Revisiting the Asset Fire Sale Discount:

Evidence from Commercial Aircraft Sales*

Julian Franks†

Gunjan Seth‡

Oren Sussman§

Vikrant Vig¶

December 28, 2020

*We are grateful to Bo Bian, John Y. Campbell, Alessandro Gavazza, Narayan Naik, Arkodipta Sarkar, and Henri Servaes for their helpful comments and suggestions. We wish to thank seminar participants at the Stockholm School of Economics, and INSEAD for their comments and suggestions. We thank the AQR Asset Management Institute at London Business School for their financial support.

†Julian Franks, London Business School, jfranks@london.edu.

‡Gunjan Seth, London Business School, gseth@london.edu.

§Oren Sussman, University of Oxford, Oren.Sussman@sbs.ox.ac.uk.

¶Vikrant Vig, London Business School, vvig@london.edu.

Revisiting the Asset Fire Sale Discount:

Evidence from Commercial Aircraft Sales

Abstract

Using a sample of commercial aircraft transactions, the paper decomposes the raw fire sale discount on sales of aircraft by distressed airlines into three components: (i) quality impairment due to under-maintenance, (ii) misallocation to lower productivity users, and (iii) a liquidity component due to the immediacy of the sale. Results indicate that financially distressed airlines sell aircraft that have a lower life expectancy and lower productivity. We combine the two effects into a quality impairment adjustment that explains around one half of the raw liquidation discount. For the remaining discount of around 9%, we find no direct evidence of misallocation to lower productivity users and industry outsiders. Rather, the post-sale users of distressed aircraft have significantly higher productivity than the distressed sellers, while their productivity is similar to that of other (non-distressed) users. In summary, our results indicate that the inefficiencies associated with fire sales are likely to be lower than have been previously documented.

1 Introduction

Recent crises have raised the economic importance of fire sales in both academic and policy circles. It is now widely accepted that fire sales are pervasive and associated with large economic inefficiencies. In a fire sale, distressed sellers are forced to liquidate their assets at discounted prices. However, the large estimates of the fire sale discount in some markets raise the question as to why potential buyers do not exploit this apparent arbitrage opportunity and restore prices closer to their fundamental value. In an influential paper, Shleifer and Vishny (1992) argue that distress is often driven by an industry-wide shock where specialist buyers of the asset are likely to be distressed at the same time, precluding them from bidding for the asset. As a result, the asset is misallocated to non-specialist users, that are assumed to have lower productivity than specialist users.[1] Besides, fire sales may generate negative externalities for the broader economy and may even contribute to systemic shocks.[2]

The empirical research on fire sales was pioneered by Pulvino (1998, 1999) in a study of secondary market transactions for used commercial aircraft. He documented that financially constrained airlines sold aircraft at a 15% average discount with significantly larger discounts, 25-35% in magnitude, for airlines operating in US Chapter 11 and Chapter 7 procedures. Similar magnitudes of fire sale discounts have been documented in other settings.[3] For example, Campbell et al. (2011) report an average fire sale discount of 27% on the value of houses precipitated by a forced sale transaction.[4]

Fire sales are not just limited to real assets. Coval and Stafford (2007) document an 8-10% discount in equity markets on fire sales by mutual funds. Mitchell and Pulvino (2012) find that nearly identical corporate securities were mispriced by 10% during the 2008 crisis. In a study of fire sales caused by

[1]Several papers extend this misallocation argument to financial assets: Allen and Gale (1994), Shleifer and Vishny (1997), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), and Duffie (2010) attribute fire sales to limited arbitrage capital, arguing that complex securities are normally held by specialized investors who can exploit their knowledge, and when these investors become severely capital-constrained the available pool of specialized capital shrinks.

[2]For example, Kiyotaki and Moore (1997), model downward price spirals due to deleveraging and fire sales by specialist users of land (farmers), leading to an amplification in the decline in asset values. Allen and Gale (1994) argue that fire sales create a downward pressure on the value of collateralised assets, which drives even more operators into financial distress in a contagion effect. Other papers also document this amplification mechanism including Krishnamurthy (2010), Geanakoplos (2003), Greenwood et al. (2015), Mian et al. (2015) and Dow and Han (2018).

[3]See Shleifer and Vishny (2011) for a comprehensive survey on the fire sale discount literature.

[4]Schlingemann et al. (2002), LoPucki and Doherty (2007), Andersen and Nielsen (2017), Strömberg (2000) and Franks et al. (2020) document the costs associated with fire sales in real assets.

regulatory pressure on insurance companies, Ellul et al. (2011) report a 6-7% discount on corporate bonds.[5]

The large size of the fire sale discount, often exceeding 25% in real asset markets, are puzzlingly high, particularly when compared with discount rates of 10% in financial markets. This raises important questions: why are investors leaving so much money on the table, and, why are lenders and borrowers not renegotiating contracts to reach a Coasian solution? While the higher discount for real assets vis-a-vis financial assets might be explained in part by a greater divergence in the private valuations of real assets as opposed to financial assets, omitted variables such as the inherent quality of the asset may also explain this difference. Campbell et al. (2011) have discussed this quality impairment channel as an important component of forced sale discounts in the housing market.[6]

In general, current methodologies of calculating fire sale discount do not control for quality differences between assets sold by distressed and healthy firms. It is natural to expect that distressed firms which are financially constrained, are more likely to under-maintain their assets, that may be a direct consequence of the debt overhang problem (Myers (1977)).[7] As a result, the estimates of fire sale discounts that ignore this quality impairment are likely to be biased upwards. Our paper aims to address this issue. Specifically, we examine whether fire sale discounts in the airlines industry, after adjusting for quality, are as large as the literature has documented. We also investigate whether fire sales result in misallocation of aircraft to lower productivity users (Shleifer and Vishny (1992)), or whether bankruptcy procedures have a cleansing effect on the industry by relocating assets to higher productivity users (Caballero and Hammour (1994)).

The issue of quality is an important one in the airlines industry. In the U.S., airworthiness maintenance requirements are mandated by the Federal Aviation Administration (FAA). Despite this, there have been instances when airlines operating under bankruptcy have been scrutinized for selling aircraft of impaired

[5] Several other papers also document fire sales in financial asset markets: Jotikasthira et al. (2012), Eisenbach et al. (2014), Merrill et al. (2014), and Acharya et al. (2007)

[6] Campbell et al. (2011) estimate the importance of the maintenance channel by identifying the motives for a forced sale. For example, they link the high discount on the sales of single family homes on the death of elderly sellers to poor maintenance. However, they do not decompose the foreclosure-related discounts into under-maintenance and liquidity components.

[7] In the real estate market, Melzer (2017) documents evidence of homeowners reducing their home improvement and maintenance expenditures when faced with mortgage debt overhang. However, debt overhang is not a necessary condition for under-maintenance. Distressed firms might be cash constrained and therefore, have to give up investments with positive NPV, such as maintenance expenditures.

quality. For example, during Eastern Airlines' bankruptcy proceedings it was revealed that the airline had failed to maintain aircraft as dictated by the terms of their capital leases, and lessors had to make major repairs to many aircraft to ensure they met the mandated operating regulations.[8] In an analysis of Eastern Airlines' bankruptcy, Weiss and Wruck (1998) noted that, "the discount on Eastern's aircraft could be due to many factors including its distressed situation and/or poor maintenance." It is also common for airlines to swap engines and other parts of an aircraft, and subsequently sell those aircraft with the second-hand parts. However, it is challenging to systematically measure these quality differences between aircraft, because they are not captured in reported aircraft characteristics nor, are they documented in our transaction price database. In this paper we suggest a novel approach to control for these quality differences that are not directly observable or documented in existing studies.

We begin by documenting evidence that aircraft sold during bankruptcy and distress have a lower life expectancy compared with aircraft sold by airlines with little or no constraints.[9] Using data on aircraft retirement age, we impute the hazard rate and expected life expectancy for aircraft. We find that aircraft sold by distressed airlines have 7% lower remaining life expectancy than aircraft sold by non-distressed airlines.[10]

An additional insight into the differential quality of aircraft sold by bankrupt and distressed airlines is provided by examining the productivity of aircraft. Using a granular measure of aircraft productivity, flying hours at the aircraft-level, we find that aircraft sold by distressed airlines have around 10% lower utilization compared with other similar aircraft flown by that *same* operator. We also find that the increase in time spent in distress is highly correlated with the quality adjustment. Taken together, our results show that not only do the distress-affected aircraft have a lower life expectancy, they also exhibit lower productivity while in use by the post-sale operator. After controlling for the decline in expected life expectancy and productivity, the quality-adjusted fire sale discount for aircraft sold by both financially distressed and bankrupt airlines is around 9%, about one half of the raw fire sale discount. Importantly,

[8] Lessors received a small legal settlement that covered about 20-25% of these additional costs.

[9] Bankruptcy sales are aircraft sales made by airlines that have filed for Chapter 11 or Chapter 7 protection. Distressed sales are sales of aircraft made by airlines one year prior to their entering bankruptcy, or while they are operating in bankruptcy.

[10] Franks et al. (2020) document higher hazard rates and lower life expectancy for sales of ships by distressed sellers. Pricing in this quality correction reduces the 26% raw fire sale discount by about a half.

the quality discount varies with the depth of distress, captured by a comparison of sales of the aircraft in Chapter 11 or Chapter 7.

We next decompose the quality-adjusted fire sale discount into a pure liquidity channel and the misallocation channel (Shleifer and Vishny (1992)). The liquidity channel represents a transfer from the seller to the buyer and as such the discount does not have any ex-post welfare implications, in contrast, to the misallocation channel.[11] According to Shleifer and Vishny (1992), the seller and the next best user of the asset are likely to be encumbered at the same time because of industry distress, and therefore, the best users are constrained from bidding for the asset of the distressed firm. This generates a welfare loss as the assets are sold and misallocated to suboptimal users.

Our granular dataset on aircraft ownership and utilization allows us to examine this question. We measure misallocation by comparing flying hours and profitability measures of the new users of distressed aircraft with new users of normal (or non-distressed) aircraft sales. Our metrics for flying hours control for the aircraft type, age, market thinness, and year fixed effects. Following Hsieh and Klenow (2009), we use Tobin's Q and the marginal product of capital to gauge the extent of misallocation. We do not find, in our sample, evidence of misallocation of aircraft to lower productivity or less profitable firms. We also document evidence that for a large percentage of bankruptcy sales, the buyers of the aircraft are operationally more efficient than the sellers. Therefore, we attribute the quality-adjusted fire sale discount of 9% largely to a transfer from the seller to the buyer due to the immediacy of the sale, i.e., the liquidity channel. Consistent with Meier and Servaes (2019), the evidence suggests that the quality-adjusted fire sale discount is primarily a consequence of the lower bargaining power of the distressed seller.

The results, also, highlight the important role played by leasing companies in the airlines industry. Since aircraft purchased by leasing companies are not directly operated by them, we track the final users of these aircraft using our granular aircraft operator level dataset. We find that leasing companies redeploy aircraft to higher productivity users, thereby performing a valuable intermediary role. In addition, they reduce the downtime of aircraft prior to the sale being completed by almost two-thirds. This evidence is consistent with Gavazza (2011a), who documents that leasing companies reduce trading frictions in second-hand aircraft markets.

[11] Notwithstanding, there still may be ex-ante welfare losses.

In summary, our paper revisits the issue of the fire sale discount in the airline industry. The recent pandemic in 2020 caused by Covid-19, and the consequent economic crisis it has engendered, has reignited the issue of the fire sale discount and the inefficiencies associated with it. Our analysis of the airline industry suggests that a significant proportion of the fire sale discount is driven by omitted quality differences between forced sales and regular sales. Our paper also reports that this quality discount varies with the length and depth of distress, which explains why the quality discount is higher for aircraft sales in Chapter 7 than in Chapter 11. Importantly, we do not find much evidence for the misallocation of assets brought about by fire sales. This may well reflect the efficiency of the bankruptcy design, which in the case of Chapter 11 allows for a more patient sale of the assets.[12] Overall, our results suggest that the welfare costs associated with fire sales might be lower than those documented in prior studies.

The rest of the paper is organized as follows. In section 2 we discuss the institutional features of the used commercial aircraft market. Section 3 describes our data and summary statistics. In section 4 we present evidence on the quality variations between aircraft sold by distressed and non-distressed sellers. Section 5 describes the empirical methodology and results on quality-adjusted fire sale discount. Section 6 presents evidence on aircraft misallocation, and investigates the extent to which the quality-adjusted fire sale discount is attributable to the pure liquidity channel, and the misallocation channel. The last section concludes our paper.

2 Institutional Details

2.1 Used Aircraft Market

The main market participants in the transactions of used commercial aircraft include airlines, aircraft lessors, banks, governments and air cargo companies. The market for used aircraft transactions is organized around privately negotiated transactions. Major airlines have employees devoted to the purchase and sale of aircraft, and independent brokers are also used to match buyers and sellers. Pulvino (1998) provides evidence that planes are rarely sold in auctions. Buyers conduct comprehensive pre-purchase

[12] Specifically, Chapter 11 allows for access to DIP finance and an automatic stay on most interest and capital repayments.

inspections of all installed avionic equipment in the aircraft to establish their condition of airworthiness and maintenance. All the maintenance records for the aircraft are transferred to the buyer upon sale. Such information is private to the parties involved in the transaction, and is not available to the econometrician.

We have selected the airlines industry to answer important questions regarding the estimation of the fire sale discount. There are various reasons that make the airlines industry an excellent laboratory to implement our framework. First, we are able to obtain a comprehensive sample of aircraft transaction prices as the Department of Transportation (DOT) regulations in the airlines industry mandated price disclosure for all used commercial aircraft transacted in the U.S. between 1978-1991. Second, aircraft of a given model are "relatively" homogeneous which makes possible the calculation of hedonic prices based on their characteristics. Third, the U.S. airline industry presents a sample of firms with widely varying capital structures, where bankruptcy filings are common. Therefore, we are able to link an airline's financial health with any discount it receives on the sale of its aircraft.

Detailed *aircraft-level* utilization data for the airlines industry allows us to overcome the empirical challenge of quantifying the impact of unobservable quality variations on the price of an asset. In real assets there could be significant quality differences between well maintained and under-maintained assets that affect their continuation value. This difference is particularly crucial for aircraft, and it is also well documented in the technical aviation literature. Lower maintenance can decrease aircraft utilization rates, and the effect is particularly strong for older aircraft (Ackert (2012)). Maintenance and safety considerations in the aviation industry have led to wide availability and high accuracy of aircraft level capacity utilization data. This granular aircraft retirement age and utilization data allows us to control for quality variations resulting from the lower life expectancy and lower productivity of distress-affected aircraft. Measuring productivity at the aircraft level enables us to examine the issue of misallocation. Additionally, rigorous aircraft registration requirements track fleet alterations and economic activity at the airline level. This micro tracking of each aircraft at the airline level allows us to consistently trace aircraft relocation from one user to another, and measure airline level productivity.

2.2 Bankruptcy Court Protection in Airlines Industry

The sizeable capital expenses needed by airlines to acquire and maintain their fleet makes them vulnerable to economic downturns, particularly given their high leverage. Bankruptcy filings are commonplace in the U.S. airlines industry, and their design and enforcement are likely to influence the fire sale discount. Out of our sample of 27 major U.S. airlines, nine filed for bankruptcy during 1978-1992. Of these nine, six were eventually liquidated in Chapter 7. Given the size of the industry and the incidence of distress and bankruptcy, creditors of airlines have been given special protection for their investments under Section 1110 of the U.S. Bankruptcy Code (Ripple (2002)). Specifically, creditors of airlines operating under court protection are provided relief from automatic stay. Section 1110 of Chapter 11 allows the financiers of aircraft and aircraft parts to repossess their collateral within 60 days after a bankruptcy filing, subject to conditions described below. Section 1110 was first introduced in 1979, and was later amended in 1994 to clarify the secured creditors' rights so as to resolve issues arising from previous litigation. These limitations on the automatic stay may affect the fire sale discount, and the company's ex ante leverage.

Seemingly the provisions in Section 1110 of the Bankruptcy Code appear to favor the financier. However, the special protection granted to aircraft financiers by this section is in conflict with one of the Bankruptcy Code's underlying premises, equality of treatment for all creditors within a similar class. For example, secured creditors who have non-aircraft collateral will be subject to the automatic stay, whereas, those creditors with collateral on aircraft will have repossession rights during bankruptcy. As a result, litigation between airline debtors and aircraft financiers has at times produced judicial opinions that have narrowed the Section's application. Airline bankruptcies in the 1980s created several ambiguities in Section 1110 that threatened to defeat its legislative purpose of providing assurances to secured creditors that they would retain their absolute right to repossess their collateral in case of default or bankruptcy.[13,14] In 1994, the amendments to Section 1110 attempted to resolve these issues by

[13] For example, during their bankruptcy, Braniff, Continental Airlines, and PanAm brought court proceedings (in 1982, 1983, and 1991, respectively) seeking a declaratory judgment that the sale-leaseback agreements were not subject to Section 1110. The airlines argued that Section 1110 only applied to acquisition agreements for the possession of new aircraft by the airlines. Continental Airlines also entered into Section 1110 agreements with several of its creditors in order to retain possession of its aircraft, and subsequently, submitted a reorganization plan that proposed to modify the terms of the pre-petition agreements. The creditors objected, arguing that these agreements should be considered post-petition agreements and, therefore, were not subject to the cramdown provisions of Section 1129. The bankruptcy court did not resolve the issue because the creditors eventually accepted the proposed plan.

[14] Refer to (Ripple (2002)) for a detailed history of Section 1110 and the challenges to its implementation.

clarifying that any lease or security interest in the aircraft fell under the umbrella of the Section. Given that our sample of aircraft transaction prices ends in 1991, Section 1110 may not have been very effective in allowing creditors to repossess aircraft.

