Do Jet Fuel Price Movements Help Forecast Airline Fares and the Demand for Air Travel?

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Abstract

The paper studies the predictive content of jet fuel prices for the U.S. aviation industry through in-sample and out-of-sample forecasting exercises. Our results suggest the possibility of limited improvements in the predictions of airline fares, and little evidence of predictability from jet fuel prices to measures of air travel demand.

JEL classification: Q41, C32

Keywords: Jet fuel; out-of-sample forecasting; Airline industry

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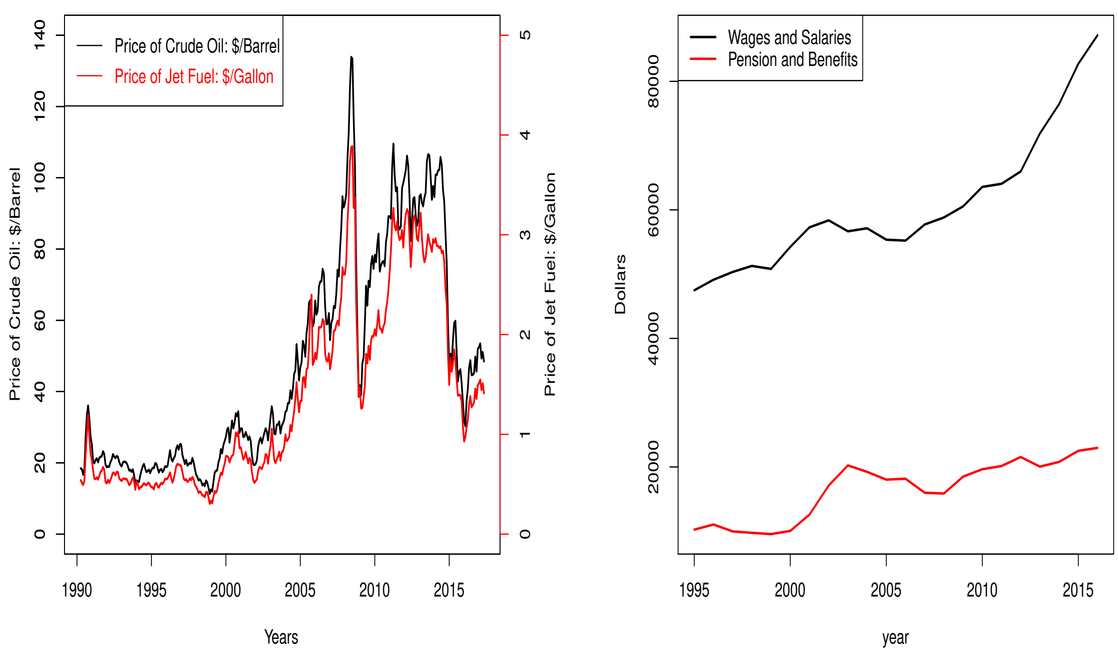
1 Introduction

Labor and fuel costs represent the major cost sources for airlines. Fuel costs constituted approximately 20% to 50% of total costs for airlines in 2014 (Koopmans and Lieshout, 2016), while labor costs accounted for about 32.9% of systemwide unit cost (Stalnaker et al., 2015). Whereas labor costs are generally stable in the short run (Figure 1B), jet fuel costs tend to fluctuate significantly depending on crude oil prices (Figure 1A).

As a consequence of the high volatility of the price of jet fuel relative to other costs, consumers, airline industry firms, and financial market participants, pay special attention to fuel costs when predicting airline industry variables. Consumers concerned about the cost and availability of air travel, time their purchases based on expected ticket prices and the possibility that preferred flights sell out. Airline industry firms need an estimate of future ticket prices and overall demand for air travel when making scheduling and related

Figure 1: Jet Fuel Prices, Crude Oil Prices, and Average Labor Cost for Airline Employees

A. Jet Fuel and Crude Oil Prices B. Wages and Salaries, and Pension and Benefits



Source: US Department of Transportation (DOT) Form 41 via Bureau of Transportation Statistics (BTS), Schedule P6 & P10.

decisions. Financial market participants value airline industry stocks based on projected future airline revenue. Despite the huge cost share of jet fuel for airlines, and the uncertainty caused by fluctuations in jet fuel prices, not much research has addressed the question of the predictability of airline variables following jet fuel price movements.

