The role of trading frictions in real asset markets

Gavazza, Alessandro

New York University, Stern School of Business

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The Role of Trading Frictions in Real Asset Markets

Alessandro Gavazza[*]

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Abstract

Almost all real assets trade in decentralized markets, where trading frictions could inhibit the efficiency of asset allocations and depress asset prices. In this paper, I use data on commercial aircraft markets to empirically investigate whether trading frictions vary with the size of the asset market. Intuitively, it is more difficult to sell assets that have a thin market. As a result, firms find it optimal to hold on longer to assets with a thinner market in case their profitability rises in the future. Thus, when markets for firms' assets are thin, firms' average productivity and capacity utilization are lower, and the dispersions of productivity and of capacity utilization are higher. In turn, prices of assets with a thin market are, on average, lower and have a higher dispersion, since prices depend on firms' productivity and capacity utilization.

The empirical analysis confirms that trading frictions vary with the size of the market, as aircraft with a thinner market have: 1) lower turnover; 2) lower capacity utilization; 3) higher dispersion of utilization levels; 4) lower mean prices; and 5) higher dispersion of transaction prices.

1 Introduction

Many assets trade in decentralized markets. Classic examples are financial assets, such as bonds and derivatives, and real assets, such as real estate and capital equipment. The fundamental characteristics of a decentralized market are that traders must incur costs to search for trading partners and that, once a buyer and a seller meet, they must bargain to determine a price. The goal of this paper is to investigate how trading frictions vary with the thickness of the asset market, analyzing patterns of asset allocations and prices in the market for commercial aircraft.[1]

Some decentralized markets are very buoyant. The paragon is the secondary market for U.S. Treasury securities, where the daily volume of trade was about $125 billion in 1994 (Fleming, 1997). Although secondary markets for real assets are less bustling, some are still rather active. For example, among consumer durables, the number of used cars traded every year in the U.S. is more than twice as large as the number of new purchases (Stolyarov, 2002); among capital equipment, the number of transactions for used commercial aircraft is about three times the number of purchases of new aircraft (Gavazza, 2009).

In most decentralized markets, each asset trades several times during its "lifetime." Therefore, parties' trading decisions incorporate not only the expected cash flow that the asset generates, but also any cost that traders will incur in selling it at a later date.[2] When the number of potential users of the asset is small, trading in decentralized markets generates substantial monetary and opportunity costs, as the search process to find buyers able to generate the highest cash-flow from the asset may be difficult. For example, most capital equipment is specialized by industry, so used assets typically have greater value inside the industry than outside (Shleifer and Vishny, 1992). Even within an industry, however, one firm's assets may not be a perfect match for another firm's.

In this paper, I employ a tractable analytical framework to focus on the effects of market thickness on asset allocations and asset prices. I use the model to motivate several empirical tests for the presence of thick-market effects, and I perform these tests by combining several datasets on markets for one class of real assets—commercial aircraft. The theoretical framework adapts Diamond's (1982) seminal paper to asset markets, in a similar way to that of a growing literature—starting with Duffie, Gârleanu and Pedersen (2005)—that applies search-and-bargaining models to financial markets. The model's key economic mechanism is that, under a standard assumption on the meeting rate between buyers and sellers,[3] the trading technology exhibits increasing returns to scale. Thus, as the mass of assets increases, the

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[1]In the course of the paper, I use the expressions market thickness/thinness and size of the market interchangeably. In the empirical analysis, I will measure market thickness/size of the market of each aircraft type in two similar ways: 1) the stock of the aircraft of that type; and 2) the number of operators using that aircraft type.

[2]House and Ozdenoren (2008) construct a model of durable goods in which consumers' demand is influenced by resale concerns. In equilibrium, resale concerns can be so strong that individuals choose to purchase a good that they like less than other available goods.

[3]The precise assumption is that buyers and sellers meet according to a Poisson process with a fixed arrival rate. This is quite standard in the literature. See Duffie, Gârleanu and Pedersen (2005 and 2007), Vayanos and Wang (2007), and Weill (2008) for a sample of recent papers adopting this assumption.

flow of meetings increases more than proportionally. Increasing returns in search capture the notion that trading costs decrease with trading volume and that assets with a thicker market are more "liquid"—i.e., easier to trade.[4,5] Moreover, increasing returns precisely fit the characteristics of aircraft markets as reported by industry experts and market participants. For example, according to Lehman Brothers (1998), "[A]ircraft with a large number in current use across a wide array of users will obviously be easier to resell or re-lease than aircraft with limited production and usage."

Through the trading technology just described, the size of the asset market has important implications for allocations and prices. Trading frictions reduce the value of searching for a trading partner, thereby affecting owners' decision over whether or not to sell when their idiosyncratic profitability drops. When assets have a thin market, firms on each side of the market do not search exhaustively for the best matches (Ramey and Shapiro, 2001), and it is optimal even for quite inefficient firms to keep them. Instead, when assets have a thick market, the matching between buyers and sellers becomes easier, and assets transfer immediately to the highest-profitability firms. Thus, assets with a thicker market trade more frequently. In turn, these trading decisions determine the cross-sectional distribution of active firms. In particular, the lower bound of firms' productivity is higher when asset markets are thicker. Hence, the average profitability of firms is higher, and, at the same time, the dispersion of their profitability is lower in thicker asset markets. In summary, assets with a thick market are more efficiently allocated than assets with a thin market.

The effects of trading frictions on asset allocations transmits to asset prices. In particular, transaction prices are determined through negotiations that depend on sellers' and buyers' ability to generate cash-flow from the asset and on alternatives to immediate trade.[6] Hence, on average, prices are higher when assets have a thicker market since firms' profitabilities are higher. Moreover, the value of searching for an additional counterparty disciplines price dispersion. Since it is easier to find a counterparty in a thicker market, the cross-sectional dispersion of transaction prices is lower. Thus, the level and the dispersion of asset prices reflect how active the market is and how efficiently assets are allocated.

In summary, the theoretical framework generates five testable implications for assets with a larger market: 1) they trade more frequently; 2) they have higher average capacity utilizations; 3) they have lower dispersion of capacity utilization levels; 4) they fetch higher average prices; and 5) they have lower dispersion of transaction prices.

In the empirical section, I combine four distinct datasets concerning the aircraft market to empirically investigate the above implications. The data allow me to construct two related

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[4]See Lippmann and McCall (1986) for a similar relationship between market thickness and liquidity.

[5]The literature on liquidity in financial markets generally uses bid-ask spreads, or market depth, or float as measures of liquidity. In markets for corporate assets, however, bid-ask spreads and market depth cannot be measured, and the variable that is conceptually closer to the float is probably the total stock of aircraft of a given type—i.e., market thickness. Starting with Demsetz (1968), several papers (Garbade and Silber, 1976; Tanner and Kochin, 1971 are early examples. Amihud, Mendelson and Uno, 1999 is a recent example) have empirically investigated the relationship between bid-ask spreads and the float or the number of shareholders (for stocks), or issue size (for bonds). All these papers consistently find lower bid-ask spreads for stocks with larger float or a larger number of shareholders, and for bonds with a larger issue size.

[6]Pulvino (1998) empirically establishes that sellers in worse financial conditions sell assets at a lower price. In Section 4.7.2, I discuss in more detail the relationship between this paper and Pulvino (1998).

measures of the market size: 1) the stock of aircraft of a given type in a given year; and 2) the number of operators using a given aircraft type in a given year. The empirical analysis is heavily guided by the theory, but is also more flexible than the model. In particular, the richness of the data allows me to control for a large number of factors that may plague the identification of the effect of market thickness in the empirical analysis, addressing two main challenges: 1) heterogeneity of carriers that may generate selection into different aircraft types, and 2) endogeneity of the measures of market size. More precisely, I control for unobservable differences across models and even unobservable differences between vintages of the same model to identify the effect of market thickness on aircraft prices. In addition, to identify the effect of market thickness on asset allocations, I can also control for unobservable differences between aircraft of the same vintage and model, as well as for unobservable characteristics of the carriers that may induce selection into different aircraft types.

Nonetheless, the use of the quantity-based measures of market size described above could still create a few potential challenges to identifying the effects of market thickness. The reason is that both measures of market thickness are stock variables that include the flows of new aircraft/operators, and time-varying unobservables that affect aircraft utilization and prices may be correlated with these new flows and, thus, with the measures of market thickness. For example, unobservable *demand* shock, such as an increase in the demand for flights, could simultaneously increase aircraft demand, production of new units and entry of new carriers on one side, and capacity utilization and/or prices on the other side. To address these issues, the empirical analysis exploits the panel dimension of the data to use Arellano and Bond's techniques, along with a rich set of instruments that shift the endogenous variable for *supply-side* reasons. In particular, several papers have empirically documented the importance of learning-by-doing in aircraft production: The costs of producing an aircraft decreases with previous cumulative production (Wright, 1936; Asher, 1956; Alchian, 1963; Argote and Epple, 1990; Benkard, 2000). Thus, everything else equal, the *supply* of new units in a given year t is higher if cumulative production of the same type of aircraft was higher in previous years. Moreover, the richness of the data also allows me to use other *supply-side* instruments that should not be correlated with year-to-year short-run variations in *demand* between different types: the number of years since the aircraft type was first released by its manufacturer; the stock of aircraft of the same type produced more than 25 years ago; the (deflated) price of aluminum and its lags; and the average number of days of strike per worker in the manufacturing sector in the country of the aircraft manufacturer and its lags.

