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Bankruptcy and the Collateral Channel

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ABSTRACT

Do bankrupt firms impose negative externalities on their nonbankrupt competitors? We propose and analyze a collateral channel in which a firm's bankruptcy reduces the collateral value of other industry participants, thereby increasing their cost of debt financing. We identify the collateral channel using novel data of secured debt tranches issued by U.S. airlines that include detailed descriptions of the underlying collateral pools. Our estimates suggest that industry bankruptcies have a sizeable impact on the cost of debt financing of other industry participants. We discuss how the collateral channel may lead to contagion effects that amplify the business cycle during industry downturns.

DO BANKRUPT FIRMS affect their solvent nonbankrupt competitors? Although a large body of research studies the consequences of bankruptcy reorganizations and liquidations for those firms that actually file for court protection (e.g., Asquith, Gertner, and Scharfstein (1994), Hotchkiss (1995), and Strömberg (2000)), little is known about the externalities that bankrupt firms impose on other firms operating in the same industry. Any such externalities would be of particular concern, as they may give rise to self-reinforcing feedback loops that amplify the business cycle during industry downturns. Indeed, the potential for contagion effects was of particular concern during the financial panic of 2007 to 2009, where insolvent bank liquidations and asset sell offs imposed "fire-sale" externalities on the economy at large (see, e.g., Kashyap, Rajan, and Stein (2008)).

In this paper, we identify one channel through which bankrupt firms impose negative externalities on nonbankrupt competitors, namely, through their impact on collateral values. We use the term "collateral channel" to describe this effect. According to the collateral channel, one firm's bankruptcy reduces the

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collateral values of other industry participants, particularly when the market for assets is relatively illiquid. Because collateral plays an important role in raising debt finance, this reduction in collateral values increases the cost and reduces the availability of external finance across the entire industry.

Theory provides two interrelated reasons for the prediction that the bankruptcy of one industry participant lowers the collateral values of other industry participants. First, a firm's bankruptcy will increase the likelihood of asset sales and hence will place downward pressure on the value of similar assets, particularly when there are frictions in the secondary market. For example, in an illiquid market, bankruptcy-induced sales of assets will create a disparity of supply over demand, causing asset prices to decline, at least temporarily (for evidence on asset fire sales, see Pulvino (1998, 1999)).[1] In the context of real estate markets, whose collapse was of crucial importance in instigating and magnifying the crisis, Campbell, Giglio, and Pathak (2009) provide evidence of spillover effects in which house foreclosures reduce the price of other houses located in the same area.

The second reason that bankruptcies will tend to reduce collateral values is related to their impact on the demand for assets. When a firm is in financial distress, its demand for industry assets will likely diminish, as the firm does not have and cannot easily raise the funding required to purchase industry assets (Shleifer and Vishny (1992), Kiyotaki and Moore (1997)). Thus, bankruptcies and financial distress reduce the demand for industry assets, again placing downward pressure on the value of collateral. Reductions in demand for assets driven by bankruptcies and financial distress are currently evident in the difficulties the Federal Deposit Insurance Corporation is encountering in selling failed banks. These difficulties have arisen because traditional buyers of failed banks—namely, other banks—are financially weak.[2]

Thus, due both to increased supply and reduced demand for industry assets, the collateral channel implies that bankruptcies increase the likelihood of asset fire sales, reducing collateral values industry wide. This weakens the balance sheet of nonbankrupt firms, thereby raising their cost of debt capital.

Empirically, a number of important outcomes have been shown to be sensitive to the announcement of the bankruptcy of industry competitors. For example, Lang and Stulz (1992) show that when a firm declares bankruptcy, on average, competitor firm stock prices react negatively. Likewise, Hertzel and Officer (2008) and Jorion and Zhang (2007) examine the effect of bankruptcy on competitors' loan yields and CDS spreads.[3]

[1] Further support for fire sales is provided by Acharya, Bharath, and Srinivasan (2007), who show that recovery rates are lower when an industry is in distress.

[2] Indeed, to partially solve this problem, the FDIC is looking outside the traditional market, at private equity funds, to infuse fresh capital into the banking system and purchase failed financial institutions. See "New Rules Restrict Bank Sales," *New York Times*, August 26, 2009.

[3] In related literature, Chevalier and Scharfstein (1995, 1996) and Phillips (1995) examine a contagion effect from firms in financial distress to other industry participants through a product market channel while Peek and Rosengren (1997, 2000) and Gan (2007a, 2007b) analyze a lending channel contagion effect from banks in distress to their corporate borrowers.

However, identifying a causal link from the financial distress or bankruptcy filings of some players in an industry to the cost of capital of these firms' solvent nonbankrupt competitors is difficult because bankruptcy filings and financial distress are potentially correlated with the state of the industry. Financial distress and bankruptcy filings themselves thus convey industry-specific information, explaining, for example, negative industry-wide stock price reactions and loan pricing effects. The question therefore remains: do bankrupt firms affect their competitors in a causal manner or do the observed adverse effects merely reflect changes in the economic environment faced by the industry at large?

Using a novel data set of secured debt tranches issued by U.S. airlines, we provide empirical support for the collateral channel. Airlines in the United States issue tranches of secured debt known as equipment trust certificates (ETCs), enhanced equipment trust certificates (EETCs), and pass-through certificates (PTCs). We construct a sample of aircraft tranche issues and then obtain the serial number of all aircraft that were pledged as collateral. For each of the debt tranches in our sample, we can identify precisely its underlying collateral. We then identify the "collateral channel" off of both the time-series variation in bankruptcy filings by airlines, and the cross-sectional variation in the overlap between the aircraft types used as collateral for a specific debt tranche and the aircraft types operated by bankrupt airlines. The richness of our data, which includes detailed information on tranches' underlying collateral and airlines' fleets, combined with the fairly large number of airline bankruptcies in our sample period, allows us to identify strategic externalities that are likely driven by a collateral channel rather than by an industry shock to the economic environment.

At heart, our identification strategy relies on analyzing the differential impact of an airline's bankruptcy on the credit spread of tranches that are secured by aircraft of different model types. According to the collateral channel hypothesis, tranches whose underlying collateral comprises model types that have a large amount of overlap with the fleet of the bankrupt airline should exhibit larger price declines than tranches whose collateral has little overlap with the bankrupt airline's fleet.

For each tranche in our sample, we construct two measures of bankruptcy-induced collateral shocks. The first measure tracks the evolution over time of the number of airlines in bankruptcy operating aircraft of the same model types as those serving as collateral for the tranche. Because airlines tend to acquire aircraft of the same model types that they already operate, an increase in the first measure is associated with a reduction in the number of potential buyers of the underlying tranche collateral. The second measure of collateral shocks tracks the number of aircraft operated by bankrupt airlines of the same model type as those serving as tranche collateral. An increase in this second measure is associated with a greater supply of aircraft on the market that are similar to those serving as tranche collateral. Increases in either of these two measures therefore tend to decrease the value of tranche collateral and hence increase credit spreads.

Using both measures, we find that bankruptcy-induced collateral shocks are indeed associated with higher tranche spreads. For example, our univariate tests show that the mean spread of tranches with no potential buyers in bankruptcy is 208 basis points, while the mean spread of tranches with at least one potential buyer in bankruptcy is 339 basis points. Moreover, our regression analysis shows that the results are robust to a battery of airline and tranche controls, as well as airline, tranche, and year fixed effects. Our identification strategy allows us to identify only price reactions to bankruptcies of other industry participants. However, through its influence on firms' cost of capital, these price effects potentially have real effects such as reducing firms' debt capacity and investment.

We further show that the effect of collateral shocks is temporary and confined to the duration of firm bankruptcies. The temporary nature of the negative externality is consistent with price pressure effects driven by the collateral channel. Still, given the long periods over which firms remain in bankruptcy, this temporary effect is sizeable. Further, because bankruptcies are more prevalent during industry downturns, the bankruptcy-induced collateral channel—while temporary—has the potential to amplify the downturn of the industry.

We continue by showing that the effect of bankruptcy-induced collateral shocks on credit spreads is higher for less senior tranches with higher loan-to-value (LTV). This is to be expected, as more junior tranches are more exposed to drops in the value of the underlying collateralized assets upon default. Next, we analyze the interaction between the collateral channel and airline financial health. Because airlines in poor financial health are more likely to default, the spread of these tranches should be more sensitive to underlying tranche liquidation values. Measuring financial health using either airline profitability or a model of airline predicted probability of default, we find that the effect of collateral shocks on tranche spreads is more pronounced in high LTV tranches of airlines in poor financial health. Finally, we analyze the interaction between collateral shocks and the redeployability of tranche underlying collateral and find that the positive relation between the number of potential buyers of tranche collateral that are in bankruptcy and tranche credit spreads is lower for tranches with more redeployable collateral.

Using a host of robustness tests and analysis, we show that our results are not driven by underlying industry conditions or by other forms of potential contagion unrelated to the collateral channel. For example, we show that our results are not likely driven by sales pressure stemming from binding balance sheet constraints of ETC and EETC security holders, nor are they likely driven by reverse causality in which adverse shocks to the productivity of certain aircraft results in the bankruptcies of those airlines using these aircraft as well as an increase in the cost of capital for other users of these aircraft. Further, our results are not driven by the provision of credit enhancement in the form of a liquidity facility.

The rest of the paper is organized as follows. Section I provides the theoretical framework for the analysis and explains our identification methodology.

Section II provides institutional details on the market for ETCs and EETCs. Section III describes our data and the empirical measures. Section IV presents the empirical analysis of the relation between bankruptcy-induced collateral shocks and credit spreads. Section V concludes.

I. Identification Strategy

To analyze the collateral channel we focus on a single industry—airlines—and employ a unique identification strategy. This strategy involves using information on collateral characteristics, collateral pricing, and the timing of airline bankruptcies in the following manner. Airlines in the United States issue tranches of secured debt to finance their operations. The debt is secured by a pool of aircraft serving as collateral. Using filing prospectuses, we identify the model type of all aircraft that serve as collateral in each pool. For each tranche, we obtain a time series of prices and obtain the dates and durations of all bankruptcy filings of airlines in the United States during the years 1994–2007.

In essence, our identification strategy consists of analyzing the differential impact of an airline's bankruptcy on the price of tranches that are secured by aircraft of different model types. The collateral channel hypothesis predicts that tranches whose underlying collateral comprises model types that have a large degree of overlap with the fleet of the bankrupt airline should exhibit larger price declines than tranches whose collateral has little overlap with the bankrupt airline's fleet. As explained above, an airline's bankruptcy and the increased likelihood of the sale of part or all of the airline's fleet will place downward pressure on the value of aircraft of the same model type. Furthermore, as in Shleifer and Vishny (1992), because demand for a given aircraft model type stems to a large extent from airlines that already operate that model type, an airline's financial distress and bankruptcy will reduce demand for the types of aircraft that it operates in its fleet. For these two reasons—both increased supply of aircraft in the used market and reduced demand for certain aircraft—tranches secured by aircraft of model types exhibiting larger overlaps with the model types of the bankrupt airline's fleet should experience larger price declines.

By using variation in the fleets of airlines going bankrupt and their degree of overlap with the type of aircraft serving as collateral for secured debt of other airlines, we can thus identify a collateral channel through which one firm's bankruptcy affects other firms in the same industry. Because we rely on the differential impact of bankruptcy on the credit spreads of tranches secured by aircraft of different model types *within* an airline, this identification strategy alleviates concerns that the results are driven by an information channel effect in which bankruptcies convey negative information common to all firms in the industry. Moreover, we test our evidence for the collateral channel against alternative contagion-based explanations. For example, we show that our results are not driven by contagion through credit enhancers or through holders of tranche securities.

In the next section, we describe in further detail the debt instruments used by airlines to issue secured debt and their development over time.

II. Airline Equipment Trust Certificates

ETCs and EETCs are aircraft asset-backed securities (ABS) that have been used since the early 1990s to finance the acquisitions of new aircraft.[4] Aircraft ABSs are subject to Section 1110 protection, which provides relief from the automatic stay of assets in bankruptcy to creditors holding a secured interest in aircraft, strengthening the creditor rights of the holders of these securities.

The U.S. Bankruptcy Code began to treat aircraft financing favorably in 1957, but it was not until 1979 that Congress amended the Bankruptcy Code and introduced Section 1110 protection, which provides creditors relief from the automatic stay. On October 22, 1994, the Bankruptcy Code was further amended, and the rights of creditors under Section 1110 were strengthened. The changes in the Bankruptcy Code increased the protection that Section 1110 provided to secured creditors and reduced the potential threat of legal challenge to secured aircraft.

This legal innovation affected the practice of secured lending in the airline industry. The market for ETCs expanded and new financial innovations such as EETCs soon became the leading source of external financing of aircraft. The amendments to Section 1110 led Moody's to revise its ratings criteria such that securities that were issued after the enactment date received a rating up to two notches above issuing airlines' senior unsecured rating.

In a traditional ETC, a trustee issues ETCs to investors and uses the proceeds to buy the aircraft, which is then leased to the airline. Lease payments are then used to pay principal and interest on the certificates. The collateral of ETCs typically includes only one or two aircraft. For example, on August 24, 1990, American Airlines issued an ETC (1990 ETCs, Series P) maturing on March 4, 2014. The certificates were issued to finance approximately 77% of the equipment cost of one Boeing 757-223 (serial number 24583) passenger aircraft, including engines (Rolls-Royce RB211-535E4B). The proceeds from the ETC issue were $35.5 million, with a serial interest rate of 10.36% and a credit rating of A (S&P) and A1 (Moody's).

Increasing issuance costs led to the development of PTCs, which pooled a number of ETCs into a single security that was then backed by a pool of aircraft rather than just a single one. Although PTCs increased diversification and reduced exposure to a single aircraft, the airline industry downturn in the early 1990s led to downgrades of many ETCs and PTCs to below investment grade and subsequently to a narrowed investor base.

