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Operational hedging against adverse circumstances☆

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ABSTRACT

This paper investigates operational hedging against severe disruptions to normal operations. It offers a new method to evaluate the extent that operations policy serves as a hedge against adverse circumstances. We apply the proposed method to explore how supply chain characteristics affect the responses of airlines to the acute demand fall off after the September 11 terrorist attacks. Results indicate that operational hedging vehicles (fleet standardization, high-fleet utilization, an aircraft ownership policy rather than leasing, and international operations) are more powerful in protecting firms than using financial instruments. The study contributes in guiding managers as to how operations policy can serve as an imperative factor in mitigating exposures to low-end performance levels.

1. Introduction

The utilization of operations to manage risks has recently attracted considerable attention and a growing interest in applying risk management concepts to manage the operations of firms. In particular, several studies focus on risk arising from disruptions to normal activities of supply chains and their consequences (e.g., Papadakis and Ziemba, 2001; Lewis, 2003; Hendricks and Singhal, 2005; Kleindorfer and Saad, 2005). Major sources of disruption arise from exogenous hazards, such as earthquakes, tornadoes and flooding, political instability, and terrorist attacks. Prior studies focus on risk management as well as on the structural and temporal pathology of operational failure. This study extends this line of research and investigates to what extent can operations policy serve as a hedge for firms facing uncertain adverse circumstances. In particular, we examine the relative impact of operational hedging vehicles compared with financial hedging vehicles.

We focus on the airline industry to investigate how attributes of operations policy, such as technology and capacity choices, affect firms' performance under adverse circumstances. The September 11 terrorist attacks provide an ultimate setting for gaining insights into the operational vehicles employed by airline carriers to reduce damage. In this study, we introduce a method to evaluate firms' total hedging level and then investigate their operational and financial determinants. We concentrate on the role of operations management in mitigating firms' exposure to

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financial distress under adverse circumstances, together with the utilization of financial instruments to manage risks.

Evaluating firms' total hedging level, we follow Hendricks and Singhal (2005) in our reliance on financial performance. We build on Stulz (1996), who argues that "the primary goal of risk management is to eliminate the probability of costly *lower-tail outcomes*" [pp. 23–24, emphasis added]. The underlying assumption is that distribution of firms' *low-end* performance levels under unfavorable circumstances signals their capabilities to protect themselves against poor performance levels. Employing time-series cash flow data for estimating performance distributions, we formalize Stulz's argument and introduce a concept of *lower-tail stochastic-dominance (LSD).* The *LSD* comparison is a variation of traditional stochastic-dominance widely used in micro-economics, except that it applies to adverse lower-tail performance—see detailed discussion in Section 3. The *LSD* concept provides a means to examine the influence of both operational choices and financial instruments on mitigating the exposure to financial distress under adverse circumstances. We use data from nine U.S. airlines over 44 quarters from 1990 through 2000 and apply the *LSD* concept to rank the total hedging level of the airlines.

The empirical results offer a ranking of U.S. airlines according to their total hedging level using *LSD*, in which Southwest and Skywest were the most hedged, whereas America West and US Airways were the least hedged. We then demonstrate the effectiveness of the *LSD* concept by showing that more hedged airlines responded better (less badly) to the demand fall off following the September 11 terrorist attacks. A higher rank of total hedging level is positively and significantly correlated with increased cash flow from operations and less depressed stock returns after the attacks.

Being aware of the small sample size implied by the airline industry, a series of robustness checks is performed to validate the proposed hedging rank and its outcome. We show that the hedging rank (i) differs from conventional risk measures because it concentrates on hedging against adverse circumstances, not on variation-reduction process control, (ii) is independent on the choice of cash flow as the primary variable for the analysis, (iii) is robust to the classification of low-end tails of the performance distributions, and, (iv) does not serve as an expected performance measure because it captures ability to reduce the probability of low-end performance levels, not to perform well on favorable events. In addition, we use both streams of cash flow and investors' response to the events on September 11 to corroborate the evidence on hedging against the adverse consequences of the attacks. Taken as a whole, the proposed rank reflects capability to hedge against the disruptions to normal airline operations caused by the terrorist attacks.

Searching for operational and financial vehicles used to alleviate the firm's exposure to lower-tail performance under severe disruptions, findings indicate several hedging vehicles. Specifically, results indicate that higher fleet standardization, higher fleet utilization (i.e., lower excess capacity), an aircraft ownership policy (rather than leasing), international operations, and cash holdings increase the hedging level of airlines and provide tools to better respond to the unfavorable event. In contrast, financial leverage and financial derivatives used to protect from fuel price volatility are insignificantly associated with the hedging rank. The findings indicate that operating hedging vehicles are more powerful in protecting airlines than using financial instruments.

Examining operational and financial vehicles separately, however, emphasizes the role of operations policy in risk management. Financial leverage and financial derivatives used to protect from fuel price volatility are significantly associated with the hedging rank when operational hedging vehicles are omitted, but this significance disappears in the presence of operational hedging vehicles. In contrast with financial hedging against market risks and volatility in commodity prices documented in the finance literature, the findings emphasize the important role of operational vehicles in hedging against adverse circumstances.

Overall, the findings provide firms with operational management guidance as to how to mitigate exposures to low-end performance levels under adverse circumstances. This study contributes to the operations management literature in two ways. First, it supports evidence concerning operational vehicles for mitigating firms' exposure to adverse circumstances firms want to avoid. The findings extend our knowledge as to how airlines employ their operations to better respond to a dramatic demand fall off and, thus, highlight operational hedging. The results highlight the substantial role of the operations function in hedging against adverse circumstances, above and beyond financial instruments. Second, it introduces the *LSD* concept for comparing firms' hedging levels. This concept can be further applied to investigate the use of operations to hedge firms' downside performance in various industries and settings.

This paper is organized as follows: Section 2 discusses potential means for operational hedging in the airline industry; Section 3 introduces the concept of *lower-tail stochastic-dominance* and applies it to the airline industry; and Section 4 demonstrates the validation of the proposed hedging measure. Section 5 examines operational and financial vehicles of hedging; and Section 6 provides a summary.

2. Vehicles of operational hedging

While the finance literature investigates various types of financial derivatives for hedging against market risks (i.e., changes in currency exchange rates, commodity prices, and interest rates), there is limited evidence concerning the way firms use their operations to hedge against the risk of substantial demand fall off due to adverse situations. Abundant hedging research has investigated the use of financial derivatives as hedge instruments (e.g., Brown, 2001; Geczy et al., 1997; Guay, 1999). However, Guay and Kothari (2003) report that firms only use derivatives to fine-tune an overall risk management program that is likely to include operational hedges. Specifically, an operational hedge is interpreted as "mitigating risk by counter-balancing actions in a processing network that do not involve financial instruments" (Van Mieghem, 2003). See a detailed review of the operational hedging literature in Boyabatli and Toktay (2004).