The empirical analysis confirms all theoretical predictions.[7] Moreover, the analysis reveals that the magnitudes of the effects are rather large. A ten-percent increase in the stock of aircraft of a given type implies: 1) a 1.9-percent increase in the hazard of trading the aircraft; 2) a 1.9-percent increase in the average capacity utilization; 3) a 2.2-percent decrease in the absolute percentage deviation of utilizations from the mean utilization; 4) a 2.7-percent increase in the average price; and 5) a 1.5-percent decrease in the absolute percentage deviation of transaction prices from the mean price.

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[7]Section 4.3 provides direct evidence on trading delays by investigating delays and idle times between leases.

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This paper is one of the first to investigate the role of the microstructure of the market for capital assets. The paper employs a unified framework to study the effects of trading frictions in real asset markets, and it provides quantitative evidence on the importance of these frictions for several economic outcomes. The empirical findings suggest that, even within a well-defined asset class such as aircraft, capital is moderately specialized, and market thinness generates frictions that are a large impediment to the efficient reallocation of capital.[8] These conclusions have several potential implications. First, the notion of asset-market thinness is similar to the notion of asset specificity, and an extensive large literature has shown the implications of asset specificity for economic institutions (Williamson, 1975), organization of firms (Hart, 1995), financial structure of firms (Shleifer and Vishny, 1992), and even macroeconomic fluctuations (Caballero and Hammour, 1998). However, quantification of specificity has remained scarce. Second, an important literature has investigated the role of costly capital reversibility on investment behavior (e.g., Dixit and Pindyck, 1994), and this paper provides estimates of these costs arising due to market thinness. Third, the paper complements a series of recent papers that study the process of capital reallocation and quantify frictions in such a process (Ramey and Shapiro, 1998, 2001; Maksimovic and Phillips, 2001; Schlingemann et al., 2002; and Eisfeldt and Rampini, 2006).

The paper further contributes to the literature on productivity dispersion. Capacity utilization is closely related to firm productivity. (Indeed, the model shows that more-productive firms choose a higher level of capacity utilization). An important literature (summarized in Bartelsman and Doms, 2000) has documented large and persistent productivity dispersion within narrowly defined industries, and most of the explanations for this dispersion have focused on technological differences between firms. The empirical patterns documented in this paper are similar to the ones uncovered in Syverson (2004 and 2007), but the economic mechanism that generates these patterns is rather different. In particular, while Syverson focuses on a demand-side factor (consumers' inability to switch between competing suppliers), I focus on a supply-side argument (frictions in the market for capital).[9,10] Hence, Syverson's papers and this paper offer complementary explanations of similar economic facts, and each explanation is better suited to describe a different industry with different characteristics (spatial differentiation versus decentralized input markets).

The paper proceeds as follows. Section 2 presents some institutional details on the markets for commercial aircraft. Section 3 introduces a theoretical framework to study the effect of market thickness on asset allocations and prices. The Section informally discusses the main

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[8]See, also, Kim (1998); Asplund (2000); Ramey and Shapiro (2001); Benmelech, Garmaise and Moskowitz (2005), and Balasubramanian and Sivadasan (2009).

[9]In independent work, Balasubramanian and Sivadasan (2009) construct an index of sunkenness of capital investments for U.S. manufacturing industries and empirically establish that the mean of industry productivity is lower and the dispersion of productivity is higher in industries with a higher value of the index of sunkenness of capital investments.

[10]By focusing on input markets, this paper shares some ideas with Melitz (2003), although the precise economic mechanism is rather different. Similarly, this paper has a few similarities with some search-theoretic analysis of the labor market. See Rogerson, Shimer and Wright (2005) for a survey. See, also, Petrongolo and Pissarides (2006), Bleakley and Lin (2007), Gan and Zhang (2006) and Teulings and Gautier (2005) for recent analyses of increasing returns to scale in labor markets.

economic forces behind the bilateral search model that is fully developed in Appendix A. Section 4 presents the data used in this paper, and tests the model's empirical predictions on the effect of market thickness on asset allocations and prices. Section 5 concludes. Appendix B calibrates the model to assess the magnitude of trading frictions.

2   Commercial Aircraft Markets

For several reasons, the aircraft market provides an ideal candidate for a general investigation of a search model of trading in decentralized markets and, in particular, of scale effects.

First, commercial aircraft are registered goods with all major "life" events (date of first flight, maintenance, scrappage, etc.) recorded, so very detailed data are available. Moreover, focusing on well-defined assets such as commercial aircraft allows control over a number of factors (e.g., technology differences, human-capital differences, market definitions, etc.) that might confound cross-industries studies. This allows for a clean identification of the effects of asset-market thickness on input allocations and prices.

Second, the secondary market for aircraft is a single, worldwide market. Aircraft are the only form of capital equipment that can be delivered to a buyer or an operator anywhere in the world within a day and get there under their own power. All airlines in the world use the same types of aircraft, and there are relatively few types. Moreover, the aircraft market is a market with almost perfect information about potential buyers and the quality of the assets.

Third, several facts suggests that trading frictions are important. In particular, aircraft are traded in decentralized markets, organized around privately-negotiated transactions.[11] Thus, there is no centralized exchange providing immediacy of trade and pre-trade price transparency. To initiate a transaction, a prospective seller must contact multiple potential buyers. Comparing two similar aircraft for sale is costly since aircraft sales involve the material inspection of the aircraft, which could be located in two different countries. In addition, a sale involves legal costs, which increase substantially if there are legal disputes over the title or if the local aviation authority has deregistered the aircraft. In some cases, there could also be outstanding bills for maintenance, fuel, and parking that have to be paid before the aircraft is released by the local authority, and sold. Thus, aircraft are seldom sold at auctions. Pulvino (1998) reports that in one of the first auctions, organized in 1994 to enhance the liquidity of the market, only nine of the 35 aircraft offered for sale were sold. Some subsequent auctions ended without even a single sale. Hence, aircraft markets share many features with other over-the-counter markets for financial assets (mortgage-backed securities, corporate bonds, bank loans, derivatives, etc.) and for real assets (real estate), in which trading involves material and opportunity costs (Duffie, Gârleanu and Pedersen, 2005 and 2007). As a result, most

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[11]This is one characteristic that Rauch (1999) uses to measure asset-specificity. The idea is that if an asset is sold on an organized exchange, then the market for this asset is thick and, hence, the asset is less specific to the transaction.

major carriers have staff devoted to the acquisition and disposition of aircraft, which suggests that trade is not frictionless.

In addition, compared to financial markets and other equipment markets, aircraft markets are "thin": The absolute number of transactions in the aircraft market is small. For example, in the 12 months between May 2002 and April 2003, of the total stock of 12,409 commercial aircraft used for passenger transportation and older than two years, only 720 (5.8 percent) traded.[12] In "thin" markets, the search costs to find high-value buyers are usually large (Ramey and Shapiro, 2001). Industry experts and market participants consider these frictions a fundamental characteristic of aircraft markets. For example, according to Lehman Brothers (1998): "The ratings agencies require an 18-month source of liquidity because this is the length of time they feel it will take to market and resell the aircraft in order to maximize value." Hence, transaction prices are very sensitive to parties' individual shocks, and the bargaining power of sellers and buyers is an important determinant of transaction prices. For example, Pulvino (1998) finds that sellers with bad financial status sell aircraft at a 14-percent discount relative to the average market price.

Fourth, aircraft are differentiated products, designed to serve different markets and different ranges. For example, a Boeing 747 is suited to markets in which both demand and distance are large. Thus, the differential number of different airline markets imply that some aircraft are more popular than others. Moreover, each type of aircraft requires human-capital investments in specific skills—for pilots, crew and mechanics—that increase the degree of physical differentiation. For a given type, the number of annual transactions can be very small: Only 21 used units of the Boeing 747 traded in the 12-month period ending April 2003. Clearly, the popularity of a given type also varies over time, as aircraft follow the typical life cycle of products. Thus, two main factors affect the thickness of the market for a specific aircraft type over time: the production of new units, and the retirement of old units. For example, the Boeing 727 was the most popular commercial aircraft during the 1970s, when production rates were high, but, today, it has a rather thin market as it has been phased out of production and many units have been retired.