During the mid-1990s, ETCs and PTCs were further modified into EETCs—which soon became the leading source of external finance of aircraft. EETC

[4] Our discussion here draws heavily from Littlejohns and McGairl (1998), Morrell (2001), and Benmelech and Bergman (2009), who provide an extensive description of the market for airline ETCs and its historical evolution.

securitization has three main advantages compared to traditional ETCs and PTCs. First, EETCs have larger collateral pools with more than one aircraft type, making them more diversified. Second, EETCs typically have several tranches with different seniority. Third, a liquidity facility, provided by a third party such as Morgan Stanley Capital Services, ensures the continued payment of interest on the certificates for a predetermined period following a default, typically for a period of up to 18 months. EETC securitization therefore enhances the creditworthiness of traditional ETCs and PTCs by reducing bankruptcy risk, tranching the cash flows, and providing temporary liquidity in the event of default.

Because of the varying LTVs, credit ratings, and yields associated with different tranches of EETCs, they are purchased by both investment grade and high yield institutional investors. These include insurance companies, pension funds, mutual funds, hedge funds, and money managers. Although the market for EETCs is not as liquid as that for corporate bonds, it is more liquid than the market for bank loans (see Mann (2009)).

Table I presents the characteristics and structures of three EETC issues in our sample. There are several tranches in each of the EETCs in Table I. For each tranche, we report the issue size (in $ million), yield, spread (in basis points), final maturity date, Moody's and S&P tranche-specific credit rating, cumulative LTV, and collateral description. For example, in the first EETC in the table (Fedex 1998-1), the most senior tranche (1-A) has a credit rating of Aa2/AAA, a cumulative LTV ratio of 38.7%, and a credit spread of 125 basis points over the corresponding Treasury. The least senior tranche in the Fedex 1998-1 issue (1-C) has a lower credit rating (Baa1/BBB+), a higher cumulative LTV ratio (68.8%), and a credit spread of 155 basis points. All three tranches of Fedex 1998-1 are secured by the same pool of assets, namely, five McDonnell Douglas MD-11F and eight Airbus A300F4-605R.

III. Data and Summary Statistics

A. Sample Construction

We use Securities Data Company (SDC) Platinum to identify all secured tranches, ETCs, PTCs, and EETCs issued by firms with four-digit SIC codes 4512 (Scheduled Air Transportation), 4513 (Air Courier Services), and 4522 (Nonscheduled Air Transport) between January 1990 and December 2005. This results in 235 debt tranches issued in U.S. public markets. We collect data on tranche characteristics (i.e., issue size, seniority, final maturity, and whether the tranche is callable) from SDC Platinum.

We supplement the SDC data with information collected from tranche filing prospectuses obtained from EDGAR Plus (R) and Compact Disclosure. For each tranche, we obtain the serial number of all aircraft that were pledged as collateral from the filing prospectus. We are able to find full information about the aircraft collateral securing the issues for 198 public tranches. We match each aircraft serial number to the Ascend CASE airline database, which

Table I

EETC Structures

This table displays the characteristics of three EETC issues by FedEx, Northwest Airlines, and Delta Airlines. Yield at issue, credit spread, credit ratings (both Moody's and S&P), and LTV are measured as the initial values at the date of the issue. Detailed variable definitions are provided in Appendix B.

EETC	Tranche	Issue Size	Yield at Issue (%)	Credit Spread (Basis Points)	Maturity	Moody's Rating	S&P Rating	LTV	Collateral
Fedex 1998-1	1-A	458.1	6.720	125	1/2022	Aa2	AAA	0.387	5 MD-11F 8 A300F4-605R
Fedex 1998-1	1-B	178.6	6.845	138	1/2019	A1	AA−	0.532	5 MD-11F 8 A300F4-605R
Fedex 1998-1	1-C	196.8	7.020	155	1/2016	Baa1	BBB+	0.688	5 MD-11F 8 A300F4-605R
NWA 1999-3	G	150.2	7.935	170	6/2019	Aaa	AAA	0.441	14 BAE Avro RJ85
NWA 1999-3	B	58.6	9.485	325	6/2015	Baa2	BBB	0.614	14 BAE Avro RJ85
NWA 1999-3	C	30.5	9.152	300	6/2010	Baa3	BBB−	0.691	14 BAE Avro RJ85
Delta 2002-1	G-1	586.9	6.718	153	1/2023	Aaa	AAA	0.519	17 B737-832 1 B757-232 8 B767-332ER 6 B767-432ER
Delta 2002-1	C	168.7	7.779	325	1/2012	Baa2	A−	0.611	17 B737-832 1 B757-232 8 B767-332ER 6 B767-432ER

contains ownership information, operating information, and information on aircraft characteristics for every commercial aircraft in the world.

We obtain tranche transactions data from the Fixed-Income Securities Database (FISD) compiled by Mergent, which is considered to be the most comprehensive source of bond prices (see Korteweg (2007) for a detailed description of the Mergent data). The National Association of Insurance Commissioners (NAIC) requires insurance companies to file all their trades in bonds with the NAIC. All transactions in our data set therefore represent trades in which at least one party was an insurance company.

Each observation of a transaction provides the flat price at which the transaction was made. We convert these prices into spreads by calculating the appropriate yield to maturity at the date of transaction, and then subtracting the yield of the duration-matched Treasury.[5] For better comparability across tranches, we exclude from our sample tranches that were issued as floating rate debt.

We match each tranche transaction to the relevant airline's previous-year characteristics (i.e., size, market-to-book, profitability, and leverage) using Compustat data. Finally, we use Thomson's SDC Platinum Restructuring database to identify airlines that are in Chapter 7 or Chapter 11 bankruptcy procedures. Our final sample consists of 18,327 transactions in 127 individual tranches, representing 12 airlines during the period January 1, 1994 to December 31, 2007.

B. Tranche and Airline Characteristics

Panel A of Table II provides summary statistics for the 127 tranches in our sample. Summary statistics are calculated over the entire sample and are therefore weighted by the number of transaction observations per tranche. Throughout our analysis, we use the tranche spread as our dependent variable. As Panel A shows, the mean tranche spread is 290.2 basis points and the standard deviation is 311 basis points. The mean tranche size in our sample is \$274.4 million, with an average term-to-maturity of 16.9 years. There are at most four different layers of tranche seniority within an issue (where seniority = 1 for most senior tranches and 4 for most junior). Further, as Panel A shows, 68% of the tranches in our sample are amortized, while 75% of the tranches in our sample have a liquidity facility—a feature common in EETCs. Finally, the average tranche LTV ratio at time of issue is 0.54, ranging between 0.33 and 0.89.

Panel B of Table II provides summary statistics for the issuing airlines. The size of the average airline in our sample, as measured by the book value of assets, is \$14.2 billion. The average airline market-to-book ratio is 1.26, while the average profitability and leverage are 8.24% and 37%, respectively.

[5] To calculate tranche yields, we distinguish between tranches that are amortized and those that have a balloon payment at maturity. These data are collected by reading the prospectuses of each issue.

Table II

Summary Statistics

This table provides descriptive statistics for the variables used in the empirical analysis. Panel A displays tranche characteristics, Panel B provides airline characteristics, Panel C provides tranche redeployability characteristics, and Panel D presents industry-level controls. Variable definitions are provided in Appendix B.

	Mean	25th Percentile	Median	75th Percentile	Standard Deviation	Min	Max
Panel A: Tranche Characteristics							
Spread	290.2	153.6	229.4	330.8	311	16.9	4,206.6
Tranche Size ($m)	274.4	127.0	207.1	385.8	181.2	3.5	828.8
Term to Maturity	16.9	14.5	18.1	20.2	4.5	1.7	24.3
Seniority	1.3	1.00	1.00	1.00	0.61	1.00	4.00
Call Provision	0.16	0.00	0.00	0.00	0.37	0.00	1.00
Amortized	0.68	0.00	1.00	1.00	0.47	0.00	1.00
Liquidity facility	0.75	0.00	1.00	1.00	0.43	0.00	1.00
LTV	0.54	0.41	0.49	0.66	0.16	0.33	0.89
Panel B: Airline Characteristics							
Size ($m)	14,151.5	9,201.0	10,877.0	20,404.0	6.972.4	1,134.9	32,841.0
Market-to-Book	1.26	1.03	1.18	1.43	0.29	0.76	2.51
Profitability	8.24%	3.55%	10.39%	13.13%	6.76%	−12.10%	23.70%
Leverage	0.37	0.18	0.40	0.52	0.17	0.03	0.658
Panel C: Redeployability Measures							
Redeployability (# of aircraft)	1,392.9	424.7	1,046.2	2,345.4	1,016.0	72.0	4,264
Redeployability (# of operators)	135.9	48.8	87.0	223.5	99.9	7.0	431.0
Panel D: Airline Industry Variables							
Jet Fuel Price	107.8	70.9	84.4	146.6	55.1	29.6	280.5
Bankrupt Airlines	5.1	4.0	6.0	6.0	2.2	0.0	8.0
Healthy Airlines	62.0	58.0	62.0	65.0	4.1	51	73
Bankrupt Assets/ Total Assets	0.075	0.060	0.083	0.095	0.033	0.000	0.119
Healthy Assets/ Total Assets	0.925	0.905	0.917	0.940	0.033	0.881	1.000

As in Benmelech and Bergman (2008, 2009) and Gavazza (2008), we measure the redeployability of aircraft by exploiting aircraft model heterogeneity.[6] The redeployability measures are based on the fact that airlines tend to operate a limited number of aircraft models, implying that potential secondary market buyers of any given type of aircraft are likely to be airlines already operating

[6] Appendix A provides a detailed description of the construction of this redeployability measure, while Appendix B provides a description of the construction and data sources for all variables used in the paper.

the same type of aircraft. Redeployability is therefore proxied by the number of potential buyers and the "popularity" of an aircraft model type.

Using the Ascend CASE database, we construct two redeployability measures in the following manner. For every aircraft type and sample year, we compute 1) the number of nonbankrupt operators flying that aircraft model type, and 2) the number of aircraft of that type used by nonbankrupt operators. This process yields two redeployability measures for each aircraft type and each sample year. To construct the redeployability measures for a portfolio of aircraft serving as collateral for a particular tranche, we calculate the weighted average of each redeployability measure across all aircraft in the collateral portfolio. For weights in this calculation, we use the number of seats in an aircraft model type—a common proxy for aircraft size (and value). Panel C of Table II provides descriptive statistics for our two redeployability measures. As can be seen, the redeployability measure based on number of aircraft has an average value of 1,392.9 aircraft. Furthermore, on average, there are 135.9 potential buyers for aircraft serving as collateral for secured tranche issue.

Finally, we add additional variables that capture the health of the airline industry. These variables are jet fuel price, number of bankrupt airlines, number of nonbankrupt or healthy airlines, the book value of bankrupt airlines divided by the book value of all airlines, as well as the book value of nonbankrupt airlines divided by the book value of all airlines. Panel D reports summary statistics for each of these variables.

C. Identifying Bankruptcy Shocks

We construct two measures of shocks to collateral driven by airlines entering bankruptcy. For each aircraft type and calendar day in our sample, we calculate (1) the number of airlines operating that particular model type that are in bankruptcy, *Bankrupt Buyers*, and (2) the number of aircraft of that particular type that are operated by airlines in bankruptcy, *Bankrupt Aircraft*.[7] Increases in the first measure capture reductions in demand for a given model type, as airlines tend to purchase aircraft of model types that they already operate. Increases in the second measure are associated with an increase in the supply of a given aircraft model type likely to be sold in the market as bankrupt airlines liquidate part or all of their fleets. Because changes in aircraft ownership are relatively infrequent, ownership information of aircraft is updated at a yearly rather than daily frequency. However, the two measures may change at a daily frequency due to airlines entering or exiting bankruptcy. In Appendix A, Figures A1 and A2 provide a timeline of airline bankruptcies in the United States and the total number of aircraft operated by bankrupt U.S. airlines over the sample period.

Figures 1 and 2 provide a graphic illustration of the two measures for the Boeing 737 and Boeing 747 model types. For each model type, the figures thus show the evolution over time of the number of operators in bankruptcy

[7] We calculate these measures using beginning and end dates of airline bankruptcies in the United States from SDC Platinum.

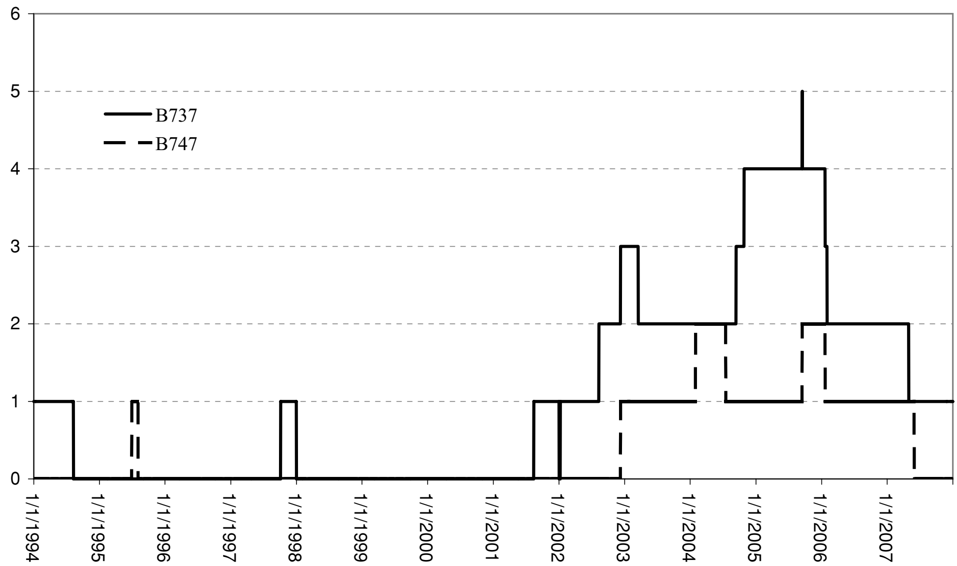

Figure 1. Total number of bankrupt potential buyers for Boeing 737 and Boeing 747. An airline is considered to be a potential buyer of a particular aircraft if in its fleet it operates aircraft of the same model type. Fleet data are obtained from the Ascend CASE database. Airline bankruptcy dates are obtained from SDC Platinum.

