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Occupancy, oil prices, and stock returns: Evidence from the U.S. airline industry

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Abstract:

This paper examines whether occupancy of seats affects stock returns of airline companies and how this relationship is affected by WTI oil prices. Our approach combines revenues (occupancy) and costs (oil prices) for 33 U.S. airline companies from 1990 to 2019. Using travel capacity utilization data from U.S. carriers at monthly frequency and exploiting fixed-effects regression models, we document a positive relation between occupancy and stock returns, which is attenuated by oil prices. The role of oil becomes larger with asymmetries: the effects of oil prices are higher when moving up than down. Airline stocks always respond by more than the overall stock market.

Keywords: airline companies, asymmetries, occupancy, oil price returns, stock returns.

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1. Introduction

We examine in this article a sector of the U.S. economy (airlines) operating in the leisure, tourism, and transportation sector that uses oil as its major input. Using oil price returns as a measure of costs, these companies are subject to flows of revenue stream, in which of utmost importance are capacity utilization measures, such as occupancy of seats, number of passengers traveling, and so on. These flows of revenues can be steady in normal economic conditions or may fluctuate enormously during abrupt events, such as the terrorist attacks of 9/11 or the pandemic, such as COVID19. The same may happen to oil prices, which move downward quickly in the presence of unforeseen circumstances of the global supply or demand for oil.

In contrast to earlier papers for the airline industry, we take into account information directly from U.S. airlines (seat-occupancy), which is available at a monthly frequency, together with oil price returns to capture jet fuel (cost) fluctuations.[1] We investigate the extent to which these two components are passed through to the market price of airline stocks, with stock returns of a representative sample of U.S. airline companies as the dependent variable. We allow in the empirical models for standard controls in the literature of stock returns, such as oil price volatility, yield spread, aggregate stock market, and Fama-French factors.

[1] This measure (seat-occupancy) is very important for the airline industry by appearing not only in frequent market reports but also by its potential to adjust quickly to demand shifts. For example, McCartney (2020) reviews the state of the U.S. airline industry in late-2020 with respect to recent measures of capacity utilization and passenger travel and notes: "The bottom line: Travel is one-third of what it used to be. Does that mean planes are only one-third full? No, since airlines have grounded many flights and substituted smaller planes on many routes. But just how full are planes? In the third quarter, which is traditionally a busy time for airlines, American, United, Delta and Southwest averaged 48.4% combined load factor, or the percentage of seats filled." McCartney (2020) also compares the coronavirus economy of 2020 to the terrorist attacks of 9/11 in the U.S. in 2001 and notes that "If you want a good measuring stick for the impact of the pandemic on airlines, compare what's happening now to the industry collapse following the 2001 terrorist attacks. The six biggest U.S. airlines have experienced losses nearly twice as big as inflation-adjusted losses those same airlines, including their merger partners, had after 9/11."

Our approach in this paper is based fundamentally on Sadorsky (2008) and Narayan and Sharma (2011), as well as more recent advances by Shaeri et al. (2016), Baur and Todorova (2018), and Killins (2020). While the first two papers combine firm-level data (sales or turnover), the latter three investigate oil price returns along with the aggregate stock market in a multi-factor approach to stock returns augmented by Fama-French factors. We implement this approach for monthly panel data of 33 airlines from 1990 to 2019, almost 30 years of data, with the following main results. The occupancy of seats is priced in stock returns of U.S. airlines, the effects of oil prices have higher effects when they move up than when they move down, and airline stocks respond by more to movements in the overall U.S. stock market.

This paper contributes to the literature in several ways. First, we show that the capacity utilization (occupancy) of airline companies is an important factor for stock returns. This finding helps investors understand the visible attribute of the revenue side of airline companies before investing in these stocks. For example, knowledge of historical trends of capacity utilization can help investors decide how and whether to invest. Second, increases in oil prices enlarge the operating costs for airline companies, which outweigh the revenue from higher occupancy rates. The role of oil prices suggests that airline companies may consider operating as efficiently as possible. Third, this study shows the moderating effects of oil prices are more visible when they move up than down. Airline companies can therefore maintain financial slack to cope up with increased operational costs due to oil prices moving up when operating efficiency is not feasible. Fourth, this study documents the higher movement of airline stocks with respect to the overall market.

We organize this article as follows. Section 3 introduces the data, section 4 presents the empirical panel data models, section 5 contains the results and interpretation of our findings, and section 6 concludes the paper.

2. Literature Review

Studies of the airline industry normally consider the effects of increasing oil prices on fuel costs and the decline in profits. Kristjanpoller and Concha (2016) study the impact of fuel price fluctuations on stock returns of 56 airlines using univariate GARCH models. Estimated rates of adjustment by Kaufmann (2017) with an error-correction mechanism indicate that the large reduction in oil prices has been passed to airfares. Demiralay and Kilincarslan (2019) verify that geopolitical risks have negative effects on travel and leisure stocks, with Asia and Pacific index the most resilient, while Yun and Yoon (2019) check for oil price changes on stock prices of 4 airlines in China and South Korea and conclude that smaller companies are more sensitive to oil prices compared to the transportation sector. Wang and Gao (2020) examine the effects of oil prices on earnings using quarterly data for 30 airlines. Csereklyei and Stern (2020) employ aircraft-level data in a translog cost function model for 1,267 airlines in 174 countries and conclude that larger and newer aircraft are more efficient.

More generally, the connection between stock returns and oil price returns have been addressed by many empirical studies. Smyth and Narayan (2018) and Herrera et al. (2019) offer recent surveys of this extensive literature. To quote a few studies, Sadorsky (2008) incorporates firm-level information (annual sales) and documents negative effects on stock returns due to firm size and negative oil price return effects for U.S. stock returns for the sample ending in 2006.

Mollick and Assefa (2013) show multivariate GARCH time-varying estimates for major aggregate indices of U.S. stock returns and the changes caused by the global financial crisis. Alsalman (2016) reports oil price uncertainty on the U.S. real stock returns based on a GARCH-in-mean VAR model, which in general do not suggest statistically significant effects, possibly due to the ability of companies to hedge against oil prices or because of their ability to transfer the higher oil costs to consumers. Baur and Todorova (2018) estimate four-factor regression models for excess returns on the market risk premium, small to big, high to low book value stocks, and oil price returns. Their results for the world's 15 largest automobile companies using daily data from 1990 to 2016 yield negative oil price sensitivity for most companies, while Tesla is the only company displaying positive oil price sensitivity consistent with its nature as a producer of electric cars. On the transformation of oil production in the U.S., Thorbecke (2019a) notes that the beneficial effects of oil price increases on the U.S. economy have increased since U.S. oil production soared after 2010. When Huang and Mollick (2020) disentangle world oil supply from U.S. oil supply of two types (conventional oil and tight/shale oil), they find an increasing role after 2010 of oil supply forces in a model with the real price of WTI oil and U.S. stock returns.