Airline industry experts and participants in the aircraft market consider the thickness of the market a fundamental characteristic of an aircraft type. For example, as noted in the introduction, Lehman Brothers considers "aircraft with a large number in current use across a wide array of users [. . .] easier to resell or re-lease than aircraft with limited production and usage." Similarly, according to Wachovia Securities (2005): "[T]he following are drivers of marketability of a commercial aircraft type: Number of current operators [. . .]; Number of Aircraft in production run [. . .]; In-production status/backlog [. . .]; Existence of a cargo conversion program [. . .]; Number of young aircraft on ground [. . .]". Further, describing the aircraft leasing market,[13] Wachovia Securities (2005) states: "From a lessor's

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[12]The comparison with other capital goods is complicated because of the heterogeneity of capital goods. In a cross-industry study of corporate asset sales, Schlingemann et al. (2002) report a cross-industry average turnover of assets (measured in dollar values) of five percent. In their sample, more than ten two-digit industries have an average value of turnover higher than ten percent, and in some two-digit industries, the average value of turnover is as high as 23 percent.

[13]Leasing is very popular in the aircraft market, with about 50 percent of the current stock of commercial

perspective, a good leasing asset is one of which, 'if I get this aircraft back, I want a lot of people that I can talk to about the plane . . . .' "[14]

Why should an aircraft with a large number in current use be easier to resell than an aircraft with limited production? There are several, often reinforcing reasons. The most important reason is that carriers tend to minimize the number of types of aircraft they operate in order to achieve economies of scale in aircraft maintenance, in purchasing spare parts, in training of pilots, crew and mechanics, and in scheduling flights.[15] Hence, the number of current operators of an aircraft type captures well the number of potential buyers (Benmelech and Bergman, 2008 and 2009; Gavazza, 2010). A larger number of potential buyers obviously increases the probability that at least one carrier is seeking to acquire an aircraft. Furthermore, multimarket contact and geographic proximity between carriers reduces some of the costs of trading, such as the costs of inspecting the aircraft or registering it with the aviation authorities.[16] As a result, aircraft trade more frequently between two carriers operating in the same country than between two carriers operating in different countries. Thus, on average, a seller is more likely to be closer to a buyer whose fleet is composed of a more popular aircraft type. Moreover, carriers finance the purchase of aircraft mainly by issuing debt secured by the aircraft, and more-popular aircraft are better collateral. Hence, purchasing more-popular aircraft facilitates the availability of external financing (Littlejohns and McGairl, 1998).

Overall, all of these observations suggest that trading frictions are important and vary with market thickness. The next section introduces a theoretical framework that illustrates more precisely how trading frictions affect equilibrium asset allocations and prices. A rich set of comparative statics implications emerge from this framework, and I test them in Section 4.

3   Theoretical Framework

In this Section, I describe how we should theoretically expect asset allocations and prices to differ in thick markets versus thin markets. In Appendix A, I set up a bilateral search model to more formally investigate the effects of a thick asset market on allocations and prices. Here, I informally discuss the main economic forces behind the model, leaving all derivations to Appendix A. The model delivers testable implications regarding how trading frictions vary with the thickness of the asset market and regarding the effects of these frictions on the (endogenously determined) equilibrium asset allocations and prices.

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aircraft being leased. Gavazza (2009) explores the effect of leasing on aircraft turnover. Gavazza (forthcoming) explores how the liquidty/redeployability of aircraft affects whether aircraft are leased or not, the equilibrium maturity and pricing of lease contracts. Section 4.7.1 presents a robustness check to control for the role of leased aircraft.

[14]Wachovia Securities, *Structured Products Research, Commercial ABS*, September 2005.

[15]For example, in the United States, a successful carrier like Southwest flies one type of aircraft only, and Jetblue flies two. Similarly, in Europe, Ryanair flies one type of aircraft only, while Easyjet flies two types. Almost all small carriers in the world (below 25 aircraft) fly one type of aircraft only.

[16]In the United States, it is more time-consuming and costly for a carrier to register an aircraft that was previously registered to another carrier in a different country than to register an aircraft that was previously registered to another carrier in the United States. For many other countries, similar rules apply.

To fix ideas, consider an industry that is populated by a continuum of firms (carriers). Firms' production function uses a single input (aircraft) to produce output (flights). For simplicity, let us assume that there is no aggregate uncertainty and all aircraft are homogenous. The model can be extended to capture these two factors explicitly, and all the empirical predictions still survive. Moreover, the exact form of product-market competition among firms is not particularly relevant for the results. The only thing that matters is that firms have heterogenous productivity. More precisely, firms are differentiated by an exogenous productivity parameter that evolves stochastically over time. Firms observe their productivity and, if they own an aircraft, choose the hours of utilization of the aircraft to maximize the per-period profits from its use, with more productive carriers choosing a higher level of utilization.[17]

The focus of the model is on the input market. Firms can choose whether or not to acquire an aircraft if they do not own one, and whether or not to keep operating the aircraft or sell it if they own one. If a firm wants to trade (either buy or sell) an aircraft, it enters a decentralized search market in which it contacts other firms willing to trade. A firm seeking to trade an asset meets other firms from the overall population according to a Poisson process. Once two firms meet and are willing to trade, they negotiate a price to trade.

In this setting, firms endogenously select based on their productivity: Higher-productivity firms choose to operate aircraft, and lower-productivity firms choose to stay out of the market. Hence, there exists a unique *buyers' cutoff:* a value in the productivity distribution such that a firm that does not currently own an aircraft and whose productivity jumps above the cutoff chooses to acquire one. Similarly, there exists a unique *sellers' cutoff:* a value in the productivity distribution such that a firm that currently owns an aircraft and whose productivity falls below the cutoff chooses to sell it. When there are trading frictions, buyers' cutoff is higher than sellers' cutoff: Frictions create a wedge that prevents sellers from selling and buyers from buying.

The main point is that the buyers' and sellers' cutoffs change with the thickness of the asset market. The key economic force is that, under the search technology described above, active sellers (buyers) meet active buyers (sellers) at a rate proportional to the measure of active buyers (sellers). Therefore, the trading technology exhibits increasing returns to scale: Doubling the masses of active buyers and active sellers more than doubles the flow of meetings. Increasing returns in search nicely capture the idea that trading costs are decreasing with trading volume and precisely fit in a simple way the facts about aircraft markets described in Section 2. Thus, in a thicker market, the contact rate between buyers and sellers is higher, so once on the market, assets with a thicker market trade faster. In this sense, assets with a thicker market are more liquid (Lippmann and McCall, 1986). Instead, trading frictions are higher for assets with a thin market, and these assets have a higher option value for their owners: Firms choose to hold on to assets with thin markets for longer periods of time in case their productivity rises in the future. As a result, sellers' cutoff value is lower in a thinner market: It is optimal for inefficient firms to keep their assets rather than selling

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[17]When the profit function exhibits complementarities between the exogenous productivity of the firm and the endogenous choice of capacity utilization, more-productive firms choose a higher level of capacity utilization. Moreover, equilibrium profits are an increasing function of productivity. Hence, profits and productivity move one-to-one with capacity utilization.

them. Similarly, buyers' cutoff value is higher in a thinner market: Only very productive firms choose to incur the trading costs to acquire an aircraft. As the asset market becomes thicker, sellers' cutoff value increases and buyers' cutoff value decreases. Indeed, in the limit as the asset market becomes infinitely thick, buyers' and sellers' cutoffs converge, and the frictionless Walrasian benchmark obtains.

Sellers' and buyers' cutoffs affect the entire (endogenous) distributions of aircraft operators. In particular, the lower bound of aircraft operators' productivity is higher when the market is thicker. Thus, the equilibrium average productivity of aircraft operators is higher and the equilibrium dispersion of productivity is lower in thicker aircraft markets. Since capacity utilization moves one-to-one with productivity, capacity utilization is, on average, higher and exhibits less dispersion for aircraft with a thicker market.[18]

Furthermore, when a buyer and a seller bargain over the price at which they trade the asset, the individual abilities to generate cash-flow from the asset and the alternatives to immediate trade determine the buyer's willingness to pay, and the seller's willingness to accept and, thus, the transaction price. Hence, the effects of market thickness on the level of firms' profitabilities transmit to the level of transaction prices. As a result, assets with a thicker market have a higher average level of asset prices. Moreover, the value of searching for an additional counterparty disciplines price dispersion. Since it is easier to find a counterparty in a thicker market, the cross-sectional dispersion of transaction prices is lower.

In summary, the model makes the following predictions. As the market becomes thicker, assets: 1) have a higher turnover; 2) have a higher average level of capacity utilization; 3) have a lower dispersion of capacity utilization; and 4) have a higher average price; and 5) have a lower dispersion of transaction prices.