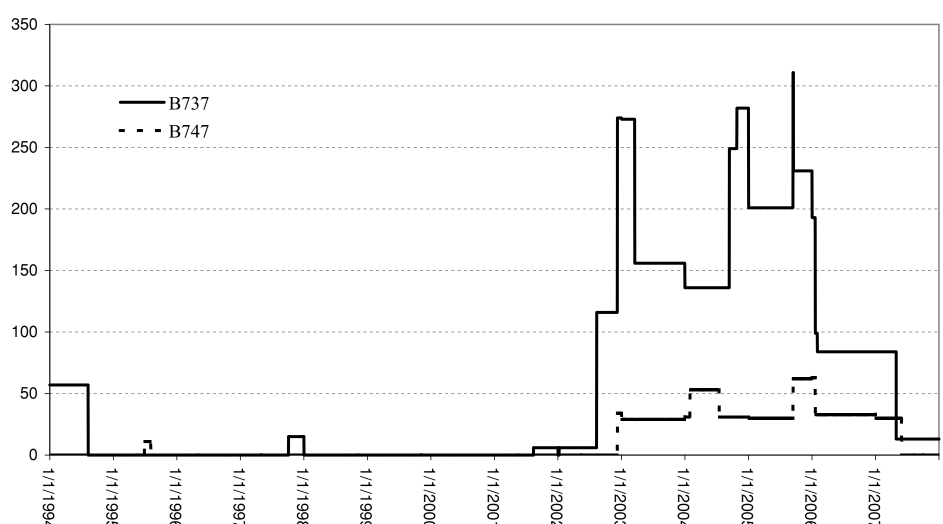

Figure 2. Total number of Boeing 737 and Boeing 747 aircraft operated by bankrupt airlines in the United States. Fleet data are obtained from the Ascend CASE database. Airline bankruptcy dates are obtained from SDC Platinum.

that operate each of these models, as well as the number of aircraft operated by bankrupt airlines. The figures clearly show the deterioration of industry conditions in the latter part of the sample period. Further, while there are some commonalities in the trends between the model types, there are also large differences between model types in both measures. Thus, for example, while the number of bankrupt B747 aircraft increased during the first part of 2004, the number of bankrupt B737 aircraft decreased during this period. This variation between model types stems from bankruptcies of airlines operating different fleets composed of different model types. As discussed in Section I, it is this variation, and the differences in the types of aircraft used as collateral, that enables identification of the collateral channel.

To construct the two bankruptcy measures for a portfolio of aircraft serving as collateral for a particular tranche, we calculate the weighted average of the aircraft type measures across all aircraft in the portfolio, using the number of seats in each aircraft as weights.

Panel A of Table III provides summary statistics for the two measures, and Panels B and C display the evolution of the bankrupt buyers and bankrupt aircraft measures over time, respectively. As can be seen, over the entire sample period, the average value of *Bankrupt Buyers* is 0.809, indicating that the average aircraft in a tranche had 0.809 potential buyers that were in bankruptcy. Similarly, the average value of *Bankrupt Aircraft* is 43.86 aircraft, indicating that there were 43.86 aircraft operated by bankrupt airlines of the same model type as the average aircraft serving as collateral in a debt tranche.

IV. Empirical Analysis

A. *Univariate Analysis*

As an initial step, it is instructive to conduct the analysis using simple comparison-of-means tests. Panel A of Table IV displays average tranche credit spreads of both bankrupt and nonbankrupt airlines. There are 1,011 transactions in 43 tranches of four bankrupt airlines. As would be expected, credit spreads of tranches issued by airlines that are currently in bankruptcy are higher than spreads of solvent airlines. The mean credit spread of a bankrupt airline is 531.7 basis points compared to a mean tranche spread of 276.1 basis points for nonbankrupt airlines (t-statistic for an equal means test = 2.81).

As a first and simple test of the credit channel, we focus only on airlines that are *not* in bankruptcy, and split this subsample between airlines with fleets that do not have any potential buyers that are in bankruptcy, and airlines with at least one bankrupt potential buyer for their fleet. As described in the previous section, an airline is considered to be a potential buyer of a particular aircraft if in its fleet it operates aircraft of the same model type. Focusing only on nonbankrupt firms ensures that credit spreads are not contaminated by the direct association of bankruptcy and credit spreads.

Of the 17,316 transactions in nonbankrupt airlines' tranches, there are 8,324 transactions with no potential collateral buyers that are in bankruptcy, and

Table III

Bankrupt Buyers and Bankrupt Aircraft Measures

This table provides descriptive statistics for the bankrupt buyers and bankrupt aircraft measures used in the empirical analysis. Panel A displays statistics for the entire sample, while Panels B and C provide statistics for different sample periods for each of the measures. Details on the construction of the *Bankrupt Buyers* and *Bankrupt Aircraft* measures are provided in Appendix B.

	Mean	25th Percentile	Median	75th Percentile	Standard Deviation	Min	Max	
Panel A: Bankrupt Buyers and Number of Aircraft in Bankruptcy								
Bankrupt Buyers	0.809	0.0	0.269	1.571	1.027	0.0	5.0	
Bankrupt Aircraft	43.860	0.0	2.628	86.177	63.275	0.0	311.0	
Panel B: Bankrupt Buyers over Time								
1994–2000	0.013	0.0	0.0	0.0	0.077	0.0	1.0	4,814
2001	0.324	0.0	0.244	0.528	0.348	0.0	1.0	3,421
2002	0.578	0.0	0.396	1.0	0.648	0.0	3.0	3,056
2003	1.411	0.608	1.725	2.161	0.872	0.0	3.0	2,937
2004	1.604	0.533	1.732	2.299	1.171	0.0	4.0	2,497
2005	2.058	0.105	2.167	3.336	1.483	0.0	5.0	1,826
2006	1.023	0.0	1.309	1.732	0.864	0.0	4.0	2,834
2007	0.372	0.0	0.0	0.619	0.514	0.0	2.0	1,003
Panel C: Bankrupt Aircraft over Time								
1994–2000	0.227	0.0	0.0	0.0	1.859	0.0	57	4,814
2001	3.042	0.0	1.461	5.751	3.817	0.0	17	3,421
2002	23.832	0.0	2.388	52.851	39.208	0.0	274	3,056
2003	93.286	31.529	111.585	128.242	61.598	0.0	273	2,937
2004	91.445	13.0	96.509	118.132	70.884	0.0	282	2,497
2005	110.021	3.206	117.976	182.282	83.939	0.0	311	1,826
2006	63.323	0.0	73.0	93.846	54.236	0.0	264	2,834
2007	14.885	0.0	0.0	8.947	34.126	0.0	181	1,003

8,992 transactions with at least one bankrupt potential collateral buyer. Panel B of Table IV compares credit spreads of tranches that do not have any bankrupt potential buyers and tranches with at least some bankrupt potential buyers for their pledged collateral. As can be seen in the table, the mean tranche credit spread of a nonbankrupt airline that has no bankrupt buyers is 208.0 basis points compared to a mean tranche spread of 339.0 basis points for nonbankrupt airlines with some bankrupt potential buyers (t-statistic for an equal means test = 7.48). Thus, consistent with a collateral channel, tranches of airlines secured by collateral with potential buyers that are in bankruptcy have a lower value than tranches for which all potential buyers are not in bankruptcy.

While still focusing only on nonbankrupt airlines, Panel C of Table IV refines the analysis in Panel B by conditioning the credit spread differential on tranche seniority levels. We conjecture that the collateral effect will be more pronounced in more junior tranches due to their higher sensitivity to the value of the

Table IV

Bankruptcy, Bankrupt Buyers, and Tranche Credit Spreads: Univariate Analysis

This table provides univariate analysis of tranche credit spreads: Panel A segments credit spreads of tranches of nonbankrupt and bankrupt airlines, Panel B focuses on nonbankrupt airlines and compares tranche credit spreads of tranches with a positive bankrupt buyer measure and those with a bankrupt buyer measure equal to zero, while Panel C stratifies the analysis in Panel B by tranche seniority, and reports means and t-statistics for t-tests of equal means using standard errors that are clustered at the tranche level.

Panel A: Tranche Credit Spreads of Bankrupt and Nonbankrupt Airlines: Summary Statistics

	Mean	10th Percentile	25th Percentile	Median	75th Percentile	Standard Deviation	Observations
Bankrupt Airlines	531.7	135.1	188.4	317.4	592.4	649.9	1,011
Nonbankrupt Airlines	276.1	94.2	152.6	226.1	322.7	273.3	17,316
Difference	255.6						
T-test for equal means	(2.81)						

Panel B: Tranche Credit Spreads of Nonbankrupt Airlines: Summary Statistics

	Mean	10th Percentile	25th Percentile	Median	75th Percentile	Standard Deviation	Observations
Bankrupt Buyers>0	339.0	135.9	197.7	271.7	363.4	336.1	8,992
No Bankrupt Buyers	208.0	75.4	129.4	177.1	253.3	156.3	8,324
Difference	131.0						
T-test for equal means	(7.48)						

Panel C: Tranche Credit Spreads of Nonbankrupt Airlines and Seniority: Means and T-tests

	1	2	3	4	Diff (2-1) (T-test)	Diff (3-1) (T-test)	Diff (4-1) (T-test)
Bankrupt Buyers>0	302.5	419.2	474.9	1,444.9	116.7	172.47	1,142.5
(Observations)	(6,755)	(1,613)	(590)	(34)	(3.79)	(2.81)	(7.54)
No Bankrupt Buyers	207.5	223.7	177.5	332.0	16.3	30.03	124.5
(Observations)	(6,481)	(1,187)	(625)	(31)	(0.51)	(1.86)	(4.77)
Difference	95.0	195.5	297.4	1,112.9			
T-test for equal means	(5.70)	(4.08)	(5.15)	(6.79)			

underlying collateral. Panel C splits the sample into four levels of seniority (1 = most senior, 4 = most junior) and compares the mean credit spread between tranches with no bankrupt potential buyers and tranches with some bankrupt potential buyers for each of the seniority levels. The first four columns of the panel report credit spreads and number of observations in each category (in parentheses), as well as t-tests for an equal means test across and within seniority levels.

As Panel C of Table IV demonstrates, the difference between credit spreads of tranches with and without bankrupt potential buyers is the highest among the most junior tranches, and decreases monotonically with tranche seniority. For the most senior tranches, the spread difference is 95.0 basis points, while the differences for seniority levels 2 and 3 (i.e., mezzanine seniority) are 195.5 basis points and 297.4 basis points, respectively. Finally, among the most junior tranches, the spread differential is much higher and equal to 1,112.9 basis points. All differences are statistically significant at the 1% level.

In the last three columns of Panel C of Table IV, we use a difference-in-differences approach. In each of these columns, we report the difference between the mean credit spreads of tranches with different seniority (1 vs. 2, 1 vs. 3, and 1 vs. 4) and the corresponding t-values for equal means tests. These differences in seniority-based credit spreads are reported separately for tranches with bankrupt potential buyers for their underlying collateral and for tranches without bankrupt potential buyers. As can be seen in the table, we find that the seniority differential in spreads is much higher for tranches with some bankrupt potential buyers. As the last column of Panel C demonstrates, among tranches with no bankrupt potential buyer, the spread differential between the most and least senior tranches is a statistically significant 124.5 basis points. In contrast, moving from the most senior to most junior tranches with some bankrupt potential buyers is associated with a spread increase of a statistically significant 1,142.5 basis points.

B. Regression Analysis

We begin with a simple test of the collateral channel hypothesis by estimating different variants of the following baseline specification:

$$\begin{aligned} Spread_{i,a,t} = {} & \beta_1 \times \log(1 + Bankrupt\,Buyers)_{i,a,t} + \beta_2 \times Bankruptcy_{i,a,t} \\ & + \beta_3 \times \log(1 + Redeployability)_{i,a,t} + \mathbf{X}_{i,a,t}\boldsymbol{\gamma} + \mathbf{b}_i\boldsymbol{\delta} + \mathbf{c}_a\boldsymbol{\eta} + \mathbf{d}_y\boldsymbol{\theta} \\ & + (Bankruptcy_{i,a,t} \times \mathbf{b}_i)\boldsymbol{\kappa} + (Bankruptcy_{i,a,t} \times \mathbf{c}_a)\boldsymbol{\psi} + \epsilon_{i,a,t}, \end{aligned} \tag{1}$$

where *Spread* is the tranche credit spread; subscripts indicate tranche (i), airline (a), and transaction date (t); *Bankrupt Buyers* is the weighted average of the number of bankrupt operators currently using the collateral pool; *Bankruptcy* is a dummy variable that equals one if the issuer of the tranche is bankrupt on the date of the transaction; *Redeployability* is one of our two measures of the redeployability of the collateral pool; $\mathbf{X}_{i,a,t}$ is a vector of tranche characteristics that includes an amortization dummy, a dummy for tranches with liquidity facility, ranking of the tranche seniority, tranche issue size, a dummy for tranches with a call provision, and the tranche term-to-maturity; $\mathbf{b}_i$ is a vector of tranche fixed effects; $\mathbf{c}_a$ is a vector of airline fixed effects; $\mathbf{d}_y$ is a vector of year fixed effects; $Bankruptcy_{i,a,t} \times \mathbf{b}_i$ is a vector of interaction terms between tranche fixed effects and the bankruptcy dummy; $Bankruptcy_{i,a,t} \times \mathbf{c}_a$ is a vector of interaction terms between airline fixed effects and the bankruptcy

