

**Finance and Economics Discussion Series
Divisions of Research & Statistics and Monetary Affairs
Federal Reserve Board, Washington, D.C.**

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Matthew Gustafson, Ivan T. Ivanov, and John Ritter

2014-63

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Matthew Gustafson[†] Ivan T. Ivanov[‡] John Ritter[§]

July 2, 2014

Abstract

We provide evidence that existing studies relating financial condition to product market cooperation produce mixed results because of unique features of the industries examined. In particular, all evidence suggesting that poor financial condition decreases cooperation comes from the airline industry during periods of high idle capacity. Using a unique data set of aggregate airfare hikes and a more recent low-idle-capacity period, we find that poor financial condition is positively associated with product market cooperation. Although financially weak airlines appear to value the immediate cash flows of increased cooperation, only liquidity-constrained firms seem willing to incur the cost of cooperative attempts.

Key Words: Financial Distress, Product Market Cooperation, Liquidity, Capacity Constraints, Airfare Price Hikes

*We wish to thank Jim Brickley, Jason Hecht, John Long, Ryan McDevitt, Jeanine Miklos-Thal, Bill Schwert, Cliff Smith, Minjae Song, Beau Page, seminar participants at Rochester, Wharton, the 2011 MFA meeting, the 2011 SWFA meeting, and especially Michael Raith for helpful comments.

[†]Smeal College of Business, Penn State University, State College, PA 16801; 814-867-4042; mtg15@psu.edu.

[‡]Federal Reserve Board, 20th Street and Constitution Avenue NW, Washington, DC 20551; 202-452-2987; ivan.t.ivanov@frb.gov. The views expressed herein are those of the authors and do not necessarily reflect the views of the Federal Reserve Board or the Federal Reserve System.

[§]William E. Simon Graduate School of Business Administration, University of Rochester, Rochester, NY 14627. Email: john.ritter@simon.rochester.edu

1 Introduction

Modigliani and Miller (1958) show that under assumptions such as no transaction costs and unfettered access to the financial markets, product market decisions should be independent of firm financial policy. Nevertheless, there is evidence that both industry- and firm-level financial condition determine the extent to which firms cooperate. For instance, Chevalier (1995a; 1995b), Chevalier and Scharfstein (1995; 1996), Phillips (1995), and Campello (2003) all find that poor financial condition leads to more cooperation or higher price markups. In contrast, Borenstein and Rose (1995), Busse (2002), and Phillips and Sertsios (2013) find that poor financial condition reduces the incentive to cooperate.

We provide evidence that the reason existing studies relating financial condition to product market cooperation produce mixed results is because of unique features of the industries examined. Specifically, all of the above evidence suggesting that poor financial condition reduces cooperation comes from the airline industry during periods of high idle capacity. In contrast, we exploit a recent shift in the airline industry towards less idle capacity and find that poor financial condition is associated with more product market cooperation. Thus, high idle capacity appears to drive existing evidence that poor financial condition reduces the incentive to cooperate.

To identify the effect of financial condition on product market cooperation, we exploit a unique form of airline pricing that has emerged over the past decade - aggregate airfare rate hikes. An airfare rate hike occurs when an airline simultaneously raises airfares on the majority of its routes by similar dollar amounts. The hike is successful if all competing airlines match the price increase. If any rival does not match the hike within several days, then the initiating airline returns prices to pre-hike levels.

Firms may benefit from aggregate rate hikes because successful hikes shift the cooperative equilibrium towards joint monopoly pricing, however rate hikes are not costless. For instance, we find that the equity prices of airlines underperform those of industry rivals by approximately 1.2% in the days following the initiation of an unsuccessful rate hike, while

the cumulative market reaction to successful hikes is essentially zero. This is consistent with hike initiation revealing negative information about the hiker but these wealth losses being offset when a successful hike increases cooperation. Thus, rate hike initiation is optimal only when it is sufficiently unlikely that a rival will initiate a hike or sufficiently likely that the hike will succeed.

We exploit this unique pricing behavior to investigate the interplay between financial distress and product market cooperation. We find that in today's airline industry both short-term liquidity and longer-term financial concerns increase an airline's propensity to cooperate. Low levels of short-term liquidity (relative to industry rivals) predict hike initiation, while the longer-term financial health of the industry determines hike success. These findings suggest that liquidity-constrained airlines are most willing to bear the cost of hike initiation. Firms with longer-term financial concerns optimally wait to match a more desperate competitor's hike.

On the surface, our findings are at odds with the existing evidence on financial condition and airline pricing. Using data spanning 1985-1992 and 1997-2008, Borenstein and Rose (1995), Busse (2002), and Phillips and Sertsios (2013) find that financial distress is associated with more competitive pricing because distressed firms benefit most from the immediate revenues generated from cutting prices. The theory of Staiger and Wolak (1992) rationalizes this apparent inconsistency by showing that the benefits of price wars are increasing in idle capacity. In essence, if airlines already have full planes then deviating from cooperative pricing is less effective in raising immediate cash. Consistent with this logic, the demise of price wars and appearance of rate hikes in the airline industry coincides with a decrease in idle capacity. Since 1985, the percentage of available airline seats sold has increased from approximately 60% to 82%, amounting to a 55% decrease in idle capacity. In addition, a substantial fraction of the decrease in idle capacity occurs between 2002 and 2006.

This trend towards less idle capacity along with our empirical evidence highlight the uniqueness of the results in Borenstein and Rose (1995), Busse (2002), and Phillips and

Sertsios (2013). These earlier results rely on three characteristics of the airline industry during earlier sample periods: empty seats on already scheduled flights are not costly to fill, empty seats on flights that have taken off have no value, and flights often take off with a substantial fraction of empty seats. In this scenario, reducing prices to fill seats is an effective way to increase short-term revenues. However, the strategy becomes less effective when any of the above criteria are not met. For instance, we find that in today's airline industry with little idle capacity distressed airlines are more likely to pursue cooperative actions even though seats remain highly perishable and have low marginal costs.

Therefore, we reconcile the findings in Campello (2003) and Chevalier and Scharfstein (1995; 1996) that financially distressed or highly levered industries are less competitive with the results in Borenstein and Rose (1995), Busse (2002), and Phillips and Sertsios (2013) that financial distress increases airline competition. In today's market, there is no such discrepancy – financial distress is associated with higher markups.

Our analysis thus far builds off the intuition in Staiger and Wolak (1992) that capacity constrained industries will often imperfectly cooperate and set prices between the jointly monopolistic and competitive prices. From this perspective, our results can be interpreted as evidence that distressed airlines are most likely to attempt to shift the equilibrium towards the joint monopoly price. Indeed, distressed airlines will benefit most from the expected short-term revenue gains caused by the combination of higher industry prices and inelastic industry demand (see, e.g., Oum, Zhang, and Zhang, 1993).

This interpretation of our findings demonstrates the importance of financial condition in predicting rate hikes, even after controlling for other common explanations, such as rising fuel costs. Although it is intuitive that prices increase with costs, there are at least two reasons why rising jet fuel prices are not the sole driver of rate hikes. First, a significant fraction of the hikes occur during a time period in which the price of jet fuel remains fairly constant. For instance, there are 38 rate hikes in 2011 and 2012 when the price of jet fuel remained between \$2.68 and \$3.27 per gallon. Second, rising costs increasing the likelihood

of rate hikes is not mutually exclusive from our hypothesis that financially distressed airlines will be the first to hike. Even if all rate hikes were responses to jet fuel price increases, our results can be interpreted as financially distressed airlines being most likely to attempt to maintain the current level of effective industry cooperation in the face of rising costs.

Another alternative explanation for airfare rate hikes is that only the largest airlines invest sufficient time and resources into pricing research, while other firms mimic their price movements (see, e.g., Nevo, 2001). For instance, Delta and United, two of the largest airlines in the United States by both passenger-miles flown and fleet size, also initiate a large number of airfare hikes. It could be argued that these two airlines are the market leaders. We do find some support for this explanation as larger airlines are more likely to initiate rate hikes, however in our main specification with time- and firm-fixed effects size becomes statistically insignificant. Overall, the results indicate that financial distress is a significant predictor of cooperation even after accounting for the market leader explanation.

Finally, our results contribute to the literature exploring the relation between airline financial distress and product market decisions. Distressed airlines reduce product quality (see, e.g., Rose, 1990; Phillips and Sertsios, 2013), conduct asset fire sales (see, e.g., Pulvino, 1998), and negotiate loans differently (see, e.g., Benmelech and Bergman, 2008). All of these consequences can be at least partially attributed to distressed firms highly valuing immediate cash. Our results are consistent with this same mechanism increasing the attractiveness of cooperation in today's airline industry.