This paper asks whether jet fuel price movements are helpful as predictors of airline industry variables. We investigate whether including jet fuel price movements in benchmark autoregressive models helps improve the in-sample fit and out-of-sample forecasts of aviation industry variables. We find some evidence of predictability of airfares. For other airline industry variables, the improvements in forecast accuracy are at best minimal.

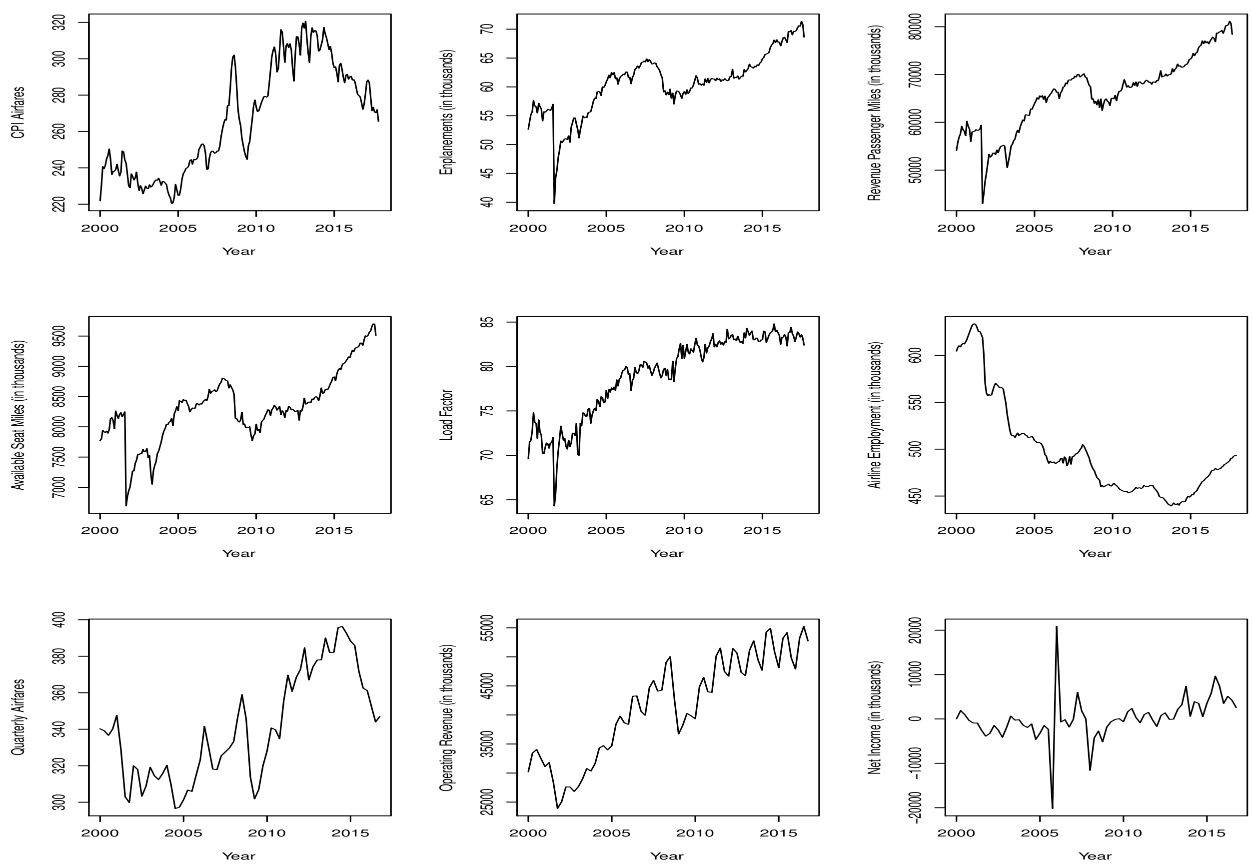
2 Methodology

2.1 Data

The aviation industry variables we consider include airfares, the consumer price index for airfares (CPI airfares), enplanements, revenue passenger miles, available seat miles, flights performed, and load factor, all for U.S. air carrier domestic and international scheduled passenger flights. Data on all employees in the air transportation and warehousing sector (employment), net income, and operating revenue of all U.S. air carriers are also used. The data are all monthly, except airfares, net income, and operating revenue which are quarterly. The monthly data were downloaded from the Federal Reserve Economic Database (FRED), for the period $2000 : M1 - 2016 : M12$. The quarterly data come from the Bureau of Transportation Statistics for the period $2000 : Q1 - 2016 : Q4$. Figure 2 plots the airline variables. We take the year-over-year growth rates when estimating the forecasting models.

