Everything you wanted to know about airline pricing but never dared to test

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Introduction

- Yield Management consists of a broad set of techniques (ex-ante pricing, price discrimination, dynamic pricing) that are used by airlines to set their fares.
- On the one hand, airline need to set prices before demand is realised; indeed, prices need to be posted well in advance (ex-ante) of the departure date, when only forecasts of expected demand are available.
- On the other, YM involves extensive Human Intervention, which can be seen as a form of Dynamic Pricing, where the ex-ante decisions may be updated.
- In this paper, we focus on the role that the former aspect plays in generating such fare dispersion, while controlling for price discrimination
- Thanks to the relatively simple YM of a Low-Cost Airline (LCA), Ryanair, we identify the impact of both
 - in-flight seat availability \rightarrow capacity-driven theory of ex-ante pricing.
 - 2. the time separating the purchase from the departure date → time-driven approach.

Theory on capacity-driven YM

- Dana (Rand, 1999) provides a theoretical model of ex-ante (contingent) pricing.
 - It studies the link between fares and seat availability.
- The basic idea is that the optimal fare is given by a constant mark-up over the capacity cost.
- Assume marginal operative cost is c; cost of capacity is k.
- In perfect competition, and with no uncertainty, F=c+k.
- Now imagine that each seat has a different probability, *R*, of being sold.

$$R = 4/5$$

$$R = 2/5$$

$$R = 1/5$$

Corresponding perfectly competitive fares in equilibrium: F=c+k/R

$$F=c+k$$

$$F=c+5k/4$$

$$F=c+5k/2$$

Intra-firm dispersion arises not because an airline is trying to segment its market, but because demand is uncertain, and the probability of selling an extra seat decreases with in-flight seat utilization.

Results 1

- In this paper, we provide the first direct test of the hypothesis that fares should increase with capacity utilization.
- This work benefits from dealing with the simpler system of a Low Cost Carrier, and allows a more direct test of the implications of YM models of seat inventory control.
- Main Finding: the relevant role played by a capacity-driven approach to airline pricing in explaining airline price dispersion.
- The existing evidence on this issue is rather mixed.
- On the one hand, Puller et al. (2009) find only modest support for capacity-driven pricing, and illustrate that much of the variation in their data may be associated with second-degree price discrimination.
- On the other, Escobari and Gan (2006) find that price quotes are on average higher in fully occupied flights. But they do not track seat availability but only consider whether a flight was sold out.

Theory 2 – Intertemporal Pricing

- The literature has indicated that airlines may design the inter-temporal profile of their fares to exploit customer's heterogeneity in terms of willingness-to-pay and uncertainty about departure time.
- Advance-purchase discounts (APD, hereafter) provide a simple way to screen consumers by their demand uncertainty (Dana, 1999b; Gale and Thomas, 1992, 1993).
- Moller and Watanabe (2009) study the conditions under which, over two consecutive periods, prices may decline (i.e., firms offer `clearance sales") or increase (i.e., firms engage in APD).
- They demonstrate that the former (the latter) is more appropriate when a consumer's demand uncertainty is absent (present) and the risk of being rationed is high (low).

Results 2

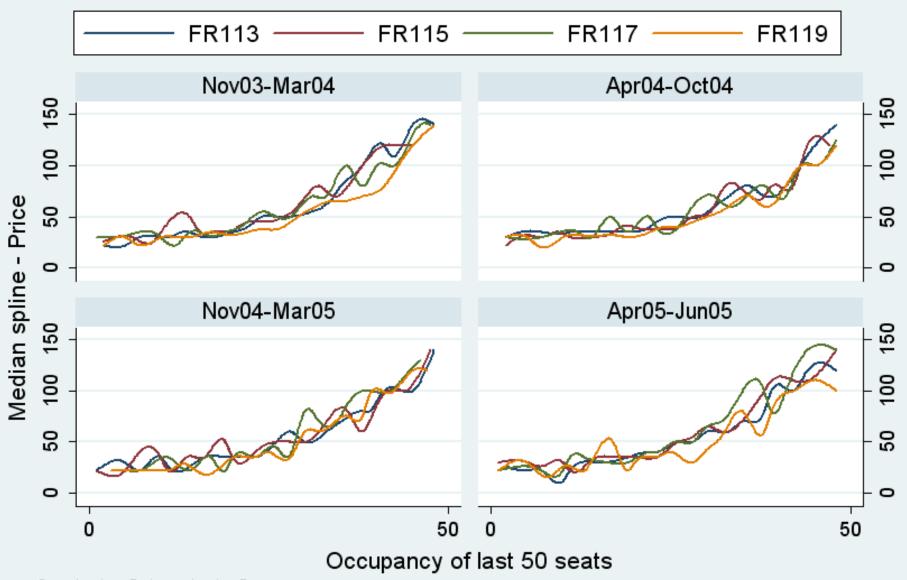
- This study sheds light on Ryanair's time-driven segmentation strategies
- A novel feature of the present work is that we do so after controlling for capacity utilization;
- thus, we can separate between fare increases due to purely capacity-driven motivation from those induced by the willingness to discriminate between customers booking at different times before departure.
- The evidence reveals that, in general, fares increase monotonically over the last 2-3 weeks before departure.
- in the two months preceding departure the intertemporal profile of a standard flight's fares often appears to be U-shaped,
- The declining part is consistent with the prediction of a declining option value of waiting that a High-demand type traveller shows up.