4   Empirical Analysis

4.1   Sources of Data

The empirical analysis in this paper combines four distinct datasets. The first dataset is an extensive database that tracks the history of each western-built commercial aircraft. I use this database to construct two measures of the thickness of each type of aircraft in each year. I then match the two measures (described in detail below) to the other datasets to investigate the effects of market thickness on asset allocations and prices. The second database reports the aircraft flying hours for the period 1990–2002, and I use this information to investigate several features of aircraft capacity utilization. The third dataset reports the prices of several aircraft models during the period 1967–2003. These prices are average values, similar to "Blue Book"

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[18]The model implies that productivity, profitability and capacity utilization are very closely related. The data seem to confirm this. For example, at the aggregate level, aircraft are parked inactive in the desert more frequently in recessions than in booms. After 9/11, when the profitability of the airline industry was severely hit, a large number of carriers decide to ground aircraft. As a result, capacity utilization decreased. Similarly, at the carrier level, the data reveal that Southwest has higher capacity utilization than other U.S. carriers, and that capacity utilization is substantially lower before a carrier enters into bankruptcy.

prices. The fourth dataset reports actual prices for a large number of transactions during the period 1978–1991. I now describe each dataset in more detail.

Aircraft History—This database, compiled by a producer of aviation-market information systems, reports the history of each Western-built commercial aircraft up to April 2003. For each aircraft serial number, the dataset contains information on the type (e.g., Boeing 737); the model (e.g., Boeing 737-600); the "birth" of the aircraft (date of the first flight); the sequence of operators with the relevant dates of operation; the operational role with each operator; and, if the aircraft is no longer in use, the date of the "death" of the aircraft (date the aircraft was scrapped).

Aircraft Utilization—This database, compiled by the producer of the aircraft history dataset, reports detailed information on the utilization of each aircraft by its operator. More precisely, the file reports the monthly flying hours of each aircraft from January 1990 to April 2003. Monthly utilization is aggregated at the year level, thus obtaining an annual panel for the 1990–2002 period. I discard observations (a serial-number–year pair) if the aircraft changes operator in the year in which the aircraft is traded, in order to be able to impute the annual utilization to a single operator.[19]

Blue Book Prices—This dataset was compiled by a consulting company that specializes in aircraft appraisals. It is an unbalanced panel reporting the historic values of prices of different vintages for the most popular models during the period 1967–2003. The prices are based on reported transactions and on the company's experience in consulting, appraisal and fleet evaluation. The prices assume that the transaction was made on the basis of a single unit bought with cash from a non-bankrupt seller. All values are in U.S. dollars, and I have deflated them using the GDP Implicit Price Deflator, with 2000 as the base year.

Transaction Prices—This dataset reports actual transaction prices for almost all aircraft traded by U.S. corporations during the period 1978–1991. Prior to 1992, the Department of Transportation (DOT) required price disclosure for all aircraft purchased or sold by U.S. corporations. The transaction prices used in this paper are based on these DOT filings. For each transaction, the filings report the aircraft serial number, buyer and seller identities, transaction price, date of transaction, and whether the transaction was a straight sale or a sale/leaseback. The dataset also reports some technical information, such as the age of the aircraft, the engine type, and the engine noise stage. In the empirical analysis of this paper, I focus on all used aircraft transactions reported in this dataset. All values are in nominal U.S. dollars, and I have again deflated them to the year 2000. Pulvino (1998) describes further details of this dataset.

4.2   Data Description

From the Aircraft History dataset, I calculate the thickness/size of the market for each aircraft in a given year in two different ways. The first is by counting the total stock outstanding of aircraft of type i in year t, and I call this variable AIRTYPE_{it}. The second is by counting the total number of carriers operating at least one aircraft of type i in year t, and I call this

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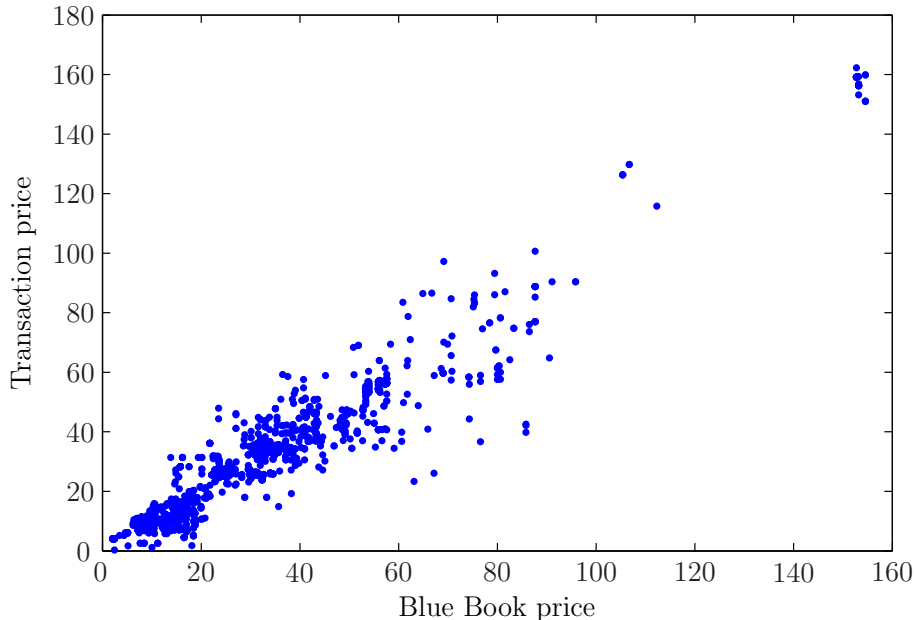[19]The results are almost identical when observations are retained.

FIG. 1: Transaction price vs. Blue Book price

variable OPTYPE_{it}. In the theoretical framework, the two variables are identical, and in the data, they are very highly correlated (the correlation is at least .91 in the samples on which the regressions are run). Note that the two variables vary across both different aircraft types i and different years t.[20]

I then match AIRTYPE_{it} and OPTYPE_{it} to the dataset on aircraft utilization and the two datasets on prices. More precisely, to investigate the effect of market thickness on allocations, I match AIRTYPE_{it} and OPTYPE_{it} to each aircraft's holding duration to study whether aircraft with a thicker market have higher turnover. Further, I match AIRTYPE_{it} and OPTYPE_{it} to the annual flying hours fh_{jkit} of aircraft j of model k type i in year t to study how average utilization and the dispersion of utilization levels covary with market thickness. More precisely, to investigate the dispersion of utilization levels, I calculate the average flying hours of all age-a–model-k–type-i–year-t tuples, $\overline{fh}_{akit}$. I then compute the absolute value of the percentage deviation of the flying hours fh_{jkit} of aircraft j of $\text{AGE}_{jkit} = a$–model-k–type-i–year-t from the average $\overline{fh}_{akit}$, i.e., $\left| \frac{fh_{jkit} - \overline{fh}_{akit}}{\overline{fh}_{akit}} \right|$.[21]

Similarly, to investigate the effect of market thickness on the average level of asset prices, I match the price $\bar{p}_{akit}$ of aircraft of age-a–model-k–type-i–year-t reported in the Blue Book

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[20]It is important to note that the measures of market thickness are at the aircraft-type level. As specified above, a type is, for example, Boeing 737, Boeing 747, MD-80, and so on. Within each type, there might be different models. For example, for the type Boeing 737, we have models B737-200, B737-300, and so on. Within each type, the technical specifications of different models are very similar. Thus, comparisons between types exactly capture differences in market size, which is consistent with industry norms.

[21]I am using the absolute percentage deviation rather than the standard deviation because the absolute percentage deviation rescales the deviations by the value of the average, while the standard deviation does not. For example, consider two aircraft types that differ in their average capacity utilization (because of their size), but have the same standard deviation of utilization. Then, one standard deviation represents a larger percentage deviation from the mean for the aircraft that has a lower mean. In summary, the absolute percentage deviation is independent of the average, and this is why I use it.

dataset with the corresponding values of AIRTYPE_{it} and OPTYPE_{it}. To investigate the effect of market thickness on the dispersion of transaction prices, I first match each transaction price from the transaction dataset with the average prices of the corresponding age-model-type-year tuple from the Blue Book dataset. Then, I construct the absolute percentage deviation of the transaction price from the Blue Book price $\left|\frac{p_{jkit}-\bar{p}_{akit}}{\bar{p}_{akit}}\right|$, where p_{jit} is the transaction price of aircraft j of $\text{AGE}_{jit} = a$–model-k–type-i–year-t, and $\bar{p}_{akit}$ is the Blue Book price just defined. Next, I match this measure of price dispersion for model k to the corresponding values of AIRTYPE_{it} and OPTYPE_{it} of type i ($k \in i$). Figure 1 shows that Blue Book prices and transaction prices are highly correlated (the correlation coefficient is equal to .96), so that the Blue Book prices capture the average price of a specific aircraft very well. Moreover, Figure 1 shows that there are some differences between the transaction prices and the Blue Book prices, and in the empirical analysis, I investigate whether these differences are systematically correlated with market thickness.[22]

Table 1 provides summary statistics of the main variables used in the empirical analysis. Panel A considers the turnover of assets by measuring holding durations. Overall, this is the largest sample, since it is based on the entire Aircraft History Dataset, and, thus, it covers a longer time period than the other datasets. The average duration is around seven years, with a standard deviation of 6.5 years. The duration of the first operator of each aircraft tends to be, on average, nine years, longer than subsequent durations. Some of the durations are ongoing—that is, they are right-censored—and around 70 percent of durations are completed. Moreover, the total number of operators is very large: the dataset reports approximately 1,500 distinct operators during the (long) period considered. Hence, panel A shows that AIRTYPE and OPTYPE vary substantially, both across types and within type over time. Some aircraft types are very popular and, thus, have been produced in large numbers and have many operators; others have been less successful or are old types that are retired during the sample period and have few operators. The average of AIRTYPE is 1167 and the standard deviation is 1007; the average of OPTYPE is 96 and the standard deviation is 85.