The financier's repossession rights may not be very valuable for three reasons. First, the debtor may elect under Section 1110A, that repossession may not take place providing it continues to observe the contractual obligations of the creditor, for example, by agreeing to make lease payments, maintaining the aircraft and curing any previous defaults specific to the aircraft.[15] Second, if the airline industry is in a downturn and the creditor is unable to find a buyer for the aircraft, seizing and repossessing the aircraft without having a secondary buyer (or lessee) forces the financier to absorb the carrying costs for an indeterminate period of time. For example, a non-operational user of an aircraft will need to rent hangar space or absorb the cost of mothballing the aircraft in a 'boneyard' so as to preserve and prevent damage to the aircraft. Adding to this expense will be the costs of repeated transactions, including regular inspections.[16] Benmelech and Bergman (2008) provide evidence on airlines successfully renegotiating their lease obligations downwards when their financial position is sufficiently poor and when the liquidation value of their fleet is low. Expensive market frictions force some financiers to take the view that restructuring the airline, and not exercising their rights of repossession, presents the best source of recovery (Kirkland and Ellis (2005)). Third, given that our sample of aircraft transaction prices ends in 1991, the litigation and the lack of clarity that led to the 1994 amendments to Section 1110, would have imposed significant restrictions on the ability of creditors to use that Section to end the automatic stay and repossess their aircraft.[17]

The alternative bankruptcy procedure in the US is Chapter 7, which may be regarded as the process of liquidation. An airline that entered Chapter 7 would be closed down and its assets sold off. The sales process would not be managed by the debtor in possession as in Chapter 11, but rather by a trustee

[15] For a description of Section 1110 and how it operates, in particular how airlines may, subject to court permission, elect for a continuance of the automatic stay, see Bankruptcy and Aircraft Finance, F.H. Top III, S. Tetro, R. Klein and J. Heiser, in The Harvard Law School Bankruptcy Roundtable posts, April 2020

[16] Gray et al. (2015) document that the inspection tasks required to return an aircraft to service can cost more than $2 million if the aircraft is left unused for one month. Another example of a costly repossession, is where aircraft leases and security agreements allow the operator to exchange engines and other parts through pooling or interchange agreements (Scheinberg (2017)). In such cases seizing the aircraft, would require the creditor to reconfigure and reinstall new parts, which can prove to be a costly and litigious exercise.

[17] Before 1992, the average time an aircraft spent in Chapter 11 prior to their sale was 267 days, and 728 days in Chapter 7. This is consistent with the view that Section 1110 was not used by creditors to repossess their aircraft in Chapter 11.

appointed by the bankruptcy court. Airlines filing for Chapter 7 suffer a longer period of distress before filing for bankruptcy, and as a result are in worse financial shape than those airlines surviving Chapter 11. As a result, we might expect that the under-maintenance effect would be larger for those aircraft that are sold in Chapter 7 compared with those sold in Chapter 11.[18] Using a ratings downgrade of the airline's bonds as a proxy for the onset of distress, we analyse the correlation between the length of time spent in distress (from the onset of distress to the sale of the aircraft) and the size of the under-maintenance effect.

3 Data

3.1 Data Sources

We combine several data sources for empirical analysis in this paper.

Transaction Prices Database: The data is based on DOT and Federal Aviation Administration (FAA) filings assembled by Avmark Inc. The dataset collects aircraft transaction prices from 1978 to 1991. Prior to 1992, the DOT required price disclosure for all aircraft purchased or sold by U.S. corporations.[19] The dataset reports information of aircraft characteristics including the aircraft's age, model, and engine noise stage. It also contains the identity of the buyer, the seller, the date of transaction, and the transaction price. In the empirical analysis section, we focus on sales of used aircraft reported in this database. The transaction prices have been adjusted for inflation.

FlightGlobal: FlightGlobal is a leading producer of aviation market statistics. The database tracks ownership (fleet description) and operations history of commercial aircraft. If the aircraft is no longer operational, then the database provides the date at which the aircraft was retired. The data on aircraft utilization and retirement age spans 1975 to 2015. It also reports comprehensive information on aircraft utilization, i.e. the monthly number of hours flown by an individual aircraft operating in the US. Monthly flying hours are aggregated at the yearly level to obtain an annual panel on aircraft utilization for the

[18] The airlines that entered Chapter 7 in our sample initially filed for Chapter 11, and subsequently switched to Chapter 7. In addition sales were also made during bankruptcy by airlines that emerged from Chapter 11.

[19] After the DOT removed the price disclosure requirement, airlines and leasing companies mostly ceased reporting transaction prices.

1975–2015 period. We restrict the utilization sample to aircraft types for which we have the transaction prices.

Bureau of Transportation Statistics: We extract traffic data of U.S. commercial airlines (available seat miles (ASMs), revenue passenger miles (RPMs) etc.) from Air Carrier Traffic Statistics (Form 41 and 298C Summary Data). The data are available quarterly beginning 1974.

Bankruptcy filing procedure (Chapter 7 or Chapter 11) and bankruptcy dates are obtained from UCLA-LoPucki Bankruptcy Research Database and Airlines for America.

COMPUSTAT: Financial data of U.S. airlines is from COMPUSTAT. Where available, quarterly data is used, otherwise annual data is collected.

S&P Ratings: Data on rating downgrades of bonds held by airline companies (prior to their filing for bankruptcy) is obtained from the S&P Ratings database. These rating downgrades are used to identify the beginning of the period of distress for an airline filing for bankruptcy. When ratings are unavailable we use the year of earnings losses as a proxy for the beginning of the distress period.[20]

3.2 Summary Statistics

For our analysis we have considered used aircraft sales occurring between 1978 and 1991. Only aircraft models for which at least 15 sales occurred over 1978-1991 period are included. We have a total sample of 1,333 secondary market transactions in which one of the parties is a U.S. airline: it includes 1,079 narrow body sales and 254 wide body sales. All of these sales have been used to establish the hedonic coefficients, that are subsequently used to calculate the hedonic price of aircraft.[21] These hedonic prices establish the benchmark price for a particular model of an aircraft, in a given calendar quarter. Using retirement dates in our database, we find that of the 1,333 transactions of narrow and wide body aircraft studied between our sample period, around 93% ceased to operate by the end of 2016. However, in some cases an aircraft is parked and is not operating for some years just prior to being retired. We reduce

[20] For around 70% of the aircraft sold in distress, we have both the ratings and earnings data for the distressed airline. We find that for all these airlines, the year of rating downgrade is the same as the year of earnings losses. Hence, when ratings are not available we use the year of earning losses as a proxy for the beginning of distress period.

[21] As a robustness check we have excluded the aircraft sold by bankrupt airlines in calculating the hedonic prices, and all our results remain almost unchanged.

the retirement age to reflect this period during which an aircraft is parked prior to its retirement.[22] We also use a subsample of 695 aircraft sales made by major U.S. airlines (listed in Appendix Table A.1), that explicitly excludes all sales made by financial intermediaries, including banks and leasing companies. While the full sample of 1,333 transactions is used to establish the hedonic prices, the subsample is used to estimate the fire sale discount.

Further we classify the aircraft sales in our sample based on the varying degree of financial distress of their seller. Following Pulvino (1999), an aircraft sale is classified as a *distressed* sale if the aircraft is sold by: (i) an airline that is being liquidated under Chapter 7 bankruptcy, (ii) an airline that is operating under Chapter 11 bankruptcy protection, or (iii) the sale is made one year prior to the airline filing for bankruptcy. To identify sales at the extreme level of distress we further segregate our *distressed* sales sample into the following categories. An aircraft sale is classified as a *bankruptcy* sale if the selling airline has filed for formal bankruptcy. A *bankruptcy* sale is subclassified into a *Chapter 7* sale if the airline is liquidated under Chapter 7 of the US Bankruptcy Code, and *Chapter 11* sale if the airline is operating under Chapter 11 bankruptcy protection. The remaining *distressed* sales, i.e. the sales of aircraft one year prior to an airline filing for bankruptcy are classified as *Bankruptcy(T-1)* sales.[23]

Table 1 describes the summary statistics. Panel A of Table 1 summarizes the complete sample of 1,333 narrow body and wide body aircraft transacted during our sample period. The average inflation adjusted price for a used commercial aircraft in terms of 1992 dollars is $11.5 million. Around 35% of aircraft are sold to financial buyers (i.e. leasing companies or banks). The average retirement age for aircraft in our sample is roughly 29.6 years. In Panel B we restrict the sample to 695 aircraft sales by the major U.S. airlines listed in Appendix Table A.1.[24] In Panel C, we further split our sample into sales by bankrupt airlines and non-bankrupt airlines. In Panel D, we segregate the bankruptcy sales into Chapter 7, and Chapter 11 sales. In our sample of the 27 major airlines, nine filed for bankruptcy during our sample period. We have 131 (around 20%) sales by airlines operating under bankruptcy. Of those, 91 planes were sold by airlines operating under Chapter 11, while 40 were sold by airlines operating under

[22]This correction is based on the fact that when an aircraft has zero flying hours for an entire year, it is described as being *parked* in the database.

[23]Where, T signifies the time at which the airline filed for bankruptcy.

[24]Restricting the sample to sales made by major U.S. airlines is motivated by Pulvino (1998, 1999). Focussing on these sales ensures that our results on fire sale discounts are not affected by uncontrolled cross-industry or cross-country effects. In the empirical analysis that follows we link airlines' financial characteristics to their sales.

Chapter 7.[25] Aircraft sold by airlines operating in bankruptcy have lower retirement age than aircraft sold by non-bankrupt airlines.

In Table 2 we describe the summary statistics for aircraft productivity for the period from 1975 to 2015, as measured by annual flying hours. We have operational data on 4,860 aircraft spanning 62,705 aircraft-years. We show in Panel A for the full sample that an average aircraft flies for 2,069 hours annually, while 5.7% of the aircraft are parked for a year. The average age of an aircraft in our sample is 18 years, and the average technological age is almost 27 years. The technological age of an aircraft is defined as the number of years since the introduction of an aircraft's type. In Panel B we split our sample into 3 subsamples. Aircraft sold by distressed airlines have average yearly flying hours of 1,309 hours for their remaining lifetime, and a higher proportion of those are parked (11%). This level of productivity is far below the average productivity of aircraft that have not been exposed to distress, as well as being below the productivity of aircraft owned by airlines that emerged from Chapter 11 as going concerns. We use this data to examine in more detail the differential quality of aircraft sold by distressed airlines and those sold by non-distressed airlines. The probability of an aircraft being parked also differs considerably across the three subsamples; it is much higher for aircraft sold in distress (11%) than it is for aircraft owned by other operators who have not suffered from distress (5.3%).

4 Evidence on Aircraft Quality Impairment

In this section, we present evidence on the quality of aircraft sold by financially distressed airlines. In the U.S. aviation industry aircraft safety standards are monitored by the Federal Aviation Administration (FAA). Even though, minimum aircraft safety standards are set by the FAA, airlines are free to set maintenance levels above these minimum targets. Discussions with an aviation expert suggest there are areas of maintenance and refurbishment of aircraft which can be postponed, or costs reduced without endangering aircraft safety.[26] In fact, it is common practice for aircraft leases and security agreements

[25] The average age of aircraft sold in Chapter 7 is 10 years, compared with 17 years for aircraft sold in Chapter 11. This may reflect that airlines sell older aircraft first in Chapter 11 because these aircraft have higher operating costs, compared with younger aircraft that have lower operating costs.

[26] For example, worn out or defective parts may be replaced with second-hand rather than new parts, and refurbishments may be postponed.

to allow the operator to exchange engines and other parts through pooling or interchange agreements (Scheinberg (2017)). It is natural to expect that the financial health of an airline is correlated with the quality and maintenance of its aircraft. Often, airlines operating under bankruptcy have been scrutinized for selling aircraft of impaired quality.[27] Discussions with an aircraft appraiser, suggest that maintenance adjustments are often a significant part of second-hand aircraft prices. In this section, we use granular aircraft level utilization and retirement age data, to systematically document the variations in quality between aircraft sold by distressed and non-distressed airlines. We analyze the two components of the quality adjustment, a shorter operating life, and lower productivity during the remaining life after the sale of the aircraft.

4.1 Aircraft Life Expectancy

Using the retirement age of aircraft, we measure the difference in lifespan of aircraft sold by distressed airlines versus other aircraft transacted in our sample. We apply duration analysis to the retirement age data to calibrate the hazard function for an aircraft. The hazard function characterizes the hazard rate for an aircraft as a function of its age, t. Conditional on surviving up to a given age, the hazard rate represents the probability of an aircraft retiring in the subsequent period. We calculate the hazard rates using the Cox proportional hazard model. The Cox relative hazard regression estimates coefficients ($\hat{\beta}$) for aircraft characteristics (X: aircraft type, age, and bankruptcy or distress of its operator) and a baseline hazard rate ($h_0(t)$). Then, $h_0(t)\exp(\hat{\beta}'X)$ gives the predicted hazard rate ($\lambda_i(t)$) for each aircraft, controlling for its specific characteristics. Figure 1 plots the hazard rate as a function of age for aircraft sold by airlines operating in bankruptcy relative to other transacted aircraft. We can conclude that the hazard rate is the highest for aircraft sold by airlines in Chapter 7, and higher for aircraft sold by airlines in Chapter 11, relative to aircraft sold by non-bankrupt airlines.

We calculate the life expectancy of an aircraft using its predicted hazard rate ($\lambda_i(t)$). Next we compute the cumulative hazard rate ($\Lambda_i(t)$), as the CDF of the hazard rate. Using $\Lambda_i(t)$ we estimate the total life expectancy for an aircraft i, as a function of its age, t. If we denote the cumulative hazard rate by $\Lambda_i(t)$,

[27] For example, Eastern Airlines failed to maintain aircraft as dictated by the terms of their capital leases, and lessors had to make major repairs on many aircraft to ensure they met the mandated operating regulations.

then its corresponding total life expectancy $L_i(t)$ can be calculated as:

$$L_i(t) = t + \int_0^{\infty} \exp[\Lambda_i(t) - \Lambda_i(t+x)]dx \tag{1}$$

Using the above method, we calculate the life expectancy separately for aircraft sold by airlines in Chapter 7, Chapter 11 and non-bankrupt airlines.[28] Figure 1 plots the life expectancy of narrow body and wide body aircraft, conditional on being alive at a given age. On average the life expectancy of narrow body aircraft is higher than that of wide body aircraft. Further we find that aircraft exposed to bankruptcy have a lower life expectancy versus non-distressed aircraft. The average age of aircraft at sale in our sample is 15 years, and at this age, the hazard model estimates that the life expectancy of a narrow body aircraft exposed to Chapter 7 is 27.6 years, 27.8 years for an aircraft exposed to Chapter 11, and 28.8 years for aircraft not exposed to distress. These estimates suggest that aircraft sold by airlines operating in bankruptcy have around 7% lower remaining life expectancy than aircraft sold by non-distressed airlines.

4.2 Evidence on Aircraft Productivity

We use aircraft level utilization metrics to provide evidence that quality impairment is reflected in lower productivity of an aircraft. The productivity measures allow us to investigate whether aircraft sold by distressed airlines are operated less intensively, while they are in use. We use yearly average flying hours, to measure aircraft's productivity. To understand the relation between financial distress of the seller and future utilization of an aircraft, we estimate the following equation:

$$\log(Hours)_{it} = \beta_1 Ch7_{it} + \beta_2 Ch11_{it} + \beta_3 Bankr(T-1)_{it} + \beta_t + \beta_{Type \times Age} + \beta_{operator} + \beta X_{it} + \epsilon_{it} \tag{2}$$

where, $\log(Hours)_{it}$ measures the yearly flying hours of aircraft i in year t.[29] $Ch7_{it}$ is a dummy variable taking value 1 if the aircraft i was ever sold by an airline in Chapter 7 in the years preceding the current

[28] In estimating the life expectancy from the post-Cox proportional hazard rates, a potential concern is that there might be substantial noise in the predicted hazard rates. Therefore, in our main specification we group our aircraft according to narrow body and wide body types. To check the robustness of our results, we also use several other approaches to group the aircraft. For example, we segregate aircraft by different engine noise levels and model types. We find that our main results are robust to different grouping procedures.

[29] The utilization data used here is a panel of yearly individual aircraft flying hours for aircraft operating in the U.S. during the period 1975-2015.

year t. $Ch11_{it}$ is a dummy variable taking value 1 if the aircraft i was ever sold by an airline operating in Chapter 11 in the years preceding the current year t. $Bankr(T-1)_{it}$ is a dummy variable taking value 1 if the aircraft was ever sold by an airline one year prior to its bankruptcy filing in the years preceding the current year t. We include year fixed effects (β_t) to control for time specific trends in aircraft flying hours. Fixed effects for Type × Age ($\beta_{Type \times Age}$) allow us to control for any model specific age differences between aircraft. Finally, operator fixed effects ($\beta_{operator}$) ensure that our results are not driven by any airline specific factor, and that aircraft acquired from distressed airlines are compared with other similar aircraft operated by the *same* carrier. This test provides a way of distinguishing the extent to which the decline in productivity is attributable to the low quality (and under-maintenance) of the aircraft sold by a distressed airline or, whether it is due to the lower productivity of the buyer as hypothesized by Shleifer and Vishny (1992). We also use controls for market thinness of the aircraft (X_{it} includes number of same type of aircraft, and operator fleet size). These measures of aircraft liquidity have been used in Gavazza (2011b), to document that when markets for assets are thin, aircraft's average productivity is lower.[30]

To sharpen our analysis of under-maintenance by financially distressed sellers on future utilization of the aircraft, we have excluded from the distress classification very young aircraft (aged less than or equal to 5 years) that are sold by distressed airlines. As expected, these very young aircraft account for a small proportion (around 5%) of the total aircraft transacted in distress.[31] The rationale for excluding these aircraft from the distress episode classification described above is that these aircraft are still under warranty and therefore, their maintenance expenses are borne by the manufacturer and not by the operating airline. New aircraft come with a basic component warranty of 4 years, and roughly have 5 years warranty on the engine, and during this time the aircraft maintenance expenses are minimal for the operator (Dixon (2006), Davies (2014)). Thus, we do not expect to find any under-maintenance effect on these aircraft as their maintenance responsibility is not borne by the seller.

Table 3 reports our results. In Panel A columns (1) and (2), we find that aircraft sold by distressed airlines fly 10% less post-sale than other similar aircraft operated by the new carrier i.e, the buyer of

[30] In commercial aircraft markets, Gavazza (2011b) documents that aircraft with a thinner market are less liquid and more difficult to sell. When markets for assets are thin firms hold on longer to their assets amid profitability shocks, and as a result, the firms' average productivity is lower in thin markets. To account for this, we include controls for aircraft market thinness in our specification.