Table V

Bankruptcy and Collateral

The table presents coefficient estimates and standard errors (in parentheses) for credit spread regressions. Panel A uses the *Bankrupt Buyers* measure while Panel B uses the *Bankrupt Aircraft* measure. For each specification, Panel C of the table provides estimates of the magnitude of the economic effect of either a one standard deviation move or a 25th to 75th percentile movement in the *Bankrupt Buyers* and *Bankrupt Aircraft* measures on tranche credit spread. All regressions include an intercept, yield curve, and default spread controls (short rate, term spread, and default spread). Standard errors are calculated by clustering at the tranche level. Variable definitions are provided in Appendix B. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Bankrupt Buyers						
Dependent Variable =	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread
Bankrupt Buyers	246.491***	151.619***	106.162***	93.614***	119.030***	118.937***
	(28.700)	(31.387)	(27.299)	(27.124)	(28.302)	(27.505)
Bankruptcy	126.600*	168.670**	144.448**	21.485	184.451***	565.409***
	(76.610)	(67.129)	(65.772)	(30.607)	(70.037)	(28.287)
Redeployability	−71.718***	−50.960***	−97.386***	−80.352**	−5.850	20.889
(operators)	(14.019)	(13.592)	(27.094)	(26.466)	(58.415)	(56.732)
Adjusted R^2	0.16	0.22	0.27	0.28	0.38	0.48
Panel B: Bankrupt Aircraft						
Bankrupt Aircraft	53.790***	26.479***	20.706***	20.323***	25.522***	26.574***
	(10.796)	(7.765)	(6.117)	(6.124)	(5.994)	(5.683)
Bankruptcy	116.066	172.344**	133.336**	9.531	182.755**	566.077***
	(80.416)	(68.805)	(66.294)	(29.499)	(70.569)	(26.773)
Redeployability	−46.139***	−21.955**	−83.065***	−73.395***	−60.464	−27.262
(aircraft)	(10.796)	(11.323)	(21.943)	(21.183)	(62.818)	(61.984)
Adjusted R^2	0.15	0.21	0.27	0.28	0.37	0.48
Fixed Effects						
Year	No	Yes	Yes	Yes	Yes	Yes
Airline	No	No	Yes	Yes	No	No
Airline × Bankruptcy	No	No	No	Yes	No	No
Tranche	No	No	No	No	Yes	Yes
Tranche × Bankruptcy	No	No	No	No	No	Yes
# of Tranches	127	127	127	127	127	127
# of Airlines	12	12	12	12	12	12
Observations	18,327	18,327	18,327	18,327	18,327	18,327
Panel C: Magnitude of the Collateral Channel (in Basis Points)						
Bankrupt Buyers						
One σ change	253.15	155.71	109.03	96.14	122.24	122.15
25%–75% change	387.24	238.19	166.78	147.07	187.00	186.85
Bankrupt Aircraft						
One σ change	114.45	56.34	44.06	43.24	54.30	56.54
25%–75% change	240.33	118.31	92.51	90.80	114.03	118.73

dummy; and $\epsilon_{i,a,t}$ is the regression residual. We report the results from estimating different variants of regression (1) in Panel A of Table V. For brevity, we do not report the coefficients of the tranche characteristics in this table—we investigate their effects in the next tables. Standard errors (reported in parentheses) are clustered at the tranche level throughout.

The first column in Panel A Table V reports the coefficients from estimating a simple version of regression (1), without any of the fixed effects or the interaction terms. As would be expected, tranche spreads of airlines in bankruptcy are higher than those of airlines not in bankruptcy—the coefficient on the bankruptcy dummy, β_2, equals 126.6 and is statistically significant. Further, consistent with Benmelech and Bergman (2009), we find that more redeployable collateral, proxied by the number of world-wide operators using the collateral pool, is associated with lower spreads. Finally, after controlling for bankruptcy and redeployability, and consistent with a collateral channel, β_1 is positive and significant at the 1% level. Increases in the number of bankrupt potential buyers for a given collateral pool—and hence commensurate reductions in the demand for the assets in that pool—are associated with larger tranche credit spreads. The economic effect of the collateral channel is sizeable—as Panel C shows, moving from the 25th percentile to the 75th percentile of the number of bankrupt buyers results in a credit spread that is 387.2 basis points higher.

In the rest of the specifications reported in Panel A, we add year and either tranche or airline fixed effects, and in some specifications include interactions between tranche or airline fixed effects and the bankruptcy dummy to soak up any direct effect of bankruptcy on tranche spreads. As can be seen, the coefficient on the number of bankrupt buyers, β_1, is consistently positive and statistically significant at the 1% level. Although the estimate of β_1 is lower in these specifications, it is still economically significant: as Panel C shows, moving from the 25th percentile to the 75th percentile of the number of bankrupt buyers in these specifications results in a credit spread that is 147.1 to 238.2 basis points higher.

Panel B of Table V repeats the analysis in Panel A using our second measure of shocks to collateral values, *Bankrupt Aircraft*, which is based on the number of aircraft operated by bankrupt airlines that overlap with the collateral channel. As can be seen, an increase in the number of aircraft operated by bankrupt airlines is associated with higher credit spreads of tranches employing similar aircraft model types as collateral. Although the magnitudes of the coefficients are smaller than those using the *Bankrupt Buyers* measure (see Panel C), the results are still statistically and economically significant.

C. The Collateral Channel: Evidence from Prices of Nonbankrupt Airlines' Tranches

The analysis presented in Table V shows that bankrupt potential buyers of collateral lead to higher credit spreads, controlling for bankruptcy status and for interaction terms between being in bankruptcy, and airline and tranche fixed effects. Although these specifications are likely to soak up non-time-varying effects related to the bankruptcy status of a tranche, we now move on to focusing only on nonbankrupt airlines. Thus, we refine our analysis by focusing on tranches of nonbankrupt airlines and examine how, while solvent, their credit spreads respond to the bankruptcy of airlines operating fleets comprised of model types that overlap with the tranche collateral pool. We estimate different variants of the following specification:

$$\begin{aligned} Spread_{i,a,t} = {} & \beta_1 \times \log(1 + Bankrupt\,Buyers)_{i,a,t} + \beta_2 \times \log(1 + Redeployability)_{i,a,t} \\ & + \mathbf{I}_t \boldsymbol{\tau} + \mathbf{X}_{i,a,t} \boldsymbol{\gamma} + \mathbf{Z}_{a,y-1} \boldsymbol{\xi} + \mathbf{R}_t \boldsymbol{\pi} + \mathbf{b}_i \boldsymbol{\delta} + \mathbf{c}_a \boldsymbol{\eta} + \mathbf{d}_y \boldsymbol{\theta} + \epsilon_{i,a,t} \\ & for\, all\, Bankruptcy_{i,a,t} = 0, \end{aligned} \tag{2}$$

where *Spread* is the tranche credit spread; subscripts indicate tranche (i), airline (a), and transaction date (t); *Bankrupt Buyers* is a weighted average of the number of bankrupt operators currently using the collateral pool; *Bankruptcy* is a dummy variable that equals one if the issuer of the tranche is bankrupt on the date of the transaction; *Redeployability* is one of our two measures of the redeployability of the collateral pool; $\mathbf{I}_t$ is a vector that includes two time-varying variables that capture the health of the airline industry—the price of jet fuel and the number of U.S. bankrupt airlines; $\mathbf{X}_{i,a,t}$ is a vector of tranche characteristics that includes an amortization dummy, a dummy for tranches with a liquidity facility, the ranking of tranche seniority, tranche issue size, a dummy for tranches with a call provision, and the tranche term-to-maturity; $\mathbf{Z}_{a,y-1}$ is a vector of beginning-of-year airline characteristics that includes the airline size, market-to-book ratio, profitability, and leverage; $\mathbf{R}_t$ is a vector of interest rate controls that includes the yield on the 1-year U.S. Treasury, the term spread between the 7-year and 1-year Treasury, and the default spread between Baa and Aaa rated bonds;[8] $\mathbf{b}_i$ is a vector of tranche fixed effects, $\mathbf{c}_a$ is a vector of airline fixed effects, and $\mathbf{d}_y$ is a vector of year fixed effects; and $\epsilon_{i,a,t}$ is the regression residual. We report the results from estimating different variants of regression (2) in Table VI. As before, we cluster standard errors (reported in parentheses) at the tranche level.

Column 1 of Table VI presents the results of regression (2) using only year fixed effects. As can be seen, the positive relation between the number of bankrupt operators and credit spreads continues to be statistically significant even after controlling for a host of tranche- and firm-level control variables. Thus, consistent with the collateral channel, increases in the number of potential buyers of collateral who are in bankruptcy are associated with increases in the spread of tranches backed by this collateral.

Turning to the control variables, we find that, as in Benmelech and Bergman (2009), the negative effect of redeployability is still significant once tranche- and airline-level controls are added to the regressions. Although the coefficient on fuel price is positive, it is not statistically significant. However, we find statistically significant evidence that when more airlines are in bankruptcy, tranche spreads tend to be higher.

Examining the tranche-level control variables, we find that amortized tranches have lower spreads, which is to be expected as their repayment schedule is more front loaded and hence their credit risk is lower. Likewise, tranches

[8] All yield data are taken from the Federal Reserve Bank of St. Louis website at http://research.stlouisfed.org/fred2/. For brevity, we do not report the coefficients of the interest rate variables.

Table VI

Bankruptcy and Collateral: Credit Spreads of Nonbankrupt Airlines

The table presents coefficient estimates and standard errors (in parentheses) for credit spread regressions. All regressions include an intercept, yield curve, and default spread controls (short rate, term spread, and default spread) and year fixed effects. Standard errors are calculated by clustering at the tranche level. Variable definitions are provided in Appendix B. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread
Bankrupt Buyers	67.340***	56.389**	64.666**			
	(29.409)	(28.274)	(27.984)			
Redeployability (operators)	−36.463**	−79.354***	−32.604			
	(16.436)	(22.800)	(79.046)			
Bankrupt Aircraft				9.230	11.681*	13.678**
				(7.035)	(6.645)	(5.686)
Redeployability (aircraft)				−22.541*	−68.859***	−20.251
				(13.980)	(17.178)	(82.924)
Fuel Price	30.945	30.922	18.396	42.151	35.107	30.562
	(36.120)	(37.415)	(32.972)	(36.609)	(37.588)	(33.405)
Number Bankrupt	12.076**	13.975**	12.034**	15.519***	16.383***	14.042**
	(5.857)	(5.908)	(5.565)	(5.713)	(5.722)	(5.476)
Amortizing	−146.340***	−149.022***		−145.937***	−148.185***	
	(29.991)	(29.355)		(30.153)	(29.385)	
Liquidity Facility	−123.517***	−115.703***		−123.579***	−112.787***	
	(39.479)	(41.827)		(39.518)	(41.478)	
Seniority	57.867**	75.399***		55.261**	74.632***	
	(24.171)	(25.042)		(23.917)	(24.579)	
Tranche Size	−52.249***	−36.730*		−54.385***	−38.217*	
	(17.691)	(20.679)		(17.202)	(19.989)	
Call Provision	8.966	13.016		10.611	13.270	
	(26.172)	(25.728)		(26.129)	(25.763)	
Term-to-Maturity	7.815***	9.761***		7.648***	9.637***	
	(2.753)	(3.034)		(2.757)	(3.024)	
Airline Size	39.289	−18.290	29.882	41.329	−5.994	15.310
	(29.077)	(54.104)	(69.825)	(28.935)	(55.018)	(72.974)
Market-to-Book	107.908**	170.989***	180.563***	102.698**	155.842***	181.503***
	(41.224)	(37.813)	(37.770)	(41.353)	(37.859)	(37.465)
Profitability	−1,003.526***	−886.778***	−967.063***	−1,073.334***	−848.450***	−1,008.489***
	(192.222)	(201.308)	(242.314)	(186.180)	(205.402)	(240.932)
Leverage	400.752***	470.405***	521.011***	405.773***	472.754***	545.577***
	(97.933)	(136.970)	(132.325)	(95.483)	(135.697)	(132.010)
Fixed Effects						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Airline	No	Yes	No	No	Yes	No
Tranche	No	No	Yes	No	No	Yes
# of Tranches	126	126	126	126	126	126
# of Airlines	12	12	12	12	12	12
Adjusted R^2	0.28	0.30	0.41	0.28	0.30	0.41
Observations	16,877	16,877	16,877	16,877	16,877	16,877

that are enhanced by a liquidity facility have lower spreads, and more senior tranches command lower spreads as well.[9] We also find that larger tranches

[9] Recall that the seniority variable is coded as a discrete variable between one and four with one being the most senior tranche, explaining the negative coefficient on the variable in the table.

are associated with lower spreads, consistent with larger tranches being more liquid (see, e.g., Bao, Pan, and Wang (2008)). We do not find a statistically significant relation between spreads and having a call provision. Finally, tranches with longer term-to-maturity have higher credit spreads.

The airline-level control variables in column 1 show that, as would be expected, airlines that are more profitable or less leveraged have lower credit spreads. This effect is economically significant, with a one standard deviation increase in profitability reducing the tranche credit spread by 67.74 basis points, and a one standard deviation increase in leverage increasing the spread by 68.13 basis points.[10] Finally, we find that airlines with high market-to-book ratios have higher credit spreads. High market-to-book may be capturing depleted, and hence less valuable, assets, which, all else equal, will tend to increase debt spreads.

Column 2 of Table VI repeats the analysis in column 1 while adding airline fixed effects to the specification. As can be seen, the results remain qualitatively and quantitatively unchanged: increases in the number of potential buyers that are in bankruptcy lead to an increase in the tranche credit spread. Column 3 repeats the analysis but adds tranche-level fixed effects to the specification and hence controls for unobserved heterogeneity among tranches. Naturally, in the tranche fixed effects specification, the tranche-level controls are dropped as they do not vary over time and hence are fully absorbed by the fixed effects. As can be seen in the table, we continue to find a positive relation between the number of buyers in bankruptcy and credit spreads.

We also note that the coefficients on the redeployability measures are still negative as in Benmelech and Bergman (2009), but no longer statistically significant once we include tranche fixed effects—a result recurrent throughout the analysis. To understand this, note that in the time series, variation in redeployability and the bankruptcy measures is driven by airlines entering or exiting bankruptcy; when a potential buyer airline enters bankruptcy, the number of bankrupt buyers increases by one, while the redeployability measure decreases by one. However, the redeployability measure also varies in the time series due to new airlines starting up and increasing the number of potential buyers. The fact that with tranche fixed effects the number of bankrupt buyers variable is significant while the redeployability measure is not suggests that in the time series, the important variation that drives changes in spreads is not the addition of new airlines but rather airlines entering or exiting bankruptcy.

In columns 4 through 6, we repeat our analysis using our second measure of shocks to collateral values, *Bankrupt Aircraft*, which is based on the number of aircraft that overlap with the tranche collateral pool that are operated by bankrupt airlines. Although our results are statistically weaker using this measure, they are consistent with the previous estimates when we control for airline or tranche (in addition to year) fixed effects—the *Bankrupt Aircraft*

[10] Also, to the extent that there is some slack in the pricing of the debt—that is, that the market for airline tranches is not perfectly competitive, but rather results in part from a negotiation between the airline and buyers of its debt capital—this result is also consistent with lower bargaining power of the "weak" issuing airlines who are willing to place debt at lower prices.

measure is significantly related to higher tranche credit spreads. Consistent with the collateral channel, increases in the number of aircraft operated by bankrupt airlines are associated with higher credit spreads of tranches employing similar aircraft model types as collateral.