Panel B considers aircraft utilizations. On average, aircraft fly around 2,700 hours per year, with a standard deviation of 1,100 hours. Around four percent of all observations in the sample have flying hours equal to zero—that is, they are parked inactive in the desert. A fraction of this mass of inactive aircraft is sold to new carriers that acquire capital to enter the industry, and the remaining fraction reenters service with the original owner. Considering only aircraft with positive flying hours, the average utilization is 2,860 hours with a standard deviation of 960 hours. Since the dataset reports utilization data only from 1990, the averages of AIRTYPE and OPTYPE are now higher and, again, they show considerable variation: The

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[22]Alternatively, I could investigate how average prices vary with the thickness of the asset market using the transaction price p_{jit} as the dependent variable. However, there are at least two disadvantages to this procedure: 1) the dataset would no longer be a panel dataset; thus, the Arellano and Bond procedure described below cannot be employed; and 2) the number of observations would be smaller, and, in particular, the time-dimension would be much shorter. Similarly, I could investigate how the dispersion of transaction prices vary with the thickness of the asset market by calculating the absolute percentage deviation of the transaction price from the *average* transaction price of comparable aircraft. The main disadvantage of this procedure is that, for many aircraft, the average would be calculated from very few observations, often just one.

TABLE 1: Summary statistics

PANEL A: ASSET TURNOVER	MEAN	ST. DEV.	MIN.	MAX.	MEDIAN
HOLDING DURATION	7.02	6.46	1	37	5
TYPES OF AIRCRAFT	33				
AIRCRAFT PER TYPE—AIRTYPE	1167.6	1007.1	2	4173	905
OPERATORS PER TYPE—OPTYPE	96.13	85.61	1	345	63
PANEL B: AIRCRAFT UTILIZATION					
FLYING HOURS fh_{jkit}	2741.13	1097.02	0	5890	2773
ABSOLUTE PERCENTAGE DEVIATION $\left\lvert\frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}}\right\rvert$	.1895	.2728	0	9.01	.11
PARKED AIRCRAFT	.043	.203	0	1	0
TYPES OF AIRCRAFT	26				
AIRCRAFT PER TYPE—AIRTYPE	1439.58	1100.63	7	4116	1105
OPERATORS PER TYPE—OPTYPE	122.16	100.84	1	345	68
AGE	12.29	7.63	3	41	10
PANEL C: BLUE BOOK PRICES					
AVERAGE PRICE $\bar{p}_{jkit}$	28.35	24.20	.24	145.5	21.27
TYPES OF AIRCRAFT	18				
AIRCRAFT PER TYPE—AIRTYPE	1057	954	45	4173	884
OPERATORS PER TYPE—OPTYPE	86.95	81.09	9	345	60
AGE	10.84	7.11	1	36	9
PANEL D: TRANSACTION PRICES					
TRANSACTION PRICE p_{jkit}	30.60	24.47	.29	162.3	28.56
ABSOLUTE PERCENTAGE DEVIATION $\left\lvert\frac{p_{jkit}-\bar{p}_{akit}}{\bar{p}_{akit}}\right\rvert$	.171	.193	0	1.26	.09
TYPES OF AIRCRAFT	13				
AIRCRAFT PER TYPE—AIRTYPE	960.6	612.2	75	2340	917
OPERATORS PER TYPE—OPTYPE	74.45	46.75	9	215	53
AGE	7.35	6.94	0	25	7

Notes—This table provides summary statistics of the variables used in the empirical analysis. Panel A presents summary statistics for the Aircraft History dataset. These data are used in the test of prediction 1 on the effect of market thickness on asset turnover. HOLDING DURATION measures the number of years the aircraft has been with an operator. Many durations are ongoing, so this is a censored sample. AIRTYPE is the total stock of aircraft of a given aircraft type in a given year. OPTYPE is the total number of carriers operating a given aircraft type in a given year. Panel B presents summary statistics for the Aircraft Utilization dataset. These data are used in the test of prediction 2 on the effect of market thickness on the level of utilization, and prediction 3 on the effect of market thickness on the dispersion of utilization. The data correspond to the years 1990-2002. PARKED AIRCRAFT is a binary indicator taking a value of one if the aircraft has zero flying hours for the entire year. FLYING HOURS fh_{jkit} is the total number of hours that the aircraft has flown in year t. ABSOLUTE PERCENTAGE DEVIATION $\left\lvert\frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}}\right\rvert$ is the absolute percentage deviation of the annual hours flown fh_{jkit} of aircraft j of $\text{AGE}_{jkit} = a$–model-k–type-i–year-t from the average $\overline{fh}_{akit}$, where the average annual hours flown $\overline{fh}_{akit}$ are calculated using all aircraft of age-a–model-k–type-i–year-t. Panel C presents summary statistics for the "Blue Book" prices dataset. These data are used in the test of prediction 4 on the effect of market thickness on the level of asset prices. Panel D presents summary statistics for the dataset of U.S. transactions. These data are used in the test of prediction 5 on the effect of market thickness on the dispersion of transaction prices. ABSOLUTE PERCENTAGE DEVIATION $\left\lvert\frac{p_{jkit}-\bar{p}_{akit}}{\bar{p}_{akit}}\right\rvert$ is the absolute percentage deviation of the transaction price p_{jit} of aircraft j of $\text{AGE}_{jit} = a$–model-k–type-i–year-t, from the Blue Book price $\bar{p}_{akit}$ of aircraft of age-a–model-k–type-i–year-t reported in the Blue Book dataset. Blue Book prices in Panel C and Transaction prices in Panel D are in millions of U.S. dollars and have been deflated using the GDP Implicit Price Deflator, with 2000 as the base year.

averages are 1,435 aircraft and 123 operators, respectively; the standard deviations are 1,101 aircraft and 101 operators, respectively.

Panel C provides summary statistics for the Blue Book dataset. There are 18 different aircraft types in the sample. The average Blue Book price of an aircraft in the sample is 28 million (year 2000) dollars, and there is substantial variation in prices (the standard deviation is 24 million dollars). AIRTYPE and OPTYPE show substantial variation, both across types and within type, over time. For example, looking at just the Boeing 737, there are as many as 4,173 units and 345 operators in 2003, and as few as 333 units and 38 operators in 1973.

Panel D considers transaction prices. The time period during which transaction prices were reported to the DOT (1978–1991) is considerably shorter than the time period of the Blue Book prices (1967–2003). Thus, the number of observations is smaller (1,555); the number of aircraft types is also smaller (13); and, overall, the variables exhibit smaller variations. Nonetheless, the main variable of interest—the absolute percentage deviation of the transaction price from the corresponding Blue Book price—shows considerable variation (the standard deviation is 19 percent) around its mean of 17 percent. Market thickness—either AIRTYPE or OPTYPE—again shows substantial variation, both across types and within type, over time.

The strengths of the data lie in their extensive coverage of many aspects of the aircraft market. In particular, the richness of the aircraft history dataset allows me to measure very precisely the thickness of the market of each aircraft type, with variation both across aircraft types and within type over time. Thus, in the empirical analysis, I can control for several features of the asset that are often unobserved in studies that rely solely on cross-sectional data. The time-series variation helps me control for several time-invariant unobserved factors and obtain convincing evidence regarding how trading frictions due to market thinness affect aircraft allocations and aircraft prices.[23]

4.3   Some Suggestive Evidence on Trading Frictions

Before turning to a more formal analysis, I present some simple conditional correlations that speak directly to the importance of search frictions generated by thin markets. In an ideal setting, we could obtain direct evidence on the importance of frictions by looking at how long an aircraft stays on the market before selling or at how many potential buyers a seller contacts before closing a sale, and see how these quantities are related to the thinness/thickness of the asset market. While this would be a very interesting exercise, these quantities are, unfortunately, unobserved in the data. However, from the data, I can reconstruct one very closely related measure of delay that can directly illustrate the frictions implied by market thinness. In particular, from the Aircraft History dataset, for each leased aircraft, I can reconstruct how many days it stays with its lessor between one lessee and the next.[24] These delays are a precise example of the frictions that the paper highlights— delays in trading— rather than, for example, transaction costs such as lawyers' fees.