The data on jet fuel prices are monthly U.S. Gulf Coast kerosene-type jet fuel prices downloaded from FRED. We also use monthly data on global crude oil production, global real economic activity (REA), and the U.S. refiner acquisition cost (RAC) of imported crude oil as a proxy for crude oil prices (Kilian and Vigfusson, 2013; Baumeister et al., 2017). Global crude

Figure 2: U.S. Airline Industry Indicators



oil production and RAC come from the U.S. Energy Information Administration. REA come from Kilian (2009), available at: http://www-personal.umich.edu/~lkilian/reaupdate.txt.[1] All nominal variables are converted to real terms by deflating by the CPI.

2.2 Forecasting Models

The benchmark model is an autoregressive (AR) model of order p:

$$x_t = \alpha + \sum_{i=1}^{p} \beta_i x_{t-i} + \varepsilon_t \tag{1}$$

where x_t is a U.S. aviation industry variable, ε_t is the error term, and p denotes the lag length, chosen using the Schwarz Information Criterion (SIC) with $1 \leq p \leq 12$.

[1] See Kilian (2009), and Kilian and Zhou (2017) for the construction of and rationale for this index.

The first alternative model is a bivariate vector autoregressive (VAR) model:

$$x_t = \alpha + \sum_{i=1}^{p} \beta_i x_{t-i} + \sum_{i=1}^{p} \delta_i \Delta jet_{t-i} + \varepsilon_t \tag{2}$$

where Δjet denotes the percentage change in real jet fuel prices.

The second alternative model recognizes that demand and supply factors underlying the crude oil market drive jet fuel prices. To disentangle these factors, we follow Kilian (2009). We only present a brief discussion of the model as details can be found in Kilian (2009). Consider the structural VAR (SVAR) model:

$$A_0 X_t = \alpha + \sum_{i=1}^{24} A_i X_{t-i} + \varepsilon_t$$

X_t contains, in the order listed, global crude oil production ($prod_t$), global real economic activity (rea_t), and real RAC oil prices (oil_t). Oil price changes are assumed to be driven by shocks to oil supply (ε_{st}), aggregate demand (ε_{yt}), and crude oil demand (ε_{ot}). Rewriting the SVAR model in reduced-form as:

$$\begin{aligned}
prod_t &= \alpha_0 + \sum_{i=1}^{24} \alpha_{1i} prod_{t-i} + \sum_{i=1}^{24} \alpha_{2i} rea_{t-i} + \sum_{i=1}^{24} \alpha_{3i} oil_{t-i} + e_{st} \\
rea_t &= \beta_0 + \sum_{i=1}^{24} \beta_{1i} prod_{t-i} + \sum_{i=1}^{24} \beta_{2i} rea_{t-i} + \sum_{i=1}^{24} \beta_{3i} oil_{t-i} + e_{yt} \\
oil_t &= \gamma_0 + \sum_{i=1}^{24} \gamma_{1i} prod_{t-i} + \sum_{i=1}^{24} \gamma_{2i} rea_{t-i} + \sum_{i=1}^{24} \gamma_{3i} oil_{t-i} + e_{ot}
\end{aligned}$$

where e_t denotes the reduced-form residuals, identification restrictions are imposed, leading to a recursively identified structural model:

$$e_t \equiv \begin{pmatrix} e_{st} \\ e_{yt} \\ e_{ot} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{pmatrix} \varepsilon_{st} \\ \varepsilon_{yt} \\ \varepsilon_{ot} \end{pmatrix}$$

These identification restrictions are discussed in Kilian (2009). Once the structural shocks are recovered, we estimate a regression of the percentage change in real jet fuel prices (Δjet) on the oil shocks:

$$\Delta jet_{st} = \alpha + \sum_{i=0}^{p} \beta_i \varepsilon_{s,t-i} + e_{jst}$$

$$\Delta jet_{ot} = \alpha + \sum_{i=0}^{p} \beta_i \varepsilon_{o,t-i} + e_{jot}$$

The fitted values, $\widehat{\Delta jet}_{st}$ and $\widehat{\Delta jet}_{ot}$, denote jet fuel price movements due to oil supply and demand factors. Jet fuel supply shocks will cause jet fuel prices to rise, hurting demand for air travel, while jet fuel demand shocks capture factors such as the macroeconomy that drive up both the demand for air travel and jet fuel prices.