Next, we estimate the duration of the effect of the collateral shock. We construct variables measuring the degree of *past* collateral shocks. Each variable is constructed in a similar manner as our collateral shock measures using airlines that have recently exited Chapter 11 rather than airlines currently in Chapter 11. For example, for $X = 120$, 240, and 360, *Ex-Bankrupt Aircraft*$_{X-120,X}$ measures how many aircraft of the same model type as in the collateral pool are operated by airlines that exited bankruptcy between X and $X-120$ days prior to the trade date. Thus, for each tranche and trade date, *Ex-Bankrupt Aircraft*$_{0,120}$ measures the weighted-average number of aircraft in the collateral pool that are operated by airlines that exited bankruptcy up to 120 days prior to that particular trade date.[11] Similarly, *Ex-Bankrupt Aircraft*$_{120,240}$ measures the weighted average of the number of aircraft of the same model type as in the collateral pool that are operated by airlines that exited bankruptcy between 120 and 240 days prior to a particular trade day. These measures of past collateral shocks are added into our baseline specification in regression (2).

As can be seen from Table VII, we find that the negative externality effect is concentrated during the period in which firms are in bankruptcy. Although the coefficients on the collateral shock variables, *Bankrupt Buyers* and *Bankrupt Aircraft*, remain positive and significant, the coefficients on the ex-bankruptcy variables are insignificant for the 120-day window following bankruptcy. In fact, the ex-bankruptcy variables are negatively related to spreads when looking at the window of 120 to 240 days post-bankruptcy.[12]

Consistent with a price pressure effect, therefore, contagion stemming from collateral shocks is not permanent. When firms enter bankruptcy, spreads of tranches operating similar assets increase. However, post-bankruptcy, the collateral effect subsides and there is no associated increase in spreads. Of course, the overall time period over which the contagion effect of collateral shocks takes effect is still quite lengthy as firm bankruptcies, and particularly those of large firms, can be long-lasting events. Indeed, the average span of airline bankruptcies during the 1990s and 2000s is 704 days.

D. Robustness: Controlling for Industry Conditions

One concern with our analysis is that we are capturing an adverse industry shock affecting all airlines in the industry. First, it should be noted that our identification strategy relies on the differential impact of an airline's bankruptcy on the credit spreads of tranches that are secured by different

[11] As before, the weights are taken over the different aircraft types in the tranche.

[12] One interpretation of this result is that having a large number of aircraft of a particular model type operated by airlines that exited bankruptcy proxies for increased redeployability of this model type, as the airlines that emerged from bankruptcy are the ones that successfully improved their financial position.

Table VII

The Time Series of the Collateral Channel

The table presents coefficient estimates and standard errors (in parentheses) for credit spread regressions. All regressions include an intercept, yield curve, and default spread controls (short rate, term spread, and default spread), as well as tranche, airline, and industry controls and year fixed effects. Standard errors are calculated by clustering at the tranche level. Variable definitions are provided in Appendix B. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread
Redeployability	−34.860**	−74.755***	29.440			
(operators)	(16.041)	(22.024)	(79.885)			
Bankrupt Buyers	76.343***	65.867**	66.696**			
	(28.470)	(28.015)	(28.272)			
Ex-Bankrupt Buyers$_{0,120}$	26.146	13.852	25.975			
	(22.402)	(22.237)	(19.782)			
Ex-Bankrupt Buyers$_{120,240}$	−70.954***	−75.615***	−72.041***			
	(17.302)	(17.644)	(14.136)			
Ex-Bankrupt Buyers$_{240,360}$	−29.938	−34.875	−39.442*			
	(26.783)	(27.989)	(28.806)			
Redeployability				−20.764	−68.985***	−11.066
(aircraft)				(13.839)	(16.551)	(80.613)
Bankrupt Aircraft				13.108**	13.167**	15.525***
				(6.738)	(6.384)	(5.738)
Ex-Bankrupt Aircraft$_{0,120}$				0.157	0.187	0.329
				(0.398)	(0.401)	(0.347)
Ex-Bankrupt Aircraft$_{120,240}$				−1.177***	−1.098***	−1.063***
				(0.273)	(0.275)	(0.204)
Ex-Bankrupt Aircraft$_{240,360}$				−0.743*	−0.673	−0.782**
				(0.402)	(0.431)	(0.367)
Fixed Effects						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Airline	No	Yes	No	No	Yes	No
Tranche	No	No	Yes	No	No	Yes
# of Tranches	126	126	126	126	126	126
# of Airlines	12	12	12	12	12	12
Adjusted R^2	0.28	0.31	0.42	0.28	0.30	0.42
Observations	16,877	16,877	16,877	16,877	16,877	16,877

aircraft model types, and, as such, an industry shock is unlikely to drive our findings. Second, our results in Table VI are robust to the inclusion of industry control variables such as fuel price and the number of bankrupt airlines. Nevertheless, in order to further alleviate this concern, we use a battery of industry controls that include, in addition to jet fuel price and the number of bankrupt airlines, the asset share of bankrupt airlines (defined as the book value of the assets of bankrupt airlines divided by the total book value of airlines in the United States) and the relative number of bankrupt airlines (number of bankrupt airlines divided by the total number of airlines). Likewise, in

Table VIII

The Collateral Channel and Industry Conditions

The table presents coefficient estimates and standard errors (in parentheses) for credit spread regressions. All regressions include an intercept, yield curve, and default spread controls (short rate, term spread, and default spread), and tranche and year fixed effects. Tranche controls are not included in the explanatory variables as they are absorbed by the tranche fixed effects. Standard errors are calculated by clustering at the tranche level. Variable definitions are provided in Appendix B. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

Dependent Variable =	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread
Bankrupt Buyers	64.666**	64.656**	73.134**			
	(27.984)	(27.920)	(29.550)			
Redeployability (operators)	32.604	32.269	25.878			
	(79.047)	(79.015)	(80.208)			
Bankrupt Aircraft				13.678**	13.676**	14.972**
				(5.868)	(5.679)	(6.023)
Redeployability (aircraft)				−20.251	−20.722	−22.148
				(82.924)	(82.891)	(84.435)
Fuel Price	18.396	18.005	17.955	30.562	30.103	31.082
	(32.972)	(32.900)	(32.040)	(33.407)	(33.336)	(32.553)
Number Bankrupt	12.034**					
	(5.565)					
Number Bankrupt/ Total		831.199**				
		(376.357)				
Bankrupt Assets/ Total Assets			7.404			
			(110.016)			
Number Healthy				−14.042**		
				(5.476)		
Healthy/Total					−969.258**	
					(371.263)	
Healthy Assets/ Total Assets						−7.937
						(100.998)
Airline Size	29.882	30.117	39.117	5.310	5.580	15.343
	(69.824)	(69.745)	(69.717)	(72.974)	(72.910)	(72.074)
Market-to-Book	180.563***	180.651***	176.786***	181.503***	181.561***	175.090***
	(37.770)	(37.761)	(37.573)	(37.465)	(37.453)	(37.233)
Profitability	−964.063***	−965.595***	−942.286***	−1,008.489***	−1,010.179***	−981.395***
	(242.314)	(242.353)	(241.644)	(240.932)	(240.968)	(239.619)
Leverage	521.011***	520.949***	503.475	545.577***	545.414***	529.795***
	(132.326)	(132.214)	(133.508)	(132.010)	(131.928)	(133.248)
Fixed Effects	Tranche+ Year	Tranche+ Year	Tranche+ Year	Tranche+ Year	Tranche+ Year	Tranche+ Year
# of Tranches	126	126	126	126	126	126
# of Airlines	12	12	12	12	12	12
Adjusted R^2	0.42	0.41	0.41	0.41	0.41	0.41
Observations	16,877	16,877	16,877	16,877	16,877	16,877

different specifications, we also control for the complements of these variables: the number of healthy airlines, as well as the asset share and the relative number of healthy airlines.

Table VIII reports the results from estimating regression (2) with tranche fixed effects and an augmented vector of time-varying industry controls. Because our industry controls exhibit intra-year variation—fuel price and airline bankruptcies are tracked at a daily frequency—we can include year fixed effects as well. For brevity, we report results with the bankrupt-based industry variables using the number of bankrupt buyers, and the healthy-based industry variables using the number of bankrupt aircraft.[13] As can be seen, the number of bankrupt airlines as well as the relative number of bankrupt airlines have the predicted positive sign and are statistically significant, while the asset share of bankrupt airlines is not significant.[14] Importantly, as Table VIII demonstrates, our results are robust to the inclusion of all of the industry controls. In fact, the coefficient β_1 becomes even stronger when we add additional industry controls that potentially soak up more of the time-series variation in tranche credit spreads.

Another concern is that while we control for a battery of industry controls, it is still possible that the negative information associated with the bankruptcy of an airline with a given fleet is of greater relevance for particular airlines. According to this view, the information channel may still be operative because some airlines may have different sensitivities to industry conditions than others. We address this concern in the Internet Appendix and conclude that our analysis is robust to various industry controls even when we allow airlines to have heterogeneous responses to industry conditions.[15] (The Internet Appendix is available online at http://www.afajof.org/supplements.asp.)

E. The Collateral Channel: The Effect of Seniority, Financial Health, and Redeployability

We continue our analysis in Table IX by examining the effects of tranche seniority and LTV ratios in the collateral channel. We hypothesize that the negative relation between the measure of the number of bankrupt buyers or the number of bankrupt aircraft and credit spreads should be concentrated in more junior tranches, or equivalently in tranches with high LTV, because these are the tranches that, upon default, would be more exposed to drops in the value of the underlying collateralized assets. As a first test of this hypothesis, column 1 of Table IX presents the results of regression (2) while adding an interaction variable between the measure of the number of bankrupt buyers, *Bankrupt Buyers*, and the seniority of each tranche.[16] The regression includes either airline or tranche (as well as year) fixed effects and standard errors are clustered at the tranche level.

As can be seen in column 1 of Table IX, we find that the coefficient on the interaction term between *Bankrupt Buyers* and tranche seniority is positive

[13] Clearly, controlling for the asset share and relative number of healthy airlines is equivalent to using the complement variables of the asset share and relative number of *bankrupt* airlines.

[14] We add these controls one at a time as they are all highly collinear. In unreported results, we include all industry controls together and our results hold for both measures of the collateral channel. Because the industry controls are highly collinear, their significance disappears when they are added together due to multicollinearity.

[15] We analyze a more subtle concern about reverse causality later in the paper.

[16] We obtain similar results using *Bankrupt Aircraft*, which we do not report for brevity.

Table IX

Bankruptcy, Collateral, Tranche Seniority, and LTV

The table presents coefficient estimates and standard errors (in parentheses) for credit spread regressions. Regressions are estimated separately for senior and junior tranches (columns 3 and 4), and for tranches with LTV lower than 0.5 (column 7) and higher than 0.5 (column 8). All regressions include an intercept, yield curve, and default spread controls (short rate, term spread, and default spread) and year fixed effects. Columns 1 and 5 include airline fixed effects, and columns 2, 3, 6, 7, and 8 include tranche fixed effects. Standard errors are calculated by clustering at the tranche level. Variable definitions are provided in Appendix B. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread
			Seniority Level				LTV	
			Senior	Junior			<0.5	≥ 0.5
Bankrupt	−163.798***	−139.771**	41.566*	429.922**	−334.580***	−271.665**	49.282***	116.535**
Buyers	(51.636)	(55.375)	(24.483)	(164.482)	(103.743)	(110.191)	(16.484)	(48.112)
×Seniority	171.992***	154.430***						
	(37.852)	(41.392)						
Redeployability	−79.995***	35.396	44.476	−330.419	−81.905***	23.951	80.757***	66.882
(operators)	(22.011)	(77.052)	(82.336)	(210.222)	(23.534)	(82.602)	(27.06)	(123.474)
Bankrupt Buyers					729.163***	628.430***		
×LTV					(228.682)	(240.669)		
Fuel Price	34.189	19.815	24.803	−140.540	35.070	28.017	32.596	−11.179
	(36.318)	(32.921)	(33.465)	(179.532)	(36.559)	(31.504)	(24.357)	(58.422)
Industry	11.646**	10.359*	11.502*	30.160	14.282***	11.658**	0.226	16.025**
Bankruptcy	(5.839)	(5.531)	(5.806)	(32.122)	(5.360)	(5.206)	(3.677)	(8.072)
Amortizing	−135.727***				−140.008***			
	(26.262)				(26.464)			
Liquidity	−103.482***				−117.690			
facility	(30.017)				(78.778)			
Seniority	14.127				55.155**			
	(14.281)				(24.483)			
LTV					−175.823			
					(198.648)			
Tranche Size	−24.237				−28.370			
	(17.534)				(19.199)			
Call Provision	12.040				6.223			
	(22.920)				(23.968)			
Term-to-	10.729***				5.887*			
Maturity	(2.968)				(3.049)			
Airline Size	22.731	55.280	11.546	488.523*	−80.246	−12.202	191.157***	−67.034
	(52.601)	(66.318)	(69.019)	(277.255)	(57.500)	(75.626)	(44.730)	(119.146)
Market-to-	171.933***	179.021***	160.287***	1,116.765*	181.290***	189.618***	46.052	237.571***
Book	(36.531)	(35.856)	(34.732)	(618.322)	(41.091)	(38.043)	(43.905)	(47.302)
Profitability	−1,011.954***	−1,066.630***	−916.369***	−1,404.840	−800.409***	−891.149***	−614.626***	−1,822.178***
	(184.776)	(220.806)	(230.722)	(996.173)	(183.056)	(226.702)	(189.368)	(473.238)
Leverage	417.267***	476.445***	474.647***	2,183.932	477.450***	500.080***	32.809	502.249*
	(128.517)	(127.056)	(130.849)	(1,491.463)	(137.739)	(111.453)	(113.266)	(293.031)
Fixed Effects	Airline+ Year	Tranche+ Year	Tranche+ Year	Tranche+ Year	Airline+ Year	Tranche+ Year	Tranche+ Year	Tranche+ Year
# of Tranches	126	126	106	20	116	116	38	78
# of Airlines	12	12	9	5	9	9	7	9
Adjusted R^2	0.33	0.43	0.41	0.49	0.34	0.45	0.57	0.45
Observations	16,877	16,877	15,649	1,228	16,174	16,174	8,285	7,889

and statistically significant. As hypothesized, we thus find that increases in the number of bankrupt potential buyers increases the spread of junior tranches more than that of senior tranches. The differential effect of moving from zero to one bankrupt buyer in most senior as compared to most junior tranches is 106.01 basis points.[17] We repeat the analysis in column 2 controlling for tranche fixed effects and obtain similar results.[18] Furthermore, we stratify the data between senior tranches (seniority levels 1 and 2) and junior tranches (seniority levels 3 and 4) and estimate regression (2) separately for senior and junior tranches. As the coefficients on the *Bankrupt Buyers* measure in columns 3 and 4 indicate, junior tranches are much more sensitive to the number of bankrupt buyers, consistent with the interaction results.