[31] There is a significant lead time between the placement of an order by an airline and delivery of the new aircraft, and the 'normal' order backlog time in the industry can range from 5-7 years (Captain (2016), Bruner et al. (2008)). This explains the need for distressed airlines to sometimes sell very young aircraft.

the distressed aircraft. In columns (3) and (4), we spilt our sample of distressed sales, into sales made by airlines while operating in Chapter 7, Chapter 11, and one year prior to bankruptcy filing. We find that aircraft sold during Chapter 7 and Chapter 11 have utilization rates post-bankruptcy that are 14% and 10% lower, respectively, than other similar aircraft operated by the new carrier. These differences persist for the remaining life of the aircraft subsequent to their sale. Aircraft sold one year prior to the airline filing for bankruptcy also have roughly 7% lower flying hours, versus other aircraft operated by the new carrier. This indicates a fundamental productivity difference between aircraft flown by the *same* operator, that have been exposed to distress and those which have not. Additionally, we do not find this under-maintenance effect for very young aircraft (aged less than 5 years) that are transacted by distressed airlines, indicating that this effect is absent for aircraft that are still under manufacturers' warranty and, where the maintenance expenses are not borne by the distressed airline. It further supports our hypothesis that at least some part of the low quality of the aircraft is due to their under maintenance when the seller of the asset is financially distressed. Our test provides direct evidence that aircraft that have suffered from a distress episode, not only have lower life expectancy, but also are less productive than other similar aircraft in the market during their remaining life after sale.

In Panel A columns (5)-(8), we report results for two additional specifications measuring the post-sale productivity of aircraft following their distress episodes. In columns (5) and (6) of Table 3, we include aircraft operator $\times$ year fixed effects. This allows us to control for time varying productivity differentials. Even after controlling for the productivity differences among operators across time, we find that aircraft sold by distressed airlines fly around 10% less compared with other similar aircraft being operated by the new carrier in a given year. In column (6), we split our sample of distressed sales by the depth of distress, and find that aircraft sold during Chapter 7 and Chapter 11 have 13% and 10% lower utilization, respectively, than other similar aircraft operated by the new carrier in the same year. This confirms that the persistent lower productivity of aircraft sold by distressed airlines is robust to time varying trends in the post-sale operators' productivity.

One potential concern is that a particular airline may possess proficiency in a specific type of aircraft and not in another. For example, suppose a buyer mostly uses Boeing 737 in their fleet, but it purchases an Airbus A320 at an attractive price from a distressed seller. The buyer may not be an efficient user of the A320 aircraft. This would imply that the lower productivity of the aircraft is due to the operator-aircraft match, and not due to the under-maintenance of the aircraft by the distressed seller. In columns (7) and (8) of Table 3, we attempt to resolve this concern by including aircraft operator × aircraft type fixed effects. We find that aircraft sold by distressed airlines fly 8% less post sale compared with other similar aircraft models operated by the new carrier. In column (8), we split our sample of distressed sales by the level of distress, and find that aircraft sold during Chapter 7 and Chapter 11 have around 8.5% lower utilization, than other similar aircraft models operated by the new carrier. Hence, our results on lower productivity of aircraft sold by distressed airlines are robust to controls for the productivity differentials between different types of aircraft operated by the same operator.

In Panel B of Table 3, we explore whether the size of the under-maintenance effect is related to the time spent in distress. For an airline we define the onset of distress using the event of a bond downgrade prior to the airline filing for Chapter 11 bankruptcy. The end of the distress period is defined as the date the aircraft is sold. In the event that an airline's bonds are not rated, we use the year of earnings losses prior to filing for bankruptcy as a proxy for the onset of distress. 73% of aircraft sold in distress were sold by airlines that experienced a bond rating downgrade prior to filing; the remaining aircraft were sold by airlines that did not have bond ratings. We find a sharp difference in the average time spent in distress for aircraft sold in Chapter 11 (2 years) compared with those sold in Chapter 7 (3.9 years). Since all airlines filing for Chapter 7 had previously entered Chapter 11, we use the common filing date to determine the length of the distress period pre-filing. For Chapter 11 sales the distress period prior to filing is 1.2 years, and 1.9 years for Chapter 7 sales. We would predict that aircraft sold in Chapter 7 are more under maintained than those sold in Chapter 11 because they have been subject to a longer period of distress.

Columns (1) and (2) of Panel B show that every year spent in distress reduces the future productivity of an aircraft by around 3%, and the coefficient is statistically significant at the 1 percent level in both specifications. This finding is confirmation that aircraft sold by distressed airlines are significantly under maintained, and this under maintenance effect increases with the time spent in distress. In columns (3) and (4) we further show that the period of distress prior to filing for bankruptcy is negatively correlated with future flying hours. In contrast, the period during bankruptcy is not significantly correlated with future flying hours. The implication is that the under maintenance effect of aircraft is largely the result of the longer distress period prior to filing rather than the time spent in bankruptcy. This result may reflect the provisions in Chapter 11 and Chapter 7 which allow for the suspension of most payments of interest and capital repayments, and in Chapter 11 to the availability of DIP financing.

We have established that aircraft sold by distressed airlines, not only have a shorter lifespan, but also have lower productivity while they are in use. Since, the quality of an aircraft is negatively correlated with the financial distress of the seller, we expect that calculating the fire sale discount ignoring the quality variations between aircraft, would overestimate this discount. The next section describes how we transform the lower life expectancy and productivity difference between distress-affected and normal aircraft into a quality correction measure.

5 Empirical Methodology and Results

In the previous section we have established that aircraft sold by distressed airlines have lower life expectancy, and lower productivity compared with other similar aircraft flown by the new operator. In this section, we begin by quantifying the raw fire sale discount, that is, the deviation of the sale price of an aircraft sold by a distressed airline from its hedonic price. As we have discussed, a crucial challenge in calculating the fire sale discount is that it subsumes a quality discount. It assumes that aircraft with the same characteristics also have the same maintenance and quality levels. To address this challenge, we describe our empirical methodology for measuring these quality variations between aircraft, and investigate their impact on the fire sale discount. We control for quality in the hedonic price model, and present the quality-adjusted fire sale discounts for different intensities of financial distress. We find that accounting for the differences in quality leads to a significant reduction in the raw fire sale discount.

5.1 Raw Fire Sale Discount

In the first stage, we calculate the total liquidation discount (i.e. the raw fire sale discount) replicating the empirical methodology followed by Pulvino (1998). Here, we briefly summarize the main steps. In the first step we calculate the hedonic prices of the aircraft that are a function of the aircraft attributes and time using all available market transactions data. For aircraft i sold by airline j in year quarter t, the hedonic model specifies:

$$log(PRICE)_{ijt} = \beta_{Age} log(1 + Age_i) + \beta_t + \beta_{Model} + \beta_{Stage} + \epsilon_{ijt} \tag{3}$$

Where, $log(PRICE)_{ijt}$ is the log of the inflation-adjusted sales price of the aircraft. Age_i represents the aircraft age at sale. We include fixed effects for calendar quarter of sale (β_t), aircraft model type (β_{Model}), and engine stage or noise level (β_{Stage}). We run the above regression separately for narrow body and wide body aircraft and use all available market transactions data.[32]

Following Pulvino (1998, 1999), in the second step we restrict our sample to the sales of aircraft by major U.S. airlines (listed in Appendix Table A.1). Sales by other parties (including financial institutions, air cargo services and foreign airlines) are excluded after establishing the hedonic prices. This ensures that our results are not affected by uncontrolled cross-industry or cross-country effects. We regress the residuals obtained from the first stage hedonic regression ($RESID$), described above on variables measuring the sellers' financial health.[33] More specifically, to quantify the raw fire sales discount, we regress:

$$RESID = \beta_1 Chapter7 + \beta_2 Chapter11 + \beta_3 Bankr(T-1) + \beta_4 FinancialBuyer + \beta_{Seller} + \eta \tag{4}$$

The variables are: *Chapter 7* is a dummy variable equal to 1 if the selling airline was in Chapter 7. *Chapter 11* equals 1 if the selling airline was in Chapter 11 bankruptcy protection. *Bankr (T-1)* equals 1 if the aircraft was sold one year prior to the selling airline filing for bankruptcy. *Financial Buyer* equals 1 if the aircraft was purchased by a financial institution or a leasing company. Seller fixed effects (β_{Seller}) are included to isolate the impact of distress on transaction prices from unobservable firm specific factors.

[32] As a robustness check we have excluded the aircraft sold by bankrupt airlines in establishing the first stage market prices (or the hedonic prices), and our main results remain almost unchanged.

[33] We transform the residuals obtained in the above regression (ϵ), to actual discounts rates via the following transformation: $Discount = \exp(\epsilon) - 1$. The log residuals approximate the actual discount rates for small discounts. Nevertheless, we transform log residuals to actual discount rates to be more precise. Our main results are robust to both specifications.

5.2 Measuring the quality variation between aircraft

We define two measures of quality adjustment. Our first measure controls for the lower life expectancy of aircraft sold by bankrupt airlines. As described previously, we use the retirement age of aircraft and apply duration analysis to estimate the aircraft's life expectancy (refer to Figure 1). For an aircraft i, the life expectancy $L_i(t)$, as a function of its age at sale t, is calculated from Equation 1. We use aircraft life expectancy as a quality adjustment measure ($Quality_{adj1}$) and include it in the first stage hedonic regression. Subsequently, we investigate its impact on the price of an aircraft and the fire sale discount.

The second measure of quality controls for both the shorter life and lower productivity of the aircraft, while in use. We compute the effective economic lifespan of an aircraft, by adjusting the residual life of distress-affected aircraft for their lower productivity. For an aircraft i, transacted at age t, we compute the effective economic life ($L_i'(t)$) as:

$$L_i'(t) = t + (L_i(t) - t)\rho_i \tag{5}$$

Where, $L_i(t)$ is calculated from Equation 1 using the hazard rate of the aircraft. The correction for lower flying hours (ρ_i) is calibrated from Table 3, that follows from Equation 2. For instance, Table 3 column (3) on Panel A, shows that the aircraft sold during Chapter 7, fly 14.4% less than other similar aircraft that have not been exposed to distress, during their remaining lives after sale (i.e., $L_i(t) - t$). Therefore, ρ_i for such aircraft equals to $e^{-0.144}$ or 0.866. Similarly, ρ_i for aircraft sold in Chapter 11 equals $e^{-0.100}$, and ρ_i for aircraft sold a year prior to bankruptcy equals $e^{-0.075}$. For aircraft not exposed to distress, ρ_i equals 1, so $L_i'(t) = L_i(t)$ for such aircraft.

We use the aircraft effective economic life ($L_i'(t)$) calculated above, as a quality adjustment measure ($Quality_{adj2}$). It captures the drop in effective lifespan of the aircraft due to two components, the lower residual life of the aircraft, and its lower productivity while in use.[34] Therefore, $Quality_{adj2}$ measures the effective lifespan of the aircraft controlling for both these factors.

[34] The two components of the quality adjustment measure, shorter life expectancy and lower productivity, are correlated, that is, it could be the case that the lower productivity of the aircraft is responsible for its shorter operating life. In our methodology, we account for both these corrections because lower productivity is captured in lower cashflows during the remaining lifetime, and in addition, life expectancy allows us to correct for the shorter duration of the cashflows.

5.3 Quality-adjusted fire sale discount

To estimate the impact of quality on aircraft pricing we include our quality measures in the first stage hedonic regression. Including them, allows us to control for the expected loss in residual life and flying hours of an aircraft following a distress event. The results of the first stage hedonic model are presented in Table 4. Consistent with Pulvino (1999), we use separate hedonic models for narrow body and wide body aircraft. In columns (1) and (2), we present the hedonic model without quality correction, which is used for calculating the raw fire sale discount (columns (1) and (2) are identical to Pulvino's hedonic model). The price of wide body aircraft depreciates faster with age than narrow body aircraft, in part because the former have shorter operating lives. In columns (3)-(6), we include our first and second quality adjustment measures, that control for the life expectancy and productivity differential between aircraft in the first stage hedonic regression. Our results indicate that an increase in effective life expectancy significantly increases the price of an aircraft. The increase is both economically and statistically significant, which confirms that quality impairment is a significant component of the liquidation value of an asset. We use the residuals from Table 4 columns (3)-(6), to calculate the quality-adjusted fire sale discount below for the sale of aircraft by distressed airlines.

The raw fire sale discounts calculated from regressing the residuals on financial health variables are reported in Table 5, Panel A columns (1) and (2). We find that distressed airlines sell aircraft at a raw fire sale discount of 16%, a significant discount to the average market price. Further, in comparison to the sales made to airlines and air cargo companies, the sales to financial institutions and leasing companies occur at an average price discount of around 9% (in column (2)). In Table 5 columns (3)-(6) we report the quality-adjusted fire sale discounts after controlling for quality variations between aircraft sold by distressed and healthy airlines. In Panel A, we find that there is a 4.2 percentage points reduction in the raw fire sale discount upon controlling for the lower life expectancy of aircraft sold by distressed airlines (comparing column (3) with column (1)). There is an even larger reduction of around 7.7 percentage points in the raw fire sale discount, when we control for both the lower life and lower productivity of aircraft sold by distressed airlines (comparing column (1) with (5)). This difference, that is the quality discount, is statistically significant at the 1% level.[35] Quality impairment explains roughly 50% of the

[35] p-value for the coefficient equality test on the *Distress* variable between columns (1) and (5), (and (1) and (3)) is 0.0000.

raw fire sale discount and, after controlling for these quality variations the fire sale discount declines to 8% for the sale of aircraft by distressed airlines . Also, we find that in comparison with the purchases made by other airlines, financial institutions and leasing companies (*Financial Buyer* dummy) purchase aircraft at a significant 10% discount (column (6)). It should be noted that this discount on aircraft purchases by financial buyers is applicable to both distressed and non-distressed sales; an issue we return to in the next section.

We also estimate how the quality adjustment impacts fire sale discounts for different degrees of distress. In Panel B of Table 5, we separate the *distress* sales into *Chapter 7*, *Chapter 11*, and *Bankruptcy (T-1)* sales. As expected, the raw fire sale discount on Chapter 7 sales of 25%, is higher than the discount of 16% on Chapter 11 sales (column (2)).[36] Comparing columns (2) and (6), we find that the raw fire sale discount reduces by around 18 percentage points (or 64%) for Chapter 7 sales and, by about 7.5 percentage points (47%) for Chapter 11 sales, reflecting the quality adjustment. The large difference in the quality adjustment between Chapter 7 and 11, reflects both the lower life expectancy of aircraft sold in Chapter 7, and their substantially lower productivity i.e. lower flying hours, for their remaining lives after the sale; see Table 3 above. For sales made one year prior to the airline filing for bankruptcy, the raw fire sale discount reduces by around 4.6 percentage points (42%) after controlling for quality (column (2) versus (6)). The fire sale discount after controlling for quality is not significantly different for aircraft sold by airlines operating under Chapter 7 liquidation or Chapter 11 reorganization, around 9.8% and 8.6%, respectively. Also, after correcting for the quality impairment, the fire sale discount is similar for aircraft sold one year prior to entering bankruptcy, and for airlines operating under Chapter 11.[37] As expected, the quality impairment on aircraft increases with the depth of distress, as proxied by the length of distress pre-filing. It is worth noting that the going concern provisions of Chapter 11, when compared with the liquidation process conducted by a trustee in Chapter 7, seem to have made only a small economic difference to the quality-adjusted fire sale discount, and this difference is not statistically significant.

[36] This difference is statistically significant at the 5% level. In column (1), the p-value for testing the null hypothesis $H_0 : Chapter7 = Chapter11$ is 0.0449, while the p-value for testing the null hypothesis $H_0 : Chapter7 = Chapter11 = Bankruptcy(T-1)$ is 0.0152.

[37] In column (6), the p-value for testing the null hypothesis $H_0 : Chapter7 = Chapter11$ is 0.8322, while the p-value for testing the null hypothesis $H_0 : Chapter7 = Chapter11 = Bankruptcy(T-1)$ is 0.7301.

Aircraft sold by distressed airlines have lower life expectancy and lower productivity, while in use. To reconcile our two measures of quality adjustment consider the following back of the envelope calculation. At the time of sale, a normal aircraft has around 15 years of residual lifetime, while a distress-affected aircraft has a 7% lower residual lifetime of 14 years.[38] We have also established that on average distress-affected aircraft have 9% lower flying hours than other similar aircraft operated by the same carrier.[39] Average aircraft flying hours depreciate at 5% every year. Assuming that flying hours proxy for cashflows and using a WACC of 7.5% for the airlines industry as the discount rate,[40] we calculate the expected continuation value of the aircraft. The present discounted value of future flying hours is calculated as $7.2x$ for non-distressed aircraft, versus $6.4x$ for distress-affected aircraft (where x is the flying hours in the first year post-sale).[41] This translates into a quality discount of roughly 11% on aircraft sold by distressed airlines. This is consistent with the reduction in raw fire sale discount from 16% to 8% (Table 5 Panel A, comparing column (1) with (5)).

To summarize our results, we have established that quality impairment is a significant part of the raw fire sale discount, an issue that has not been adequately addressed in the literature. In Appendix A.1, we repeat the analysis for aircraft sold by airlines with low spare debt capacity, and find that quality correction explains a significant portion of the raw fire sale discount. By controlling for quality in the hedonic regression model, we can conclude that around half of the raw liquidation discount can be attributed to financially distressed airlines selling low quality aircraft.[42] The remaining half can be attributed to the fire sales discount. Crucially, the quality adjustment for aircraft sold by distressed airlines is attributable to the lower productivity of the asset and its under-maintenance, and not to the

[38] The average lifespan of a non-distressed aircraft is around 30 years. Therefore, the remaining lifetime for an aircraft sold by non-distressed airlines is 30-15 = 15 years on average (refer to Table 1 for average age at sale and retirement age of an aircraft).

[39] Refer to Table 3 Panel A column (1). Distress-affected aircraft fly $(1 - e^{-0.10})$ or 9.4% less than other similar aircraft that have not been exposed to distress.

[40] Refer to Pearce (2013) for calculation of WACC for the airlines industry

[41] This is calculated as the sum of geometric progression, that for a normal (non-distressed) aircraft is PV(Flying Hours) = $x(1-(\frac{1-0.05}{1+0.075})^{15})/(1-\frac{1-0.05}{1+0.075}) = 7.2x$. For a distress-affected aircraft PV(Flying Hours) $= x(1-0.09)(1-(\frac{1-0.05}{1+0.075})^{14})/(1-\frac{1-0.05}{1+0.075}) = 6.4x$.

