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Article

Systematic and Idiosyncratic Risks of the U.S. Airline Industry

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Abstract: Understanding the risky nature of the airline industry has received attention in the tourism literature from separate angles. Although the systematic risk of the airline industry has been examined before, idiosyncratic risk has largely been ignored. This study fills this gap in the tourism literature by investigating the effect of passengers' air travel on systematic and idiosyncratic risks of the U.S. airline industry. Using historical air travel data and utilizing both OLS and fixed-effect models, this paper documents negative relationships between the occupancy of airline seats and idiosyncratic risks for 21 U.S. airline companies. This negative effect of occupancy is more pronounced if air travel distances are shorter, companies have lower leverage ratios, and companies are smaller in size. Policy implications for both airline managers and investors are provided.

Keywords: airline industry; beta; idiosyncratic risk; occupancy of seats; systematic risk

JEL Classification: G12; G32

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1. Introduction

The airline industry is subject to volatile demand, cost factors (fuel, labor), and regulatory constraints that make it unique. Among its major players, manufacturers of jet engines and carriers operating on travel routes face a mix of both permanent and temporary challenges. The coronavirus pandemic of 2020 brought enormous challenges to an industry that is particularly vulnerable to seasonal and economic factors. For jet engine makers, recent indicators are far from promising: " … , two top U.S. industrial conglomerates, General Electric and Raytheon Technologies, reported first-quarter earnings showing the continuing impact of the pandemic. GE lost USD 2.8 billion due to a 28% year-over-year drop in aviation revenue. Raytheon notched a USD 753 million profit, 44% below 2019 levels … Based on the median of analyst estimates collected by Visible Alpha, GE's aviation sales will not recover to pre-pandemic levels until 2023 and profits will take even longer." (Sindreau 2021). For U.S. airline companies, the latest data show improvements: measures of Transportation Security Administration (TSA) screenings are up, prices in average round-trip tickets sold have recovered, and there are fewer planes in storage (McCartney 2021).

The impact on the supply chain, and more severely on oil prices, was exacerbated when the Ukraine–Russia war caused disruption to the airline industry and to all sectors around the world. NATO's decision to bring harsh sanctions against Russia, Russia's blockade of the Black Sea to disrupt shipping routes, and the threat of closing gas pipelines to Europe combined to create a major supply chain shock. First COVID, and then unexpected war, have produced a major blow to the economic growth of all countries; this is particularly relevant to the airline industry that faces both occupancy issues due to COVID's derivatives and cost issues due to rising oil prices.

In this paper we examine a measure of seat occupancy in U.S. airlines, and conjecture a positive impact on market returns of airline companies. While the systematic risk of the airline industry (how the return of a company stock responds to the overall market return) has been examined before, idiosyncratic risk (the standard deviation of residuals of company stock returns estimated on the overall market and other factors) has largely been ignored. This study fills this gap in the tourism literature by investigating the effect of passengers' air travel on systematic and idiosyncratic risks of the U.S. airline industry. It is more common to read studies of systematic risks, such as Lee and Jang (2007), for the determinants of systematic risk for 16 U.S. airline companies from 1997 to 2002 using the CAPM as a framework. Studies on the management of airports reviewed by Trinkner et al. (2020) assess airport characteristics that capture differences in Beta risk on how an airport's systematic risk varies.

Previous studies of the airline industry have investigated general finance propositions or other types of risks. Becken and Shuker (2019) look at carbon risks in airports of the world with case studies. Trinkner et al. (2020) quantify Beta risk for several French airports. Borochin (2020) uses daily passenger flight delay data for 20 domestic U.S. airlines from 1996 to 2016 to create six operating ROA measures to evaluate their sensitivity to flight delays. Using event studies, Borochin (2020) finds that operating return on sales is the measure most sensitive to the real operating performance by outperforming traditional operating ROA measures. Seo et al. (2021) calculate the asset-light business model (the sum of franchised and managed properties divided by the total number of properties) for U.S. lodging firms from 1998 to 2019 and use panel regressions to find that asset-light business affects firm performance (ROA and Tobin's q) at standard confidence levels.

The key research question in this article pertains to how seat occupancy impacts both types of risks: systematic and idiosyncratic. We examine the passengers' air travel by aircraft for a given year, which is a fairly accurate measure of demand for air travel. Following Mollick and Amin (2021), we construct the occupancy of airline seats as the total number of passengers scaled by the total number of aircraft seats. We hypothesize that with more demand for travel the systematic risk and idiosyncratic risk of a certain airline stock will decline. This is because higher demand for air tickets will boost revenues and thus market returns of firms, which makes those firms less responsive to the market. Errors become smaller in the case of idiosyncratic risk since higher seat occupancy indicates less risk unique to the firm. Our empirical findings below suggest that the idiosyncratic risk of airline companies' stock is negatively associated with a higher level of seat occupancy.[1]

The rest of the manuscript is organized as follows: A literature review is presented in Section 2 and the empirical models are discussed in Section 3. Section 4 summarizes the results and implications, and Section 5 concludes the paper.

