Dynamic Optimality of Airline Fuel Cost Hedging

Xiaolu Hu* | Malick Sy† | Liuren Wu‡

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*School of Economics, Finance and Marketing, College of Business, RMIT University, Melbourne, Victoria 3000, Australia. E-mail: xiaolu.hu@rmit.edu.au.

†School of Economics, Finance and Marketing, College of Business, RMIT University, Melbourne, Victoria 3000, Australia. E-mail: malick.sy@rmit.edu.au.

‡Zicklin School of Business, Baruch College, The City University of New York, One Bernard Baruch Way, New York, NY 10010, USA. E-mail: liuren.wu@baruch.cuny.edu.

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Abstract

Hedging creates value only when the policy is near optimal but can be harmful otherwise. This paper takes the US airline industry as an example and derives the optimal fuel cost hedging ratio as a function of firm-specific revenue and cost sensitivities, as well as the relative composition of demand and supply shocks in the oil price movement. We construct a market hedging demand index based on rolling-window regression of crude futures returns on equity index returns and use the index to capture the time-variation in the fuel cost hedging demand for a typical airline. By regressing the logarithm of Tobin's Q against the hedging ratio under different market conditions, we show that fuel cost hedging increases firm value only when the market hedging demand is high. More important, we use the time-series correlation between an airline's hedging ratio and the market hedging demand to measure the dynamic optimality of the airline's fuel hedging practice. Out of the 33 US airlines in our sample over a 25-year period, one third do not hedge at all, while the hedging ratios for more than another one third move in the opposite direction of the market hedging demand. Only less than one third of airlines show positive dynamic optimality for their hedging practice. The cross-sectional diversity of the optimality estimates highlights the inherent difficulty of implementing an optimal policy. Still, we find strong value in staying dynamically optimal in an airline's fuel cost hedging practice: The dynamic optimality of each airline's hedging practice strongly and positively predicts its valuation as measured by the logarithm of its Tobin's Q. The value increase comes from both reduced variation in its return on asset and increased average return. Airlines with negative hedging dynamic optimality not only are ineffective in reducing their return on asset variation, but also incur extra costs from setting up and maintaining a costly hedging program and from entering and exiting hedging positions. Such extra costs lower the airlines' average return and hurt their valuation. As a result, their average Tobin's Q is even lower than the average for airlines that do not hedge at all.

JEL Classification: C13, G32, L93, Q41, Q47

Keywords: hedging dynamic optimality; crude futures; supply shocks; demand shocks; airline industry; optimal fuel cost hedging

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We are what we repeatedly do. Excellence, then, is not an act but a habit. — Aristotle

1. Introduction

The literature has proposed several channels through which corporate hedging with derivatives can increase firm value.[1] Many studies use dummy variables or notional principals of derivative positions to test whether corporate use of derivatives conforms with the theory predictions.[2] The empirical evidence on the benefit of hedging is inconclusive.

In this paper, we argue that what matters for value accretion is not about whether a firm hedges or not or how much it hedges, but rather about whether a firm's hedging policy matches its actual hedging demand. Just like a medicine that can either cure a disease or kill a patient, hedging enhances a firm's value only when its hedging policy optimally and consistently matches its actual hedging demand. Ad hoc hedging practices can actually hurt a firm's performance, especially when the variation of the hedging ratio runs against the variation of the firm's hedging demand. Such practices not only become ineffective in reducing the firm's risk, but can incur extra costs from setting up and maintaining a costly hedging program and from entering and exiting hedging positions. Such extra costs can reduce the firm's average profits and hurt the firm's valuation.

Accurately identifying a firm's hedging demand and its variation is not easy. Hedging contracts are signed ex ante to hedge expected notional exposures down the road. The actual exposure can

[1] See for example, Stulz (1984, 1996, 2003), Smith and Stulz (1985), Froot, Scharfstein, and Stein (1993), Bessembinder (1991).

[2] Recent examples include Haushalter (2000), Petersen and Thiagarajan: (2000), Allayannis and Weston (2001), Graham and Rogers (2002), Guay and Kothari (2003), Jin and Jorion (2006), Cornaggia (2013), and Pérez-González and Yun (2013).

differ from the expectation. Strict accounting rules for the use of hedge account can make such mis-projections costly. More importantly, a firm's notional exposure can differ significantly from its net exposure because both revenue and cost streams can have direct and indirect exposures to the same set of underlying shocks. Many firms, especially small ones, may not have the resources to accurately measure its risk exposures and optimal hedging ratios (Doshi, Kumar, and Yerramillia (2018)). Even for firms who can accurately determine the optimal hedging ratio, due to the inherent difficulty in accurately measuring the ex post success of a hedging practice within a short period of time, temporary hedging account losses may pressure managers to abandon a hedging program or deviate from the optimal policy.[3] Faced with such difficulties, we hypothesize that the hedging practices of many firms can deviate from their optimal policy, and hedging practices running against the optimal policy prescription can end up hurting a firm's performance rather than enhancing its value.

To test our hypothesis, we take the US airline industry as an example and consider the optimal hedging policy for its jet fuel cost variation. Our study builds on the earlier work of Carter, Rogers, and Simkins (2006a,b), who explain how the airline industry is particularly suited for analyzing the effect of derivative hedging on the firm value, and who have identified strong positive value benefits for jet fuel hedging. Airline profits tend to be volatile, and many airlines finance their assets through debt or leases, such that small variations in operating profits produce large swings in the cash available to stockholders. Therefore, appropriately hedging the variation of fuel cost, one of the most volatile parts of an airline's operation cost, has the great potential of bringing stability to its operating profit, reducing the cost of potential financial distress, and enhancing the firm's valuation.

[3]Using derivative positions of upstream oil and gas firms, Kumar and Rabinovitch (2013) find that hedging intensity is positively related to factors that amplify chief executive officer (CEO) entrenchment, presumably because entrenched CEOs can better handle the pressure from the board and investors on short-term profit and loss variations to pursue the long-run goal of risk reduction.

Nevertheless, we argue that the optimal fuel cost hedging ratio for an airline can deviate substantionally from its notional jet fuel exposure and can vary strongly over time. This complication makes it possible that the hedging practices of some airlines are less optimal than the practices of others. The resulting cross-sectional variation in the optimality of the hedging practices allows us to test the relation between the degree of optimality of a hedging policy and its value effect.

To derive the optimal hedging ratio for an airline's fuel cost, we decompose the oil price movement into demand shocks and supply shocks. We take the return on the S&P 500 Index as a proxy for the demand shock, and project oil futures return on the equity index return via a rolling-window regression. We treat the projection residual as the idiosyncratic supply shock, and assume that while an airline's fuel cost variation depends on the variation of the oil futures price, the variation of the demand for air travel and cargo transport and accordingly the airline's revenue depends on the demand shock component of the oil price movement. Under a simple structural setting, we optimize the fuel cost hedging ratio for an airline by minimizing the variation on the company's operating profit per unit of its available seat mile capacity.

The optimal hedging ratio for an airline depends on its revenue sensitivity to the market demand variation and its fuel cost exposure per unit available seat mile capacity. It also depends on the relative composition of demand and supply shocks in the oil price movement. While the revenue sensitivity and cost exposures capture firm-specific exposures, the relative composition of the demand versus supply shocks in the oil price movement represents an aggregate market condition. Based on the rolling-window regression estimates, we construct a time-varying market hedging demand index capturing the hedging demand of a representative airline company. The market hedging demand declines with the demand shock contribution but increases with the supply shock contribution to the oil price movement. Intuitively, while hedging oil supply shocks can reduce the company's bottom-line fluctuation, fuel cost hedging becomes less desirable when the oil price variation is mainly driven by demand shocks. This is because the demand shock component affects both the fuel cost and the travel demand in the same direction, and thus serves as a natural hedge of the fuel cost variation, reducing the airline's net exposure to oil price movement.

Over our sample period from 1992 to 2016, the market hedging demand shows large intertemporal variations, from as low as 45% to as high as 133%. We examine how the value benefit of hedging varies with the market condition as captured by the time-varying market hedging demand index. We find that at times when the market hedging demand is high, the values of airline companies, as measured by the logarithm of their Tobin's Q, increase strongly and positively with their hedging ratio, confirming the finding by Carter, Rogers, and Simkins (2006a) for the earlier sample period from 1992 to 2003. However, when the market hedging demand is low, firm values no longer increase with fuel hedging activity. Conditional on low market hedging demand, the pooled firm value regression generates a negative and insignificant slope estimate on the hedging ratio.

Although different airlines can have different revenue sensitivities and fuel cost exposures, as long as their firm-specific exposures are reasonably stable over time, we expect that each company's hedging ratio, when optimally determined, is to positively co-vary with the market hedging demand. We propose to use the time-series correlation between an airline's hedging ratio and the market hedging demand index as a measure of the dynamic optimality of the airline's hedging practice. The dynamic optimality is not determined by how large the hedging ratio is at any one point in time, but by how it consistently co-varies with the market hedging demand.

The US airlines show great disparity in the dynamic optimality of their hedging practices. Out of the 33 airlines in our sample, one third never hedge at all, and the hedging ratios of more than another one third of the airlines co-vary *negatively* with the market hedging demand index, suggesting that their hedging policies run against the prescription of our derived optimal hedging policy. Only the remaining less than one third of the airlines have hedging ratios positively co-moving with the market hedging demand index, and hence somewhat near our prescribed optimal policy.

When we link the dynamic optimality of the hedging practice to the airline's Tobin's Q, we identify a strongly positive relation between the two. In particular, the average logarithm of Tobin's Q for the airlines with positive hedging dynamic optimality estimates is strongly significantly higher than the average logarithm of Tobin's Q for the airlines with negative dynamic optimality estimates. In fact, for firms with negative dynamic optimality estimates, their average Tobin's Q is even lower than the average Tobin's Q of firms that do not hedge at all. Hedging the wrong way is worse than not hedging all together.

To control for potential endogeneity, we also perform a 10-year rolling window estimation on the dynamic optimality of the airline's hedging practice and use the rolling dynamic optimality estimates to predict next year's airline valuation as measured by the logarithm of Tobin's Q. The time-series average of the slope estimates from the cross-sectional predictive regressions is strongly positive and highly statistically significant, confirming the robustness of the relation.

To trace the sources of the value benefit of a dynamically optimal jet fuel hedging strategy, we examine the relation between the dynamic optimality of each airline's hedging practice and the airline's average operational, investment, and financing behaviors. We measure an airline's operational performance using the classic return on asset measure and find that that, as an airline's hedging dynamic optimality increases, not only its return on asset shows smaller time-series variation, but the return also enjoys a higher sample average. Hedging activities with negative optimality not only become ineffective in reducing risk, but also induce extra cost in setting up and maintaining the program and in entering and exiting expensive hedging positions.

We also find that optimal fuel cost hedging is only weakly associated with higher capacity growth, but it is strongly associated with increasing financial leverage and higher credit rating. These findings suggest that the main motivation of fuel cost hedging for airlines is less about capacity growth, but more about reducing the probability of financial distress and reducing financing cost.

In examining the benefit of hedging, the vast majority of the literature either assumes that the existing hedging practice is optimal by using a dummy variable to indicate whether a firm is hedging or not, or assumes that the more hedging the better by regressing the firm value on the proportion of notional exposure hedged. In this paper, we argue that the net exposure can differ substantially from the notional exposure, can vary strongly over time, and can be difficult to determine accurately for firms that do not have the resources. Empirically, we show that the hedging practices of most US airline firms are far from dynamically optimal, and only those that are close to dynamically optimal are value accretive.

In related literature, Ghoddusi, Titman, and Tompaidis (2019) build a model of a commodity processing chain with endogenously determined input and output prices, and show that the variance minimizing hedging ratio depends on many operational characteristics, and that even with stable supply and demand factor dynamics, the optimal hedge ratio can change over time as capacity utilization in the industry changes. In this paper, we show how the strong variation in the relative contribution of supply and demand shocks to the oil price movement can lead to large variations in the optimal fuel cost hedging ratio for airlines.

In other related work on the airline industry, Morrell and Swan (2006) discusses the general practice of airline fuel cost hedging. Rao (1999) estimates the benefit of fuel cost hedging with futures and find a 23% decline in quarterly income volatility from his assumed hedging policy. Lim and Hong (2014) show evidence that hedging reduces airline operating cost. Rampini, Sufi, and Viswanathan (2014) show how collateral requirements can constraint the hedging practice of firms in financial distress. In this paper, we highlight the dynamic nature of airline fuel cost hedging and show that hedging is value enhancing only when the practice is dynamically optimal.

The rest of the paper is organized as follows. The next section derives the optimal fuel cost hedging policy for an airline company when the oil price dynamics can have time-varying contributions from demand and supply shocks. Section 3 describes the data collection procedure and the summary statistics. Section 4 presents the results from the empirical analysis. Section 5 concludes.

2. Optimal fuel cost hedging for the airline industry

Heavy energy consumers such as the airline industry often confront the difficult but important task of determining how much it is appropriate to hedge their fuel cost variation with crude oil futures. Intuitively, large oil price fluctuations can induce large and undesirable fluctuations to the bottom line of these companies, suggesting a need to hedge. Nevertheless, when market dynamics shift, such seemingly innocuous hedging practices can result in large losses.

In this section, by decomposing oil price movements into demand and supply shocks with time-varying intensities, we show that the optimal fuel cost hedging policy is not a static decision, but depends crucially on the relative strength of the two types of shocks in the oil price fluctuation. Time variation in the relative composition of the two types of shocks calls for dynamic rebalancing in the optimal hedging position.

2.1. Time-varying supply and demand shocks in crude price dynamics

Crude oil price movements can be driven by both supply shocks and demand shocks. Major events and structural economic changes can induce large variations in the magnitudes of the two types of shocks, as well as their impacts on the crude price movements. We model the dynamics of the US West Texas Intermediate (WTI) crude futures by decomposing its movements into these two types of shocks, and highlight the effects of time variation in both their magnitudes and their impacts on the crude futures price variation. WTI refers to oil extracted from wells in the US and sent via pipeline to Cushing, Oklahoma. Its futures contracts are actively traded on the NYMEX futures exchange, and are one of the most liquid jet fuel cost hedging instruments used by the US airline industry.

We use dW_t^s and dW_t^d to denote the supply and demand Brownian shocks, respectively, and model their time-varying impacts on the oil futures price dynamics O_t as,

$$dO_t/O_t = \eta_t^d \sqrt{v_t^d}\, dW_t^d - \eta_t^s \sqrt{v_t^s}\, dW_t^s, \tag{1}$$

where positive demand shocks lead to oil price increase while positive supply shocks lead to oil price decline. Equation (1) captures the time-varying intensities of the two types of shocks via the two instantaneous variance rates v_t^d and v_t^s, and captures their time-varying impacts on the crude futures price via the two loading coefficients η_t^d and η_t^s. Since this paper focuses on variance decomposition and variance reduction via optimal hedging, but does not propose speculative trading based on directional forecasts, we omit the directional forecast, i.e., the drift term, all together in this and other dynamics specifications. This omission reduces notation cluttering and highlights the true meaning of hedging as a practice to reduce variability via cancellation of risk rather than via directional bets.