[42] Our quality adjustment measures quality based on the operational characteristics of the aircraft like utilization and life expectancy. However, anecdotal evidence suggests that there can be significant differences in the interior furnishing of aircraft operated by different airlines. Aircraft owned by distressed airlines might have lower quality furnishing as opposed to aircraft operated by healthy airlines. This reflects another dimension of quality that our measure is unable to capture. However, we expect it to be correlated with our measures of operational quality, i.e. it is likely that the internal quality of an aircraft is negatively correlated with the financial health of the selling airline. Nevertheless, the quality-adjusted fire sale discount which we calculate might still overestimate the actual fire sale discount.

attributes of the purchaser. The productivity of these aircraft is lower than the normal aircraft operated by the non-distressed purchaser. In Table 6 we summarize the fire sale discounts for different definitions of financial distress. Interestingly, we find that after controlling for quality, financially distressed airlines sell aircraft at around 8% fire sale discounts. In magnitude, this is similar to the fire sale discounts reported in the financial assets literature by Coval and Stafford (2007) and Mitchell and Pulvino (2012) among others.[43] Finally, the quality adjusted fire sale discounts are only marginally larger in Chapter 7 than in Chapter 11, and this difference is not statistically significant.

6 Evidence on Aircraft Misallocation

In the previous sections we compared the productivity of aircraft sold in distress with other similar aircraft operated by the new user, and established that quality variations between aircraft explain roughly half of the raw fire sale discount. In this section, we investigate the extent to which this quality-adjusted fire sale discount is attributable to the pure liquidity channel, and the misallocation channel. The liquidity channel represents a transfer from the seller to the buyer as a consequence of the lower bargaining power of the distressed seller, and as such this channel does not have any ex-post welfare implications, in contrast, to the misallocation channel.[44] We compare the average productivity of the post-sale users of distress-affected aircraft with other users of normal aircraft, i.e. users of aircraft purchased from non-distressed sellers. We also compare the average productivity of the post-sale users of distress-affected aircraft with the average productivity of the sellers of these aircraft. We address the question whether aircraft sold by distressed airlines are misallocated to suboptimal users. Shleifer and Vishny (1992) argue that this is an alternate, or additional, channel that could generate a fire sale discount and, the inefficiencies associated with it. Our granular data of aircraft productivity coupled with aircraft level ownership data allows us to empirically isolate this channel, and directly address whether it is present in the airlines industry.[45]

[43] Coval and Stafford (2007) document 8-10% discount in equity markets owing to fire sales in mutual funds. Mitchell and Pulvino (2012) document that corporate securities were mispriced at 10% discount during 2008 crisis. Ellul et al. (2011) document 7% discount in corporate bonds from fire sales caused by regulatory pressure on insurance companies.

[44] Notwithstanding, there may still be ex-ante welfare losses associated with the liquidity channel.

[45] Shleifer and Vishny (1992) were referring to fire sales in the absence of Chapter 11 type procedures. It maybe that in the absence of such procedures the fire sale discounts would be much larger.

An alternative conjecture is that bankruptcy and distress in the airlines industry are the means by which the industry restructures and reallocates resources to more productive users. To distinguish these two effects, whether forced sales of aircraft lead to misallocation to suboptimal users, or such sales are simply a mechanism for transferring resources, we begin by identifying the operators and status of aircraft post their sale. Stringent aircraft registration requirements allow us to track airline level fleet alterations. This micro tracking of each aircraft at its operator level allows us to consistently trace aircraft redeployment. Pulvino (1998) documents that aircraft sold by distressed airlines are often purchased by financial institutions. He argues that, "Financial institutions (e.g., banks and aircraft leasing companies) tend to be lower-value users of used aircraft." However, Gavazza (2011a) documents that in the airlines industry leasing companies are the most productive owners of aircraft, because by acting as intermediaries and creating rental markets, lessors are able to improve resource allocation and quickly redeploy assets to higher productivity users.[46] Even though leasing companies might purchase aircraft from distressed sellers, they are not the final users of the aircraft. Therefore, our analysis focuses on the post-sale users of the asset. When the aircraft is sold to a leasing company or a financial buyer, in the year of sale we are able to match the aircraft with the user (i.e. the lessee) of the aircraft, using our aircraft level operator database.[47] Using this methodology, the transacted aircraft are matched to their post-sale operators.

Following Gavazza (2011a) and Bernstein et al. (2019), we measure asset allocation and utilization at the aircraft level using statistics on parking and flying hours. Parking indicates that an aircraft is inactive and involves costly downtime. We find that aircraft sold by distressed airlines do not have a higher probability of being parked post sale. At the end of the same year as the sale, 24 of the 164 (14.6%) aircraft sold by distressed airlines are parked by their new users, as opposed to 162 of the 1,134 (14.3%) aircraft sold by non-distressed sellers. By the end of the second year following the sale, 3% of the aircraft sold by distressed airlines are parked, versus 6% of the aircraft sold by non-distressed operators. We find no evidence of misallocation even at the extreme level of distress, i.e. aircraft sold by bankrupt airlines do not have a higher probability of being parked post sale.[48] This provides suggestive evidence

[46] Around 30% of the aircraft currently operated by major airlines are under an operating lease, a rental contract between a lessor and an airline for use of the aircraft for a period of 4–8 years.

[47] For example, of the 131 bankruptcy sales 82% were directly sold to the final users, and 18% were sold to leasing companies.

[48] At the end of the same year as the sale, 15 of the 131 (11%) aircraft sold by bankrupt airlines are parked with their new users. By the end of the next year following the sale, only 3 (or 2%) of the aircraft sold by bankrupt airlines are parked.

that most aircraft sold by distressed airlines are quickly redeployed to operational use. In the analysis that follows, we develop several measures to compare aircraft redeployment on the basis of a comparison between post-sale users of distressed aircraft with those of non-distressed aircraft.

6.1 Measures of user productivity using flying hours

To measure the intensity of economic activity for an airline we use the aircraft flying hours of its fleet. Aircraft flying hours have been used extensively to measure productivity (Gavazza (2011a,b), Benmelech and Bergman (2011) and Bian (2020)). They are considered as a key performance indicator in the airline industry. An advantage of using operational metrics like flying hours, rather than other performance measures such as load factor or profitability is the wide availability and extreme accuracy of these data, due to maintenance and safety considerations. In contrast, the measures of financial performance are mostly available only for large, listed airlines. Nevertheless, in the next subsection we will also use financial measures to ascertain the robustness of our analysis.

Using aircraft flying hours, we compare the productivity of the user of the aircraft to other airlines in the industry. We restrict our sample to aircraft flown by US operators post their sale, as we are then able to measure the productivity of the operator using flying hours.[49] We construct the following measures of aircraft operators' productivity. The first measure is the average flying hours of the operator across all the aircraft that are flown by that operator. Our next productivity measures control for differences in aircraft flying hours owing to aircraft type, aircraft age, and other macro trends in aircraft productivity. More specifically, we regress, for plane i flown by operator j in year t:

$$\log(Hours)_{ijt} = \beta_t + \beta_{Type \times Age} + \epsilon_{ijt} \tag{6}$$

where, $\log(Hours)_{ijt}$ measures the yearly flying hours of an aircraft i, flown by operator j, in year t. From the above regression we calculate the residuals (ϵ_{ijt}), after effectively partitioning out aircraft specific factors ($\beta_{Type \times Age}$), and year specific trends (β_t) in aircraft productivity. The unexplained differences

[49] Post sale, 155 of the 164 (95%) aircraft sold by distressed operators are flown by US operators. Post sale, 126 of the 131 (97%) aircraft sold by bankrupt operators are flown by US operators. In 78% of sales by non-distressed owners, the aircraft are used by US operators post sale.

in flying hours in the residuals of the above regression capture the productivity of the operator. Our second measure averages these residuals across all the aircraft that are flown by the operator j. Our final measure of productivity also controls for market thinness of the aircraft, by controlling for the number of same type of aircraft in operation, and the fleet size of the operator.[50] After adding these controls to the previous regression we calculate the residuals. This measure of productivity averages these residuals over all the aircraft operated by the same operator.

Panel A of Table 7 compares these measures for post-sale operators of aircraft sold by distressed airlines with the operators of aircraft purchased through normal sales. We find that there is no significant difference in the means of average flying hours of the two groups. The log average flying hours of post-sale users of aircraft sold by distressed airlines is 7.4, which is identical to the log average flying hours of post-sale users of non-distressed aircraft sold in normal transactions. Even after controlling for aircraft specific features, and time trends in productivity, the residuals for the two groups are similar. To examine the evidence of misallocation at extreme levels of distress, in Appendix Table A.3 we repeat our analysis for post-sale users of aircraft sold by bankrupt airlines. Our results indicate that there is no evidence of misallocation for aircraft sold by bankrupt airlines. Figure 2 plots the kernel density for operator productivity residuals, after controlling for aircraft type $\times$ age, year, and market thinness. The distributions of residuals for post-sale users of the distressed and normal sales further confirm that the users of the distress-affected aircraft are not on average less productive than other airlines in the industry.[51] We discuss Panels B and C of the table in the next subsection.

An alternate test of the misallocation hypothesis is based on whether the aircraft sold by bankrupt airlines are allocated to operators that are less productive than their sellers. The presence of misallocation, as proposed by Shleifer and Vishny (1992) would imply that assets sold in fire sales get allocated to less productive buyers, and thereby, the productivity of the buyer (or user) is lower than that of the seller. Conversely, the reallocation of aircraft to more productive users in the economy, would imply that the buyer is operationally more efficient than the seller. In our sample, we test these hypotheses empirically by comparing the differential productivity across the buyer and seller of the asset. Using the previously

[50] The same measures of market thinness have been used in Table 3.

[51] The standard Kolmogorov-Smirnov test of the equality of distributions rejects the null hypothesis of equal distributions at the 1 percent level (the asymptotic p-value is equal to 0.002).

defined measures of productivity, we calculate the productivity of the buyer and the seller of the aircraft using our transactions data ending in 1991. We do this by averaging the residuals (ϵ_{ijt}) obtained from Equation 6 across all the aircraft flown by the same operator.[52] Next we calculate δ, as the difference between the buyer and the seller productivity. δ is positive if the productivity of the buyer (or user) is higher than that of the seller. Figure 3 plots δ for aircraft sold by bankrupt airlines (blue curve), and for aircraft sold during other transactions (red curve). As δ is positive in the majority of the sales made by bankrupt operators, we can conclude that post their sale, these aircraft are operated by users that are more productive than the seller.

We now use our data on flying hours for the entire sample period (1975 to 2015) to test whether aircraft are relocated to higher productivity users following distress episodes. In Table 8, we specify the dummy variable *Non-distressed Seller*, that equals 1 for all the aircraft that are operated by the non-distressed seller in the year it sells an aircraft. In a given year, for all aircraft operated by the carrier, *Buyer of non-distressed aircraft* equals 1 if the carrier purchases an aircraft from a non-distressed seller. In case an operator sells an aircraft while in distress, *Distressed Seller* equals 1 for all aircraft being operated by that distressed seller in the sale year. *Buyer of distressed aircraft* equals 1 for all aircraft operated by the buyer in the year it purchases an aircraft from a distressed seller. Controlling for aircraft type $\times$ age, usage, and year fixed effects, this specification allows us to extract the operator-level time varying productivity of the sellers and buyers of aircraft. In Table 8, column (1) we report that the non-distressed sellers of aircraft are on average 5% more productive than airlines that don't transact aircraft in that year. The buyers of non-distressed aircraft are on average 3% more productive than airlines that don't transact aircraft. The productivity of *distressed sellers* is 3.6% lower than the industry average, and 9% lower than non-distressed sellers. While the productivity of distressed sellers is lower, the productivity of the buyers of distressed aircraft is 5% higher than the industry average, and around 1.8% higher than the productivity of other buyers in the second-hand aircraft market. In column (2), we include additional controls for market thinness, and find that the productivity of buyers of distressed aircraft is around 9% higher than their sellers, and 3.2% higher than other buyers in the market.

[52] The residuals are calculated by regressing aircraft flying hours on controls for aircraft type $\times$ age, year, fleet size, and the number of same type of aircraft operating in the market.

While we find no direct evidence of misallocation to low productivity users for our full sample period, this effect may operate during recessions. To address this concern, in columns (3) and (4) of Table 8, we restrict our sample to NBER recession periods. We continue to find that the productivity of buyers of distressed aircraft is higher than the distressed sellers, and higher than other buyers of non-distressed aircraft. We find that during recessions the difference between buyer and distressed seller's productivity is very high (almost 21%), compared with 8% for the entire period. These results indicate that aircraft sold by distressed operators, are relocated to high productivity users, that are more productive than the seller, and at least as productive as other buyers of second-hand aircraft.

Reallocation of aircraft to more productive users in an economy would imply that these airlines would be able to grow and use modern technology at the cost of their less productive competitors (Hsieh and Klenow (2009), Bartelsman et al. (2013), Bian (2020)). To further test this hypothesis we measure whether there is a differential impact of productivity on firms' growth prospects when firms purchase distress-affected aircraft, versus when firms purchase normal aircraft.

In Table 9 we directly test this hypothesis using fleet size, and a younger vintage of aircraft with newer technology as proxies for firm growth. The unit of observation is firm-year. In column (1) we use the log of total number of aircraft in a firm's fleet as the dependent variable, and measure its sensitivity to pre-determined measures of average productivity of the firm. Lagged productivity is measured as the average flying hours of the operator across all its aircraft that are flown in the previous year. More productive airlines invest more in new aircraft, as is reflected by the coefficient on *Productivity*. In addition, the coefficient on the interaction term of (*Productivity* $\times$ *Distress User*) is positive, and statistically significant, although not significantly different from the coefficient on productivity of users of normal sales (*Productivity* $\times$ *Normal User*). This further strengthens our claim that the sensitivity of productivity to firms' growth is not different for users of distress-affected aircraft versus the users of normal aircraft, thereby indicating that there is no evidence of misallocation in the airlines industry following instances of distress. In column (2) of Table 9, the dependent variable is the average age of the firm's fleet. More productive airlines are able to maintain a younger vintage of aircraft, and the difference between the interaction terms for distress-affected aircraft users and normal users is not statistically significant.

The results are similar when we proxy for firms' growth prospects using the average technological age of the fleet in column (3) of Table 9. The technological age of an aircraft is defined as the number of years since the introduction of an aircraft's type (our definition is similar to Benmelech and Bergman (2011)). Our results in column (3) indicate that airlines with higher productivity acquire modern technologically advanced aircraft, while the less productive airlines are left with obsolete fleet. We find no significant differences between the sensitivity of productivity to firms' growth prospects for post-sale users of distress-affected aircraft versus post-sale users of normal aircraft.[53] We repeat the above analysis by comparing the users of bankruptcy-affected aircraft with the users of normal aircraft. We find no differential impact of aircraft purchases from bankrupt airlines versus aircraft purchases through normal sales, on the proxies for firm growth (results are reported in Appendix Table A.4). Therefore, we conclude that in the airlines industry during our sample period there is no evidence of misallocation of aircraft following the bankruptcy of their seller.

6.2 Robustness tests for misallocation

We also use financial variables of the airlines as evidence for whether there is resource misallocation in the airlines industry. Using COMPUSTAT, we match the financial data of the users, for the fiscal year preceding the purchase of the aircraft. Since financial data are not available for all operators, we are left with only a subsample of users for which we have the financial data. Bian (2020) documents that aircraft flying hours are closely related to profitability and other financial performance variables of the firm. To address the selection concern that there could be a systematic difference in users for which we have the financial data in the distress and normal sales groups, we undertake the following test. We compare our previously defined measures of productivity for the subsample for which we do not have all the financial data. Table 7 Panel B shows our results. In the subsample of operators for which we do not have the financial data, there is no difference in average productivity of the users in the distress and non-distress groups. Also, Table 7 Panel C compares operator productivity for the subsample for which we have all the financial data. We again find that controlling for aircraft type, age, market thinness, and year fixed

[53] The same airline may appear as a Distress User and as a Normal User at different time periods. In our specification we use a lag of one year in productivity. As a robustness check, we increase the lag in productivity to 2 years, and our results are virtually unchanged (results available on request).

effects there is no significant difference in operator productivity between the distress and normal sales group. Therefore, since there is no difference in productivity between the two groups, we are able to rule out the concern that our subsamples for which financial data exist are different due to a selection issue.[54]

An alternative test of the misallocation channel used in the literature is based upon the sensitivity of capital expenditure to financial metrics such as Tobin's Q and marginal product of capital (see for example, Ozbas and Scharfstein (2010), and Hsieh and Klenow (2009)). We construct the following financial measures to determine whether there is resource misallocation in the economy. We estimate the responsiveness of users to acquiring aircraft using *Tobin's Q*. We follow the data definition of Kaplan and Zingales (1997), and compute *Tobin's Q* as MVA/BVA, where the market value of assets equals the book value of assets plus the market value of common equity less the book value of common equity and balance sheet deferred taxes. Following the methodology of Cong et al. (2019), we use the log of marginal product of capital as another measure of resource misallocation.[55] $Log(MPK)$ is defined as the natural log of sales divided by book value of fixed assets. We define $Profitability$ of the operator as operating income before depreciation, interest and taxes scaled by lagged assets. For these financial variables we compare the performance of post-sale users of aircraft sold by distressed airlines, to the post-sale users of aircraft sold by non-distressed airlines (normal sales).

Table 10 Panel A reports our results. Using measures of *Tobin's Q*, $log(MPK)$, and $Profitability$ we can conclude that the users operating distress-affected aircraft are at least as efficient users of capital as other users of normal aircraft. Our comparison using Tobin's Q suggests that post-sale users of distressed aircraft have a higher average Tobin's Q of 1.31, versus the average of other users' at 1.14. There is no significant difference in the other measures of profitability across the two groups. Figure 4 plots the kernel density for operators' Tobin's Q. It confirms that the users of distress affected aircraft have a higher Tobin's Q versus other users.[56] To control for macroeconomic trends affecting the financial performance of firms we demean all our measures using year fixed effects. Our comparisons on the demeaned variables

[54] In Appendix Table A.3 in Panels B and C, we repeat this analysis for users of bankruptcy-affected aircraft and normal aircraft, for the two subsamples for which we do and don't have the financial data. Results indicate that there is no difference in productivity between the two groups, which allows us to rule out potential concerns over selection issues.