2. Literature Review and Hypothesis Development

The literature typically considers systematic risk (the response of company stock returns to the overall market) independently from idiosyncratic risk (the standard deviation of residuals obtained from regressions of company stock returns estimated on the overall market). Lee and Jang (2007) estimate the determinants of systematic risk for 16 U.S. airline companies from 1997 to 2002 in an unbalanced panel. Using the CAPM as a framework, they retrieve the beta measuring the response of firm stock returns to the market returns (S&P 500 and NYSE Index). The betas are then regressed on liquidity (defined as (cash + marketable securities + accounts receivable)/current liabilities), leverage (total debt/total assets), operating efficiency (total revenue/total assets), profitability (ROA: net income/total assets), firm size (total assets), EBIT growth (annual percentage change in EBIT), and safety (maintenance cost/book value of flight equipment). The mean value of beta in their sample is 1.80 with a standard deviation of 1.57. They report for systematic risks that leverage and firm size have positive effects (at a 10% level), referring to the latter as a "paradoxical relationship to beta", and propose some explanations for the airline industry, heavily affected by the 2001 recession and 9/11 terrorist attacks (Lee and Jang

2007, p. 439). Effects are found to be negative (at 1% level) for profitability, and at 10% for growth and safety. They find no effects on liquidity and operating efficiency. When they report the findings for the total risk test, the statistically significant factors are leverage with positive effects (at 5% level), negative effects for profitability (at 1% level), growth (at 10%), and safety (at 5%), and firm size loses statistical significance

Park et al. (2017) revisit this model of systematic risk for 39 U.S. publicly traded restaurant firms between 2000 and 2013, with an interest in corporate social responsibility (CSR) and the moderating role of geographical diversification (DIV). They regress company returns on market and factors SMB (small minus big), HML (high minus low book to market stocks), and UMD (difference between the average return on two high prior return portfolios and two low prior return portfolios). After performing the regression, the beta coefficient for the market premium is considered the systematic risk for the firm and is regressed on CSR, DIV, and firm characteristics. Their beta is 0.92 with a standard deviation of 0.26, both much lower than those for airlines shown in Lee and Jang (2007). Park et al. (2017) report negative effects of DIV and liquidity on beta for restaurants at a 5% level and negative effects of size, yet marginally significant with a p-value of 0.088. They propose a model with interactive values of CSR with DIV and find positive effects for positive CSR (socially responsive) interacting with DIV and no effects for negative CSR (socially irresponsive) interacting with DIV.

Liu and Wang (2021) decompose total volatility into idiosyncratic volatility (IV) and systemic volatility using the market model as a benchmark. They use two measures of investment growth: Tobin's q and past investment levels. Their dependent variable is the investment rate (investment to assets ratio) regressed on idiosyncratic volatility and controls. They report strong negative effects in all specifications using a large panel of U.S. firms from 1967 to 2017. In addition to the negative investment to IV relation, this relation is stronger for firms with more growth options relative to their assets. Their results suggest that separating idiosyncratic volatility from systematic risk is important in the context of the theory of investment. They also report systematic risk (SV) and total risk (TV) measures and use the market model as a benchmark.

Idiosyncratic risks are applied to the U.S. restaurant industry by Ozdemir et al. (2020), who investigate 43 firms from 1995 to 2015 using CSR involvement and idiosyncratic risks. They hypothesize that as CSR involvement increases their idiosyncratic risks will decrease. They also allow for a moderating effect due to brand diversification. Their second hypothesis is that the risk reduction effect of CSR on firms' idiosyncratic risk becomes stronger with higher brand diversification. Net-CSR is based on social responsibility ratings from the MSCI ESG database: responsible corporate activities are CSR strengths and irresponsible activities are CSR concerns. They find negative effects of brand diversification on idiosyncratic risks as well as negative effects of Net-CSR on idiosyncratic risks. When they interact with the two forces in their fixed-effects model, the effects of brand diversification on idiosyncratic risks disappear and the negative effects of Net-CSR on idiosyncratic risks remain at a 10% level. However, the interactive term becomes negative and statistically significant at the 1% level. They next decompose their Net-CSR into positive CSR and negative CSR and re-estimate their model.

The literature review suggests separate approaches to verify financial risks in tourism-related industries: airlines and restaurants. In a sense to be made precise below, the dependent variables in this study are either the systematic risk or the idiosyncratic risk of U.S. airline companies' stock. The former is the beta coefficient when company returns are regressed on the aggregate market. The latter (idiosyncratic risk) for stock i is the standard deviation of residuals from each of the empirical models. For our key measure, which comes from the demand (revenue) side, we construct the occupancy of airline seats as the total number of passengers scaled by the total number of aircraft seats. We hypothesize that with more demand for travel the systematic risk and idiosyncratic risk of stock i will decline. This is because higher demand for air tickets will boost revenues and thus market returns of the firms, which makes errors lower.

3. Data and Methodology

3.1. Sampling

To construct the final sample, we collect U.S. airline companies' daily stock return data from the *CRSP* database, passengers' air travel data from the T-100 Segment (U.S. carriers only) of the *Bureau of Transportation Statistics*[2], daily risk-free rates of one-month Treasury bills and the Fama–French five factors from Kenneth R French's website[3], and U.S. airline carriers' accounting information from the Compustat database. This study restricts the final sample to U.S. carriers that have both domestic and international flight information recorded in the T-100 Segment and appear in the Compustat database within a two-digit SIC code of 45. After merging all datasets, we end up with 21 unique airline companies[4]. The final sample consists of 273 airline company year observations spanning from 1990[5] to 2019.