Sector-based approaches with various methodologies include Sadorsky (2001) for the Canadian oil and gas sector; Nandha and Faff (2008) for global sectors; Arouri (2011) for Gulf Cooperation Council countries; Mohanty and Nandha (2011) for U.S. oil and gas companies; Degiannakis et al. (2013) for the European industrial sector; Mollick and Nguyen (2015) for asymmetric oil price effects in U.S. oil and gas companies; Shaeri et al. (2016) for comparisons between U.S. financial and non-financial subsectors; Kang et al. (2017) for major oil and gas companies; Thorbecke (2019b) for Asian economies and sectors (airlines, food, and industrial transportation) more severely harmed by oil price increases; Stamolampros and Korfiatis (2019) for aggregated data to study the impact of interest rates, fuel prices, and market oncentration on airline service measures, such as on-time performance and cancelled flights; and Hadi et al. (2020) for cointegration among the U.S. travel and leisure index responding to industrial production, commercial and industrial loans, and international tourist arrivals.

3. Data & Sampling

We combine several datasets to build our final sample for this study. Firstly, we collect airline travel capacity utilization data from the T-100 Domestic Segment (U.S. Carriers) of the Bureau of Transportation Statistics.[2] Transportation statistics provides airline travel capacity utilization data on a monthly basis for all flights record from 1990. The dataset provides airline company name, origin and destination locations, service class for passengers on a plane, total passengers, available capacity/total seats, and distance. From this data, we measure the occupancy ratio (OR) as the ratio of the total number of passengers to the total number of aircraft seats over the month for a particular carrier. However, the *occupancy* is our firm-level key independent variable for the model of stock returns below. In order to remove the persistence in the raw series and to make it consistent with the return series of stock and oil price returns, as a key independent variable in our estimation, we use *occupancy* as the growth rate of occupancy ratio ($(OR_t - OR_{t-1})/OR_{t-1}$), where occupancy ratio (OR_t) is the ratio of the total number of passengers to the total number of aircraft seats in a month.

Secondly, we obtain stock returns and S&P 500 composite index data from the daily CRSP database. Using the daily CRSP stock returns data, we compute the company's monthly stock

[2] We collect airline capacity utilization data from https://www.transtats.bts.gov/tables.asp?DB_ID=110&DB_Name=&DB_Short_Name=

returns as continuously compounded daily returns. We also compound the daily S&P composite index to make a monthly S&P composite index as market returns. Thirdly, the yield spread (the difference between 10-Year and 3-Month U.S. Treasury Constant Maturity rates) and WTI oil price data come from the Federal Reserve Bank of St. Louis.[3] Finally, we collect the monthly Fama-French factors from the Kenneth R. French website.[4] Since we focus on the airline company's stock returns, we restrict our sample to two-digit SIC code 45. We manually match the airline company's monthly occupancy data with monthly stock returns data, which are compounded from daily CRSP stock returns data. We first get 479 unique airline companies' names from the T-100 Domestic Segment (U.S. Carriers) dataset retrieved from the Bureau of Transportation Statistics. Second, we get 135 unique airline companies' names under the two-digit SIC code: 45 (airline industry) from the daily CRSP database. Since we link airline companies' occupancy to their stock returns, we carefully look for airline companies that have a presence in both datasets (the T-100 Domestic Segment (U.S. Carriers) from the Bureau of Transportation Statistics and the CRSP databases). Out of 479 unique airline companies retrieved from the T-100 Domestic Segment (U.S. Carriers), we get 39 unique companies that have stock returns data available in the daily CRSP database. Our sample is unbalanced panel data. Once we drop missing observation after merging all other datasets, we end up with 33 unique airline companies listed in Appendix B. Our final sample consists of 4,246 company-year-month observations spanning from 1990-2019. Our sample begins in January 1990 since prior to that there are no airline travel data

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[3] We collect Treasury constant maturity data from https://fred.stlouisfed.org/series/T10Y3M#0 and WTI oil price data from https://fred.stlouisfed.org/series/DCOILWTICO

[4] Fama and French 3 factors are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research

from the Bureau of Transportation Statistics. To address the effect of outliers, we winsorize all continuous variables at the 1 percent level in each tail.

Figure 1 shows the growth rate of seat occupancy[5] and stock returns of U.S. airline companies over the sample. Stock returns of U.S. carriers show sharp declines during the 2001 recession and terrorist attacks of 9/11 and the 2008 global financial crisis. The growth rate of occupancy moves sharply up in the early 1990s, and after 9/11. In 2001-2002 stock returns respond downwards to the drop in occupancy. Stock returns comove slightly (correlation coefficient of 0.099 in Table 2A) with the growth rate of occupancy ratio over the sample. From an operating cost perspective, Figure 2 shows that stock returns comove with oil price changes (correlation coefficient of -0.106 in Table 2A). Airline companies incur large costs due to oil price increases, which puts pressure on airline stocks. Note, however, that in 2008 oil prices fall by 8% versus 4% of stock returns, consistent with temporary positive comovement when both asset classes were affected by the global financial crisis. This can also be explained by the time-varying relationship between stocks and oil discussed in the Introduction. Figure 3 shows the comovement of the occupancy growth rate and oil price returns over the sample with a low correlation coefficient of 0.023 reported in Table 2A.

4. Empirical Methodology

We employ the following baseline empirical fixed-effect model that links the stock returns of airline carrier j in the month t to the growth rate of seat occupancy, WTI log returns, yield spread, and Fama-French factors.

[5] We interchangeably use the growth rate of seat occupancy and occupancy.

$$Ret_{ity} = a_0 + \beta_1 Occupancy_{ity} + \beta_2 Oil\_ret_{ty} + \beta_3 Oil\_ret\_\,vol_{ty} + \gamma`\mathrm{Z}_{ty} + \varepsilon_{ity} \qquad (1),$$

$$Ret_{ity} = a_0 + \beta_1 Occupancy_{ity} + \beta_2 Oil\_ret_{ty} + \beta_3 Occupancy_{ity} * Oil\_ret_{ty} + \beta_4 Oil\_ret\_vol_{ty} + \gamma`\mathrm{Z}_{ty} + \varepsilon_{ity} \qquad (2),$$

where, Ret_{it} is the key independent variable, measured as compounded daily CRSP returns over a month for carrier i in month t of year y.[6] $Occupancy$ represents the growth rate of occupancy ratio ($(OR_t - OR_{t-1})/OR_{t-1}$), where occupancy ratio (OR_t) is the ratio of the total number of passengers to the total number of aircraft seats over a month for carrier i in month t of year y. We also define a dummy variable, High Occupancy, which indicates 1 if the growth rate of occupancy is above the sample median, and 0 otherwise. Oil return is the daily WTI log price difference compounded monthly. Oil return volatility is computed as the square root of the sum of squared daily WTI log price difference return for each month. Other controls include spread, which is the 10-Year Treasury Constant Maturity minus 3-Month Treasury Constant Maturity. Z_t is a vector of market characteristics (such as yield spread, CRSP value-weighted returns/Market return, SMB, and HML) assumed to affect a company's stock returns. To incorporate market returns, we use either the CRSP value-weighted market return or S&P 500 composite index. S&P500 stock return is the S&P 500 return, defined as: (SPINDX(t)/SPINDX(t-1)) – 1 and continuously compounded the S&P 500 return for monthly returns. SMB (Small Minus Big) is the average