2 Airfare Rate Hikes

2.1 Airline Tacit Collusion in the 1990s

During the early 1990s, a common practice in airline pricing was for a major air carrier to use the Airline Tariff Publishing Company (ATPCO) system to pre-announce route-specific fare increases together with the ATPCO codes of their relevant rivals and wait for the re-

sponses of its competitors. If rival firms matched the fare increases, airfares would increase on the specific route. Moreover, it was common for the allegedly colluding airlines to punish non-cooperative competitors by sharply reducing some fares on overlapping routes (see, e.g., Borenstein, 1994).

These pricing practices led to a Department of Justice (DOJ) investigation and settlements as well as other lawsuit settlements totaling approximately \$0.5 billion.¹ According to Borenstein (1994), one difficulty throughout the DOJ investigation was determining how to regulate this apparent collusion. The DOJ recognized that it could “not easily prevent airlines from proposing fare increases and then withdrawing those fare increases relatively quickly if competitors didn’t match.” Because of this, “the Department decided to pursue remedies that would make it more costly and less effective to use the system for collusive behavior.” Thus, although these pricing practices may not represent easily preventable collusion, the DOJ clearly believed that collusive pricing was occurring.

The ensuing ten-year settlement between the DOJ and the eight major United States air carriers took two strides to mitigate the ability of airlines to effectively collude. First, the settlement prohibited the pre-announcement of fare changes in most cases. Second, the agreement prohibited an airline from disseminating fares to competitors that are primarily intended to communicate contemplated future fares. More generally, the settlement was “intended to ensure that the airline defendants do not continue to use the ATP fare system or any similar mechanism in a manner that unnecessarily facilitates fare coordination or that enables them to reach specific price-fixing agreements.”²

2.2 Aggregate Rate Hikes and Tacit Collusion

We argue that the airline industry has adopted a new pricing practice that circumvents the spirit of the 1994 DOJ settlement and appears to facilitate collusion in airline pricing.

¹“Governments to Benefit in Airline Accord: Transportation Settlement granting discount fares stems from class-action lawsuit over alleged price fixing.” LA Times, October 12 1994.

²Civil Action Number 92-2854, The U.S. Department of Justice.

Since 2005, airlines have begun performing aggregate price increases that simultaneously raise prices on the majority of routes. Industry experts refer to these events as rate hikes. We observe 118 airfare hikes from January 2005 to December 2012. The FareCompare website³ began using custom-made software to identify rate hikes in 2007. In order to expand the sample back to 2005 and to identify which competitors match a given rate hike, we use FACTIVA searches to hand collect press releases of the rate hikes. Almost all of the articles prior to 2007 cite Tom Parsons, another industry expert, and his BestFares website.

For each rate hike we obtain the identity of the initiating airline, the dollar amount, and a list of competitors that match the hike leader. The eight major US air carriers (American Airlines, Southwest, Continental Airlines, AirTran Airways, US Airways, United Airlines, Delta Airlines, and Northwest) are the firms to usually initiate rate hikes during our sample period, while regional carriers normally match the aggregate rate increases.

An advantage of relying on industry experts and newspaper articles for our data is that we can identify the timing of the rate hike, the initiating airline, and the competitors' reactions. None of the standard data sources such as the route-by-route and the aggregate price data available quarterly at the Bureau of Transportation Statistics (BTS) or the monthly price data available from the Bureau of Labor Statistics provide any of these benefits. The BTS data, based on a Department of Transportation (DOT) sample of 10% of itineraries flown, records prices at the time of ticket use. The BLS pricing data selects samples from 87 CPI pricing areas to construct the airfare CPI with probability of itinerary selection that is proportional to the presence of trips in the DOT sample. The BLS source records prices as of the time of ticket purchase but uses the lowest available fare for a substantial portion of the calculation sample.

The lack of matching between purchase and ticket use dates, the limited availability of sale/'deep discount' fares, and the complexity of airline pricing schemes makes it difficult to detect day-to-day price movements with standard pricing data sources, let alone identify

³We thank the CEO of FareCompare, Rick Seaney, for providing summary hike data on his website.

hike leaders and followers.⁴

The example below describes an airfare rate hike initiated by Delta Airlines and illustrates the typical progression of rate hikes:

“Delta Air Lines on Tuesday announced an increase of \$4 to \$10 in ticket prices for one-way trips across much of the USA, with United Continental following. Southwest and AirTran matched it by raising \$2 to \$5 one-way on nearly all domestic fares, says Jamie Baker, an airline analyst at JP Morgan... Fare increases don’t always stick because some airlines balk and carriers don’t like to price themselves too high against competitors. But Southwest’s match is a pretty good sign it’ll cost more to fly.” Roger Yu, USA Today, October 2011

The above quote portrays airfare rate hikes as a way for hiking airlines to test whether industry rivals are willing to charge the higher price levels instituted by the hiker. These actions are consistent with conventional oligopoly models, in which firms can increase their profits through cooperating at higher pricing levels. If the excess profits are high enough or the chance of being caught is small enough, firms will take the risk of colluding, even when price-fixing is illegal and can lead to costly fines and lawsuits.

A firm’s decision to change price is based on both the absolute level of the new price and the expected reaction of competitors, while a shift in the cooperative (collusive) level seeks to maintain relative prices, but alter the absolute price. This type of price change is particularly attractive given the finding in Oum, Zhang, and Zhang (1993) that airline industry demand is inelastic while firm-specific demand exhibits a large price elasticity. We argue that many peculiar characteristics of rate hikes are intuitive if the firm’s goal is to shift the level of cooperation, but seemingly inconsistent with firms initiating price changes in a competitive setting.

First, Table I indicates that the majority of rate hikes raise rates on most of an airline’s routes by the same dollar amount or a narrow range of dollar amounts (\$10-20). In fact, approximately half (53.3%) of rate hikes in our sample raise prices on the majority of an

⁴Please see Busse (2002) for further discussion on the potential advantages of her price wars dataset as compared to standard airline pricing data sources. Our airfare hikes dataset has similar advantages.

airline's routes by the exact same dollar amount. Considering the differences in the types of routes operated by the largest air carriers in the United States, this does not appear to be an optimal way to institute a price change in a competitive setting. On the other hand, a fixed dollar increase represents an obvious pricing signal for competitors making it more likely that the cooperative invitation will be noticed and matched. After the 1994 DOJ Settlement made it difficult to signal collusive intent to rivals on a route-by-route basis, such a pricing signal appears to be a crude but effective way to communicate higher contemplated future fares.

A second important characteristic of rate hikes is that in order for a rate hike to be successful it must be matched by all industry peers. Otherwise, the hike leader undoes the price increase within the next several days, thus returning prices to their initial levels. This pattern is consistent with either cooperation (tacit collusion) or rational pricing in the presence of demand uncertainty, but is a necessary feature of a cooperative invitation. Moreover, this practice is similar to the one identified by the DOJ on a route-by-route basis in the early 1990s.

Finally, rate hikes occur almost always on Thursday or Friday when consumer attention has historically been lowest (McCartney, WSJ 2011).⁵ This reduces the short-term costs associated with the hiker's price being higher than that of competitors. If the new price were optimal then there would be no such incentive.

2.3 The Price Impact of Rate Hikes

If airfare rate hikes are meaningful changes in the pricing equilibrium then rate hikes should be associated with higher ticket prices. A limiting factor for this part of the analysis is the low quality of airfare price data. Nonetheless, the empirical association between rate hikes and future aggregate prices partially illustrates the economic impact of rate hikes.

⁵As a result of airfare hikes occurring late in the week, experts advise consumers to abstain from purchasing tickets over the weekend. See "Airfare Expert: Why it's risky to book flights on weekends" USA Today, September 15 2013.

To assess the economic significance of rate hikes, we regress the monthly changes in the airfare CPI on the number of rate hikes in the current and prior 3 months, including year-quarter fixed effects. We use the airfare CPI provided by the BLS because it reflects flight prices at the time of purchase. In some specifications we also control for changes in jet fuel price, which we obtain from the BTS website.

Column 1 of Table II presents our base specification and indicates that a rate hike in the current month is associated with an expected increase in contemporaneous airfare of approximately 0.2%. There is also weak evidence that hikes in previous months are positively associated with changes in future airfare.

Both panels of Table I indicate that a substantial fraction of hikes fail. To the extent that only successful hikes increase price levels, the empirical relation between hikes and airfare should be driven by successful hikes. Column 2 of Table II separately identifies the price impact of successful and unsuccessful hikes. Collectively, the results suggest that not only are successful hikes associated with approximately a 0.6% increase in current ticket prices, but also that rate hikes affect purchase prices over the next two months by approximately 0.5%. This evidence on the relation between current hikes and future prices is consistent with airlines using aggregate rate hikes to pre-announce contemplated price increases, effectively circumventing the spirit of the 1994 DOJ settlement.