3.2. Variable Construction

3.2.1. Dependent Variables

The key dependent variables are the systematic risk and idiosyncratic risk of U.S. airline companies' stock. We closely follow Lee and Jang (2007) and Park et al. (2017) to develop our methodology that comprises a two-step procedure explained in more detail below. To construct annual estimates of systematic risk and idiosyncratic risk, we use daily stock returns data of U.S. airline companies from CRSP. We run the following models in turn: the market model, the CAPM model, and the Fama–French five-factors regression model by the firm and year level:

i. Market model

$$R_{i,d,y} = a_0 + \beta_1 R_{m,d,y} + \varepsilon_{i,d,y} \tag{1}$$

where $R_{i,d,y}$ is the raw stock return on day d for a company i in year y, $R_{m,d,y}$ is the daily return from the CRSP value-weighted market index, β_1 is the estimated yearly beta, and $\varepsilon_{i,d,y}$ is the idiosyncratic return. Following previous literature (Fu 2009; Kim et al. 2012; Ozdemir et al. 2020), we estimate this market model and measure the systematic risk as β_MKT proxied by β_1 and idiosyncratic risk of stock i with the standard deviation of the residuals (idiosyncratic return) from the model (1) within the year. We require that each aircraft-year regression must have at least 100 observations in any given year. The result of this procedure is a panel of airline company-year idiosyncratic risk, which is our IRV_MKT estimates.

ii. CAPM model

$$R_{i,d,y} - R_{f,d,y} = a_0 + \beta_1 (R_{m,d,y} - R_{f,d,y}) + \varepsilon_{i,d,y} \tag{2}$$

where $R_{i,d,y}$ is the raw stock return on day d for aircraft i in the year of y, $R_{f,d,y}$ is the daily risk-free rates of a one-month Treasury bill, $R_{m,d,y}$ is the daily return from the CRSP value-weighted market index, β_1 is the estimated yearly beta, and $\varepsilon_{i,d,y}$ is the idiosyncratic return. Following Bali et al. (2005), Bley and Saad (2012) and Lee et al. (2015), we estimate this CAPM model and measure the systematic risk as β_CAPM proxied by β_1 and idiosyncratic risk of stock i with the standard deviation of the residuals from the model (2) within the year. We require that each aircraft-year regression must have at least 100 observations in any given year. The result of this procedure is a panel of airline company-year idiosyncratic risk, which is our IRV_CAPM estimates.

iii. Fama–French five-factor model

$$R_{i,d,y} - R_{f,d,y} = a_0 + \beta_1 (R_{m,d,y} - R_{f,d,y}) + \beta_2 SMB_{d,y} + \beta_3 HML_{d,y} + \beta_4 RMW_{d,y} + \beta_5 CMA_{d,y} + \varepsilon_{i,d,y} \tag{3}$$

where $R_{i,d,y}$ is the raw stock return on day d for aircraft i in the year of y, $R_{f,d,y}$ is the daily risk-free rates of a one-month Treasury bill. $R_{m,d,y}$ is the daily return from the CRSP value-weighted market index. $SMB_{d,y}$ is the size premium (small minus big), which is measured as the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios (Fama and French 2015). $HML_{d,y}$ is the value premium (high minus low), which is measured as the average return on the two value portfolios minus the average return on the two growth portfolios (Fama and French 2015). $RMW_{d,y}$ is the operating profitability premium (robust minus weak), which is measured as the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios (Fama and French 2015). $CMA_{d,y}$ is the investment premium (conservative minus aggressive), which is measured as the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios (Fama and French 2015). $\varepsilon_{i,d,y}$ is the idiosyncratic return. Following Fama and French (2015) and Ozdemir et al. (2020), we estimate the Fama–French five-factor empirical asset pricing model and measure the systematic risk as β_FF5 proxied by β_1, and idiosyncratic return volatility of stock i with the standard deviation of the residuals from the model (3) within the year. We require that each aircraft-year regression must have at least 100 observations in any given year. The result of this procedure is a panel of airline company-year idiosyncratic return volatility, which is our IRV_FF5 estimates.

3.2.2. The Key Independent Variable

The key variable of interest in this study is the passengers' air travel by aircraft for a given year. This represents an accurate measure of demand for air travel with reliable data. We proxy the yearly occupancy of airline seats for passengers' air travel by the U.S. carrier. Following Mollick and Amin (2021), we construct the occupancy of airline seats as the total number of passengers scaled by the total number of aircraft seats. We hypothesize that with more demand for travel the systematic risk and idiosyncratic return volatility (IRV) of stock i will decline. This is because higher demand for air tickets will boost revenues and thus market returns of the firms, which makes errors smaller. It is an open question whether the negative relationship holds in beta or IRV. The latter is the risk that is unique to a specific firm (firm-specific risk). Fu (2009) notes that idiosyncratic risk or IRV is independent of the common movement of the market. Accordingly, we expect that higher seat occupancy will reduce IRV or the firm-specific risk.