To enhance the separation of demand and supply shocks on crude oil futures, we use the variation of the US stock market, and specifically the S&P 500 Index (SPX), to proxy the demand variation. Historically, the literature often chooses to proxy demand shocks with some aggregate real economic strength measures, such as the global real economic activity measure used by Kilian (2009). Our choice of a financial security index allows us to better identify the time variation in the intensities of demand. By using the SPX as the proxy, we are highlighting the systematic market demand and how it interacts with crude oil price movements. The market demand not only affects the oil price movement, but also influences demand for air travel and cargo transport, and therefore serves as a bridge between the oil price movement and airline revenue variation.

With the SPX as a proxy for the demand shock (D_t), we model its dynamics as

$$dD_t/D_t = \sqrt{v_t^d} dW_t^d. \tag{2}$$

With the demand shock specification in (2), we can think of the specification in equation (1) as a projection of the crude futures movement onto the SPX movement dW_t^d, and treat the projection residual dW_t^s as the orthogonalized, idiosyncratic supply shock. By nature of the projection, the two types of shocks are orthogonalized: $\mathbb{E}[dW_t^d dW_t^s] = 0$.

Sy and Wu (2019) propose to identify the time-varying demand shock and its impact on the crude futures price movement via a joint analysis of the stock index options and crude futures options. Since reliable options data are available only for the more recent period, this paper estimates the demand shock loading and the variance contribution from the two types of shocks over an extended sample period using rolling-window regression estimation on the two daily return series.

It is inherently difficult to predict the direction of financial security price movements, but predicting the financial security return variance is much easier based on the well-documented volatility clustering behavior (Engle (2004)). We use simple rolling-window regressions to generate risk and loading estimates and highlight the value of such predictions in enhancing the hedging efficiency for the airline industry. In practical implementation, one can in principle further enhance the prediction accuracy and accordingly the hedging efficiency by specifying and estimating better variance dynamics models and by incorporating more informative data sources such as options and high-frequency data.

2.2. Optimal fuel cost hedging ratio

To determine the time-t optimal fuel cost hedging strategy of an airline company i, it is convenient to perform a stylized decomposition of its operating income ($I_{t,i}$) into two components: its revenue ($R_{t,i}$) and its operating expense ($C_{t,i}$),

$$I_t = R_{t,i} - C_{t,i}. \tag{3}$$

The revenue for an airline comes mainly from passenger air travel demand. Cargo transport also contributes to revenue, but for a much smaller portion. The passenger travel revenue is commonly decomposed into the multiplication of three components: (i) Available seat miles (ASM, henceforth denoted as $A_{t,i}$) as a measure of capacity, (ii) load factor, defined as the ratio of revenue passenger miles (RPM) to ASM, as a measure of capacity utilization, and (iii) revenue yield, defined as the revenue per passenger mile. Since it takes time to acquire new fleets and open new routes, an airline's capacity tends to be stable and only adjusts slowly and strategically over a longer horizon, whereas short-run revenue fluctuations are mainly driven by variations in the yield and the load factor, or taken together, the revenue per available seat mile. Short-run variations in revenue per available seat smile are mainly driven by the market demand for air travel, and are expected to co-move positively with the business cycle and hence the stock index performance. We capture this co-variation via the following dynamics specification,

$$\frac{dR_{t,i}}{A_{t,i}} = \beta^r_{t,i}\frac{dD_t}{D_t} + \sigma^r_{t,i}dW^r_{t,i}, \tag{4}$$

where we project the revenue variation onto the equity index return, with $\beta^r_{t,i}$ measuring the sensitivity of the airline's revenue variation per available seat mile to variations in the stock index. The Brownian shock $dW^r_{t,i}$ denotes the idiosyncratic variation in the airline's revenue, with $\sigma^r_{t,i}$ measuring the idiosyncratic volatility.

Among the operating expense for an airline company, the most volatile component is the jet fuel cost. The industry commonly decomposes the fuel cost into three multiplicative components: (i) the capacity as measured by ASM, (ii) the fuel cost efficiency, which is measured by fuel usage (in gallons) per ASM and which depends on both the fuel efficiency of the fleet types and the distances of the routes, and (iii) the unit jet fuel cost per gallon. The unit jet fuel cost is linked to the crude oil price O_t by the crack ratio, which is the ratio of spot jet fuel price to spot crude oil price, plus the into-plane margin, capturing the additional cost that the airline pays for transporting the jet fuel from the refinery or a storage point to the aircraft:

$$\text{Unit jet fuel cost} = O_t \text{ x crack ratio} + \text{into-plane margin.}$$

Non-fuel cost is not nearly as volatile as fuel cost, and can also be represented as a fraction of the ASM capacity.

If we assume that the crack ratio, the into-plane margin, and the non-fuel cost as a fraction of ASM are all stable over time, we can represent the short-run operating expense variation in terms of the variation in the crude oil futures price as,

$$\frac{dC_{t,i}}{A_{t,i}} = \varphi^c_{t,i}\,\frac{dO_t}{O_t}, \tag{5}$$

where we normalize the operating expense by the airline's capacity (ASM), and use $\varphi^c_{t,i}$ to measure the airline's fuel cost exposure as a fraction of its ASM capacity. When other components of the operating expense also vary over time, we can treat equation (5) as a projection equation, with the projection residual omitted as it does not affect the hedging decision.

Combining the specifications for the revenue variation in (4) and the operating expense variation in (5), and assuming that the airline company does not hedge its fuel cost, we can write changes in the airline's operating income ($I^U_{t,i}$) per available seat mile as,

$$\frac{dI^U_{t,i}}{A_{t,i}} = \beta^r_{t,i}\frac{dD_t}{D_t} - \varphi^c_{t,i}\frac{dO_t}{O_t} + \sigma^r_{t,i}dW^r_{t,i}. \tag{6}$$

Since the crude oil futures price movements are by itself driven by crude supply shocks and demand shocks, we can plug in the crude oil futures dynamics in (1) and the equity index dynamics for demand in (2) to have

$$\frac{dI^U_{t,i}}{A_{t,i}} = (\beta^r_{t,i} - \varphi^c_{t,i}\eta^d_t)\sqrt{v^d_t}dW^d_t + \varphi^c_{t,i}\eta^s_t\sqrt{v^s_t}dW^s_t + \sigma^r_{t,i}dW^r_{t,i}. \tag{7}$$

If the airline decides to hedge its notional exposure of the fuel cost with crude futures, the cost variation in equation (5) will be fully hedged and the operating income (I^H_t) will only vary with the revenue,

$$\frac{dI^H_{t,i}}{A_{t,i}} = \frac{dR_{t,i}}{A_{t,i}} = \beta^r_{t,i}\frac{dD_t}{D_t} + \sigma^r_{t,i}dW^r_{t,i}, = \beta^r_{t,i}\sqrt{v^d_t}dW^d_t + \sigma^r_{t,i}dW^r_{t,i}. \tag{8}$$

The two equations (7) and (8) allow us to compare the relative benefits and costs of hedging fuel costs with crude futures. When oil price fluctuation is dominated by supply shocks, $\eta_t^s \gg \eta_t^d$, hedging can remove the second component of the variation term and reduces the variation of the company's bottom line. On the other hand, when the supply shocks are muted and the crude variation is dominated by demand shocks, hedging the fuel cost can actually increase the volatility of the profit margin, chiefly because the demand shock component of the crude movement can partially cancel out the revenue fluctuation for a pro-cyclical company through the loading coefficient differential $(\beta_{t,i}^r - \varphi_{t,i}^c \eta_t^d)$.

In practice, the optimal hedging strategy depends on the relative composition of the crude oil futures variation, as well as the sensitivities of the company's revenue and cost to the stock market index and the crude futures movements, respectively. If we can estimate the revenue and cost sensitivities and can predict the time variation in the relative variance contribution of demand and supply shocks to crude oil futures, we can devise a dynamic hedging strategy that minimizes the conditional variation of the bottom line.

For an airline that partially hedge its fuel exposure, we use $h_{t,i}$ to denote its hedging ratio, i.e., the fraction of notional fuel cost exposure hedged. In this case, the airline's profit is only subject to the remaining fraction $(1 - h_{t,i})$ of the cost variation. We can write the dynamics for the partially hedged operating income $I(h_{t,i})$ as a function of the hedging ratio $h_{t,i}$ as

$$\begin{aligned}
\frac{dI(h_{t,i})}{A_{t,i}} &= \frac{dR_{t,i}}{A_{t,i}} - (1 - h_{t,i})\frac{dC_{t,i}}{A_{t,i}} \\
&= (\beta_{t,i}^r - (1 - h_{t,i})\varphi_{t,i}^c \eta_t^d)\sqrt{v_t^d}\, dW_t^d + (1 - h_{t,i})\varphi_{t,i}^c \eta_t^s \sqrt{v_t^s}\, dW_t^s + \sigma_{t,i}^r dW_{t,i}^r. \qquad (9)
\end{aligned}$$

Theorem 1 *Assume that an airline company strives to minimize the variation of its operating profit per unit ASM capacity. The optimal hedging ratio depends on its revenue sensitivity to market* *demand ($\beta^r_{t,i}$), its fuel cost exposure per unit ASM capacity ($\varphi^c_{t,i}$), and the relative contribution of demand shocks to the oil price variation (η^d_t, v^d_t, v^o_t),*

$$h^*_{t,i} = 1 - \frac{\beta^r_{t,i}}{\varphi^c_{t,i}} \frac{\eta^d_t v^d_t}{v^o_t}. \tag{10}$$

Proof. By way of projection, $\mathbb{E}[dW^d_t dW^s_t] = 0$. Thus, given a hedging ratio $h_{t,i}$, from the dynamics in equation (9), the time-t conditional variance rate on the variation of the operating profit per ASM is,

$$V(h_{t,i}) = \left(\beta^r_{t,i} - \varphi^c_{t,i}(1-h_{t,i})\eta^d_t\right)^2 v^d_t + \left(\varphi^c_{t,i}\right)^2 (1-h_{t,i})^2 (\eta^s_t)^2 v^s_t + \sigma^2_{t,i}. \tag{11}$$

If the airline chooses the hedging ratio $h_{t,i}$ to minimize the variance rate,

$$\min_{h_{t,i}} \quad V(h_{t,i}), \tag{12}$$

we can solve for the optimal hedging ratio via the first-order condition,

$$\frac{\partial V(h_{t,i})}{\partial h_{t,i}} = 2\left(\beta^r_{t,i} - \varphi^c_{t,i}(1-h_{t,i})\eta^d_t\right) v^d_t \varphi^c_{t,i}\eta^d_t - 2\left(\varphi^c_{t,i}\right)^2 (1-h_{t,i})(\eta^s_t)^2 v^s_t = 0. \tag{13}$$

Rearrange, and plug in the variance rate for the oil futures return, $v^o_t = (\eta^d_t)^2 v^d_t + (\eta^s_t)^2 v^s_t$, we obtain the optimal hedging ratio in (10). ■

The optimal hedging policy asks for a full 100% fuel cost hedge when crude futures movements have zero loading on demand shocks ($\eta^d_t = 0$). In fact, when supply shocks dominate and impose an negative impact to the aggregate economy, it is impossible that the oil futures returns can show a negative loading on the equity index return $\eta^d_t < 0$. In this case, it is appropriate to over-hedge with $h_t > 100\%$. On the other hand, as demand shocks contribute more to the oil futures variation, and accordingly as $\eta_t^d v_t^d$ increases relative to v_t^o, the optimal hedging ratio declines.

The optimal hedging strategy that we derive in Theorem 1 assumes that the airline company performs dynamic hedging with the WTI crude oil futures. Hedging with futures on jet fuel would have matched the airline fuel cost variation better as the crack ratio can also vary over time, but futures contracts on jet fuel are not actively traded. Futures on ICE Brent Crude Oil are also actively traded, but WTI is the main benchmark for oil consumed in the US. In addition, over-the-counter swap contracts and option contracts are also among the commonly used instruments for hedging jet fuel cost. While the sensitivities and trading costs can differ, the different hedging instruments can all allow an airline company to alter its exposure to the oil price movements.

In our setting, the main reason for the optimal hedging ratio to be different from the airline's notional exposure is that the airline's revenue and fuel cost share a common component, which we label as the demand shock, that can serve as a natural hedge so that the airline's net exposure to oil price movement can be smaller than its notional exposure. To the extent that the proportion of this common component varies over time, the net exposure and hence optimal hedging ratio also vary with it.

In addition to such natural hedges via common exposures to demand shocks, airlines can also adjust their operation ex post in response to oil price changes to mitigate the impact. Operational hedging activities can include both short-term and long-run adjustments. In the short run, airlines can respond through pricing, by raising the base ticket price and imposing higher surcharges; nevertheless, these responses will lead to lower load. Furthermore, imposing higher fuel surcharges can attract regulatory scrutiny and can therefore add another layer of risk. In the medium run, the airline can alter its capacity allocation, by changing its routes, brands, and fleets. In the long run, if an airline perceives high fuel price as a long-term trend to stay, the airline can improve on fleet efficiency and fuel type by changing fleet units, fleet type, and fuel type.

In a theoretical setting, by allowing firms to have the optionality to adjust their output levels in response to realized production costs, Adam, Dasgupta, and Titman (2007) identify cases where the volatility of cash flows can actually benefit the firm because of the optionality and accordingly hedging the production cost variation is no longer beneficial to the firm. For our particular application to the airline industry, the short-term operational hedging options are limited and costly, and the long-run adjustments are viable only if one is certain of the long-run oil price trend. Dynamic hedging via crude futures remains the most cost-effective option to reduce the operation profit variation.

2.3. Separating time-varying market conditions from firm-specific exposures

The net exposure of a company's operating profit to a risk source depends on this risk's loading on both the company's input and its output. Facing the task of minimizing the variation of an airline's operating profit with crude futures, we capture the common exposure of the airline's revenue and expense to crude futures through their common exposure to the demand shock. The higher is this common component, the more the risk can be naturally cancelled out, and the less crude futures contracts are needed for risk minimization.

We use the equity index return to proxy the demand shock and use it as the intermediary to capture the common risk exposure of revenue and expense. By using the equity index return as an intermediary, we can create a market benchmark to capture the time variation in aggregate market conditions. The variation of the optimal hedging ratios for different airlines are all tied to this market condition through their different firm-specific exposures.

To separate the time-varying market condition from firm-specific exposures, we first define a *market hedging demand index*, $\mathcal{H}_t$, to capture the overall hedging demand variation for the airline industry due to variations in the market condition,

$$\mathcal{H}_t = 1 - \frac{\eta_t^d v_t^d}{v_t^o}. \tag{14}$$

The market hedging demand index is high when the demand shock variance contribution $\eta_t^d v_t^d$ is small relative to the total oil return variance v_t^o. This is the case when the oil futures movement is mainly driven by supply shocks, an airline's revenue variation is not highly correlated with the fuel cost variation, and it is therefore beneficial to fully hedge the fuel cost variation. On the other hand, the market hedging demand is low when demand shocks dominate the variation of the oil futures. Since demand shocks represent natural hedges between revenue and expense, a higher demand shock component implies that the net risk exposure can be much smaller than the notional fuel exposure.

