

# How Do Firm Financial Conditions Affect Product Quality and Pricing?

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We analyze the interaction of firm product quality and pricing decisions with financial distress and bankruptcy in the airline industry. We consider an airline's choices of quality and price as dynamic decisions that trade off current cash flows for future revenue. We examine how airline mishandled baggage, on-time performance, and pricing are related to financial distress and bankruptcy, controlling for the endogeneity of financial distress and bankruptcy. We find that an airline's quality decisions are differentially affected by financial distress and bankruptcy. Product quality decreases when airlines are in financial distress, consistent with financial distress reducing a firm's incentive to invest in quality. In contrast, in bankruptcy product quality increases relative to financial distress. In addition, we find that firms price more aggressively when in financial distress consistent with firms trying to increase short-term market share and revenues.

*Key words:* finance; corporate finance; industrial organization; market structure; firm strategy; market performance; firm objectives; organization and behavior

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## 1. Introduction

Financial distress is frequently cited as influencing firm value by causing firms to take actions that would be suboptimal in normal times to reduce their chance of entering bankruptcy and potentially being liquidated.<sup>1</sup> Among these actions, a financially distressed firm may produce a lower-quality product and attempt to sell this product as higher quality to stave off bankruptcy, as modeled by Maksimovic and Titman (1991). Additionally, in case the firm does not avoid bankruptcy and is reorganized, it might face different incentives, which can also have an impact on product quality. A firm operating under Chapter 11 does not face the severe conflicts of interest between equity holders and debt holders that it faced when it was financially distressed. Thus, a firm's incentives to produce high-quality products might be restored when the firm enters into bankruptcy. Empirically, the importance of these effects is unknown.

We examine how product quality decisions, including on-time performance and lost baggage, vary with financial distress and bankruptcy in the airline

industry. We analyze whether managers reduce product market quality in periods of financial distress before the firm actually defaults, as well as quality decisions in bankruptcy. Our measure of financial distress is a firm's probability of default, calculated using Merton's distance to default measure. Changes in the probability of default may reduce a firm's incentives to produce a high-quality product since a reduction in quality may increase current cash flows at the expense of bondholders who may receive less in the future. In bankruptcy, the time horizon of firm managers may be longer, because debt holders and other fixed claimants are closer to becoming future owners of the firm, and management may also wish to be involved in the firm after bankruptcy.<sup>2</sup> In addition, firm claimants' incentives to invest in customer retention may increase under bankruptcy, because they need to demonstrate to the bankruptcy judge that the firm is viable as a going concern. Thus, the firm managers and claimants to the firm may have incentives to increase quality in bankruptcy relative to periods of financial distress to keep existing customers.

<sup>2</sup> Hotchkiss (1995) examines firms after bankruptcy and finds that the management of many bankrupt firms does not change after emerging from Chapter 11. Strömberg (2000) documents that conflicts of interest in bankruptcy auctions can lead to inefficient continuation decisions.

<sup>1</sup> See, for example, Dodes et al. (2008). Also see Asquith et al. (1994) for firm-specific actions taken by a sample of junk-bond issuers to avoid bankruptcy.

Although our primary focus is product quality, we also analyze airline pricing as part of an integrated simultaneous equation approach. We analyze the airline's pricing decisions with product quality because these decisions are interrelated and may also be affected by a firm's financial distress and bankruptcy. We examine whether a financially distressed firm might have incentives to lower prices to increase market share and current cash flow even if this triggers a price war in the future. Changes in a firm's pricing strategies in bankruptcy relative to financial distress are less straightforward. The firm may face incentives to restore a previous implicit cooperative equilibrium with its competitors, which can lead to an increase in prices in bankruptcy relative to financial distress. However, the firm might choose to invest in customer retention in bankruptcy, leading to a further price reduction.

We find that airlines' quality and pricing decisions are differently affected by financial distress and bankruptcy using a simultaneous equation approach that controls for the endogeneity of these decisions. Financial distress reduces a firm's incentive to invest in quality. In addition, firms price more aggressively when in financial distress, consistent with them trying to increase short-term market share and revenues. Interestingly, the negative effects of financial distress on product quality are not present during bankruptcy. In bankruptcy, product quality increases relative to the prebankruptcy financial distress period, consistent with airlines investing in customer retention and reputation through product quality. Regarding prices, we find that firms further reduce prices in bankruptcy relative to periods of financial distress, although this reduction is not statistically significant. Our results are robust to using route-level analysis with firm-route fixed effects for the only quality measure available at that level of aggregation (on-time performance).

Our central contribution is that our paper is the first to examine the different product market implications between bankruptcy and financial distress. Our paper is an integrated study of financial distress and bankruptcy. Previous literature has either examined financial distress or bankruptcy without considering how these states have different implications.<sup>3</sup> In airlines, a set of papers examines financial distress but does not consider the differential effects of bankruptcy,<sup>4</sup> whereas a second set of papers focuses just on bankruptcy and does not consider

financial distress nor the endogeneity of bankruptcy.<sup>5</sup> We are the first to show that a firm's product quality decisions differ substantially in financial distress and bankruptcy. Our findings are of particular importance because bankruptcy is commonly perceived as an extreme case of financial distress, although we actually show that the implications for product market competition are considerably different.

A second contribution of our paper is methodological. We simultaneously estimate a firm's product market decisions of price and product quality along with a firm's demand and financial conditions. To identify the casual impact of financial conditions on a firm's supply choices (product quality and pricing), we rely on multiple instruments that affect demand and financial conditions but do not have a direct impact on a firm's supply choices. This is the first paper that attempts to address endogeneity concerns regarding firms' financial conditions and product market behavior. By addressing endogeneity concerns, we can shed light on how financial conditions affect product market behavior from a different angle than previous papers in the literature. Previous papers study the product market implications of firms' voluntary changes in financial structure (see Phillips 1995, Chevalier 1995, Kovenock and Phillips 1997). We, on the other hand, study how involuntary/exogenous changes in financial conditions affect product market behavior.

Our paper proceeds as follows. In §2 we give the theoretical background and also present our econometric model. In §3, we describe our data. Section 4 presents the results for financial distress and bankruptcy. Section 5 concludes.

## 2. Quality and Pricing in Financial Distress and Bankruptcy

In this section we describe how financial distress and bankruptcy may affect a firm's quality and pricing decisions. In §2.1 we describe the theoretical background and also describe the implications we test from the prior theoretical literature. In §2.2 we present the econometric model we estimate.

### 2.1. Theoretical Background

Consider a firm with some degree of market power, to the extent it can choose product quality. Assume also that the good sold by the firm is an experience good, so the quality is not known beforehand. In this setting, Maksimovic and Titman (1991) show that in periods of financial distress when firms are in danger of not meeting their financial obligations, firm managers—acting on behalf of equity holders—may have

<sup>3</sup> See, for example, Hoshi et al. (1990), Asquith et al. (1994), Hotchkiss (1995), Andrade and Kaplan (1998), Maksimovic and Phillips (1998), Pulvino (1998), Campello (2003), and Khanna and Tice (2005).

<sup>4</sup> See Rose (1990), Dionne et al. (1997), Pulvino (1998), Busse (2002), and Noronha and Singal (2004).

<sup>5</sup> Borenstein and Rose (2003), Benmelech and Bergman (2011), and Ciliberto and Schenone (2012a, b) focus on bankruptcy in airlines.

incentives to lower the quality of the product they sell if they can earn higher profits until the lower quality is observed. Firms can cut quality and given that quality provision is costly; this will lower the marginal cost of production. Until consumers realize the good sold is of lower quality, firms will earn higher profits.

Once the lower quality is observed, firms will face reduced demand. If a firm faces a significant chance of defaulting on its debt, it may choose to cut quality today to survive in the hopes that there is a positive demand shock before consumers discover the lower quality. The positive demand shock may enable survival, despite the demand reduction that comes as a consequence of lower past quality. Afterward, the firm can rebuild its reputation. However, if there is no positive demand shock and the firm defaults on its debt, debt holders rather than equity holders bear the loss of the future profits. Put differently, in financial distress, the firm chooses to reduce the quality of its product because equity holders do not fully bear the downside consequences of that action. On our websites<sup>6</sup> we make available a theoretical analysis that gives the details behind this argument.

This argument is analogous to the firm's shareholders getting an involuntary loan from customers by raising cash flows today due to the reduced cost of providing lower quality. If reputation is valuable, however, the increase in current cash flows today should be smaller than the expected decrease in cash flow the firm will experience later due to the loss of reputation. Thus, without debt there would not be a reason to cut quality.<sup>7</sup> It is the possibility of default combined with shareholders' limited liability that makes the intertemporal cash flow shift valuable to shareholders, because in the future, under low states of demand, debt holders bear the cost of low quality today. This argument is different from a typical asset substitution argument, because it does not require an increase in the variance of future cash flows. However, asset substitution arguments may not be completely irrelevant: To the extent that a reputational loss reduces future cash flows more strongly under low states of demand than under high states of demand, the variance of future cash flows increases if quality is cut under financial distress. This would further reinforce a firm's incentives to cut quality during financial distress.

The setting described above fits well the airline industry. In the airline industry, a firm's provision of

future quality is unobserved at the time an airline ticket is sold. Consumers can observe lagged measures of quality, but quality at the actual time the flight is taken may be quite different than past quality. From an airline's perspective, the probability of default enters its supply of quality decision. The airline's supply of quality will be affected by a higher probability of default because the future benefits of quality diminish, given that there is a higher probability that the airline will enter into bankruptcy (equivalent to a higher discount rate). To the extent that not all consumers are aware of this present cut in quality (or that there is a stochastic component on the firm's cost of quality provision that is not costlessly observed by customers), the airline optimally reduces quality, taking an involuntary loan from consumers.