3.2.3. Control Variables

This study includes several firm-level control variables that have previously been shown to affect firms' systematic risk and idiosyncratic risk. The firm-level control variables include profitability (*Prof*), sales growth (*Grwth*), leverage (*Lev*), firm size (*Size*), stock market liquidity (*Liq*), and tangibility (*PPE*). A firm's profitability is controlled because prior studies suggest that profitability is negatively related to idiosyncratic return volatility and systematic risk (Lee and Jang 2007; Rajgopal and Venkatachalam 2011; Park et al. 2017). Sales growth is controlled because Mishra and Modi (2013) and Sorescu and Spanjol (2008) suggest that sales growth is a strong predictor of a firm's cash flow, which has a negative influence on idiosyncratic return volatility. We control for firm leverage in our model because Brown and Kapadia (2007), Fink et al. (2010a), and Rajgopal and Venkatachalam (2011) argue that levered firms tend to experience financial distress, leading to a positive relation between leverage and idiosyncratic return volatility. Firm size is a significant predictor of idiosyncratic return volatility (Lee and Jang 2007; Sorescu and Spanjol 2008). Liquidity is controlled because liquidity risk is likely to affect current or future earnings (Chaudhry et al. 2004; Wagner and Winter 2013). They argue that liquidity risk exposure allows fund managers to take advantage of a positive liquidity risk premium or if fund managers are unable to liquidate assets/stocks. Abdi and Ranaldo (2017) develop a simple estimator of bid-ask spreads from daily close, high and low prices, which exploits wider information set than daily closing prices. Finally, we control for Tangibility as a proxy for a firm's maturity, which has been shown to affect a firm's idiosyncratic risk (Fink et al. 2010b; Adjei and Adjei 2017). All variables are defined in Appendix A.

3.3. Empirical Model

To investigate the relation between the occupancy of airline companies' seats and their risks, we estimate the following baseline empirical ordinary least square (OLS) model. This model links the systematic risk and idiosyncratic risk of airline carrier i in the year t to its occupancy and airline carrier-specific characteristics:

$$Y_{it} = a + \beta_1 Occup_{it} + \sum_{j=2}^{n} \beta_j X_{it} + \theta_t + \varepsilon_{it} \quad (4)$$

where the dependent variable, Y, (a proxy for Risk) indicates either the systematic risk (beta) or the idiosyncratic risk (*IRVs*) of firm, i, for a given year, t, and j and n are integers. θ is the year fixed effects. The systematic risk could be any of the three beta coefficients (β*_MKT*, β*_CAPM*, and β*_FF5)* from models (1) to (3) and idiosyncratic risk could be any of the three measures (*IRV_MKT*, *IRV_CAPM*, *and IRV_FF5*) from models (1) to (3). The key variable of interest is *Occup*, measured as the ratio of the total number of passengers to the total number of aircraft seats over a year for carrier i in the year of y. X is a vector of airline carrier-specific control variables that include profitability (*Prof*), sales growth (*Grwth*), leverage (*Lev*), firm size (*Size*), stock market liquidity (*Liq*), and tangibility (*PPE*). We expect that the coefficient on β_1 be negative to support our hypothesis that higher occupancy will lower either risk of the firm. Standard errors are corrected for clustering at the airline carrier level.

4. Results and Discussion

4.1. Descriptive Statistics

Table 1 provides descriptive information of airline companies within our sample period. Our sample consists of 21 unique airline companies listed in Appendix A which have 273 airline company year observations spanning from 1990 to 2019. Beta, our proxy for systematic risk, ranges from −0.33 to 4.157 with a mean of 1.26 and a standard deviation of 0.55 when we use the market model. The mean value of 1.26 for beta from the market model indicates that airline companies on average, exhibit higher systematic risk than the market risk of 1. Mean Beta from different models (FF5 and CAPM) remains around 1.25. The annual measures of the mean (standard deviation) of IRV, based on market and CAPM models, are 0.033 (0.017), whereas the mean (standard deviation) of IRV, based on the Fama–French five-factor model, is 0.032 (0.017). The median values of IRVs from the market, CAPM, and FF5 models are 0.028, 0.029, and 0.027, respectively. This indicates that the idiosyncratic risk measures are very similar with respect to mean relative to standard deviation. The descriptive statistics of betas and IRs indicate a symmetric distribution around the mean. These statistics of Betas and IRs are comparable to those reported by Andersen et al. (2001), Vo (2016), and Ozdemir et al. (2020). When we turn our attention to the variable of interest, we see that, on average, U.S. airline companies have 68% occupancy of seats, with a standard deviation of about 17%. On average, airline companies exhibit profitability with high volatility. The mean profitability of airline companies in our sample is 1.6% with a standard deviation of 8.7%. The mean (standard deviation) value of leverage is about 37.9% (16.9%), which indicates that these companies are fairly leveraged firms (debt stands on average at about 40% of their assets). However, these values are significantly lower than those reported by Lee and Jang (2007); Lee and Park (2010); and Moon et al. (2015). Lee and Jang (2007) show about 70% of debt in the capital structure of airline companies with a standard deviation of 22%. We winsorize all of our continuous variables, which helps make debt to assets lower than theirs. Airline companies are big. The liquidity, *PPE*, and size of the company remain relatively high with a low level of volatility indicating the stability of these companies. The companies in our sample also have, on average, about a 13.1% growth rate measured by sales growth rates.