[6] Stock returns of airlines have been studied for abnormal returns, following catastrophic events. Carter and Simkins (2004) cover the case of U.S. airline stock returns right after the September 11th attacks. Due to the nature of case studies, the effect on stock returns is measured for the period right after the events and thus do not constitute evidence for stock returns in the long-term based on a longer time span as we do in this paper.

return on the nine small stock portfolios minus the average return on the nine big stock portfolios. HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios, from the Kenneth R. French website.

The general set-up of equations (1) and (2) follows from Carter and Simkins (2004), Sadorsky (2008), Narayan and Sharma (2011), Shaeri et al. (2016), Baur and Todorova (2018), and Killins (2020), among others. We estimate stock returns of airline companies using a multi-factor model that includes the aggregate stock market, the state of the economy, and Fama-French controls. The key variables of interest here are the occupancy of seats in airlines (or its dummy variable relating airline occupancy to industry median) and oil price returns, representing revenues and costs, respectively. We verify the interaction between the occupancy and oil returns in equation (2) to calculate marginal effects. Asymmetries of oil prices when moving up or down are also investigated, following Sadorsky (2008) for low frequency (annual data) and Tsai (2013) for high-frequency studies, among others.

Following Baltagi et al. (2009) for models of panel data, baseline model (1) and model (2) with interaction terms imply different responses when the interactive terms are found to be statistically significant. For model (1), for example, the partial derivative of stock returns to oil returns is given by β_2, which becomes $\beta_2 + \beta_3 Occupancy$ in the model (2). In the latter model with interactive terms, the estimated responses can be evaluated at sample mean or, alternatively, at the minimum and maximum levels of occupancy of seats. In the same way, for the model (1), the partial derivative of stock returns to occupancy is only given by β_1, which becomes $\beta_1 + \beta_3 Oil\_ret$ in the model (2). We implement a panel data fixed-effects model to (1) and (2) with standard errors corrected for clustering at the airline (company) level. This method allows for fixed effects that vary by airlines and may be correlated with the series in the (RHS) of the models (1) and (2).

5. Results and discussion

In this section, we present the empirical results. Section 5.1 provides descriptive statistics of the variables used in this study. Section 5.2 discusses our main results from empirical models (1) and (2). Section 5.3 reports the asymmetric effect of the occupancy and oil returns on the relation between the occupancy and stock returns.

5.1 Descriptive statistics

Our final sample consists of 4,246, company- year -month observations with 33 unique carriers spanning from 1990 to 2019. We focus on investigating stock returns for only U.S. carriers with domestic travel data records from the Bureau of Transportation Statistics. Table 1 provides summary statistics based on the final sample.

Table 1 provides summary statistics for occupancy, macro variables, and Fama-French factors. The average growth rate of occupancy is 0.4% per month with a standard deviation of 6.9%, suggesting high variability. The raw series, the occupancy ratio (not shown in Table 1), has in our sample mean of 0.692 (or about 69% of seats) with a standard deviation of 0.114. This indicates that little more than two-thirds of an average carrier seat capacity is occupied for monthly travel. Airline carriers have on average 0.6% stock returns with a standard deviation of 15%. The maximum (monthly) return of a carrier is 50%, while the minimum return is -42%. The monthly average (median) value of WTI log return is 0.2% (0.6%) with a standard deviation of 9%. WTI log return volatility has a mean of 2.3%. Yield spread has a mean of 1.653%, with some inversions (-0.556 minimum value) and a maximum spread of 3.672% between long and short interest rates. Market returns are 0.7% (for either S&P500 composite index or market returns), slightly higher than airlines at 0.6% mean stock returns. The mean SMB is 0.001 and the mean HML is 0.002.

5.2 Main results

We start our empirical analysis with bivariate correlation coefficients and double sorting stock returns on oil price returns and occupancy ratio terciles. Table 2 presents these results. Panel A provides bivariate correlation coefficients. The correlation results show that our main variable of interest, occupancy, is positively related to airline carrier's stock returns. The correlation between *Occupancy* and *stock returns* is 0.099. The correlation indicates that stock returns of airline carriers are higher when those carriers have a higher occupancy in the U.S. domestic travel. This positive correlation complements the idea that airline carrier's occupancy induces a higher level of operating margin, lower level of earnings volatility, and operating efficiency, which leads to higher stock returns. The correlation between oil price returns and stock returns is negative with a correlation coefficient of -0.106, suggesting that airline carriers may incur large operating costs due to oil price increases. Our bivariate correlation also shows that oil price return volatility is negatively associated with airline carrier stock returns, with an almost zero correlation coefficient of -0.009. Market returns are positively correlated with stock returns (0.361 or 0.365 depending on the market definition): airline stocks comove in the same direction as the overall stock market. Panel B reports the stock returns based on tercile groups by occupancy and oil price returns.[7]

Since univariate analysis lacks different controls and fixed effects as well as heteroskedastic robust standard errors, we need to evaluate this finding with a multivariate setting using our models (1) and (2). We proceed to multivariate analysis. Table 3 provides the results from our models (1) and (2) and forms the baseline of our analysis for all U.S. airline carriers. The coefficients on occupancy from all specifications are positively and statistically significant. In column (1), the coefficient on occupancy is 0.201 (t-statistic = 6.57), which is statistically significant at the 1 percent level. Economically, a one standard deviation increase in a U.S. carrier occupancy ratio leads to stock return increases by 1.39% [standard deviation of occupancy growth rate times the coefficient by 0.0139 = 0.069*0.201]. Interactions between occupancy and oil price returns in columns (2) and (4) are not statistically significant.[8] The occupancy has a consistently positive effect on stock returns at 0.184 using the alternative market definition of CRSP value-weighted, which is only slightly lower from 0.201. Overall, our univariate results suggest that occupancy has positive effects on stock returns.

For model (1), the partial derivative of stock returns to oil returns is given by -0.221 = β_2 from columns (1) and (2) and -0.254 or -0.253 from columns (3) and (4). Economically, a one standard deviation increase in WTI oil price returns leads to stock return decreases by 1.99%

[7] The upper row (left column) with a number (1-3) represents a tercile group based on occupancy ratio (oil price returns). Consistent with our correlation matrix showing stock returns correlating positively with occupancy, we find that when we move from occupancy ratio first tercile (1) to top tercile (3), stock returns increase from 1.15% to 2.23%. We see the same increasing trend for rows if we read the table from top to down row-wise.