Although our main implications are with respect to product quality, pricing can also be affected by financial distress. Morrison and Winston (1996) and Busse (2002) found evidence that the prices in the airline industry are characterized by alternating periods of tacit collusive agreements and price wars, consistent with the early work on trigger strategies in repeated games (see Friedman 1971). Price wars can be triggered as a firm reduces prices and deviates from the tacit collusive agreement to gain market share in the short run. Because a higher default probability is equivalent to a higher discount rate, a firm in financial distress will be more prone to reducing prices even if this triggers a price war in the future, given that debt holders may bear the loss from price wars. This logic holds only if there is no immediate detection of the price deviation.

Although the reduction in prices can be observed, airlines can modify the average price of their tickets by changing the composition of seats sold without changing their posted prices, and this action may go unnoticed by other airlines for a significant period, giving scope for a nonimmediate detection from competitors.<sup>8,9</sup> This logic differs from Borenstein and

<sup>8</sup> It is well known that airlines charge different prices even within the economy class. Each airline decides how many seats to offer at each price using an optimization package (e.g., PROS<sup>®</sup> (Passenger Revenue Optimization System)). The cheapest seats are sold first, and as time passes the more expensive ones start to sell as well. If an airline decides to sell all the economy seats at the cheapest price, the average price of that airline will be reduced, yet the posted price might not have changed. This makes the detection of price deviations difficult because other firms will find out only after observing that their bookings are not behaving as expected.

<sup>9</sup> A change in seat composition that lowers average prices is consistent with financially distressed firms' catering to a clientele that has a lower valuation for quality assurance, as when firms are in distress they might not have the reputational capital to ensure a more uniform level of product quality. We thank the associate editor for pointing this out.

<sup>6</sup> See <http://www.marshall.usc.edu/faculty/directory/gordonphillips> and <http://sertsios.weebly.com>.

<sup>7</sup> Our theoretical background relates more broadly to prior theoretical papers that study a firm's trade-off between short-term gains from cheating against long-term forgone earnings from a reputational loss (see Klein and Leffler 1981, Shapiro 1983, Titman 1984, among others).

Rose's (1995) interpretation of prebankruptcy price reduction. They argue that prices go down because demand is lower for a distressed firm. Our hypothesis is that even after controlling for demand changes, there is still an incentive to reduce prices as a firm's financial distress increases.

We thus test the following central implication:

**HYPOTHESIS 1.** *Firms cut product quality and price as the probability of default increases.*

We also consider the effect of operating in Chapter 11 bankruptcy on firms' decisions. Chapter 11 bankruptcy is a state in which the firm continues to operate while it is attempting to reorganize. Firm management has the right to propose a reorganization plan. The plan is then voted upon by claimants to the firm, with each class approving the plan if one-half by number and two-thirds of the aggregate face value agree to the plan. The plan involves offering new securities to existing claimants under which they exchange their old debt securities for less senior and covenant free securities like equity. This exchange offer is also called the exit consent provision. Management's right to propose a plan legally exists for the first 120 days, but extensions are generally automatically granted by the bankruptcy judge. This bankruptcy reorganization plan also has to pass a feasibility test; specifically, management has to demonstrate to the judge that the firm is viable as a going concern under the new plan.

We hypothesize that Chapter 11 bankruptcy affects a firms' incentives differently than financial distress. Management wishes to emerge from bankruptcy, and the shareholders of the reorganized firm will fully face the downside of not investing in reputation, as after the exit consent debt holders typically become equity holders. As a consequence, there will be no conflict between financial claimants and the firm's horizon becomes longer. For these reasons, we hypothesize that in bankruptcy, the firm's incentives to treat existing customers well and to increase quality will increase relative to when the firm was financially distressed.<sup>10</sup>

The effect on price is less clear. There are three conflicting incentives. Two of them imply that prices do not increase with respect to the distress period, and one of them implies that they increase. First, the management does not have to make interest and principal payments and as such has more flexibility to

reduce price.<sup>11</sup> Second, airlines need to convince consumers to fly with them in spite of potential recent quality cuts and the consumer's potential belief that the firm may be liquidated. Therefore, prices should not increase. However, airlines might want to reestablish tacit collusive agreement with competitors, as the new shareholders now have a much longer-term perspective for the company than what the previous shareholders had when the company was financially distressed. Given the ambiguity in the effect of bankruptcy on prices, we are only able to state our second central hypothesis in terms of product quality:

**HYPOTHESIS 2.** *In bankruptcy, firms increase product quality relative to prebankruptcy financial distress periods.*

## 2.2. Empirical Strategy and Econometric Model

Our empirical strategy analyzes the effects of financial distress, measured as default probability, and bankruptcy on a firm's supply decisions (product quality and price). We analyze financial distress separately from bankruptcy because a firm's default probability is not defined when a firm is in bankruptcy. We use only nonbankruptcy firm-quarter observations in analyzing the effect of financial distress, and we use only distressed and bankrupt firm-quarters to analyze the differential effects of bankruptcy and financial distress. By analyzing financial distress and bankruptcy separately, we do not impose any value on the default probability when it is not defined (during bankruptcy). This is important because we hypothesize that before bankruptcy the default probability plays the role of a higher discount rate, shortening the firm's horizon, but while in bankruptcy a higher financial distress does not have any direct implication regarding a firm's horizon.

In unreported results (available upon request) we also use the whole sample to estimate simultaneously a system that contains both financial distress and bankruptcy. As mentioned above, the main limitation of this analysis is that we cannot estimate the probability of financial distress when the firm is in bankruptcy. Thus, in this case, we set the financial distress variable to be undefined with a value of 0 when the firm is in bankruptcy and let a "predicted" bankruptcy dummy pick up the full effect of distress and bankruptcy. We end up finding similar results using this approach as when we estimate financial distress and bankruptcy separately.

We now present the econometric approach that we use to analyze financial distress and bankruptcy separately. We first present the econometric model we use to analyze financial distress and then follow with the model for bankruptcy.

<sup>10</sup> We are not claiming that product quality during bankruptcy needs to be exactly the same as product quality during financially healthy periods. In bankruptcy firms might be trying harder than ever to regain customer trust. Thus, it is possible that product quality can actually be higher during bankruptcy than in healthy periods.

<sup>11</sup> Additionally, airlines can renegotiate pension benefits, reducing their costs (U.S. Bankruptcy Code, Chapter 11, Section 1113). See Benmelech et al. (2012).

**2.2.1. Financial Distress.** In this analysis of financial distress, we initially drop firm-quarter observations where the firm is in bankruptcy because financial distress is not defined in bankruptcy. We use a simultaneous equation approach to estimate the impact of the probability of default on supply decisions. Specifically, we jointly examine a firm's supply decisions of quality ( $S$ ) and price ( $P$ ) with its quantity demanded ( $Q$ ) and the probability of default ( $\text{Pr\_def}$ ).

The following four simultaneous equations describe the airline economic environment:

$$S_{it} = h(P_{it}, Q_{it}, \text{Pr\_def}_{it}, Y_{it}); \quad (1a)$$

$$P_{it} = g(S_{it}, Q_{it}, \text{Pr\_def}_{it}, X_{it}); \quad (2a)$$

$$Q_{it} = f(\text{Pr\_def}_{it}, P_{it}, S_{it}, W_{it}); \quad (3a)$$

$$\text{Pr\_def}_{it} = j(Q_{it}, P_{it}, S_{it}, Z_{it}). \quad (4a)$$

In the above equations,  $S$  is a product quality measure, either mishandled bags rate or on-time arrivals;  $P$  is our measure of price, which, following the airline industry convention, is calculated as a yield or average price per mile;  $Q$  is the total quantity of total enplaned passengers (TEP); and  $\text{Pr\_def}$  is the default probability. Equations (1a) and (2a) can be obtained from the optimization problem of a firm that maximizes profits,  $\Pi(P(\cdot), S(\cdot), Q(\cdot), \text{Pr\_def}(\cdot))$ , with respect to  $S$  and  $P$ . Equations (3a) and (4a) are the demand and default probability equations. Both of them can be affected by the firm's pricing and quality decisions.

To choose the simplest setting to generate these first-order conditions, we assume linear demand and assume that the marginal cost of transporting a passenger and the marginal cost of providing quality are independent. In this simpler setting, which we adopt for the remaining equations we present, the marginal effect of quality on price and vice versa are independent, and we can drop  $P$  from Equation (1a) and  $S$  from Equation (2a). However, the results we obtain are invariant to their inclusion.

Exogenous variables  $Y$ ,  $X$ ,  $W$ , and  $Z$  affect quality, price, quantity, and default probability, respectively. Variables in  $Y$  that affect the supply of quality are fleet age, and airport decongestion. The variables in  $X$  that affect pricing are oil fuel cost, average miles per flight, oil efficiency, fleet age, and airport decongestion. The variables in  $W$  that affect quantity demand are competition, income, unemployment, fleet age, and airport decongestion, and the variables in  $Z$  are percentage of liquidable assets and fleet redeployability. We will discuss these variables in the data section.

Equations (1a)–(4a) imply that the quantity demanded,  $Q$ , affects the pricing strategy, as usual, but might also affect the quality supply decision because when there are high numbers of passengers, providing higher quality might be more costly. Additionally,  $Q$  affects the default probability, because lower

demand presumably increases the default probability. Given that pricing and quality decisions might affect the default probability, they are included in Equation (4a) as well. Finally,  $Q$  is affected by the default probability because consumers might anticipate the incentives of the airlines to underprovide quality while in financial distress.