Table 1. Descriptive statistics.

Variable	N	Mean	SD	Min	P25	Median	P75	Max
β_MKT	273	1.259	0.553	−0.329	0.946	1.245	1.559	4.157
β_CAPM	273	1.254	0.540	−0.329	0.935	1.232	1.555	4.412
β_FF5	273	1.242	0.573	−0.486	0.907	1.193	1.500	5.428
IRV_MKT	273	0.033	0.017	0.012	0.021	0.028	0.038	0.128
IRV_CAPM	273	0.033	0.017	0.012	0.021	0.029	0.038	0.128
IRV_FF5	273	0.032	0.017	0.011	0.021	0.027	0.036	0.127
Occup	273	0.681	0.172	0.000	0.627	0.715	0.798	0.889
Prof	273	0.016	0.087	−0.351	−0.020	0.024	0.063	0.245
Grwth	273	0.131	0.261	−0.403	0.021	0.089	0.172	1.865
Lev	273	0.379	0.169	0.001	0.261	0.400	0.498	0.753
Size	273	7.856	1.773	3.434	6.675	8.070	9.148	11.007
Liq	273	4.392	0.488	2.749	4.122	4.454	4.732	5.336
PPE	273	0.564	0.178	0.098	0.465	0.594	0.685	0.856

This table reports summary statistics for measures of airline seat occupancy, systematic risk (Betas), idiosyncratic risk (IRs), and other firm-specific control variables. *β_MKT* is the Beta coefficient estimated from the market model (Equation (1)). *β_CAPM* is the Beta coefficient estimated from CAPM model (Equation (2)). *β_FF5* is the Beta coefficient estimated from Fama–French five-factor model (Equation (3)). *IRV_MKT* is Idiosyncratic return volatility estimated from the market model (Equation (1)). *IRV_CAPM* is the Idiosyncratic return volatility estimated from CAPM model (Equation (2)). *IRV_FF5* is idiosyncratic return volatility estimated from Fama–French five-factor model (Equation (3)). *Occup* is the occupancy ratio, measured as the total number of passengers scaled by the total number of airline seats in a year. *Prof* is the profitability, measured as income before extraordinary items scaled by total assets. *Grwth* is the firms' sales growth, measured as the changes in sales scaled by lagged sales. *Lev* is the sum of short-term and long-term debt scaled by the total assets. *Size* indicates firm size, measured as the natural logarithm of total assets. *Liq* is stock market liquidity, which is the negative bid-ask spread measured using daily closing, high, and low stock price as in Abdi and Ranaldo (2017). *PPE* is the net property, plant, and equipment scaled by the total assets. We winsorize all of our continuous variables. Our sample consists of 273 firm-year observations (unbalanced panel) with 21 unique airline companies covering the period 1990–2019. All independent variables are winsorized at the top and bottom 1% levels.

4.2. Main Results

In Table 2, we examine the relation between the occupancy of airline companies' seats and their systematic risk and idiosyncratic risk using our baseline OLS model. The dependent variables are systematic risk and idiosyncratic risk, which are proxied by betas and the standard deviation of residuals from the models (1), (2), and (3), respectively. The key independent variable is occupancy, measured as the ratio of the total number of passengers to the total number of aircraft seats in a year. All other independent variables are defined above and also in Appendix A. Columns (1) to (3) report results for systematic risk from the model (4), whereas columns (4) to (6) report results for idiosyncratic risk from model (4). Columns (1) to (3) represent systematic risks (*β_MKT*, *β_CAPM*, and *β_FF5*), measured by the beta from the market model (1), CAPM model (2), and the Fama–French five-factor model (3), respectively. Columns (4) to (6) represent the idiosyncratic risks (*IRV_CAPM*, and *IRV_FF5*), measured by the standard deviation of the residuals from the market model (1), CAPM model (2), and the Fama–French five-factor model (3), respectively.

Panel A of Table 2 reports the results from the OLS regression model (4) estimations. The coefficient estimates on *Occup* are negative and statistically highly significant across all models. In particular, the coefficients on *Occup* in columns (1) to (6) are −0.542 (t = −2.62), −0.543 (t = −2.74), −0.486 (t = −2.24), −0.007 (t = −2.03), −0.007 (t = −2.03), and −0.006 (t = −1.83), respectively. These coefficient estimates suggest that airline companies with a higher level of seat occupancy throughout the year have significantly lower systematic risk and idiosyncratic risk after controlling for other known firm-specific controls. These results support our primary hypothesis that occupancy of airline seats reduces systematic risk and idiosyncratic risk of airline stocks. Economically speaking, the estimated effect of *Occup* on beta and IRVs measures is very meaningful. For example, in column (1), a one standard deviation increase in an airline company's seat occupancy is associated with a drop of systematic risk (captured by beta from the market model) by 0.093, which is about a 7.40% reduction in beta relative to the mean. For idiosyncratic risk in column (4), a one standard deviation increase in an airline company's seat occupancy is associated with a drop of IRV by 0.0012, which is about a 3.60% reduction in IRV relative to the mean. Similar economic meaning is also equally applicable to the results reported in all other columns.[6] The results in Table 2 also show that size (for beta risk) and liquidity, *PPE*, and growth (for IRV risk) are statistically significant. Increased sales growth reduces IRV as shown in columns 4–6 with a 10% level of significance. It is, however, not significant in influencing systematic risks (beta of *MKT*, *CAPM*, *FF5*). Size, on the other hand, has a significantly positive impact on betas at a 5% level with no influence on IRVs. Liquidity, just like sales growth, also significantly reduces IRVs (at a 5% level) and has no impact on betas. Finally, *PPE* also reduces IRVs at a 10% level of significance with no impact on systematic risk, betas.