In addition to the above result, column (2) indicates that the number of unsuccessful hikes does not exhibit a significant association with changes in the airfare CPI. Overall, successful rate hikes appear to lead to price increases in the airline industry, while unsuccessful rate hikes do not.

In columns (3) and (4) of Table I we also include the percentage change in the price of jet fuel to test if hikes have an effect on airfare incremental to marginal cost shocks due to increases in oil prices.⁶ Although jet fuel price changes appear to subsume the effect of the

⁶We lag all values of the $\Delta\text{JetFuelPrice}$ variables ($\Delta\text{JetFuelPrice}_t$, $\Delta\text{JetFuelPrice}_{t-1}$, $\Delta\text{JetFuelPrice}_{t-2}$, and $\Delta\text{JetFuelPrice}_{t-3}$) by 15 days since cost increases at the end of the current month will not have as large of an effect on average airfare. The coefficient estimate of contemporaneous successful hikes, as well as those of the first and the second lags are all statistically significant at the 5% level if we do not lag

total number of rate hikes on airfare (column (3)), contemporaneous successful rate hikes remain strongly significantly associated with changes in the airfare CPI. Thus, even if rate hikes are partially used to pass cost increases to consumers, they seem to have an incremental effect on fares not attributable to oil cost shocks.

2.4 Are Rate Hikes Costly?

Although the empirical evidence is consistent with hikes shifting airfare price level, it is useful to analyze if it is costly to initiate price hikes in order to better understand the incentives of industry participants. In this section we investigate the wealth effects associated with initiating aggregate price increases. The stock market reaction to announced rate hikes provides an aggregate measure of the perceived net benefits to the hike combined with the information signaled by the hike.

To evaluate the existence of wealth effects, we calculate the cumulative abnormal returns in the three day window including the day of the hike and the two subsequent trading days.⁷ We focus on the three day window rather than the day of the hike because sometimes airlines initiate hikes after normal trading hours and because most of the uncertainty with respect to hike success is resolved within a few days. Abnormal returns are calculated using the actual stock returns from day 0 to day 2 and the corresponding industry stock returns over the same window, where day 0 is the day of the airfare rate hike (the event date).⁸

Panel A of Table III presents the average returns to the hiking airlines in the event window relative to the industry index. This average is negative but statistically insignificant. When we partition the sample, we find a statistically and economically significant price drop of -1.2% for unsuccessful hikes but a positive and statistically insignificant price reaction for the $\Delta\text{JetFuelPrice}$ variable by 15 days. The coefficients of the $\Delta\text{JetFuelPrice}$ variables are all statistically insignificant in that scenario.

⁷The stock returns data come from CRSP.

⁸We use the returns on the Bloomberg U.S. Airline Index (BUSAIRL) to measure airline industry returns. BUSAIRL includes the largest air carriers in the U.S. and the respective data come from Bloomberg. To obtain the abnormal returns, we first run regressions of firm-specific hiker returns on airline industry returns, estimated from day -130 to -30 relative to the event date. We then use these estimates to obtain the predicted hiker industry-adjusted returns in the event window.

successful hikes. This evidence suggests that hikes reveal negative information about the hiker relative to rival airlines but that these negative abnormal returns are offset if the hike succeeds in increasing airfare. Thus, there is a cost to initiating rate hikes – it reveals negative information to the market. This means that even if airlines prefer additional cooperation they have incentives to wait for a competitor to initiate a hike as opposed to initiating one themselves.

To make sure the three day window we select contains most of the information associated with airfare rate hikes, we also hand collect the hike resolution dates (where available). Again, we compute the hike initiator’s returns relative to the industry index returns. In this case the event window is from day -2 to day 1 where day 0 is the day of the rate hike completion. We include days -1 and -2 relative to the hike completion date because often times most of the uncertainty about the outcome of a hike is determined earlier than the final date. We also include day $+1$ because sometimes hikes are completed after trading hours. Panel B of Table III presents results on the cumulative abnormal returns around airfare rate hikes completion. These tests yield qualitatively similar empirical results as those in Panel A even though the sample is smaller.

3 Hypothesis Development

Poor financial condition increases effective discount rates. This means that distressed firms are more likely to make product market decisions that increase current revenue at the expense of future revenue. In this paper, we investigate how this affects the decision to initiate airfare rate hikes, which we argue are attempts to increase industry cooperation.

Whether poor financial health increases or decreases the attractiveness of rate hike initiation depends on the rate hike’s effect on the timing and amount of cash flows. Borenstein and Rose (1995), Busse (2002), and Phillips and Sertsios (2013) all find that financially distressed airlines are more likely to reduce prices, implicitly reducing their level of cooperation. The

authors rationalize this finding in two ways. First, the airline cutting prices gains short-term revenues if competitors do not immediately match the price war. Second, the price reduction allows the industry to inter-temporally shift cash flows to the current period by borrowing from future demand.

Although the above arguments are intuitive, Staiger and Wolak (1992) show theoretically that the short-term revenue benefits of a price war critically depend on the level of idle capacity. When idle capacity is high, price wars are likely to increase short-term profits, but when idle capacity is low firms are likely to imperfectly cooperate near the joint monopoly prices. The authors also show that the effect of capacity constraints are most important in industries with high capacity costs such as the airline industry. Thus, if airlines are operating near full capacity, and capacity is fixed in the short run, a price war is not likely to raise short-term revenues.

Idle capacity in today's airline industry is substantially lower than that in earlier time periods. Panel (a) of Figure 1 shows that the loadfactor, which is a measure of average capacity utilization, has increased from approximately 60% in 1990 to over 80% in 2012. Panel (b) of Figure 1 compares the average sample loadfactors for the data employed in Phillips and Sertsios (2013) and in our study. It indicates that a substantial fraction of the decrease in idle capacity happens between 2002 and 2006 (the dashed line) and after that the industry appears to have reached a more steady state in terms of capacity utilization during our sample period (the solid line). According to Staiger and Wolak (1992), this reduction in idle capacity makes price wars less likely to raise short-term revenues today as compared to the sample periods of Borenstein and Rose (1995), Busse (2002), and Phillips and Sertsios (2013). These trends motivate our empirical investigation of aggregate airline pricing with recent data.

We argue that when binding capacity constraints make price wars less attractive, financial distress will increase an airline's incentive to pursue cooperative actions. Since airlines are pricing below monopoly levels (see, e.g., Staiger and Wolak, 1992), an increase in coop-

eration will immediately increase sales. Such increase in revenue will be most valuable to distressed airlines because of their pressing need for capital.⁹

The idea that financial distress increases cooperation is not new. Chevalier (1995a; 1995b) and Phillips (1995) show that increases in industry leverage lead to a softer competitive environment, while Chevalier and Scharfstein (1995; 1996) and Campello (2003) show that liquidity-constrained firms charge higher prices, especially during recessions. Although the above arguments that cooperation benefits financially distressed airlines more can rationalize this behavior, the costs to rate hike initiation also partially determine the types of airlines that are most likely to initiate rate hikes.

If there are no costs to rate hike initiation then all airlines have strong incentives to initiate rate hikes if and only if the hike is expected to increase the present value of future revenues. If cash flows are also perfectly predictable then all airlines will be equally likely to initiate rate hikes. If, on the other hand, there is some uncertainty in future cash flows or fixed costs to hike initiation then the financially distressed airlines will be more likely to initiate rate hikes because they benefit more from an increase in cooperation.

We discuss two categories of rate hike initiation costs, either of which is sufficient to motivate our hypothesis that financially distressed airlines are more likely to initiate rate hikes. First, in Section 2.4 we find that rate hike initiation reveals negative information about the hike initiator relative to industry rivals. Initiators under perform industry rivals by 1.2% in the days surrounding an unsuccessful hike. Not only does this suggest that hike initiation reveals negative information, but the concentration of the negative returns around unsuccessful hikes also reveals that hike initiators benefit more than their rivals from successful hikes. This result is intuitive if hiking is costly but there are significant benefits to

⁹Binding capacity constraints not only reduce immediate defection profits as developed in Staiger and Wolak (1992) but also increase long-run profits during the subsequent punishment period. Thus, under certain assumptions, the ex-ante effect of binding capacity constraints on the incentive to start a price war could be ambiguous. We argue that the first channel (the reduction in defection profits), which is the focus of Staiger and Wolak (1992), will be most relevant for the incentives of distressed airlines to initiate a rate hike because of the need to raise immediate capital. In other words, the high discount rate of distressed airlines magnifies the effect of the reduced defection profits and reduces the value of the increased punishment period profits.

hike success.