Data Collection #1

- Primary data on posted fares and secondary data on routes' traffic
- posted fares collected using an "electronic spider" from Ryanair's website
- Simple pricing structures one passenger class; fares only cover basic transport SAME RESTRICTIONS.
- Data on seats availability could be obtained for up to the last 50 seats Algorithm.
- This was possible due to the features of the carrier's on-line reservation system
- LCA fares collected for "booking days before departure" at intervals of 1, 4, 7, 10, 14, 21, 28, 35, 42, 49, 56, 63 and 70 days
- Period for this study: 2004-June 2005



Pricing Profile - Route London Gatwick-Dublin



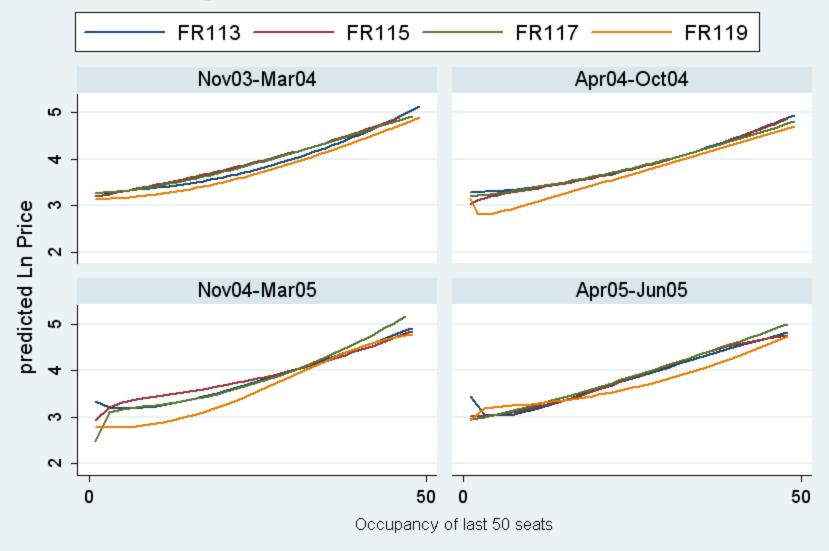
Graphs by Categorical - Seasons

Revenue Manager sets a distribution of prices

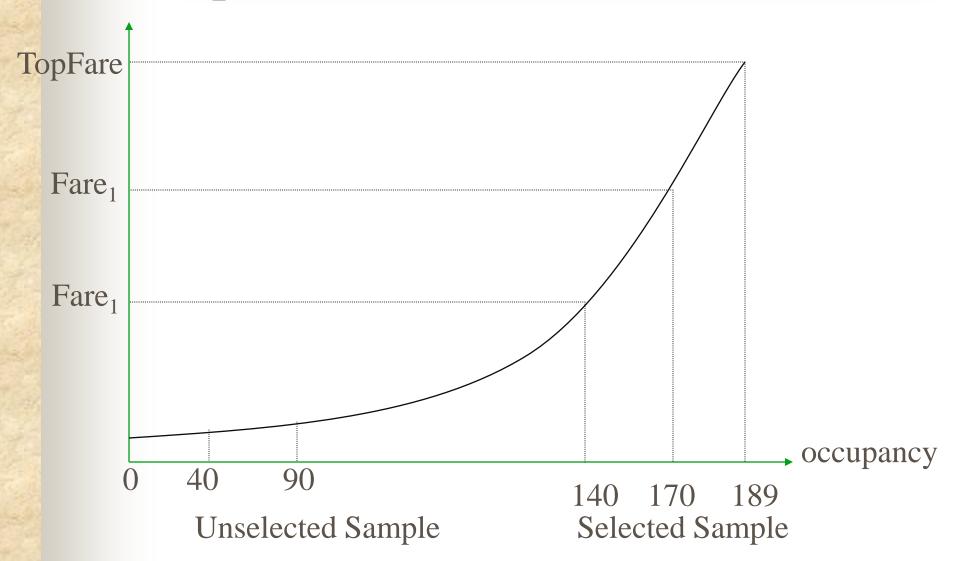


Consumers observe only one at a time, the one which is shown after the query. As the plane fills up, the classes of lower fares disappear from the system, leaving only the higher fares.