[55] Cong et al. (2019) present a model of resource misallocation based on Hsieh and Klenow (2009). The measure log(MPK) is a rough estimation of productivity under the following assumptions: marginal product of capital equals average product of capital; labor share and mark-ups are the same within a given industry-year.

[56] The standard Kolmogorov-Smirnov test of the equality of distributions rejects the null hypothesis of equal distributions at the 1 percent level (the asymptotic p-value is equal to 0.000).

are presented in Table 10 Panel B. In Appendix Table A.5 we repeat our analysis by comparing the profitability metrics for users of bankruptcy-affected aircraft with normal users. Our results indicate that there is no evidence of misallocation even at the extreme levels of distress, and users of bankruptcy-affected aircraft are at least as profitable as users of normal aircraft. Our analysis allows us to conclude that operators of distress and bankruptcy-affected aircraft do not perform worse than other operators using measures of Tobin's Q, marginal product of capital, and profitability.

The evidence presented in this section illustrates that the resource misallocation channel does not appear to operate in the airlines industry. On all measures of productivity and financial indicators, the post-sale users of distress and bankruptcy-affected aircraft perform just as well as post-sale users of normal aircraft. Therefore, we can conclude that in the airlines industry fire sales resulting from forced sales do not lead to ex-post misallocation of resources.

6.3 The Role of Financial Buyers in Aviation Industry

Efficiency dictates that assets should be allocated to the most productive users. In the previous subsection we investigated the misallocation channel hypothesized by Shleifer and Vishny (1992), by testing whether assets sold by distressed firms are misallocated to low productivity users. Using granular aircraft level productivity data, we find no difference between the patterns of assets allocated in regular sales and distressed sales, suggesting that misallocation may not be the driver for fire sale discounts in the airlines industry during our sample period.

In this section, we explore the role played by leasing companies in improving the market efficiency of the airlines industry. The Airline Deregulation Act of 1978 increased competition, and made airline profits more volatile, thereby, requiring airlines to adjust their fleet more frequently. This need for flexibility, and increased trading of aircraft in the secondary market, led to the growth of intermediaries (leasing companies) that helped in matching sellers and buyers of aircraft across geographies. According to an aircraft financing report by Boeing, there are 153 leasing companies and, roughly 41% of the global fleet is leased.[57] Shleifer and Vishny (1992) note that the financial innovation of operating leases and its rapid growth was a response to the high fire sale discount in the airline industry.

Aircraft leasing companies, however, have been an object of much discussion in the academic literature (Pulvino (1998), Gavazza (2010, 2011a), Gilligan (2004), Shleifer and Vishny (1992)) with differing perspectives on their efficiency roles. Pulvino (1998) considers leasing companies as low-valuation industry outsiders that are potentially sub-optimal users of aircraft, as opposed to other airline companies that are considered to be high-valuation buyers. He interprets the high discount associated with aircraft sales to financial buyers as evidence consistent with the misallocation of assets (Shleifer and Vishny (1992)). Leasing companies are not the final users of aircraft. They act as intermediaries and allocate the aircraft to other airline companies.

A distinct perspective on the role of aircraft leasing companies is provided by Gavazza (2011a). While Gavazza does not directly examine the issue of the fire sale discount, his micro-level dataset tracks the utilization and ownership of aircraft, allowing him to establish the role of leasing companies in reducing the trading frictions in secondary aircraft markets. This allows aircraft to be relocated from low to high productivity carriers. By mitigating trading frictions in the industry, leasing companies lubricate the market for used commercial aircraft. He concludes that leasing companies, acting as market makers, improve the allocation of resources, and "if there is no leasing, trading frictions prevent capital goods from being efficiently allocated." Furthermore, a leasing contract may have provided lessors with greater control rights in the event of default. This strengthening of creditor rights generated by the operating lease contract, potentially relaxes financial constraints and improves access to finance.[58]

Using our granular data on aircraft utilization and ownership, we document that leasing companies provide a valuable intermediary service in second-hand aircraft transactions by reducing the time it takes for an airline to sell an aircraft. We find that the probability of an aircraft being parked by the seller increases to 16.4% the year before the aircraft is sold to another airline (a non-financial buyer). This is much higher than the probability of an aircraft being parked in the year before its sale, when the aircraft is purchased by a leasing company (5.8%). This indicates that after the decision to sell an aircraft, the

[57] Refer to Current Aircraft Finance Market Outlook by Boeing (2019).

[58] In a separate setting of used business jets market, Gilligan (2004) documents that innovative institutions such as leasing contracts can mitigate the consequences of asymmetric information about the quality of aircraft.

airline needs to wait longer in those cases where the sale is made to a non-financial buyer. In Table 11, we formally test this by comparing the flying hours (if the aircraft is not parked) of an aircraft in the last year of its sale, with other aircraft that are not subject to sale. We report in column (1) that aircraft fly 9.5% less one year prior to sale compared with other aircraft that are not subject to sale. In columns (3) and (4), we control for operator fixed effects, and find that these aircraft fly around 16% less prior to sale, compared with other aircraft being operated by the *same* carrier that are not subject to sale. This under-utilization of aircraft is avoided in those cases where the purchaser is a leasing company. To examine this issue, in Table 11, we specify the productivity of an aircraft one year prior to sale, for the cases in which it is sold to a leasing company (*Pre-sale* × *Financial Buyer*). We find that being purchased by a financial buyer reverses this under utilization effect, and these aircraft have almost the same flying hours as similar aircraft not subject to sale. These effects are even stronger in cases when the airlines selling the aircraft are distressed.[59] We find that an airline that is distressed, flies its aircraft around 34% less than other non-distressed sellers (*Distressed aircraft pre-sale*). Further, we document that this under-utilization of aircraft prior to sale by distressed airlines, is greatly reduced when the sale is made to a financial buyer (*Distressed aircraft pre-sale* × *Financial Buyer*). The results are similar when we control for operator fixed effects in columns (3) and (4). In summary, we document that leasing companies improve allocative efficiency by reducing the time it takes to sell an aircraft, and their involvement provides further efficiency gains when the seller is in distress.

We repeat our tests on misallocation based on the average flying hours of the user. Our results suggest that there is no difference in productivity of users, for distressed aircraft purchased by financial buyers versus those purchased by non-financial buyers.[60] We can therefore conclude that in our sample, we find no evidence of misallocation of aircraft following sales by distressed airlines to financial buyers. In contrast, we find that leasing companies significantly reduce the under-utilization of an aircraft in the hands of a distressed seller.

[59] The probability of an aircraft being parked with a distressed seller the year before the aircraft is sold to a non-financial buyer is 20.7%. This probability reduces to 2.1% in cases the distressed aircraft is being purchased by a leasing company.

[60] The log average user flying hours is 7.46 for distressed aircraft purchased by financial buyers, versus 7.43 for distressed aircraft purchased by non-financial buyers. The difference in productivity of the users of distressed aircraft brought by financial versus non-financial buyers is not statistically significantly different, even after controlling for aircraft type × age, market thinness, and year fixed effects (results available on request).

Another consideration is the price discount of 10% that is associated with a financial buyer purchasing an aircraft (Table 5 column (6)). As discussed earlier, this discount on purchases by financial buyers is also present when they purchase aircraft from non-distressed airlines.[61] We believe this discount should not be interpreted as a forced sale discount, but instead should be considered a convenience yield effect. By selling the aircraft to a leasing company, the airline unloads the costs of maintenance and parking and the uncertainty (risk) it would otherwise have to incur in a regular sale. Industry specialists and market participants consider these frictions an important fundamental characteristic of aircraft markets. For example, according to Lehman Brothers (1998, 82) (as quoted in Gavazza (2011a)), "The ratings agencies require an 18-month source of liquidity because this is the length of time they feel it will take to market and resell the aircraft in order to maximize value." According to back of the envelope calculations using costs estimates provided in Pulvino (1998), the total costs of storing and maintaining a narrow body aircraft in running condition for 18 months approximates to 6.5% of the value of the asset.[62] Further, calibrating a structural model for wide body aircraft, Gavazza (2011a) estimates the total transaction costs to be around 16% of the value of the aircraft.[63] Our price discount of around 10% for sales to financial buyers, in the combined sample of narrow and wide body aircraft transactions, lies within the range of these estimates.

The leasing business is extremely competitive with several leasing companies providing essential market making services to airline companies. The high competition in this industry practically eliminates any risk adjusted rents leasing companies may make from these transactions. As market makers, leasing companies charge a fee for their services. When carriers want to shed excess capacity, the leasing companies undertake the task of finding a new operator and the risk associated with the uncertainty of the transaction. Our price discount on aircraft purchased by financial buyers, therefore, reflects the convenience yield and should not be construed as a forced sale discount.

[61] Table 1 shows that 41% of sales by non-bankrupt airlines are to financial buyers, and 18% of sales by bankrupt airlines are to financial buyers.

[62] According to Pulvino (1998), aircraft parking and maintenance costs are typically around \$1000 per month, and transporting an aircraft to a storage location costs \$10,000 to \$20,000. The average price of a narrow body aircraft in the sample is around \$6 million.

[63] In his model Gavazza (2011a) specifies that for an aircraft sold at price p, the transaction costs amount to τp. Calibrating the model to match utilization moments for wide body aircraft in the data, he estimates that parameter $\tau = 0.1583$.

The following points are worth reiterating. First, leasing companies act as intermediaries (market makers), matching sellers to users of assets. They are *not* the final users of the assets. Second, leasing companies reduce trading frictions and facilitate the reallocation of aircraft to more productive users. In doing so, they lubricate the secondary market thereby increasing the overall efficiency. Finally, leasing companies operate in a competitive space and the financial buyer discount should not be treated as a forced sale discount. But instead, it should be interpreted as a convenience yield – an inventory holding fee charged by the leasing companies. The growing presence of leasing companies in the aviation industry should, thus, be construed as a Coasian response to the high market frictions and increased volatility in this industry (Shleifer and Vishny (1992)). Lessors, through their knowledge of secondary markets, their scale economies, and reach across geographies, operate as specialists facilitating the reallocation of aircraft to more productive operators.

7 Conclusion

In this paper we revisit empirical evidence from the airline industry to quantitatively disentangle the quality impairment channel from the fire sale discount in used commercial aircraft sales. While the quality might be observable to a potential buyer, an econometrician does not easily observe this variable, leading to upward biases in reported fire sale discounts. We find that financially distressed airlines sell lower quality aircraft, that have lower life expectancy and lower productivity while in use, compared with aircraft sold by healthy airlines. After accounting for these quality differentials between aircraft, the quality-adjusted fire sale discount can be interpreted as the cost of immediacy, or the cost of selling an asset quickly in an illiquid market.

The quality impairment channel explains about half of the raw fire sale discount. The raw fire sale discount for aircraft sold by distressed airlines is 16%, and the quality impairment component is 8%, giving a quality-adjusted discount rate of 8%. The quality impairment component is higher at 18% for aircraft sold in Chapter 7, versus 7% in Chapter 11. We find that the quality adjustment is highly correlated with the time spent in distress prior to filing for Chapter 11. This pre-filing period is longer for aircraft sold in Chapter 7 than in Chapter 11, and therefore, explains the higher quality adjustment for Chapter

7 sales. After adjusting for quality, we find similar fire sale discounts in both Chapter 7 and Chapter 11 bankruptcies, 10% and 9%, respectively. It appears that the stronger going concern provisions of Chapter 11, for example DIP financing, do not seem to have resulted in a much lower quality-adjusted fire sale discount when compared with Chapter 7. It is also worth noting that the quality-adjusted discount rates in airlines are similar to those documented in the financial assets' literature.

Our paper also sheds light on whether the asset misallocation mechanism proposed by Shleifer and Vishny (1992) operates in the airlines industry. While this is a plausible channel that may generate further inefficiencies, we find no direct evidence of misallocation of aircraft to lower productivity users, at least in this particular industry during our sample period. Rather we find that purchasers of distressed aircraft are significantly more productive than distressed sellers, indicating that bankruptcy procedures may have a cleansing effect on the industry. The problem of misallocation may also be mitigated by provisions in Chapter 11 that permit a more patient sale of assets.

Moreover, the airlines industry includes many leasing companies which act as intermediaries, and are able to improve the resource allocation in the industry. While these firms buy assets at discounted prices, such a discount may represent a fee for taking on market making risks that would otherwise be borne by airlines. This may reflect the ability of lessors to relocate aircraft to ultimate users without the additional costs of being parked. Our results are in line with Gavazza (2011a) who finds that lessors deploy assets to more productive users. However, it contrasts with Pulvino's (1998) interpretation of the role played by leasing companies as less efficient (outside) buyers of the aircraft.

Notwithstanding, our results should not be interpreted as understating the importance of fire sales. Fire sale discounts are still large at around 10%. Furthermore, it has been well documented that fire sales create negative externalities that might amplify the downward spiral in asset prices, and thereby, affect the borrowing capacity and investment of firms.

The size of fire sale discounts have had an important policy influence in so far as they have been used as an important justification for mandatory bankruptcy codes like the U.S. Chapter 11. By refining the methodology on the measurement of the fire sale discount, our evidence connects to that debate, as to whether going concern bankruptcy codes are able to significantly mitigate the size of the fire sale discount. Such an analysis would require comparisons across jurisdictions that have weak going concern bankruptcy procedures. These issues have re-emerged in the economic crisis resulting from the pandemic of 2020, where the airlines industry has been particularly badly hit, and where it is likely that several airlines will file for bankruptcy protection, and their assets might be sold at fire sale prices.

References

Acharya, V. V., S. T. Bharath, and A. Srinivasan (2007). Does industry-wide distress affect defaulted firms? evidence from creditor recoveries. *Journal of Financial Economics 85*(3), 787–821.

Ackert, S. (2012). Basics of aircraft maintenance reserve development and management. *Aircraft Monitor August*.

Allen, F. and D. Gale (1994). Limited market participation and volatility of asset prices. *The American Economic Review*, 933–955.

Andersen, S. and K. M. Nielsen (2017). Fire sales and house prices: Evidence from estate sales due to sudden death. *Management Science 63*(1), 201–212.

Bartelsman, E., J. Haltiwanger, and S. Scarpetta (2013). Cross-country differences in productivity: The role of allocation and selection. *American Economic Review 103*(1), 305–34.

Benmelech, E. and N. K. Bergman (2008). Liquidation values and the credibility of financial contract renegotiation: Evidence from us airlines. *The Quarterly Journal of Economics 123*(4), 1635–1677.

Benmelech, E. and N. K. Bergman (2011). Vintage capital and creditor protection. *Journal of Financial Economics 99*(2), 308–332.

Bernstein, S., E. Colonnelli, and B. Iverson (2019). Asset allocation in bankruptcy. *The Journal of Finance 74*(1), 5–53.

Bian, B. (2020). Globally consistent creditor protection, reallocation, and productivity. *Working Paper*.

Bruner, R. F., D. Gollish, H. Clausen, N. Koggersbol, and P. Christey (2008, Oct). The boeing 777. *Darden Case No. UVA-F-1017*.

Brunnermeier, M. K. and L. H. Pedersen (2009). Market liquidity and funding liquidity. *The Review of Financial Studies 22*(6), 2201–2238.

Caballero, R. J. and M. L. Hammour (1994). The cleansing effect of recessions. *American Economic Review 84*(5), 1350–1368.

Campbell, J. Y., S. Giglio, and P. Pathak (2011). Forced sales and house prices. *American Economic Review 101*(5), 2108–31.

Captain, T. (2016, Jul). Global commercial aerospace industry: Aircraft order backlog analysis.

Cong, L. W., H. Gao, J. Ponticelli, and X. Yang (2019). Credit allocation under economic stimulus: Evidence from china. *The Review of Financial Studies 32*(9), 3412–3460.

Coval, J. and E. Stafford (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics 86*(2), 479–512.

Davies, M. (2014, Aug).

Dixon, M. C. (2006). *The maintenance costs of aging aircraft: insights from commercial aviation*, Volume 486. Rand Corporation.

Dow, J. and J. Han (2018). The paradox of financial fire sales: The role of arbitrage capital in determining liquidity. *The Journal of Finance 73*(1), 229–274.

Duffie, D. (2010). Asset price dynamics with slow-moving capital. *The Journal of Finance 65*(4), 1237–1267.

Eisenbach, T., F. Duarte, et al. (2014). Fire-sale spillovers and systemic risk. In *2014 Meeting Papers*, Number 541. Society for Economic Dynamics.

Ellul, A., C. Jotikasthira, and C. T. Lundblad (2011). Regulatory pressure and fire sales in the corporate bond market. *Journal of Financial Economics 101*(3), 596–620.

Franks, J. R., G. Seth, O. Sussman, and V. Vig (2020). The privatization of bankruptcy: evidence from financial distress in the shipping industry. *Working Paper*.

Gavazza, A. (2010). Asset liquidity and financial contracts: Evidence from aircraft leases. *Journal of Financial Economics 95*(1), 62–84.

Gavazza, A. (2011a). Leasing and secondary markets: Theory and evidence from commercial aircraft. *Journal of Political Economy 119*(2), 325–377.

Gavazza, A. (2011b). The role of trading frictions in real asset markets. *American Economic Review 101*(4), 1106–43.

Geanakoplos, J. (2003). Liquidity, default, and crashes. In *Advances in economics and econometrics: theory and applications: eighth World Congress*.

Gilligan, T. W. (2004). Lemons and leases in the used business aircraft market. *Journal of Political Economy 112*(5), 1157–1180.

Gray, D., J. MacIntyre, and J. Wool (2015). The interaction between cape town convention repossession remedies and local procedural law: a civil law case study. In *Cape Town Convention Journal*, Volume 4, pp. 17–52. Taylor & Francis.

Greenwood, R., A. Landier, and D. Thesmar (2015). Vulnerable banks. *Journal of Financial Economics 115*(3), 471–485.

Gromb, D. and D. Vayanos (2002). Equilibrium and welfare in markets with financially constrained arbitrageurs. *Journal of Financial Economics 66*(2-3), 361–407.

Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and manufacturing tfp in china and india. *The Quarterly Journal of Economics 124*(4), 1403–1448.