The second category of costs to rate hike initiation motivate Chevalier and Scharfstein (1996). Greenwald, Stiglitz, and Weiss (1984), Gottfries (1990), and Klemperer (1995) show that high current prices lead to lower future market share. Thus, not only does rate hike initiation lead to a loss in immediate revenue, but it also leads to a loss of future market share.

A related channel through which hike initiation could reduce future market share is a decrease in firm reputation. Phillips and Sertsios (2013) provide evidence of such behavior with respect to airline service quality. Building off the idea in Maksimovic and Titman (1991) that cutting service quality is similar to receiving an involuntary loan from customers, Phillips and Sertsios argue that when an airline becomes distressed it has incentive to reduce quality while still attempting to sell the product as if it were high quality. The short run effects of such a strategy raise cash for equity holders, serving to stave off bankruptcy, and the long run reputational effects are likely to be borne by bondholders. The authors find evidence of this as airline quality dips prior to bankruptcy and subsequently increases in bankruptcy as debt holders take control. These findings are also consistent with Rose (1990) who shows that airline safety records decline upon entering financial distress.

The above arguments motivate our primary hypothesis. In today's airline industry, which is characterized by binding capacity constraints, financially weak airlines will be more likely to initiate airfare rate hikes than their healthy competitors. Two corollaries of this hypothesis are that financially weak competitors will be more likely to match a rate hike and thus rate hikes will be more likely to succeed when the overall financial health of the industry is low.

4 Data and Descriptive Statistics

To complement the data on aggregate airfare rate hikes, we collect financial statement information from the quarterly COMPUSTAT files and monthly information on airlines' loadfactors and jet fuel prices from the BTS Website. We obtain GDP growth and aggregate disposable income data from the Bureau of Economic Analysis. We use these national level variables as in Busse (2002) instead of airlines specific controls such as the weighted competition or unemployment measures in Phillips and Sertsios (2013) because we focus on the eight largest airlines that are all national in scope. Finally, to predict future loadfactor (See Appendix A) we obtain weather-related data from the National Oceanic and Atmospheric Administration (NOAA) Website.

We employ three measures of financial health to test the hypothesis that financially distressed airlines are more likely to pursue cooperative actions through aggregate rate hikes – the current ratio, the cash flow-to-debt ratio, and the long-term debt-to-assets ratio. The current ratio is equal to the sum of cash, short-term investments, and accounts receivable divided by current liabilities, the cash flow-to-debt ratio equals to the past year's operating income before amortization and depreciation expenses divided by current liabilities, and the long-term debt-to-assets ratio equals to long-term debt divided by the book value of total assets.

We benchmark all three measures of financial health to the airline industry by subtracting the value of the specific variable for the least healthy airline in the industry. More positive values of the relative current ratio, denoted (*Current Ratio*), and the cash flow-to-debt ratio, denoted (*CFDebt*), and more negative values of the long-term debt-to-assets ratio, denoted (*LTDAssets*), represent relatively healthier airlines. We argue that defining financial health relative to the industry is more appropriate than the overall level of financial health for testing our hypothesis that the least financially healthy airlines will be most likely to initiate

rate hikes.¹⁰

Table IV shows that the average airline quarter in our sample has a current ratio of approximately 0.61, a cash flow-to-debt ratio of 0.19, and a long-term debt-to-assets ratio of 0.35. In all three cases, the median is almost identical to the mean. The relative financial health measures show that no single airline is consistently in the worst financial condition as none of the median relative financial health measures are zero. Such variation has the potential to allow us to better isolate the effects attributed to our hypotheses from confounding time-invariant factors.

In addition, Table IV indicates that all eight airlines have average value of *Loadfactor* between 75% and 85% with Southwest and AirTran having the lowest average and United and Delta having the highest. Also, the predicted values of *Loadfactor* for each airline, *PredLF*, look very similar to the actual values of *Loadfactor*. Finally, Delta is the largest airline in the sample and has median total assets of about twice that of American, which is the second largest airline by total assets. AirTran is by far the smallest airline in the sample and is approximately one quarter the size of US Airways, which is the next smallest.

5 The Hike Lead Decision

Our primary hypothesis is that airlines in need of immediate cash will be more likely to initiate rate hikes than their industry peers. Although all forms of financial distress increase a firm's discount rate, we argue that airlines with low levels of short-term liquidity will be the first to initiate rate hikes. This is because all airlines benefit from a rate hike, if successful, but not all firms are willing to incur the costs associated with hike initiation. Thus, the optimal course of action for a financially distressed airline is to bear the costs of hike initiation when no other airline is likely to. This logic suggests that, even though overall financial distress might have a direct effect on the benefits of a rate hike to the hiker,

¹⁰Our main findings are robust to using raw measures of financial health instead of the industry-benchmarked measures.

short-term considerations are a more likely determinant of the hike initiation decision than longer-term financial concerns.

5.1 Descriptive Evidence

Figure 2 provides descriptive evidence of the association between short-term financial health and rate hike initiation. The three airlines most likely to initiate a rate hike (American, United, and Delta) are also the ones with the lowest average current ratio. These three firms combined perform approximately 75% of the rate hikes.

In unreported results, we also find that airlines initiate rate hikes in approximately 20% of airline-quarters whenever they are below their time series median current ratio as compared to only 14% of airline-quarters whenever firms are above their median current ratio. In other words, airlines are approximately 50% more likely to hike at times when they are financially weak. Taken together the descriptive evidence suggests that rate hikes are most frequent amongst airlines that are chronically financially weak and that airlines hike more often during periods of financial distress.

5.2 Empirical Approach

Since our goal is to analyze the determinants of the number of hikes in a quarter, a natural choice of an estimation model is the Poisson regression. A drawback of the Poisson model is that it assumes equality of the conditional mean and variance of the dependent variable. Descriptive evidence indicates that the unconditional mean and variance in the 200 firm-quarters in our sample are 0.545 and 0.782, respectively. To avoid overdispersion problems we follow the suggestion of Wooldridge (2001) and employ the negative binomial model of Cameron and Trivedi (1986). Specifically, we employ the popular negative binomial specification NegBin II, in which the conditional variance of the dependent variable is a quadratic function of the conditional mean. Our sample is an unbalanced panel of the eight

largest United States air carriers as of 2005.¹¹

The base specification we use to test our hypotheses is:

$$\begin{aligned}
 HikesNum_{it} = & \beta_0 + \beta_1 * CRratio_{it-1} + \beta_2 * CFDratio_{it-1} + \beta_3 * LDTratio_{it-1} \\
 & + \beta_4 * Log(PredLF)_{it-1} + Controls + \gamma
 \end{aligned}
 \tag{1}$$

We define all financial health variables relative to contemporaneous industry levels. We also control for the expected loadfactor, $Log(PredLF)$. An airline's expectation about future capacity is an important input into the rate hike decision because airlines expecting to have less idle capacity will benefit more from hiking rates. In Appendix A we estimate the predicted change in *Loadfactor* over the current quarter using the beginning of quarter airline and industry level *Loadfactor* changes, the quarterly change in *Loadfactor* during the same period last year, and current weather indexes that predict weather conditions during the coming quarter. We then add this change to the beginning of the quarter *Loadfactor* to estimate the end-of-quarter predicted *Loadfactor*, $PredLF$.

In addition, the regression specifications include $Log(TotalAssets)$, as well as macroeconomic controls. $\Delta JetFuelPrice$ is the monthly change of the market price of jet fuel. $RealGDPGrowth$ and $DisposableIncome$ measure the quarterly GDP growth and the quarterly seasonally adjusted disposable personal income. We lag firm-specific financial statement information one quarter to alleviate concerns that current prices affect our measures of firm financial condition. In addition, to ensure that our tests isolate the effect of financial distress rather than bankruptcy we drop the 26 airline quarters during which airlines are in Chapter 11.

¹¹The panel is unbalanced because we treat airlines as a single entity after mergers obtain regulatory approval.

5.3 Regression Results

The results in Table V support the prediction that financially weak airlines are more likely to initiate rate hikes. Columns 1 through 3 show that all industry-adjusted measures of financial health are significant predictors of rate hike initiation in the predicted direction. When all three measures of financial health are included together, all three take the expected sign, but only the current ratio remains statistically significant. This suggests that short-term liquidity concerns rather than long-term financial distress determine the rate hike initiator.