Equation (10) connects the market hedging demand index to each airline's optimal hedging ratio through the particular airline's revenue sensitivity to the stock market variation ($\beta_{t,i}^r$) and the company's fuel cost exposure per ASM capacity ($\varphi_{t,i}^c$). We measure an airline's *firm-specific exposure* ($\gamma_{t,i}$) via the ratio of the two,

$$\gamma_{t,i} = \frac{\beta_{t,i}^r}{\varphi_{t,i}^c}. \tag{15}$$

The airline has a high firm-specific exposure $\gamma_{t,i}$ when its revenue is sensitive to the equity market fluctuation (high $\beta_{t,i}^r$) and its fuel cost is small relative to its capacity. On the other hand, an airline's firm-specific exposure is low if the company can manage to generate stable revenue streams independent of the equity market fluctuation.

With these definitions, we can decompose the time-t optimal hedging ratio for a particular airline i as a combination of the market hedging demand $\mathcal{H}_t$ at that time t and the airline's firm-specific exposure $\gamma_{t,i}$.

Proposition 1 *The time-t optimal fuel cost hedging ratio for an airline i depends both on the time-t level of the market hedging demand $\mathcal{H}_t$ and on the particular airline's firm-specific exposure $\gamma_{t,i}$,*

$$h^*_{t,i} = (1-\gamma_{t,i}) + \gamma_{t,i}\mathcal{H}_t. \quad (16)$$

The derivation follows by plugging in the market hedging index definition in (14) into the optimal hedging ratio in (10) while combining the effect of the airline's revenue sensitivity $\beta^r_{t,i}$ and its fuel cost exposure $\varphi^c_{t,i}$ via the exposure coefficient $\gamma_{t,i}$ defined in (15).

Equation (16) in Propostion 1 shows that when an airline's firm-specific exposure is zero, which happens when the airline's revenue has zero sensitivity to market demand variation, its optimal hedging ratio becomes constant at 100%, regardless of variations in market condition. The optimal hedging strategy is essentially a static one. On the other hand, when an airline's firm-specific exposure is high, which happens when the airline's revenue is highly sensitive to market demand variation, its optimal hedging ratio becomes highly variable and dependent on the market hedging demand variation. In particular, the market hedging demand index $\mathcal{H}_t$ represents the optimal hedging ratio of a representative airline with a unit firm-specific exposure $\gamma = 1$.

2.4. Testable hypotheses

Based on our derived optimal hedging demand, we can generate several testable hypotheses on when and how hedging jet fuel cost enhances an airline's firm value.

2.4.1. Value impact of fuel cost hedging under different market conditions

Theorem 1 highlights that the optimal fuel cost hedging ratio for an airline can vary with the relative contribution of demand shocks to the oil price movements. We capture this relative contribution through the construction of the market hedging demand index in (14). The index will be high when supply shocks dominate oil price movement, but low when demand shocks dominate the oil price movement. Hedging is more beneficial to airlines only when the market hedging demand is high. Thus, based on the estimated market hedging demand index time series, we propose the following empirically testable hypothesis that links the value benefits of hedging to the market hedging demand condition.

Hypothesis 1 *Hedging fuel cost is more beneficial for airlines when the market hedging demand index is high, and less so when the market hedging demand index is low.*

To estimate the value benefit of fuel cost hedging, we follow Carter, Rogers, and Simkins (2006a) and regress the logarithm of Tobin's Q of airline companies against their fuel cost hedging ratio while controlling other firm characteristics. A positive slope estimate on the hedging ratio captures the marginal benefit in enhancing the firm's value per each unit of fuel cost hedging.

To test our hypothesis that the value benefit of fuel cost hedging is larger when the market hedging demand is high, we classify the sample into high and low hedging demand periods, and perform the regressions conditional on the market condition classification. Under our hypothesis, we expect the slope coefficient to be more positive when the market hedging demand index is high, and less so when the market hedging demand index is low.

2.4.2. Dynamic optimality of fuel cost hedging and value accretion

The optimal hedging ratio for a particular airline company i at any given time is a combination of the market condition at that time as captured by the market hedging demand index $\mathcal{H}_t$ and its firm-specific exposure $\gamma_{t,i}$. For an airline with a stable business structure, we can assume that its revenue sensitivities to market demand and its fuel cost exposures per capacity are stable and only vary slowly over time. With a constant firm-specific exposure, $\gamma_{t,i} = \gamma_i$ for all t, the airline's optimal fuel cost hedging ratio is to co-vary linearly, positively, and perfectly with the market hedging demand. We can therefore use the time-series correlation between an airline's hedging ratio $h_{t,i}$ and the market hedging demand index $\mathcal{H}_t$ as a measure of the *dynamic optimality* of the airline's fuel cost hedging policy.

Proposition 2 *If an airline company's revenue sensitivity to market demand (β^r) and fuel cost exposure per capacity (φ^c) are positive and stable over time, so that the airline has a positive and stable firm-specific exposure γ, the time-series correlation estimate ρ between the company's fuel cost hedging ratio and the market hedging demand can be used as a measure of dynamic optimality for the company's fuel cost hedging policy: The higher the correlation estimate, the more optimal is the variation of its fuel cost hedging strategy.*

Under the assumption of positive and stable firm-specific exposures, if an airline's hedging policy is dynamically optimal, its hedging ratio correlation with the market hedging demand will be 100%. In reality, the correlation estimate can be less than perfect even for a dynamically optimal hedging strategy when the firm-specific exposures also vary over time and when the market hedging demand is estimated with noise; nevertheless, the correlation estimate should remain highly positive as long as the firm-specific exposure is reasonably stable over time so that its variation does not counteract and overwhelm the market hedging demand variation. If, on the other hand, an airline's hedging ratio varies haphazardly, with no relation to the market hedging demand, the correlation estimate would be close to zero.

Worse yet, it is also possible that a firm's hedging strategy is driven by factors that happen to run against the variation of the market hedging demand. This behavior will lead to a negative correlation estimate, and will represent the very opposite of an optimal hedging policy. This can happen in the *purely hypothetical* case when the airline's hedging ratio is determined based on the recommendation of an agent whose incentive is not fully aligned with the airline, but to sell a target amount of (illiquid and expensive) derivative contracts for commissions. When the market hedging demand is low and the aggregate demand for the derivative contracts becomes low as a result, the agent may have the extra incentive to recommend a higher hedging ratio to the unbeknown airline so as to fulfill the agent's own commission target. In this case, the airline's hedging ratio will negatively co-vary with the market hedging demand, and the hedging practice is effective less for reducing its profit variation, but more for incurring hefty trading costs and generating commissions for its agent.

By shifting the focus from the magnitude of a hedging ratio to the dynamic optimality of a hedging policy, we formulate another testable hypothesis:

Hypothesis 2 *The value benefit of an airline's fuel cost hedging practice increases with the dynamic optimality of its hedging policy, as measured by the correlation between its hedging ratio variation and the variation of the market hedging demand index.*

If we measure firm performance via Tobin's Q, we would expect airlines with higher estimates of dynamic optimality to have higher Tobin's Q estimates on average.

When a company places a directional bet on next year's oil price movement, the company can see the result of this bet next year through its realized profit or loss and determine whether the bet is correct or wrong. Hedging, however, has a more subtle effect on a company's profit, so subtle that one cannot easily determine the validity of a hedging strategy based on a single period's realization. The purpose of hedging is to reduce variance, but it is impossible to effectively measure variance based on a single realization. Only through repeated realizations can one determine whether a strategy has successfully reduced variance or not. Therefore, the success of a hedging strategy is not determined by whether the hedging ratio at any one point in time is too high, too low, or just optimal; but rather it is determined by the hedging ratios covarying repeatedly and consistently with the variation of the hedging demand through many time periods. According to what is attributed to Aristotle, *we are what we repeatedly do. Excellence, then, is not an act but a habit.* The dynamic optimality measure that we construct does not try to measure the optimality of one particular act of an airline, but rather it measures the optimality of an airline's repeated hedging behaviors in consistently following the variation of the market hedging demand.

Our discussion so far shows that it is not easy to design and maintain an optimal fuel cost hedging policy for an airline. The fact that the net exposure to oil price movement can differ from the notional exposure of the fuel cost and can vary strongly with varying market conditions makes it a nontrivial task to design a dynamically optimal hedging strategy. The fact that the benefit of hedging cannot be accurately measured over a short period of time makes it difficult for managers to stick with a hedging policy, even if it is optimal. It's because of these complications that we do not expect every airline to maintain a dynamically optimal hedging policy. We expect the dynamic optimality of the hedging practices to vary widely across airlines. This cross-sectional variation allows us to identify the value benefit of maintaining a dynamically optimal hedging strategy.

3. Data collection and summary behaviors

We perform empirical analysis on US airline companies over the sample period from 1992 to 2016. We collect all US airline companies from EDGAR under the SIC code 4512 over this sample period, download their corresponding annual financial data from Compustat, and obtain their share price data from the Center for Research in Financial Securities (CRSP). We match the annual financial data with market values computed with year-end stock prices and shares outstanding, and we manually collect information regarding each airline's hedging practice from the company's SEC 10-K filings.

At each year, for each company, we manually collect information from the company's 10-K report on that year to construct the company's hedging ratio, $h_{t,i}$, defined as the percentage of next year's fuel requirements hedged. We use Tobin's Q ($Q_{t,i}$) as a firm's performance measure and construct it based on the simple approximation method of Chung and Pruitt (1994), as the ratio of firm value to total assets, and approximate the firm value as the sum of the market value of equity, liquidation value of preferred stock, the book values of long-term debt and current liabilities minus current assets, and the book value of inventory.

Tobin (1969) introduces the Tobin's Q measure for analyzing monetary policy as he argues that the major way for monetary policy to affect aggregate demand is by changing the valuation of physical assets relative to their replacement costs. Lindenberg and Ross (1981) and Morck, Shleifer, and Vishny (1988), among others, help to popularize the measure in finance applications. With replacement cost as a normalization benchmark, the measure allows one to perform comparative analysis of relative value across different firms and time periods. In reporting summary statistics and performing regressions and statistical tests, we take natural logarithm on the Tobin's Q for better distributional behaviors. The log Tobin's Q of a company can be interpreted as the continuously compounding deviation of the company's firm value from its replacement cost.

Our analysis also considers a list of firm characteristics and indicators for other risk management practices. The hedging indicators and firm characteristics are annual data. We also obtain daily return series on each firm, as well as daily returns on the S&P Index and front-month WTI oil futures, to perform rolling-window risk sensitivity estimates. The stock returns data are obtained from CRSP. The stock index and oil futures data are from Bloomberg.

3.1. Summary statistics on hedging ratios and Tobin's Q

The hedging data sample includes 451 company-year observations, with a total of 33 publicly traded US airline companies spanning over 25 years from 1992 to 2016. Table 1 reports the summary statistics of the hedging ratio and the logarithm of Tobin's Q for each company in our sample. The table sorts the company based on each company's mean hedging ratio. Out of the 33 airlines, one third (11) of them have never hedged during our sample period. Either because of their lack of fuel cost hedging or by coincidence, only one airline (Skywest) out of the 11 has survived till the end of our sample. By contrast, the last three airlines at the bottom of the table, Delta (DAL), Alaska (ALK), and Southwest (LUV), hedge on average 33%, 35%, and 43% of their fuel cost exposures, respectively. Thus, the airlines exhibit large cross-sectional variation in their hedging practices.

[Table 1 about here.]

In addition to the mean hedging ratio, Table 1 also reports the standard deviation, the minimum, and the maximum hedging ratio for each company. The maximum hedging ratio goes over 100% for Delta, and reaches 95% for Southwest. On the other hand, even for companies with large average values, their hedging ratios do not necessarily stay large over the whole sample period, but show large time series variation. The minimum hedging ratio is zero for 31 of the 33 companies.

The average log Tobin's Q also varies greatly across airlines, from -64% for United to 70% for Vanguard. There is no visible cross-sectional relation between the average hedging ratio and the average log Tobin's Q. The cross-correlation estimate between the average hedging ratio and the average log Q across the 33 airlines is small and negative at -8.3%.

Table 2 reports the cross-sectional summary statistics of the hedging ratio and the log Q at each year. The time-series variation of the cross-sectional average hedging ratio is smaller. The average hedging ratios were below 10% during the first few years of our sample from 1992 to 1997 as the fuel cost hedging practice was not yet as commonly adopted at that time. Since then, the average hedging ratio has been fluctuating between 11% and 24%.

[Table 2 about here.]

Over the time series, the average log Q does not positively co-vary with the average hedging ratio, either. If anything, most of the more negative values for the average log Q occur during the second half of the sample when the average hedging ratios are higher. The two average time series show a strongly negative correlation at -36%. As such, it is possible that the time-series variation of the average log Q reflects more of the market and industrial trend, than the variation of the average hedging practice.

The sample includes 12 airline companies at the beginning of the sample in 1992. The number of airlines increases with time and reaches the maximum of 25 in 1997 and 1998. Since then, the number of airline companies starts to decline due to a slew of corporate activities and bankruptcy filings. For example, Ccair (CCAR) was acquired in 1999 by Mesa (MESA), which filed for bankruptcy in 2010. Comair (COMR) was acquired by Delta (DAL) in 2000. ExpressJet (XJT) was merged with SkyWest (SKYW) in 2010. World Airways (WLDA) went public in 1995, became a subsidiary of World Air Holdings in 2006, and was later acquired by ATA Holdings. Trans World Airlines (TWA) underwent Chapter 11 restructurings in 1992 and 1995. It filed for a third and final bankruptcy in 2001, and was acquired by American Airlines (AAL). Pinnacle Airlines (PNCL) went public in 2003, filed for bankruptcy protection in 2012, and emerged from the filing in 2013 as a wholly owned subsidiary of Delta. Midwest (MEH) was delisted and acquired by TPG Capital in 2008, which was acquired by Republic Airways (RJET) in 2009. America West (AWA) was merged with US Airways Group (LCC) in 2005. US Airways itself filed for bankruptcy in August 2002 but emerged from it in March 2003. It filed another bankruptcy protection in 2004 and merged with AWA in 2005 while keeping the US Airways name. In 2013, US Airways merged with AMR group, forming the largest airline around the world, American Airlines Group (AAL). AirTran (AAI) went public in 1994 and was acquired by Southwest Airlines (LUV) in 2011. Frontier (FRNT) filed bankruptcy in 2008, was acquired by RJET in 2009, and was then sold to a private equity firm in 2013. Republic Airways went public in 2004, filed bankruptcy in 2016, and was delisted in 2017 before it emerged from bankruptcy protection later. In addition, six companies ended with bankruptcy and terminated their operations — Tower (TOWR), Midway (MDWY), Vanguard (VGDA), ATA Holdings (ATA), FLYi (FLYI, successor of Atlantic Coast Airlines) and Gulfstream (GIGI) filed for bankruptcy in 2000, 2001, 2002, 2004, 2005 and 2010, respectively.

By the end of our sample, the data only contain 10 airline companies in 2016. Among the 10 airlines left standing, four had filed for bankruptcy protection at least once in our sample period but emerged from the protection later: Delta filed for protection in 2005 and emerged in 2007; United filed for protection in 2002 and emerged from it in 2006; American Airlines (AAL) filed for protection in 2011 and emerged in 2013 and merged with US Airways Group; Hawaiian Holdings

(HA) filed for protection in 2003 and emerged in 2005. These frequent occurrence of financial difficulties highlights the dear need for appropriate hedging practices to mitigate the cash flow fluctuation.