Concentrating on operational hedging against adverse circumstances, we view the consequences of the terrorist attacks on September 11 and the subsequent shutdown of the U.S. airline industry for several days as a harsh situation for airlines. The September 11 attacks generated a severe demand shock, resulting in an acute disruption to normal operations of the airlines' supply chains. Motivated by the increasing interest in operational hedging against severe disruptions to the normal operation of supply chains, we follow the literature and find four potential operational hedges in the airline industry.

First, the literature highlights the role of flexible operations in hedging against unfavorable situations. Huchzermieir and Cohen (1996) define operational flexibility as the ability to switch among different manufacturing strategy options and locations. Sawhney (2006) suggests using flexibility for both coping with uncertainty and create competitive advantage. Beja and Weiss (2006) show that flexibility serves as a hedging tool in allowing firms to reduce downside risks. In a similar vein, Iravani et al. (2005) argue that multi-purpose resources provide flexibility in responding to variability in the operational environment. The argument is also consistent with Correa (1994), who suggests that the capability to adapt to changing environmental conditions is beneficial in reducing risks in adverse situations.

Specifically, Don Carty (2002), former chief executive officer of American Airlines, states that American Airlines was building flexibility into its fleet by significantly reducing the number of fleet types, thus enabling it to *perform better during recessions*. Similarly, Doganis (2001) points out that a standardized fleet makes it easier to re-assign pilots to flights as a response to significant changes, such as falling demand. Having fewer aircraft types also provides superior flexibility due to increased capabilities for switching routes, substituting crews, and performing aircraft maintenance in shorter lead-times. On the other hand, it may also constitute a constraint preventing the airline from taking full advantage of a rise in demand for flights. We employ fleet standardization as our proxy for flexible operations. Fleet standardization is measured based on Banker and Johnston (1993, Table 2), who measure the number of aircraft types of airlines based on aircraft categories and characteristics, which indicates the fleet diversification level (i.e., the reciprocal of fleet standardization).

Second, the operations management literature has explored the role of capacity, as a means for responding to fluctuations in customer demand. Fine and Freund (1990) and Roller and Tombak (1990) associate greater capacity with the capability to perform more tasks and to better respond to uncertain conditions. Both studies emphasize that higher capacity allows greater ability to respond to changes in market conditions.

A critical examination of capacity as a hedging tool raises a question about the symmetry in the argument. Excess capacity can be viewed as a capacity cushion (capacity over and above what is required to meet normal demand), which offers flexibility to take advantage of prosperous circumstances. It can clearly be seen that greater capacity cushion is useful in responding to an abrupt increase in customer demand. However, it is less obvious why having excess capacity would be beneficial in responding to a sharp decline in customer demand (see Harrison and Van Mieghem, 1999). The impact of operational hedging through capacity imbalance in a risk-averse, mean variance setting is analyzed by Van Mieghem (2003), who does not associate increased capacity with a higher level of hedging. Rather, Van Mieghem suggests a risk-optimal capacity as a hedge. We expect a smaller capacity cushion, measured by a load factor, to be a hedge against adverse situations in the airline industry. Load factor of a carrier is the ratio between the number of seat miles filled with revenue passengers and the number of available seat miles. Available seat miles (ASMs) are determined by multiplying the number of seats available for passengers by the number of miles flown by each airline.

Third, Pulvino (1998) argues that an airline's financial condition significantly affects the prices it receives for used aircraft. Specifically, Pulvino reports a substantial discount to the fundamental value of aircraft sold by financially constrained airlines. Nonetheless, canceling a leasing contract under adverse circumstances involves the cash payment of cancellation fees, while selling a used aircraft results in a positive cash flow stream. While a leasing policy is likely to have important advantages in prosperous periods, the cancellation fees prevalent in the airline industry are likely to diminish the advantages of such a policy during periods of recession. Keeping in mind that a buy versus lease policy is a fundamental issue in operations management, we examine the effect of an aircraft leasing policy on airlines' hedging and employ the percentage of leased aircraft as our proxy for the airlines' leasing policy.

Fourth, Lapre and Scudder (2004) examine differences in performance improvement paths between global operations and geographical specialists in the airline industry. Allayannis et al. (2001) use geographic dispersion as a proxy for operational hedging, where international activity is assumed to mitigate risks. We use a dummy variable to examine the effect of domestic versus international carriers on the ability to hedge. U.S. airlines are defined as international if they fly to Europe, the Far East, or South America.

While focusing on operational hedging, it is essential to control for financial hedging in examining operational hedging. The literature on financial hedging against adverse circumstances is quite sparse. Froot (2001) examines the market for natural catastrophe risks. Later, Cummins et al. (2003) analyze effectiveness of catastrophic-loss index options in hedging hurricane losses. In contrast to our operational approach, both studies focus on financial markets for hedging instruments. Nonetheless, we follow the finance literature and employ three variables to control for potential financial hedging: (i) financial derivatives—airlines use financial derivatives traded in capital markets to hedge against market risks. Specifically, some airlines hedge against changes in jet fuel prices through financial derivatives, measured by the percentage of next year's fuel requirements hedged (Carter et al., 2005). (ii) Cash holdings—airlines' cash holdings can serve as a hedge when it saves transaction costs to raise funds and eliminates the need to liquidate assets to make payments (Opler et al., 1999). It is measured by the ratio of cash and marketable securities divided by total assets at year end. (iii) Financial leverage—motivated by Southwest Airlines' (2000, p. 17) claim that "... financial strength provides our team enormous hedging to grow and maximize long-term employee and shareholder value, regardless of industry consolidation or an economic slowdown." We measure financial leverage by total liabilities divided by total assets at year end.

Empirically examining potential vehicles of operational and financial hedges, we use data from airlines' financial statements reported to the Securities Exchange Commission (known as 10-K statements) and from the US Department of Transportation. Our sample consists of nine U.S. airlines which operated during the period 1990–2000. Descriptive statistics of the potential hedging vehicles for our sample firms are presented in Table 1. They indicate considerable variations in all potential drivers of hedging. For instance, panel A indicates that Southwest Airlines operates a single type of aircraft (Boeing 737), while US Airways used up to 14 different types of aircraft in the late 1990s. Airlines also exhibit significant variations in their load factors, leasing policy and among the financial variables.

Results from examining correlations between the potential hedging variables are reported in panel B of Table 1. Particularly, load factor is insignificantly correlated with a diversified fleet, but significantly correlated with a leasing policy, 0.199. However, the number of aircraft types is negatively and significantly correlated with holdings of cash, −0.218. The financial leverage is positively correlated with a diversified fleet, 0.327. The correlations between the potential hedging vehicles are not particularly high (with the exception of Domestic) and allow for a regression analysis.

Facilitating an examination of the operational and financial hedging vehicles, the study consists of two stages. First, we propose a new method to evaluate firms' total level of hedging against adverse circumstances and generate a HedgeScore for each carrier. We use the consequences of the September 11 terrorist attacks to demonstrate the validation of the proposed score. Second, we use a regression analysis to gain insights into the effect of each of the operational and financial hedging vehicles on the total hedging level.

3. Evaluation of total hedging against adverse circumstances

Several operations management studies employ the real options concept to model various aspects of operational

Table 1
Descriptive statistics of potential hedging vehicles.