The results are robust to controlling for hiker, year, and month fixed effects. Thus, time invariant differences in the airlines or a spurious correlation between financial distress and rate hike popularity are unlikely to be driving the results. In addition, because we are regressing a change in price on the beginning of the period financial health, reverse causality is not an issue.

The airline's predicted future loadfactor is a positive predictor of hike initiation in all specifications and marginally significant in columns (1) and (4). The lack of stronger significance could be because most airlines already have high loadfactors and this makes small variations in idle capacity less relevant for the initiation decision. Nevertheless, the signs of the estimates are in line with the airlines that expect to have less idle capacity being more likely to initiate rate hikes.

The results in Table V reconcile the findings in Campello (2003) and Chevalier and Scharfstein (1995; 1996) that financially distressed or highly levered industries are less competitive with the results in Borenstein and Rose (1995) and Busse (2002) that financial distress increases airline competition through more frequent price wars. In today's market, there is no discrepancy – financial distress is associated with higher markups.

We also find some evidence that rising fuel costs are associated with more frequent rate hikes. Indeed, prices must be adjusted upward to maintain a given level of cooperation in the face of rising costs. To the extent that a first order determinant of rate hike timing is

rising costs, our results are consistent with the notion that financially distressed airlines are most likely to attempt to maintain the current level of effective industry cooperation. In essence, the explanation of rising costs increasing the likelihood of rate hikes is not mutually exclusive from our hypothesis that financially distressed airlines will be the first to hike.

Another alternative explanation for the airfare rate hikes is that a few airlines with the largest market share invest sufficient time and resources into pricing research while other airlines mimic their price movements (see, e.g., Nevo, 2001). For instance, Delta and United initiate a large number of airfare hikes and it could be argued that these two airlines are the market leaders. We do find some support for this story via a positive coefficient on total assets before fixed effects are included; however, including time and firm-fixed effects eliminates the significance of the size variable. Thus, the evidence suggests that our hypothesis is significant after accounting for any possible effects of the market leader story.

6 The Hike Following Decision

If financial distress makes rate hikes more attractive as our hypothesis predicts, then financially weak airlines should also be more likely to match a competitor's rate hike. Unlike the hike initiation decision, we expect both short-term liquidity constraints and long-term financial distress to be positive predictors of matching.

6.1 Empirical Approach

We examine the matching decision in two ways. First, we estimate a logit regression analyzing the determinants of a successful hike. Industry experts define a successful rate hike as one that all non low-cost carriers match. We use press releases to identify the firms that match each rate hike and to create the dependent variable for our analysis, which equals to one when a hike is successful and zero otherwise.

For this empirical test, the primary variables of interest reflect the overall financial con-

dition in the airline industry. The more distressed the industry, the more likely a given hike should be to succeed. Throughout this analysis, we control for characteristics of the rate hike and the initiating airline. We also control for macro-economic conditions using changes in jet fuel prices, GDP growth, and personal disposable income.

Finally, we include the difference between the hiker's stock returns and the industry returns at the hike announcement date and the following day (in case the hike is initiated after hours), *AbRetDiff*. This variable attempts to control for the fact that rate hike success could be dependent on the initial market reaction to a hike. We find evidence consistent with this idea as the more positive the industry adjusted stock returns of the hiker are, the more likely is an aggregate price increase to succeed.

We also investigate the probability that a given competitor matches a rate hike. In this analysis, each observation represents a hike-follower pair. Thus, each rate hike contributes between five and seven observations depending on the number of competitors at the time of the hike. The dependent variable equals to one if a competitor matches a rate hike and zero otherwise.

The explanatory variables of interest for this part of the analysis reflect the financial health of the following airline. We predict that distressed airlines will be more likely to match a rate hike. As in the previous tests, we control for follower characteristics and macro-economic conditions.

6.2 Results

If financial distress makes rate hikes more attractive as our hypothesis predicts, then financially weak airlines should be more likely to match a competitor's rate hike. Table VI provides evidence consistent with this idea on the aggregate level. Both low industry-level cash flow-to-debt ratios and high industry-level long-term debt-to-assets ratios are significantly positively associated with success. In other words, rate hikes are more likely to be successful when the industry is in worse financial condition.

In addition, the results indicate that the expected industry loadfactor is positively associated with the probability of hike success in all four specifications. This means that rate hikes are more likely to be successful when the industry has little idle capacity. This finding also suggests that when the idle capacity rate is low, rate hikes are more desirable than price wars, which indirectly reconciles our findings with Borenstein and Rose (1995), Busse (2002), and Phillips and Sertsios (2013).

An auxiliary finding in Table VI is that the hiker's loadfactor is negatively related to the probability of the rate hike being followed. Maskin and Tirole (1988) provide a potential explanation. An extension of their result supports the notion that a firm's incentives to cooperate are weaker and thus collusion is less effective when rivals are capacity constrained.

Next, we investigate the determinants of matching a rate hike from the perspective of individual competitors. Table VII shows that airlines in worse financial health and with lower idle capacity are more likely to match a competitor's hike. Columns (2) through (4) indicate that the follower's relative cash flow-to-debt and long-term debt-to-assets ratios are highly significantly associated with the probability of matching. In addition, the follower's predicted future loadfactor is a strong positive predictor of matching in all specifications.

Unlike in the hike initiation setting, longer-term financial considerations affect the decision to match a rate hike. This is consistent with distressed or highly levered firms preferring to increase the level of industry cooperation (Campello, 2003), but recognizing that their more liquidity constrained rivals are likely to bear the costs of hike initiation. This can also explain the insignificance of the current ratio throughout this section. If the most liquidity-constrained airlines are always initiating rate hikes, they are never in a position to match.¹²

Overall, our findings suggest that competition weakens and cooperation increases as industry financial distress increases. In the case of airfare rate hikes, which are costly to initiate, this manifests itself in the most desperate airlines initiating the hikes and the rest of the industry being more likely to follow suit when they are financially distressed.

¹²More precisely, this rationalizes our lack of power in identifying the effect of the current ratio.

7 Conclusion

Using a unique dataset of aggregate airfare rate increases, we identify pricing behavior that is suggestive of tacit collusion. This framework allows us to attack the more general question of how financial distress affects a firm's decision to cooperate in the product market. We find that financial distress makes firms more likely to pursue cooperative actions.

Our results bridge the gap between the existing evidence suggesting that financially distressed or highly levered industries are less competitive with that in Borenstein and Rose (1995) and Busse (2002) that financial distress is associated with increased airline competition. Our evidence suggests that the results in Borenstein and Rose (1995) and Busse (2002) are unique to an airline industry with high levels of idle capacity. When idle capacity is low, as in today's airline industry, financial distress increases the attractiveness of cooperative actions.

This result is important to policy makers. Our findings suggest that reduced idle capacity increases the incentives of airlines to tacitly collude, especially when the industry is in poor financial condition.

Appendix A: Predicting Future Loadfactor

The level of idle capacity is an important input into the rate hike initiation. The economically relevant idle capacity measure is the airlines expected future idle capacity over the horizon of flights affected by the rate hike. Although this is intuitive, it is difficult to empirically measure. Last periods loadfactor is inaccurate and the future loadfactor is potentially biased by the rate hike itself. The goal of this section is to create a measure of expected future loadfactor using past data. Specifically, we use data available at the beginning of a fiscal quarter to estimate the end of quarter loadfactor.

We empirically measure expected future loadfactor by regressing the quarterly change in loadfactor on the following: the airline’s previous quarterly change in loadfactor, the airline’s quarterly change in loadfactor during the dependent variable’s quarter one year ago, the industry’s previous quarterly change in loadfactor, the industry’s quarterly change in loadfactor during the dependent variable’s quarter one year ago, current weather indexes that are associated with future weather, and month and year fixed effects.

$$\begin{aligned} \Delta Loadfactor_{it} = & \beta_0 + \beta_1 * \Delta Loadfactor_{it-1} + \beta_2 * \Delta Loadfactor_{it-4} + \beta_3 * \Delta IndLoadfactor_{t-1} \\ & + \beta_4 * \Delta IndLoadfactor_{t-4} + WeatherIndices + TimeIndicators + \gamma \end{aligned} \quad (2)$$

We obtain weather data from the National Oceanic and Atmospheric Administration (NOAA). In general, we predict that bad weather, especially high precipitation, is associated with negative changes in the loadfactor. The two weather indices most directly related to precipitation in the United States are The Arctic Oscillation (AO) and the Pacific Decadal Oscillation (PDO). The Arctic Oscillation (AO) is positively associated with warm weather in the eastern United States and negatively associated with precipitation in the Western United States. Similarly, the Pacific Decadal Oscillation (PDO) is positively associated with precipitation in the western United States. Both of these weather predictors take the expected sign and suggest that higher predicted precipitation is associated with lower future loadfactors.