We take into account the endogeneity of price ( $P$ ), quantity ( $Q$ ), quality ( $S$ ), and  $\text{Pr\_def}$  using a simultaneous instrumental variable approach. Our instruments for price ( $P$ ) are the elements of  $X$  that are excluded from the other three equations. Similarly, the instruments of quality ( $S$ ), quantity ( $Q$ ), and  $\text{Pr\_def}$  are the excluded components of  $Y$ ,  $W$ , and  $Z$ . We instrument price or yield ( $P$ ) with average miles per flight, oil fuel cost, and oil efficiency; we instrument total enplaned passengers ( $Q$ ) with local income, competition, and local unemployment; and we instrument the default probability with the percentage of liquidable assets and fleet redeployability. We discuss these instruments and our identification strategy below in §3.5. For now, we just limit ourselves to give a brief intuition of why they satisfy the exclusion restriction. Local area income and unemployment are exogenous to a firm's decisions. Competition affects demand, but it does not affect directly a firm's supply decisions. The percentage of liquidable assets is likely to satisfy the exclusion restriction because it is unlikely that having more valuable assets in case of liquidation will affect directly the quality of a firm's product or its prices. What can be argued is that this measure of tangibility has a relationship with performance, because better performance can lead a firm to acquire more fixed assets, which increase the percentage of liquidable assets. In that case, our instrument could directly affect the firms' real outcomes, because it might be capturing unmeasured productivity to the extent that our controls are not perfect. Nevertheless, this is unlikely, because we observe that a higher percentage of liquidable assets is positively related with high financial distress and bankruptcy, states in which productivity is unlikely to be high. Finally, fleet redeployability is also likely to satisfy the exclusion restriction. This variable is a weighted average of the popularity of an airline's aircrafts, measured by the number of active aircrafts by type under other operators. Thus, this variable depends largely on the current popularity of aircraft types, which is not under the firm's control.

We do not have any variable that belongs to the set  $Y$  and is excluded from the other three equations. As a consequence, we are unable to instrument  $S$  directly; thus, we replace quality in Equations (3a) and (4a), and estimate the following:

$$S_{it} = h(Q_{it}, \text{Pr\_def}_{it}, Y_{it}); \quad (1a')$$

$$P_{it} = g(Q_{it}, Pr\_def_{it}, X_{it}); \quad (2a')$$

$$Q_{it} = f(Pr\_def_{it}, P_{it}, Y_{it}, W_{it}); \quad (3a')$$

$$Pr\_def_{it} = j(Q_{it}, P_{it}, Y_{it}, Z_{it}). \quad (4a')$$

We estimate this system using three-stage least squares (3SLS) to take advantage of the potential error correlation structure between the equations. In this specification, we are able to analyze the effect of financial distress on the price and quality supply decisions. We also use firm and time fixed effects.

**2.2.2. Bankruptcy.** After considering the effect of financial distress, we examine the differential impact of bankruptcy relative to financial distress. We examine all firm-quarters in bankruptcy and compare them to observations in which firms are in high financial distress but are not in bankruptcy. We thus drop firm-quarters where the firms have a low probability of default. This sample does include firms that have a high probability of default that do not enter bankruptcy. Econometrically, we estimate a similar set of equations as for the financial distress case. The main difference is that we now examine the differential impact of bankruptcy (a dummy variable) on a firm's supply decisions relative to the control state, which is financial distress. Thus, we estimate

$$S_{it} = h(Q_{it}, Bankrupt_{it}, Y_{it}); \quad (5a')$$

$$P_{it} = g(Q_{it}, Bankrupt_{it}, X_{it}); \quad (6a')$$

$$Q_{it} = f(Bankrupt_{it}, P_{it}, Y_{it}, W_{it}); \quad (7a')$$

$$Bankrupt_{it} = j(Q_{it}, P_{it}, Y_{it}, Z_{it}). \quad (8a')$$

### 3. Data and Summary Statistics

#### 3.1. Airline Data

Our data consist of an unbalanced quarterly panel of 21 airlines from the first quarter of 1997 to the fourth quarter of 2008. The data were constructed using information from Transtats, a site managed by the Bureau of Transportation Services (BTS); Air Travel Consumer Reports (ATCR), also from the BTS; Compustat; the Center for Research in Security Prices (CRSP); the Bureau of Economic Analysis (BEA); and the ASCEND airline data set, a database containing information on commercial aircraft worldwide.

Our final sample is limited to firms included in all data sets. Airlines must have annual operating revenues of at least US\$20 million to be included in Transtats, they have to have a domestic revenue market share greater than 1% to appear in ATCR, and they must be publicly traded to have their financial information included in Compustat and CRSP. Given that we have an unbalanced panel with some firms entering and exiting the panel, our final sample contains 645 firm-quarter observations for the 21 airlines in our

**Table 1 Carriers and Bankruptcies**

Carrier	Quarters in the sample	Bankruptcy episodes	Quarters in bankruptcy
ATA Airlines	15	1	6
Air Tran Airways	23	0	
Alaska Airlines	36	0	
America West Airlines	34	0	
American Airlines	48	0	
American Eagle Airlines	31	0	
Atlantic Southeast Airlines	23	0	
Comair	19	1	7
Continental Airlines	48	0	
Delta Airlines	48	1	7
ExpressJet Airlines	22	0	
Frontier Airlines	14	1	3
Hawaiian Airlines	20	1	6
JetBlue Airways	23	0	
Mesa Airlines	11	0	
Northwest Airlines	48	1	7
SkyWest Airlines	23	0	
Southwest	48	0	
Trans World Airways	15	0	
United Airlines	48	1	15
US Airways	48	2	8
Total airlines: 21	Total firm-quarters: 645	Bankruptcy episodes: 9	Bankrupt quarters: 59

*Notes.* The left column of this table presents the names of the 21 carriers that had annual operating revenue greater than US\$20 million, had a domestic revenue market share greater than 1%, and were publicly traded, for any quarter between the first quarter of 1997 and the fourth quarter of 2008. The second column shows how many quarters each firm appears in the sample. All 21 firms appear in consecutive quarters. The third column shows how many bankruptcy episodes each carrier has in the sample. The fourth column shows how many quarters each company stayed in bankruptcy in the sample.

sample. Table 1 summarizes the names of the carriers, the number of quarters they appear in the sample, whether each of these carriers had a bankruptcy episode during those quarters, and the number of quarters these companies stayed in bankruptcy in case they had a bankruptcy episode. Of the 21 carriers, 13 never entered into bankruptcy in our sample, 7 had one bankruptcy episode, and only 1 firm, US Airways, had two bankruptcy episodes.

From Transtats we obtain each airline's domestic operating passenger revenue (DOPR), domestic passenger revenue miles (DPRM), and domestic total enplaned passengers (TEP) by segment.<sup>12</sup> TEP represents our measure of quantity, measured in millions of passengers; dividing DORP by DRPM we obtain the

<sup>12</sup> We measure TEP on a segment basis; measuring TEP on a leg basis leads to similar results. The difference between legs and segments is best understood by an example. Suppose an airline flies from A to B, and from B to C. A passenger flying from A to B or B to C would be counted as one segment and one leg. A passenger flying from A to C with a stopover in B would be counted as one passenger in terms of segments, but two passengers in terms of legs.

“yield,” which is our measure of price. Yield is a common price indicator in the airline industry, measuring the average price per mile a passenger is paying. Yield is measured in U.S. cents following common industry practice. Prices are measured at the time tickets are purchased, not when they are used.

We study two measures of quality: on-time performance from Transtats and mishandled bags per 1,000 customers from ATRC. We do not consider accidents because these are rare events and because Rhoades and Waguespack (2000) found safety and service quality to be highly correlated. We also considered including the number of customer complaints, but the Department of Transportation (DOT) reports that it has not determined the validity of the complaints; thus, our measures are more objective.<sup>13</sup> The BTS classifies a flight as late if it is 15 or more minutes late from the scheduled arrival time. Nevertheless, constructing a dummy variable that takes a value of 1 if the flight is late and 0 otherwise may hide information on how late flights are.<sup>14</sup>

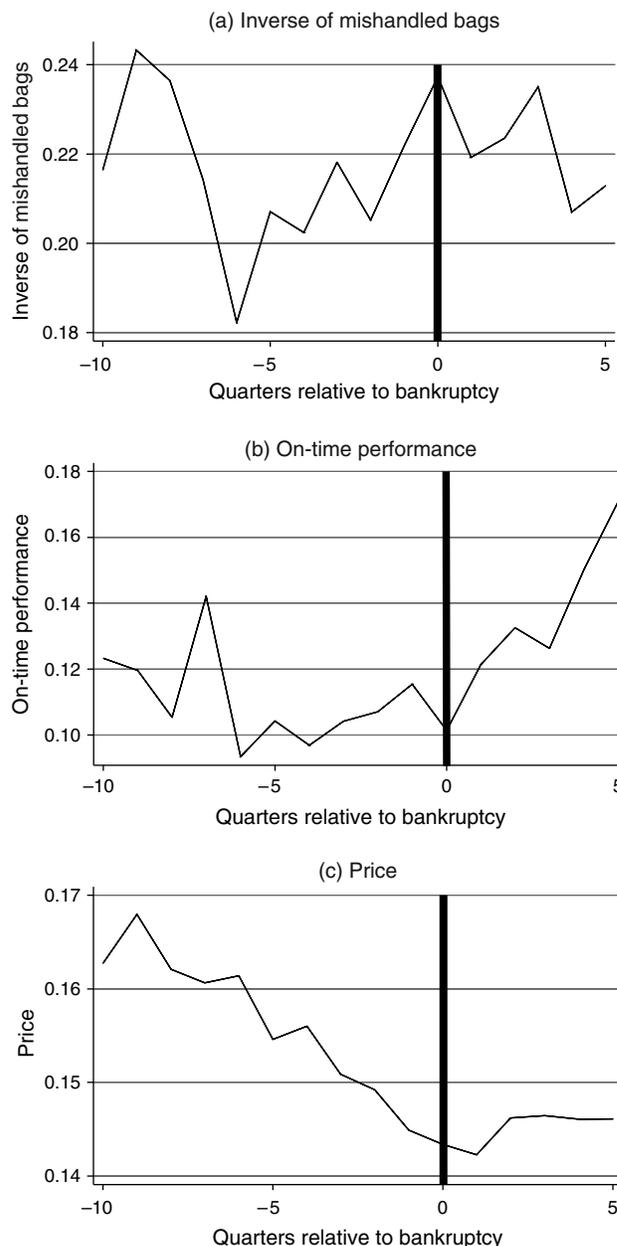
Our variable *Late* is constructed as the average delay of late flights times the percentage of late flights. For instance, if a firm in a quarter has 20% of its flights arriving late and their late flights are on average 50 minutes late, the variable *Late* takes a value of  $50 * 0.2 = 10$ . To get higher quality as an increasing function, we define *On-Time Performance* as the inverse of *Late*.