[8] Previous versions of this paper had the occupancy rate in levels interacting with oil price returns, in which we reported negative interactive coefficient negative and statistically significant at the 1% level, estimated to be from -0.775 to -0.891 across columns (2) and (4), meaning that the positive relation between occupancy and stock returns is attenuated by oil price increases. We argued that the operating cost due to increases in oil price exceeds the operating margin from higher level of occupancy. The statistical significance of the marginal effects disappears with occupancy ratio in growth rate form and we thank one anonymous referee for this insight.

[standard deviation of oil returns times the coefficient moves by 0.0199 = 0.090*-0.221]. The baseline model in Table 3 therefore implies slightly higher effects of costs (growth of oil prices) than demand (growth of occupancy ratio), all else constant.

The other results from Table 3 can be interpreted as follows. The U.S. airline industry responds by more than one-to-one to the overall stock market since the coefficient of aggregate market stock returns in the first two columns is estimated at 1.362, which remain positive and statistically significant and close to these values in columns (3) and (4) when we change market returns from S&P 500 to CRSP value-weighted portfolio, varying between 1.315 and 1.317. Oil return volatility has positive and not statistically significant effects on stock returns. The FF controls have positive effects as expected: size and value stocks. The coefficient on the yield curve is estimated negative and statistically significant in all columns. In banking, a steeper yield curve tends to improve operating margins and thus stock returns of financial institutions, since they borrow short and lend long. In airlines, however, the negative responses may be due to their exposure to loans with long maturity which typically charge higher rates.

5.3 Asymmetric effects

In this section, we investigate the asymmetric effects of occupancy and oil price returns. Tables 4 and 5 display the asymmetric effects of occupancy growth and oil prices, respectively. In Table 4, we regress stock returns on the high occupancy dummy, where high occupancy indicates a value of 1 if the occupancy is above the sample median, and 0, otherwise. In column (1) of Table 4, the coefficient on the high occupancy dummy is 0.021 (t = 4.09), which is statistically significant at the 1 percent level. On average, U.S. carriers whose growth rate of occupancy is above the sample median have higher stock returns by 2.1%, compared to carriers that have occupancy ratio below/equal to the sample median. When we turn our attention to the interaction between the high growth rate of occupancy dummy and oil price returns, we observe again that high occupancy interacted with oil price returns has no statistically significant coefficients. This suggests only minor changes (2.1% versus 2.0%) when using the model (2) with interactive terms when the growth rate of occupancy of seats is used as a dummy variable compared to the continuous occupancy of seats in Table 3. Qualitatively, the direct effects of oil returns are always negative and statistically significant for the stock returns of airline companies, consistent with the cost side interpretation. The other coefficients of Table 4 remain as in Table 3.

Table 5 reports the asymmetric effects of oil prices (up or down) on stock returns with the occupancy. The coefficients on the occupancy remain positive and statistically significant with values varying in the first row for the baseline model in columns (1) and (4) at 0.201 and 0.184, respectively. The comparison of coefficients of oil returns up or down indicates significant variation. Stocks of airlines fall by more when oil returns move up than when oil returns go down: -0.340 versus -0.088 in column (1), -0.322 versus -0.176 in column (4), and so on. This finding is noted across all specifications: there are always higher values of negative coefficients on oil returns up than on oil returns down. Only in column (6) one of the interactive terms is statistically significant at the 10% significance level. While the interactive term coefficient is estimated at -1.145 with t-ratio of -1.83, the direct effect of the growth rate of occupancy on stock returns is estimated at 0.142 versus 0.184 in column (4). The direct effect of occupancy growth rate on stock returns becomes smaller when we account for asymmetric oil price effects in column (6).

The coefficient on oil returns volatility becomes statistically significant at the 10% level in half of the specifications and at a 5% level in the other half. All other findings are consistent with prior results: the yield curve has negative effects on airline stocks and the coefficient on the aggregate stock market is higher than 1 in all cases, suggesting stocks of airline companies respond by more than one to one movements in the aggregate market, all else constant. The Fama-French controls also have positive effects. The overall message is that the growth rate of seat occupancy is priced in stock returns of U.S. airlines, the effects of oil prices have higher effects when they move up than when they move down, and that airline stocks respond by more to movements in the overall U.S. stock market.

Table 6 contains estimations by splitting the sample into two-time subsets: before the 9/11 terrorist attacks (pre 9/2001 in columns (1) to (4)) and after the 9/11 terrorist attacks (post 8/2001 in columns (5) to (8)). After the shock airlines respond more to both factors. First, the coefficients of occupancy move up from 0.174 in column (1) to 0.213 in column (5). Second, the coefficients of oil price increase move up as well: from negative and barely significant of -0.078 in column (1) to -0.367 in column (5). The sensitivity simply increased in both cases in the post- 9/11 environment, in line with higher market responses to both growth rate in seat occupancy and oil price returns.[9]

6. Concluding Remarks

[9] Following the suggestion of an anonymous referee, we have introduced post global financial crisis dummy variable and generated additional tables with results for this as well as for post 9/11 dummy. When we define a post financial crisis dummy (=1 if observation year-month is after 2010 and =0 if observation year-month is before 2008, the interactive of Ocuppancy*Fin crisis has negative and statistically significant coeffients, with Occupancy coefficients estimated positive and and statistically significant around 0.20 and oil returns negative and statistically significant between -0.155 and -0.188. We have also defined a dummy variable for post-9/11 since in the article we have Table 6 for the partition of pre and post 9/11 observations. We define dummy as Post=1 if observation year month is after 9/11. However, the statistical significance of the interaction of growth rate of occupancy and post 9/11 dummy is lost. The estimates continue to show positive effects of growth rate of occupancy and negative effects of oil returns. Values for these key coefficients are in between those of the coefficients reported in Table 6 in the paper. We are making these alternative tables with crisis and 9/11 dummy variables availables upon request.

We implement monthly panel data models of 33 U.S. airline companies from 1990 to 2019 with the following main results. First, the growth rate of occupancy of seats is priced positively in stock returns of U.S. airlines. Second, the negative effects of oil prices have higher effects when they move up than when they move down. Third, airline stocks respond by more than one to one to movements in the overall U.S. stock market. Our approach relies on Sadorsky (2008), Narayan and Sharma (2011), and other recent financial studies that control for Fama French factors. Our novel approach herein takes into account, on the revenue side, the key target variable of the growth rate of occupancy of seats, as well as a dummy variable of growth of seat occupancy relative to the industry mean. These revenue terms are compared with oil prices to gauge cost fluctuations of airlines. Our approach integrates for stock returns what others have documented for the microeconomics of the industry. Csereklyei and Stern (2020) conclude, for example, that larger and newer aircraft are more efficient and report that aircraft have become larger over time: the regression line between seat number (size) and aircraft fuel economy is -0.298: for a 1% increase in size, fuel economy improves by 0.3%. To the best of our knowledge, the seat-occupancy has not been used before in empirical studies between stock returns of airlines and oil price returns.