Jotikasthira, C., C. Lundblad, and T. Ramadorai (2012). Asset fire sales and purchases and the international transmission of funding shocks. *The Journal of Finance 67*(6), 2015–2050.

Kaplan, S. N. and L. Zingales (1997). Do investment-cash flow sensitivities provide useful measures of financing constraints? *The Quarterly Journal of Economics 112*(1), 169–215.

Kirkland and Ellis (2005, Jan). Restructuring aircraft fleets under section 1110 of the bankruptcy code: Selected issues — publications.

Kiyotaki, N. and J. Moore (1997). Credit cycles. *Journal of Political Economy 105*(2), 211–248.

Krishnamurthy, A. (2010). Amplification mechanisms in liquidity crises. *American Economic Journal: Macroeconomics 2*(3), 1–30.

LoPucki, L. M. and J. W. Doherty (2007). Bankruptcy fire sales. *Mich. L. Rev. 106*, 1.

Meier, J.-M. and H. Servaes (2019). The bright side of fire sales. *The Review of Financial Studies 32*(11), 4228–4270.

Melzer, B. T. (2017). Mortgage debt overhang: Reduced investment by homeowners at risk of default. *The Journal of Finance 72*(2), 575–612.

Merrill, C. B., T. Nadauld, R. M. Stulz, and S. M. Sherlund (2014). Were there fire sales in the rmbs market? *Charles A. Dice Center Working Paper* (2014-09).

Mian, A., A. Sufi, and F. Trebbi (2015). Foreclosures, house prices, and the real economy. *The Journal of Finance 70*(6), 2587–2634.

Mitchell, M. and T. Pulvino (2012). Arbitrage crashes and the speed of capital. *Journal of Financial Economics 104*(3), 469–490.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics 5*(2), 147–175.

Ozbas, O. and D. S. Scharfstein (2010). Evidence on the dark side of internal capital markets. *The Review of Financial Studies 23*(2), 581–599.

Pearce, B. (2013). Profitability and the air transport value chain. *IATA Economics Briefing* (10).

Pulvino, T. C. (1998). Do asset fire sales exist? an empirical investigation of commercial aircraft transactions. *The Journal of Finance 53*(3), 939–978.

Pulvino, T. C. (1999). Effects of bankruptcy court protection on asset sales. *Journal of Financial Economics 52*(2), 151–186.

Ripple, G. P. (2002). Special protection in the airline industry: The historical development of section 1110 of the bankruptcy code. *Notre Dame L. Rev. 78*, 281.

Scheinberg, R. (2017). *The Commercial Aircraft Finance Handbook*. Routledge.

Schlingemann, F. P., R. M. Stulz, and R. A. Walkling (2002). Divestitures and the liquidity of the market for corporate assets. *Journal of Financial Economics 64*(1), 117–144.

Shleifer, A. and R. Vishny (2011). Fire sales in finance and macroeconomics. *Journal of Economic Perspectives 25*(1), 29–48.

Shleifer, A. and R. W. Vishny (1992). Liquidation values and debt capacity: A market equilibrium approach. *The Journal of Finance 47*(4), 1343–1366.

Shleifer, A. and R. W. Vishny (1997). The limits of arbitrage. *The Journal of Finance 52*(1), 35–55.

Strömberg, P. (2000). Conflicts of interest and market illiquidity in bankruptcy auctions: Theory and tests. *The Journal of Finance 55*(6), 2641–2692.

Weiss, L. A. and K. H. Wruck (1998). Information problems, conflicts of interest, and asset stripping:: Chapter 11's failure in the case of eastern airlines. *Journal of Financial Economics 48*(1), 55–97.

Figure 1: Hazard Rate and Life Expectancy for Aircraft

In this figure, we plot the probability of a breakup, i.e. hazard rate (top panel), and life expectancy (bottom Pane) for an aircraft sold by an airline operating in Chapter 7 (green line), Chapter 11 (red line) and non-bankrupt airline (blue line). The hazard rates and life expectancies for aircraft of a given age are estimated using a Cox Proportional Hazard model.

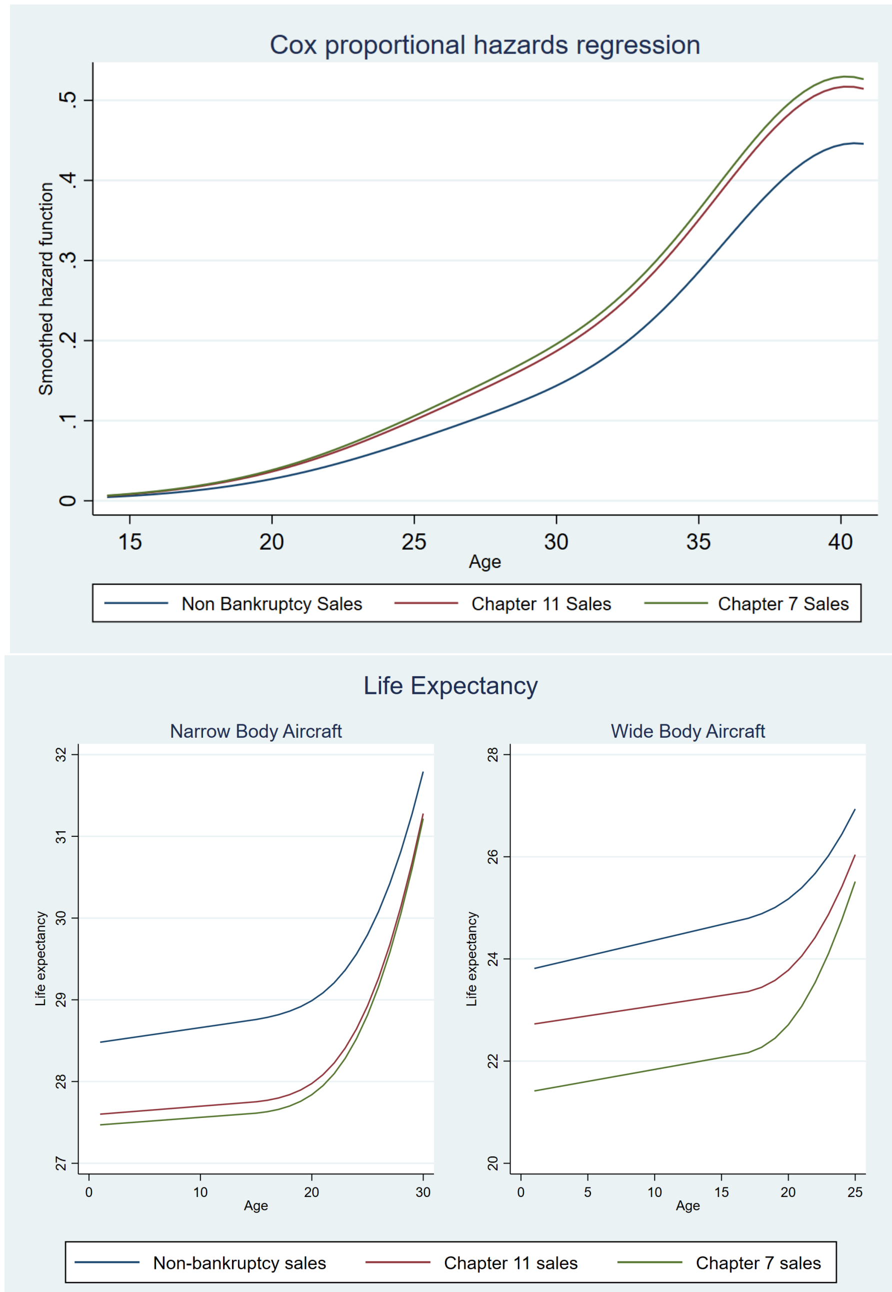

Figure 2: Average Flying Hours Residuals for Post-Sales Users of Aircraft

In this figure, we plot the kernel density of average demeaned operator flying hours for post-sale users of distress-affected aircraft and normal aircraft. We compute the flying hours' residuals from the regression of log flying hours on controls for aircraft type × age, year, fleet size, and number of same type of aircraft operating in the market. We average the residuals predicted from this regression across all aircraft flown by the operator, and thereby, calculate the average demeaned operator flying hours.

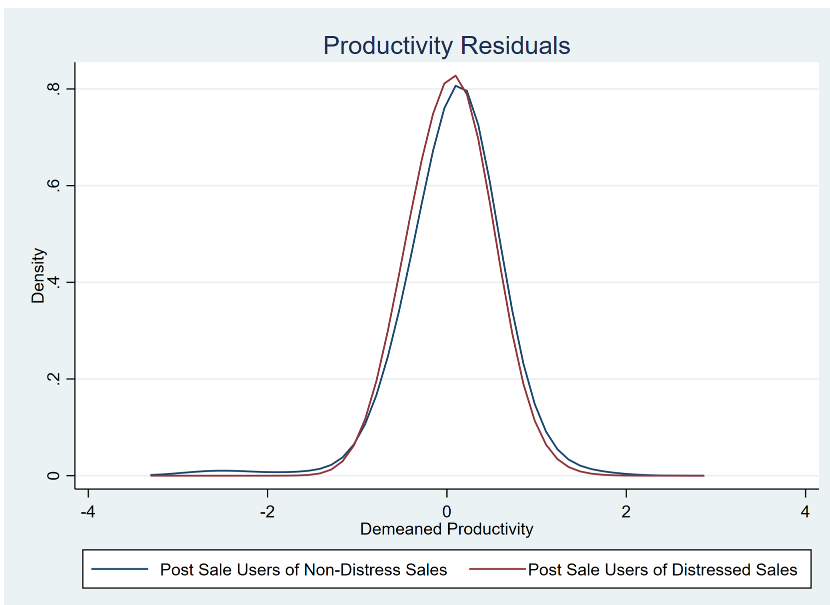

Figure 3: Difference in Productivity between the Buyer and Seller of Aircraft

In this figure, we plot the kernel density for the difference in productivity of the buyer and seller of the aircraft. We compute the flying hours' residuals from the regression of log flying hours on controls for aircraft type $\times$ age, year, and market thinness. We average the residuals predicted from this regression across all aircraft flown by the operator, and thereby, calculate the average operator productivity. Then the difference is calculated by subtracting the seller's productivity from the buyer's productivity for a given aircraft.

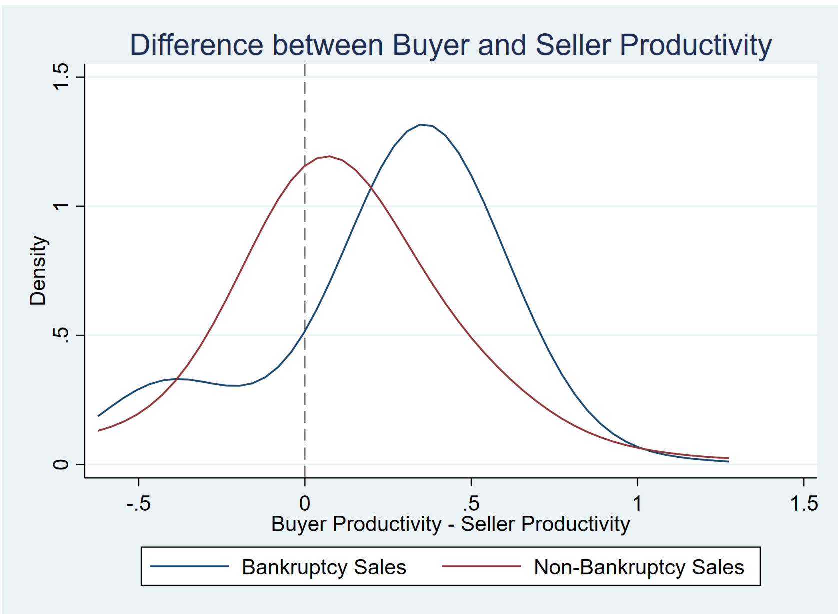

Figure 4: Tobin's Q for Post-Sales Users of Aircraft

In this figure, we plot the kernel density of Tobin's Q for post-sale users of distress-affected aircraft and normal aircraft.

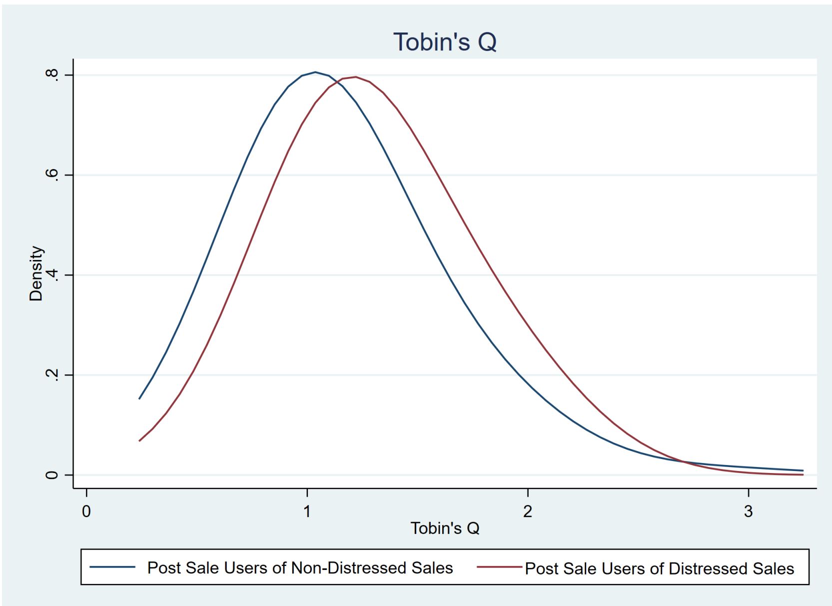

Table 1: Summary Statistics: Narrow & Wide Body Aircraft Sales

This table reports the summary statistics for the sample of used narrow and wide body aircraft transacted in the U.S. between 1978-1991. *Aircraft Price* is the inflation-adjusted price of a second-hand aircraft in million dollars (in terms of 1992 index). *Aircraft Age at Sale* is the age of the aircraft in years at sale. *% sales to Financial Buyers* represent the percentage of sales to a financial buyer (i.e. bank or leasing company). *Aircraft Retirement Age* is the age at which the aircraft was retired from service. Panel A reports the complete sample of sales, while Panel B restricts the sample to sales by major U.S. airlines listed in Appendix Table A.1. In Panel C we split the sample between bankruptcy and non-bankruptcy sales. Panel D reports the summary statistics for *Chapter 7* and *Chapter 11* sales.

Panel A: Complete Sample of Sales of Narrow & Wide Bodied Aircraft Sales

	Obs.	Mean	SD
Aircraft Price ($ million)	1,333	11.54	11.12
Aircraft Age at Sale (years)	1,333	14.26	5.65
% sales to Financial Buyers	1,333	35%	
Aircraft Retirement Age (years)	1,231	29.58	5.92

Panel B: Subsample of Aircraft sold by Major U.S. Airlines*

	Obs.	Mean	SD
Aircraft Price ($ million)	695	8.34	7.41
Aircraft Age at Sale (years)	695	14.59	5.53
% sales to Financial Buyers	695	37%	
Aircraft Retirement Age (years)	642	29.69	5.92

Panel C: Bankruptcy and Non-Bankruptcy Sales

	Bankrupt Airlines			Non-Bankrupt Airlines		
	Obs.	Mean	SD	Obs.	Mean	SD
Aircraft Price ($ million)	131	8.01	5.60	564	8.42	7.79
Aircraft Age at Sale (years)	131	14.92	6.04	564	14.50	5.40
% sales to Financial Buyers	131	18%		564	41%	
Aircraft Retirement Age (years)	120	28.95	4.75	522	29.86	6.15

Panel D: Subsample of Bankruptcy Sales

	Chapter 7 Sales			Chapter 11 Sales		
	Obs.	Mean	SD	Obs.	Mean	SD
Aircraft Price ($ million)	40	9.10	4.28	91	7.52	6.05
Aircraft Age at Sale (years)	40	10.13	3.15	91	17.03	5.80
% sales to Financial Buyers	40	0%		91	26%	
Aircraft Retirement Age (years)	35	27.4	3.92	85	29.59	4.54

*Panel B excludes sales made by financial intermediaries (banks and leasing companies), and foreign airlines.

Table 2: Summary Statistics: Aircraft Productivity

This table reports the summary statistics for aircraft operating in the U.S. for the period 1975 to 2015. The unit of observation is aircraft-year. *Annual flying hours* measure the total annual flying hours of an aircraft. *Parked Aircraft* measures the proportion of aircraft being parked for a year. *Age* is defined as the age of the aircraft in years. *Technological Age* of an aircraft is defined as the number of years since the introduction of an aircraft's type. Panel A reports the summary statistics for the entire sample. In Panel B we split our sample into 3 sub samples of: (i) aircraft sold by distressed airlines post their sale, (ii) aircraft that were owned (and not sold) by airlines that emerged from Chapter 11 as going concerns (after the distress event ends), and, (iii) aircraft that have not been exposed to a distress event in the past.