Table 2. Baseline Model.

Variable	Predicted Sign	(1) β_MKT	(2) β_CAPM	(3) β_FF5	(4) IRV_MKT	(5) IRV_CAPM	(6) IRV_FF5
				Panel A: OLS model			
Occup	−	−0.542 **	−0.543 **	−0.486 **	−0.007 *	−0.007 *	−0.006 *
		(−2.62)	(−2.74)	(−2.24)	(−2.03)	(−2.03)	(−1.83)
Prof	−	−0.023	−0.003	0.328	−0.006	−0.006	−0.004
		(−0.06)	(−0.01)	(0.83)	(−0.59)	(−0.60)	(−0.43)
Grwth	−	0.020	0.044	−0.018	−0.006 *	−0.006 *	−0.006 *
		(0.13)	(0.29)	(−0.11)	(−1.95)	(−1.96)	(−2.01)
Lev	−	−0.113	−0.142	−0.366	0.008	0.008	0.008
		(−0.44)	(−0.56)	(−1.14)	(1.56)	(1.55)	(1.62)
Size	−	0.151 ***	0.144 ***	0.128 ***	0.001	0.001	0.000
		(5.21)	(5.16)	(5.21)	(0.87)	(0.88)	(0.59)
Liq	−	−0.119	−0.132	−0.093	−0.027 ***	−0.027 ***	−0.026 ***
		(−1.04)	(−1.09)	(−0.51)	(−7.97)	(−7.97)	(−8.00)
PPE	+	−0.107	−0.087	−0.032	−0.009 **	−0.009 **	−0.009 **
		(−0.33)	(−0.28)	(−0.09)	(−2.32)	(−2.31)	(−2.18)
Constant	+/−	1.104 *	1.183 *	1.123	0.149 ***	0.149 ***	0.147 ***
		(1.98)	(2.04)	(1.21)	(9.82)	(9.83)	(9.74)
Year FE		Yes	Yes	Yes	Yes	Yes	Yes
N		273	273	273	273	273	273
Adj. R^2		0.410	0.382	0.229	0.701	0.702	0.685
				Panel B: Fixed Effect model			
Occup		0.435	0.314	−0.059	−0.016 **	−0.015 **	−0.014 *
		(1.07)	(0.84)	(−0.11)	(−2.14)	(−2.13)	(−1.97)
Controls		Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes	Yes
N		273	273	273	273	273	273
Adj. R^2		0.518	0.485	0.342	0.701	0.702	0.684

This table presents the results from the OLS regressions model (1). Columns (1) to (3) report results for systematic risk from model (4), whereas columns (4) to (6) report results for idiosyncratic risk from model (4). Appendix A provides more details of all variables. 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.

Panel B reports the results from the fixed effect empirical model. Our choice of fixed-effect models emanates from the concerns about omitted, unobserved, and time-invariant firm-specific characteristics. We find very robust evidence on the link between occupancy of the seat and idiosyncratic risk but not with systematic risk. The effect we get in our OLS model (results reported in Panel A) on systematic risk is absorbed by firm-specific un-observables. These results support our hypothesis, although with weaker evidence for systematic risk of airline stocks. When we turn our attention to firm-specific control variables, we observe that, except for *PPE*, all other variables show a similar relation as in Table 2 retaining their expected sign and similar significance level: occupancy, growth, and liquidity all have negative effects on IRV in all three models. The effects of *PPE* become absorbed by fixed effects. Overall, the results support the main hypothesis in this paper, especially with respect to the negative effects of occupancy on IRV.

4.3. Subsample Analysis

In this section, we show the heterogeneous effect of occupancy on the risk measures of airline stocks. We restrict our analysis for idiosyncratic risk since we find weak evidence on the link between occupancy and systematic risk from our fixed effect results reported in Table 2. The T-100 segment of the Bureau of Transportation Statistics database records airline companies' monthly domestic and international flight information that includes the number of passengers, origin, destination, the number of miles traveled, and so on. The number of miles traveled has a cost implication for airline companies' operations, such as fuel cost, customer service, food, or maintenance. If the distance traveled is shorter, the operating cost may be lower due to less fuel consumption and vice-versa. Considering this cost implication with respect to the distance traveled by the airline companies, we focus on two subsamples: the low mileage travel distance and the high mileage travel distance. The low (high) milage travel distance subsample consists of airline companies that travel lower than (less or equal to) our full sample median travel distance. The yearly aggregate median distance traveled by an airline company is 6,263,441 miles (sum of all monthly flight travel distances over a year). From the cost implication, we expect that the negative effect of occupancy on idiosyncratic risk would be more pronounced for the subsample of airline companies with shorter travel distances.