Lessors appear to be more sophisticated than carriers at turning their aircraft over (Gavazza, 2009). Hence, delays between two consecutive lessees can be interpreted as a lower bound on

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[23]All empirical results are robust to dropping the smallest and the largest one percent of the observations.

[24]Thus, I can have multiple observations for the same aircraft (a serial number).

TABLE 2: Delays before Leasing Transactions: Negative Binomial Regressions

DAYS BETWEEN TWO LESSEES	(1)	(2)	(3)	(4)
AGE	.06795	.06410	.04029	.03633
	(.00782)	(.00779)	(.01310)	(.01305)
AGE SQUARED	−.00054	−.00041	−.00034	−.00019
	(.00024)	(.00023)	(.00039)	(.00039)
LOG(AIRTYPE)	−.20638		−.25078	
	(.02087)		(.04050)	
LOG(OPTYPE)		−.13902		−.16737
		(.02411)		(.04649)
LOG-LIKELIHOOD	−30637.14	−30667.57	−7782.05	−7793.91
# OBS	9358	9358	4396	4396

Notes—This table presents maximum likelihood estimates of the coefficients of negative binomial regressions. The dependent variable is equal to the number of days that an aircraft stays with its lessor after it has been returned from a lessee and before it is delivered to a new, different lessee. AGE is the age of the aircraft (in years). AIRTYPE is the total stock of aircraft of a given aircraft type in a given year. OPTYPE is the total number of carriers operating a given aircraft type in a given year. Standard errors clustered at the aircraft-type–year level in parentheses. The equations estimated in columns (1) and (2) contain aircraft type fixed effects and year fixed effects (not reported). The equations estimated in columns (3) and (4) contain aircraft (serial number) fixed effects and year fixed effects (not reported).

the delays that carriers expect when they put their owned aircraft up for sale. Indeed, the data show that a large fraction of these delays are very short: the median is zero days. However, the distribution has a long tail, thus increasing the average: 67 (90) percent of the observation have delays within one month (year) and the average delay is 115 days. Clearly, if there were no frictions, we would expect no delay at all between consecutive lessees. Moreover, if frictions did not vary with market thickness, we would expect AIRTYPE and OPTYPE to be uncorrelated with delays.

In Table 2, I report the results of several negative binomial regressions in which the dependent variable is the number of days between two consecutive lessees, and the main explanatory variable of interest is the (log of the) thickness of the aircraft market.[25] I also include year fixed effects and aircraft type fixed effects in columns (1) and (2), and year fixed effects and individual aircraft (a serial number) fixed effects in columns (3) and (4).[26] As the table clearly

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[25]I employ a negative binomial specification to more precisely account for the many zeros (about 55 percent of the observations have zero days of delay between two consecutive leases), and the small set of values that the dependent takes on.

[26]As Neyman and Scott (1948) first observed, estimating fixed effects in a non-linear model could generate the incidental parameter problem if the number of observations per each fixed effect were small. However, when using year and aircraft type fixed effects, we have a large number of observations and not too many fixed effects, so the incidental parameter problem is not a concern in the specifications of columns (1) and (2). In the specifications of columns (3) and (4), we have many more fixed effects. Hence, as shown by Hausman, Hall and Griliches (1984), we can use a conditional likelihood approach to consistently estimate the parameters of a negative binomial regression with a large number of fixed effects. However, the use of individual aircraft fixed effects in the specifications of columns (3) and (4) substantially reduces the number of observations compared

shows, aircraft with a larger market are redeployed faster to a new lessee, and the results are robust to different ways of measuring market thickness. Moreover, the negative binomial specifications imply that the coefficients of LOG(AIRTYPE) and LOG(OPTYPE) are equal to the elasticities. Thus, according to the more conservative estimates of columns (1) and (2), a ten-percent increase in the stock of aircraft AIRTYPE is associated with a two-percent decrease in the days between two consecutive lessees, and a ten-percent increase in the stock of operators OPTYPE is associated with a 1.4-percent decrease in the days between two consecutive lessees. At the average value of the variables, these elasticities imply that doubling market thickness (either 158 aircraft per type or 12 operators per type in this sample) decreases the days between consecutive lessees by about two to three days.[27]

While the results reported in Table 2 are consistent with the idea that market thickness generates frictions that affect the allocation of (leased) aircraft, they should also be interpreted with some caution, for several reasons. First, the data do not allow us to identify leases that have been renewed by the previous operator. Thus, the inference is based on the selected sample of leased aircraft for which the old lessee decided not to renew the lease. However, a few robustness checks using the cumulative number of days of delay for each leased aircraft throughout its "life" confirm the results of Table 2.[28] These checks suggest that sample selection is not a big concern and corroborate that delays before transactions are shorter for aircraft with a thicker market. Second, in the data, the precise date on which the lessor puts the aircraft on the market and starts searching for a new lessee—after the old lessee decides not to renew the lease—is unobserved. However, there does not seem to be any good reason why lessors of aircraft with a thinner market should start searching for a new lessee *later* than lessors of aircraft with a thicker market. Indeed, the above evidence suggests that lessors should anticipate longer delays and start searching for a lessee *earlier* when aircraft have a thinner market. Third, since the distribution of delays has a long right tail, the presence of some outliers may drive the estimates of the regression coefficients. However, I have also estimated regressions in which the dependent variable is a binary indicator taking the value of zero if there were zero days of delay, and one if delays were strictly positive, and these regressions (not reported) confirm that aircraft with a thicker market are redeployed faster to a new lessee. Fourth, the magnitude of the estimated effects seems small. However, since the precise date on which the lessor starts searching for a new lessee is unobserved, it is not possible to assess the true extent of these delays. Nonetheless, we can conclude that the evidence suggests that market thinness generates frictions that affect transactions. I next turn to a more formal empirical analysis of the causal effects of asset market thickness on

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to the specifications of columns (1) and (2). The reason is either because there is just one observation per serial number, or because all outcomes within a serial number are identical (and equal to zero.)

[27]The results are robust to the inclusion of the fraction of all aircraft of a given type that is leased in a given year as an additional explanatory variable.

[28]More precisely, I calculate the cumulative number of days of delay for each leased aircraft throughout its "life" and investigate how it covaries with the size of the aircraft market. Due to some coding issues, calculating the cumulative number of days of delay is not obvious for aircraft that were owned and later became leased, and vice versa. In any case, using different imputation assumptions, or discarding aircraft that switched from owned to leased or vice versa, I always obtain the same result as the regressions of Table 2: Delays are shorter for aircraft with a thicker market. This suggests that sample selection is not a big concern.

asset allocations and prices.

4.4   Empirical Framework and Identification

The theoretical framework of Section 3 guides the empirical tests of the effects of market thickness on allocations and prices. The empirical specification is more flexible than the model, thus allowing departures from some of its simplifying assumptions (such as no depreciation, one asset type, and no aggregate shocks). More precisely, I specify the following equation:

$$
\begin{aligned}
y_{jkit} &= \beta Z_{jkit} + \zeta_k + \eta_t + \epsilon_{jkit} \\
&= \beta_0 + \beta_A \text{LOG}(\text{THICKNESS}_{it}) + \beta_X X_{jkit} + \zeta_k + \eta_t + \epsilon_{jkit}
\end{aligned}
\tag{1}
$$

where the dependent variable y_{jkit} is one of the outcomes of interest (holding duration, utilization, dispersion of utilization, average price, price dispersion) for aircraft j of model k type i in year t. THICKNESS$_{it}$ is either AIRTYPE or OPTYPE. X_{jkit} is specific to each individual aircraft—i.e., AGE$_{jkit}$. ζ_k is an aircraft-model fixed effect, η_t is a year fixed effect, and ϵ_{jkit} is an idiosyncratic unobserved component. Thus, the variables X_{jkit}, ζ_k and η_t control for vintage, aircraft-type, and year effects that the model does not consider.

The use of the quantity-based measures AIRTYPE and OPTYPE creates a few potential challenges to identifying the effects of the size of the asset market in equation (1). The reason is that both measures of market thickness are stock variables that include the flows of new aircraft/operators, and time-varying unobservables that affect the outcome variables might be correlated with these new flows and, thus, with AIRTYPE and OPTYPE. In particular, unobservable *demand* shocks can pose a threat to the identification of the role of market thickness. For example, an increase in the demand for flights could simultaneously increase aircraft demand, production of new units—and, thus, AIRTYPE—and entry of new carriers—and, thus, OPTYPE—on one side, and capacity utilization and/or prices on the other side. Similarly, if resale costs or aircraft-maintenance costs change over time, they could simultaneously affect aircraft demand—and, thus, AIRTYPE and OPTYPE—and capacity utilization and prices. Moreover, if the unobservables are serially correlated, the unobservables are correlated also with lags and leads of market thickness.