#	Variable	Mean	Median	Standard deviation	Min.	Max.
(Panel A) Descriptive statistics						
Operational hedging						
1.	Fleet diversification	8.326	9.000	3.683	1	14
2.	Load factor	0.679	0.677	0.025	0.596	0.724
3.	Lease	0.519	0.445	0.212	0.260	0.940
4.	Domestic					
Financial hedging						
5.	Fuel hedging	0.168	0.110	0.192	0.000	0.720
6.	Cash	0.120	0.081	0.150	0.022	0.292
7.	Financial leverage	0.876	0.826	0.547	0.284	4.18

#		Fleet diversification	Load factor	Lease	Domestic	Fuel hedging	Cash	Financial leverage
(Panel B) Correlations matrix								
1.	Fleet diversification	1.000						
2.	Load factor	0.182	1.000					
3.	Lease	0.017	0.199*	1.000				
4.	Domestic	0.791*	0.128	−0.371*	1.000			
5.	Fuel hedging	−0.140*	−0.022	−0.428*	−0.123*	1.000		
6.	Cash	−0.218*	0.127	0.268*	−0.174*	−0.131*	1.000	
7.	Financial leverage	0.327*	0.070	0.083*	0.320*	−0.231*	−0.156*	1.000

Variables definition: Fleet diversification = number of aircraft types for each airline at the end of each year, based on Aircraft Categories and Characteristics (Banker and Johnston, 1993, Table 2, p. 581); Load factor = the ratio between the number of seat miles filled with revenue passengers and available seat miles. Available seat miles are determined by multiplying the number of seats available for passengers by the number of miles flown by each airline (ASM); Lease = number of leased aircraft divided by total number of aircraft by each airline in each year; Domestic = 0 for airlines flying to destinations outside North America, and 1 for domestic airlines; Fuel hedging = the percentage of fuel requirements on year $t + 1$ hedged using financial derivatives in each year for each airline; Cash = the ratio of cash and marketable securities to total assets at year end for each airline; Financial leverage = total liabilities divided by total assets at year end. Years with negative stockholders' equity are excluded. Data sources are the airlines' 10-K statements, published financial statements, Bureau of Transport Statistics, and Compustat data for 1990–2000. Sample airlines are America West—AWA, American Airlines—AMR, Continental Airlines—CAL, Delta Airlines—DAL, Northwest Airlines—NWA, Southwest Airlines—LUV, Skywest Airlines—SKYW, United Airlines—UAL, and US Airways—U.

* Significant at $\alpha = 5\%$.

hedging. This stream of research derives from options theory and operational hedging is interpreted as a real (compound) option that is exercised in response to realized market conditions. For instance, Cohen and Huchzermieir (1999) model an option to switch production and sourcing strategies, contingent on realized demand and holding excess capacity, as a means to respond to changes in market conditions. However, the real options approach is rarely useful for an empirical estimation of firms' total capabilities to hedge against severe disruptions. As an alternative to the real options approach, this section introduces a new method to evaluate the total capabilities of firms to hedge against adverse circumstances.

We follow Stulz (1996) and compare firms' probability of costly *lower-tail outcomes*. We formalize this concept and then compute a hedging score for the sample airlines. Concentrating on a distribution of firms' performance levels, the lower-tail of a performance distribution for each firm indicates its capabilities to reduce the probability of poor performance levels. We view lower-tail outcomes as performance levels with respect to unfavorable contingencies, taking into account that some situations may be good for one firm and bad for another.

An examination of performance distributions allows a direct comparison of lower-tail performance probabilities between firms. We employ operating cash flow as our primary performance criteria, because managers are expected to take hedging actions to reduce or even eliminate the occurrence of a cash shortage for funding firms' activities. In other words, hedging alleviates the likelihood of financial distress. Consequently, we focus on firms' distribution of cash flows. However, the suggested method is presented for a general performance criterion.

We follow Weeks' (1985) early suggestion to apply stochastic-dominance in operations management studies, since the idea of *lower-tail outcomes* is strongly related to it (see Levy (1992) for a review of stochastic-dominance). Formalizing Stulz's idea, initial (partial) information concerning potential world states in an uncertain future environment is modeled by a probability on a finite set Ω, say X, that is defined by a real function X: $\Omega \rightarrow \Re$, with $X(s) \geq 0$ for all states $s \in \Omega$, and $\sum X(s) = 1$. For firm j, $W_j(X)$ denotes a random variable that takes performance values $W_j(s)$ with probabilities $X(s)$. Function W represents a performance criterion, which we choose to be cash flow from operations. We compare firms' performance levels on the basis of their respective probabilities of exceeding certain performance levels in a way that is analogous to the stochastic-dominance concept. Recalling the definition of first-order stochastic-dominance (**FSD**) for two random variables W_1 and W_2:

$$W_1 \ \boldsymbol{FSD} \ W_2 \quad \text{if} \quad P[W_1 \leq \alpha] \leq P[W_2 \leq \alpha] \quad \text{for all} \ \ \alpha \in \Re \tag{1}$$

For all performance levels α, the first-order stochastic-dominance relation expresses lower probability to perform no higher than α. First-order stochastic-dominance is too restrictive to be used in comparing firms' hedging against *lower-tail outcomes*, as it requires stochastic-dominance for *all* performance levels. The first-order stochastic-dominance relation does not admit the possibility of capabilities to better performance in particular circumstances only, such as adverse situations.

Focusing on firms' attempts to reduce the probability of downside performance levels, we need to set the lower-tail performance range by determining the upper boundary of this range. This is a subjective task. The upper boundary of a range of lower-tail performance levels can either be derived from an industry standard or be set as a performance objective by top management. We denote the upper boundary of the lower-tail performance range as $\beta \in \Re$. Our approach is in line with Gan et al. (2005), who measure downside risk by a probability that return is below a target level.

We introduce a less restrictive relation, *lower-tail stochastic-dominance* ($\mathbf{LSD}_\beta$). This focuses directly on lower-tail performance realizations ($W_j \leq \beta$):

$$W_1 \ \boldsymbol{LSD}_\beta \ W_2 \quad \text{if} \ \ P[W_1 \leq \alpha] \leq P[W_2 \leq \alpha] \quad \text{for all} \ \ \alpha \leq \beta \tag{2}$$

Fig. 1 illustrates an example of *lower-tail stochastic-dominance*.

The $\mathbf{LSD}_\beta$ relation is a comparison of performance distributions of two firms. It expresses a reduced probability for lower-tail outcomes. $\mathbf{LSD}_\beta$ extends the **FSD** relation because, if W_1 **FSD** W_2, then, for any given performance level β, W_1 $\mathbf{LSD}_\beta$ W_2 holds.

The introduced *lower-tail stochastic-dominance* reflects Stulz's idea in a natural and direct way by comparing probabilities of performing *lower-tail outcomes.* The underlying assumption is that the $\mathbf{LSD}_\beta$ comparison captures the consequences of long-term operational hedging activities, as well as financial hedging actions taken in order to ensure reasonable performance in adverse situations. Furthermore, if the performance distribution of firm 1 $\mathbf{LSD}_\beta$ dominates the performance distribution of firm 2, then the worst-case performance of firm 1 will not fall short of that of firm 2. In that sense, the $\mathbf{LSD}_\beta$ comparison captures hedging against extremely unfavorable events.