Pricing Profile - Route London Gatwick-Dublin



Templates and retrieved fares



Adding Temporal Effects

Table: Mean Fare by occupancy rate and booking day

Booking Day		Available Seats						
	1-9	10-19	20-29	30-39	40-49	50 or more	Total	
1	125.5	95.4	83.7	78	74.2	64.3	84.5	
4	114.3	75.3	57.8	49.4	43.6	36.1	57.2	
7	110.9	69.5	49.1	37.9	31.1	19.4	40.6	
10	109.3	68.8	48.2	37.7	31.3	19.7	36.3	
14	106.4	72.5	48.1	35.9	28.0	13.5	27.3	
21	116.4	82.1	56.2	41.8	32.7	15.4	24.1	
28	130.9	92.9	64.3	47.0	36.9	16.5	21.6	
35	135.6	97.6	71.3	53.0	41.9	17.3	20.4	
42	128.0	97.9	74.9	57.1	49.4	18	20	
49-70	124.5	107.4	88.6	66.1	54.9	18.4	19.3	
Total	116.9	78.6	58.8	47.1	39.5	20	31.1	

For each booking day, the fare increases with the occupancy rate Within each occupancy class, fares appear to be U-shaped over time Not controlling for occupancy, fares are increasing over time

Pure Temporal Effects

Table 5: Fare changes between two consecutive booking periods when flight occupancy remains unchanged. (Percentage values), by flight characteristics.

		Fare Change							
		Large	Moderate	No	Moderate	Large	N		
		Drop	Drop	Change	Increase	Increase			
Average Change in £		-46.21	-12.45	0	14.27	49.78			
Available Seats > 20	(% row)	3.94	6.45	64.98	13.09	11.54	4,141		
Available Seats ≤ 20	(% row)	3.63	4.13	78.19	5.68	8.36	6,301		
Booking Day > 14	(% row)	5.49	8.89	74.56	6.61	4.45	1,529		
Booking Day ≤ 14	(% row)	3.46	4.39	72.68	8.96	10.51	8,913		
Winter	(% row)	5.37	5.50	70.25	8.88	10.00	3,129		
Summer	(% row)	3.06	4.85	74.11	8.51	9.46	7,313		
High Competition	(% row)	2.88	4.83	74.89	7.93	9.47	6,496		
Low Competition	(% row)	5.20	5.40	69.77	9.76	9.88	3,946		
N	(% row)	3.75	5.05	72.96	8.62	9.62			
N		392	527	7,618	900	1,005	10,442		

Note: Large (Moderate) increases/drops refer to changes strictly greater than (smaller than) £20.0 in absolute terms.

Price drops/increases are observed even if in-flight occupancy is unchanged.

More price variation when competition is low, and when more seats are available. More increases (and fewer drops) when flight is due to depart within 2 weeks.

Estimation

- Available seats are measured from 49 to 1
- So av_seat is censored. For many observations, we only know that there were AT LEAST 50 seats left to sell.
- The Q variable used in the estimation is
- sold=50 av_seat (this gives a positive slope).

Panel Fixed Effect

The central point is to estimate



i is a specific daily flight, *t* identifies booking days.

So the idea is to track the evolution of fares, and the related evolution of occupancy for each flight *i*

Any correlation between Q_{it} and δ_i is taken care of by the fixed effect estimator (Gerardi and Shapiro, JPE, 2009).

We cannot rule out that Q_{it} and p_{it} , are both correlated with ε_{it} and that they are jointly determined; hence we treat Q_{it} as endogenous. Alternatively, endogeneity is due to an omitted variable problem.

$$p_{i}^{*} = \beta_{1}Q_{it} + \beta_{2}X_{it} + \gamma HYM(Q) + \delta_{i} + \varepsilon_{it}$$

HYM is unobserved and $cov(Q_{it}, HYM)>0 \rightarrow positive bias in OLS.$

What to do when a regressor is censored and endogenous

$$Sold Seats^* = \max(0, \mathbf{z}\delta_3 + v_3) \tag{4}$$

- 1. We estimate a Tobit specification for equation (4) using all observations;
- 2. We retrieve the residuals: $\hat{v}_3 = Sold\ Seats^* \mathbf{z}\hat{\delta}_3$ for the selected subsample;
- 3. On the selected subsample, we estimate a modified version of (5), where instead of v_3 , which is not observed, we include \hat{v}_3 among the regressors. As $Sold\ Seats$ is endogenous, we adopt an Instrumental Variable 2 Stage Fixed Effect (IVFE) estimator, using as instruments \mathbf{z}_1 and \hat{v}_3 .¹⁸

$$Fare1 = \mathbf{z}_1 \delta_1 + \alpha Sold \ Seats + \gamma v_3 + e \tag{5}$$

¹⁸Our approach therefore strictly follows the Procedure 17.4 in Wooldridge (2002, p.574).