From ATRC we obtain the mishandled baggage rate per 1,000 passengers. According to the DOT, the definition of mishandled baggage is “lost, damaged, delayed or pilfered baggage.” Note that airlines, and not airports, control important aspects of baggage handling given that airlines have to relabel baggage when there is a change in schedule. Also airlines can decide whether to invest in a better monitoring technology in terms of bar-coding and decide how many personnel to assign to the monitoring of bags. Again, to get higher quality as an increasing function, we define our variable as the inverse of the mishandled baggage rate, so the higher this rate is, less baggage is lost. Our sample starts in the first quarter on 1997

<sup>13</sup> We do not consider other measures of service quality, such as the flight cancellation rate, not because we think they are not important, but because they do not satisfy the Maksimovic and Titman (1991) framework in which quality cuts increase short-term profits. There is no short-term benefit of canceling a flight since passengers have to be relocated in other flights in the short run. The determinants of flight cancellation can be better explained at the route level (see Rupp and Holmes 2006).

<sup>14</sup> Airlines sometimes are able to manipulate arrival times for flights that are on the border of being on time. Our measure does not suffer as significantly from these potential manipulations. For a comprehensive study of airline on-time performance, see Mayer and Sinai (2003).

**Figure 1 Evolution of Quality and Prices Relative to Bankruptcy**



*Notes.* “Quarters relative to Bankruptcy” are the number of quarters before and after a firm enters into bankruptcy. Quarter 0 is defined as the quarter when firms enter into bankruptcy, if they do. The mean quality, in terms of inverse of mishandled baggage and on-time performance, and the mean price are plotted for each quarter relative to bankruptcy, for firms that entered into bankruptcy. Panel (a) shows the evolution of the inverse of mishandled bags, panel (b) shows the evolution of on-time performance, and panel (c) shows the evolution of prices.

because there is no previous information about mishandled baggage.

Figures 1(a)–1(c) present some initial summary statistics for firms in the quarters preceding and following bankruptcy. Figure 1(a) presents the inverse of mishandled bags, Figure 1(b) presents on-time performance, and Figure 1(c) presents airline pricing or

**Table 2** Quality, Price, and Firm Financial Situation

	Predistress	Distress	Bankruptcy
Detrended within variation			
Quality: Inverse of Mishandled Baggage	29.02 (41.29)	-105.72*** (46.87)	165.53*** (56.36)
Quality: On-Time Performance	3.92 (24.66)	-66.069** (30.20)	16.25 (58.06)
Price (Yield)	-7.51 (14.38)	-50.873*** (14.62)	-15.07 (13.89)
N	103	32	59

Notes. This table presents detrended summary statistics for Price (Yield) and two measures of quality (Inverse of Mishandled Baggage and On-Time Performance) for firms that experienced bankruptcy. We detrend each variable by regressing it against quarterly time fixed effects and firm fixed effects. The table presents the median, standard deviation, and number of observations of these detrended measures (scaled by 10,000), according to firms' financial situation in a quarter. The predistress period contains all the firm-quarter observations five quarters or more before firms filed into bankruptcy. The distress period contains all the firm-quarter observations for the four quarters before firms filed for bankruptcy. Bankruptcy includes the 59 firm-quarter bankruptcy observations in the sample. The omitted category is post-bankruptcy.

\*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

yield. All data are quarterly, with quarter 0 representing the first quarter a firm is in bankruptcy.

The figures show that quality and price measures decrease in the quarters prior to bankruptcy. Additionally, Figures 1(a) and 1(b) show that quality increases after bankruptcy is declared.

Table 2 presents similar summary statistics. However, in this table we report detrended data, where we detrend the quality and price variables by regressing the raw measures on-time and firm dummies. We use the residuals of these equations to construct Table 2. This table includes data only for firms that go into bankruptcy at some point in the sample and splits the data into observations more than four quarters before bankruptcy, the four quarters right before bankruptcy, and the period the firm is in bankruptcy itself. The omitted default category is after bankruptcy.

Table 2 shows several striking patterns. First, both measures of quality decrease sharply in the four quarters prior to bankruptcy—a period of time we label as the “distress” period. Yield (our measure of price) also decreases sharply during the distress period. The differences in the medians of the residuals of the quality and price measures, between the predistress and distress periods, are statistically different from zero at the 5% level of significance using a one-sided Fisher test for a nonparametric two-sample comparison. Second, during bankruptcy both measures of quality and price increase relative to the distress period. However, only the differences in the medians of the quality measures for the bankruptcy and distress periods are significantly different from zero.

This initial evidence is interesting, but it does not consider firms in financial distress that do not enter

into bankruptcy, nor does it control for the endogeneity of distress or bankruptcy. These simple differences may thus be driven by other exogenous changes and merely related to firm's financial conditions. Thus, in what follows, we define more precisely our measure financial distress (i.e., default probability) and then turn to the task of disentangling whether bankruptcy and default probability affect firms' decisions after controlling for other exogenous demand and supply changes and the endogeneity of a firm's financial condition itself.

### 3.2. Probability of Default and Bankruptcy

In our analysis of financial distress we examine both firms that manage to avoid bankruptcy and those that do not. We construct a measure of the probability of default and use this to examine firm quality and pricing decisions. Our measure of default probability is based on Bharath and Shumway's (2008) probability of default, which, in turn, is based on the Merton (1974) model. The idea is to compare the firm to a bond using the standard deviation of its equity and the value of its debt to construct its default probability.

Merton (1974) derived that a firm's probability of default follows the following formula:  $\pi_{\text{Merton}} = N[-(\ln(V/D) + (\mu - 0.5\sigma_V^2)T)/(\sigma_V\sqrt{T})]$ , where  $V$  is the economic value of the firm,  $D$  is the economic value of the firm's debt, and  $T$  is the forecasting horizon. This model uses a system of nonlinear equations to numerically infer the economic value of the firm and its standard deviation from the value of equity. Bharath and Shumway (2008) show that a naïve version of this default probability performs better in hazard models and in out-of-sample forecasts than the one that uses the numerical solution to obtain the economic value of the firm and its standard deviation. They proxy the economic value of debt,  $D$ , to its face value  $F$ ; they proxy the standard deviation of debt value with  $\sigma_D = 0.05 + 0.25\sigma_E$ ; and they proxy the economic value of the firm  $V$  as the sum of the face value of the debt plus the value of equity,  $E$ , implying that the standard deviation of the firm value can be derived as  $\sigma_V = (E/(E + F))\sigma_E + (F/(E + F))\sigma_D$ . They also replace the expected return,  $\mu$ , with the last period return,  $r_{it-1}$ . Thus, the naïve Merton default probability, for a one period forward forecast can be expressed as

$$\pi_{\text{Merton-naïve}} = N \left[ - \left( \ln \left( \frac{E + F}{F} \right) + \left( r_{it-1} - 0.5 \left( \frac{E}{E + F} \sigma_E + \frac{F}{E + F} (0.05 + 0.25\sigma_E) \right)^2 \right) \right) \cdot \left( \frac{E}{E + F} \sigma_E + \frac{F}{E + F} (0.05 + 0.25\sigma_E) \right)^{-1} \right].$$

This expression is based on stock price and debt value information only.

We compute Bharath and Shumway's (2008) naïve Merton default probability using daily stock price information from CRSP and short- and long-term debt from quarterly Compustat. We incorporate as an additional component of long-run debt the underfunding of pension liabilities given their importance in airline default.<sup>15</sup> We require at least 25 stock price observations to construct the standard deviation of equity. A default probability of, say, 50% is interpreted as implying that the firm has a 50% of chance of entering bankruptcy in the next quarter.

We impute the probability of default when a corporation owns more than one airline in the sample, as is the case of AMR, which owns American Airlines and American Eagle Airlines. In this case, the probability of default was calculated for AMR and used for both companies. A similar situation occurs in the case of mergers. When one airline buys another, the subsequent probability of default for both is constructed using the information of the consolidated firm after the merger takes place.

We choose Merton's default probability over other traditional distress measures, like Altman's *Z*, because the latter is not robust to changes in industry financial structure, such as the increasing trend in operational leases (see Gavazza 2011a). Altman's *Z* is constructed using multiple discriminant analysis, a technique similar to econometric regressions that selects the financial ratios with the best ability to discriminate between distressed and not distressed firms. The final computation of the distress indicator assigns weights to financial ratios equivalent to reduced-form regression parameters. However, changing trends in the financing of aircrafts makes those parameters (weights) quite unstable. Our measure of financial distress does not suffer as much from changes in financing trends because it is a more structural measure: it is theoretically derived and depends on basic elements of a firm's risk like its debt and the standard deviation of its equity. In addition, in preliminary regressions, Merton's naïve default probability predicted the bankruptcy episodes in our sample far better than Altman's *Z*.<sup>16</sup>

In our analysis of bankruptcy, we examine all firm-quarters for firms that are in bankruptcy and compare them to observations in which firms are in high financial distress but not in bankruptcy. These high distress firm-quarters include firms that eventually

enter bankruptcy but also firms that do not enter bankruptcy. Bankruptcy takes a value of 1 when a firm declares itself (or is declared) in Chapter 11 and 0 otherwise. There are 59 firm-quarter observations where the firm is in Chapter 11 bankruptcy in our sample, but there are no Chapter 7 episodes.

For the nonbankruptcy sample that we compare to the bankrupt sample, we use firm-years in which the firms are highly distressed. Some of the distressed firms enter into bankruptcy; others remain distressed in this subsample. Given that we are using firm fixed effects, we are estimating a difference in differences where the treatment is being bankrupt and the control state is financial distress.