We now apply *lower-tail stochastic-dominance* to compare airlines' hedging based on financial performance measures. The terrorist attacks on September 11, 2001, in

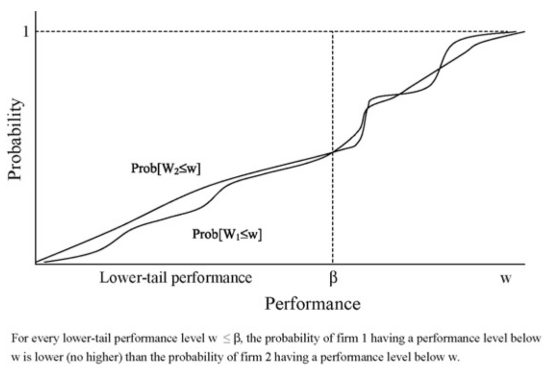

Fig. 1. Lower-tail stochastic-dominance, W_1 LSD_β W_2. For every lower-tail performance level $w \leq \beta$, the probability of firm 1 having a performance level below w is lower (no higher) than the probability of firm 2 having a performance level below w.

which terrorists used four airplanes as weapons, provide the circumstances that allow us to empirically examine the role of hedging against severe adverse financial circumstances. In this analysis, we focus on nine U.S. airline carriers for which Compustat data and 10-K statements were available in respect of the entire period from 1990–2000 (a total of 44 quarterly observations for each firm). These nine carriers, and their ticker symbols, are: America West—AWA; American Airlines—AMR; Continental Airlines—CAL; Delta Airlines—DAL; Northwest Airlines—NWA; Southwest Airlines—LUV; Skywest Airlines—SKYW; United Airlines—UAL; and US Airways—U.

The $\mathbf{LSD}_\beta$ comparison is based on ex-post observations of the financial results and we infer the hedging comparison from the low-tails of two estimated performance distributions. Specifically, we compare the hedging level of airlines based on their cash flow from operations (CFO) in relation to their total assets, which is used as a size normalization parameter. CFO represents a key operating performance criterion of airline carriers and expresses a consistent performance measure that incorporates benefits generated by hedging activities.

A lower-tail performance level is assumed to be below the mean quarterly CFO calculated for the nine airlines, where the mean CFO is $\beta = 1.8\%$ per quarter. Taking the mean CFO as a reference for setting the lower-tail range is a conservative choice. To see why, suppose one performance distribution $\mathbf{LSD}_\beta$ dominates a second performance distribution, given β. Then the first performance distribution also $\mathbf{LSD}_\lambda$ dominates the second performance distribution, given any *lower* performance threshold, $\lambda \le \beta$. Fig. 1 illustrates that, if W_1 $\mathbf{LSD}_\beta$ W_2, then the distribution of W_1 lies below the distribution of W_2 for every performance level lower than β. Consequently, for a finite number of observations, $\lambda \le \beta$, W_1 $\mathbf{LSD}_\beta$ W_2 implies W_1 $\mathbf{LSD}_\lambda$ W_2.

To illustrate $\mathbf{LSD}_\beta$, we demonstrate a hedging comparison between two airlines—Delta Airlines (DAL) and American Airlines (AMR). Setting $\beta = 1.8\%$, Fig. 2 depicts that American Airlines has lower-tail outcomes in fewer quarters than Delta Airlines: Delta Airlines' performance is lower than 1.8% in 31 quarters and American Airlines' performance is lower than 1.8% in 29 quarters.

Assuming an equal weight for each of the 44 quarters from Q1-1990 through Q4-2000, the cumulative distribution of quarterly CFO for airline j is defined by

$$F_j(w) = \frac{1}{n}\sum_{k=1}^{n} 1(w_k \le w) \tag{3}$$

where $1\ (w_k \le w)$ is an indicator that equals 1, if the condition in $(w_k \le w)$ is true, and zero otherwise. Fig. 3 indicates cumulative distributions of quarterly CFO for American Airlines (AMR) and Delta Airlines (DAL). From the estimated distributions, it can observed that American Airlines is more likely to perform better (less badly) than Delta Airlines given adverse circumstances based on the estimated distributions. American Airlines is less likely to have lower-tail outcomes than Delta Airlines. It should be noted that the comparison holds for lower values of β as well (as we mentioned $\lambda < \beta$), meaning that it holds relative to all ranges of lower-tail performance levels with upper bounds below β.

For each pair of airlines j and i, we hypothesize that airline j is more hedged than airline i, if j *lower-tail stochastically dominates* i. The statistical testing of $\mathbf{LSD}_\beta$ relies on a first-order stochastic-dominance test suggested by McFadden (1989). The hypothesis is

$$\mathrm{H_0}: \text{airline}_j\ \boldsymbol{LSD_\beta}\ \text{Airline}_i, \quad \mathrm{H_1}: \text{NOT}[\text{airline}_j\ \boldsymbol{LSD_\beta}\ \text{airline}_i], \quad \text{where } \beta = 1.8\%.$$

McFadden (1989) suggests using the Smirnov statistic for statistically testing first-order stochastic-dominance. His test is based on the greatest vertical distance between two distribution functions. We employ McFadden's test,

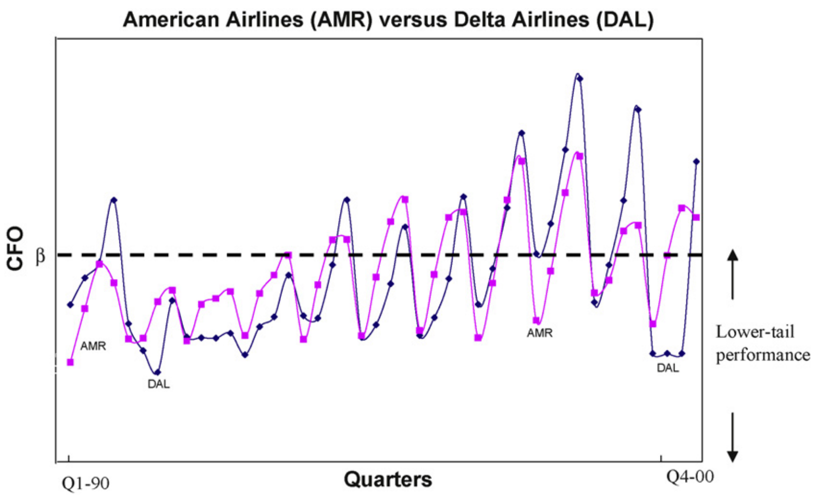

Fig. 2. Quarterly cash flow from operations (CFO) of American Airlines (AMR) and Delta Airlines (DAL) from Q1-1990 through Q4-2000. CFO is defined as cash flow from operations divided by total assets at quarter end. The perforated line marks the industry-average, quarterly CFO for the period Q1-1990 through Q4-2000, calculated for nine airlines (America West—AWA; American Airlines—AMR; Continental Airlines—CAL; Delta Airlines—DAL; Northwest Airlines—NWA; Southwest Airlines—LUV; Skywest Airlines—SKYW; United Airlines—UAL; and US Airways—U). The plot illustrates that Delta Airlines has lower-tail performance in 31 quarters and American Airlines has lower-tail performance in 29 quarters.