Panel A: Full Sample

	Mean	SD	Obs.
Annual flying hours	2,069.5	1,134.6	62,705
Parked Aircraft	0.057	0.23	62,705
Age (years)	18.37	8.52	62,705
Technological Age (years)	26.89	9.33	62,705

Panel B: Distress Episodes

	Aircraft sold in distress			Aircraft surviving distress			Aircraft not exposed to distress		
	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.
Annual flying hours	1,309.4	924.1	2,811	2,170.8	1,130.5	2,922	2,101.8	1,130.9	56,972
Parked Aircraft	0.110	0.31	2,811	0.093	0.29	2,922	0.053	0.22	56,972
Age (years)	23.63	7.03	2,811	21.85	8.43	2,922	17.94	8.47	56,972
Technological Age (years)	32.64	6.34	2,811	30.97	9.73	2,922	26.40	9.29	56,972

Table 3: Productivity of Aircraft and Distress History

Panel A: Flying Hours of Aircraft with History of Distress

The table shows how a history of distress affects the future productivity of an aircraft. *Distress* is an indicator variable that equals 1 if the aircraft was ever operated by an airline operating in bankruptcy, or one year prior to the airline entering bankruptcy. *Chapter 7* is an indicator that equals 1 if the aircraft was ever sold by an airline liquidating in Chapter 7. *Chapter 11* is an indicator that equals 1 if the aircraft was ever sold by an airline operating in Chapter 11 protection. *Bankruptcy (T-1)* is an indicator that equals 1 if the aircraft was sold by an airline one year prior to its entering bankruptcy (T signifies the time at which the airline filed for bankruptcy protection). The dependent variable is the log of yearly flying hours for an aircraft. Controls are included for the fleet size of an airline (*ln(Fleet Size)*), and the number of same model aircraft operating during that time period (*ln(#type aircraft)*). Aircraft type × age, aircraft operator, and year fixed effects are included in all specifications. Additionally, aircraft operator × year fixed effects are included in columns (5) and (6). Aircraft operator × type fixed effects are included in columns (7) and (8). The unit of observation is aircraft-year. Standard errors clustered by aircraft type are denoted in parentheses. *** denotes significance at 1%, ** at 5%, and * at 10%.

	ln(Flying Hours)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distress	-0.104***	-0.105***			-0.0991***		-0.0751***	
	(0.017)	(0.017)			(0.014)		(0.016)	
Chapter 7			-0.144***	-0.138***		-0.133***		-0.0848***
			(0.029)	(0.030)		(0.031)		(0.016)
Chapter 11			-0.100***	-0.102***		-0.0960***		-0.0849***
			(0.020)	(0.022)		(0.026)		(0.025)
Bankruptcy(T-1)			-0.0763*	-0.0834**		-0.0740*		-0.0426
			(0.033)	(0.035)		(0.035)		(0.031)
ln(#type aircraft)		0.129		0.128	0.101	0.0997	0.170	0.169
		(0.092)		(0.092)	(0.069)	(0.069)	(0.112)	(0.112)
ln(Fleet Size)		0.0419		0.0420			0.0391	0.0392
		(0.024)		(0.024)			(0.028)	(0.028)
Year FE	YES	YES	YES	YES	-	-	YES	YES
Type × Age FE	YES	YES	YES	YES	YES	YES	YES	YES
Operator FE	YES	YES	YES	YES	-	-	-	-
Operator × Year FE	NO	NO	NO	NO	YES	YES	NO	NO
Operator × Type FE	NO	NO	NO	NO	NO	NO	YES	YES
Observations	58,844	58,844	58,844	58,844	57,269	57,269	58,749	58,749
Adjusted R^2	0.595	0.596	0.595	0.596	0.633	0.633	0.626	0.626

Panel B: Flying Hours of Aircraft and Time spent in Distress

The table shows how time spent in distress affects the future productivity of an aircraft. *Time in distress* measures the total time spent in distress (in years) for an aircraft that was ever sold by an airline operating in distress. *Time before bankruptcy filing* measures the time that was spent in distress before filing for bankruptcy (in years) for an aircraft. *Time after bankruptcy filing* measures the time that was spent in distress after the airline operating the aircraft filed for bankruptcy (in years). The dependent variable is the log of yearly flying hours for an aircraft. Controls are included for the fleet size of an airline (*ln(Fleet Size)*), and the number of same model aircraft operating during that time period (*ln(#type aircraft)*). Aircraft type × age, aircraft operator, and year fixed effects are included in all specifications. The unit of observation is aircraft-year. Standard errors clustered by aircraft type are denoted in parentheses. *** denotes significance at 1%, ** at 5%, and * at 10%.

	ln(Flying Hours)			
	(1)	(2)	(3)	(4)
Time in distress (years)	-0.0315***	-0.0304***		
	(0.005)	(0.006)		
Time before bankruptcy filing (years)			-0.0493***	-0.0450***
			(0.013)	(0.013)
Time after bankruptcy filing (years)			-0.0108	-0.0133
			(0.022)	(0.022)
ln(#type aircraft)		0.125		0.124
		(0.091)		(0.091)
ln(Fleet Size)		0.0414		0.0414
		(0.024)		(0.024)
Observations	58,844	58,844	58,844	58,844
Adjusted R^2	0.595	0.596	0.595	0.596
Year FE	YES	YES	YES	YES
Type × Age FE	YES	YES	YES	YES
Operator FE	YES	YES	YES	YES

Table 4: Hedonic Model (Two-stage model: First stage)

This table reports the results from the first stage hedonic regression. The dependent variable is log of the sales price of aircraft. In columns (1) and (2) we report the first stage regression with no quality correction, by regressing used narrow body and wide body aircraft's log(Sale Price) on log(1+Age). In columns (3) and (4) we control for quality by including a measure for quality adjustment ($Quality_{adj1}$) in the specification. $Quality_{adj1}$ measures aircraft life expectancy, and is estimated from Equation 1. In columns (5) and (6) we control for quality by including quality adjustment ($Quality_{adj2}$) for lower life expectancy and lower productivity of aircraft (from Equation 5). Fixed effects for aircraft characteristics - aircraft model, noise level(stage), and year quarter are included in all the regressions. Robust standard errors are reported in parentheses. *** denotes significance at 1%, ** at 5%, and * at 10%.

	Dependent Variable: log(Sales Price)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Narrow Body	Wide Body	Narrow Body	Wide Body	Narrow Body	Wide Body
ln(1+Age)	-0.174***	-0.334***	-0.173***	-0.715***	-0.162***	-0.740***
	(0.060)	(0.100)	(0.060)	(0.123)	(0.060)	(0.105)
$Quality_{adj1}$			0.079**	0.315***		
			(0.030)	(0.093)		
$Quality_{adj2}$					0.055***	0.398***
					(0.014)	(0.067)
Aircraft Model FE	YES	YES	YES	YES	YES	YES
Aircraft Stage FE	YES	YES	YES	YES	YES	YES
Year Quarter FE	YES	YES	YES	YES	YES	YES
Observations	1,079	254	1,079	254	1,079	254
Adjusted R^2	0.754	0.739	0.755	0.778	0.756	0.808

Table 5: Fire Sale Discount for Distressed Airlines (Two-stage model: Second stage)

This table reports the results from the second stage which regresses the price discount (residuals from the first stage hedonic regression) on dummy variables indicating whether the airline selling the aircraft was distressed. In columns (1), and (2) the price discount is calculated ignoring the quality correction in the first stage, while in columns (3) and (4) the price discount is calculated by including the life expectancy quality adjustment ($Quality_{adj1}$) in the first stage hedonic model. In columns (5) and (6) the price discount is calculated by including quality adjustment ($Quality_{adj2}$) for both life expectancy and productivity differential in the first stage hedonic model. The *Distress* dummy takes value 1 if the aircraft was sold by an airline (i) liquidating in Chapter 7 bankruptcy, (ii) operating in Chapter 11 bankruptcy protection, or (iii) at most 1 year prior to the airline filing for bankruptcy. The *Chapter 7* dummy takes value 1 if the airline selling the aircraft was operating under Chapter 7 liquidation. The *Chapter 11* dummy takes value 1 if the airline selling the aircraft was operating under Chapter 11 protection. The *Bankruptcy (T-1)* dummy takes value 1 if the sale of the aircraft was sold one year prior to the airline filing for bankruptcy protection (T signifies time at which the airline filed for bankruptcy). The *financial buyer* dummy takes value 1 if the aircraft was purchased by a bank or a leasing company. Panel A reports the fire sale discounts for aircraft sold by *distressed* airlines. In Panel B, we segregate the sales by *distressed* airlines, into *Chapter 7*, *Chapter 11* and *Bankruptcy (T-1)* sales. Robust standard errors are reported in parentheses. *** denotes significance at 1%, ** at 5%, and * at 10%.

Panel A: Fire Sale Discount for Distressed Airlines						
	W/O Quality Correction		With $Quality_{adj1}$ Correction		With $Quality_{adj2}$ Correction	
	(1)	(2)	(3)	(4)	(5)	(6)
	Discount	Discount	Discount	Discount	Discount	Discount
Distress	-0.160***	-0.159***	-0.118***	-0.117***	-0.083**	-0.081**
	(0.034)	(0.034)	(0.034)	(0.033)	(0.035)	(0.034)
Financial Buyer		-0.090***		-0.099***		-0.105***
		(0.029)		(0.029)		(0.029)
Seller FE	YES	YES	YES	YES	YES	YES
Observations	694	694	694	694	694	694
Adjusted R^2	0.178	0.194	0.157	0.177	0.152	0.175
Panel B: Fire Sale Discount on sales by Bankrupt Airlines						
Chapter 7	-0.251***	-0.280***	-0.099*	-0.128**	-0.067	-0.098*
	(0.044)	(0.044)	(0.059)	(0.060)	(0.057)	(0.057)
Chapter 11	-0.161***	-0.161***	-0.116***	-0.116***	-0.085**	-0.086**
	(0.038)	(0.039)	(0.040)	(0.040)	(0.040)	(0.039)
Bankruptcy (T-1)	-0.126***	-0.109***	-0.131***	-0.113***	-0.083**	-0.063*
	(0.042)	(0.037)	(0.040)	(0.036)	(0.042)	(0.037)
Financial Buyer		-0.098***		-0.100***		-0.108***
		(0.029)		(0.030)		(0.029)
Seller FE	YES	YES	YES	YES	YES	YES
Observations	694	694	694	694	694	694
Adjusted R^2	0.177	0.197	0.154	0.174	0.149	0.173

Table 6: Summary of Fire Sale Discount Results

This table summarizes raw fire sale discounts, quality-adjusted fire sale discounts and the quality discount for different definitions of financial distress. Table 5 Panel A columns (2) and (6) report the fire sale discounts on sale of aircraft by airlines operating under *Distress*. Table 5 Panel B columns (2) and (6) report the fire sale discounts on sale of aircraft by airlines in *Chapter 7*, *Chapter 11*, and *Bankruptcy (T-1)*. Comprehensive results for fire sale discount on sale of aircraft by low spare debt capacity (*CAPLO*) airlines are reported in Table A.2, columns (2) and (4). *Quality Discount* in column (3) is calculated by subtracting the quality-adjusted fire sale discount (in column(2)) from the raw fire sale discount (in column (1)).

Selling Airline	(1) Raw Fire Sale Discount	(2) Quality-Adjusted Fire Sale Discount	(3) Quality Discount
Distressed	16%	8%	8%
Chapter 7	28%	10%	18%
Chapter 11	16%	9%	7%
Bankruptcy (T-1)	11%	6%	5%
Low Spare Debt Capacity (CAPLO)	15%	10%	5%

Table 7: Comparison of Productivity across Post-Sale Users of Aircraft

This table reports the differences in average user productivity for post-sale users of aircraft sold by distressed airlines and post-sale users of aircraft sold by normal (or non-distressed) airlines. We measure average user productivity using the following three metrics. *Average Flying Hours* for a user averages the yearly flying hours across all the aircraft that are flown by that user. For an operator, *Residuals Flying Hours** averages residuals across all aircraft flown by the operator, where the residuals are obtained by regressing log flying hours on aircraft *Type* × *Age*, and *Year* fixed effects. For an operator, *Residuals Flying Hours*** averages residuals across all aircraft flown by the operator, where the residuals are obtained by regressing log flying hours on aircraft *Type* × *Age*, *Year*, *ln(Fleet Size)* and *ln(no. of same type aircraft)*. The last column reports the p-values for mean comparison tests between the users of distress-affected aircraft and the users of normal aircraft, without the assumption of equal variance. Panel A compares our productivity measures for the complete sample. Panel B restricts the sample to users for which financial data are not available. Panel C reports comparisons across users for which financial data are available (these users are further compared using profitability variables in Table 10).

	Normal Sales			Distressed Sales			Difference
Panel A: Complete Sample of Sales							
	Obs.	Mean	SD	Obs.	Mean	SD	p-value
Average Flying Hours	862	7.45	0.022	154	7.44	0.039	0.5832
Residuals Flying Hours*	862	0.003	0.017	154	-0.003	0.021	0.8349
Residuals Flying Hours**	862	0.065	0.016	154	0.041	0.026	0.4100
Panel B: Subsample of Users without financial data							
	Normal Sales			Distressed Sales			Difference
	Obs.	Mean	SD	Obs.	Mean	SD	p-value
Average Flying Hours	432	7.18	0.035	65	7.08	0.042	0.2277
Residuals Flying Hours*	432	-0.116	0.031	65	-0.157	0.028	0.6003
Residuals Flying Hours**	432	0.058	0.028	65	-0.027	0.042	0.2537
Panel C: Subsample of Users with financial data							
	Normal Sales			Distressed Sales			Difference
	Obs.	Mean	SD	Obs.	Mean	SD	p-value
Average Flying Hours	426	7.72	0.016	89	7.70	0.041	0.4585
Residuals Flying Hours*	426	0.121	0.010	89	0.110	0.024	0.6858
Residuals Flying Hours**	426	0.071	0.014	89	0.091	0.032	0.5661

*Residuals demeaned for Aircraft Type × Age, and year fixed effects

**Residuals demeaned for Aircraft Type × Age, market thinness, and year fixed effects

Table 8: Average productivity of aircraft operators during transactions

This table reports the productivity of sellers and buyers of aircraft. *Non-distressed Seller* equals 1 for all aircraft that are operated by the non-distressed seller in the year it sells an aircraft. In a given year, for all aircraft operated by the carrier, *Buyer of non-distressed aircraft* equals 1 if the carrier purchases aircraft from a non-distressed seller. When a distressed operator sells an aircraft, *Distressed Seller* equals 1 for all aircraft being operated by the distressed seller in the sale year. *Buyer of distressed aircraft* equals 1 for all aircraft operated by the buyer in the year it purchases an aircraft from a distressed seller. The dependent variable is the log of yearly flying hours for an aircraft. Controls are included for the fleet size of an airline (*ln(Fleet Size)*), and the number of same model aircraft operating during that time period (*ln(#type aircraft)*). Aircraft type × age, aircraft usage, and year fixed effects are included in all specifications. Columns (1) and (2) report results for our full sample. In columns (3) and (4), we restrict our sample to NBER recession years. The unit of observation is aircraft-year. Robust standard errors are denoted in parentheses. *** denotes significance at 1%, ** at 5%, and * at 10%.

	ln(Flying Hours)			
	Full Sample		Recessions	
	(1)	(2)	(3)	(4)
Non-distressed seller	0.053***	0.022***	-0.009	-0.073***
	(0.007)	(0.007)	(0.020)	(0.022)
Buyer of non-distressed aircraft	0.033***	0.006	0.027	-0.020
	(0.008)	(0.008)	(0.030)	(0.032)
Distressed seller	-0.036***	-0.055***	-0.081**	-0.135***
	(0.014)	(0.014)	(0.037)	(0.038)
Buyer of distressed aircraft	0.051***	0.038***	0.134***	0.139***
	(0.013)	(0.013)	(0.025)	(0.025)
ln(#type aircraft)		0.010***		0.183***
		(0.020)		(0.066)
ln(Fleet Size)		0.051***		0.078***
		(0.004)		(0.012)
Year FE	YES	YES	YES	YES
Type × Age FE	YES	YES	YES	YES
Aircraft Usage FE	YES	YES	YES	YES
Observations	59,109	59,109	8,635	8,635
Adjusted R^2	0.498	0.501	0.495	0.501

Table 9: Impact of Purchasing Distressed Aircraft on Airlines' Growth

The table shows how aircraft reallocation across firms contributes to firms' growth, and compares the post-sale users of distress-affected aircraft with the post-sale users of normal (or non-distressed) aircraft. The following dependent variables proxy for firm growth: in column (1) *ln(Fleet Size)* is calculated as the log of the number of aircraft in the operator's fleet in a given year; in column (2) *Fleet Age* is calculated as the average age of all aircraft flown by the operator in a given year; in column (3) *Fleet Tech Age* is calculated as the average tech age of the operators' fleet in a given year. Tech Age measures aircraft technological age, and is defined as the number of years since the introduction of the underlying aircraft's type. These variables for firm's growth prospects are regressed on previous year's firm productivity. The lagged variable, *Productivity* is defined as the average yearly flying hours of the operator across all the aircraft that are flown by that operator in the previous year. *Productivity* $\times$ *Distress User* is equal to the operator's lagged productivity if the operator purchased a distress-affected aircraft in a given year (i.e. the operator is the post-sale user of a distress-affected aircraft). *Productivity* $\times$ *Normal User* is equal to the operator's lagged productivity if the operator is the post-sale user of a normal aircraft. The unit of observation is airline-year. The p-values of coefficient equality t-test comparing the sensitivity of productivity to firms' growth prospects for the users of distress-affected aircraft with the users of normal aircraft are reported in the last row. Robust standard errors are included in parenthesis. *** denotes significance at 1%, ** at 5%, and * at 10%.

	(1)	(2)	(3)
	ln(Fleet Size)	Fleet Age	Fleet Tech Age
Productivity	0.715***	-1.623***	-1.012***
	(0.030)	(0.114)	(0.094)
Productivity $\times$ Distress User	0.242***	-0.201*	-0.081
	(0.042)	(0.115)	(0.061)
Productivity $\times$ Normal User	0.200***	-0.110***	-0.081**
	(0.015)	(0.042)	(0.036)
Year FE	YES	YES	YES
Observations	1,671	1,671	1,671
Adjusted R^2	0.385	0.503	0.632
(Productivity $\times$ Distress User) versus (Productivity $\times$ Normal User) t-test			
p-value	0.3481	0.4544	0.9945

Table 10: Comparison of Financial Variables across Post-Sale Users of Aircraft

This table reports the differences in lagged financial variables for post-sale users of aircraft sold by distressed airlines and post-sale users of aircraft sold by normal airlines. For a user, *Tobin's Q* is measured as MVA/BVA, where the market value of assets equals the book value of assets plus the market value of common equity less the book value of common equity and deferred taxes. $Log(MPK)$ for a user is defined as the natural log of sales divided by book value of fixed assets. $Profitability$ of the user is measured as operating income before depreciation, interest and taxes scaled by lagged assets. Panel A compares the performance of users of distress-affected aircraft to users of normal aircraft on these financial variables. In Panel B, we report this comparison after demeaning the financial variables using year fixed effects. The last column reports the p-values for mean comparison tests between the users of distress-affected aircraft and the users of normal aircraft, without the assumption of equal variance.