3.2. Fuel cost exposures and revenue sensitivities

Table 3 reports summary statistics on the fuel cost exposures. Panel A reports the statistics on fuel cost exposures in percentages of the total operating expense. We are able to collect fuel cost information for 436 of the 451 company-year observations. The fuel cost percentages vary from a low of 0.88% to a high of 54.07%, with a standard deviation of 10.62% and an average of 21.19%. Looking into the time-series variation, we find that the average fuel cost stays below 20% for all years before 2004 but stays above 20% every year since then. The average is 14.31% before 2004 and 29.09% since then, potentially reflecting the higher oil prices in the second half of the sample.

[Table 3 about here.]

In addition to the pooled statistics, we also compute the cross-sectional (CS) statistics of the time-series averages across the 33 airlines and the time-series (TS) statistics of the cross-sectional averages for the 25 years of the sample. The cross-sectional and time-series variations are of similar magnitudes, with a cross-sectional standard deviation of 8.17% and a time-series standard deviation of 8.63%.

Apart from traditional full service network carriers (FSC), a new trend in the airline industry is the rapid growth of low cost value carriers (LCC). These airlines primarily engage point-to-point operations serving short-haul routes with a fleet of only one or two types of aircrafts to streamline maintenance and reduce cost. They tend to provide limited passenger services and focus strongly on price competition with low average fares. Compared with full service carries who can provide luxury services, especially for business classes, these low cost carriers provide the bare minimum of necessity with low price. Accordingly, we expect that these airlines have different cost structures and their revenues show lower sensitivities to market conditions.

To examine how the two types of airlines differ in their fuel cost exposures, we separate the sample into LCC and FSC, and compute the statistics for the two subsamples separately. The classification of LCC is based on the definition and classification of the International Civil Aviation Organization (ICAO). The rest of the sample is classified as FSC. The full sample includes 137 observations on LCCs and 314 on FSCs, with 134 and 302 having available fuel expense data, respectively. The last two rows of Panel A report the summary statistics for the two carrier types. On average, LCCs spend a higher percentage of its operating expense on fuel cost, at 25.40% as compared to the full sample average of 21.19% and the lower average for the FSCs at 19.32%.

In deriving the optimal hedging ratio, we represent the revenue and cost variations relative to an airline's passenger capacity as measured by ASM. Panel B of Table 3 reports the statistics of the fuel cost in cents per ASM. We have both the fuel cost and ASM information on 421 of the company-year observations. The pooled sample has a grand average of 2.64 cents per ASM, and a standard deviation of 2.96 cents. The cross-sectional and time-series variations show similar magnitude, at 1.70 and 1.68 cents, respectively. The statistics for the two carrier types show that the fuel cost per ASM averages higher for LCCs at 2.72 cents, relative to the 2.61 cents for FSCs, potentially because LCCs tend to fly shorter routes and FSCs tend to spend more money in services.

We derive the optimal hedging ratio to minimize the variance of the operating profit per ASM. Panel C of Table 3 reports the summary statistics of the operating profit in cents per ASM. The pooled sample has a grand average of 0.73 cents, relative to a standard deviation of 1.56 cents, more than twice as large as the average profit. The cross-sectional standard deviation of the time-series averages for each firm is 1.02 cents, larger than the time-series standard deviation of cross-sectional averages at 0.65 cents. Comparing the statistics for the two carrier types, we find that the LCCs on average have a higher operating profit per ASM at 0.84 cents than the FSCs at 0.68 cents. Operating profits for LCCs also enjoy smaller variation at 1.27 cents than for FSCs at 1.67 cents.

An airline's optimal hedging ratio depends on its revenue sensitivity to the equity market variation. To estimate the revenue sensitivity to market demand changes, we compute the annual returns on the S&P 500 Index and match them with the revenue changes in cents per ASM for the next calendar year for each airline. Table 4 reports the regression estimates on the loading coefficients based on three different specifications. The first specification ("Pooled") performs the regression on the pooled sample, generating a pooled sensitivity estimate of $\beta^r = 2.62$ cents. Combining this pooled sensitivity estimate to the pooled average of the fuel cost exposure at $\varphi^c = 2.64$ cents results in an average firm-specific exposure coefficient of $\gamma = \beta^r/\varphi^c = 0.99$. The fact that this coefficient is very close to one suggests that the market hedging demand index $\mathcal{H}_t$ is a very close approximation of the optimal hedging ratio for a representative airline company.

[Table 4 about here.]

The second specification ("FFE") adds firm fixed effects to allow for different revenue growth rates for different firms while still using one slope coefficient to capture the average revenue sensitivity. Adding firm fixed effects leads to a slightly lower sensitivity estimate at $\beta^r = 2.36$ cents. Under "Intercept," we report the average of intercept estimates and its standard errors across firms. The sample average of the standard errors is large relative to the sample average of the intercept estimates, indicating that it is difficult to fully identify a separate growth rate for each firm.

The third specification groups the data into two sub-groups based on whether the airline is classified as a LCC or a FSC. We apply the carrier type dummy variable to both the intercept and the slope, and report the estimates in the last two rows of the table. The intercept estimates show that the revenue growth rate per capacity for LCCs is much higher than that for FSCs. On the other hand, the slope estimates suggest that revenue variations for LCCs are less sensitive to the equity market variation. The slope estimate for LCCs at 1.39 cents is less than half of the slope estimate for FSCs at 3.12 cents.

While the sparsity of data makes it difficult to accurately estimate the firm-specific exposure for each airline, we can compute the average firm exposure for the two carrier types. Combining the revenue sensitivity estimates in the last two rows of Table 4 with the corresponding fuel cost exposure estimates in the last two rows of Panel B in Table 3, we compute the average firm exposure coefficients γ for the two types of carriers, at 0.51 for LCCs and 1.19 for FSCs. The higher exposure to the market condition for FSCs mainly comes from their higher revenue sensitivity to the equity market variation, which dictates that FSCs should vary their hedging ratios more with the variation of the market hedging demand index.

4. The value benefit of airline fuel cost hedging

This section analyzes the value benefit of fuel cost hedging for US airlines from several perspectives. First, we estimate the market hedging demand index via a rolling window regression and examine how the market hedging demand for jet fuel cost varies over time. Second, we regress the logarithm of Tobin's Q on the hedging ratio of each firm to estimate the value benefit of hedging in a pooled regression. We first perform this regression unconditionally to replicate the literature finding, and then repeat the regressions conditional on market hedging demand being high and low, respectively, to examine how the market condition on hedging demand influences the value benefit of hedging. Third, we argue that the benefit of hedging does not come from one single practice at any one year, but from consistently following the variation of the market hedging demand. We measure the dynamic optimality of each airline's hedging practice via its time-series correlation with the market hedging demand and examine how the dynamic optimality of each airline's hedging practice is related to the airline's Tobin's Q. Fourth, we trace the source of value benefit of hedging to the airline's operational, investment, and financing behaviors. We end the section with a comparative case analysis of two airlines, which share similarly large average and standard deviation statistics on their hedging ratios, but exhibit sharply different dynamic optimality in terms of their covariation with the market hedging demand index.

4.1. The time variation of the market fuel cost hedging demand

Under our structural setting, the optimal fuel cost hedging ratio depends crucially on the relative composition of demand and supply shocks in the oil price movement. To estimate the demand shock contribution to crude futures movements, we regress daily returns on crude futures (R_t^o) against daily returns on the S&P 500 Index (R_t^d) with a quarterly rolling window,

$$R_t^o = \alpha_t + \eta_t^d R_t^d + e_t. \tag{17}$$

From the rolling-window regression estimation, we construct a time series for the market hedging demand index $\mathcal{H}_t$,

$$\mathcal{H}_t = 1 - \frac{\eta_t^d v_t^d}{v_t^o}, \tag{18}$$

where η_t^d is obtained from the regression slope, v_t^d denotes the rolling-window annualized variance estimator of the stock index return, and v_t^o denotes the rolling-window annualized variance estimator of the crude futures return. The rolling-window length choice balances the need for a short enough window to capture timely variation in the hedging demand and the need for a long enough window to mitigate the effect of estimation error.

Figure 1 plots the time series of the market hedging demand index, which can be interpreted as the optimal fuel cost hedging ratio for a representative airline with a firm-specific exposure of one. The hedging demand shows large time variation from as low as merely 45% to as high as 133%. Demand for hedging more than 100% can happen when crude futures return has a negative loading on the index return ($\eta_t^d < 0$). A negative loading can happen when supply-driven oil movement imposes a negative impact on the aggregate economy. On the other hand, when oil price movements are mostly driven by demand shocks, the regression will generate a strongly positive slope estimate with a high regression R-squared, and the market hedging demand index will be low.

[Figure 1 about here.]

The plot reveals a broad shifting pattern similar to that observed by Sy and Wu (2019) based on options data: Before the 2008 financial crisis, the oil price movements are dominated by supply shocks and the market hedging demand is high, hovering around 100%. Since 2009, demand shocks start to play a larger role in oil price movements, and the hedging demand estimates become much lower. The sample average of the demand index estimates from 1992 to 2008 is about 100%, while the average over the rest of the sample from 2009 to 2016 is 78%.

Sy and Wu (2019) attribute the shift in dynamics to several factors, including the direct impact of the large negative demand shocks from the 2008-2009 financial crises, the indirect impact of the crisis on the monetary policy environment, and the shale revolution in the US that has significantly weakened the pricing power of the Organization of the Petroleum Exporting Countries (OPEC).

Regardless of the sources, the dynamics shift has direct implications on the optimal hedging policy for airlines.

In addition to the broad dynamics shift, the market hedging demand index also shows strong intertemporal variation. Over the whole sample period, the demand index has a sample average of 93%, and a standard deviation of 15%. The strong intertemporal variation of the hedging demand index highlights the dynamic nature of the optimal fuel cost hedging strategy for the airline industry. Hedging ratios that have worked out during one time period can lead to hedging failures during another period when the hedging demand has changed significantly.

4.2. The value benefit of fuel cost hedging under different market conditions

To test whether hedging fuel cost enhances an airline company's value, Carter, Rogers, and Simkins (2006a) regress the logarithm of Tobin's Q of US airline companies from 1992 to 2003 on their hedging ratios, while controlling a long list of firm characteristics. To gain comfort on our data collection and methodology, we replicate their pooled regression with fixed time effects over their same sample period. Table 5 reports the slope coefficient estimates, robust standard errors (in parentheses), and R-squared of the regression under Model 1. The results are similar to theirs. Our R-squared estimate of 49.54% is close to their estimate of 46.27%. Our slope estimate on the hedging ratio is 0.4354, also close to their estimate of 0.3476. Both estimates are statistically significant.

The slope coefficient estimates on other control variables are also similar.[4] In particular, other risk management practices do not show significant impacts on firm value except the fuel pass-

[4] We have excluded credit rating from the control variable list due to a large number of missing values for the rating data. The coefficient estimates on credit rating are insignificant in all their specifications. Dropping the variable from the regression does not significantly alter the regression results on other variables.

through indicator. The airlines with fuel pass-through have agreements with major airline partners or charter arrangements to allow for fuel costs to be passed along to the organization chartering the flight. These agreements reduce the impact of fuel price variation on the airline's profit margin and hence reduces the need for additional fuel cost hedging. Indeed, airlines with pass-through agreements rarely hedge as much. Among our pooled sample of 451 year-company observations, we have recorded 137 observations as having pass-through agreements. While the full-sample average of the hedging ratio is 13%, the sub-sample of observations with recorded pass-through agreements have an average hedging ratio of merely 0.89%. Out of the 137 observations, 126 of them have a hedging ratio of zero. Nevertheless, the slope estimate on the pass-through indicator is strongly negative, suggesting that although the arrangement can reduce an airline's sensitivity to fuel cost variation, it reduces the airline's valuation and therefore may not be the most cost efficient approach for managing fuel cost risk.

[Table 5 about here.]

In Model 2, we apply the same specification to the full sample from 1992 to 2016. The R-squared estimate becomes slightly lower at 49.18%. While remaining statistically significant, the slope estimate on the hedging ratio becomes lower at 0.2628. Therefore, the estimated average value benefit of hedging becomes smaller over the whole sample period.

We conjecture that the reduction in hedging benefit is potentially related to the time variation in the market hedging demand, and in particular to the broad dynamics shift in the oil price movements. Demand shock contribution to the oil price movement is small during the first half of the sample but becomes much larger in the second half, leading to reduced hedging demand and accordingly reduced hedging benefit in the second half.

To test Hypothesis 1 that the value benefit of fuel cost hedging is more significant when the market hedging demand is high than when the market hedging demand is low, we replace the time fixed effects with a market condition dummy variable that classifies the market condition as either high hedging demand ($\mathcal{H}_t \geq 100\%$) or low hedging demand ($\mathcal{H}_t < 100\%$). The dummy variable classifies 250 observations into high hedging demand condition and 201 observations into low hedging demand condition. We apply the dummy variable to all regressors and report the coefficient estimates, standard errors, and separate R-squared estimates under Models 3 and 4, respectively, for the two types of market conditions.

Conditional on high market hedging demand, the sloping estimate on the hedging ratio in Model 3 is 0.388, 48% higher than the unconditional estimate of 0.2628. The slope estimate remains highly statistically significant despite the smaller sample size. By contrast, conditional on low market hedging demand in Model 4, the slope estimate on the hedging ratio becomes negative at -0.0985, and it is no longer statistically significant.

The different value effects of fuel cost hedging under different market conditions highlight the dynamic nature of the optimal hedging policy. The same hedging ratio can enhances firm value when the market hedging demand is high, but can become even harmful when the hedging demand is low. It is thus crucially important for an airline company to accurately estimate the demand contribution in oil futures price movement so that the company can optimally update its hedging ratio. Luckily, the demand contribution can be determined via a variance decomposition on the crude futures return, and due to the well-documented and strong volatility cluttering behavior, forecasting future variance and covariances can be done much more accurately than forecasting future directions of oil price movements.

4.3. Value maximization at optimal hedging ratio

If there exists an optimal fuel cost hedging ratio for an airline, the airline's firm value should not increase monotonically with its hedging ratio, but rather the relation should exhibit a hump shape, with the maximum value achieved at the optimal hedging ratio. In this sense, the linear regressions reported in Table 5 are misspecified. To examine whether there exists such a hump shape, we perform conditional local linear regression of the log Q, $\ln Q_{t,i}$, on the company's hedging ratio $h_{t,i}$, conditional on the market hedging demand index being around the high-demand region and the low-demand region, respectively.

Based on the distribution of the market hedging demand index, we set the centers of the two regions in the conditional regression at 100% and 70%, respectively, corresponding to two modes of the empirical distribution of the market hedging demand. The local linear regression is performed with a Gaussian kernel, with the bandwidth chosen to be twice as large as the default choice for a smoother relation. We incorporate the conditional weighting based on the distance of each data point to the two centers of the market hedging demand index. The conditional weights are also computed based on a Gaussian kernel, with the bandwidth set to the default choice. Furthermore, since airlines with passthrough agreements have little fuel cost hedging need, we exclude the observations with recorded pass-through agreements from the conditional regression estimation. Figure 2 plots the estimated relations, with the solid line denoting the relation conditional on high market hedging demand ($\mathcal{H}_t = 100\%$) and the dash-dotted line denoting the relation conditional on low market hedging demand ($\mathcal{H}_t = 70\%$).