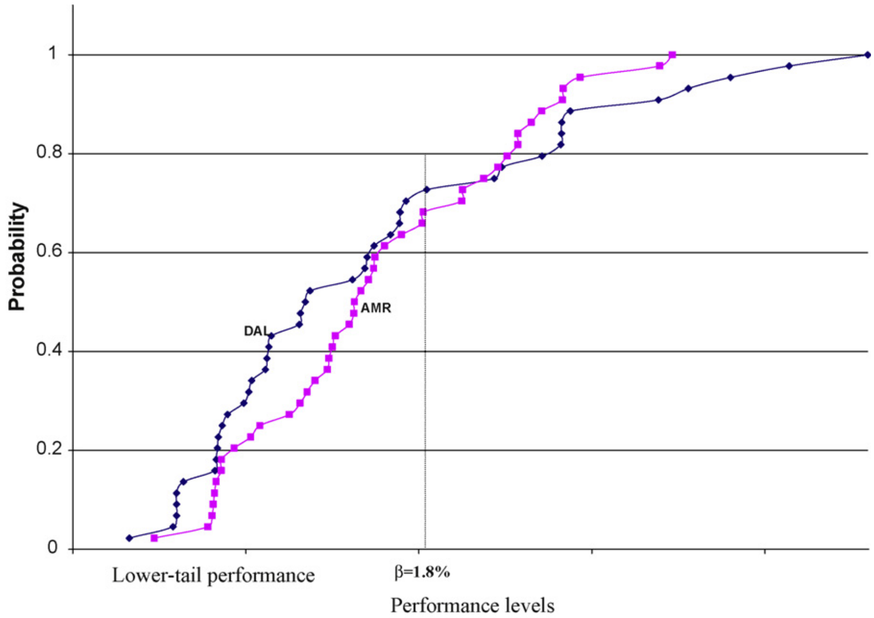

Fig. 3. Lower-tail stochastic-dominance comparison—cumulative distributions of quarterly CFO for American Airlines (AMR) vs. Delta Airlines (DAL). Cumulative distributions of quarterly CFO of American Airlines (AMR) and Delta Airlines (DAL), giving equal weight to each of the 44 quarters from Q1-1990 through Q4-2000. Quarterly CFO is defined as cash flow from operations divided by total assets at quarter end. The perforated line marks the industry-average, quarterly CFO for the period Q1-1990 through Q4-2000, calculated for nine airlines (America West—AWA; American Airlines—AMR; Continental Airlines—CAL; Delta Airlines—DAL; Northwest Airlines—NWA; Southwest Airlines—LUV; Skywest Airlines—SKYW; United Airlines—UAL; and US Airways—U).

but only on the left-hand side of β. For demonstration purposes, Table 2 presents representative results of comparing $\mathbf{LSD}_\beta$ between American Airlines (AMR) and eight other airlines. We perform McFadden's test between eight pairs of distributions of quarterly CFO. Following our earlier example comparing American Airlines (AMR) and Delta Airlines (DAL), we note that the fifth row in Table 2 indicates that AMR $\mathbf{LSD}_\beta$ DAL, and H_0 is not rejected at $p < 0.05$.

The next step is to generate a hedging rank, based on the pair comparisons and using Kendall's (1945) scoring method. Although pair-comparisons may imply a partial order on the set of airlines, Kendall's (1945) scoring method implies a complete order on the set of airlines, ensuring the generality of the suggested ranking method. For each pair of airlines, if H_0 is not rejected at the 5% significance level, meaning that W_1 $\mathbf{LSD}_\beta$ W_2, then the airline that is more hedged scores 2 and the less hedged airline scores 0. If H_0 is rejected at the 5% significance level, meaning that neither airline $\mathbf{LSD}_\beta$ dominates the other at the 5% significance level, then each of the airlines scores 1. Table 3 shows the results of these tests. To interpret Table 3, compare AMR (American Airlines) and DAL (Delta Airlines): AMR $\mathbf{LSD}_\beta$ DAL, and H_0 is not rejected at the 5% significance level, so AMR gets a 2 in the AMR column and the DAL row, while DAL gets a 0 in the DAL column and the AMR row. Consequently, the bottom row in Table 3 is a complete ranking of airlines expressing their hedging,

Table 2
Results of lower-tail stochastic-dominance ($\mathbf{LSD}_{\beta=1.8\%}$) comparisons of American Airlines (AMR) and eight other airlines. This table reports the results of statistically testing for lower-tail stochastic-dominance ($\mathbf{LSD}_{\beta=1.8\%}$) between eight pairs of quarterly CFO[a] distributions, based on data from Q1-1990 through Q4-2000. H_0: airline j $\mathbf{LSD}_\beta$ airline i, where β = 1.8%; H_1: NOT [airline j $\mathbf{LSD}_\beta$ airline i], where $i, j \in$ {AMR, AWA, CAL, DAL, LUV, NWA, SKYW, UAL, U}. H_0 states that the quarterly CFO of American Airlines is more likely to be higher than the quarterly CFO of airline i, given adverse circumstances, such that quarterly CFO levels are equal to or below 1.8%. Following McFadden (1989), we use the Smirnov statistic to statistically test H_0. D is the value of the one-sided Smirnov statistic, defined as the greatest vertical distance between the two left-tails of the estimated distribution functions, such that β = 1.8%. S is the 95% quantile of the Smirnov test statistic for two samples of different size, based on Conover (1999), Table A20, p. 557. We reject H_0 at a 5% significance level, if D is smaller than S. For example, in the fifth row, we do not reject the hypothesis that American Airlines (AMR) lower-tail stochastically dominates Delta Airlines (DAL), because $D = 0.330 > S = 0.315$, meaning that the distance between the two distributions is sufficiently large.

	Compared airlines		D		S	Result
1.	AMR	LUV	0.044	<	0.363	Reject $H_0 \rightarrow$ NOT [AMR $\mathbf{LSD}_{\beta=1.8\%}$ LUV]
2.	AMR	SKYW	0.067	<	0.430	Reject $H_0 \rightarrow$ NOT [AMR $\mathbf{LSD}_{\beta=1.8\%}$ SKYW]
3.	AMR	UAL	0.100	<	0.347	Reject $H_0 \rightarrow$ NOT [AMR $\mathbf{LSD}_{\beta=1.8\%}$ UAL]
4.	AMR	NWA	0.083	<	0.378	Reject $H_0 \rightarrow$ NOT [AMR $\mathbf{LSD}_{\beta=1.8\%}$ NWA]
5.	AMR	DAL	0.330	>	0.315	H_0: AMR $\mathbf{LSD}_{\beta=1.8\%}$ DAL is not rejected
6.	AMR	CAL	0.033	<	0.315	Reject $H_0 \rightarrow$ NOT [AMR $\mathbf{LSD}_{\beta=1.8\%}$ CAL]
7.	AMR	AWA	0.133	<	0.358	Reject $H_0 \rightarrow$ NOT [AMR $\mathbf{LSD}_{\beta=1.8\%}$ AWA]
8.	AMR	U	0.371	>	0.310	H_0: AMR $\mathbf{LSD}_{\beta=1.8\%}$ U is not rejected

[a] CFO = cash flow from operations divided by total sales.