Table 6: Tobit and First Stage estimates. Dependent Variable: Sold Seats

		Tobit			First stage		
	Slope	2.536	$(0.072)^{***}$	2.388	$(0.005)^{***}$		
	Booking Day1	63.752	$(0.697)^{***}$	61.354	$(0.112)^{***}$		
	Booking Day4	58.949	$(0.705)^{***}$	56.374	$(0.110)^{***}$		
	Booking Day7	54.357	$(0.713)^{***}$	52.006	$(0.110)^{***}$		
	Booking Day10	49.909	$(0.707)^{***}$	47.345	$(0.109)^{***}$		
	Booking Day14	44.182	(0.706)***	41.966	$(0.106)^{***}$		
	Booking Day21	34.468	$(0.695)^{***}$	32.538	$(0.103)^{***}$		
	Booking Day28	25.293	$(0.694)^{***}$	23.756	$(0.101)^{***}$		
	Booking Day35	17.162	(0.700)***	16.005	$(0.099)^{***}$		
	Booking Day42	10.144	$(0.696)^{***}$	9.429	$(0.090)^{***}$		
	Booking Day49	5.395	$(0.698)^{***}$	5.039	$(0.087)^{***}$		
	Booking Day56	2.754	$(0.658)^{***}$	2.537	$(0.080)^{***}$		
	Booking Day63	1.651	$(0.627)^{***}$	1.529	$(0.077)^{***}$		
	N. UK airports serving arrival	-1.138	(0.185)***				
	Tobit residual			0.925	$(0.001)^{***}$		
	Booking Day is in Holiday period			-0.186	(0.025)***		
	Constant	110.826	(5.209)***			•	
	DUMMIES:						
	Month booking	No		Yes			
	Week	Yes		No			
	Route	Yes		No			
	DOW Booking	7	Yes	No			
	Time Departure	7	Yes	No			
	Number of obs.	51	1,226		107,729		
	Pseudo R2	0.	1621				
	Centered R2				0.9731		
Test es	xcluded instruments:			F(2,449)	90) = 1.0e + 05	5***	
Underidentification K-P LM Test				$\chi^2(2$	e)=1.0e+05***		
Ander	son-Rubin Wald test			F(2,4)	490)= 908.97*	***	
	son-Rubin Wald test			$\chi^2(2$	2)=1818.79***		
Stock-V	Wright LM S statistic			χ^2	2)=726.44***		
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As exclusion restrictions, we consider two instruments.

The first is a dummy indicating whether the booking day (i.e., the day the fare was posted) is during a holiday period (i.e., the week before and after Christmas, Easter and main UK Bank Holidays). Its effect on *Sold Seats* may be driven by the fact that the ticket purchasing activity in such periods is likely to be different from non-holiday periods (e.g., when on holiday a person is less likely to spend time planning future trips).

The two procedures yield very similar estimates, an indication that we correctly manage the selection problem.

Table 6: Tobit and First Stage estimates. Dependent Variable: Sold Seats

		Т	obit	I	First stage	
	Slope	2.536	(0.072)***	2.388	$(0.005)^{***}$	
	Booking Day1	63.752	(0.697)***	61.354	(0.112)***	
	Booking Day4	58.949	(0.705)***	56.374	(0.110)***	
	Booking Day7	54.357	(0.713)***	52.006	(0.110)***	
	Booking Day10	49.909	(0.707)***	47.345	(0.109)***	
	Booking Day14	44.182	(0.706)***	41.966	(0.106)***	
	Booking Day21	34.468	$(0.695)^{***}$	32.538	$(0.103)^{***}$	
	Booking Day28	25.293	$(0.694)^{***}$	23.756	(0.101)***	
	Booking Day35	17.162	(0.700)***	16.005	$(0.099)^{***}$	
	Booking Day42	10.144	$(0.696)^{***}$	9.429	$(0.090)^{***}$	
	Booking Day49	5.395	$(0.698)^{***}$	5.039	$(0.087)^{***}$	
	Booking Day56	2.754	$(0.658)^{***}$	2.537	$(0.080)^{***}$	
	Booking Day63	1.651	$(0.627)^{***}$	1.529	$(0.077)^{***}$	
	N. UK airports serving arrival	-1.138	(0.185)***			
	Tobit residual			0.925	(0.001)***	
	Booking Day is in Holiday period			-0.186	(0.025)***	
	Constant	110.826	(5.209)***			
	DUMMIES:				**	
	Month booking		No		Yes	
	Week		Yes		No	
	Route		Yes		No	
	DOW Booking		Yes		No	
	Time Departure		Yes		No	
	Number of obs.		1,226		107,729	
	Pseudo R2	0.	1621		0.0791	
Toot	Centered R2 excluded instruments:			E/9 440	0.9731	
Test				F(2,44)	$90) = 1.0e + 05^{***}$	
	Underidentification K-P LM Test			$\chi^2(2)=1.0e+05^{***}$		
Ande	erson-Rubin Wald test			F(2,44)	$490) = 908.97^{***}$	
Ande	erson-Rubin Wald test			$\chi^2(2)=1818.79***$		
Stock-	Wright LM S statistic			χ^2	2)=726.44***	

As exclusion restrictions, we consider two instruments.

The second instrument uses the slope of the template. Given the convex relationship in previous figures, we expect that the slope of the booking curve is expected to increase with occupancy and can therefore be considered as a valid candidate for an instrument.

Slope is given by the difference between *TopFare* and *Fare1* divided by the number of available seats (50 – SoldSeats).