The criterion for selecting distressed firms is that our measure of default probability exceeds 10%. We select this criterion balancing not dropping too many nonbankrupt observations while ensuring that the included are, on average, quite distressed, with an average default probability of 60%. Nevertheless, relaxing this criterion does not change the results.<sup>17</sup> We get a final sample of 192 observations: 59 bankrupt firm-quarters and 133 distressed firm-quarters.

### 3.3. Demand and Supply Variables

To identify any effect of distress or default on firm quality it is critically important to control for demand and supply shocks. To construct demand shift variables (denoted *W* above), we use the average income and unemployment rate per state-quarter from the BEA.<sup>18</sup> We use these state-level variables in the following way for each airline. For each airline, we compute the total number of passengers originating from each state for each quarter and divide them by the total number of passengers that the firm carried in that quarter. This gives us the percentage of origin passengers that each state represents for each airline. These percentages are lagged one period, to avoid potential endogeneity problems, and are multiplied by the average income, and unemployment of each state in each quarter, yielding weighted average income and unemployment at origin for each airline. We do the same for destinations. To minimize

<sup>17</sup> All the results hold if we drop observations with default probabilities lower than 5%, 15%, and 20%, or even higher. However, results do get weaker if we do not drop any observations. This is to be expected because when dropping observations with default probabilities lower than 5%, 10%, 15%, and 20%, the average default probabilities of the nonbankrupt firms in the sample are 54%, 60%, 67%, and 71% respectively. Comparing those observations with the bankrupt firm-quarters correctly compares distressed firms with bankrupt firms. However, when we do not drop any observations, the average default probability of the nonbankrupt firm-quarters is 14%, which implies that these firm-quarters are not that distressed and thus are not good candidates to be compared with bankrupt firm-quarters.

<sup>18</sup> Average income is in thousands of dollars. Income and yield are in 2009 dollars (cents).

<sup>15</sup> Not incorporating pension liabilities or even the long-run debt in the default probability does not affect the results of this paper.

<sup>16</sup> Merton's default probability is also potentially more accurate than bond ratings given that bonds ratings barely vary over time and are frequently adjusted downward after a default.

the collinearity between weighted unemployment and weighted income, we use average income weighted at the origin state and the average unemployment rate weighted at the destination state.<sup>19</sup> We call these variables local income and local unemployment.

Another variable that shifts the demand of a firm is the competition it faces. Our measure of competition is the weighted average number of competitors that an airline faces by route. We do the computation in a similar way as the one for weighted income and unemployment. We sort the data by route and see how many airlines operate on a given route, measured as a pair of cities. Then, we weight routes using lagged passengers to obtain our measure of competition.

Our supply variables, denoted as  $X$  in the previous equations, are based on cost items that vary over time. The two most important supply variables are oil prices and the efficiency with which each airline uses fuel. *Oil Fuel Cost* is constructed as the actual price per gallon that an airline pays in a quarter. This is obtained by dividing the total fuel cost of an airline by the number of gallons it used in that quarter. This price measure has two advantages over the oil spot price per gallon. First, it incorporates airlines' fuel hedging strategies because this price incorporates future or forward contracts the airlines signed. Second, it is not perfectly collinear with the time fixed effects. Thus, the overall economic conditions are captured by time fixed effects, whereas the specific conditions on an airline's oil price are captured by this variable. Efficiency, on the other hand, is defined as the number of available seat miles an airline produces for each gallon of fuel they use. The more efficiently airlines use oil, because of better aircraft technology, the lower the costs of the firm.

Another variable that influences supply, through cost, is average distance of flights. The longer the distance that an airplane flies, the lower the cost of the flight per mile, because the take-off and landing use more fuel, and thus firms with shorter flights will look less efficient, all other things equal. This variable can be obtained by dividing domestic revenue passenger miles (which is the product of passengers and miles) by total enplaned passengers.

Finally, we consider two variables that might affect both demand and supply conditions: *Fleet Age* and *Congestion*. From the ASCEND database we obtain quarterly information about our 21 airlines' fleets, including the year in which each aircraft started its service. With this information we constructed each airline's average fleet age per quarter. An airline's fleet age can affect its supply of product quality, as handling baggage might be more difficult in older air-

craft types, and older models might take longer to take off, affecting an airline's on-time performance. An airline's pricing decision might also be affected by the age of its fleet, because operating costs can be affected. Finally, an airline's fleet age can also affect its demand because consumers might have a higher disposition to pay for flying in newer aircrafts.

The variable *Congestion* measures how congested the markets in which an airline operates are, on average. Given that we are measuring positive characteristics as increasing variables, we will construct a measure of decongestion rather than congestion. To construct this measure we take the average percentage of on-time flights (arriving within 15 minutes of the scheduled arrival time) of each airport, for each firm, excluding the firm's own flights. Then, we multiply the share of passengers each airport represents for each firm the previous quarter with the average on-time performance of the airport. With this variable we can control for airport quality independent of the firm itself.

Congestion might affect the firms' pricing decision, because operating in congested markets is similar to facing capacity constraints in that the firm cannot increase supply as much as it would want to. Because operating under capacity constraints makes competition softer, we expect that (de)congestion should increase (decrease) prices. Congestion might affect demand as well, because congestion might reflect high consumer valuation for those markets. Finally, congestion can also affect our measures of quality, because it is easier to improve on-time performance and decrease the rate of mishandled baggage in less congested markets. Thus, by controlling for congestion we will not penalize a firm because it operates a large proportion of its flights in congested airports like JFK or La Guardia.

Notice that the quality supply shift variables *Fleet Age* and *Decongestion* also affect the pricing and demand equation. Thus, we cannot instrument quality as pointed out in §2.2.

### 3.4. Variable Summary Statistics

Table 3 presents summary statistics for all our variables for the full sample of firms. Table 3 shows the 10th percentile, mean, 90th percentile, standard deviation, and number of observations for the variables shown in the left column. The data consist of an unbalanced panel of 21 airlines for 48 quarters (first quarter of 1997 to fourth quarter of 2008).

The main message that Table 3 conveys is that there is high variation in our measures of quality and default probability over the sample. Note that the statistics on default probability do not include the quarters the firm is actually in bankruptcy, because we cannot calculate Merton's default probability for

<sup>19</sup> Including both variables at the origin or destination states does not affect the results.

**Table 3** Summary Statistics

Variables	10th percentile	Mean	90th percentile	Std. dev.	<i>N</i>
<i>Quality: Inverse of Mishandled Baggage</i>	0.102	0.209	0.313	0.080	645
<i>Quality: On-Time Performance</i>	0.062	0.106	0.154	0.061	645
<i>Price (Yield)</i>	118.3	164.2	234.2	51.2	645
<i>Total Enplaned Passengers</i>	2.532	9.501	19.284	6.787	645
<i>Default Probability</i>	0.000	0.138	0.692	0.293	584
<i>Bankruptcy</i>	0.000	0.091	0.000	0.288	645
<i>Fleet Age</i>	4.28	10.00	16.55	4.354	645
<i>Decongestion</i>	0.718	0.766	0.815	0.038	645
<i>Average Miles per Flight</i>	487.4	886.5	1,225.9	276.4	645
<i>Oil Fuel Cost</i>	70.54	153.31	258.30	81.01	645
<i>Competition</i>	1.224	2.013	2.977	0.693	645
<i>Efficiency</i>	0.411	0.578	0.705	0.115	645
<i>Income</i>	72,547	79,197	85,261	4,968	645
<i>Unemployment</i>	0.041	0.051	0.062	0.085	645
<i>% Liquidable Assets</i>	0.230	0.348	0.430	0.149	645
<i>Fleet Redeployability</i>	376.3	1,437.5	2,961.1	947.5	645

*Notes.* We present the 10th percentile, mean, 90th percentile, standard deviation, and number of observations for the variables shown in the left column. The data consist of an unbalanced panel of 21 airlines for 48 quarters (first quarter of 1997 to fourth quarter of 2008). *Price (Yield)* is defined as domestic operating passenger revenue divided by domestic revenue passenger miles, expressed in 2009 U.S. cents. *Inverse of Mishandled Baggage* is defined as one divided by the rate of mishandled baggage per 1,000 customers. *On-Time Performance* is defined as one divided by *Late*, where *Late* is the average flight delay by airlines of their late flights times the percentage of late flights. A flight is considered late if it arrives 15 minutes or later after its schedule arrival time. *Total Enplaned Passengers* is the domestic total passengers by segment each airline transports, expressed in millions. *Fleet Age* is the average age of an airline's fleet. *Decongestion* is average on-time performance by airport excluding the airline's own flights, weighted by the airline's lagged share of customers. *Oil Fuel Cost* is the actual fuel cost per gallon after hedging contracts are considered, expressed in 2009 U.S. dollars. *Competition* represents the weighted average number of competitors an airline faces across its markets. *Efficiency* is defined as available seats miles divided by gallons of fuel utilized. The *Default Probability* is computed following Bharath and Schumway (2008). The information used to construct this variable comes from Compustat and CRSP. From the 645 observations, 59 of them are bankruptcy firm-quarters; thus, we should have 586 default probability observations. However, for nine firm-bankruptcy episodes it was possible to construct the default probability measure, because there was enough prebankruptcy information within those quarters. Additionally, there was not enough information to construct this measure for 11 nonbankruptcy quarters. Thus, the total number of default probability observations is 584. *% Liquidable Assets* is the fraction of the face value of assets a firm can recover in case of liquidation, constructed following Berger et al. (1996). *Fleet Redeployability* is a weighted average of the popularity of an airline's aircrafts, measured by the number of active aircrafts by type under other operators.

companies without publicly traded stock. Despite not covering these quarters, the default probability goes from 0% at the 10th percentile to 69.2% at the 90th percentile. The maximum for this variable is close to 1. The two variables in the bottom of Table 3—percentage of liquidable assets and fleet redeployability—are the instruments we use for financial conditions (denoted *Z* above). We describe these variables along with our identification strategy below.