[Figure 2 about here.]

Both lines indeed show hump shapes, but with the maximum of the hump happening at different hedging ratio levels. Conditional on high market demand $\mathcal{H}_t = 100\%$, the firm value reaches its maximum at a hedging ratio close to 100% hedging. Indeed, based on our derived optimal hedging ratio relation, $h^*_{t,i} = (1-\gamma_{t,i}) + \gamma_{t,i}\mathcal{H}_t$, when the market hedging demand is 100%, the optimal hedging ratio for all airlines is 100% regardless of its firm-specific exposures.

Conditional on low market demand $\mathcal{H}_t = 70\%$, the firm value reaches its maximum at a much lower hedging ratio of 68%. When the market hedging demand deviates from 100%, the optimal hedging ratio for an airline becomes a weighted average of 100% and the market hedging demand index, with the weight determined by the airline's firm-specific exposure coefficient $\gamma_{t,i}$. The estimated optimal hedging ratio of 68% corresponds to an average firm exposure of $\gamma = 1.07$.

The presence of a hump-shaped relation in both market conditions corroborates our arguments that for fuel cost hedging, it is not the more the better, but rather there exists an optimal hedging ratio that varies strongly with market conditions. Deviating from this optimal hedging ratio at any point in time, from either direction, can reduce an airline's valuation. Therefore, the optimality of an airline's hedging policy is not defined by how much it hedges, but by how much it deviates from the optimal hedging ratio at any point in time.

Figure 2 also shows that the maximum valuations happen at the far right side of the sample range of actual hedging ratios, suggesting that most firms at most times hedge below the optimal amount. Indeed, out of the 451 company-year observations, only one observation has hedging ratio greater than 100% and only 13 observations have hedging ratios over 68%. The one-sidedness of the actual hedging ratio distribution allows the regressions in Table 5 to capture a seemingly monotonic relation.

Several reasons contribute to the prevalent under-hedging behavior. The first is related to the strict requirement for the use of hedge account in financial reporting.[5] To avoid artificial fluctuation due to accounting treatment changes, firms tend to hedge below some conservative projections of their future notional exposures. Another reason relates to the aversion to the uncertainty around the hedging result. With drastic dynamics changes and stumbling fuel hedging experience over the last two decades, managers tend to choose to lower subsequent hedging activities when facing uncertain hedging results or previous hedging failures. A third reason is the significant cost for initiating and maintaining a hedging program (Brown (2001)). Finally, since the objective of hedging is to reduce cash flow variation over a long time period, it is inherently difficult to accurately measure the effectiveness of a hedging program over a short sample period. Managers can face large pressures from the board and from investors when a firm endures a hedging loss at any given year even if the hedging program is indeed variance minimizing in the long run. Using derivative positions of upstream oil and gas firms, Kumar and Rabinovitch (2013) find a positive relation between hedging intensity and factors that amplify the power of chief executive officers.

4.4. Dynamic optimality of fuel cost hedging and firm valuation

The nature of hedging is such that its benefit cannot be measured with one single realization, nor can its objective be met with one single great hedging act. To achieve the variance minimizing objective of hedging, one must maintain a dynamically optimal policy consistently and persistently over a long period of time. In this sense, the magnitude of a hedging ratio at any given point in time is not a sufficient metric for the optimality of a hedging strategy. For a hedging policy to be dynamically optimal, it must co-vary positively, consistently, and persistently with the variation of the market hedging demand.

[5] Statements of Financial Accounting Standards (SFAS) No. 133 (effective since June 1999) has strict criteria for using hedge account, which affects whether the derivative positions should be marked to market in the report.

We measure the dynamic optimality of an airline's hedging strategy with the time-series correlation ρ_i of its hedging ratio with the market hedging demand index. To test Hypothesis 2 that the more dynamically optimal a company's hedging policy is, the more value enhancing is its hedging, we perform a pooled regression of the logarithm of Tobin's Q against the dynamic hedging optimality measure,

$$\ln Q_{i,t} = a + b\widehat{\rho}_i + e_{i,t}. \tag{19}$$

Out of the 33 companies, 11 companies have never hedged. We exclude these 11 companies from the regression, resulting in a sample of 324 company-year observations for 22 companies. For companies with very few number of observations, the correlation estimate can become extreme and noisy, exacerbating the errors-in-variable issue in the regression. We mitigate their impacts via two remedies. First, for companies with few observations, we patch the hedging ratio series with average observations from positively co-moving companies during their common sample period. Specifically, we choose companies with 21 or more annual observations as the reference series, and measure the correlations between their hedging ratios and the hedging ratio of the company in question over the common sample period. We take the reference series with positive correlation estimates to form a correlation-weighted average hedging ratio series and use this series to fill in the missing values of the target company's hedging ratio. We then measure the correlation between the patched hedging ratio series and the market hedging demand index and use it as the dynamic optimality measure. To reduce the impact of the patched data in the dynamic optimality estimate, we give each patched data point one-fifth of the weight of the original data point. For companies with very few observations, this process tends to reduce the absolute magnitude of the correlation estimate toward zero, thus mitigating their impact to the relation estimation. Furthermore, we perform the regression in (20) in the pooled company-year data sample so that companies with more years of observations naturally have a higher weighting.

Table 6 reports the regression results in the first row under Model 1 ("Pooled"). The slope estimate is $b = 0.388$ with a robust standard error estimate of 0.089. The estimate is highly positive and strongly statistically significant, confirming our hypothesis that the more dynamically optimal a company's fuel cost hedging policy is, the higher is the company's valuation.

[Table 6 about here.]

Figure 3 plots the relation between the dynamic hedging optimality measure ρ_i and the average logarithm of Tobin's Q for each of the 22 companies. Each circle represents the average relation for one company, with the size of the circle made proportional to the number of observations for that company. The solid line denotes the fitted relation.

[Figure 3 about here.]

For companies that do not hedge at all, we treat their hedging strategy as having a zero correlation with the market hedging demand index and represent their average logarithm of Tobin's Q with a diamond in Figure 3. The diamond sits right on top of the fitted relation. For illustration, Figure 3 also labels the tickers for the three airlines with the highest average hedging ratio, the last three companies listed in Table 1. Among the three airlines, the hedging ratios for Southwest (LUV) show positive comovements (15%) with the market hedging demand index and enjoy a higher average log Tobin's Q at 0.18. The hedging ratios for Delta (DAL) and Alaska (ALK) both show negative correlation with the market hedging demand index, at -14% and -50%, respectively. Their average log Tobin's Q are also lower, at -42% and -38%, respectively.

Out of the 22 companies, nine have positive correlation estimates, suggesting that their hedging ratios positively co-vary with our estimated market hedging demand. More surprising are the observations for the remaining 13 companies, whose hedging ratios show negative co-movement with the market hedging demand. If the revenue sensitivity to market demand and the cost exposure in cents per available seat mile are positive and stable over time, a positive correlation estimate that is less than 100% can be regarded as sub-optimal, but a negative correlation estimate would indicate the opposite of any optimality.

We classify the companies into three categories: (i) the nine companies with positive dynamic optimality estimates, (ii) the 13 companies with negative optimality estimates, and (iii) the 11 companies that do not hedge at all. We compute the average logarithm of Tobin's Q for the three groups. The whole sample grand average of the log Tobin's Q is -0.2117. The nine companies with positive optimality estimates have an average of -0.0678, much higher than the grand average, whereas the 13 companies with negative optimality estimates have an average of -0.3056, much lower than the grand average. The mean log Tobin's Q difference between the two groups are strongly statistically significant, with a t-statistic of 4.04. Importantly, the 11 companies that do not hedge at all have an average log Tobin's Q of -0.1969, close to the grand average, but is much higher than the average log Q for the companies with negative optimality estimates. For hedging policies with negative dynamic optimality, the airlines are better off not hedging at all.

It is staggering to observe that among the airlines that perform fuel cost hedging, more than half of them do so with variations running against the variation of the market hedging demand. This observation reflects the inherent difficulty in understanding the key determinants of a successful hedging policy. In a survey of Fortune 500 companies, Dolde (1993) finds that a significant portion of the firms in the survey determine the degree of hedging based not on their forecasts of the variance decomposition, but on their directional views of the underlying risk, thus effectively turning the risk management practice into a speculation exercise. Given the inherent difficulty in directional forecasts, the results of the speculation are more often than not unsatisfactory.

The Tobin's Q can vary strongly over time due to market conditions. The pooled regression in Model 1 of Table 6 can generate biased estimates when different companies span over different sample periods. Model 2 ("FTE") in Table 6 controls for this market condition variation by adding a year dummy variable to capture the fixed time effect on firm value. Compared to Model 1, the R-squared estimate increases greatly from 5.75% to 23.8%, due to the added flexibility of the fixed time effect, but the story remains the same. Under intercept we report the average estimates and standard errors on the year dummy variable. The average of year fixed effects is similar to the pooled intercept estimate, but with much larger standard errors. The slope estimate at 0.406 is also similar to the estimate from the pooled regression in Model 1, and remains strongly statistically significant with a robust standard error estimate of 0.081.

Linking the average dynamic optimality of a hedging practice over the whole sample period to the average firm valuation during the same sample period is illuminating in showing the relation between the long-run dynamic optimality of an airline's hedging practice and its average performance, but it also raises the issue of endogeneity. To mitigate the endogeneity concern, we also perform a rolling-window estimation of the airline's dynamic optimality and link this rolling optimality estimate to the airline's logarithm of Tobin's Q for next year with a cross-sectional forecasting regression,

$$\ln Q_{i,t+1} = a_t + b_t \widehat{\rho}_{t-9,t,i} + e_{i,t+1}. \tag{20}$$

To capture an airline's repeated"habit" rather than its single "act," we use a reasonably long rolling-window of 10 years to estimate the dynamic optimality of its hedging practice. For airlines with missing data within the 10-year rolling window, we use the same patching approach as described before to reduce the impact of small sample, with the references constructed by airlines with the full 10-year data for the rolling window. We perform the rolling-window forecasting cross-sectional regression from 2002 to 2016 for 15 years. Under Model 3 ("RWF"), Table 6 reports the time-series averages of the rolling-window forecasting regression coefficient estimates, the standard errors of the averages in parentheses, and the time-series average of the R-squared estimates. The average of the R-squared estimates at 19.40% is slightly lower than that for Model 2 with the fixed year effect. The average of the slope estimates at 0.378 is close to the pooled regression estimates in Models 1 and 2. The standard error of the average is 0.118. The average slope coefficient remains significantly positive, confirming the robustness of the relation.

4.5. Trace value creation to operation, investment, and financing behaviors

Despite some limitations (Bartlett and Partnoy (2018)), Tobin's Q provides a simple way of summarizing a firm's value creation relative to its replacement cost, analogous to the perspective of the residual income model for firm valuation (Magni (2009)). The deviation of a firm's value from its replacement cost reflects the present value of the company's future residual income, i.e., gross income net of its cost of capital. Hedging and other corporate decision affect the present value by altering its future residual income stream and its risk. In our particular application to the fuel cos hedging of the airline industry, by minimizing the variation of the company's operating profit, a dynamic optimal fuel cost hedging strategy can reduce the company's financing cost due to the reduced probability of financial distress. The reduced financing cost not only boosts the company's future residual income but also reduces the discount rate, contributing to a present value of residual income and accordingly a higher Tobin's Q measure.

In this section, we trace the value effect of a dynamically optimal fuel cost hedging strategy to the airline's operation, investment, and financing behaviors. First, we examine the effect of hedging dynamic optimality on the airline's return on book asset (RoA) behavior. We compute the full-sample mean, standard deviation, and the information ratio (the ratio of mean to standard deviation) of the return on asset for each airline, and regress them against the full-sample dynamic optimality estimate for that airline. Table 7 reports the regression results in Panel A. The regression on the mean return on asset generates a highly positive and strongly statistically significant slope estimate at 6.077, with a standard error of 0.9, and an R-squared of 12.33%. In performing the regression, we represent the return on asset in percentages and keep the dynamic optimality measure in decimals. The regression estimates suggest that when the dynamic optimality of the fuel cost hedging strategy improves from purely random ($\rho = 0$) to fully optimal ($\rho = 100\%$), the mean return on asset is expected to increase by 6.077% from 5.915% (the intercept) to more than double at 11.996%.

[Table 7 about here.]

Meanwhile, the regression on the standard deviation of the return on asset generates a highly negative and strongly statistically significant slope estimate at -5.567, with a standard error of 0.658. The regression generates an R-squared estimate of 11.59%. When we divide the mean by the standard deviation to generate the information ratio measure and regress it on the dynamic optimality measure, the regression R-squared estimate almost doubles at 21.99%, and the slope estimate at 1.947 is strongly statistically significant with a standard error of 0.227. In particular, the regression estimates suggest that as the dynamic optimality of the hedging strategy increases from purely random ($\rho = 0$) to fully optimal ($\rho = 100\%$), the information ratio of the return on asset increases drastically from 1.206 to 3.153.

By design, a dynamically optimal hedging strategy is supposed to reduce the variation in return on asset. Our regressions in Panel A of Table 7 confirm this effect of fuel cost hedging. Somewhat surprisingly, we find that optimal fuel cost hedging is also associated with significantly higher mean return on asset. We contribute the mean return effect to several potential sources. First, when an hedging program is ineffective, the airline becomes more likely to resort to ex post operational hedging practices, which can induce extra costs that reduce the airline's average profits. Second, hedging activities themselves can be costly. This includes the personnel and infrastructure cost of setting up and maintaining the hedging program, as well as the transaction cost for entering and exiting hedging positions. In particular, some banks may pitch over-the-counter contracts to the airlines for their "customizable" feature, but such customization can benefit the banks more for their hefty fees than for better fitting of the airline's hedging needs. The less successful is a hedging program, the more reliant the airline tends to become on their investment banks for such costly consultations and customizations. Therefore, when a hedging program is not successful in reducing the return on asset variation, it may end up showing a negative impact on the company's profits due to its costly setup and transactions.

Airlines usually employ four broad types of instruments to hedge their fuel cost exposure: futures, swaps, forwards, and options. Our optimal hedging design proposes to use the highly liquid oil futures contracts as the primary hedging instruments. One can also use liquid over-the-counter swap contracts to hedge oil exposures for a longer term. Forward contracts tend to be more costly than futures, and option contracts tend to have much wider bid-ask spreads under the underlying futures. Custom-designed option contracts usually have exorbitant spreads built in and can be the most expensive in terms of trading costs. To examine how a firm's performance and valuation is related to the hedging instruments types they choose, we have gone through the 10-K reports to determine the percentage of contracts from each type. The information is far from complete and accurate as airlines do not always break down the details of their hedge in their reports. We have information on the percentages of futures, swaps, forwards, and options for 435, 359, 443, and 362 of the company year observation. Measuring the simple pooled correlation shows that the airline's Tobin's Q is positively correlated with futures and swap usage, at 2.25%

and 5.69%, respectively, but negatively correlated with forwards and options usage, at –1.69% and –16.85%, respectively.