However, template changes are specific to each daily flight. So we use the three lagged values (lagged templates of same flight same DOW) of this slope and still retain the important information about the template, without any correlation with other flights' idiosyncratic shocks.

Full Sample Estimates

Pricing equation results using the full sample and different estimation methods. Variable: LnFare1

	I	VFE	FE-OLS		
Sold seats	0.0311	$(0.001)^{***}$	0.0343	(0.001)***	
Booking Day1	0.4121	$(0.053)^{***}$	0.2248	$(0.054)^{***}$	
Booking Day4	0.1213	$(0.051)^{**}$	-0.0542	(0.053)	
Booking Day7	-0.0962	(0.049)**	-0.2560	(0.050)***	
Booking Day10	-0.1205	$(0.047)^*$	-0.2631	$(0.049)^{***}$	
Booking Day14	-0.2589	$(0.044)^{***}$	-0.3815	$(0.047)^{***}$	
Booking Day21	-0.2062	(0.042)***	-0.2963	(0.044)***	
Booking Day28	-0.1316	$(0.039)^{***}$	-0.1948	$(0.042)^{***}$	
Booking Day35	-0.0804	(0.038)**	-0.1210	$(0.040)^{***}$	
Booking Day42	-0.0710	$(0.037)^*$	-0.0944	(0.041)**	
Booking Day48	-0.0399	(0.038)	-0.0524	(0.040)	
Booking Day56	-0.0129	(0.038)	-0.0190	(0.042)	
Booking Day63	-0.0009	(0.037)	-0.0046	(0.036)	
Tobit residual	-0.0005	(0.0004)	-0.0025	$(0.0004)^{***}$	
DUMMIES:					
Month booking	YES		YES		
Number of obs.	10	7,729	107,729		
Centered R2	0.568		0	.5683	
Excluded instruments:	2				
Underidentification K-P LM Test	$\chi^2(2) = 1151.62^{***}$				
Hansen J statistic	$\chi^2(1) =$	2.158			

An extra sold seat induces an average fare increase of 3.11%.

Temporal Fare Profile U-Shaped in both IV and OLS.

Interaction of time/Seats

		Interaction with dummy for			Interaction with dummy for	
		ays before dep.		Interaction with dummy for 10 days before dep.		ays before dep.
G 11		-	· ·		-	
Sold seats	0.0314	$(0.001)^{***}$	0.0314	$(0.002)^{***}$	0.0295	$(0.003)^{***}$
sold seats*booking period	-0.0010	(0.002)	-0.0006	(0.003)	0.0024	(0.005)
Booking Day1	0.4155	(0.053)***	0.4120	(0.053)***	0.4204	(0.053)***
Booking Day4	0.1218	(0.051)**	0.1197	$(0.051)^{**}$	0.1333	$(0.053)^{**}$
Booking Day7	-0.0991	$(0.049)^{**}$	-0.0995	(0.050)**	-0.0797	(0.055)
Booking Day10	-0.1258	$(0.048)^{***}$	-0.1253	(0.051)**	-0.1002	$(0.058)^*$
Booking Day14	-0.2639	$(0.045)^{***}$	-0.2633	$(0.048)^{***}$	-0.2340	$(0.063)^{***}$
Booking Day21	-0.2102	$(0.042)^{***}$	-0.2098	$(0.044)^{***}$	-0.1910	$(0.050)^{***}$
Booking Day28	-0.1343	(0.039)***	-0.1340	(0.041)***	-0.1211	(0.044)***
Booking Day35	-0.0820	$(0.038)^{**}$	-0.0818	$(0.039)^{**}$	-0.0745	$(0.039)^*$
Booking Day42	-0.0721	$(0.037)^{**}$	-0.0719	$(0.037)^{**}$	-0.0673	$(0.037)^*$
Booking Day48	-0.0404	(0.038)	-0.0404	(0.038)	-0.0378	(0.038)
Booking Day56	-0.0133	(0.038)	-0.0132	(0.038)	-0.0116	(0.038)
Booking Day63	-0.0012	(0.037)	-0.0012	(0.037)	0.0005	(0.037)
Tobit residual	-0.0006	(0.0004)	-0.0005	(0.0004)	-0.0004	(0.0004)
DUMMIES:						
Month booking		YES		YES		YES
Number of obs.		100031		100031		100031
Centered R2		0.5673		0.5676		0.5693
Excluded instruments:		2		2		2
$\begin{array}{c} {\rm Underidentification} \\ {\rm K-P\ LM\ Test} \end{array}$	$\chi^2(2) = 363.314^{***}$		$\chi^2(2) = 248.265^{**}$		$\chi^2(2) = 88.711^{**}$	
Hansen J statistic	2	$\chi^2(2) = 2.330$,	$\chi^2(2) = 2.212$,	$\chi^2(2) = 2.080$