This paper applies panel data to address the competing roles of revenues versus costs in the market pricing of airline stocks. Having shown the positive and negative effects of occupancy and oil prices in explaining stock returns for 33 companies and 30 years, future work includes extending our analysis to data on international flights by U.S. carriers, in which occupancy ratio of flight seats and fuel costs may be fundamentally different from those in domestic flights.

References

Alsalman, Z. 2016. Oil price uncertainty and the U.S. stock market analysis based on a GARCH-in-mean VAR model. *Energy Economics* 59: 251-260.

Arouri, M. E. 2011. Does crude oil move stock markets in Europe? A sector investigation. *Economic Modelling* 28: 1716-1725.

Baur, D. G., and Todorova, N. 2018. Automobile manufacturers, electric vehicles and the price of oil. *Energy Economics* 74: 252-262.

Baltagi, B., Demetriades, P. and Law, S. H. 2009. Financial development and openness: Evidence from panel data. *Journal of Development Economics* 89: 285-296.

Carter, D. A., and Simkins, B. J. 2004. The market's reaction to unexpected, catastrophic events: The case of airline stock returns and the September 11th attacks. *Quarterly Review of Economics and Finance* 44: 539-558.

Csereklyei, Z., and Stern, D. I. 2020. Flying more efficiently: Joint impacts of fuel prices, capital costs and fleet size on airline fleet fuel economy. *Ecological Economics* 175: Article 106714.

Degiannakis, S., Filis, G., and Floros, C. 2013. Oil and stock returns: Evidence from European industrial sector indices in a time-varying environment. *Journal of International Financial Markets, Institutions & Money* 26: 175-191.

Demiralay, S., and Kilincarslan, E. 2019. The impact of geopolitical risks on travel and leisure stocks. *Tourism Management* 75: 460-476.

Hadi, D. M., Irani, F., and Gokmenoglu, K. K.. 2020. External determinants of the stock price performance of tourism, travel and leisure firms: Evidence from the United States. *International Journal of Hospitality & Tourism Administration*: DOI: 10.1080/15256480.2020.1842838

Herrera, A. M., Karaki, M. B., and Rangaraju, S. K. 2019. Oil price shocks and U.S. economic activity. *Energy Policy* 129: 89–99.

Huang, W., and A. V. Mollick (2020). Tight oil, real WTI prices and U.S. stock returns. *Energy Economics* 85: Article 104574.

Kang, W., Perez de Gracia, F., and R. Ratti 2017. Oil price shocks, policy uncertainty, and stock returns of oil and gas corporations. *Journal of International Money and Finance* 70: 344-359.

Kaufmann, R. K. 2017. Airlines and oil prices: 'Feathers and Rockets' adjustments. *Energy Economics* 68: 515-521.

Killins, R. 2020. The impact of oil and equity returns of Canadian and U.S. railways and airlines. *North American Journal of Economics & Finance*: Article 101178.

Kristjanpoller, W., and Concha, D. 2016. Impact of fuel price fluctuations on airline stock returns. *Applied Energy* 178: 496-504.

McCartney, S. 2020. How coronavirus ravaged travel in 2020. *The Wall Street Journal*, November 4, 2020.

Mohanty, S. K., and Nandha, M. 2011. Oil risk exposure: The case of the U.S. oil and gas sector. *The Financial Review* 46: 165-191.

Mollick, A. V., and Assefa, T. 2013. U.S. stock returns and oil prices: The tale from daily data and the 2008-2009 financial crisis. *Energy Economics* 36: 1-18.

Mollick, A. V., and Nguyen, K. H. 2015. U.S. oil company stock returns and currency fluctuations. *Managerial Finance* 41 (9): 974-994.

Nandha, M., and R. Faff. 2008. Does oil move equity prices? A global view, *Energy Economics* 30: 986-997.

Narayan, P. K., and Sharma, S. S. 2011. New evidence on oil price and firm returns. *Journal of Banking & Finance* 35: 3253-3262.

Sadorsky, P. 2001. Risk factors in stock returns of Canadian oil and gas companies. *Energy Economics* 23: 17-28.

Sadorsky, P. 2008. Assessing the impact of oil prices on firms of different sizes: Its tough being in the middle. *Energy Policy* 36: 3854-3861.

Shaeri, K., Adaoglu, C., and Katircioglu, S. 2016. Oil price risk exposure: A comparison of financial and non-financial subsectors. *Energy* 109: 712-723.

Smyth, R., and Narayan, P. K. 2018. What do we know about oil prices and stock returns? *International Review of Financial Analysis* 57: 148-156.

Stamolampros, P., and Korfiatis, N. 2019. Airline service quality and economic factors: An ARDL approach on US airlines. *Journal of Air Transport Management* 77: 24-31.

Thorbecke, W. 2019a. Oil prices and the U.S. economy: Evidence from the stock market. *Journal of Macroeconomics* 61: Article 103137.

Thorbecke, W. 2019b. How oil prices affect East and Southeast Asian economies: Evidence from financial markets and implications for energy security. *Energy Policy* 128: 628-638.

Tsai, C.-L. 2013. The high-frequency asymmetric response of stock returns to monetary policy for high-oil price events. *Energy Economics* 36: 166-176.

Wang, H., and Gao, X. 2020. Oil price dynamics and airline earnings predictability. *Journal of Air Transport Management* 87: Article 101854.

Yun, X., and Yoon, S.-M. 2019. Impact of oil price change on airline's stock price and volatility: Evidence from China and South Korea. *Energy Economics* 78: 668-679.