### 3.5. Financial Condition and Identification

One of the central problems that researchers face when attributing effects to financial variables like the probability of default or bankruptcy is that these variables are endogenous and potentially related to firm quality and prices. Thus, we face a typical identification problem. Having low quality might have driven the airline into distress or bankruptcy in the first place. A similar argument can be made for high or low prices. Using airline fixed effects and time fixed effects partially mitigates this problem, but clearly does not solve it.

We solve the identification problem using instrumental variables. To solve the problem, we need instruments that affect the probability of default, but

do not affect prices, quantity, or quality. This also needs to hold for bankruptcy. We use the percentage of liquidable assets and the airline's fleet redeployability as instruments for both financial conditions.

The percentage of liquidable assets proxies for the tangibility of assets and follows the Berger et al. (1996) formulation. Berger et al. (1996) used data from Lexis/Nexis on the proceeds from discontinued operations reported by a sample of COMPUSTAT firms from 1984 to 1993 to compute how much the firms' assets were worth in case of liquidation. They found that a dollar of book value yields 72¢ in liquidation value for accounts receivable, 55¢ in liquidation value for inventory, and 54¢ in liquidation value for their fixed assets. Our variable percentage of liquidable assets is the expected amount that can be recovered in case of liquidation, using those parameters, divided by the book value of assets.<sup>20</sup>

<sup>20</sup> This measure of asset tangibility was originally computed using several industries. For the particular case of the airline industry, inventories play a negligible role in the computation of this measure. Not considering inventories in this computation does not alter our results. We keep the original definition of percentage of liquidable assets for consistency.

The percentage of liquidable assets captures what proportion of a firm's assets creditors can recover in case the firm is liquidated. The more creditors can obtain in case of liquidation, the more they are willing to lend to the firm (see Almeida and Campello 2007, 2011). Thus, a higher percentage of liquidable assets is likely to be related with higher leverage and also with a higher probability of default and bankruptcy.

We are not the first to use the percentage of liquidable assets as an instrument for a financial variable. Campello (2006) uses the percentage of liquidable assets, following the Berger et al. (1996) specification, to instrument leverage when analyzing the effect of leverage on firms' sales growth. We just go one step ahead and use it to instrument default probability and bankruptcy directly.

Conceptually, the percentage of liquidable assets is likely to satisfy the exclusion restriction. It is unlikely that having more valuable assets in case of liquidation will affect directly the quality of a firm's product or its prices. What can be argued is that this measure of tangibility has a relationship with performance, because better performance can lead a firm to acquire more fixed assets, which increases the percentage of liquidable assets. In that case, our instrument could directly affect the firms' real outcomes, because it might be capturing unmeasured productivity to the extent that our controls are not perfect. Nevertheless, this is unlikely, because we observe that higher percentage of liquidable assets is positively related with high financial distress and bankruptcy, states in which productivity is unlikely to be high. Moreover, any story that tries to directly relate the percentage of liquidable assets with product quality in one direction faces the hurdle that using the same instrument product quality is shown to have opposite effects in financial distress and bankruptcy.

In the particular context of the airline industry, the percentage of liquidable assets can be further justified as a valid instrument following the logic from Gavazza's (2011a) model. In his model, an airline does not continuously buy or sell aircraft to adjust its capacity. The decision of buying or selling aircraft has wide inaction ranges due to the high transaction costs involved with it. A firm acquires an aircraft only if it has a high enough productivity shock such that it is worth it to adjust its capacity in the long run (rather than adjusting it in the short run using operational leases). One consequence of his model is that getting rid of aircraft is difficult when the firm needs to downsize its fleet. Thus, a firm that acquired aircrafts in the past—and has increased its asset tangibility—is more vulnerable to adverse shocks because it might be highly indebted and not able to sell its aircraft to adapt its capacity quickly. Yet, in this story, the initial factors that might have led a firm to the purchase an aircraft are not contemporaneously related

with the factors driving the firm into financial distress, which occurs *ex post*. They cannot be contemporaneous because a firm facing a negative shock (which is the most likely scenario in financial distress) will not be likely to acquire any aircraft. Therefore, the positive relationship that the percentage of liquidable assets and default probability display in our data is likely to be due to the fact that the percentage of liquidable assets was high from a period previous to financial distress and remains high thereafter.

The "buying first with potential distress later" story is consistent with the persistence patterns of the percentage of liquidable assets and default probability that we find in our data. When running a regression between the percentage of liquidable assets on its lag using firm and time fixed effects as controls, we find that the coefficient of the lag is 0.77, whereas when doing the same analysis for default probability it is just 0.25 (both are statistically significant at the 1%). This implies that the percentage of liquidable assets evolves slowly through time, consistent with airlines having wide inaction bands, as proposed by Gavazza (2011a), and with the fact that distress is much less predictable.<sup>21</sup>

Our second instrument is based on the Benmelech and Bergman (2009) measure of asset redeployability. From the ASCEND database we obtain quarterly information about airlines' fleet by aircraft type for the 21 airlines in our sample. From this database we also obtain the total number of active commercial aircrafts per aircraft type in the world for each quarter in our sample. Thus, for each airline-aircraft-quarter we can construct the total number aircrafts per type that operate outside each airline by subtracting the number of aircrafts per type that operate in an airline from the worldwide number of operating aircrafts for that type. This measure captures how "thick" the market for each aircraft type is, and thus its redeployability (see Gavazza 2011b). Then, for each airline, we weight our measure of redeployability at the aircraft-airline-quarter level using the fraction that each aircraft type represents on the total of an airline's fleet.

To better understand how our measure of fleet redeployability is constructed, consider the following example. Suppose airline X operates 100 aircrafts in a

<sup>21</sup> A less obvious channel that could potentially violate the exclusion restriction is the following. An airline could acquire more assets to expand faster to other markets. In this scenario, the percentage of liquidable assets may be correlated with faster market expansion. To the extent that expanding faster reduces the airline's ability to provide high quality, it can be argued that the percentage of liquidable assets may have a direct effect on quality. We test for this potential effect and find that even after controlling for revenue growth in the quality and price equations, the effects of instrumented financial distress and bankruptcy on quality and prices were unaltered.

given quarter: 40 767s and 60 MD-80s. Suppose further that the worldwide numbers of 767s and MD-80s in that quarter are 1,000 and 380, respectively. Thus, the total numbers of aircrafts not operated by airline  $X$  in that quarter are 960 and 320. Our measure of asset redeployability for this airline-quarter is 576 ( $= 0.4 * 960 + 0.6 * 320$ ) and represents the average “market thickness” of airline’s  $X$  fleet. The larger this number, the more likely an airline can redeploy its aircrafts with other operators if it wants to, because it is easier to find other operators that are already familiar with the aircraft types in its fleet.

Fleet redeployability has differential effects on a firm’s financial conditions. When the fleet of a firm is more redeployable, it is less likely that a firm affected by a negative shock suffers from financial distress, because the firm can more easily sell some of its aircrafts, downsize its fleet, and meet debt payments. Thus, we expect fleet redeployability to have a negative impact on a firm’s default probability. When a firm is already in distress, however, higher redeployability plays a role similar to that of asset tangibility, regarding the possibility of entering into Chapter 11. More redeployable assets are more valuable to a firm’s creditors. Thus, higher asset redeployability makes reorganization under bankruptcy more likely.

Our measure of asset redeployability is also likely to satisfy the exclusion restriction. Changes in asset redeployability depend largely on the current popularity of aircraft types, which is not under the firm’s control. In the short run, airlines cannot have important changes in their fleet composition, because these changes require their pilots, mechanics, and crew members to adapt to those changes. Although unlikely, it can be argued that an airline’s slow changes in fleet composition that lead to changes in redeployability can be related to a fleet’s age, which might have a direct impact on our product quality measures. However, in our setting, we control for airlines’ fleet age, ruling out this possibility.

Although we argue that the percentage of liquidable assets and fleet redeployability are likely to be exogenous to airlines’ quality and pricing decisions, we directly test for their exogeneity to further allay concerns. In just-identified models (i.e., models with equal number of endogenous variables and instruments) it is not possible to test for the overall exogeneity of the instruments. For overidentified models, however, we can directly test their exogeneity using the Sargan–Hansen test.<sup>22</sup> Our equations of interests (Equations (1a’) and (2a’)) are overidentified as they have two

endogenous explanatory variables (financial condition and quantity) and five instruments (percentage of liquidable assets, fleet redeployability, local income, local unemployment, and competition). We perform the Sargan–Hansen test separately for the financial distress and bankruptcy estimations.

The test is as follows. For each variable of interest (i.e., our two quality measures and price), we run a two-stage least squares estimation using all exogenous variables and instrumental variables as explanatory variables. From this regression we obtain the residuals and run them against all exogenous variables, including the instrumental variables. We consider the  $F$ -test of significance of this regression. The null hypothesis can be interpreted as exogeneity of all variables in the model. Rejecting the null implies that one (or more) of the instrumental variables used are not exogenous. Our results do not do not reject the null hypothesis of exogeneity for any of the three variables of interest, for both set of estimations (i.e., when the financial condition of interest is financial distress and when it is bankruptcy). This evidence favors the hypothesis that an airline’s prices, on-time performance, and mishandled bags are not endogenously determined with its percentage of liquidable assets, fleet redeployability, local income, local unemployment, and competition.

#### 4. Results: Multivariate Evidence

We analyze the differential effects of financial distress and bankruptcy on product quality and prices at the airline level. These results are presented in §§4.1 and 4.2. Later, in §4.3, we analyze the differential effects of financial distress and bankruptcy at the route level for the only quality measure available at that level of aggregation: on-time performance. We end up finding similar results.