Results are reported in Table 3, Panel A. Columns (1) to (3) represent regression results for the low mileage traveled subsample, whereas Columns (4) to (6) represent regression results for the high mileage traveled subsample. The results show that the occupancy of airline seats has a significant impact on idiosyncratic risk for the lower mileage traveled group but no significant impact for the other group. For example, the coefficient estimate on Occup reported in column (1) is negative and statistically significant (-0.020 and t-statistics = -3.04), whereas it is insignificant (0.033 and t-statistics = -0.63) for the counterpart reported in column (4). This coefficient on occupancy for the low mileage subsample is different from that for the high mileage subsample at the 1 percent level. The difference in coefficients remains statistically the same for all the models compared in Table 3. This result suggests that idiosyncratic risk is reduced for airline companies with higher occupancy of seats when these airline companies travel lower than the median yearly aggregated travel distance. This finding is consistent with our conjecture that traveling longer distances has a cost implication for airline companies, which absorbs the significant effect of occupancy on idiosyncratic return volatility. We also argue that airline companies, with high seat occupancy traveling shorter mileage, have a higher free cash flow for funding their value-maximizing investment opportunity. However, we do not claim that the effect is the same for airline companies that operate only within the U.S. We show that the negative effect of occupancy varies with respect to the number of miles traveled, which could include a combination of domestic and international transport.

Panel B of Table 3 presents the effect of occupancy on IRVs after controlling for leverage. Columns 1–3 show results with a low level of leverage and Columns 4–6 show results with a high level of leverage. If the companies maintain a low level of leverage, occupancy significantly and negatively affects IRVs. However, if the level of leverage is high, occupancy shows positively significant IRVs. It seems that high leverage is very sensitive to a firm's IRVs and with higher occupancy, IRVs increase for the companies. It should be noted that leverage also increases systematic risks, betas, as presented in Table 3 and as expected. It is a clear signal to the industry that any company with higher occupancy cannot lower the risk level of the firm in the presence of high leverage.

Table 3. Subsample Analysis.

Variable	Low/Small			High/Big		
	(1)	(2)	(3)	(4)	(5)	(6)
	IRV_MKT	*IRV_CAPM*	*IRV_FF5*	*IRV_MKT*	*IRV_CAPM*	*IRV_FF5*
			Panel A: Travel Distance (Mileage)			
Occup	−0.020 ***	−0.020 ***	−0.020 ***	−0.033	−0.033	−0.046
	(−3.04)	(−3.02)	(−3.05)	(−0.63)	(−0.63)	(−0.88)
N	136	136	136	137	137	137
Adj. R^2	0.626	0.627	0.616	0.841	0.841	0.815
			Panel B: Leverage			
Occup	−0.044 *	−0.044 *	−0.044 *	0.023 **	0.023 **	0.024 **
	(−2.08)	(−2.08)	(−2.05)	(2.14)	(2.13)	(2.20)
N	137	137	137	136	136	136
Adj. R^2	0.512	0.513	0.501	0.830	0.830	0.818
			Panel C: Firm size			
Occup	−0.025 ***	−0.025 ***	−0.025 ***	0.004	0.004	0.011
	(−3.51)	(−3.51)	(−3.53)	(0.16)	(0.16)	(0.43)
N	136	136	136	137	137	137
Adj. R^2	0.637	0.638	0.627	0.804	0.804	0.772

This table reports the relation between the occupancy and idiosyncratic risk for subsamples with respect to different sensitivities. Panel A provides results on the subsample based on the aggregated mileage an airline carrier traveled throughout a given year. Panel B provides results on the subsample based on the airline carrier's leverage. Panel C provides results on the subsample based on the airline carrier's total assets. Columns 1–3 report the results for the below or equal to the sample average of the respective category, whereas Columns 4–6 report the results for the sample above-average of the respective category. We restrict our analysis for idiosyncratic risk since we find weak evidence on the link between occupancy and systematic risk from our fixed effect results reported in Table 2. The low (high) consists of respective characteristics that is lower than (less or equal to) our full sample median travel. All models include control variables. Appendix A provides more details of all variables. t-statistics are computed using robust standard errors and reported in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

In Panel C of Table 3, we classify firms as small aircraft and large aircraft and provide a relation between IRVs and occupancy. We notice that smaller aircraft show a significantly negative relationship between occupancy and IRVs at a 5% level and no significance when firm size is large. The large firm-based relation is similar to the findings in Table 3, where it shows that size has no influence on IRVs and or betas of the firm. It is, however, very relevant for smaller aircraft. It implies that large firms are, on average, immune to any variabilities in occupancy and has no impact on IRVs.