Figure 1: Occupancy and stock returns

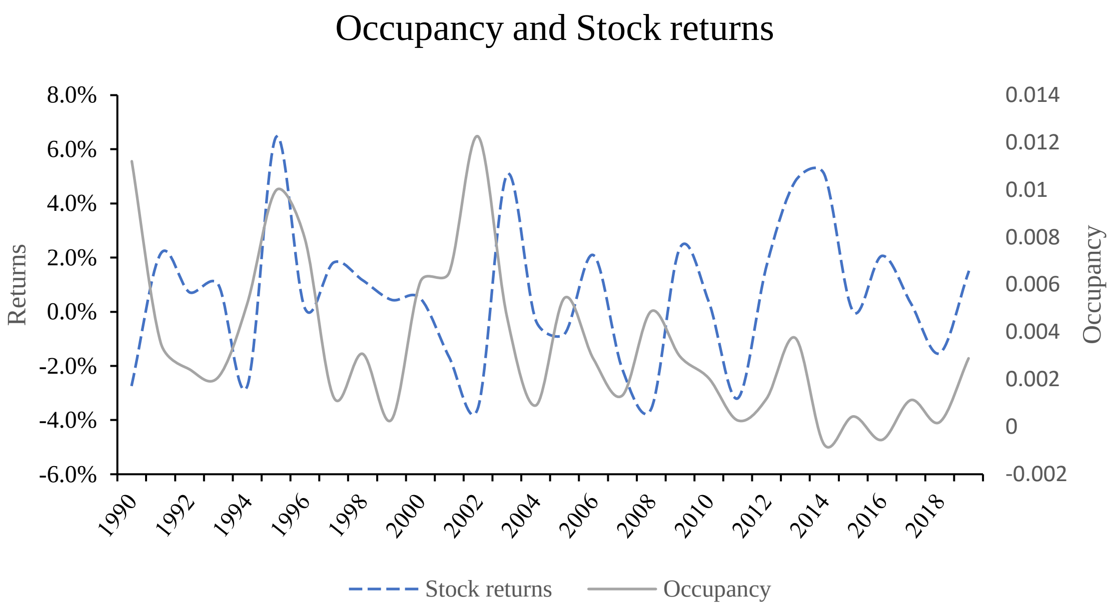

Figure 2: Oil price returns and Stock returns

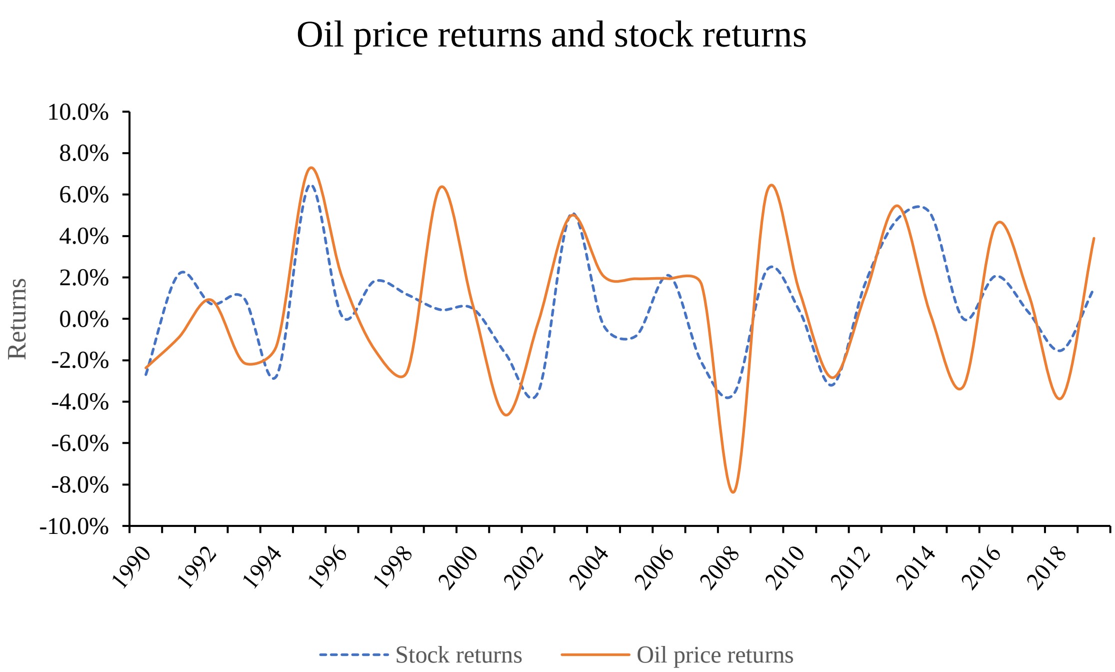

Figure 3: Occupancy and oil price returns

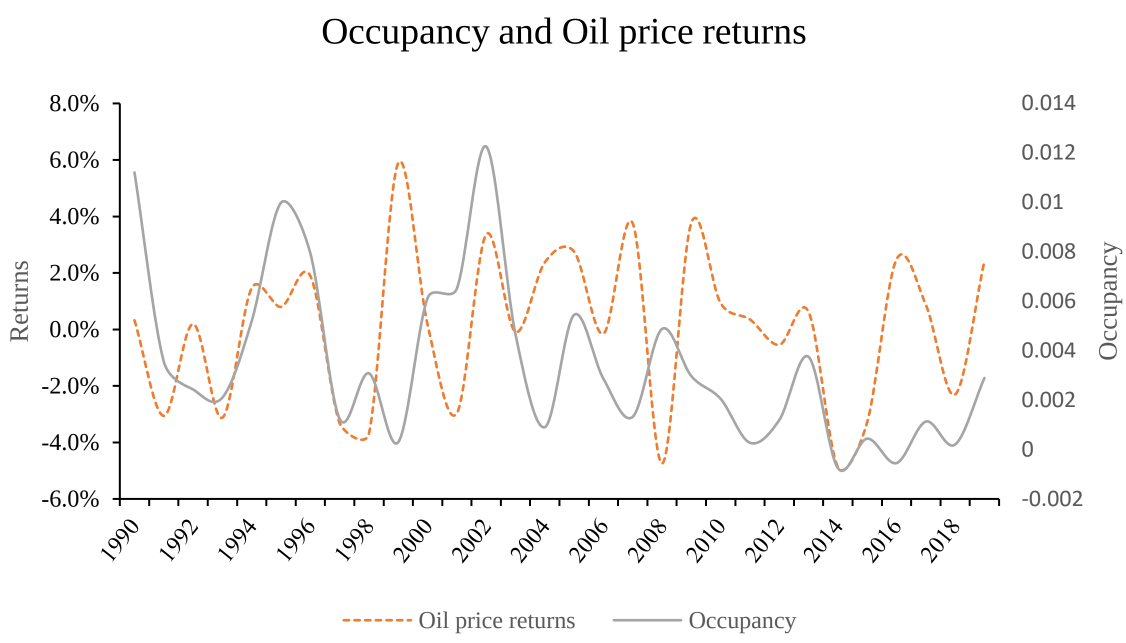

Table 1: Descriptive statistics

This table reports summary statistics for measures of airline seat occupancy, oil price returns, stock returns, and macro-economic control variables. Our sample consists of 4,246 firm-year-month observations (unbalanced panel) with 33 unique airline company covering the period 1990-2019. The key dependent variable is stock returns, whereas the key independent variables are the growth rate of occupancy ratio and oil price returns. All continuous variables are winsorized at the top and bottom 1% level. Appendix A provides more details of all variables.