The previous *demand-side* argument could invalidate the tests of some of the predictions— in particular, the predictions on the effect of market thickness on the average level of capacity utilization and on the average level of prices. However, the argument does not have obvious effects on the other predictions that are more unique to the search-frictions framework that is the focus of the paper—the predictions on the effect of market thickness on the turnover of assets, on the dispersion of capacity utilization, and on the dispersion of transaction prices. At the same time, it is clearly possible that some demand shocks that are heterogenous across different aircraft types generate predictions similar to those of the theoretical framework of Section 3. For example, an increase in demand for regional aircraft may lead to an increase in turnover because of an increase in the reallocation of aircraft across regional carriers.

The inclusion of year dummies η_t allows me to control for all aggregate effects and any type of serial correlation of all these effects and, thus, to capture aggregate increase in demand

and the serial correlation of aggregate demand. Nonetheless, there might still be within-year variations in demand between models correlated with Airtype and Optype, and persistent. In principle, the direction of the bias caused by variations in demand between models within a given year is ambiguous: Deviations from year fixed effects could very well be *negatively* correlated with market thickness. The reason is that the effect of an increase in demand could be bigger for "marginal" aircraft types—that is, aircraft that are used by few operators and flown only when demand is very high.

In any case, when I perform the analysis on panel data—capacity utilization, dispersion of capacity utilization, Blue Book price—I deal with these endogeneity concerns using a procedure that uses the insights of Arellano and Bond (1991), but that employs a richer set of *supply-side* instruments. Arellano and Bond suggest estimating a panel-data regression as equation (1) first-differencing the variables to eliminate the persistent component of the unobservable, and then instrumenting the first-difference of a potentially endogenous variable $\Delta z_{it} = z_{it} - z_{it-1}$. More formally, let the outcome equation and the error term be:

$$y_{jkit} = \beta Z_{jkit} + \zeta_k + \eta_t + \epsilon_{jkit}, \qquad (2)$$

$$\epsilon_{jkit} = \rho \epsilon_{jkit-1} + \nu_{jkit}. \qquad (3)$$

Simply taking first-differences of the variables in equation (2) eliminates the aircraft-model fixed effect ζ_i, as well as any fixed term constant within aircraft j. However, first-differences do not eliminate the persistent component of the error term, as $\Delta y_{jkit} = \beta \Delta Z_{jkit} + \Delta \eta_t + \Delta \epsilon_{jkit}$. Subtracting ρy_{jkit-1} from y_{jkit} eliminates $\epsilon_{jkit} - \rho \epsilon_{jkit-1}$, leaving only the innovation ν_{jkit} of the unobservable:

$$y_{jkit} = \rho y_{jkit-1} + \beta Z_{jkit} - \beta \rho Z_{jkit-1} + (1-\rho) \zeta_k + \eta_t - \rho \eta_{t-1} + \nu_{jkit}. \qquad (4)$$

Taking first-differences, the following equation obtains:

$$\Delta y_{jkit} = \rho \Delta y_{jkit-1} + \beta \Delta Z_{jkit} - \beta \rho \Delta Z_{jkit-1} + \Delta \eta_t - \rho \Delta \eta_{t-1} + \Delta \nu_{jkit}. \qquad (5)$$

In the differenced form, however, the new errors $\Delta \nu_{jkit}$ are correlated with the differenced lagged dependent variable Δy_{jit-1} by construction, and potentially with the variables ΔZ_{jkit} and ΔZ_{jkit-1}, as well. Therefore, a vector W of instruments is required to construct moments $E(\Delta \nu_{jkit} * W)$, and to estimate equation (5) via GMM.

Arellano and Bond use the lagged values y_{jkit-h} and Z_{jkit-h} with lags $h \geq 2$ as instruments for Δy_{jkit-1} and ΔZ_{jkit-l} $l = 0, 1$, respectively, as the new error term $\Delta \nu_{jkit}$ is uncorrelated by construction with lags of order higher than two.[29] These instruments y_{jkit-h} and Z_{jkit-h}

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[29]First-differencing the data introduces serial correlation in the new errors Δv_{jkit}. Arellano and Bover (1995) suggest an alternative procedure that does not introduce serial correlation in the new errors. The procedure—called Orthogonal Deviations—consists of constructing the deviation for each observation from the average of future observations in the sample for the same panel-id. However, this approach does not work with autocorrelated errors, as in equation (3). Alternatively, Arellano and Bover (1995) and Blundell and Bond (1998) suggest adding the original equation (1) in levels to the GMM criterion, instrumenting the endogenous variable in levels with first-differences. However, these additional moments are valid under the assumption that first-differences of the endogenous variables are uncorrelated with the persistent component

with lags $h \geq 2$ are "mechanically" correlated with the potentially endogenous variables Δy_{jkit-1} and ΔZ_{jkit-l}. Hence, following Arellano and Bond, I use y_{jkit-h} with lags $h = 2$ as the instrument for the lagged endogenous variable Δy_{jkit-1}.

The commercial-aircraft setting provides me with instruments for the main endogenous variable—changes in market thickness—that have a stronger economic content than Arellano and Bond's instruments—i.e., instruments that shift the endogenous variable for *supply-side* reasons. In particular, I previously discussed that the production of new units and the retirement of old units are the two main factors affecting the thickness of the market for a specific aircraft type over time. The instruments shift one of these two factors for *supply-side* reasons. More precisely, several papers have empirically documented the importance of learning-by-doing in aircraft production: The costs of producing an aircraft decrease with previous cumulative production (Wright, 1936; Asher, 1956; Alchian, 1963; Argote and Epple, 1990; Benkard, 2000). Thus, everything else equal, the *supply* of new units in year t is higher if cumulative production of the same type of aircraft was higher in year $t-2$. In other words, cumulative production in year $t-2$ is correlated for *supply-side* reasons with one component of the endogenous variable—changes in market thickness—but, by construction, is uncorrelated with the innovation in *demand* in period t—i.e., it is a good instrument. Moreover, lags of cumulative production of order higher than $t-2$ are good instruments too, in particular given the time it takes to build an aircraft (12 to 18 months).

Furthermore, the richness of the data also allows me to use other *supply-side* instruments that should not be correlated with year-to-year short-run variations in *demand* between different types. In particular, I use the number of years since the aircraft type was first released by its manufacturer; the stock of aircraft of the same type produced more than 25 years ago; the (deflated) price of aluminum,[30] and the one-year and two-year lags, each interacted with aircraft characteristics (the number of seats, the number of engines, the maximum take-off weight, and the number of years since the release date);[31] and the average number of days of strike per worker in the manufacturing sector in the country of the aircraft manufacturer,[32] the lags up to three years, and their interactions with aircraft characteristics (the number of seats, the number of engines, the maximum take-off weight, and the number of years since the release date). The idea of these instruments is the following. For a similar learning-by-doing argument, we can expect the *supply* of new units to be lower if the aircraft type was recently released by the manufacturer. The number of aircraft retired is, on average, higher if the existing stock of aircraft is old—i.e., if the number of aircraft produced more than 25 years ago is high. The *supply* of new units should be lower if the price of the aluminum—one of the main materials used in the production of aircraft—is higher. The *supply* of new units

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of the unobservable, an assumption that is likely to be violated in the current context.

[30] The price of aluminum is obtained from the EconStats website, from data collected by the U.S. Geological Survey. Available at `http://www.econstats.com/spot/rt_alum.htm`

[31] I use only two- and three-year lags of the deflated price of aluminum in the construction of all instruments used in the regressions that investigate the effect of market thickness on the level of prices reported in Section 4.6.1. This is because the use of the contemporaneous price of aluminum may not satisfy the exclusion restriction needed for the validity of the instruments.

[32] The strike data are obtained from the Laborsta database operated by the International Labour Office, Bureau of Statistics. Available at `http://laborsta.ilo.org/`.
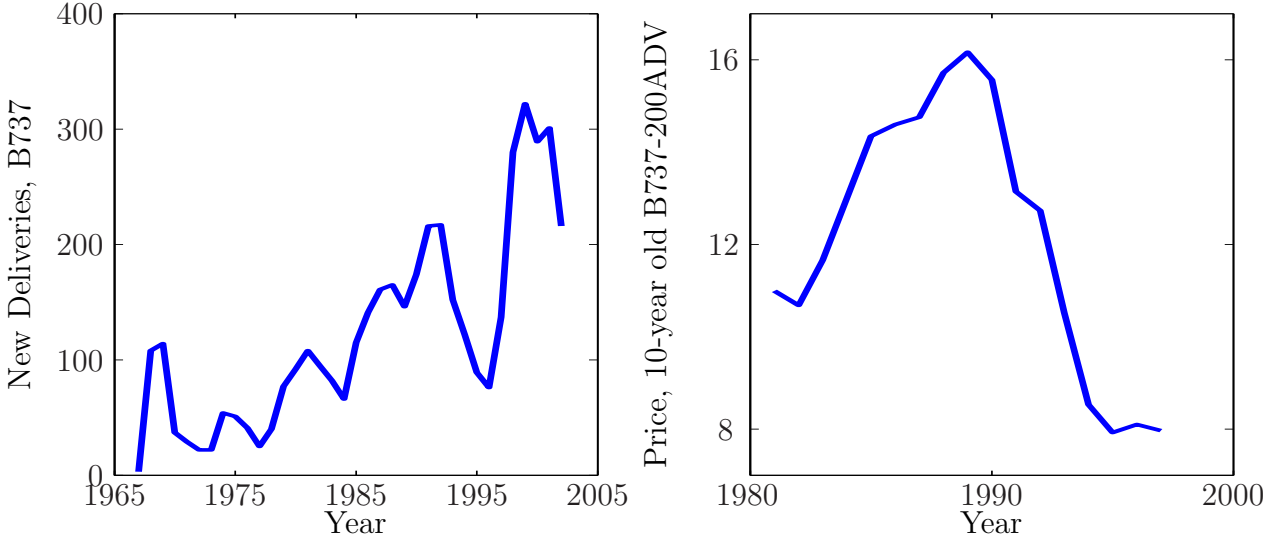
FIG. 2: Deliveries of new Boeing 737 (left panel) and price of a ten-year old Boeing 737-200ADV (right panel).