Panel A: Financial Variables							
	Normal Sales			Distressed Sales			Difference
	Obs.	Mean	SD	Obs.	Mean	SD	p-value
Tobin's Q	426	1.14	0.017	89	1.31	0.034	0.0001
Log(MPK)	512	0.52	0.014	109	0.57	0.028	0.3127
Profitability	482	0.15	0.004	99	0.15	0.006	0.9865
Panel B: Financial Variables demeaned for Year Fixed Effects							
	Normal Sales			Distressed Sales			Difference
	Obs.	Mean	SD	Obs.	Mean	SD	p-value
Tobin's Q	426	-0.060	0.019	89	0.019	0.030	0.0337
Log(MPK)	512	-0.092	0.013	109	-0.104	0.023	0.6891
Profitability	482	0.038	0.004	99	0.064	0.006	0.0045

Table 11: Productivity of aircraft one year before sale

This table reports the productivity of aircraft in the last year of their sale with the seller. *Pre-sale (last year with seller)* equals 1 if the aircraft is in its final year of operation with its seller. *Pre-sale* × *Financial buyer* equals 1 if the aircraft is in its final year of operation with the seller, and post-sale is purchased by a leasing company. *Distressed aircraft pre-sale (last year with distressed seller)* equals 1 if the aircraft is in its final year of operation with a seller that is operating in distress. *Distressed aircraft pre-sale* × *Financial buyer* equals 1 if the aircraft is in its final year of operation with a distressed seller and post-sale it is purchased by a leasing company. The dependent variable is the log of yearly flying hours for an aircraft. Controls are included for the fleet size of an airline (*ln(Fleet Size)*), and the number of same model aircraft operating during that time period (*ln(#type aircraft)*). Aircraft type × age, aircraft usage, and year fixed effects are included in all specifications. Aircraft operator fixed effects are included in columns (3) and (4). The unit of observation is aircraft-year. Robust standard errors are denoted in parentheses. *** denotes significance at 1%, ** at 5%, and * at 10%.

	ln(Flying Hours)			
	(1)	(2)	(3)	(4)
Pre-sale (last year with seller)	-0.0951***	-0.0876***	-0.169***	-0.163***
	(0.030)	(0.030)	(0.029)	(0.028)
Pre-sale × Financial buyer	0.129***	0.140***	0.120***	0.114***
	(0.047)	(0.047)	(0.044)	(0.044)
Distressed aircraft pre-sale (last year with distressed seller)	-0.426***	-0.412***	-0.351***	-0.343***
	(0.073)	(0.073)	(0.070)	(0.070)
Distressed aircraft pre-sale × Financial buyer	0.334***	0.332***	0.335***	0.339***
	(0.090)	(0.090)	(0.088)	(0.088)
ln(#type aircraft)		0.0920***		0.115***
		(0.020)		(0.019)
ln(Fleet Size)		0.0531***		0.0320***
		(0.004)		(0.009)
Year FE	YES	YES	YES	YES
Type × Age FE	YES	YES	YES	YES
Aircraft Operator FE	NO	NO	YES	YES
Aircraft Usage FE	YES	YES	-	-
Observations	59,032	59,032	58,762	58,762
Adjusted R^2	0.500	0.503	0.598	0.598

Appendix

A.1 Fire Sale Discount on Financially Constrained Airlines

In this section, we will explore the quality variations between aircraft sold by airlines operating under low spare debt capacity, versus the aircraft sold by healthy airlines. Following Pulvino (1998), we classify an airline as a low spare debt capacity airline if its leverage ratio is above the industry median, and its current ratio is below the industry median in the calendar quarter preceding the aircraft sale.[64]

We replicate Pulvino (1998), to calculate the raw fire sale discount on sale of aircraft by airlines operating under low spare debt capacity. In the first stage, we calculate the hedonic price of an aircraft from Table 4. In the second stage, we restrict our sample to sales by major U.S. airlines (listed in Appendix Table A.1, for which financial data is available for the quarter preceding the transaction. We regress the residuals (ϵ) obtained from the first stage on variables measuring airlines' financial health.[65] More specifically, to quantify the raw fire sales discount, we regress:

$$\epsilon = \beta_0 + \beta_1 CAPLO + \beta_2 CAPHI + \beta_3 Q + \beta_4 REV + \beta_5 COST + \beta_6 N + \beta_7 FIN + \beta_8 OTHER + \eta \quad \text{(A-1)}$$

We do this only for the sample of used narrow body aircraft sold by the airlines whose financial data are available for the quarter preceding the transaction. The variables are: $CAPLO$ is a dummy variable equal to 1 if the selling airline had a leverage ratio above the industry median and a current ratio below the industry median in the calendar quarter preceding the transaction; $CAPHI$ is a dummy variable equal to 1 if the airline had a leverage ratio below the industry median and a current ratio above the industry median in the preceding quarter[66]; Q equals (Market value of assets/Book value of assets)[67]; REV equals (Revenue/Available-seat-miles); $COST$ equals (Cost-of-goods-sold/Available-seat-miles); N equals the number of narrow-body sales by the selling airline in the calendar quarter of the transaction; FIN equals 1 if the aircraft was purchased by a financial institution or a leasing company; $OTHER$ equals 1 if the buyer of the aircraft is a regional airline, foreign airline, foreign government, or cargo company (i.e. the buyer is neither a financial buyer, nor one of the major U.S. airlines listed in Table A.1). In order to separate the effects of financial distress from the effects of economic distress, the above specification

[64] These sales are identical to the $CAPLO$ sales in Pulvino (1998).

[65] We transform the residuals obtained in the above regression (ϵ), to actual discounts rates via the following transformation: $Discount = \exp(\epsilon) - 1$. The log residuals approximate the actual discount rates for small discounts. Nevertheless, we transform log residuals to actual discount rates to be more precise. In what follows our results differ slightly from Pulvino (1998) due to this correction. Our main results are robust to both specifications.

[66] Leverage ratio is defined as book value of debt plus capitalized lease obligations divided by the sum of book value of debt, capitalized lease obligations, and book value of equity. Current ratio is defined as current assets divided by current liabilities. Airlines with both high leverage ratios and low current ratios are classified as CAPLO.

[67] The market value of assets equals the book value of assets plus the market value of common equity less the book value of common equity and balance sheet deferred taxes

controls for firm prospects (using three variables: Q, Revenue/ASM and COGS/ASM).[68] Transactions are only included in the above regression if financial data for the quarter preceding the sale date are available. To be consistent with Pulvino (1998), in this specification we drop sales by bankruptcy-affected airlines where there is a lack of availability of financial data.

Further to understand the quality variations between aircraft sold by airlines operating under low spare debt capacity, we track the flying hours of these aircraft post sale. Following identical methodology, as in Table 3 we find that aircraft sold by airlines in low spare debt capacity fly 5.3% lesser than other similar aircraft operated by the *same* new carrier. This difference in flying hours is statistically significant at the 1% level. We control for this difference, in measuring $Quality_{adj2}$ from Equation 5. That is, for aircraft sold by low spare debt capacity airlines, we set ρ as equal to $e^{-0.053}$ and calculate their effective economic life.

The raw fire sale discounts calculated from regressing the residuals on financial health variables are reported in Table A.2, columns (1) and (2). The discounts are identical to Pulvino (1998). Airlines with low spare debt capacity sell aircraft at an average discount of 15%, a significant discount to the average market price. Further, in comparison to sales made to major U.S. airlines, the sales to financial institutions and leasing companies occur at an average price discount of around 12% (in column (2)). In Table A.2 columns (3)-(4) we report the quality-adjusted fire sale discounts after controlling for quality variations between aircraft sold by constrained and healthy airlines in the first stage. We find that there is a 4.4 percentage points reduction in the raw fire sale discount upon controlling for the lower quality of aircraft sold by low spare debt capacity airlines (comparing column (4) with column (2)). This reduction is statistically significant at the 1% level.[69] Quality impairment explains roughly 30% of the raw fire sale discount and, after controlling for it the fire sale discount on the sale of aircraft by low spare debt capacity airlines ($CAPLO$) declines to around 10%.

[68] To avoid potential control problems, we have repeated this regression using firm level control variables (Q, Revenue/ASM, Cost/ASM) from the quarter preceding the transaction. The discount on aircraft sales by financially distressed airlines remains almost unchanged. Results available on request.

[69] p-value for the coefficient equality test on the $CAPLO$ variable between columns (2) and (4), (and (1) and (3)) is 0.0000.

Table A.1: Summary of Narrow & Wide Body Aircraft Sales

This table reports the total number of sales of narrow body and wide body aircraft by major U.S. airlines from 1978-1991. Airlines that filed for bankruptcy at least once during that period are in bold face.

	Narrow Body Sales	Wide Body Sales	Total Sales
Air Florida	10	0	10
AIRCAL	0	0	0
Alaska Airlines	6	0	6
Aloha Airlines	3	0	3
America West Airlines	8	0	8
American Airlines	38	3	41
Braniff Airlines	55	1	56
Braniff Liq. Trust	26	0	26
Continental Airlines	12	0	12
Delta Airlines	50	16	66
Eastern Airlines	132	21	153
Frontier Airlines	0	0	0
Hawaiian Airlines	4	0	4
Midway Airlines	6	0	6
Muse Air	0	0	0
New York Air	0	0	0
Northwest Airlines	49	0	49
Ozark Airlines	2	0	2
Pacific Southwest	21	0	21
Pan Am World Airways	33	30	63
People Express Airlines	0	1	1
Piedmont Airlines	5	0	5
Republic Airlines	4	0	4
Southwest Airlines	0	0	0
TWA	40	4	44
United Airlines	54	8	62
US Air	25	0	25
Western Airlines	25	3	28
TOTAL	608	87	695

Table A.2: Fire Sale Discount for Low Spare Debt Capacity Airlines

This table reports the results from the second stage which regresses the price discount (residuals from the first stage hedonic regression) on dummy variables indicating whether the airline selling the aircraft was operating under low spare debt capacity ($CAPLO$-high leverage and low current ratio), or high spare debt capacity ($CAPHI$). In columns (1), and (2) the price discount is calculated ignoring the quality correction in the first stage, while in columns (3) and (4) the price discount is calculated by including quality adjustment ($Quality_{adj2}$) in the first stage hedonic model. There are control variables for Revenue/Available Seat Mile (REV), Costs/Available Seat Mile (COST), Tobin's Q (TQ), and number of aircraft sold by an airline in a given calendar quarter ($NSALE$). Also included is a dummy variable for whether the aircraft was purchased by a *financial buyer*, that takes a value one if the aircraft buyer is a bank or leasing company. *Other buyer* is a dummy variable that takes a value 1 if the buyer is not a financial institution, leasing company, or a large U.S. airline listed in Appendix Table A.1. Robust standard errors are reported in parentheses. *** denotes significance at 1%, ** at 5%, and * at 10%.

	W/O Quality Correction		With $Quality_{adj2}$ Correction	
	(1)	(2)	(3)	(4)
	Discount	Discount	Discount	Discount
CAPLO	-0.145***	-0.148***	-0.101***	-0.104***
	(0.033)	(0.033)	(0.033)	(0.033)
CAPHI	-0.025	-0.037	-0.033	-0.044
	(0.042)	(0.043)	(0.042)	(0.043)
TQ	0.061**	0.033	0.066**	0.044
	(0.029)	(0.034)	(0.028)	(0.032)
REV	3.742	1.359	3.916*	2.001
	(2.363)	(2.756)	(2.336)	(2.703)
COST	-4.481*	-1.616	-4.689*	-2.367
	(2.703)	(3.182)	(2.660)	(3.108)
NSALE	-0.006	-0.007*	-0.007**	-0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
Financial Buyer		-0.116***		-0.095**
		(0.040)		(0.040)
Other Buyer		-0.057		-0.037
		(0.040)		(0.040)
Constant	0.021	0.121*	0.007	0.082
	(0.045)	(0.064)	(0.044)	(0.063)
Observations	467	467	467	467
Adjusted R^2	0.058	0.070	0.041	0.048

Table A.3: Comparison of Productivity across Post-Sale Users of Aircraft

This table reports the differences in average user productivity for post-sale users of aircraft sold by bankrupt airlines and post-sale users of aircraft sold by non-bankrupt airlines. We measure average user productivity using the following three metrics. *Average Flying Hours* for a user averages the yearly flying hours across all the aircraft that are flown by that user. For an operator, *Residuals Flying Hours** averages residuals across all aircraft flown by the operator, where the residuals are obtained by regressing log flying hours on aircraft *Type* × *Age*, and *Year* fixed effects. For an operator, *Residuals Flying Hours*** averages residuals across all aircraft flown by the operator, where the residuals are obtained by regressing log flying hours on aircraft *Type* × *Age*, *Year*, *ln(Fleet Size)* and *ln(no. of same type aircraft)*. The last column reports the p-values for mean comparison tests between the users of bankruptcy-affected aircraft and the users of other aircraft, without the assumption of equal variance. Panel A compares our productivity measures for the complete sample. Panel B restricts the sample to users for which financial data are not available. Panel C reports comparisons across users for which financial data are available.

	Panel A: Complete Sample of Sales						
	Non-Bankruptcy Sales			Bankruptcy Sales			Difference
	Obs.	Mean	SD	Obs.	Mean	SD	p-value
Average Flying Hours	891	7.45	0.021	125	7.48	0.043	0.5206
Residuals Flying Hours*	891	-0.002	0.016	125	0.034	0.024	0.2024
Residuals Flying Hours**	891	0.058	0.015	125	0.093	0.026	0.2604
	Panel B: Subsample of Users without financial data						
	Non-Bankruptcy Sales			Bankruptcy Sales			Difference
	Obs.	Mean	SD	Obs.	Mean	SD	p-value
Average Flying Hours	454	7.18	0.035	43	7.12	0.060	0.3477
Residuals Flying Hours*	454	-0.123	0.030	43	-0.097	0.040	0.6029
Residuals Flying Hours**	454	0.041	0.027	43	0.112	0.046	0.1858
	Panel C: Subsample of Users with financial data						
	Non-Bankruptcy Sales			Bankruptcy Sales			Difference
	Obs.	Mean	SD	Obs.	Mean	SD	p-value
Average Flying Hours	433	7.74	0.016	82	7.68	0.045	0.2164
Residuals Flying Hours*	433	0.122	0.010	82	0.103	0.026	0.5052
Residuals Flying Hours**	433	0.073	0.014	82	0.083	0.033	0.7874

*Residuals demeaned for Aircraft Type × Age, and year fixed effects

**Residuals demeaned for Aircraft Type × Age, market thinness, and year fixed effects

Table A.4: Impact of Purchasing Bankruptcy-affected Aircraft on Airlines' Growth

The table shows how aircraft reallocation across firms contributes to firms' growth, and compares the post-sale users of bankruptcy-affected aircraft with the post-sale users of aircraft purchased in other sales. The following dependent variables proxy for firm growth: in column (1) *ln(Fleet Size)* is calculated as the log of the number of aircraft in the operator's fleet in a given year; in column (2) *Fleet Age* is calculated as the average age of all aircraft flown by the operator in a given year; in column (3) *Fleet Tech Age* is calculated as the average tech age of the operators' fleet in a given year. Tech Age measures aircraft technological age, and is defined as the number of years since the introduction of the underlying aircraft's type, similar to Benmelech and Bergman (2011). These variables for firm's growth prospects are regressed on previous year's firm productivity. The lagged variable, *Productivity* is defined as the average yearly flying hours of the operator across all the aircraft that are flown by that operator in the previous year. *Productivity* × *Bankruptcy User* is equal to the operator's lagged productivity if the operator purchased a bankruptcy-affected aircraft in a given year (i.e. the operator is the post-sale user of a bankruptcy-affected aircraft). *Productivity* × *Non-Bankruptcy User* is equal to the operator's lagged productivity if the operator is the post-sale user of an aircraft that is not sold in bankruptcy. The unit of observation is airline-year. The p-values of coefficient equality t-test comparing the sensitivity of productivity to firms' growth prospects for the users of bankruptcy-affected aircraft with the users of other aircraft are reported in the last row. *** denotes significance at 1%, ** at 5%, and * at 10%.

	(1)	(2)	(3)
	ln(Fleet Size)	Fleet Age	Fleet Tech Age
Productivity	0.717***	-1.625***	-1.014***
	(0.031)	(0.114)	(0.093)
Productivity × Bankruptcy User	0.214***	-0.152	-0.035
	(0.047)	(0.136)	(0.058)
Productivity × Non-Bankruptcy User	0.204***	-0.118***	-0.085**
	(0.016)	(0.043)	(0.037)
Year FE	YES	YES	YES
Observations	1,671	1,671	1,671
Adjusted R^2	0.384	0.504	0.632
(Productivity × Bankruptcy User) versus (Productivity × Non-Bankruptcy User) t-test			
p-value	0.8409	0.8071	0.4273

Table A.5: Comparison of Financial Variables across Post-Sale Users of Aircraft

This table reports the differences in lagged financial variables for post-sale users of aircraft sold by bankrupt airlines and post-sale users of aircraft sold by non-bankrupt airlines. For a user, *Tobin's Q* is measured as MVA/BVA, where the market value of assets equals the book value of assets plus the market value of common equity less the book value of common equity and deferred taxes. $Log(MPK)$ for a user is defined as the natural log of sales divided by book value of fixed assets. $Profitability$ of the user is measured as operating income before depreciation, interest and taxes scaled by lagged assets. Panel A compares the performance of users of bankruptcy-affected aircraft to users of other aircraft on these financial variables. In Panel B, we report this comparison after demeaning the financial variables using year fixed effects. The last column reports the p-values for mean comparison tests between the users of bankruptcy-affected aircraft and the users of aircraft not purchased in bankruptcy, without the assumption of equal variance.

Panel A: Financial Variables							
	Non-Bankruptcy Sales			Bankruptcy Sales			Difference
	Obs.	Mean	SD	Obs.	Mean	SD	p-value
Tobin's Q	436	1.15	0.018	82	1.33	0.035	0.0000
Log(MPK)	534	0.53	0.013	90	0.57	0.035	0.3565
Profitability	504	0.16	0.004	80	0.15	0.007	0.1093
Panel B: Financial Variables demeaned for Year Fixed Effects							
	Non-Bankruptcy Sales			Bankruptcy Sales			Difference
	Obs.	Mean	SD	Obs.	Mean	SD	p-value
Tobin's Q	436	-0.06	0.018	82	0.04	0.033	0.0102
Log(MPK)	534	-0.10	0.013	90	-0.10	0.026	0.9636
Profitability	504	0.04	0.004	80	0.05	0.007	0.1035