##### 4.1. Financial Distress

We now examine in a multivariate setup how distress affects firm’s quality and pricing (yield) decisions. For quality we examine two different quality supply decisions: mishandled baggage (the inverse of mishandled bags per 1,000 customers) and on-time performance. The key variable we use to examine financial distress is the Bharath and Shumway (2008) naïve probability of default. Table 4 presents results from estimating Equations (1a’)–(4a’).

We estimate the system using 3SLS to take advantage of the potential error correlation in the set of equations. We use firm fixed effects to isolate firms’ within variation in their pricing and quality strategies. We also use time fixed effects to absorb time-varying shocks that affect all firms’ quality and prices and that might be correlated with firm financial distress. We are able to identify temporary shocks from financial

<sup>22</sup> The current version of the test was proposed by Hansen (1982) as an extension of Sargan (1958). See Cameron and Trivedi (2005, p. 277) for a simple version of this test.

**Table 4** Quality and Price with Endogenous Default Probability

Variables	(1) <i>Quality: Inverse of Mishandled Baggage</i>	(2) <i>Quality: On-Time Performance</i>	(3) <i>ln(Price)</i>	(4) <i>Total Emplaned Passengers</i>	(5) <i>Default Probability</i>
<i>Default Probability</i>	−0.0796** (0.0322)	−0.1127*** (0.0258)	−0.5388*** (0.0719)	7.1914*** (1.6365)	
<i>Total Emplaned Passengers</i>	0.0031* (0.0018)	0.0026* (0.0015)	0.0208*** (0.0051)		0.0245*** (0.0087)
<i>ln(Price)</i>				0.3700 (1.8114)	−0.5024*** (0.1424)
<i>Fleet Age</i>	−0.0007 (0.0015)	−0.0062*** (0.0013)	−0.0068* (0.0040)	−0.1195 (0.0795)	0.0021 (0.0077)
<i>Decongestion</i>	0.4406*** (0.0893)	0.0442 (0.0755)	−0.6863*** (0.2155)	12.3399*** (4.4923)	0.0021 (0.0077)
<i>Average Miles per Flight</i>			−0.0005*** (0.0001)		
<i>ln(Oil Fuel Cost)</i>			0.1557*** (0.0341)		
<i>ln(Efficiency)</i>			−0.1666*** (0.0332)		
<i>Competition</i>				−2.0959*** (0.2923)	
<i>ln(Income)</i>				41.7165*** (9.4574)	
<i>Unemployment</i>				−44.5572 (31.7114)	
<i>% Liquidable Assets</i>					0.6293*** (0.1731)
<i>ln(Fleet Redeployability)</i>					−0.0574** (0.0243)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
<i>R</i> <sup>2</sup>	0.7843	0.5978	0.8385	0.9146	0.572
<i>N</i>	575	575	575	575	575

*Notes.* This table reports estimated relationships among quality, price (measured by yield), and financial status using three-stage least squares. The five dependent variables, *Quality: Inverse of Mishandled Baggage*, *Quality: On-Time Performance*, *Price*, *Total Emplaned Passengers*, and *Default Probability*, are in columns (1)–(5). *Total Emplaned Passengers*, *Default Probability*, and *Price* are used as right-hand-side variables as well. *Fleet Age* is the average age of an airline's fleet. *Decongestion* measures the average on-time performance by airport, excluding an airline's own flights, weighted by the airline's lagged share of customers. *Oil Fuel Cost* is the actual fuel cost per gallon after hedging contracts are considered. *Efficiency* is defined as available seats miles divided by gallons of fuel utilized. Income and unemployment are quarterly for each state and weighted by the airline's share of passengers in that state, lagged one quarter. Competition represents the weighted average number of competitors an airline faces across its markets. *% Liquidable Assets* is the fraction of the total value of assets a firm can recover in case of liquidation, following Berger et al. (1996). *Redeployability* is a weighted average of the popularity of an airline's aircrafts, measured by the number of active aircrafts by type under other operators. Data are quarterly from the first quarter of 1997 to the fourth quarter of 2008. Only nonbankrupt observations are considered. All regressions include firm and time fixed effects. Standard errors are in parentheses.

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

distress because financial distress affects different firms at different points in time. Last, we express our constructed variables in logarithms, whenever possible, to be able to interpret our results as elasticities. We use logarithms of price (yield), oil fuel cost price, efficiency, income, and fleet redeployability.<sup>23</sup>

<sup>23</sup> Some variables like average miles per flight, competition, percentage of liquidable assets, unemployment, and decongestion have a straight forward interpretation, so we do not express them in logarithms. We do not express quantity in logarithms because the within difference in passengers through time is close to zero in logarithms. Finally, our quality measures are already in ratios, so the logarithmic transformation does not provide any further insight.

Econometrically we identify the direct effect of financial distress on price and quality by instrumenting quantity and the default probability. The instruments that satisfy the exclusion restriction for the quantity equation are competition, income, and unemployment, and for the default probability they are the percentage of liquidable assets and fleet redeployability. Columns (4) and (5)—which can be thought as equivalents to first-stage regressions—show that all the instruments but unemployment are strong.

Table 4 shows that firms' price and quality are negatively affected by their financial distress as captured

by the default probability. These results are consistent the conflict of interest between equity holders and debt holders that arises in financial distress. These results as a whole are inconsistent with a cash-constrained firm being unable to invest in quality as a firm does not need cash to cut prices.

To understand the economic impact of these results, we compare the quality and price decisions of a firm with zero default probability with itself when it is highly distressed, with a 60% of default probability. Thus, the parameter of default probability has to be multiplied by 0.6 for its interpretation. We select this number because it will allow us to compare our results for financial distress with the later results on bankruptcy, for which sample firms have, on average, a 60% default probability when they are not in bankruptcy.

According to the estimates reported in Table 4, a firm that has a probability of 60% of going bankrupt next period charges 32% less than a healthy firm with zero default probability. The effect on quality is also large. A firm with a 60% probability of defaulting next period decreases the inverse of bags mishandled by 0.048, which represents 0.6 standard deviations, with respect to a firm with zero default probability. Thus, financial distress represents a change from the sample mean of 5.8 mishandled bags per 1,000 passengers to 7.6 mishandled bags per 1,000 passengers. Similarly, a firm with a 60% probability of defaulting next quarter decreases its on-time performance by 0.068 which represents 1.1 standard deviations, with respect to a firm with zero default probability. Assuming that the overall percentage of late flights remains at its sample mean, financial distress represents a change from late flights arriving 52 minutes late, at the sample mean, to late flights arriving 71 minutes late.

The results for our control variables also make economic sense: both measures of quality increase when airports are less congested, but only the effect on baggage handling rate is statistically significant, and they decrease with the airline's fleet age, although this effect is significant only for on-time performance. In the pricing equation, prices are higher when quantity increases, when oil prices are higher, when congestion is higher, when the fleet is younger, when efficiency is lower, and when average miles per flight decrease.

#### 4.2. Bankruptcy

We now examine the impact on price and quality of Chapter 11 bankruptcy. We compare bankrupt firm-quarters with highly distressed firm-quarters—including both firms that enter bankruptcy, their bankrupt periods and their high distress quarters, and also firms that are highly distressed but do not enter bankruptcy. We estimate a similar set of equations

as for the financial distress case, but now we use a bankruptcy indicator rather than the probability of default as the relevant financial condition. Thus, we estimate Equations (5a')–(8a') using three-stage least squares. The results of are presented in Table 5.

Table 5 shows that both of our measures of quality, the inverse of bags mishandled and the on-time performance, increase in bankruptcy relative to the distressed firm-quarters examined (which have a 60% default probability on average). Prices continue to fall in bankruptcy relative to financial distress, although this further decrease is not statistically significant. Keeping prices low during bankruptcy is consistent with lower short-term cost pressures as interest is deferred via the automatic stay provision when the firm is in bankruptcy. They are also consistent with bankrupt firms making an effort to retain customers.

Percentage of liquidable assets and fleet redeployability are strong and significant predictors of bankruptcy even in this small subsample (192 firm-quarter observations). The effect of instrumented bankruptcy on both quality measures is positive and strongly significant. When a firm goes from financial distress into bankruptcy, it increases the inverse of bags mishandled by 0.082, which represents a one standard deviation increase. Thus, bankruptcy represents a change from the estimated 7.6 mishandled bags per 1,000 passengers in financial distress to 4.6 mishandled bags per 1,000 passengers. Similarly, a firm in bankruptcy increases its on-time performance by 0.031, which represents 0.51 standard deviations, with respect to when it was financially distressed. Thus, bankruptcy represents a change from late flights arriving 71 minutes late in financial distress to 61 minutes late during bankruptcy. In sum, firms in bankruptcy increase their product quality with respect to when they are financially distressed. For mishandled bags, quality in bankruptcy is actually higher than when the firm was financially healthy. This pattern is consistent with firms during bankruptcy trying hard to regain the confidence of consumers and convince the bankruptcy judge that they are viable in the long run.<sup>24</sup>

Overall, these results on quality in bankruptcy compared to quality in financial distress are unique. We show that quality increases in bankruptcy relative to financial distress. Our results that prices fall with financial distress are in agreement with those of Borenstein and Rose (1995) and Busse (2002). Our results on prices, however, do not support Borenstein

<sup>24</sup> In the combined analysis of financial distress and bankruptcy, which we omit for space reasons, we find a similar pattern: quality of mishandled bags is actually higher in bankruptcy than in nondistress periods, whereas on-time performance is almost identical in bankruptcy and in nondistress periods.