Variable	N	Mean	SD	Min	P50	Max
Stock returns	4,246	0.006	0.147	-0.417	0.000	0.500
Occupancy	4,213	0.004	0.069	-0.334	0.004	0.550
Oil returns	4,246	0.002	0.090	-0.224	0.006	0.273
Oil returns volatility	4,246	0.023	0.010	0.008	0.020	0.062
Spread	4,246	1.653	1.137	-0.556	1.583	3.672
S&P 500 returns	4,246	0.007	0.040	-0.110	0.011	0.094
MKT returns	4,246	0.007	0.043	-0.172	0.012	0.113
SMB	4,246	0.001	0.032	-0.149	0.000	0.183
HML	4,246	0.002	0.031	-0.112	-0.001	0.129

Table 2: Univariate Analysis:

This Table presents the Pearson correlation among variables used in our analysis. All continuous variables are winsorized at the top and bottom 1% level. Appendix A provides more details of all variables.

Panel A: Correlation matrix:

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Stock returns	1.000								
(2) Occupancy	0.099	1.000							
(3) Oil returns	-0.106	0.023	1.000						
(4) Oil returns volatility	-0.009	-0.027	-0.290	1.000					
(5) Spread	-0.025	0.003	0.012	-0.046	1.000				
(6) S&P 500 returns	0.365	0.022	0.099	-0.142	-0.052	1.000			
(7) MKT returns	0.361	0.026	0.135	-0.146	-0.005	0.977	1.000		
(8) SMB	0.099	0.059	0.152	-0.060	0.108	0.044	0.196	1.000	
(9) HML	0.050	0.023	-0.047	-0.027	-0.016	-0.143	-0.205	-0.149	1.000

Panel B: Double sorting stock returns (by terciles)

Stock return by tercile	Oil price returns		
Occupancy ratio	Low (Tercile-1)	2	High (Tercile-3
Low (Tercile 1)	0.0115	0.0051	-0.0345
2	0.0171	0.0142	-0.0129
High (Tercile 3)	0.0223	0.0316	-0.0071

Table 3: Baseline regressions: Occupancy and oil returns on stock returns

This table presents the results from the OLS regressions models (1) and (2), where the key dependent variable is stock return, which is continuously compounded monthly company return using the daily CRSP stock return. The key independent variables are Occupancy measured as the growth rate of occupancy ratio ((ORt - ORt-1)/ORt-1), where occupancy ratio (ORt) is the ratio of the total number of passengers to the total number of aircraft seats in a month, and oil price return, measured by the daily WTI log price difference compounded monthly. All other independent variables are defined in Appendix A. Columns (1) and (3) report results from the model (1) whereas columns (2) and (4) report results from the model (2). t-statistics are computed using standard errors corrected for clustering at the airline company level and reported in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Variable	Stock returns			
Occupancy	0.201***	0.201***	0.184***	0.184***
	(6.57)	(6.51)	(6.06)	(6.03)
Oil returns	-0.221***	-0.221***	-0.254***	-0.253***
	(-6.39)	(-6.43)	(-6.67)	(-6.72)
Oil returns volatility	0.430	0.427	0.467	0.486
	(1.44)	(1.43)	(1.59)	(1.65)
Spread	-0.013***	-0.013***	-0.010**	-0.010**
	(-2.88)	(-2.88)	(-2.24)	(-2.24)
S&P 500 returns	1.362***	1.362***		
	(14.36)	(14.34)		
Occupancy # Oil returns		0.018		-0.147
		(0.06)		(-0.48)
MKT returns			1.317***	1.315***
			(12.90)	(12.87)
SMB			0.305***	0.306***
			(3.23)	(3.23)
HML			0.635***	0.635***
			(7.02)	(7.03)
Constant	-0.013	-0.013	0.003	0.002
	(-0.93)	(-0.92)	(0.19)	(0.11)
Year FE	Yes	Yes	Yes	Yes
N	4,213	4,213	4,213	4,213
Adj. R2	0.178	0.178	0.193	0.193

Table 4: Asymmetric effect of occupancy on stock returns

This table presents the results from the asymmetric effect of occupancy, where the key dependent variable is stock return, which is continuously compounded monthly company return using the daily CRSP stock return. High occupancy is a dummy variable indicating 1 if the growth rate of occupancy ratio is above the sample median, and 0, otherwise. Oil price return, measured by the daily WTI log price difference compounded monthly. All other independent variables are defined in Appendix A. Columns (1) and (3) report results from the model (1) whereas columns (2) and (4) report results from the model (2). t-statistics are computed using standard errors corrected for clustering at the airline company level and reported in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Variable	Stock returns			
High occupancy	0.021***	0.021***	0.020***	0.020***
	(4.09)	(4.04)	(3.93)	(3.89)
Oil returns	-0.225***	-0.244***	-0.258***	-0.265***
	(-6.60)	(-5.74)	(-6.88)	(-5.97)
Oil returns volatility	0.375	0.355	0.421	0.413
	(1.27)	(1.20)	(1.45)	(1.41)
Spread	-0.013***	-0.013***	-0.010**	-0.010**
	(-2.86)	(-2.80)	(-2.22)	(-2.18)
S&P 500 returns	1.371***	1.375***		
	(14.22)	(14.16)		
High occupancy # Oil returns		0.037		0.014
		(0.62)		(0.24)
MKT returns			1.327***	1.328***
			(12.75)	(12.64)
SMB			0.313***	0.312***
			(3.34)	(3.29)
HML			0.652***	0.652***
			(7.22)	(7.22)
Constant	-0.021	-0.020	-0.005	-0.005
	(-1.43)	(-1.37)	(-0.35)	(-0.32)
Year FE	Yes	Yes	Yes	Yes
N	4,213	4,213	4,213	4,213
r2_a	0.168	0.168	0.184	0.184