Forecasts of x due to demand and supply factors can then be estimated using the model:

$$x_t = \alpha + \sum_{i=1}^{p} \beta_i x_{t-i} + \sum_{i=1}^{p} \delta_i \widehat{\Delta jet}_{s,t-i} + \sum_{i=1}^{p} \gamma_i \widehat{\Delta jet}_{d,t-i} + \varepsilon_t \quad (3)$$

If one does not distinguish between movements in jet fuel prices driven by supply and demand factors, it is unclear what the relationship will be between jet fuel price movements and aviation industry variables, or if there should be a systematic relationship at all.

We also compare the forecast performance of the models against that of a random walk model. Random walk model forecasts are commonly used as benchmarks in forecast evaluation (see e.g. Alquist et al., 2013). The inability to beat random walk forecasts is often interpreted as evidence that a variable cannot be forecast.

2.3 Forecast Evaluation

We use the mean squared forecast errors ($MSFE$) of the models relative to the benchmark $AR\,(p)$ model to evaluate forecast performance. Let $\hat{x}_{j,t+h}$ denote the recursive out-of-sample forecast of x_{t+h} based on the j^{th} forecasting model. Denote recursive forecasts from the $AR(p)$

benchmark by $\hat{x}_{1,t+h}$. The $MSFE$ of model j relative to the $AR(p)$ benchmark is:

$$relative\ MSFE = \frac{\sum_{t=T_1}^{T_2-h} \left(x_{t+h} - \hat{x}_{j,t+h}\right)^2}{\sum_{t=T_1}^{T_2-h} \left(x_{t+h} - \hat{x}_{1,t+h}\right)^2} \tag{4}$$

where T_1 and T_2 denote the start and end dates over which the h-step-ahead forecasts are constructed. In this paper, $T_1 = 2010 : M1$ and $T_2 = 2016 : M12$ when using monthly data, and $T_1 = 2010 : Q1$ and $T_2 = 2016 : Q4$ for quarterly data. A $relative\ MSFE < 1$ indicates that the j^{th} model outperforms the $AR(p)$ benchmark.

3 Empirical Results

3.1 In-Sample Evidence of the Predictive Content of Jet Fuel Price Movements

We investigate the in-sample predictability of jet fuel prices using the heteroskedasticity-robust Granger-causality test statistic (Table 1). For flights, the tests reject the null of no predictive content, providing evidence of predictability of jet fuel prices. Model 2 further provides evidence of predictability for airfares, CPI airfares, available seat miles and employment, while model 3 shows that jet fuel price movements driven by oil supply and demand factors are helpful in predicting operating revenue.

The finding of predictability of airfares is not surprising. Jet fuel costs represent the single most significant cost to airlines. To the extent that airlines pass these costs through to passengers in the form of higher airfares, this evidence of predictability is exactly what one would expect. We also find that jet fuel prices have no predictive content for the remaining airline variables, suggesting that jet fuel price movements in either direction are offset by changes in prices only to the extent that it does not affect travel demand.

Table 1: In-Sample Evidence of the Predictive Content of Jet Fuel Price Movements

$Airline\ industry\ Variable$	$Model\ 2$	$p-value$	$Model\ 3$	$p-value$
$Airfares$	4.368**	(0.017)	1.990	(0.109)
$CPI\ Airfares$	10.578***	(0.000)	1.493	(0.206)
$Enplanements$	0.272	(0.762)	0.801	(0.526)
$Flights\ Performed$	4.087**	(0.019)	3.091**	(0.018)
$Revenue\ Passenger\ Miles$	0.434	(0.649)	1.045	(0.385)
$Available\ Seat\ Miles$	2.226	(0.111)	0.726	(0.575)
$Load\ Factor$	0.213	(0.808)	2.720**	(0.031)
$Airline\ Employment$	2.564*	(0.080)	1.699	(0.152)
$Net\ Income$	2.193	(0.121)	1.114	(0.359)
$Operating\ Revenue$	1.387	(0.258)	3.341***	(0.016)

Notes: Numbers are Wald $F-$statistics, and numbers in parentheses are p-values. '*', '**', and '***' indicate significance at the 10%, 5%, and 1%.