Instrument: LSlope*timedummy. The two effects appear to operate separately

Competition Effects

	Low Co	mpetition	High Competition			
*	0.0332	$(0.001)^{***}$	0.0296	(0.001)***		
*	0.3355	$(0.087)^{***}$	0.4596	$(0.068)^{***}$		
	0.0687	(0.085)	0.1513	(0.065)**		
	-0.1380	$(0.082)^*$	-0.0744	(0.063)		
	-0.1518	$(0.078)^*$	-0.1071	$(0.060)^*$		
	-0.2827	$(0.075)^{***}$	-0.2505	$(0.057)^{***}$		
	-0.2028	(0.070)***	-0.2176	(0.053)***		
	-0.1154	$(0.066)^*$	-0.1521	$(0.050)^{***}$		
	-0.0661	(0.063)	-0.0944	$(0.047)^{**}$		
	-0.0398	(0.064)	-0.0979	(0.047)**		
	-0.0242	(0.062)	-0.0552	(0.045)		
	-0.0723	(0.072)	0.0214	(0.045)		
	0.0246	(0.068)	-0.0239	(0.045)		
	-0.0013	$(0.001)^*$	0.0001	(0.001)		
	v	ES	,	ÆS		
		1536	58495			
		5499	0.5825			
		2	2			
	$\chi^2(2) =$	621.4***	$\chi^2(2) = 584.1^{***}$			
	$\chi^{2}(1) =$	0.698	$\chi^{2}(1) =$	1.254		

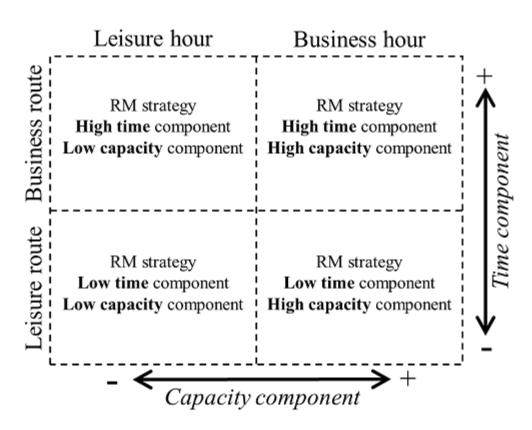
In less competitive routes/markets, the slope of the template is steeper.

This accords with intuition (higher prices at the right side of the distribution), but contrasts with Dana's prediction that fare distributions should be more dispersed in competitive routes/markets.

Competition includes flights in routes/city-pairs where Ryanair is at most a duopolist. In High Competition Ryanair operates with two or more other carriers at either the route or the city-pair level. Bootstrap Standard Errors (SE) are reported in parenthesis, clustered by route

The sequel – Focus on Business-Leisure categories

Figure 1: Hypothesis 3: RM Strategy combines time and capacity components



Business-Leisure routes

Table 4: Estimates on Business and Leisure Routes

		Route	e type				
	Busir		Leisu	ire			
AvailableSeats	-0.030***	(0.001)	-0.031***	(0.001)			
BookingDay1	0.777***	(0.047)	0.507***	(0.036)			
BookingDay4	0.479***	(0.040)	0.240***	(0.033)			
BookingDay7	0.230***	(0.034)	0.075***	(0.028)			
BookingDay10	0.169***	(0.029)	0.051**	(0.023)			
BookingDay14	-0.015	(0.024)	-0.059***	(0.019)			
BookingDay28	0.046*	(0.025)	0.095***	(0.021)			
BookingDay35	0.144***	(0.036)	0.119***	(0.030)			
BookingDay42	0.106**	(0.053)	0.108***	(0.042)			
BookingDay49	0.163***	(0.060)	0.129***	(0.047)			
BookingDay56	0.189**	(0.087)	0.158***	(0.051)			
BookingDay63	0.166**	(0.066)	0.186***	(0.058)			
BookingDay70	-0.024	(0.108)	0.274***	(0.063)			
Tobit residual	-0.000	(0.001)	0.001	(0.001)			
DUMMIES:							
MonthOfBooking	YE	S	YE	S			
Number of obs.	27,7	16	30,8	70			
R2	0.61	17	0.54	12			
Excluded instruments:	2		2				
KP LM stat.	$\chi^2(2) = 2$	58.9***	$\chi^2(2) = 34$	13.3***			
Hansen J stat.	$\chi^{2}(2) =$	0.040	$\chi^2(2) = 0.000$				

Note: The dependent variable, Fare, is the natural log of the fare obtained from a query for one seat. Bootstrap Standard Errors (SE) are reported in parenthesis, clustered by route and week. 250 repetitions. Significant at *10%, **5%, and ***1%.