Table 3

Ranking operational hedging of airlines. Scores of operational hedging of nine airlines is calculated based on 72 $\mathbf{LSD}_{\beta=1.8\%}$ pair-comparisons of airlines. For each pair of airlines, the tested hypothesis is: H_0: airline$_j$ $\mathbf{LSD}_\beta$ airline$_i$ – $F_i^C(w) \geq F_j^C(w)$ for $w \leq \beta = 1.8\%$, H_1: NOT [airline$_j$ $\mathbf{LSD}_\beta$ airline$_i$] – $F_i^C(w) < F_j^C(w)$ for some $w \leq \beta = 1.8\%$, where $F^C(w) = F(w)|w \leq \beta = 1.8\%$, and $i, j \in$ {AWA, AMR, CAL, DAL, LUV, NWA, SKYW, UAL, U}. H_0 states that the quarterly CFO of airline *i* is lower than the quarterly CFO of airline *j*, such that lower-tails of quarterly CFO levels are equal to or below 1.8%. Following McFadden (1989), we use the Smirnov statistic to statistically test H_0. *D* is the value of the one-sided Smirnov statistic, defined as the greatest vertical distance between the two left-tails. *S* is the 95% quantile of the Smirnov test statistic for two samples of different size, based on Conover (1999), Table A20, p. 557. The scores in the table follow Kendall's (1945) scoring method. Each airline in the pair scores "1", if H_0 is rejected. If H_0 is not rejected, then airline *j* scores "2" and airline *i* scores "0". Results of Table 1 demonstrate the statistical tests for the AMR column in the following table. For example, from Table 2 we learn that AMR $\mathbf{LSD}_\beta$ DAL and H_0 is not rejected at the 5% level. Hence, DAL gets a "0" in the DAL column and the AMR row, while AMR gets a "2" in the AMR column and the DAL row. The HedgeScore of an airline is the sum of its column, thereby defining its rank in the set of nine airlines.

j *i*	LUV[a]	SKYW	UAL	AMR	NWA	DAL	CAL	AWA	U
LUV	1	1	1	1	0	0	0	0	0
SKYW	1	1	1	1	1	0	0	0	0
UAL	1	1	1	1	1	1	0	0	0
AMR	1	1	1	1	1	0	1	1	0
NWA	2	1	1	1	1	1	1	1	0
DAL	2	2	1	2	1	1	1	0	1
CAL	2	2	2	1	1	1	1	1	1
AWA	2	2	2	1	1	2	1	1	1
U	2	2	2	2	2	1	1	1	1
HedgeScore	14	13	12	11	9	7	6	5	4

[a] America West—AWA; American Airlines—AMR; Continental Airlines—CAL; Delta Airlines—DAL; Northwest Airlines—NWA; Southwest Airlines—LUV; Skywest Airlines—SKYW; United Airlines—UAL; and US Airways—U.

termed HedgeScore. The hedging rank indicates that Southwest Airlines and Skywest Airlines were the most hedged, while America West and US Airways were the least hedged.

The suggested hedging ranking has appealing properties. First, the proposed **LSD** pair-wise comparison is not a complete order. In other words, hedging of two airlines may not be ranked when the capability to better perform under adverse events afforded by neither airline is superior to that afforded by the other. In other words, the low-end tails of their respective performance distributions intersect each other. The fact that the comparison does not completely rank all conceivable airlines is inherent in the multidimensional nature of hedging, not a limitation of the yardstick used for the comparison.

Second, the advantage of hedging need not, and typically will not, express itself in *all* possible contingencies and improved hedging is not likely to involve higher mean financial performance. The new approach makes a clear distinction between hedging and superior performance advantage. Focusing on hedging against adverse circumstances, the **LSD** comparison does not depend on, nor does it imply, a higher mean CFO of the more hedged airline. The correlation between mean CFO for each of the nine airlines and HedgeScore, 0.357, is statistically insignificant (p-value = 0.266). For example, the mean CFO generated by America West, 0.090, is higher than mean CFO generated by seven of the eight other airlines although its hedging rank is second lowest. Therefore, we conclude that the **LSD** comparisons capture capabilities to hedge against low-end performance levels, not increased mean performance levels. There is another noteworthy insight here. A pair-wise first-order stochastic-dominance comparison indicates that no airline significantly **FSD** another airline (at 5% level). While **FSD** requires stochastic-dominance on *all* performance levels, which is highly restrictive, the **LSD** comparison focuses only on low-tail performance levels. Therefore, the **LSD** comparison is much less restrictive than **FSD**.

Third, **LSD** comparison is designed to capture hedging against low-end performance levels, not to be a risk measure in the conventional sense. Accordingly, it neither does imply, nor is it implied by, lower variance. The correlation between variance of CFO for each of the nine airlines and HedgeScore, 0.246, is statistically insignificant (p-value = 0.524). In a similar vein, the correlation between the coefficient of variation for each of the nine airlines and HedgeScore, −0.127, is also statistically insignificant (p-value = 0.744).

Fourth, it is noted that the suggested approach provides means to employ various performance functions for a **LSD** comparison. We check the sensitivity of the hedging rank to the choice in CFO as our primary performance criterion. As an alternative, we employ a different performance criterion: net income divided by total assets, instead of CFO. Running the pair-comparison analysis results in a hedging rank that is identical to the hedging rank presented in Table 3 (although the numerical scores show slight changes that do not affect the rank).

Fifth, we check the sensitivity of the hedging rank to the choice in β by setting the boundary of the lower-tail performance level $\beta = 0.5\%$, instead of $\beta = 1.8\%$. This boundary is one standard deviation below the mean value of the quarterly CFO, as calculated for all nine airlines from Q1-1990 through Q4-2000. We consider two hedging ranks as similar, if there exist no more than a single pair of airlines, such that one airline has a higher rank than the other on the first hedging score and a lower rank than the other on the second hedging score. Running the pair-comparison analysis results in a hedging rank (untabulated) that is similar to the hedging rank presented in Table 3.

Sixth, we note that a pair-wise **LSD** comparison is not affected by other airlines. This is a meaningful property of the comparison because the airline industry offers only nine carriers with available data for the analysis. Consequently, the relative hedging rank between the nine airlines is not influenced by a potential addition of more airlines to the analysis.

Seventh, we check sensitivity of rank to the length of the sample period by computing HedgeScore using data from 36 quarters (1992–2000), not 44 quarters. The results indicate a similar rank (as defined above).

Overall, the proposed hedging rank captures the likelihood of low-tail performance levels under unfavorable circumstances, which is the essence of hedging against poor performance levels. The subsequent section examines whether better hedging capabilities were useful to protect airlines against adverse circumstances. Then, we explore operational sources of hedging.