3.2 Out-of-Sample Forecasts

The one-step-ahead $MSFE$ of the random walk model relative to the $AR(p)$ benchmark is displayed in column 1 of Table 2. The *relative* $MSFE > 1$ in all cases, implying that there is a substantial predictable component in each series. The question is whether jet fuel price movements can help to identify the predictable component.

The *relative* $MSFE$ forecasts of Models 2 and 3 are in columns 2 and 3 of Table 2. The table shows that both models yield gains in forecast accuracy relative to the benchmark for airfares ($MSFE < 1$). For the remaining variables, improvements in forecast accuracy are sporadic. Including Δjet into the benchmark improves forecasts of only CPI airfares and operating revenue (Model 2), while the model with $\widehat{jet}_{st}$ and $\widehat{jet}_{ot}$ (Model 3) shows forecast gains for flights and load factor.

Until now, we have only considered one-step-ahead forecasts. Changes in jet fuel prices may not immediately affect variables like revenue passenger miles because those decisions are made several months in advance. Reported in Table 3 are the *relative* $MSFE$ of Models 2 and 3 at $h = 3, 6, 12$. Lag lengths are selected using the SIC. Airfares continue to be predictable after three months, but at longer horizons, improvements in forecast performance are minor. Jet fuel prices have strong predictive power for airline employment at all horizons.

Table 2: One-Step-Ahead MSFE of Candidate Models Relative to $AR(p)$ Benchmark

Airline Industry Variable	*Random Walk*	*Model 2*	*Model 3*
Airfares	7.373	**0.865**	**0.980**
CPI Airfares	7.072	**0.951**	1.111
Enplanements	5.579	1.023	1.326
Flights Performed	1.499	1.090	**0.982**
Revenue Passenger Miles	3.256	1.026	1.263
Available Seat Miles	17.097	1.101	1.157
Load Factor	7.143	1.060	**0.991**
Airline Employment	50.245	1.126	1.088
Net Income	2.831	1.237	1.116
Operating Revenue	23.900	**0.844**	1.273

Notes: Boldface indicates gains in accuracy relative to the benchmark model.

Table 3: Multi-Steps-Ahead $MSFE$ of Candidate Models Relative to $AR(p)$ Benchmark

	3-Steps-Ahead		6-Steps-Ahead		12-Steps Ahead	
Airline Industry Variable	*Model 2*	*Model 3*	*Model 2*	*Model 3*	*Model 2*	*Model 3*
Airfares	1.043	**0.689**	1.388	1.336	1.627	**0.995**
CPI Airfares	**0.837**	1.018	1.074	1.015	**1.080**	**0.984**
Enplanements	1.107	1.949	1.096	1.480	1.750	1.098
Flights Performed	1.310	1.056	1.560	1.117	1.907	1.082
Revenue Pass. Miles	1.040	2.272	1.012	1.550	1.285	1.311
Available Seat Miles	1.131	1.651	1.282	1.452	**0.917**	1.051
Load Factor	1.084	1.472	1.139	1.127	1.112	1.344
Airline Employment	**0.942**	1.163	**0.827**	1.023	**0.893**	**0.997**
Net Income	1.678	**0.990**	1.355	2.307	1.265	1.007
Operating Revenue	1.457	1.265	2.126	1.567	1.297	**0.872**

Notes: Boldface indicates gains in accuracy relative to the benchmark model.

When forecasting at longer horizons, it is no longer clear whether the SIC estimate of lag lengths makes sense (Kilian and Lütkepohl; 2017). To ensure that the multi-step-ahead forecasts are not biased because the SIC selects too few lags, we now report *relative* $MSFE$ for $h = 3, 6, 12$, and $p = 3, 6, 9, 12$ (Table 4) for the seven monthly variables. We omit the quarterly variables because using more than 4 lags is generally not recommended for quarterly data. In addition, over 4 lags causes serious degrees of freedom problems given our small sample size. The table shows minimal gains in forecast accuracy. Worth noting are the gains in accuracy of our models for the six step-ahead forecasts of airfares.