Figure 4 estimates the effects of the dynamic optimality of the fuel cost hedging on the return on asset behavior via local linear regressions. The three lines plot the effects of the dynamic optimality estimates ρ_i on the mean (solid line, scale on the left), the standard deviation (dashed line, scale on the left), and the information ratio (dash-dotted line, scale on the right) of the return on asset. The three lines highlight the combined effects of optimal fuel cost hedging on both improving mean returns and reducing the return variation.

[Figure 4 about here.]

Via local linear regressions, Figure 4 reveals the nonlinearities in the relations that are not captured from the pooled regressions in Table 7. In particular, we observe that the estimated relations become stronger as the hedging practice is closer to optimality. The slopes for all three lines are very much flat at the region of negative optimality, but become much stepper when the dynamic optimality estimates become positive. This observation suggests that the closer the airline's hedging policy is to optimality, the more benefit it can gain from further refining its policy.

Another often argued benefit of hedging is that by reducing the operational risk and financing cost, the firm can take on more investment opportunities. This expansion effect does not necessarily increase the firm's Tobin's Q. Indeed, some (e.g., Dybvig and Warachka (2015)) even argue that an overly high Tobin's Q may be an indicator of under-investment. To examine this potential investment effect, we measure each airline's average growth rate in passenger ASM capacity and examine how the growth rate is related to the airline's fuel cost hedging dynamic optimality. Model 4 in Table 7 reports the regression results. The regression has a very low R-squared estimate at 0.55%. The slope estimate is positive but not statistically significant, suggesting that airlines with dynamically optimal hedging strategies have not expanded significantly more in capacity than those with negative optimality estimates. The airline industry is an industry with thin profit margin and high fixed cost. Rapid capacity expansion is a risky choice even for airlines with optimal hedging practices. Indeed, a recent analysis by Stalnaker, Usman, Taylor, and Alport (2018) shows that a major driver of the recent sustained profitability for airlines is the added discipline in keeping their capacity growth below GDP growth.

With capacity expansion a risky choice, an airline with lower financing cost can seek to use more debt financing to replace its equity investment and accordingly increase its return on equity. To test whether the hedging optimality affects an airline's financing behavior, Model 5 in Table 7 uses the long-term debt to total asset as the dependent variable and regresses it against the dynamic optimality measure. In this case, the slope estimate is positive and statistically significant. The significantly positive slope estimate suggests that with dynamically optimally hedging, an airline can afford a higher leverage ratio while maintaining its financial viability.

Finally, Model 6 in Table 7 directly examines the relation between hedging optimality and the credit rating as a proxy for the airline's financing cost. The credit rating data are from Standard & Poor's long-term credit rating on the airlines' senior debt. The original ratings are in letter grades. Compustat converts the letter rating into numerical values, with a smaller number representing a higher credit rating, from a value of 2 for AAA rating to a value of 27 for D rating. Regressing the numerical credit rating on the dynamic optimality measure generates a negative and strongly statistically significant slope estimate at -2.124, with a standard error of 0.372 and an R-squared estimate of 9.49%. Therefore, on average, airlines with more dynamically optimal hedging practices not only employ higher leverage, but also do so with higher credit ratings.

4.6. A tale of two airlines

To better understand the hedging practices of different airline companies and their relations with the company's valuation, we compare two large airline companies, Southwest (LUV) and Delta (DAL). The data for the two airlines are available for the full sample period. The two companies are among the highest in both the average hedging ratio and their intertemporal variation. The hedging ratios for Southwest average the highest at 43%, and also with the highest time-series variation, with the standard deviation estimate at 34%. The hedging ratios for Delta share similar summary statistics. The sample average is at 33% and it standard deviation 32%. Therefore, based on the summary statistics, the two airlines share the very similar hedging behaviors.

Nevertheless, when we estimate the hedging ratio's time series correlation with the market hedging demand index, we find that the two airlines are at the very opposite ends of the spectrum in their fuel cost hedging dynamic optimality. Southwest's hedging ratios positively co-vary with the market hedging demand index, with a full-sample dynamic optimality estimate of 15%, whereas Delta's hedging ratios negatively co-vary with the market hedging demand index, with a full-sample dynamic optimality estimate of -14%. The two airlines also show large differences in the firm valuation in terms of Tobin's Q. The logarithm of the Tobin's Q averages at 18% for Southwest but much lower at -42% for Delta.

Figure 5 compares the hedging ratio behavior between the two airlines, with Panel A plotting the hedging ratio time series for Southwest and Panel B plotting the hedging ratio time series for Delta. In both panels, the dashed line plots the variation of the market hedging demand index as a reference. Panel A shows that Southwest's fuel cost hedging positions are insignificant before 1998. Since then, Southwest quickly built up its hedging positions from 33% in 1998 to above 80% in 1999. The airline's hedging positions remained at high levels and varied within a narrow range until 2008, when the airline cut its hedging positions drastically, coinciding with the drop in our estimated market hedging demand. Southwest's hedging ratios stayed low until 2015, when the airline started to increase its hedging ratio again, just as our estimated market hedging demand also started to recover from its lows. Since Southwest started its hedge program in earnest in 1998, its hedging ratios match very well overall with our estimated hedging demand. If we start the sample in 1999, the correlation estimate between the two series is as high as 66%.

[Figure 5 about here.]

According to the accounting reports that we have collect between 1999 and 2016, fuel cost hedging has saved Southwest a total of $1 billion. Although it has some ups and downs recently, the hedging program has gained competitive advantage for Southwest during its aggressive expansion. The managers of Southwest see their hedging program as a strategic advantage over time and are devoted to maintain an active hedging practice in the future.

While Southwest keeps its hedging insight as a tight secret, some of the comments reveal its appropriate focus on the variance decomposition rather than directional speculation as suggested by many other companies in Dolde (1993)'s survey. For example, in raising its hedging ratio from 15% in 2012 to 43% in 2013, the 10-K report states that "although jet fuel prices were less volatile in 2013 than in some previous years, they remain at high levels and continue to be subject to extreme volatility based on a variety of factors."

Despite the similar summary statistics, the sample path of Delta's hedging ratios in Panel B of Figure 5 looks quite different from the sample path of Southwest in Panel A. Similar to Southwest, Delta started serious fuel cost hedging in 1998, with a hedging ratio of 80% for both 1998 and 1999. While the airline benefited from the early hedges, the company started to reduce their hedging positions based on directional oil forecasts. Delta decreased its hedging ratio to 32%

in 2003 and further settled all of the fuel hedge contracts prior to the scheduled settlement dates in February 2004. As Delta stated in its annual report, the key consideration in its hedging decision is their forecast on where the oil price will go, and their directional forecast did not work out well.[6] On September 14, 2005, Delta filed bankruptcy, citing rising fuel costs. After emerging from bankruptcy in 2007, Delta rebuilt its hedging position. In the summer 2008, when the fuel price reached a record high, Delta added fuel hedges to protect against further escalating fuel costs. However, Delta made another wrong directional bet. Fuel prices fell dramatically thereafter in 2008, resulting in a $1.4 billion fuel hedge loss at year end. The hedging loss was further aggravated in 2009 by the weakened demand for air travel.

Delta reduced hedging in 2009 potentially due to the loss in 2008. It kept an approximate 38% hedging ratio between 2010 and 2012, when the fuel price started to pick up again from $2.33 per gallon to $3.25 per gallon. Without any detailed explanation, Delta aggressively used fuel hedging in 2013 and 2014 (105% and 82%). After repeated failures, Delta restructured its fuel hedging by deferring settlement of a portion of hedge portfolio and terminating early some of these deferral transactions in 2015 and 2016. Overall, during this period, Delta's hedging decisions have experienced large swings, but without apparent good reason. Our rolling-window estimates on Delta's hedging dynamic optimality are actually positive in the early half of the sample but the estimates become increasingly negative since 2012 as they swing their practices wildly. In 2012, Delta even acquired an oil refinery, Monroe Energy, as part of its strategy to mitigate the jet fuel cost and maintain supply sufficiency to the New York operations. The Monroe acquisition would look tangential in our optimal hedging design, and in practice it did not save much cost for Delta.

When we look into the hedging instruments employed by the two airlines, we find that South-

[6]DAL addressed this action in their 2004 10-K file that "Oil prices do not decline significantly... Our business plan assumes that the average jet fuel price per gallon in 2005 will be approximately $1.22. ... We have no hedges or contractual arrangements that would reduce our jet fuel costs below market prices".

west reports mostly usage of swaps whereas the largest reported percentage for Delta is the much more costly options contracts. On top of the unexplained swing in their hedging ratio, Delta's choice of using options contracts can add an extra layer of cost that cuts further into Delta's bottom line.

The financial performances of the two airlines are in line with the dynamic optimality of their respective fuel cost hedging practices. Just as dynamically optimal and consistent as Southwest's fuel cost hedging program, the company has delivered profits consistently over time. Indeed, by the end of our sample period in 2016, the company has managed to be profitable for 44 consecutive years. Over our sample period from 1992 to 2016, the company's revenue has grown from $1.68 billion to $20.43 billion, with an annual compounding growth rate of nearly 11%. Its net income has growth from $104 million in 1992 to $2.24 billion in 2016, with an annual compounding growth rate of nearly 14%. By contrast, Delta's financial performance is much more uneven. Over the 25-year period of our sample, Delta's net income is negative in 11 years. Compared to Southwest, Delta's bottom line shows much more volatility.

5. Concluding Remarks

As a major energy source, crude oil plays a vital role in the proper functioning of the modern economy. Crude oil price fluctuates in response to both demand and supply shocks. Major events and structural changes can induce large variations in the magnitude of the shocks, as well as their relative contribution to the oil price movements. Seemingly identical oil price movements with different underlying driving forces can have vastly different implications for the aggregate economy, and for risk management practices across different industries.

This paper examines the implications of oil price dynamics changes on the fuel cost hedging practice in the airline industry. Crude supply shocks represent unexpected and harmful shocks to the airline industry. When crude price movements are dominated by supply shocks, it is prudent to hedge the crude price variation via crude futures contracts to mitigate excess volatility in the bottom line of the industry. On the other hand, when crude price movements are dominated by demand shocks, fully hedging the fuel cost variation becomes less desirable, because demand-driven crude price movements tend to positively co-move with demand for the airline travel and cargo transport. The co-movement makes revenue fluctuations natural hedges of the fuel cost variation, reducing the airline's net risk exposure. This paper decomposes the crude futures movement into demand and supply shocks and derives the optimal fuel cost hedging policy for an airline company as a function of the company's revenue sensitivity to the demand shocks, the company's fuel cost exposure per available seat mile capacity, and the relative demand shock contribution to the crude futures movements. Timely identification of demand shock contribution to oil price movements allows a company to dynamically update its fuel cost hedging to minimize the volatility in its operating profits.

We use a rolling-window regression to estimate the time-varying demand contribution to oil price movements. With the estimation results, we propose to create a market hedging demand index that captures the time variation of the airline industry's overall fuel cost hedging demand due to variations in the oil price dynamics. We show that when the market hedging demand index is high, hedging fuel cost can significantly increase airline's firm value; however, the value benefit completely disappears when the market hedging demand is low. Via conditional local linear regressions, we are able to identify a hump-shaped relation between airlines' hedging ratios and their Tobin's Q, where the top of the hump can be regarded as pinpointing the optimal hedging ratio. The pinpointed optimal hedging ratio is indeed high when our estimated market hedging demand is high, and low when the market hedging demand is low.

It is fundamentally important to realize that the hedging decision is a dynamic one and the variation of the optimal hedging ratio depends on the variation of the demand shock contribution to oil price movements. It is equally important to realize that the success of a hedging program is not determined by one single great act, but relies on being consistently and persistently co-varying with the market hedging demand. The former realization can help airline companies to explain their past unexplained hedging losses and help them to realize the benefit of fuel cost hedging when hedging is the most needed. The latter realization urges airlines to maintain a consistent and optimal hedging policy without making sudden changes based on the accounting hedging losses over a short period of time. We propose a dynamic optimality measure for an airline's fuel cost hedging practice based on the time-series correlation between the airline's hedging ratio and our estimated hedging demand index. We find that the more dynamically optimal an airline's hedging practice is, the more value accretion the firm enjoys from its fuel cost hedging program. By contrast, for airlines with negative dynamic optimality estimates, their average Tobin's Q is even lower than the average for airlines that do not hedge at all. Hedging practices with negative dynamic optimality are not only unsuccessful in reducing the volatility of the airline's return on asset, but also harmful to their average profitability.

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Table 1
Summary statistics of fuel cost hedging and valuation across airline companies

Name	Ticker	Hedging ratio				Log Tobin's Q				Sample		
		Mean	Stdev	Min	Max	Mean	Stdev	Min	Max	Start	End	Years
Ccair	CCAR	0.00	0.00	0.00	0.00	0.22	0.51	-0.37	1.09	1992	1998	7
Comair	COMR	0.00	0.00	0.00	0.00	0.53	0.36	0.04	1.03	1992	1998	7
Expressjet	XJT	0.00	0.00	0.00	0.00	-0.50	1.18	-2.37	0.77	2002	2009	8
Great Lakes	GLUX	0.00	0.00	0.00	0.00	-0.20	0.38	-1.12	0.25	1994	2014	21
Mair	MAIR	0.00	0.00	0.00	0.00	-0.51	1.04	-2.31	0.76	1992	2006	15
Mesa	MESA	0.00	0.00	0.00	0.00	-0.30	0.44	-0.92	0.86	1992	2008	17
Midway	MDWY	0.00	0.00	0.00	0.00	-0.32	0.27	-0.54	0.04	1997	2000	4
Skywest	SKYW	0.00	0.00	0.00	0.00	-0.35	0.53	-1.15	0.73	1992	2016	25
Tower Air	TOWR	0.00	0.00	0.00	0.00	-0.13	0.24	-0.31	0.30	1993	1998	6
Vanguard	VGDA	0.00	0.00	0.00	0.00	0.70	0.40	0.21	1.21	1995	2000	6
World Air	WLDA	0.00	0.00	0.00	0.00	-0.24	0.25	-0.60	0.23	1995	2005	11
Trans World	TWA	0.01	0.02	0.00	0.04	-0.34	0.11	-0.47	-0.20	1995	1999	5
Allegiant	ALGT	0.01	0.03	0.00	0.10	0.65	0.20	0.32	0.92	2006	2016	11
Pinnacle	PNCL	0.01	0.03	0.00	0.10	-0.04	0.67	-0.69	1.18	2003	2011	9
Republic	RJET	0.01	0.02	0.00	0.07	-0.25	0.17	-0.46	0.02	2004	2015	12
Global	ATA	0.03	0.07	0.00	0.23	-0.34	0.13	-0.53	-0.10	1993	2003	11
Flyi	FLYI	0.05	0.12	0.00	0.40	0.14	0.75	-1.58	0.82	1993	2004	12
Frontier	FRNT	0.06	0.10	0.00	0.34	-0.16	0.34	-0.88	0.53	1994	2007	14
Midwest	MEH	0.07	0.07	0.00	0.21	-0.10	0.78	-1.35	0.84	1995	2006	12
Gulfstream	GIGI	0.07	0.12	0.00	0.20	0.11	0.26	-0.18	0.33	2007	2009	3
Spirit	SAVE	0.08	0.14	0.00	0.35	0.48	0.46	0.10	1.19	2011	2016	6
Northwest	NWA	0.11	0.17	0.00	0.60	-0.47	0.70	-2.51	0.17	1994	2007	14
US Airways	LCC	0.11	0.11	0.00	0.30	-0.46	0.50	-1.92	0.01	1992	2012	21
America West	AWA	0.13	0.16	0.00	0.42	-0.44	0.20	-0.78	-0.18	1992	2004	13
United	UAL	0.18	0.19	0.00	0.75	-0.64	0.64	-2.12	0.08	1992	2016	25
Airtran	AAI	0.19	0.17	0.00	0.52	0.19	0.40	-0.32	1.38	1994	2010	17
Jetblue	JBLU	0.20	0.13	0.05	0.40	-0.07	0.34	-0.53	0.53	2002	2016	15
American	AAL	0.22	0.15	0.00	0.48	-0.41	0.27	-0.94	0.25	1992	2016	25
Hawaiian	HA	0.25	0.17	0.00	0.50	-0.43	0.29	-0.93	0.28	1995	2016	22
Virgin	VA	0.31	0.06	0.27	0.35	0.37	0.36	0.11	0.62	2014	2015	2
Delta	DAL	0.33	0.32	0.00	1.05	-0.42	0.27	-0.98	0.05	1992	2016	25
Alaska	ALK	0.35	0.17	0.00	0.50	-0.38	0.36	-0.85	0.51	1992	2016	25
Southwest	LUV	0.43	0.34	0.00	0.95	0.18	0.41	-0.56	1.00	1992	2016	25

Entries report the summary statistics, including the mean, standard deviation (Stdev), minimum, and maximum, of the hedging ratio and the logarithm of Tobin's Q for each airline. The airlines are sorted on the mean log hedging ratio. The last three columns report the starting year, the ending year, and the number of years in the data for each company.