Business-Leisure hours

Table 5: Estimates on Business and Leisure Hour

	Hour type						
	Business		Leisı	re			
AvailableSeats	-0.036***	(0.002)	-0.029***	(0.001)			
BookingDay1	0.615***	(0.054)	0.608***	(0.036)			
BookingDay4	0.371***	(0.048)	0.314***	(0.031)			
BookingDay7	0.171***	(0.041)	0.110***	(0.026)			
BookingDay10	0.138***	(0.033)	0.069***	(0.021)			
BookingDay14	-0.021	(0.028)	-0.058***	(0.016)			
BookingDay28	0.100***	(0.032)	0.065***	(0.018)			
BookingDay35	0.105**	(0.043)	0.143***	(0.025)			
BookingDay42	-0.013	(0.066)	0.163***	(0.035)			
BookingDay49	0.102	(0.074)	0.177***	(0.040)			
BookingDay56	0.113	(0.093)	0.209***	(0.053)			
BookingDay63	0.202**	(0.089)	0.212***	(0.051)			
BookingDay70	0.168	(0.115)	0.226***	(0.060)			
Tobit residual	0.001	(0.001)	0.000	(0.001)			
DUMMIES:							
MonthOfBooking	YE	S	YE	S			
Number of obs.	20,3	97	38,1	89			
R2	0.59	93	0.54	12			
Excluded inst.:	2		2				
KP LM stat.	$\chi^2(2) = 3$	43.1***	$\chi^2(2) = 393.5***$				
Hansen J stat.	$\chi^{2}(2) =$	0.098	$\chi^2(2) = 0.007$				

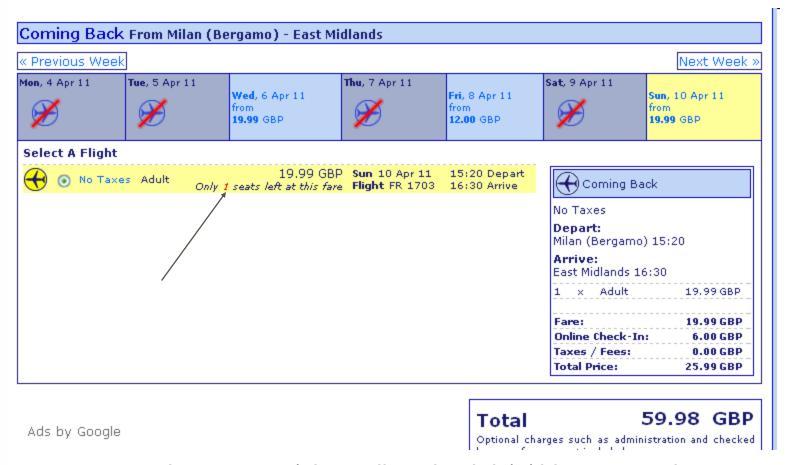
Note: The dependent variable, Fare, is the natural log of the fare obtained from a query for one seat. Bootstrap Standard Errors (SE) are reported in parenthesis, clustered by route and week. 250 repetitions. Significant at $^*10\%$, ** 5%, and *** 1%.

All combined

Table 6: Combining Route and Hour Dimensions

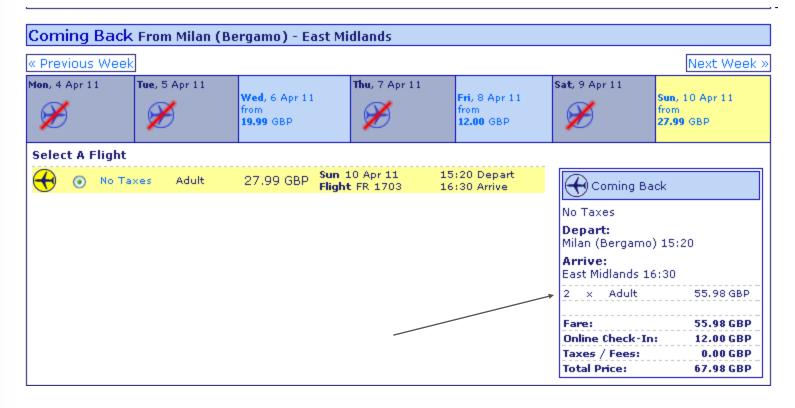
	Route/Hour type							
	Bus/l	Bus	Lei/Bus		Bus/Lei		Lei/Lei	
AvailableSeats	-0.035***	(0.002)	-0.035***	(0.002)	-0.027***	(0.002)	-0.029***	(0.001)
BookingDay1	0.795***	(0.081)	0.529***	(0.080)	0.794***	(0.053)	0.484***	(0.047)
BookingDay4	0.538***	(0.071)	0.282***	(0.068)	0.471***	(0.046)	0.210***	(0.041)
BookingDay7	0.288***	(0.057)	0.109*	(0.059)	0.216***	(0.040)	0.053	(0.036)
BookingDay10	0.221***	(0.048)	0.094**	(0.048)	0.152***	(0.031)	0.025	(0.029)
BookingDay14	0.020	(0.042)	-0.039	(0.040)	-0.027	(0.027)	-0.066***	(0.024)
BookingDay28	0.078	(0.053)	0.103**	(0.046)	0.020	(0.029)	0.089***	(0.023)
BookingDay35	0.101	(0.070)	0.090	(0.060)	0.139***	(0.039)	0.123***	(0.034)
BookingDay42	-0.085	(0.120)	-0.003	(0.092)	0.143***	(0.055)	0.142***	(0.045)
BookingDay49	0.138	(0.108)	0.050	(0.111)	0.165**	(0.070)	0.148***	(0.055)
BookingDay56	0.183	(0.132)	0.023	(0.134)	0.168	(0.111)	0.180***	(0.060)
BookingDay63	0.164	(0.120)	0.197	(0.136)	0.160**	(0.075)	0.176***	(0.068)
BookingDay70	-0.076	(0.212)	0.289*	(0.169)	0.004	(0.139)	0.256***	(0.068)
Tobit residual	0.001	(0.001)	0.002	(0.002)	-0.001	(0.001)	0.001	(0.001)
DUMMIES:								
MonthOfBooking	YE	S	YE	S	YE	S	YE	S
Number of obs.	9,06	69	11,328		18,647		19,542	
R2	0.64	14	0.54	19	0.60)7	0.54	19