In the last four columns of Table IX, we repeat the analysis but categorize tranches based on LTV rather than seniority. LTVs are obtained from the tranche filing prospectus, and reflect cumulative LTV ratios as of the time of issue.[19] Specifically, these are defined as the ratio between the sum of the principal amount of that tranche and all tranches senior to it, divided by an appraisal of the value of the assets serving as collateral.

We begin with specifications in which LTV is interacted with *Bankrupt Buyers* (columns 5 and 6) and find results that are consistent with the seniority interactions—credit spreads are more sensitive to the *Bankrupt Buyer* measure among tranches with high LTVs. Increasing the *Bankrupt Buyer* measure from zero to one for tranches at the 25th percentile of LTV (0.41) reduces tranche credit spreads by 10.7 basis points. In contrast, the same increase for tranches at the 75th percentile of LTV (0.66) causes tranche spreads to decrease by 44.15 basis points. In the last two columns of Table IX, we stratify the sample into tranches with LTVs below 0.5 (column 7) and those with LTVs at or above 0.5 (column 8). We choose 0.5 as the breakpoint to ease interpretation because it is only slightly higher than the median LTV (0.49). As columns 7 and 8 demonstrate, credit spreads of tranches with LTVs higher than 0.5 are more sensitive to the number of bankrupt buyers than those with LTVs lower than 0.5. Indeed, the coefficient on *Bankrupt Buyers* more than doubles in high as compared to low LTV subsamples.

We investigate the transmission of the collateral channel further in Table X by studying the joint impact of airline financial health and the number of bankrupt buyers on tranche spreads. We hypothesize that the positive relation between the number of potential buyers in bankruptcy and tranche credit spreads should be larger for airlines with low profitability. Less profitable airlines are more likely to be in financial distress, making the value of their tranches more sensitive to the liquidation value of their collateral. Further, as in the previous section, we expect that the effect should be more pronounced among more junior, high LTV tranches. We therefore introduce an interaction variable between profitability and *Bankrupt Buyers* into the specification of

[17] To see this, we calculate the joint effect of seniority and number of bankrupt buyers on credit spreads using the total differential of both the level of *Bankrupt Buyers* as well as the interaction with seniority. Thus, this differential is $-163.798 \times 0.301 + (171.992 \times 0.301 \times 4) - (171.992 \times 0.301 \times 1) = 106.01$.

[18] Clearly, the variable *Seniority* is being absorbed by the tranche fixed effects in this specification.

[19] We are unable to obtain dynamic LTVs along the economic life of the tranche as we do not have a time series of aircraft value estimates.

Table X

The Collateral Channel and Airlines' Financial Strength

The table presents coefficient estimates and standard errors (in parentheses) for credit spread regressions. Regressions are estimated separately based on seniority (columns 1 vs. 2, and columns 5 vs. 6), and LTV (columns 3 vs. 4, and columns 7 vs. 8). All regressions include an intercept, yield curve, and default spread controls (short rate, term spread, and default spread), as well as tranche and year fixed effects. Standard errors are calculated by clustering at the tranche level. Variable definitions are provided in Appendix B. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread
	Seniority Level		LTV		Seniority Level		LTV	
	Senior	Junior	<0.5	≥0.5	Senior	Junior	<0.5	≥0.5
Bankrupt Buyers	84.618**	873.766***	49.684*	312.007***	62.537	450.407**	93.076***	45.452**
	(40.390)	(240.505)	(25.142)	(86.494)	(39.957)	(168.984)	(21.073)	(80.668)
Redeployability (operators)	53.370	−355.682**	80.796***	86.712	52.873	−172.991	48.316	78.510
	(81.042)	(169.308)	(26.496)	(115.963)	(66.243)	(143.143)	(31.294)	(108.399)
Bankrupt Buyers ×Profitability	−620.859*	−6,782.759***	−8.591	−2,159.232***				
	(341.277)	(2,005.524)	(36.351)	(577.889)				
Bankrupt Buyers ×Pr(Bankruptcy)					57.179	−71.805	−147.238**	472.031*
					(137.833))	(662.581)	(63.333)	(280.010
Fuel Price	19.618	−172.159	32.543	−13.641	−18.047	−196.045	14.168	−56.953
	(33.372)	(186.495)	(23.992)	(56.464)	(29.475)	(133.623)	(24.511)	(51.225)
Industry Bankruptcy	12.384**	42.083	0.266	16.940**	−0.548	17.797	−3.927	8.017
	(5.807)	(32.475)	(4.223)	(8.117)	(5.547)	(21.531)	(4.074)	(9.102)
Pr(Bankruptcy)					30.450	408.291	53.253	37.183
					(54.969)	(476.970)	(36.658)	(139.682)
Airline Size	50.254	705.267***	191.194***	123.501				
	(76.971)	(247.669)	(44.997)	(128.668)				
Market-to-Book	144.177***	1,109.505**	46.201	184.908***				
	(34.441)	497.782)	(46.534)	(40.491)				
Profitability	−754.646***	571.176	−611.588***	−1,428.775***				
	(218.162)	(1,660.159)	(169.520)	(420.363)				
Leverage	426.302***	1,882.593	33.434	187.569				
	(134.184)	(1,337.861)	(122.091)	(301.548)				
Fixed Effects	Tranche+ Year	Tranche+ Year	Tranche+ Year	Tranche+ Year	Tranche+ Year	Tranche+ Year	Tranche+ Year	Tranche+ Year
# of Tranches	106	20	38	78	106	20	38	78
# of Airlines	9	5	7	9	9	5	7	9
Adjusted R^2	0.41	0.51	0.57	0.46	0.38	0.46	0.55	0.42
Observations	15,649	1,228	8,285	7,889	15,649	1,228	8,285	7,889

regression (2). Similar to the analysis in Table IX, we run the analysis separately for senior and junior tranches (columns 1 and 2) as well as for tranches with LTVs below and above 0.5 (columns 3 and 4). In essence, these regressions test the triple interaction between our measure of the number of bankrupt buyers, airline profitability, and either tranche seniority or LTV. Each regression includes tranche and airline fixed effects with standard errors clustered at the tranche level.

As can be seen in Table X, the coefficient on the interaction term between *Bankrupt Buyers* and profitability is more negative for junior tranches and for tranches with high LTV ratios. In particular, for junior tranches, the impact of profitability on the importance of *Bankrupt Buyers* in determining tranche spreads is approximately 10 times larger than the same effect for senior tranches. Having one potential bankrupt buyer and moving from the

25th to the 75th percentiles of airline profitability is associated with a decrease of 89.45 basis points in credit spreads of senior tranches, compared to 265.64 basis points for junior tranches.[20] Likewise, while the interaction term between *Bankrupt Buyers* and profitability is small and not statistically significant for tranches with low LTVs, the effect is much higher and statistically significant for tranches with high LTV.

As a final robustness check, we investigate further the role of the probability of airline bankruptcy. Although we find support for the conjecture that the collateral channel is stronger when profitability is lower, our analysis thus far does not account for situations in which an airline's current profitability is low but its balance sheet is still strong, making the airline's default unlikely. To allow for such cases, we construct a more complete measure of airline health by estimating the probability that an airline will file for Chapter 11 in a given year. We then use an airline's predicted probability of bankruptcy as a more comprehensive measure of the airline's financial health.

Similar to Shumway (2001), we regress the probability of bankruptcy on lagged values of size, leverage, market-to-book, profitability, the ratio of short-term debt to assets, and both year and airline fixed effects. Our estimated linear probability model (standard errors clustered by airline are reported in parentheses) is:

$$
\begin{aligned}
\Pr(\mathit{Bankruptcy}=1)_{a,t} = {} & \underset{(0.040)}{0.037} \times \mathit{Size}_{a,t-1} + \underset{(0.323)}{0.009} \times \mathit{Leverage}_{a,t-1} + \underset{(0.100)}{0.124} \times \mathit{MtoB}_{a,t-1} \\
& - \underset{(0.365),}{0.787} \times \mathit{Profitability}_{a,t-1} + \underset{(0.238)}{0.747} \times \mathit{STDebt}_{a,t-1} \\
& + \mathbf{c}_a \boldsymbol{\eta} + \mathbf{d}_y \boldsymbol{\theta} + \epsilon_{a,t}.
\end{aligned} \tag{3}
$$

Subscripts indicate airline (a) and transaction date (t), $\mathbf{c}_a$ is a vector of airline fixed effects, $\mathbf{d}_y$ is a vector of year fixed-effects, and $\epsilon_{a,t}$ is the regression residual.

As can be seen, the two significant determinants of bankruptcy are profitability and the ratio of short-term debt to assets. We next calculate imputed bankruptcy probabilities, Pr(*Bankruptcy*), for each airline-year based on airline characteristics. The last four columns of Table X report the coefficients from estimating regressions with interactions between *Bankrupt Buyers* and this Pr(*Bankruptcy*) measure. As before, we split the sample between junior and senior tranches, and high versus low LTV tranches. Given that Pr(*Bankruptcy*) is a linear combination of airline characteristics, we do not include airline-level variables in these regressions.

Although the estimates based on seniority level are not statistically significant, we find that using LTV to stratify our sample (columns 7 and 8) yields results consistent with the profitability interaction regressions. We find that

[20] To see the former, note that $(-754.646 \times (0.131 - 0.036) - 620.859 \times 0.301 \times (0.131 - 0.036)) = -89.45$. The latter effect is calculated in an analogous manner.

for tranches with high LTV ratios, that is, those more exposed to default, the effect of *Bankrupt Buyers* on credit spreads increases when the probability of airline bankruptcy is higher. For example, for tranches with LTV > 0.5 the incremental effect of one additional bankrupt buyer, evaluated at the 75th percentile of bankruptcy probability (0.22), is 44.9 basis points. In contrast, for tranches with low LTV ($<$0.5), the effect of *Bankrupt Buyers* on credit spreads is low even when the probability of default is high, consistent with the protection that the underlying collateral provides for these relatively senior tranches. For example, evaluated at the 75th percentile of bankruptcy probability, the incremental effect of an additional bankrupt buyer is only 18.3 basis points.[21]

To summarize, our results are consistent with the notion that the effect of the collateral channel is more pronounced for more junior and more highly leveraged securities of weaker firms. Even if the airline defaults on its tranche obligations, the most senior claimants will be least exposed to fluctuations in the value of the underlying collateral and hence do not require particularly strong demand for the assets serving as collateral. In contrast, for tranches of lower seniority, profitability plays a much larger role in determining the relation between potential demand for collateral, as proxied by *Bankrupt Buyers*, and tranche spread. For these more junior tranches, when the financial health of the firm deteriorates and hence default probabilities go up, being able to find a buyer for the underlying collateral is of crucial importance. Put differently, when profitability is low, junior secured creditors are very much harmed when a large number of potential buyers are experiencing financial difficulty and are in bankruptcy.

Finally, we analyze the interaction between the *Bankrupt Buyers* measure and tranche redeployability. Following Shleifer and Vishny (1992), we hypothesize that if assets are more redeployable, potential buyers entering financial distress should have a smaller impact on collateral values and credit spreads. Therefore, the positive relation between *Bankrupt Buyers* and tranche credit spreads should be lower for tranches with more redeployable collateral.

We regress tranche credit spreads on the *Bankrupt Buyers* measure, our measure of tranche redeployability that is based on the number of aircraft, and an interaction between *Bankrupt Buyers* and tranche redeployability. As independent variables, we also include our regular set of tranche and airline controls, employing both year and either airline and tranche fixed effects. As can be seen in the Internet Appendix, we find that, consistent with our hypothesis, the interaction term between *Bankrupt Buyers* and the tranche aircraft redeployability measure is negative and significant. Although increases in *Bankrupt Buyers* lead to increased spreads, this effect is weaker in more redeployable tranches. For example, for tranches in the 25th percentile of redeployability, having one bankrupt buyer increases spreads by 76.6 basis points, while, in

[21] In calculating these figures, we use the total differential, taking into account both the level and the interaction term.

contrast, the same effect in tranches at the 75th percentile of redeployability is only 20.3 basis points.

F. Robustness: Reverse Causality

One concern regarding our analysis relates to the issue of the direction of causality. We argue that bankruptcies of potential buyers lead to a decline in asset values, increasing the cost of debt financing of nonbankrupt airlines. However, an alternative explanation is that an adverse shock to the productivity of some aircraft results in the bankruptcy of airlines using them, as well as a decline in value and increased cost of capital for other users of these aircraft.

The reverse causality explanation is best illustrated by the case of the Arospatiale-BAC Concorde—the famous supersonic passenger airliner. Although the Concorde was designed for supersonic long-haul trips, such as between London and New York, it was used in the late 1970s by Braniff International Airways on shorter range subsonic flights within the United States. The flights were usually less than 50% booked, leading Braniff to terminate Concorde operations in May 1980. Braniff filed for bankruptcy in May 1982. To the extent that Braniff's bankruptcy reflected a failed strategy associated with operating the Concorde, the reverse causality argument would suggest that market priors about the viability of the Concorde aircraft would be updated, resulting ultimately in higher costs of capital for other users of this aircraft.

