finite-sample corrected standard errors of the GMM two-step estimates. ‡ significant at 10%; † significant at 5%; * significant at 1%. Figures in square brackets are p-values. [a] The null hypothesis is that the errors in the first-difference regression exhibit no second-order serial correlation (valid specification). [b] The null hypothesis is that the instruments are not correlated with the residuals (valid specification).