Useful theory to save when booking a flight



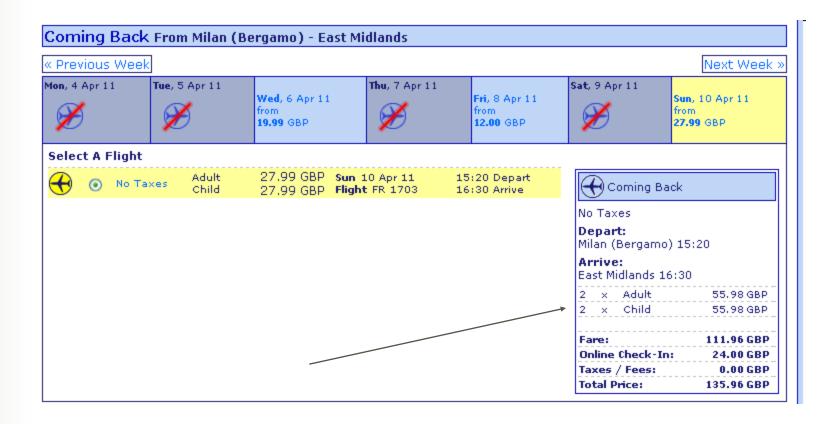
Buy one seat, and pay 19.99 (plus online check-in) (this was not the case when data was collected)

How to save

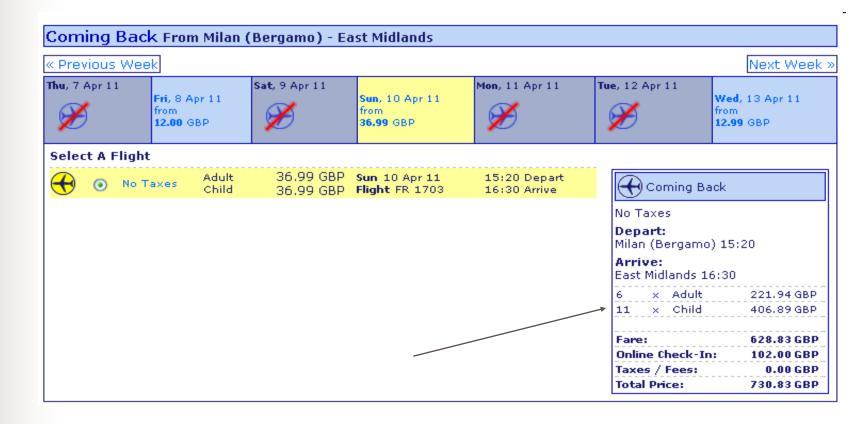


Buy two seats, and each seat will cost 27.99£ (so best to buy each seat separately. From experience, pricing curve will not change in between bookings: bought 3+1 tickets and saved on the first 3.)

Size of the party does not matter



Unless size is so large...



... That the next "fare class" is reached (hence, the £27.99 fares applies to a batch of 15 seats)

Thanks for your attention.

QUESTIONS?

"But I have seen fares go down"

Various ways to do this. Still under study! Possibilities:



Some seats are moved to a lower fare class.

"But I have seen fares go down"

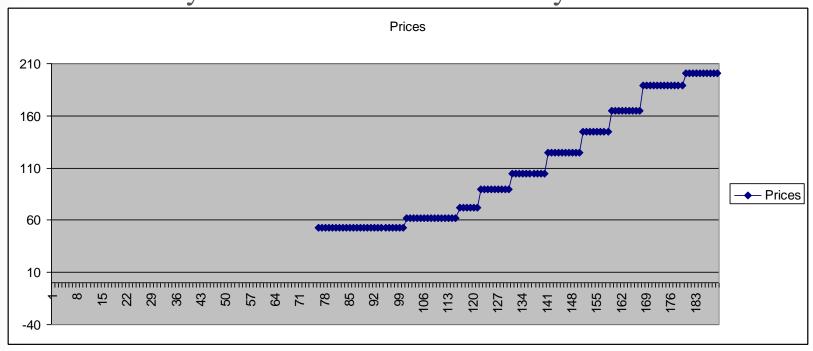
Various ways to do this. Still under study! Possibilities:



ALL fare classes are shifted down.

"But I have seen fares go down"

Various ways to do this. Still under study! Possibilities:



SOME fare classes are shifted down.