We deal with the reverse causality argument suggested by the Braniff case empirically in Table XI. First, however, it is important to note that while the Concorde is a specialized aircraft with limited efficient uses outside supersonic long-haul travel, all the aircraft used as collateral in our sample are commonly used general purpose aircraft. Our sample includes the most popular models of Airbus (A300, A310, A319, A320, A321, A330), Boeing (B737, B747, B757, B767, and B777), and McDonnell Douglas (MD11, MD80), as well as regional aircraft made by BAE and Embraer. None of these models are specialized or esoteric, and none of the models experienced an idiosyncratic shock during the sample period that made it less desirable. Nevertheless, we address the reverse causality concern empirically.

We construct dummy variables for each of the different aircraft models that take the value of one if there is at least one aircraft of that model in the tranche collateral pool. We then rerun our regressions with tranche fixed effects as well as year$\times$model fixed effects, allowing different aircraft models to have a time-varying effect on credit spreads. As the first two columns of Table XI show, our results are even stronger using both the bankrupt buyers and bankrupt aircraft measures. We also run the regression for tranches that employ only Airbus and Boeing aircraft as collateral (column 3) or even only Boeing aircraft (column 4)—Airbus and Boeing are the leading aircraft manufacturers in the world and their aircraft are both general purpose and highly reliable. In our sample, 105 tranches use only Airbus and Boeing, and 69 tranches use only Boeing. In focusing on these subsamples, we are identifying off of variation in the number of potential buyers of Airbus and Boeing aircraft that are in

Table XI

The Collateral Channel and Tranche Fleet

The table presents coefficient estimates and standard errors (in parentheses) for credit spread regressions. All regressions include an intercept, yield curve, and default spread controls (short rate, term spread, and default spread), and tranche fixed effects. Columns 1 and 2 also include aircraft model×year fixed effects. Columns 3 and 4 focus on aircraft manufactured by either Airbus and Boeing (column 3) or Boeing only (column 4). The last two columns of the table also include a dummy variable for wide-body aircraft interacted with month-year fixed effects. Tranche controls are not included in the explanatory variables as they are absorbed by the tranche fixed effects. Standard errors are calculated by clustering at the tranche level. Variable definitions are provided in Appendix B. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

			Airbus and Boeing	*Boeing only*		
Dependent Variable=	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread
Bankrupt Buyers	164.072***		103.499***	112.696***	123.376***	
	(40.917)		(36.759)	(41.124)	(42.468)	
Redeployability (operators)	15.783		−38.579	77.172	17.332	
	(103.268)		(81.353	(97.071)	(69.988)	
Bankrupt Aircraft		30.028***			26.121***	
		(8.772)			(8.764)	
Redeployability (aircraft)		41.212			−27.966	
		(101.099)			(70.416)	
Fuel Price	15.128	30.548	61.196	−18.773	35.010	49.094
	(35.081)	(34.520)	(40.156)	(39.344)	(71.103)	(70.261)
Number Bankrupt	−2.907	3.506	7.948	0.946	−22.516	−16.864
	(5.681)	(5.384)	(7.833)	(7.012)	(13.744)	(12.319)
Airline Size	83.260	30.844	122.048	−28.924	−80.478	−86.821
	(179.591)	(179.205)	(94.711)	(116.073)	(96.941)	(102.811)
Market-to-Book	47.254	14.459	146.193***	217.955**	106.684**	113.051**
	(164.964)	(164.320)	(46.055)	(91.490)	(43.154)	(43.827)
Profitability	−1,369.364***	−1,521.139**	−2,149.84***	−1,846.818**	−1,259.009***	−1,285.796***
	(619.761)	(642.168)	(417.980)	(703.254)	(303.186)	(303.611)
Leverage	252.650	268.310	−187.420	−214.891	478.857***	514.745***
	(467.657)	(477.368)	(185.463)	(418.264)	(145.710)	(140.212)
Fixed Effects	Tranche+ Year× Aircraft Model	Tranche+ Year× Aircraft Model	Tranche+ Year	Tranche+ Year	Tranche+ Month-Year× Widebody	Tranche+ Month-Year× Widebody
# of Tranches	126	126	105	69	126	126
# of Airlines	12	12	8	7	12	12
Adjusted R^2	0.47	0.47	0.40	0.43	0.51	0.51
Observations	16,877	16,877	14,204	9,368	16,877	16,877

bankruptcy. As Table XI demonstrates, our results hold both for Airbus and for Boeing, as well as only for Boeing. Our results therefore hold, also for general purpose, popular aircraft for which it is unlikely that new information about productivity is being revealed.

For additional robustness, we further control for the aircrafts' main usage in our analysis. The main difference between aircraft in our collateral pool is whether they are short-haul narrow-bodied (e.g., A319, A320, A321, B737, B757, etc.) or long-haul wide-bodied (A300, A310, A330, B747, B767, B777).

A narrow-body aircraft is one with a single passenger aisle, while a wide-body aircraft has two such aisles. We construct a dummy variable that equals one for wide-bodied aircraft and interact it with month-year fixed effects (i.e., every month-year combination in our data corresponds to a particular dummy variable). As the last two columns of Table XI show, our results continue to hold. Again, it is therefore unlikely that our results are driven by new information about the productivity associated with the main usage of the aircraft models used as collateral.

G. Robustness: Liquidity Facility and Credit Enhancement

As described in Section II, 75% of the tranches in our sample are EETCs, which include a liquidity facility that enhances their credit worthiness. The credit enhancer, which is typically a financial institution, commits to pay interest payments in case of default for a prespecified amount of time, usually 18 months. The standard reason given for such an enhancement is to enable a more orderly sale of aircraft, providing "breathing room" to prevent fire sales. For example, in an EETC issued by Continental Airlines in 2002 (2002–1) the primary liquidity facility is provided by Landesbank Hessen-Thüringen Girozentrale, supplemented by a liquidity facility from Merrill Lynch Capital Services, Inc. Likewise, in EETC Series 2000–3 issued by U.S. Airways in 2000, the liquidity facility was provided by Morgan Stanley Capital Services, while the 1998–1 Series EETC issued by U.S. Airways had its liquidity facility provided by the Chicago Branch of ABN ARMO Bank N.V.

Because the liquidity facility credit enhancements are provided by third parties and not the airline itself, they do not expose the tranche to further airline liquidity risk. Still, our results could be explained by a contagion effect through the quality of credit enhancers if, for some reason, tranches backed by aircraft of similar type were enhanced by the same institutions or by institutions with stronger links.[22] We control for the provision of a liquidity facility in our analysis above and our results are always robust. Nevertheless, to deal with the concern of contagion through liquidity enhancers, we rerun our regressions separately for tranches without a liquidity facility. The analysis is reported in the Internet Appendix. Our results continue to hold for both measures of redeployability, even among those tranches with no liquidity enhancement, and hence without the possibility of contagion through credit enhancers.

Additionally, we find that credit spreads of tranches without a liquidity facility are more sensitive to airline profitability and leverage as compared to tranches with such a liquidity facility. Again, this is to be expected, because the higher probability of fire sales in default associated with the lack of a liquidity facility implies that airline financial condition becomes more important in determining spreads.

[22] As a related example, during the peak of the financial crisis in 2008, concerns about Ambac and the Municipal Bond Insurance Association led to downgrades of collateralized debt obligation tranches insured by these companies.

H. Robustness: Accounting for Contagion through Security Holders

Another potential contagion effect arises through holders of ETC and EETC securities. Because the Mergent FISD used in our analysis contains transactions undertaken by insurance companies, it is possible that when airlines enter financial distress, insurance companies operating subject to prudent investment regulations or guidelines sell their holdings of tranches issued by the distressed airlines. In this case, the contagion operates through fire sales of risky-airline securities and not necessarily though an underlying collateral channel.

We address the concern of contagion through holders of securities in a number of ways. First, for each observation in our data set, we have information on whether the reported transaction was a purchase or a sale by the reporting insurance company. We conjecture that contagion through holders of securities should be reflected mainly in sell-side transactions in which a binding balance sheet or investment policy constraint triggered by equity losses forces an insurance company to rebalance its portfolio by selling part of its holdings of corporate debt. Our results (in the Internet Appendix) show that both of our measures are statistically significant and positively related to credit spreads for both purchases and sales of securities by insurance companies.

Moreover, in an attempt to control for the identities of the insurance companies transacting in tranches, we split the sample into transactions made by Life Insurance firms and those made by Property & Casualty firms.[23] Our sample includes 4,780 transactions made by Property & Casualty firms and 11,297 transactions by Life Insurance firms. The analysis, which is contained in the Internet Appendix, demonstrates that our results are almost identical across insurance company types. Using both measures of redeployability, we obtain very similar statistically significant relations between either the number of bankrupt buyers or the number of bankrupt aircraft and tranche credit spreads. Our results therefore do not appear to be driven by institutional details specific to a particular type of insurance company. The Internet Appendix further shows that our results are also robust to the inclusion of vendor (broker or dealer) fixed effects.

As an additional method of dealing with the alternative hypothesis of contagion through security holders, we employ data on tranche credit rating at the time of the transaction. We conjecture that contagion due to regulation or investment policy constraints should be concentrated in downgrades of corporate bonds from investment to noninvestment grade. We therefore match each tranche transaction to its Moody's credit rating at the time of the transaction using Moody's Default Risk Service (DRS) Database. We then subdivide our sample based on the rating of the tranche at the time of the transaction, running our regressions on the subsample of transactions of investment grade tranches (i.e., the top 10 credit rating notches, Aaa through Baa3), the subsample of transactions of tranches rated Aaa through Aa3 (the top four notches),

[23] The FISD data do not provide the identity of the insurance companies—only their type.

and the subsample of transactions of tranches rated Aaa (the top notch). Although examining subsamples separately naturally reduces the sample size in each individual regression, and considerably so for the third subsample in which we only examine Aaa tranches, as Table XII shows, we find that our results continue to hold for both buy and sell transactions in all three subsamples: investment grade (columns 1 and 2), Aaa through Aa3 (columns 3 and 4), and Aaa (columns 5 and 6). Thus, our results hold for both purchases and sales of tranches that are very highly rated, alleviating concerns about contagion through rating-based regulation fire sales.[24]

One concern with the analysis is the possibility that unusual circumstances related to forced asset sales during the current financial crisis are driving our results. The Internet Appendix reports regression results for the years 2006 to 2007 only, and confirms that indeed the bankruptcy channel had a much greater effect during these years. To alleviate concerns that the financial crisis is driving our results, we exclude the last 2 years of our sample from our regressions. Our results (columns 7 and 8 of Table XII) continue to hold using this slice as well.[25] Hence, while the collateral channel may be even more important during financial crises, our results are not driven by the sell-off of asset-backed securities of 2007 to 2008.

In summary, our results are not likely to be driven by fire sales, rating-based investment rules and regulations, insurance company type, or the identity of the vendor. We conclude that contagion through investors does not seem to explain the strong relation between bankruptcy shocks and credit spreads.

V. Conclusion

Our analysis shows that bankrupt firms impose negative externalities on their nonbankrupt competitors through a collateral channel mechanism in which industry bankruptcies lead to reductions in collateral values of other industry participants. This, in turn, increases the cost of external debt finance across the industry. Although our analysis focuses on one particular industry, the collateral channel has broader, economy-wide implications. Indeed, the collateral channel should be viewed as a particular form of financial accelerator in which frictions in raising external finance amplify and propagate industry downturns. Following a negative shock, a fraction of firms enter bankruptcy and sell part of their assets. As a result, collateral values drop industry-wide, increasing the cost of external finance, and magnifying the shock further. Recent events in the financial crisis of 2007 to 2009 suggest that bankruptcy-induced contagion through collateral shocks are of crucial importance in magnifying shocks to the economy at large. If such bankruptcy-induced externalities are

[24] Although our results hold using both measures of redeployability, for brevity we only report results using the *Bankrupt Buyers* measure.

[25] Our results hold whether we use the 1994 to 2005 or the 1994 to 2006 periods. Although the year 2007 arguably marks the beginning of the crisis, we exclude trades during the year 2006 as well out of an abundance of caution.

Table XII

Bankruptcy Collateral and Investment Grade

The table presents coefficient estimates and standard errors (in parentheses) for credit spread regressions. Regressions are estimated separately for buy vs. sell transactions. All regressions include an intercept, yield curve, and default spread controls (short rate, term spread, and default spread), as well as airline and year fixed effects. The first two columns compare buy vs. sell transactions of tranches with Moody's investment grade credit ratings. Columns 3 and 4 compare buy vs. sell transactions of tranches with Moody's ratings that are between Aaa and Aa3. Columns 5 and 6 compare buy vs. sell transactions of tranches with Aaa Moody's credit rating. The last two columns compare buy vs. sell transactions of tranches with Moody's investment grade credit ratings for the 1994 to 2005 period, excluding the years 2006 and 2007. Standard errors are calculated by clustering at the tranche level. Variable definitions are provided in Appendix B. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread	Tranche Spread
Transaction Type:	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
Rating:	Investment Grade	Investment Grade	Aaa-Aa3	Aaa-Aa3	Aaa	Aaa	Investment Grade	Investment Grade
							Sample Period	
							1994–2005	1994–2005
Bankrupt	48.801***	28.436***	43.177***	12.188***	31.962***	39.931***	64.910***	32.211***
Buyers	(16.680)	(10.831)	(11.165)	(3.979)	(7.533)	(12.343)	(13.259)	(10.393)
Redeployability	−0.222**	−0.442***	−0.579**	−0.278***	−0.507***	−0.482**	−0.269**	−0.545***
(operators)	(0.111)	(0.156)	(0.284)	(0.093)	(0.107)	(0.194)	(0.107)	(0.146)
Fuel Price	36.150	6.791	156.707	13.314	−86.534*	41.391	6.416	4.472
	(34.020)	(31.589)	(96.294)	(21.353)	(47.505)	(60.800)	(21.428)	(37.453)
Industry	3.029	−6.618	−25.724	3.739	−9.492	−19.736	6.262	−1.925
Bankruptcy	(5.262)	(5.264)	(16.225)	(4.279)	(7.247)	(17.619)	(4.932)	(5.575)
Amortizing	−60.338***	−117.907***	−334.867**	225.178			−71.500***	−121.490***
	(21.925)	(31.827)	(148.341)	(134.912)			(19.818)	(31.718)
Liquidity	−35.768*	−28.082**					−49.237***	−46.239*
Facility	(18.637)	(23.238)					(17.273)	(23.818)
Seniority	28.724**	18.541***	72.287	−24.276			33.440***	27.793*
	(11.972)	(13.576)	(91.376)	(45.892)			(12.108)	(14.565)
Tranche Size	−19.156	−26.360*	43.698*	−79.007**			−15.443	−19.493
	(12.685)	(15.353)	(24.614)	(32.571)			(12.787)	(15.161)
Call Provision	−46.212*	−30.865	−24.609***	−4.278			−42.646	−30.022
	(26.038)	(28.396)	(4.359)	(5.010)			(25.834)	(27.365)
Term-to-	2.630	7.817***	32.431**	−19.504*			4.395**	7.733***
Maturity	(2.599)	(2.568)	(14.141)	(11.111)			(2.034)	(2.663)
Airline Size	−34.097	75.192	−458.837	106.547	−232.743	−516.561***	15.698	122.178**
	(67.988)	(48.534)	(329.577)	(69.108)	(251.141)	(97.509)	(50.102)	(48.699)
Market-to-	13.758	80.397***	−146.136	85.104***	−124.277	−181.185**	14.335	50.870**
Book	(32.354)	(20.457)	(139.575)	(18.108)	(135.766)	(78.374)	(36.162)	(22.563
Profitability	−436.356***	163.745	809.942	99.093	−1,776.354***	−1,191.614***	−480.859***	58.557
	(157.622)	(214.282)	(1,010.792)	(209.242)	(241.397)	(58.610)	(143.742)	(210.623)
Leverage	158.462	131.025	504.531	1.292	612.351***	58.698**	80.305	98.440
	(166.102)	(85.686)	(430.307)	(106.396)	(35.894)	(22.308)	(151.204)	(86.284)
Fixed Effects	Airline+ Year	Airline+ Year	Airline+ Year	Airline+ Year	Airline+ Year	Airline+ Year	Airline+ Year	Airline+ Year
# of Tranches	93	96	17	17	5	4	93	95
# of Airlines	8	9	7	6	4	3	8	9
Adjusted R^2	0.34	0.33	0.64	0.86	0.96	0.79	0.38	0.32
Observations	2,374	7,196	591	966	74	259	2,285	6,101