We also include other weather indices, however there is no clear prediction regarding their effect on weather in the United States as their effect varies by region. For example, the Pacific North American teleconnection pattern (PNA) is associated with high precipitation in the western part of the country and lower precipitation in the central United States. Other indices we include are the North Atlantic Oscillation (NAO), the Scandinavia Pattern, and the West Pacific Pattern. All results are robust to excluding these last three predictors of weather.

The results in the Appendix Table also suggest that the quarterly change in loadfactor is negatively related to the change in loadfactor over the same quarter in the previous year. This result coupled with the presence of month fixed effects suggests that if last year's change in load factor was abnormally positive for the current month then this years change is expected to be negative. In other words, there is some mean reversion in the change in loadfactor. All of the weather indexes are significant predictors of the change in loadfactor.

To complete our measure for predicted loadfactor, we add the predicted future change as estimated by the above empirical model to the loadfactor at the beginning of the quarter.

Although we use weather (and other variables) to predict future loadfactor and do not instrument for the loadfactor, some discussion of whether the weather variables affect supply, demand, or both is worthwhile. To predict future loadfactor we regress the quarterly change in loadfactor on beginning of the quarter measures including indexes designed to predict weather several months out in the future. If airlines predict future weather using these (or similar) indexes then the weather indexes we use are related to the perceived future supply of airline capacity. If passengers also use these indexes then demand could also be affected. In predicting future loadfactor, it does not matter which of these channels are at play, although we believe that the supply side channel is more likely.

Appendix: Predicting Loadfactor This table presents monthly regression results in which the dependant variable is the change in *Loadfactor* from month t to month $t + 3$. We include several lagged values of the change in *Loadfactor* as well as the following weather variables: *NAO* is the North Atlantic Oscillation, *PNA* is the Pacific-North American Teleconnection Pattern, *AO* is the Atlantic Oscillation, *PDO* is the Pacific Decadal Oscillation, *SCA* is the Scandinavia Pattern, *WP* is the Western Pacific Oscillation.

	(1)
	$\Delta\text{Loadfactor}_{t,t+3}$
$\Delta\text{Loadfactor}_{t-3,t}$	0.0618 (0.0615)
$\Delta\text{Loadfactor}_{t-12,t-9}$	-0.1832*** (0.0551)
$\Delta\text{Ind. Loadfactor}_{t-3,t}$	-0.1176 (0.0921)
$\Delta\text{Ind. Loadfactor}_{t-12,t-9}$	-0.2816*** (0.1057)
NAO_{t-1}	-0.0056* (0.0029)
PNA_{t-1}	0.0069*** (0.0021)
AO_{t-1}	0.0065** (0.0032)
PDO_{t-1}	-0.0062*** (0.0021)
SCA_{t-1}	-0.0049** (0.0023)
WP_{t-1}	-0.0042** (0.0019)
Constant	0.0590*** (0.0112)
Month Indicators	YES
N	718
R-Squared	67.53%

Standard errors in parentheses

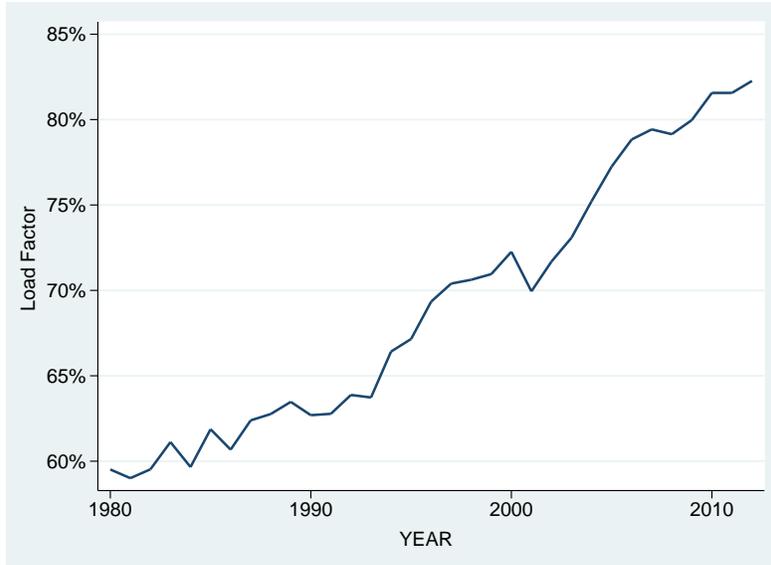
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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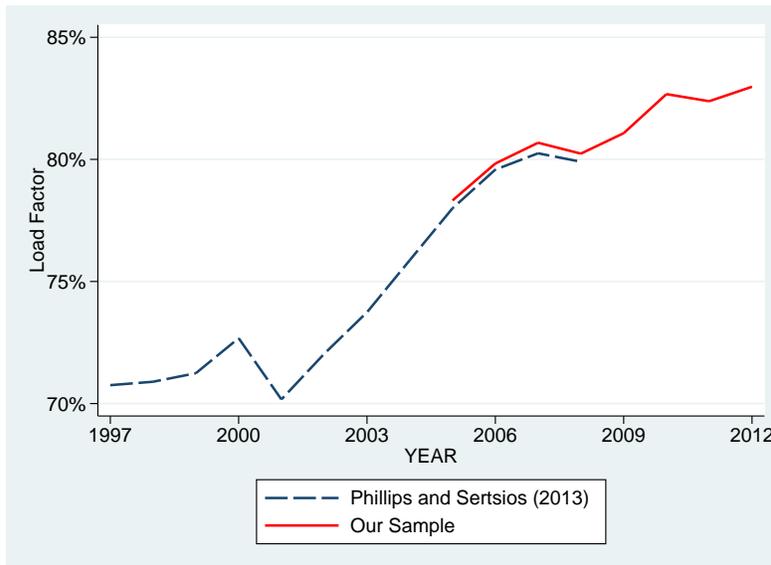
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(a) U.S. Domestic Loadfactor



(b) Average Sample Loadfactors

Figure 1: Domestic Load Factor 1980-2012. Panel (a) of this figure depicts the annual series of the average US Domestic Loadfactor in the airline industry for the period 1980-2012. Panel (b) compares the average sample Loadfactor in our study with that in Phillips and Sertsios (2013). Data source: Air Transport Association of America website.

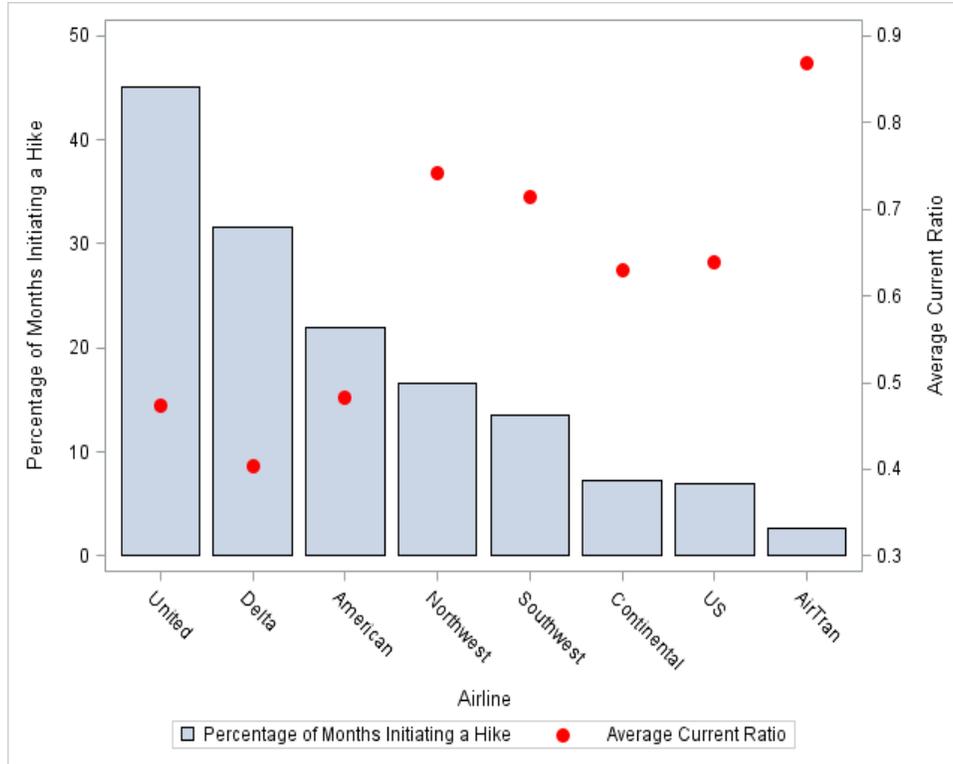


Figure 2: Number of Rate Hikes and Mean Current Ratio by Airline. This figure shows the number of rate hikes initiated by each airline and the mean Current Ratio of each airline over the sample period from January, 2005 through December, 2012. The number of hikes is depicted as the gray bars, while firm short-term liquidity (the current ratio) appears in red.