Table 5: Asymmetric effect of oil price return on stock returns

This table presents the results from the asymmetric effect of oil returns, where the key dependent variable is stock return, which is continuously compounded monthly company return using the daily CRSP stock return. Oil returns up is the positive monthly compounded WTI oil returns and 0, otherwise. Oil returns down is the negative monthly compounded WTI oil returns and 0, otherwise. All other independent variables are defined in Appendix A. t-statistics are computed using standard errors corrected for clustering at the airline company level and reported in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Stock returns					
Occupancy	0.201***	0.179***	0.173***	0.184***	0.165***	0.142***
	(6.56)	(4.84)	(5.50)	(6.08)	(4.46)	(4.69)
Oil returns up	-0.340***	-0.340***	-0.340***	-0.322***	-0.322***	-0.322***
	(-7.92)	(-7.83)	(-7.94)	(-7.72)	(-7.64)	(-7.76)
Oil returns down	-0.088	-0.090	-0.082	-0.176**	-0.178**	-0.167**
	(-1.44)	(-1.47)	(-1.38)	(-2.59)	(-2.61)	(-2.54)
Oil returns volatility	0.686**	0.653*	0.742**	0.610*	0.581*	0.699**
	(2.08)	(1.98)	(2.27)	(1.85)	(1.77)	(2.13)
Spread	-0.014***	-0.014***	-0.014***	-0.010**	-0.010**	-0.011**
	(-2.97)	(-2.98)	(-3.00)	(-2.30)	(-2.31)	(-2.36)
S&P 500 returns	1.377***	1.378***	1.368***			
	(14.23)	(14.21)	(14.24)			
Occupancy # Oil returns up		0.542			0.480	
		(1.33)			(1.19)	
Occupancy # Oil returns down			-0.740			-1.145*
			(-1.28)			(-1.83)
MKT returns				1.325***	1.326***	1.313***
				(12.75)	(12.73)	(12.79)
SMB				0.292***	0.290***	0.294***
				(3.09)	(3.06)	(3.10)
HML				0.623***	0.625***	0.625***
				(6.87)	(6.93)	(6.85)
Constant	-0.005	-0.003	-0.007	0.007	0.010	0.004
	(-0.38)	(-0.19)	(-0.51)	(0.51)	(0.68)	(0.29)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,213	4,213	4,213	4,213	4,213	4,213
Adj. R2	0.174	0.174	0.174	0.187	0.187	0.188

Table 6: Subsample Analysis

This table reports the relation between the occupancy and stock returns for subsamples based on 9/11. Columns 1-4 report the results from Pre <9/2001 subsample, whereas Columns 5-8 report the results from Post >8/2001 subsample. The key dependent variable is stock return, which is continuously compounded monthly company return using the daily CRSP stock return. The key independent variables are occupancy measured as the growth rate of occupancy ratio ((ORt - ORt-1)/ORt-1), where occupancy ratio (ORt) is the ratio of the total number of passengers to the total number of aircraft seats in a month,, and oil price return, measured by the daily WTI log price difference compounded monthly. All other independent variables are defined in Appendix A. t-statistics are computed using standard errors corrected for clustering at the airline company level and reported in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Stock returns							
Occupancy	0.174***	0.170***	0.153***	0.148***	0.213***	0.212***	0.231***	0.231***
	(3.85)	(3.62)	(3.41)	(3.14)	(3.36)	(3.36)	(3.71)	(3.70)
Oil returns	-0.078*	-0.079*	-0.062	-0.061	-0.367***	-0.366***	-0.442***	-0.440***
	(-1.96)	(-2.00)	(-1.62)	(-1.61)	(-8.11)	(-7.92)	(-8.95)	(-8.80)
Oil returns volatility	1.214***	1.143***	1.074***	0.979***	-0.072	-0.059	-0.216	-0.197
	(3.72)	(3.58)	(3.28)	(3.09)	(-0.18)	(-0.14)	(-0.52)	(-0.48)
Spread	-0.021***	-0.021***	-0.018***	-0.018***	-0.006	-0.006	-0.007	-0.007
	(-3.71)	(-3.69)	(-2.94)	(-2.86)	(-0.84)	(-0.84)	(-0.97)	(-0.96)
S&P 500 returns	1.066***	1.072***			1.627***	1.624***		
	(15.61)	(15.78)			(10.28)	(10.09)		
Occupancy # Oil returns		0.408		0.530		-0.171		-0.234
		(1.22)		(1.59)		(-0.35)		(-0.44)
MKT returns			1.138***	1.150***			1.364***	1.361***
			(11.76)	(11.81)			(9.00)	(8.84)
SMB			-0.026	-0.034			0.730***	0.723***
			(-0.32)	(-0.42)			(6.23)	(6.16)
HML			0.444***	0.460***			0.603***	0.611***
			(3.33)	(3.45)			(4.62)	(4.51)
Constant	-0.041***	-0.038***	-0.027**	-0.023*	-0.021	-0.022	-0.003	-0.003
	(-3.19)	(-2.94)	(-2.16)	(-1.84)	(-1.62)	(-1.66)	(-0.21)	(-0.24)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,777	1,777	1,777	1,777	2,436	2,436	2,436	2,436
Adj. R^2	0.151	0.151	0.150	0.150	0.215	0.215	0.245	0.245

Appendix A: Variable definition

Variables	Definitions
Dependent variables	
Stock returns	Continuously compounded monthly company return using the daily CRSP stock return.
Independent variables	
Occupancy	The growth rate of occupancy ratio ((ORt - ORt-1)/ORt-1), where occupancy ratio (ORt) is the ratio of the total number of passengers to the total number of aircraft seats in a month.
High occupancy	A dummy variable = 1, if the growth of occupancy ratio is above the sample median, and 0, otherwise.
Oil returns	The daily WTI log price difference compounded monthly.
Oil return volatility	The standard deviation of daily WTI log price difference return for each month.
Oil return up	The positive monthly compounded WTI oil returns and 0, otherwise.
Oil return down	The negative monthly compounded WTI oil returns and 0, otherwise.
Control variables	
S&P 500 return	S&P 500 return is the return on the Standard & Poor's Composite Index defined as: (SPINDX(t)/SPINDX(t-1)) – 1. Continuously compounded the S&P 500 return for month.
Market return	CRSP VWRETD indices contain continuously compounded daily returns, including all distributions, on a value-weighted market portfolio (excluding American Depository Receipts (ADRs)).
Spread	10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity
SMB	SMB (Small Minus Big) is the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios. From the Kenneth R. French website.
HML	HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios, From the Kenneth R. French website.

Appendix B: List of airline companies

Sl. No	Carrier Name	Observations
1	SkyWest Airlines Inc.	207
2	Mesa Airlines Inc.	112
3	Air Wisconsin Inc.	25
4	Spirit Air Lines	104
5	Atlantic Southeast Airlines	71
6	United Air Lines Inc.	160
7	American Airlines Inc.	338
8	Delta Air Lines Inc.	190
9	Alaska Airlines Inc.	360
10	US Airways Inc.	152
11	AirTran Airways Corporation	166
12	Midway Airlines Inc.	21
13	Southwest Airlines Co.	360
14	Westair Airlines Inc.	29
15	Reno Air Inc.	72
16	Atlantic Coast Airlines	24
17	Continental Air Lines Inc.	89
18	Trans World Airlines Inc.	10
19	Northwest Airlines Inc.	139
20	Frontier Airlines Inc.	166
21	Valujet Airlines Inc.	44
22	America West Airlines Inc.	133
23	Hawaiian Airlines Inc.	294
24	Midwest Airlines, Inc.	59
25	Vanguard Airlines Inc.	45
26	Western Pacific Airlines	24
27	United Parcel Service	23
28	JetBlue Airways	213
29	ExpressJet Airlines Inc.	104
30	Pinnacle Airlines Inc.	102
31	Republic Airlines	127
32	Allegiant Air	157
33	Gulfstream Int	36
All		4,246