4. The predictive power of HedgeScore

Testing capability to hedge against adverse circumstances is a tough task because adverse circumstances are hard to define. In this section, we test the predictive power of HedgeScore (computed based on the 1990–2000 data) on performance reflecting the direct consequences of the September 11, 2001 events. We assume a wide agreement that the September 11, 2001 terrorist attacks represent an adverse situation for the airline industry (and for others as well). First, we examine the correlation between airlines' hedging scores and their cash flow from operations. Second, we examine whether investors recognize firms' hedging by estimating the correlation between airlines' hedging scores and their stock returns after the attacks. The results demonstrate airlines' hedging capabilities captured by the proposed HedgeScore through an out-of-sample prediction.

The first two lines of Table 4 report positive Pearson (Kendall tau) correlations of 0.720 (0.751) and 0.699 (0.742) between HedgeScore and CFO in the fourth quarter of 2001 and in the year 2002, respectively. Both correlations are statistically significant ($\alpha = 5\%$). The results indicate that more highly hedged airlines are associated with a performance advantage after the attacks. Excluding American Airlines and United Airlines from the analysis, because they directly suffered the terrorist attacks and might thus perform more poorly than other airlines, leads to stronger positive Pearson correlations: 0.930 and 0.931 between HedgeScore and CFO for the fourth quarter of 2001 and for the whole of 2002, respectively (not reported in the table). Again, both correlations are statistically significant at $\alpha = 5\%$.

To gain insights into the market assessment of capabilities of airlines to hedge against the September 11 attacks, we also examine the stock returns of airlines. Table 4 presents correlations between stock returns on the first trading day, September 17, 2001, for the period September 17–28, and for the period from September 17 through December 31, 2001, and hedging scores. The Pearson (Kendall tau) correlations are positive and significant, 0.822 (0.808), 0.816 (0.798), and 0.805 (0.755), respectively, $\alpha = 5\%$. Again, excluding American Airlines and United Airlines from the sample results in even higher Pearson correlations of 0.854, 0.828, and 0.915, respectively (not reported in the table).

Further, the correlations between HedgeScore and either CFO or stock returns is much smaller and generally insignificant on subsequent years, 2003 till 2006. These findings indicate that HedgeScore reflects hedging against poor performance under adverse events, but does not predict performance levels on subsequent years. Overall, the results support evidence that hedging, as ranked by *lower-tail stochastic-dominance*, is a useful tool for capturing hedging activities against adverse circumstances in the airline industry. The evidence concerning the cash-flow hedging effect and the market response for out-of-sample data indicates the relevancy of HedgeScore as a measure of airlines' programs for hedging against adverse events.

Table 4
Correlations between HedgeScore and performance variables. The table presents correlations between HedgeScore and two performance variables: cash flow from operations divided by total assets (CFO) and stock returns. The correlations are calculated based on nine observations (America West—AWA; American Airlines—AMR; Continental Airlines—CAL; Delta Airlines—DAL; Northwest Airlines—NWA; Southwest Airlines—LUV; Skywest Airlines—SKYW; United Airlines—UAL; and US Airways—U).[a].

Performance variable	Pearson correlation with HedgeScore[b]	Kendall tau correlation with HedgeScore[b]
Cash flow from operations (CFO)[c]		
Q4-2001	0.720*	0.751*
2002	0.699*	0.742*
2003	0.344	0.444
2004	0.355	0.442
2005	0.327	0.342
2006	0.356	0.285
Stock returns[c]		
September 17, 2001	0.822*	0.808*
September 17–28, 2001	0.816*	0.798*
September 17–December 31, 2001	0.805*	0.755*
2002	0.333	0.283
2003	−0.391	−0.277
2004	0.352	0.422
2005	−0.381	−0.331
2006	−0.142	−0.223

[a] The trade of United Airlines shares terminated from 2003 till 2006 and of America West was acquired by US Airways on 2005.
[b] The airlines' HedgeScore is presented in Table 3.
[c] *Data sources*: Compustat and The Center for Research in Security Prices (CRSP).
* Significant at $\alpha = 5\%$.

5. Operational hedging in airlines

In this section, we examine the relationship between hedging vehicles described in Section 2 and HedgeScore. Table 5 presents the correlations between the potential operating and financial hedging vehicles and HedgeScore. We find significant Pearson and Kendall tau correlations between the hedging variables and HedgeScore ($\alpha = 5\%$), supporting a hedging effect of each of these vehicles. Yet, the relatively low correlations documented among some of the seven hedging vehicles (reported in panel B of Table 1) indicate potential differences in the usage of each vehicle as a part of a hedging program. Exploring the relationship

Table 5
Correlations between HedgeScore and hedging variables.

Variable	Pearson correlation with HedgeScore[a]	Kendall tau correlation with HedgeScore[a]
Operational hedging		
Fleet diversification	−0.564*	−0.402*
Load factor	0.215*	0.114
Lease	−0.412*	−0.244*
Domestic	−0.268*	−0.314*
Financial hedging		
Fuel hedging	0.328*	0.211*
Cash	0.268*	0.180*
Financial leverage	−0.289*	−0.356*

[a] The airlines' HedgeScore is presented in Table 3. Hedging variables are defined in Table 1. Data source is the airlines' 10-K statements and Compustat data for 1990–2000.
* Significant at $\alpha = 5\%$.

between HedgeScore and those vehicles, we estimate the following regression model:

$$\begin{aligned}\text{HedgeScore}_j = {} & \alpha_0 + \alpha_1\text{Fleet diversification}_{tj} \\ & + \alpha_2\text{Load factor}_{tj} + \alpha_3\text{Lease}_{tj} \\ & + \alpha_4\text{Domestic}_{tj} + \alpha_5\text{Fuel hedging}_{tj} \\ & + \alpha_6\ \text{Cash}_{tj} \\ & + \alpha_7\ \text{Financial leverage}_{tj} + \alpha_8\ \text{Size}_{tj} \\ & + \alpha_9\ \text{ROA}_{t-1,j} + \alpha_{10}\text{Chapter11}_{tj} + e_{tj} \qquad (4)\end{aligned}$$

We employ three control variables. First, the finance literature tells us that larger firms are less likely to suffer low-end performance levels than small firms (e.g., Fama and French, 1992). Therefore, we add SIZE measured by the natural logarithms of annual sales. Second, we control for a potential performance effect by using a performance measure on the preceding year; i.e., net income divided by total assets. Finally, we also control for airlines that operate under Chapter11.

Three issues must be addressed in estimating model (4) using panel data. First, we add time-dummy variables to control for year-specific effects (Greene, 2008). Second, we check for potential heteroscedasticity in estimating a regression model with the hedging rank as a dependent variable. Heteroscedasticity, if exists, causes OLS to tend to underestimate the variance and standard errors of the coefficients. Accordingly, we test for heteroscedasticity by running White's test (1980). Findings indicate that we cannot reject the null hypothesis of homoscedasticity (p-value = 0.05). Thus, it is unlikely that we have heteroscedasticity.