Table I: Rate Hike Descriptive Statistics. Panel A of this table presents descriptive statistics of the rate hikes initiated by each airline. The second column presents the total number of hikes initiated by each airline, while the third column shows the fraction of these hikes that were successful. The fourth and the fifth columns present the median of the minimum and median of the maximum values of the rate hikes. Panel B provides similar statistics partitioned by year.

Panel A: Rate Hike Descriptive Statistics Across Firms				
Airline	Num. Hikes	Percentage Successful	Median Min.	Median Max.
Delta	27	0.59	10	10
Continental	5	0.60	10	10
US Airways	5	0.20	10	10
American	20	0.70	10	16
Southwest	15	1.00	6	10
United	40	0.53	10	10
Northwest	4	0.50	30	35
AirTran	2	1.00	6	10
Total	118	0.63	10	10
Panel B: Rate Hike Descriptive Statistics Over Time				
Year	Num. Hikes	Percentage Successful	Median Min.	Median Max.
2005	10	0.60	8	20
2006	10	0.70	10	20
2007	21	0.76	10	10
2008	22	0.68	10	20
2009	11	1.00	10	10
2010	6	0.50	6	10
2011	21	0.43	6	10
2012	17	0.41	10	10

Table II: The Effect of Rate Hikes on Airfare Prices This table presents estimation results from monthly regressions of the percentage change in the airfare CPI on the number of airfare rate hikes and the percentage change in the price of crude oil. In Columns (1) and (3) we have all attempted rate hikes, while Columns (2) and (4) partition rate hikes by whether they were successful. The standard errors (in parenthesis) are adjusted for heteroskedasticity.

	(1)	(2)	(3)	(4)
	$\Delta\text{AirfareCPI}_t$			
Hikes _t	0.0023** (0.0011)		0.0011 (0.0011)	
Hikes _{t-1}	0.0018 (0.0014)		-0.000009 (0.0014)	
Hikes _{t-2}	0.0028* (0.0014)		0.0012 (0.0014)	
Hikes _{t-3}	0.00004 (0.0014)		-0.0007 (0.0015)	
Successful _t		0.0058*** (0.0018)		0.0046** (0.0021)
Successful _{t-1}		0.0050** (0.0022)		0.0038 (0.0023)
Successful _{t-2}		0.0053** (0.0025)		0.0045* (0.0026)
Successful _{t-3}		0.0009 (0.0017)		0.0005 (0.0018)
Unsuccessful _t		-0.0011 (0.0016)		-0.0016 (0.0015)
Unsuccessful _{t-1}		-0.0010 (0.0028)		-0.0027 (0.0030)
Unsuccessful _{t-2}		0.0035* (0.0020)		0.0018 (0.0024)
Unsuccessful _{t-3}		0.0010 (0.0021)		-0.0002 (0.0024)
$\Delta\text{JetFuelPrice}_t$			0.0423** (0.0193)	0.0308 (0.0206)
$\Delta\text{JetFuelPrice}_{t-1}$			0.0370 (0.0229)	0.0248 (0.0239)
$\Delta\text{JetFuelPrice}_{t-2}$			0.0182 (0.0253)	0.0033 (0.0242)
$\Delta\text{JetFuelPrice}_{t-3}$			0.0188 (0.0227)	0.0173 (0.0221)
Constant	-0.0255** (0.0117)	-0.0294** (0.0125)	-0.0182* (0.0107)	-0.0209 (0.0139)
Year-Quarter Fixed Effects	YES	YES	YES	YES
R-Squared	71.63%	75.22%	74.46%	76.99%
Observations	93	93	93	93

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table III: Cumulative Abnormal Returns Around Rate Hikes Panel A of this table presents results on the cumulative abnormal returns around airfare rate hikes. Abnormal returns are calculated using the actual stock returns from day 0 to day 2 and the corresponding industry stock returns over the same window, where day 0 is the day of the airfare rate hike (the event date). We use the returns on the Bloomberg U.S. Airline Index (BUSAIRL) to measure airline industry returns. BUSAIRL includes the largest air carriers in the U.S. and the respective data come from Bloomberg. To obtain the abnormal returns, we first run regressions of firm-specific hiker returns on airline industry returns, estimated from day -130 to -30 relative to the event date. We then use these estimates to obtain the predicted hiker industry-adjusted returns in the event window. Results are partitioned on whether a hike is eventually successful. Panel B presents results on the cumulative abnormal returns around airfare rate hikes competition. Abnormal returns are calculated as the difference between the actual stock returns from day -2 to day 1 and the predicted stock returns in the same event window, where day 0 is the day of the airfare rate hike completion (the event date). The predicted stock returns are calculated in the same way as in Panel A.

Panel A: CAR to Hiking		
Full Sample	Unsuccessful	Successful
-0.00352	-0.0121**	0.00161
(0.00354)	(0.00580)	(0.00439)
N=110	N=41	N=69
Panel B: CAR around Hike Completion		
Full Sample	Unsuccessful	Successful
-0.00832*	-0.0187**	-0.00172
(0.00499)	(0.00910)	(0.00561)
N=72	N=28	N=44

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IV: Key Variables. This table presents the mean, median, and standard deviation for selected variables for each firm in the sample. These include the current ratio (CR), the current ratio minus the industry minimum current ratio ($Current\ Ratio$), the cash flow-to-debt ratio (CFD), the cash flow-to-debt ratio minus the industry minimum cash flow-to-debt ratio ($CFDebt$), the long-term debt-to-assets ratio (LTD), the long-term debt-to-assets ratio minus the industry maximum long-term debt-to-assets ratio ($LTDAssets$), the Loadfactor, the predicted Loadfactor ($PredLF$), as well as firm total assets ($TotalAssets$).

Airline	CR			$Current\ Ratio$		CFD		
	Mean	Median	St.Dev.	Mean	Median	Mean	Median	St.Dev.
Delta	0.553	0.564	0.103	0.071	0.032	0.220	0.266	0.116
Continental	0.774	0.769	0.064	0.238	0.233	0.139	0.123	0.063
US Airways	0.774	0.741	0.167	0.250	0.262	0.155	0.203	0.157
American	0.582	0.588	0.089	0.053	0.026	0.090	0.094	0.064
Southwest	0.789	0.754	0.160	0.277	0.326	0.341	0.342	0.079
United	0.648	0.693	0.103	0.129	0.096	0.157	0.173	0.116
Northwest	0.892	0.960	0.197	0.386	0.403	0.231	0.278	0.155
AirTran	0.954	0.867	0.271	0.421	0.335	0.187	0.192	0.121
Total	0.732	0.712	0.199	0.213	0.193	0.190	0.192	0.134
	$CFDebt$			LTD		$LTDAssets$		
	Mean	Median	Mean	Median	St.Dev.	Mean	Median	
Delta	0.188	0.200	0.341	0.311	0.109	-0.167	-0.193	
Continental	0.121	0.112	0.423	0.420	0.040	-0.146	-0.099	
US Airways	0.113	0.130	0.496	0.473	0.257	-0.043	0.000	
American	0.062	0.020	0.322	0.317	0.037	-0.233	-0.193	
Southwest	0.306	0.294	0.160	0.158	0.049	-0.384	-0.327	
United	0.108	0.083	0.334	0.336	0.066	-0.161	-0.164	
Northwest	0.164	0.184	0.400	0.325	0.134	-0.122	-0.185	
AirTran	0.164	0.149	0.422	0.403	0.057	-0.140	-0.091	
Total	0.156	0.149	0.353	0.354	0.155	-0.184	-0.161	
	$Loadfactor$			$PredLF$		$Total\ Assets$		
	Mean	Median	St.Dev.	Mean	Median	Mean	Median	St.Dev.
Delta	83.80	84.51	4.61	84.01	83.98	38,308	43,519	8,500
Continental	83.71	84.16	3.49	83.82	84.59	12,101	12,443	974
US Airways	82.44	83.20	4.49	81.89	82.73	7,985	7,995	540
American	82.36	82.32	4.19	82.35	82.81	24,669	25,385	1,770
Southwest	75.36	76.36	6.23	75.36	75.84	15,785	14,800	2,290
United	84.14	84.79	3.77	84.02	84.62	21,617	20,525	2,770
Northwest	85.53	84.10	4.73	83.94	84.18	19,811	20,867	4,416
AirTran	76.78	77.35	6.12	76.81	76.86	1,859	2,096	457
Total	81.16	82.01	5.90	81.13	82.42	17,541	15,143	11,237