4.4. Implications

Our empirical findings suggest that systematic risk and idiosyncratic risk of airline companies' stock are negatively associated with a higher level of seat occupancy. These findings have several implications for various groups: First, the U.S. airline industry historically experiences higher systematic risk and excessive operating costs (Lee and Jang 2007). To reduce their total risk and become operationally efficient, they should focus on the revenue side when their risk exposures are difficult to manage. Airline companies can undertake different initiatives to increase their occupancy since that reduces idiosyncratic risk. They could engage in more corporate socially responsible activities, marketing promotions, or anything that increases customer satisfaction. Second, there is intense competition among U.S. airlines and overseas airline companies, where some carriers (airlines from oil-producing overseas countries such as Gulf Cooperation Council (GCC)) have a significant cost advantage. Instead of increasing the number of flights competing against each other, a strategic partnership with other international carriers can improve the occupancy level without further debt-financed addition of more aircraft, but rather have a revenue-sharing alliance among airlines. Third, in the airline industry, most aircraft are either leased or financed. As a result, every airline company has an annual fixed debt servicing requirement. Occupancy, which results in sales revenue, is a significant factor in servicing those debt financing and to further continue. Airline companies could increase flights in routes that have shorter travel distances. It also increases mode debt servicing. Larger debt ratios can put a strain on a company's financing ability as its risk level gets higher. This also indicates that keeping investment lower through debt financing is desirable for the company's long-run stability. Finally, investors can pay attention to the frequency of air travel and the financial health of a particular aircraft before investing in those companies. Airline companies can also rebuild investors' confidence in them by stressing on reducing firm-specific heterogeneity that causes higher-level idiosyncratic return volatility. Finally, the credit market may consider the revenue potential of those aircraft due to high occupancy and relax their loan contract requirements.

5. Conclusions

In this research, we investigate the impact of occupancy rate on systematic risks (betas) and idiosyncratic risks (IRVs) after controlling for various firm-level control variables. Using panel data of both domestic and international travels for all U.S. airlines, we run fixed-effect models to investigate the relationship among various betas, IRVs, and occupancy ratios. Our findings suggest that airline companies with a higher level of seat occupancy throughout a year have significantly lower idiosyncratic risk after controlling for other known firm-specific control variables. These results support our primary hypothesis that occupancy of airline seats reduces the systematic risk and idiosyncratic risk of airline stocks. While the former is not very robust across empirical models, the latter indicates that risk, unique to a firm, essentially goes down with higher seat occupancy. To the best of our knowledge, we are the first to contribute to the literature by providing relationship between occupancy and idiosyncratic risk for the airline industry. This study complements those who investigate the firm-specific factors for idiosyncratic risk and investors' consideration of selecting airline stocks.

When we conduct sub-sample analysis, our results show that the occupancy of airline seats has a significant impact on various idiosyncratic return volatilities for the lower mileage traveled group but no significant impact for the higher mileage travel group. Occupancy also remains significant with expected signs for airlines with a low level of leverage and smaller-sized firms. Our results further contribute to the literature by showing that traveling longer distances has a cost implication for airline companies, which absorbs the significant effect of occupancy on systematic risk and idiosyncratic risk. When we estimate our models for two groups of travel, we could not separate the portion of short-distance passengers from long-distance passengers (i.e., travel to China could have three legs in taking flights of which two legs are low mileage domestic travel and one long-distance international travel). We consider this a limitation to our research. Perhaps, future research addressing this breakdown could provide further insights into the impact of international travel-based occupancy on the profitability and various types of risk measures on airline companies. Moreover, we focus solely on U.S. airlines. A broader sample of firms from other countries that serve mostly high mileage passengers could shed more light on the comparative impact of occupancy on different types of risk between domestic and international airlines.

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Appendix A

Table A1. Variable definition.

Variables	Definitions
β_MKT	Beta coefficient estimated from the market model (Equation (1)).
β_CAPM	Beta coefficient estimated from CAPM model (Equation (2)).
β_FF5	Beta coefficient estimated from Fama–French five-factor model (Equation (3)).
IR_MKT	Idiosyncratic return volatility estimated from the market model (Equation (1)).
IR_CAPM	Idiosyncratic return volatility estimated from CAPM model (Equation (2)).
IR_FF5	Idiosyncratic return volatility estimated from Fama–French five-factor model (Equation (3)).
Occup	Occup is the occupancy ratio, measured as the total number of passengers scaled by the total number of aircraft seats in a year.
Prof	Prof is the profitability, measured as income before extra-ordinary items scaled by total assets
Grwth	Grwth is the firms' sales growth, measured as the changes in sales scaled by lagged sales.
Lev	The sum of short-term and long-term debt scaled by the total assets.
Size	Size indicates firm size, measured as the natural logarithm of total assets.
Liq	Liq is stock market liquidity, which is the negative bid-ask spread measured using daily closing, high, and low stock price as in Abdi and Ranaldo (2017).
PPE	PPE is the net property, plant, and equipment scaled by the total assets.

Notes

1. We explore the effects of seat occupancy on both systematic and idiosyncratic risks, since it should affect profits and then the return of airline shares in the marketplace. Others analyze correlation between air passenger transport and economic activity for various geographical areas of the world.
2. See at https://www.transtats.bts.gov/tables.asp?DB_ID=110&DB_Name=&DB_Short_Name= (accessed on 21 July 2022).
3. See at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (accessed on 21 July 2022).
4. The list of 21 unique companies is available upon request.
5. Our sample begins in 1990 due to the non-availability of airline seat occupancy data from the T-100 segment of the Bureau of Transportation Statistics.
6. These figures can be checked as follows using the sample means and standard deviations from Table 1. The drop of −0.093 is achieved by the estimated coefficient in column (1) of −0.542 multiplied by the standard deviation of Occupancy (0.172). This −0.093-reduction divided by the mean of IRV_MKT (1.259) yields 0.074, or 7.4%.

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