Table 2
Summary statistics of fuel hedging and valuation across time

Year	Hedging ratio				Log Tobin's Q				No. of
	Mean	Stdev	Min	Max	Mean	Stdev	Min	Max	Companies
1992	0.06	0.11	0.00	0.28	0.00	0.38	-0.43	0.86	12
1993	0.05	0.09	0.00	0.28	0.08	0.45	-0.55	0.83	15
1994	0.04	0.12	0.00	0.50	-0.24	0.29	-0.70	0.42	19
1995	0.03	0.09	0.00	0.45	0.05	0.54	-0.58	1.38	24
1996	0.02	0.05	0.00	0.22	-0.08	0.35	-0.44	0.62	24
1997	0.04	0.07	0.00	0.23	0.04	0.38	-0.43	0.85	25
1998	0.11	0.21	0.00	0.80	0.10	0.54	-0.88	1.12	25
1999	0.16	0.28	0.00	0.86	-0.11	0.40	-0.61	0.70	22
2000	0.16	0.23	0.00	0.80	-0.10	0.53	-0.69	1.00	21
2001	0.15	0.20	0.00	0.60	-0.28	0.60	-1.89	0.75	19
2002	0.23	0.25	0.00	0.83	-0.53	0.74	-2.12	0.74	21
2003	0.13	0.21	0.00	0.82	-0.38	0.74	-2.10	1.18	22
2004	0.14	0.22	0.00	0.85	-0.42	0.74	-1.92	0.89	22
2005	0.13	0.19	0.00	0.70	-0.56	0.83	-2.51	0.37	20
2006	0.18	0.23	0.00	0.95	-0.25	0.42	-1.19	0.56	20
2007	0.13	0.18	0.00	0.70	-0.46	0.42	-1.28	0.44	19
2008	0.15	0.17	0.00	0.50	-0.45	0.61	-2.37	0.80	17
2009	0.18	0.20	0.00	0.50	-0.45	0.49	-1.72	0.52	16
2010	0.24	0.21	0.00	0.54	-0.40	0.34	-0.86	0.59	14
2011	0.15	0.17	0.00	0.50	-0.49	0.36	-0.94	0.32	14
2012	0.17	0.20	0.00	0.50	-0.48	0.45	-1.12	0.54	13
2013	0.22	0.32	0.00	1.05	-0.23	0.60	-1.15	0.93	12
2014	0.20	0.25	0.00	0.82	0.15	0.60	-0.93	1.19	13
2015	0.18	0.21	0.00	0.63	0.11	0.40	-0.64	0.92	12
2016	0.17	0.25	0.00	0.63	0.18	0.30	-0.26	0.73	10

Entries report the cross-sectional summary statistics, including mean, standard deviation (Stdev), minimum, and maximum of the hedging ratio and the logarithm of Tobin's Q at each year from 1992 to 2016. The last column reports the number of airline companies included in our sample on each year.

Table 3
Summary statistics of airline fuel cost exposures

Statistics	Mean	Median	Stdev	Min	Max	Nobs
Panel A. Fuel cost in percentages of total expense						
Pooled	21.19	17.79	10.62	0.88	54.07	436
CS	20.73	20.13	8.17	8.90	45.85	33
TS	22.00	20.31	8.63	11.87	36.51	25
LCC	25.40	21.80	11.11	9.15	54.07	134
FSC	19.32	15.76	9.85	0.88	42.58	302
Panel B. Fuel cost in cents per ASM						
Pooled	2.64	1.93	2.96	0.07	50.41	421
CS	2.64	2.32	1.70	1.12	10.09	32
TS	2.77	2.06	1.68	1.29	8.33	25
LCC	2.72	2.07	4.33	0.82	50.41	133
FSC	2.61	1.86	2.05	0.07	13.67	288
Panel C. Operatin profit in cents per ASM						
Pooled	0.73	0.75	1.56	-18.28	6.64	430
CS	0.72	0.60	1.02	-1.45	4.17	32
TS	0.80	0.74	0.65	-0.21	2.41	25
LCC	0.84	0.86	1.27	-2.39	6.64	136
FSC	0.68	0.72	1.67	-18.28	5.92	294

Entries report mean, median, standard deviation (Stdev), minimum (min), and maximum (max) of fuel cost in percentages of the total operating expense in Panel A, fuel cost in cents per available seat mile in Panel B, and operating income in cents per available seat mile in Panel C. The statistics are computed over the pooled sample, the cross section (CS) of the time-series averages of the 33 airlines, the time series (TS) of the cross-sectional averages for the 25 years, as well as the subsample for low cost carriers (LCC) and full service carriers (FSC), respectively.

Table 4
Revenue sensitivity to equity market variation

Model	Intercept, %		β^r, %		R^2, %
Pooled	0.94	(0.15)	2.62	(0.73)	3.18
FFE	0.85	(0.85)	2.36	(0.69)	16.40
LCC	1.64	(0.26)	1.39	(1.28)	5.65
FSC	0.64	(0.17)	3.12	(0.86)	5.65

Entries report the intercept, slope (β^r), and R^2 estimates from regressions of next year's revenue change in cents per available seat miles against annual returns on the S&P 500 index. In parentheses are the standard errors of the estimates. The regressions are performed in three different specifications. The first row ("Pooled") reports the results from the pooled regression. The second row ("FFE") reports the results from a pooled regression while controlling for fixed firm effects. The last two rows report results of a pooled regressions with carrier type dummies (LCC or FSC) on both the intercept and the slope. In the regression with fixed firm effects, the intercept reports the average estimates of intercepts and their standard errors.

Table 5
Value benefits of fuel cost hedging under different market conditions

Models	1. Sub-sample	2. Full-sample	3. High demand	4. Low demand
Variables	1992-2003	1992-2016	$\mathcal{H}_t \geq 100\%$	$\mathcal{H}_t < 100\%$
Hedging ratio h	0.4354	0.2628	0.3880	-0.0985
	(0.1416)	(0.0971)	(0.1425)	(0.1319)
ln(Assets)	-0.1373	-0.0953	-0.1560	-0.0145
	(0.0271)	(0.0214)	(0.0271)	(0.0294)
Dividend Indicator	0.2069	0.1376	0.2208	0.1252
	(0.0578)	(0.0462)	(0.0650)	(0.0721)
LT Debt-to-Assets	0.6346	0.7800	0.8889	0.5544
	(0.1751)	(0.1446)	(0.1750)	(0.2349)
Cash Flow-to-Sales	0.5253	0.6779	1.1161	0.4472
	(0.4377)	(0.1976)	(0.2855)	(0.2899)
Cap Exp to Sales	0.3675	0.3056	0.2885	0.6437
	(0.2141)	(0.1617)	(0.2219)	(0.2395)
Z-score	0.1762	0.1710	0.1501	0.3033
	(0.0369)	(0.0280)	(0.0333)	(0.0460)
Advertising-to-Sales	14.1143	13.1685	14.0942	13.9874
	(2.7362)	(2.7905)	(3.1322)	(5.2504)
Cash-to-Sales	-0.1093	0.3510	-0.0780	0.3923
	(0.2924)	(0.2535)	(0.2590)	(0.4218)
Charter Indicator	0.1149	0.0566	0.0591	0.0853
	(0.0648)	(0.0565)	(0.0763)	(0.0919)
Fuel Pass-through Indicator	-0.1656	-0.1813	-0.2475	-0.2240
	(0.0681)	(0.0589)	(0.0783)	(0.0911)
FX Hedge Indicator	0.1062	0.0505	0.1462	0.0924
	(0.0742)	(0.0582)	(0.0791)	(0.0799)
Interest Rate Hedge Indicator	0.0694	0.0292	0.0887	0.0327
	(0.0717)	(0.0449)	(0.0696)	(0.0618)
R^2	0.4954	0.4918	0.4521	0.4803
Nobs	249	451	250	201

Entries report the results from the pooled regression of the logarithm of airline companies' Tobin's Q on the hedging ratio and a list of control firm characteristics. Model 1 performs the pooled regression with time fixed effects (year dummy) for the sub-sample from 1992 to 2003. Model 2 applies the same specification to the full sample from 1992 to 2016. Models 3 and 4 replace the year dummy with a market condition dummy classifying the market as either high hedging demand ($\mathcal{H}_t \geq 100\%$) or low hedging demand ($\mathcal{H}_t < 100\%$), and apply the dummy to all regressors.

Table 6
Dynamic optimality of fuel cost hedging and its effects on firm valuation

Model		Intercept		Slope		R^2, %
1.	Pooled	-0.163	(0.031)	0.388	(0.089)	5.75
2.	FTE	-0.149	(0.130)	0.406	(0.081)	23.80
3.	RWF	-0.287	(0.089)	0.378	(0.118)	19.40

Entries report the coefficient estimates, standard errors (in parentheses), and R-squared estimates from regressing the logarithm of Tobin's Q on the dynamic optimality estimates of airline's fuel cost hedging practice. Model 1 is a pooled regression with the dynamic optimality estimated from the full sample. Model 2 uses the same full-sample dynamic optimality estimates and performs the pooled regression with year dummy to capture the fixed time effect. The reported intercept represents the average of the estimates and standard errors on the year dummies. Model 3 estimates the dynamic optimality with a 10-year rolling window and performs a rolling-window forecasting cross-sectional regression on next year's logarithm of Tobin's Q. Entries for Model 3 report the time-series average of the coefficient estimates, the standard errors on the average, and the average of the cross-sectional regression R-squared estimates.

Table 7
Effects of hedging dynamic optimality on operation, investment, and financing behaviors

Model	Metrics	Intercept		Slope		$R^2, \%$
Panel A. Return on asset behaviors						
1.	Mean	5.915	(0.369)	6.077	(0.900)	12.33
2.	Stdev	7.784	(0.256)	-5.567	(0.658)	11.59
3.	IR	1.206	(0.095)	1.947	(0.227)	21.99
Panel B. Investment and financing behaviors						
4.	ASM Growth	7.408	(0.421)	0.998	(0.989)	0.55
5.	Debt Ratio	29.899	(0.741)	6.453	(2.014)	3.46
6.	Credit Rating	15.511	(0.172)	-2.124	(0.372)	9.49

Entries report the results from regressing the mean, the standard deviation (Stdev), the information ratio (IR, mean-to-standard deviation) of the return on asset, the total ASM growth rate, the long term debt to total asset ratio, and credit rating against the dynamic optimality of the airline's fuel cost hedging practice. Return on asset, ASM growth, and debt ratios are represented in percentages. The letter grade from the Standard & Poors' credit rating is converted to numerical values, with higher values denoting lower credit rating.

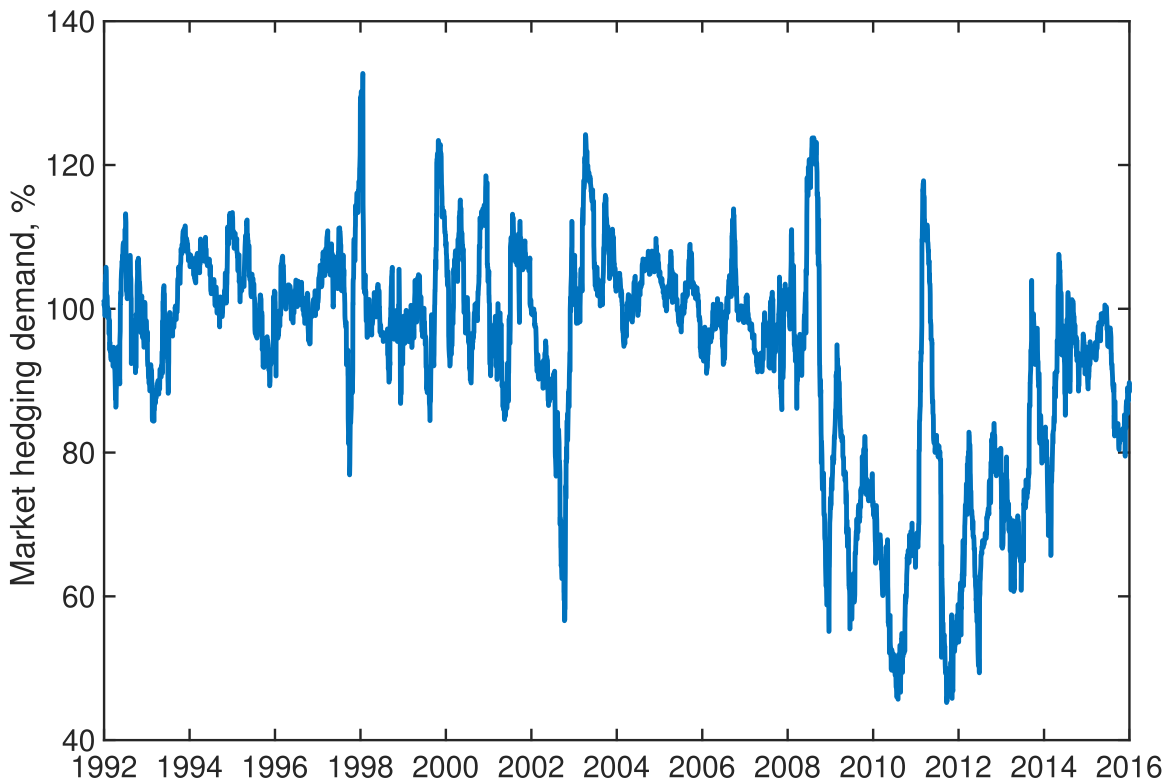


Figure 1

Time variation of market hedging demand.

The line plots the rolling-window estimates of the market hedging demand index, constructed based on quarterly rolling-window regressions of daily WTI crude futures returns on S&P 500 Index returns.