**Table 5** Quality, Price, and Endogenous Bankruptcy

Variables	(1) <i>Quality: Inverse of Mishandled Baggage</i>	(2) <i>Quality: On-Time Performance</i>	(3) <i>ln(Price)</i>	(4) <i>Total Enplaned Passengers</i>	(5) <i>Bankruptcy</i>
<i>Bankruptcy</i>	0.0821*** (0.0144)	0.0312** (0.0156)	−0.0156 (0.0431)	0.1193 (0.4797)	
<i>Total Enplaned Passengers</i>	0.0217** (0.0091)	−0.0431*** (0.0088)	−0.0995*** (0.0367)		0.1578** (0.0738)
<i>ln(Price)</i>				−1.6543 (1.8356)	0.1516 (0.5342)
<i>Fleet Age</i>	0.0005 (0.0036)	−0.0059 (0.0039)	0.0136* (0.0081)	0.1449 (0.1120)	−0.1086*** (0.0314)
<i>Decongestion</i>	0.7052*** (0.1699)	0.2609 (0.1824)	−0.1701 (0.3576)	3.7526 (4.9800)	−7.1906*** (1.3174)
<i>Average Miles per Flight</i>			−0.0006*** (0.0002)		
<i>ln(Oil Fuel Cost)</i>			0.1390 (0.1092)		
<i>ln(Efficiency)</i>			−0.6811*** (0.1547)		
<i>Competition</i>				−0.1331 (0.2064)	
<i>ln(Income)</i>				−11.1471 (6.8731)	
<i>Unemployment</i>				30.3810 (26.2682)	
<i>% Liquidable Assets</i>					0.7425*** (0.1148)
<i>ln(Fleet Redeployability)</i>					0.5295** (0.2567)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
<i>R</i> <sup>2</sup>	0.8038	0.4723	0.9038	0.9742	0.583
<i>N</i>	192	192	192	192	192

*Notes.* This table reports estimated relationships among quality, price (measured by yield), and financial status using three-stage least squares. The five dependent variables, *Quality: Inverse of Mishandled Baggage*, *Quality: On-Time Performance*, *Price*, *Total Enplaned Passengers*, and *Bankruptcy* are in columns (1)–(5). *Total Enplaned Passengers*, *Bankruptcy*, and *Price* are used as right-hand-side variables as well. *Fleet Age* is the average age of an airline's fleet. *Decongestion* measures the average on-time performance by airport, excluding an airline's own flights, weighted by the airline's lagged share of customers. *Oil Fuel Cost* is the actual fuel cost per gallon after hedging contracts are considered. Efficiency is defined as available seats miles divided by gallons of fuel utilized. *Income* and *Unemployment* are quarterly for each state and weighted by the airline's share of passengers in that state, lagged one quarter. *Competition* represents the weighted average number of competitors an airline faces across its markets. *% Liquidable Assets* is the fraction of the total value of assets a firm can recover in case of liquidation, following Berger et al. (1996). *Redeployability* is a weighted average of the popularity of an airline's aircrafts, measured by the number of active aircrafts by type under other operators. Data are quarterly from the first quarter of 1997 to the fourth quarter of 2008. The default state is financial distress without bankruptcy. The sample considers only firm-quarters with a default probability higher than 10% or in bankruptcy. We include firm and time fixed effects in all estimations. Standard errors are in parentheses.

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

and Rose's (1995) interpretation. Borenstein and Rose (1995) argued that consumers might anticipate the firm's incentive to reduce quality in financial distress and thus lower their demand, which leads to a price reduction. In our setting, even after controlling for firm demand, we find that firms reduce price in the presence of financial distress. This finding is consistent with firms in financial distress having a higher discount rate, which gives firm managers incentives to cut prices in the short run to generate cash by stealing market shares from its competitors. Thus, our finding on prices support a mechanism similar to the one proposed by Busse (2002), as she also argued that

firms in distress cut prices to get higher profits in the short run even if this triggers a price war in the future.

### 4.3. Route-Level Analysis

Our previous results are from analyses conducted at the firm level because this is the level where bankruptcy and financial distress affect firms. Although firm-level estimations are conceptually correct, they could mask market (route) heterogeneity, which can further help us to understand the implications of a firm's financial condition on its product quality. Thus, we now turn to estimate the impact of financial conditions product quality at route level

for the only quality measure available at this level of aggregation: on-time performance.

Because we only have one dependent variable of interest, we collapse our system of Equations (1a')–(4a') into a simple two-stage least squares by replacing Equation (2a') into (3a') and (4a'), and then Equations (3a') into (4a') and vice versa. Thus, the first-stage equations estimate quantity and default probability on all the elements of  $W$ ,  $X$ ,  $Y$ , and  $Z$ , and the second-stage equation is simply Equation (1a'). We do the same for the system (5a')–(8a'), which estimates the impact of bankruptcy relative to financial distress.

Given that on-time performance is now at the route level, we also compute income, unemployment, and competition at this level of aggregation and drop variables such as decongestion or average miles per flight, which only make sense when estimating at the airline level. We weight observations inversely corresponding to the number of routes each carrier operates in a quarter, to not overrepresent carriers that operate a large number of routes, given bankruptcy and financial distress are firm-level phenomena. Standard errors are clustered at the route level.

We present the result of the second-stage estimations in Table 6. Columns (1) and (2) present our results for default probability, and our results for

bankruptcy are presented in columns (3) and (4). Columns (1) and (3) use firm fixed effects, whereas columns (2) and (4) use firm-route fixed effects. Studying the difference between firm fixed effects estimations and firm-route fixed effects estimations is important, because with firm fixed effects, parameter identification exploits firms' variation within and across routes—similar to our results from Tables 4 and 5—whereas firm-route fixed effects estimations exploit only within-route variation for a given firm.

The first takeaway from Table 6 is that the results from Tables 4 and 5 hold when using route-level data and are robust to the inclusion of firm-route fixed effects: product quality decreases with financial distress and increases in bankruptcy relative to periods of financial distress. The fact that the parameters of default probability are almost identical in columns (1) and (2) highlights that variation across-routes does not play an important role in identifying the default probability parameter: financially distressed firms decrease their on-time performance within their routes, and this averages out to a decrease at the firm level. The bankruptcy parameter, on the other hand, is larger when using firm fixed effects than when using firm-route fixed effects. This indicates that the increase in on-time performance at

**Table 6** Route-Level Analysis for On-Time Performance

Variables	(1) Quality: On-Time Performance	(2) Quality: On-Time Performance	(3) Quality: On-Time Performance	(4) Quality: On-Time Performance
<i>Default Probability</i>	−0.0988** (0.0503)	−0.0998** (0.0493)		
<i>Bankruptcy</i>			0.0594*** (0.0116)	0.0307** (0.0120)
<i>Total Enplaned Passengers</i>	3.8405*** (0.6876)	6.8392*** (0.6279)	0.5369 (0.8855)	3.9417*** (1.1856)
<i>Fleet Age</i>	−0.0026 (0.0020)	−0.0054** (0.0024)	−0.0040** (0.0019)	−0.0075*** (0.0023)
Firm fixed effects	Yes	No	Yes	No
Firm-route fixed effects	No	Yes	No	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Route cluster	Yes	Yes	Yes	Yes
Route weights	Yes	Yes	Yes	Yes
Instruments	Yes	Yes	Yes	Yes
<i>N</i>	193,489	193,489	57,694	57,694

*Notes.* This table reports second-stage regressions of the estimated relationships between on-time performance and financial status using two-stage least squares. Observations are at the firm-route-quarter level. *On-Time Performance* is measured as  $1/Late$ , where *Late* is the percentage of late flights a route has on a quarter times the average lateness of the late flights. Columns (1) and (2) study the impact of financial distress relative to financially healthy firms. They include only firm-route-quarters for which the operating airline was not in bankruptcy. Columns (3) and (4) study the differential effect of bankruptcy relative to financial distress. They consider firm-route-quarters where the firm's default probability is higher than 10% or the firm is in bankruptcy. Columns (1) and (3) use firm fixed effects. Columns (2) and (4) use firm-route fixed effects. *Default Probability* is Merton's naïve default probability for the firm as constructed by Bharath and Shumway (2008). *Bankruptcy* is an indicator variable that takes a value of 1 if the firm is bankrupt and 0 otherwise. *Total Enplaned Passengers* are measured at the route level (in millions). *Fleet Age* is the average age of an airline's fleet. A firm's financial condition (i.e., default probability and bankruptcy) and total enplaned passengers are instrumented using the firm-level variables % *Liquidable Assets*, *Fleet Redeployability*, *Efficiency*, and *Oil Fuel Cost*, and the firm-route-level variables *Competition*, *Unemployment*, and *Income*. Observations are weighted by the inverse of the number of routes operated by a firm in a quarter. All regressions include time fixed effects. Standard errors are clustered at the route level and are shown in parentheses.

\*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

the firm level has two sources: an increase in on-time performance within routes and an increase across routes. The latter is consistent with firms' restructuring in bankruptcy by probably shedding problematic routes (see Ciliberto and Schenone 2013a, b).

## 5. Conclusions

Our paper examines the impact of financial distress and bankruptcy on airlines' quality and pricing decisions in an integrated analysis. Our paper is the first to examine how the product market implications of financial status differ between bankruptcy and financial distress. We show that firms reduce quality when faced with financial distress. These findings are consistent with firms facing incentives to take advantage of other stakeholders such as customers when faced with financial distress.

We find different results in bankruptcy. In bankruptcy, we document that firms increase quality relative to prebankruptcy financial distress. These findings are consistent with managerial incentives changing in bankruptcy and with firms in Chapter 11 trying to retain customers and invest in reputation to emerge as a viable company.

Our results for financial distress are consistent with firms in financial distress having a higher discount rate, which gives firm managers incentives to reduce quality and cut prices in the short run to generate cash even though this might imply lower profits in the future. The different results in bankruptcy highlight the different incentives firms face in this state and the necessity to examine financial distress and bankruptcy in an integrated fashion.

Our analysis can be extended in several directions. Currently, we do not make a distinction between healthy firms that came out of bankruptcy and firms that never went into bankruptcy. Their product market behavior might differ given more apprehension from customers or creditors about the firm's continued reputation for product quality. Additionally, financial conditions might have an effect not only on the average quality of products, but on quality assurance (the second moment of product quality). It is possible that bankrupt firms have not only higher product quality than when they are financially distressed, but also that the product quality is provided with lower variance. We leave these extensions for future research.

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