Table V: The Hike Initiation Decision and Firm Financial Health. This table reports negative binomial regression estimates for the relation between airline financial health and the propensity to initiate airfare rate hikes. The dependent variable is the number of airfare rate hikes initiated by an airline in a given quarter, excluding bankrupt firm-quarters. *Current Ratio* is defined as the current ratio minus the minimum industry current ratio. *CFDebt* is defined as the cash flow-to-debt ratio minus the minimum industry cash flow-to-debt ratio. *LTDAssets* is defined as the long-term debt-to-assets ratio minus the maximum industry long-term debt-to-assets ratio. $\text{Log}(\text{PredLF})$ is the predicted quarterly loadfactor of a given airline using data as of the end of the previous quarter. $\Delta\text{JetFuelPrice}$ is the quarterly change of the market price of jet fuel. *RealGDPGrowth* and *DisposableIncome* measure the quarterly GDP growth and the quarterly seasonally adjusted disposable personal income, respectively. The standard errors (in parenthesis) are adjusted for heteroskedasticity.

	(1)	(2)	(3)	(4)
	The Number of Hikes in a Quarter			
Current Ratio _{t-1}	-2.604*** (0.968)			-2.208** (1.018)
CFDebt _{t-1}		-2.946** (1.208)		-1.560 (1.365)
LTDAssets _{t-1}			1.771** (0.879)	0.887 (0.651)
Log(PredLF)	9.769* (5.307)	5.764 (4.195)	2.899 (4.136)	9.866* (5.097)
Log(TotalAssets) _{t-1}	-0.981* (0.591)	-0.494 (0.552)	-0.452 (0.565)	-0.775 (0.601)
$\Delta\text{JetFuelPrice}$	0.040*** (0.011)	0.031*** (0.010)	0.031*** (0.010)	0.037*** (0.010)
RealGDPGrowth	0.509 (5.805)	3.401 (5.796)	3.883 (5.681)	1.533 (5.949)
Disposable Income	0.069 (0.352)	0.146 (0.355)	0.223 (0.344)	0.079 (0.357)
Constant	-35.30 (22.96)	-22.45 (18.82)	-10.48 (18.40)	-37.47* (22.17)
Quarter Indicators	YES	YES	YES	YES
Year Indicators	YES	YES	YES	YES
Firm Indicators	YES	YES	YES	YES
N	200	200	200	200
Log Likelihood	-148.9	-150.2	-151.2	-147.6
Pseudo R-Squared	25.7%	25.0%	24.5%	26.3%

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table VI: The Determinants of Successful Hikes. This table reports logistic regression estimates for specifications investigating the determinants of airfare rate hike success. The dependent variable takes the value of one whenever a rate hike is successful and zero otherwise. *IndustryCR* is the average industry current ratio, *IndustryCFD*, *IndustryLTD*, and *IndustryLF* are defined analogously. *AbRetDiff* is the difference in abnormal stock returns to the hiker and those of its industry rivals. *Min* is the minimum dollar amount of the hike. *Fixed* is an indicator variable taking the value of one for a fixed-rate hike, 0 otherwise. *Current Ratio*, *CFDebt*, and *LTDAssets* are defined as the current, cash flow-to-debt, and long-term debt ratios of the hiking airline minus the industry minimum (maximum in the last case). *Log(PredLF)* and *Log(TotalAssets)_{t-1}* are the predicted quarterly loadfactor and the Log(TotalAssets) for the hiking airline. *ΔJetFuelPrice* is the monthly change of the market price of jet fuel. *RealGDPGrowth* and *DisposableIncome* measure the quarterly GDP growth and the quarterly seasonally adjusted disposable personal income, respectively. The standard errors (in parenthesis) are adjusted for heteroskedasticity.

	(1)	(2)	(3)	(4)
	Indicator for a Successful Hike			
IndustryCR	-4.351 (4.201)			3.300 (5.352)
IndustryCFD		-11.34*** (3.73)		-9.198** (4.573)
IndustryLTD			30.73*** (11.13)	24.78** (11.58)
IndustryLF	19.44* (10.32)	27.47* (14.31)	28.05** (13.91)	30.74** (15.22)
AbRetDiff	16.96** (7.98)	19.79** (8.10)	15.70* (8.02)	18.18** (8.30)
Min	0.011 (0.059)	-0.015 (0.047)	0.022 (0.068)	-0.00009 (0.060)
Fixed	0.205 (0.616)	0.399 (0.595)	-0.236 (0.685)	-0.041 (0.672)
Current Ratio _{t-1}	-2.182 (2.088)	-0.850 (2.220)	0.357 (1.893)	1.289 (2.193)
CFDebt _{t-1}	-2.999 (3.558)	-2.774 (3.462)	-4.877 (3.982)	-4.492 (4.075)
LTDAssets _{t-1}	-4.578 (3.724)	-4.855 (4.207)	-7.163 (4.717)	-7.225* (4.290)
Log(PredLF)	-31.63*** (10.88)	-40.38** (16.05)	-40.11*** (14.95)	-42.98** (16.85)
Log(TotalAssets) _{t-1}	-0.419 (0.702)	-0.174 (0.837)	0.249 (0.855)	0.442 (0.980)
ΔJetFuelPrice	0.039** (0.016)	0.051*** (0.019)	0.044*** (0.016)	0.052*** (0.019)
RealGDPGrowth	-26.95 (17.21)	-33.62* (18.47)	-26.31* (15.99)	-31.54* (17.71)
DisposableIncome	0.034 (0.290)	0.160 (0.389)	0.055 (0.276)	0.114 (0.341)
Constant	61.69*** (19.69)	61.81*** (20.37)	40.96** (17.77)	41.39* (21.81)
N	106	106	106	106
Log Likelihood	-54.06	-50.08	-49.05	-47.16
Pseudo R-Squared	22.5%	28.2%	29.7%	32.4%

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table VII: The Hike Following Decision and Firm Financial Health. This table reports logistic regression estimates for the relation between airline financial health and the likelihood of following airfare rate hikes. The dependent variable takes the value of one whenever a rival airline follows a given airfare rate hike and zero otherwise. Naturally, the hiking airlines are excluded from the sample. *Current Ratio* is defined as the current ratio of a potential follower minus the minimum industry current ratio. *CFDebt* is defined as the cash flow-to-debt ratio of a potential follower minus the minimum industry cash flow-to-debt ratio. *LTDAssets* is defined as the long-term debt-to-assets ratio of a potential follower minus the maximum industry long-term debt-to-assets ratio. *Log(PredLF)* is the log of the predicted quarterly loadfactor of a potential follower using data as of the end of the previous quarter. *ΔJetFuelPrice* is the monthly change of the market price of jet fuel. *RealGDPGrowth* and *DisposableIncome* measure the quarterly GDP growth and the quarterly seasonally adjusted disposable personal income, respectively. The top part of each row presents coefficient estimates, while standard errors are in parentheses.

	(1)	(2)	(3)	(4)
	Indicator for Matching a Hike			
Current Ratio _{t-1}	-0.627 (0.646)			0.970 (0.702)
CFDebt _{t-1}		-4.704*** (1.124)		-3.660*** (1.231)
LTDAssets _{t-1}			7.641*** (1.662)	6.977*** (1.759)
LogLF	29.03*** (3.19)	25.42*** (2.99)	20.71*** (3.16)	18.66*** (3.28)
Log(TotalAssets) _{t-1}	0.645*** (0.149)	0.758*** (0.137)	1.395*** (0.228)	1.474*** (0.260)
ΔJetFuelPrice	0.009 (0.009)	0.008 (0.010)	0.010 (0.010)	0.009 (0.010)
RealGDPGrowth	3.181 (7.913)	4.348 (8.099)	5.753 (8.096)	6.312 (8.108)
DisposableIncome	0.487*** (0.176)	0.413** (0.180)	0.426** (0.167)	0.382** (0.170)
Constant	-132.28*** (13.61)	-116.55*** (12.96)	-100.11*** (13.35)	-91.53*** (13.56)
Month Indicators	YES	YES	YES	YES
Year Indicators	YES	YES	YES	YES
N	711	711	711	711
Log Likelihood	-295.2	-287.4	-280.2	-276.1
Pseudo R-Squared	35.8%	37.5%	39.1%	40.0%

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$