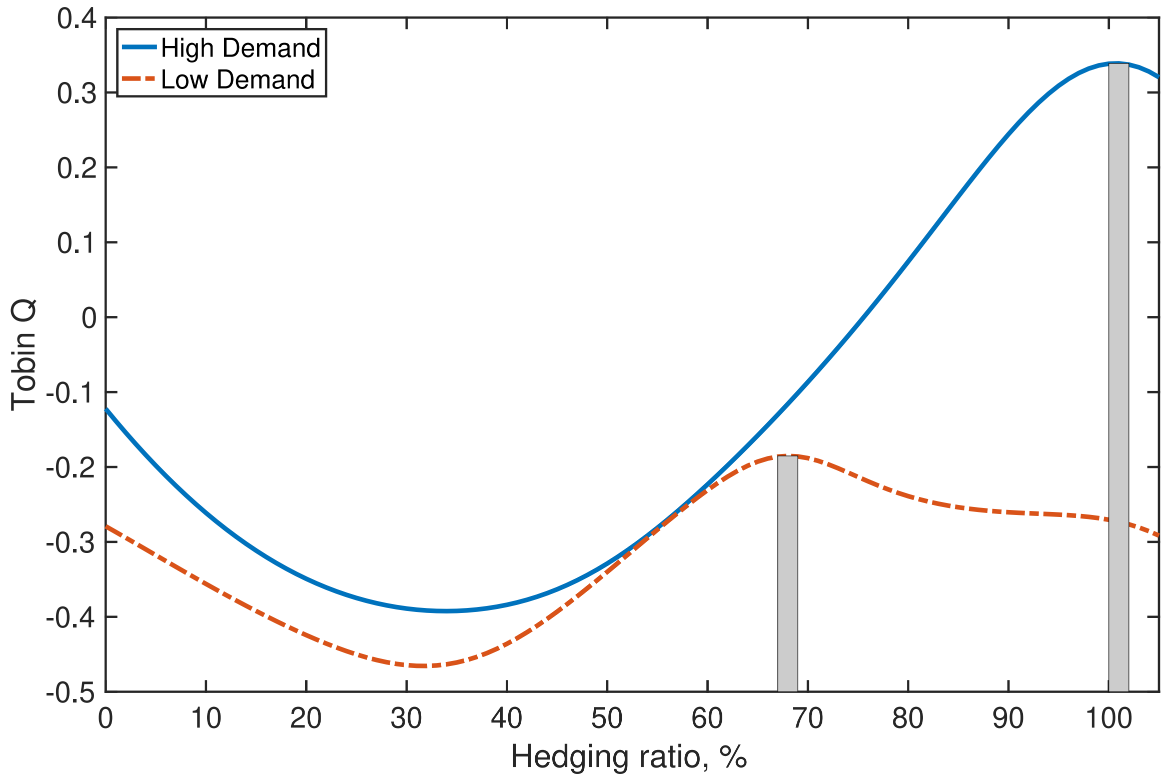


Figure 2

The hump shaped relation between hedging ratio and firm valuation.

Lines denote the estimated relation between the hedging ratio and firm's Tobin's Q (with scale on the left size of *y*-axis) conditional on the market hedging index being around 100% (solid line, high demand) and 70% (dash-dotted line, low demand), respectively. The relations are estimated with a conditional local linear regression with a Gaussian kernel and with a bandwidth twice as large as the default choice. The conditional weighting is also constructed with a Gaussian kernel with default bandwidth choice. The two shaded bars highlight the hedging ratios under which the company's Tobin's Q reaches the maximum under the two types of market conditions.

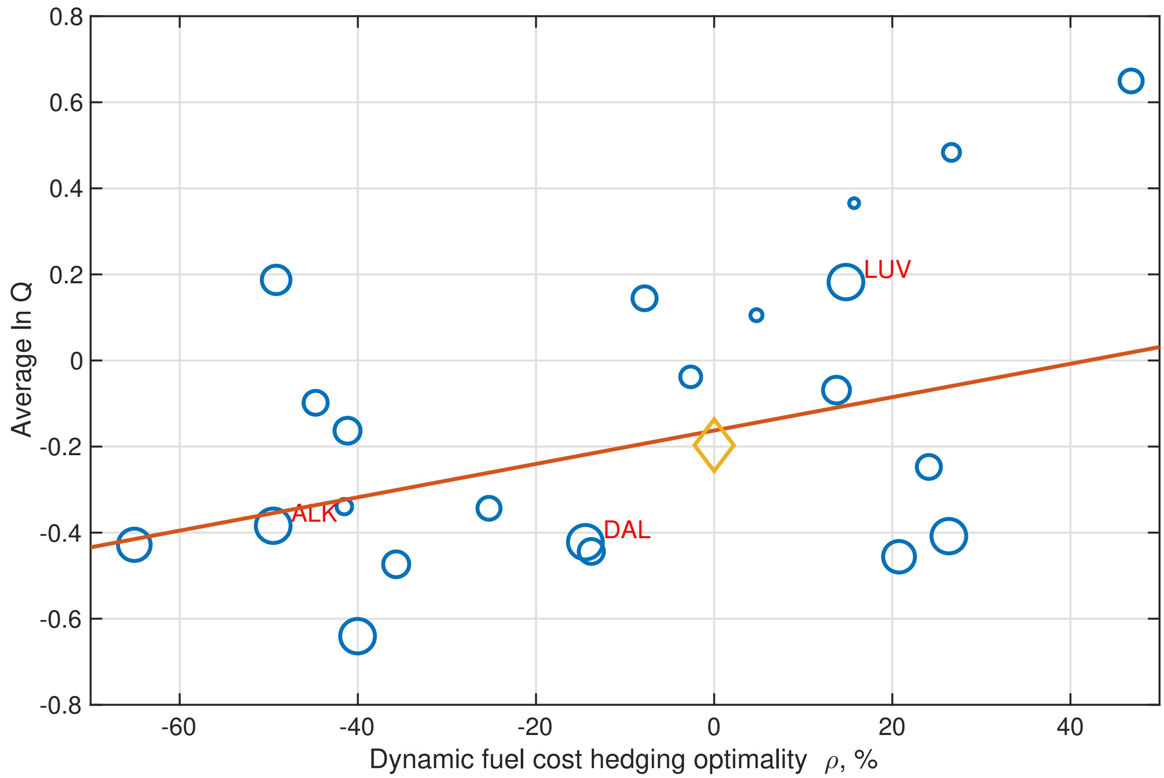


Figure 3
Dynamic optimality of fuel cost hedging and average firm value accretion.
Each circle represents the average relation for a company between its dynamic optimality estimate ρ_i and its average logarithm of Tobin's Q. The size of the circle is made proportional to the number of observations for that company. The solid line denotes the fitted relation. The diamond denotes the average logarithm of the Tobin's Q for the 11 companies that never hedge.

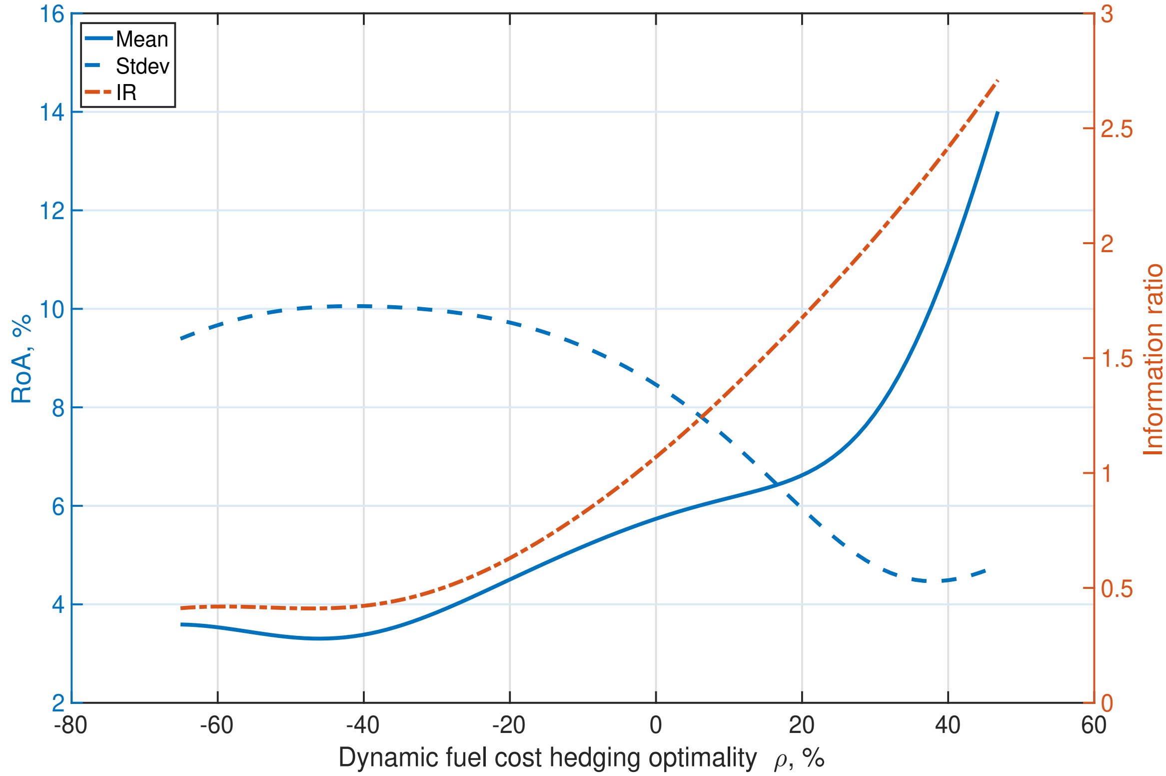
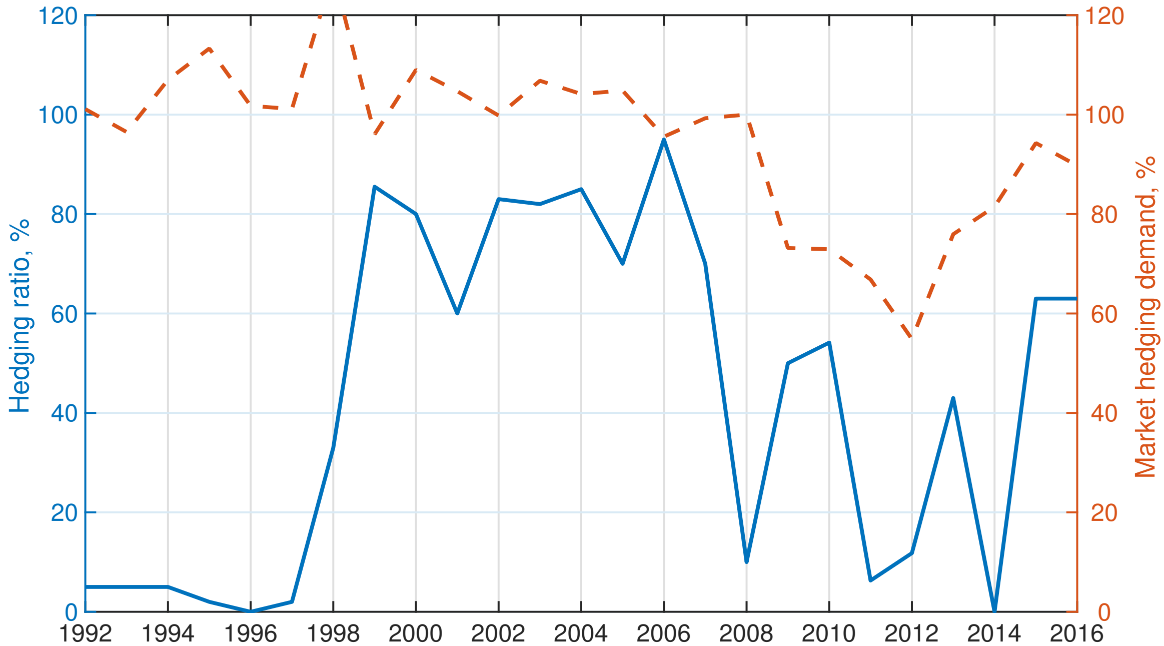


Figure 4

Dynamic optimality of fuel cost hedging and return on asset behavior.

Lines plot the effects of fuel cost hedging dynamic optimality ρ_i on the mean (solid line, scale on the left), standard deviation (dashed line, scale on the left), and the information ratio (dash-dotted line, scale on the right) of the airline's return on asset. The relations are estimated by a local linear regression on the pooled sample with a Gaussian kernel and default bandwidth choice.

Panel A. Southwest Airlines



Panel B. Delta Airlines

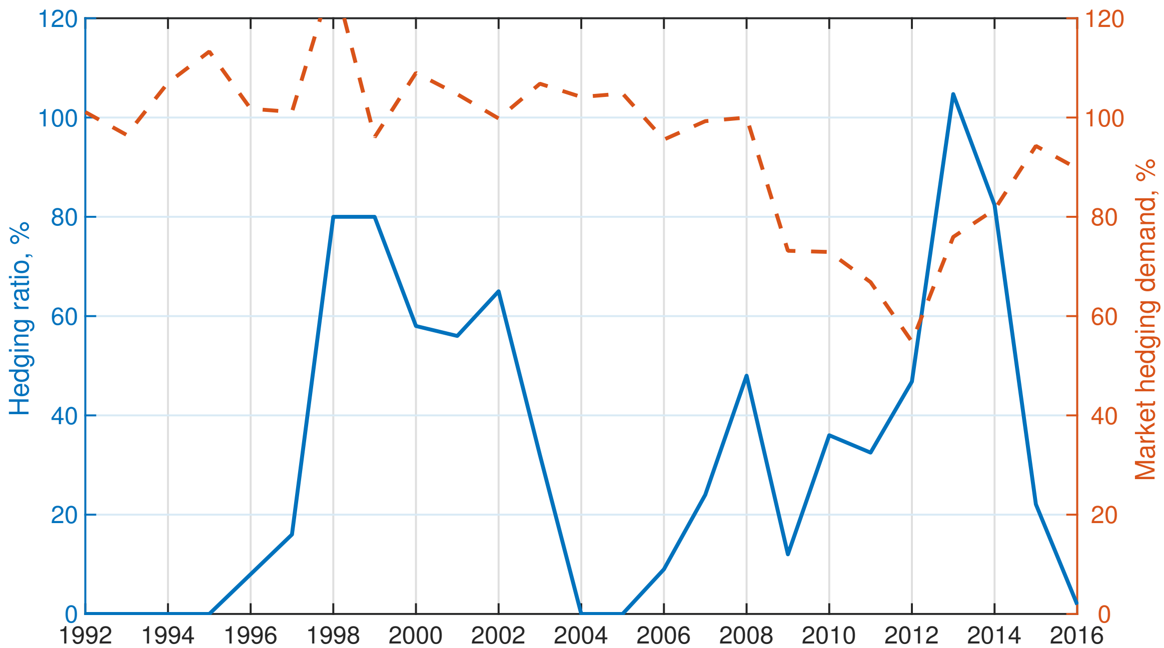


Figure 5
Fuel cost hedging behavior comparison between Southwest and Delta.
The solid lines plot the time series of the hedging ratios for Southwest Airlines (Panel A) and Delta Airlines (Panel B). The dashed lines represent the market hedging demand benchmark.