4 Conclusion

This paper has investigated whether jet fuel prices are helpful in forecasting airline fares and the demand for air travel. We rely on mean squared forecast errors (MSFE) to evaluate the out-of-sample forecast performance of our models relative to the benchmark model. We find some evidence of predictability of airfares. For measures of air travel demand and other variables, improvements in forecast accuracy, however, are minimal. Our findings are consistent with complementary evidence provided in Baumeister and Kilian (2017) on the absence of a stimulus from the 2014/15 oil price decline on the U.S. transportation sector in general, and on airline passenger revenue miles in particular.

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Table 4: Multi-Steps-Ahead MSFE of Candidate Models Relative to $AR(p)$ Benchmark

A. Lag Length : 3

Airline Industry Variable	3−Steps−Ahead Model 2	3−Steps−Ahead Model 3	6−Steps−Ahead Model 2	6−Steps−Ahead Model 3	12−StepsAhead Model 2	12−StepsAhead Model 3
CPI Airfares	**0.83**	1.02	**0.98**	**0.96**	1.08	1.01
Enplanements	1.11	2.34	1.36	2.26	1.82	1.40
Flights Performed	1.19	1.02	1.49	1.08	1.57	1.25
Revenue Pass. Miles	1.03	2.86	1.08	2.24	1.60	1.92
Available Seat Miles	1.19	1.90	1.41	1.91	**0.94**	1.29
Load Factor	1.12	1.62	1.18	1.22	1.13	1.48
Airline Employment	**0.87**	1.13	**0.81**	1.03	**0.88**	1.02

B. Lag Length : 6

Airline Industry Variable	3−Steps−Ahead Model 2	3−Steps−Ahead Model 3	6−Steps−Ahead Model 2	6−Steps−Ahead Model 3	12−StepsAhead Model 2	12−StepsAhead Model 3
CPI Airfares	**0.86**	1.05	**0.96**	**0.80**	1.12	1.11
Enplanements	1.42	3.36	5.12	1.86	3.12	1.66
Flights Performed	1.16	1.05	1.49	1.06	1.59	1.51
Revenue Pass. Miles	1.11	3.77	3.13	1.79	4.02	2.64
Available Seat Miles	1.27	2.47	1.61	1.76	2.04	2.20
Load Factor	1.24	1.61	1.26	1.33	1.13	1.75
Airline Employment	**0.90**	1.10	**0.77**	1.03	0.97	1.17

C. Lag Length : 9

Airline Industry Variable	3−Steps−Ahead Model 2	3−Steps−Ahead Model 3	6−Steps−Ahead Model 2	6−Steps−Ahead Model 3	12−StepsAhead Model 2	12−StepsAhead Model 3
CPI Airfares	**0.90**	**0.95**	**0.97**	**0.89**	1.25	1.20
Enplanements	3.40	2.47	4.89	2.55	4.87	2.15
Flights Performed	1.21	1.12	1.60	1.94	3.10	3.07
Revenue Pass. Miles	2.38	2.55	5.40	3.43	6.91	4.11
Available Seat Miles	1.34	1.98	2.20	2.49	4.44	3.23
Load Factor	1.30	1.42	1.08	1.56	1.37	1.85
Airline Employment	**0.84**	1.27	**0.79**	1.31	1.63	1.52

D. Lag Length : 12

Airline Industry Variable	3−Steps−Ahead Model 2	3−Steps−Ahead Model 3	6−Steps−Ahead Model 2	6−Steps−Ahead Model 3	12−StepsAhead Model 2	12−StepsAhead Model 3
CPI Airfares	1.03	1.11	1.20	**0.96**	1.52	1.49
Enplanements	2.43	2.25	7.71	3.42	5.63	2.49
Flights Performed	1.27	1.41	2.20	4.49	4.91	3.81
Revenue Pass. Miles	2.52	2.71	8.50	4.13	9.32	6.21
Available Seat Miles	1.86	2.09	4.05	3.53	6.01	4.04
Load Factor	1.04	1.80	1.08	1.92	1.76	2.31
Airline Employment	1.03	2.05	1.41	1.89	2.46	2.10

Notes: Boldface indicates gains in accuracy relative to the benchmark model.

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