sufficiently large, the collateral channel may ultimately result in downward spirals—bankruptcies lead to declines in collateral values and capital availability industry-wide, thereby inducing even more bankruptcies.

Appendix A: Constructing Redeployability and Bankruptcy Measures

In this appendix, we provide more detail regarding the construction of the redeployability variables and the bankruptcy variables used in the analysis.

As in Benmelech and Bergman (2008, 2009) and Gavazza (2008), we measure the redeployability of aircraft by exploiting aircraft model heterogeneity. To reduce costs associated with operating different aircraft types, airlines tend to operate a limited number of aircraft models. Potential secondary market buyers of any given type of aircraft are therefore likely to be airlines already operating the same type of aircraft. Thus, redeployability is proxied by the number of potential buyers and the "popularity" of an aircraft model type.

Using the Ascend CASE database, we construct two redeployability measures in the following manner. We first construct annual redeployability measures for each aircraft type. For every aircraft type and sample year, we compute 1) the number of nonbankrupt operators flying that aircraft model type, and 2) the number of aircraft of that type used by nonbankrupt operators. This process yields two redeployability measures for each aircraft type and each sample year. To construct the redeployability measures for a portfolio of aircraft serving as collateral for a particular tranche, we aggregate the aircraft type redeployability measures across all aircraft in the portfolio. Specifically, we define the redeployability of the collateral portfolio to be the weighted average of the redeployability index corresponding to each of the aircraft in the portfolio. The two measures are given by

$$Redeployability_{i,t}^{aircraft} = \sum_{s}^{S} \omega_{i,t,s}\left(Redeployability_{s,t}^{aircraft}\right)$$

$$Redeployability_{i,t}^{operators} = \sum_{s}^{S} \omega_{i,t,s}\left(Redeployability_{s,t}^{operators}\right),$$

where i denotes the tranche, t the sample year, and s the aircraft type, and $\omega_{i,t,s}$ is defined as

$$\omega_{i,t,s} = number_{i,t,s} \times seats_s \Big/ \sum_{s}^{S} number_{i,t,s} \times seats_s.$$

We use the number of seats in an aircraft model as a proxy for its size (and value) in our weighted-average calculations.

We construct two measures of shocks to collateral driven by airlines entering bankruptcy. For each aircraft type and calendar day in our sample, we calculate (1) the number of airlines operating that particular model type that are in bankruptcy, and (2) the number of aircraft of that particular type that are operated by airlines in bankruptcy.[26] Since changes in aircraft ownership are relatively infrequent, ownership information of aircraft is updated at a yearly rather than daily frequency. However, the two measures may change at a daily frequency due to airlines entering or exiting bankruptcy.

As for the redeployability measures described above, to construct the bankruptcy measures for a portfolio of aircraft serving as collateral for a particular tranche, we aggregate the aircraft type measures across all aircraft in the portfolio. To do so, we calculate the weighted average of the bankrupt buyer measure corresponding to each of the aircraft in the portfolio. Specifically, we calculate

$$BankruptBuyers_{i,t} = \sum_{s}^{S} \omega_{i,t,s}(BankruptBuyers_{s,t})$$

$$BankruptAircraft_{i,t} = \sum_{s}^{S} \omega_{i,t,s}(BankruptAircraft_{s,t}),$$

where i denotes the tranche, t the sample date, and s the aircraft type, and $\omega_{i,t,s}$ is a seat-based weighting scheme defined as above. Thus, for each tranche collateral pool, this process produces two measures of bankruptcy-induced collateral shocks for each trading day.

Figure A1 provides a timeline of airline bankruptcies in the United States over the sample period. The figure displays the timeline of the bankruptcies (on the horizontal axis) against the number of aircraft operated by the airline on the date the airline filed for bankruptcy. Fifteen airlines went bankrupt over the sample period, with three of them—TWA, Hawaiian, and US Airways—going through bankruptcy twice. The average (median) duration of an airline bankruptcy in our sample is 1.51 (1.35) years. As can be seen from the figure, the recession that began in March 2001 and the subsequent September 11, 2001 attacks mark a period of increased bankruptcy activity. Furthermore, several of the airlines that went bankrupt in the post 9/11 periods were very large (e.g., United, Delta, Northwest, and U.S. Airways) and involved a large number of aircraft operated by bankrupt airlines.

Finally, Figure A2 presents the total number of aircraft operated by bankrupt U.S. airlines over the sample period. The figure shows how, following the recession that started on September 11, 2001, the number of aircraft of bankrupt airlines increases dramatically to a maximum of 1,706 aircraft in 2005 when ATA, Delta, Northwest, United, and U.S. Airways were all in Chapter 11. This number decreases as United exits from bankruptcy in February 2006, and falls further in 2007 as both Northwest and Delta exit bankruptcy in 2007.

[26] We calculate these measures using beginning and end dates of airline bankruptcies from SDC Platinum.

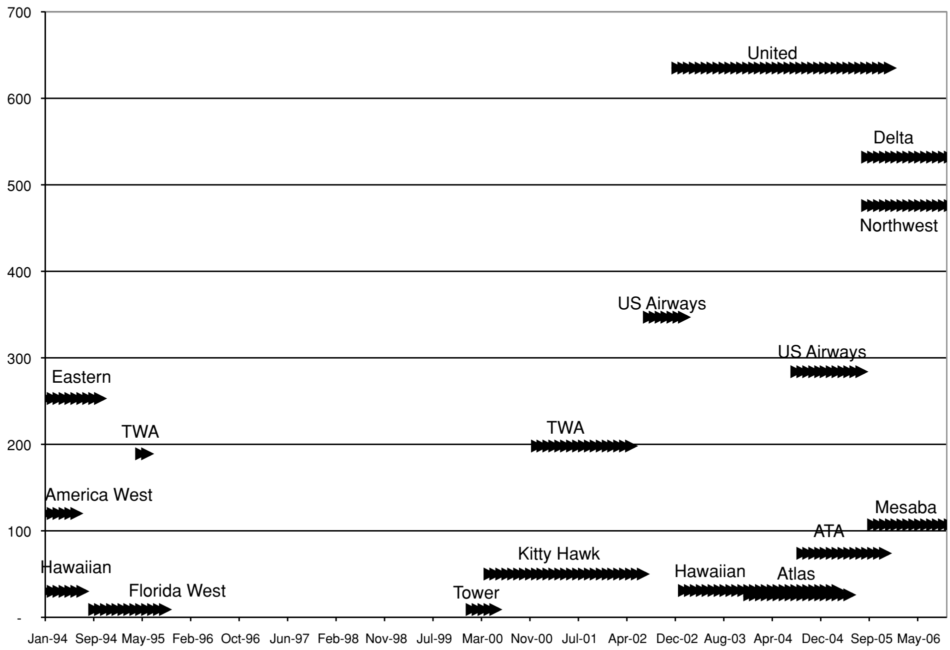

Figure A1. Timeline of airline bankruptcies in the United States, 1994 to 2006. Airline bankruptcy dates are obtained from SDC Platinum.

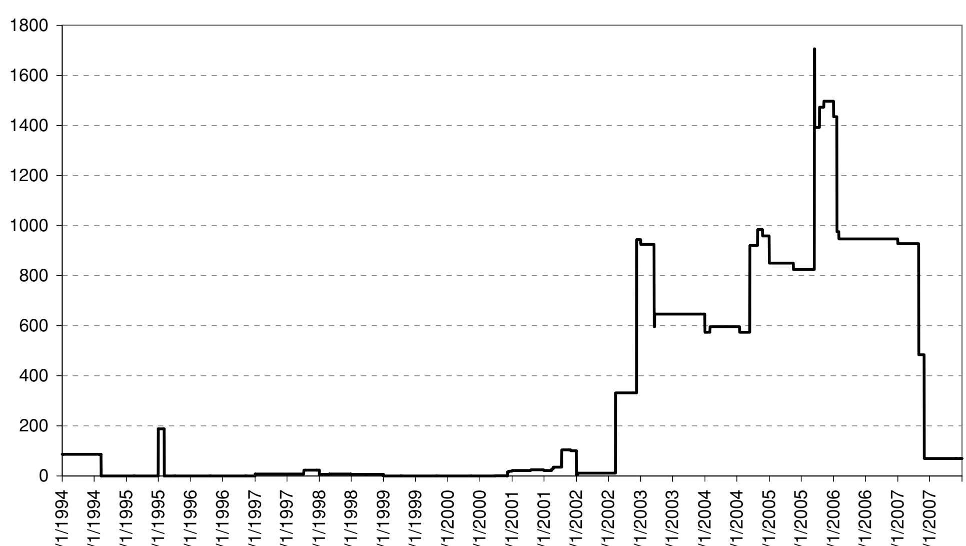

Figure A2. Total number of aircraft in bankruptcy. Total number of aircraft operated by bankrupt airlines in the United States, 1994 to 2007. Airline bankruptcy dates are obtained from SDC Platinum. Fleet data are obtained from the Ascend CASE database.

Appendix B: Variable Description and Construction

For reference, the following is a list of variables used in the paper, their sources, and a brief description of how each variable is constructed.

(i) *Amortizing*: Takes the value of one if the tranche is amortized. (Source: SDC and Issue Prospectus from EDGARPlus(R).)
(ii) *Bankrupt Assets / Total Assets*: The aggregate book asset value of airlines with current filings under Chapter 11 divided by the aggregate book asset value of all airlines in the United States (Source: SDC and Bureau of Transportation Statistics.)
(iii) *Bankruptcy dummy*: Takes the value of one if the airline has filed for bankruptcy protection during a particular year, and zero otherwise. (Source: SDC.)
(iv) *Call Provision*: Takes the value of one if the tranche is callable. (Source: SDC.)
(v) *Fuel Price*: The barrel price of kerosene jet fuel in $dollars. (Source: the Energy Information Administration website.)
(vi) *Healthy Assets / Total Assets*: The aggregate book asset value of nonbankrupt airlines divided by the aggregate book asset value of all airlines in the United States (Source: SDC and Bureau of Transportation Statistics.)
(vii) *Leverage*: The firm's total current liabilities + long-term debt [Compustat Annual Items 9+34+84] all divided by book value of assets [Compustat Annual Item 6]. (Source: Compustat.)
(viii) *Liquidity Facility*: Takes the value of one if the tranche has a liquidity facility enhancement. (Source: Issue Prospectuses from EDGARPlus(R).)
(ix) *LTV*: The tranche initial cumulative loan-to-value. (Source: Issue Prospectuses from EDGARPlus(R).)
(x) *Market-to-book*: The airline's market value of equity [Compustat Annual Items 24∗25] + book value of assets [Compustat Annual Item 6] minus book value of equity [Compustat Annual Item 60] all over book value of assets [Compustat Annual Item 6]. (Source: Compustat.)
(xi) *Number Bankrupt*: The number of airlines with current filings under Chapter 11. (Source: SDC.)
(xii) *Number Bankrupt / Total*: The number of airlines with current filings under Chapter 11 divided by the total number of airlines in the United States (Source: SDC and Bureau of Transportation Statistics.)
(xiii) *Number Healthy*: The number of nonbankrupt airlines. (Source: SDC.)
(xiv) *Number Healthy / Total*: The number of nonbankrupt airlines divided by the total number of airlines in the United States (Source: SDC and Bureau of Transportation Statistics.)
(xv) *Post 9/11 Dummy*: Takes the value of one for transaction dates after September 11, 2001.
(xvi) *Profitability*: Earnings [Compustat Annual Item 13] over total assets [Compustat Annual Item 6]. (Source: Compustat.)

(xvii) *Seniority*: Takes the value of one (senior) two, three, and four (junior). (Source: SDC and Issue Prospectuses from EDGARPlus(R).)

(xviii) *Size*: The logarithm of the airline's total book assets. (Source: Compustat.)

(xix) *Spread*: The tranche credit spread (in basis points) over a maturity-matched Treasury. (Source: Mergent.)

(xx) *Term-to-Maturity*: The tranche term-to-maturity (in years). (SDC and Mergent.)

(xxi) *Tranche Size*: The logarithm of the tranche issue size (in millions). (SDC.)

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