Third, the measurement of HedgeScore is based on a pair-wise comparisons resulting in repeated use of data. To incorporate a potential effect of repeatedly using data on the standard errors of the estimated coefficients, we use the Newey and West (1987) procedure to adjust the standard errors. We correct for serial dependence by estimating autocorrelations up to five lags. The choice of five lags is logical because we find that autocorrelations beyond the fifth lag are fairly small. In addition, since we have only 11 annual observations per airline, adjustment for dependence beyond five lags is not warranted (see Andrews, 1991; Newey and West, 1994). Nonetheless, the tenor of the results is unchanged using standard errors corrected for either three or four lags.

Coefficient estimates of the regression model (4) are presented in Table 6. Consistent with prior literature, results indicate that fleet diversification is negatively and significantly correlated with the hedging rank (coefficient = −0.740, t-statistic = −5.001), meaning that a lower number of aircraft types, i.e., a more standardized fleet, is associated with an increased hedge. Based on the literature discussed earlier, a more standardized fleet offers increased flexibility to respond to adverse events. Load factor is positively and significantly correlated with the hedging rank (coefficient = 9.216, t-statistic = 2.002).

Table 6
Estimated coefficients from regressing HedgeScore on hedging and control variables (Eq. (4)).

Variable	Coefficient estimate		
	All hedging vehicles	Operational hedging vehicles only	Financial hedging vehicles only
Intercept	2.205 (0.240)[a]	−0.317 (−0.030)[a]	6.066 (2.108)[a]
Operational hedging			
Fleet diversification	−0.740 (−5.001)	−0.882 (−5.993)	
Load factor	9.216 (2.002)	13.631 (1.978)	
Lease	−3.002 (−2.378)	−2.116 (−2.121)	
Domestic	−4.045 (−4.041)	−3.677 (−3.990)	
Financial hedging			
Fuel hedging	1.502 (0.737)		5.930 (2.744)
Cash	5.749 (3.339)		7.343 (3.586)
Financial leverage	−0.961 (−1.270)		−1.674 (−1.998)
Control variables			
Size	0.962 (3.165)	1.054 (3.407)	0.575 (2.003)
ROA (on prior year)	1.358 (0.130)	3.068 (1.111)	2.854 (0.815)
Chapter11	2.223 (1.406)	1.009 (0.779)	3.403 (1.550)
Adjusted R^2	75.5%	68.8%	25.3%
N	99	99	99

The airlines' HedgeScore is presented in Table 3. Hedging variables are defined in Table 1. *Control variables definition*: Size = natural logarithms of annual sales; ROA = net income divided by total assets on prior year; Chapter11 = 1 if the airline operates under Chapter 11 and 0 otherwise.
[a] t-Statistics appear in parentheses.

This evidence indicates that higher fleet utilization (i.e., smaller capacity cushion) is associated with a higher hedging rank. While a capacity cushion is likely to help in taking advantage of prosperous market conditions, excess capacity is not useful under adverse demand conditions. In other words, high utilization of the fleet (that results in a small capacity cushion) is shown beneficial in protecting the firm from a decline in demand. A policy of leasing aircraft is negatively and significantly correlated with the hedging rank (coefficient = −3.002, *t*-statistic = −2.378), indicating that fleet ownership contributes to a better (less bad) response to adverse circumstances. If ownership of aircraft does not requires out-of-pocket payment, in contrast with leasing fees, then ownership offers an advantage under substantially unfavorable circumstances characterized by cash flow shortage. International operations are found to increase hedging capabilities as the Domestic coefficient is negative and significant (coefficient = −4.045, *t*-statistic = −4.041). Cash on hand is also shown to be positively and significantly correlated with the hedging rank (coefficient = 5.749, *t*-statistic = 3.339), indicating that cash holdings provide means to cope with unfavorable situations.

In contrast, Fuel Hedging does not exhibit a significant association with HedgeScore. While hedging against changes in fuel prices is likely to be beneficial in hedging against normal volatility in commodity markets, it does not contribute in hedging against a severe decline in demand. Again, this result emphasizes the distinction between hedging against uncertainty, for which protecting the firm against changes in fuel prices is expected to be important, and hedging against a fall in demand for flights. Similarly, financial leverage is insignificantly associated with HedgeScore, indicating that it plays a weak role under adverse circumstances.

Results from estimating the control variables coefficients reveal that large firms are better protected against adverse circumstances, in line with prior literature. Findings also indicate that the coefficient estimates for ROA and Chapter11 are insignificant.

We run two sensitivity checks to confirm the results. First, we note that the performance level of Southwest airlines exceeded other airlines on most of the quarters during our sample period. Results from estimating model (4) are substantially the same when Southwest airlines observations are removed from our sample (untabulated). Second, we estimate the model using negative binomial probability for the response variable since HedgeScore may be viewed as counts. The negative binomial dispersion parameter was estimated by maximum likelihood. Again, the results from estimating model (4) are substantially the same.

Apparently, the extant hedging literature, particularly in the finance discipline, tends to focus on financial hedging vehicles. We split the analysis between operational and financial hedging vehicles to gain insights on their relative ability to hedge against adverse circumstances. While the explanation power of the full model is 75.5%, results reported in Table 6 show that operational hedging vehicles explain 68.8% of the hedging rank on their own, omitting financial hedging vehicles. Conversely, the financial hedging vehicles explain only 25.3% of the hedging rank. Interestingly, Fuel hedging and Financial leverage are significantly associated with HedgeScore when operational hedging vehicles are omitted, but this significance is washed away in the presence of operational hedging vehicles. While numerous studies report the importance of financial hedging against market risks and volatility in commodity prices, the findings emphasize the important role of operational hedging against adverse circumstances.

Overall, we find that airlines employ their operations as part of their hedging against low-end performance levels. Fleet standardization, fleet utilization, fleet ownership and globalization are operations policies which contribute to enhancing airlines' hedging capabilities. We conclude that airlines use operational hedging as an inherent component of their risk management programs.

6. Summary

This paper extends the operations management literature by showing that operations policies are a critical part of hedging against adverse circumstances. We formalize Stulz's (1996) approach and rank the hedging level of airlines on the basis of their low-tail financial performance from 1990 through 2000, showing that highly ranked airlines had a better (less bad) response to the terrorist attacks on September 11, 2001. The evidence shows that operations policy complements financial instruments in hedging against severe disruptions. Particularly, fleet standardization, fleet utilization, fleet ownership (rather than leasing), and globalization enhance operational hedging. The findings provide guidance to firms as to how to use their operations in their risk-management programs.

The contribution of an industry study crucially depends on the ability to gain more general insights from the analysis. In that sense, the implications of this study go beyond supplying evidence concerning operational hedging in the airline industry. This study offers a general lower-tail stochastic-dominance method to rank hedging capabilities among firms. This method can be broadly applied to industries characterized by different types of hedging vehicles and various types of adverse circumstances. Further, the suggested lower-tail stochastic-dominance method does not depend on the choice of a performance criterion. Future research can apply the **LSD** concept to extend our knowledge concerning firms' operational hedging.

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