should be lower if the number of strikes in the manufacturing sector in the country where the aircraft is assembled is higher. Indeed, these instruments are jointly significant, and they are not weak: The F-test on the exogenous instruments has values above 30 in regressions equivalent to the "first stage" of Two-Stage Least Squares.

In summary, the Arellano-Bond procedure described by equations (2) to (5) removes any type-specific fixed component—e.g., time-invariant aircraft quality—and any type-specific persistent component—e.g., demand shocks, fuel efficiency, resale costs, and maintenance costs. In addition, the supply-side instruments directly address the possibility of spurious correlations due to type-specific innovations in unobservable demand.

As Blundell and Bond (1998) demonstrate, the difference-GMM procedure does not work well if the dependent variable—in this case, capacity utilization, dispersion of capacity utilization, and Blue Book price—is very persistent. However, this does not appear to be a concern in this case since the notorious cyclicality of the airline industry implies that capacity utilization and prices vary over time (Pulvino, 1995; Benmelech and Bergman, 2009). Similarly, the two main shifters of AIRTYPE and OPTYPE (production of new aircraft and retirement of old aircraft) exhibit substantial year-to-year variation. For example, Figure 2 depicts the time-series of deliveries of new aircraft and the price (in millions of year-2000 dollars) of a ten-year-old model of the most popular aircraft type, the Boeing 737.

In the analysis of the effect of market thickness on asset turnover and on the dispersion of transaction prices, either panel-data are not available or the difference-GMM procedure is not appropriate, as will become clear below. However, the instruments can still be exploited. In particular, I use the following instruments for the potentially endogenous variable: cumulative production in year $t - 5$; the stock of aircraft of the same type produced more than 25 years ago; the (deflated) price of aluminum, interacted with aircraft characteristics (the number of seats, the number of engines, the maximum take-off weight, and the number of years since the release date); and the average number of days of strike per worker in the manufacturing

sector in the country of the aircraft manufacturer, alone and interacted with aircraft characteristics (the number of seats, the number of engines, the maximum take-off weight, and the number of years since the release date). When panel-data are not available, the assumptions required for the instruments to yield consistent estimates are stronger than when panel-data are available and difference-GMM can be employed. More precisely, as pointed out previously, if the unobservables are very persistent, even distant lags of the endogenous variable remain correlated with the unobservables. Hence, to reduce endogeneity concerns to a minimum, I am using very distant lags of cumulative production (year $t-5$). Moreover, the other *supply-side* instruments are arguably uncorrelated with *demand-side* shocks.

4.5 Results: the Effect of Market Thickness on Asset Allocations

This subsection investigates the effect of market thickness on two aspects related to asset allocations. The first is the effect on asset turnover. The second is the effect on capacity utilization—I analyze the effect of asset market thickness on both the average level of utilization and the dispersion of utilization levels.

4.5.1 Asset Turnover

The first implication of the model that I test is that assets trade more frequently when their market gets thicker. The theoretical framework highlights that the combination of two factors should affect assets' trading patterns. First, assets with a thicker market should trade more frequently because they stay "on the market" for a shorter period of time. The economic intuition is that the trading technology exhibits increasing returns to scale, and, thus, trading frictions decrease with the size of the market. Indeed, this is exactly what the analysis of delays between two consecutive lessees indicates. Second, the time it takes to cash in on the asset is a cost for the seller. When assets have a thin market, this cost is higher, making the owner less likely to put the asset on the market for sale. Hence, owners choose to hold on to assets with a thin market for longer periods of time.

As mentioned in the description of the data, the data do not allow me to separately identify these two effects in a precise way for all aircraft (owned and leased). The analysis of delays between two consecutive lessees indicates that the first factor has an effect on the allocation of leased aircraft. In any case, it is plausible to expect that the second factor has a bigger economic relevance. Here, I simply analyze the effect of asset-market thickness on asset turnover, investigating the holding durations of each aircraft. More precisely, I use a Cox proportional hazard model for the probability of trading an aircraft. Since the specification I use is slightly different from equation (1), I now describe it in some detail. The Cox model assumes that the probability of trading aircraft jit after s years from the acquisition, given that the aircraft has not been traded before, is equal to:

$$h_{jkit}(s) = h_{0i}(s)\exp\left(\beta_A \text{LOG}(\text{THICKNESS}_{it}) + \beta_X X_{jkit} + \eta_t\right). \tag{6}$$

where k denotes a model, i denotes a type, and t denotes a year; $h_{0i}(s)$ is the baseline hazard

function, allowed to vary across aircraft types; THICKNESS$_{it}$ is either AIRTYPE or OPTYPE; X_{jkit} is the AGE of the aircraft at the beginning of the spell; η_t is a year fixed effect.[33],[34] Equation (6) represents a very flexible specification of the conditional probability of trading an aircraft, since the entire shape of the baseline hazard $h_{0i}(s)$ is allowed to vary across aircraft types.[35] Moreover, this specification does not impose any functional form on the type-specific baseline hazard $h_{0i}(s)$, so the effect of market thickness is identified purely from variation in AIRTYPE or OPTYPE within a type i.[36]

As highlighted in the previous section, a potential concern with estimating equation (6) is that the quantity-based measure AIRTYPE or OPTYPE could be correlated with some unobserved components of demand. For example, an unobserved increase in the demand for flights could simultaneously increase production of aircraft and volume of trade, and AIRTYPE or OPTYPE might be correlated with this shock. A few papers in the literature document patterns consistent with this idea in the aggregate economy: Maksimovic and Phillips (2001) report that the number of plants sold is higher in expansion years than in recession years, and Eisfeldt and Rampini (2006) document that the amount of capital reallocation between firms is procyclical. Thus, a positive correlation between AIRTYPE or OPTYPE and asset turnover could be a confirmation of Maksimovic and Phillips's and Eisfeldt and Rampini's findings. Year fixed effects already capture most of the year-to-year variation in demand, but there might still be within-year variations in demand between aircraft types that are correlated with the size of the asset market.

To address this potential concern, I use a two-step control function approach as in Blundell and Powell (2003), with instruments for LOG(AIRTYPE) or LOG(OPTYPE).[37] As the previous section describes, I employ instruments that arguably shift the thickness of the asset market variable independently of short-run demand shocks: cumulative production in year $t-5$; the stock of aircraft of the same type produced more than 25 years ago; the (deflated) price of aluminum and its lags, interacted with aircraft characteristics (the number of seats, the num-

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[33]To prevent the incidental parameter problem when there were few observations within a fixed effect, I have grouped all years prior to 1960 in a single time fixed effect (the excluded category), and in the specifications that include carriers' fixed effects, all carriers with fewer than 50 observations in a single carrier-fixed effect (the excluded category).

[34]I have also estimated a version of equation (6) that includes aircraft-vintage fixed effects to control for the year of birth of the aircraft instead of year fixed effects. The results are almost identical to the results in Table 3 and, thus, are omitted.

[35]I have also estimated a more restrictive specification that allows aircraft-type fixed effects ζ_i to shift the hazard only proportionally. The precise equation is:

$$h_{jkit}(s) = h_0(s)\exp\left(\beta_A \text{LOG(THICKNESS}_{it}) + \beta_X X_{jkit} + \zeta_i + \eta_t\right).$$

The results are almost identical to those reported in Table 3, and, thus, are omitted.

[36]The coefficient of the variable AGE AT THE BEGINNING OF SPELL is identified since each aircraft has multiple operators during its lifetime. If we were considering only the duration of the first operator (i.e., when the aircraft is acquired new), clearly the coefficient of AGE AT THE BEGINNING OF SPELL would not be identified.

[37]The control function approach requires running a first-step regression of the endogenous variable on the instrument plus the other explanatory variables, and computing the residuals. In the second step, the hazard is estimated including the residual from the first step as a regressor. These residuals control for the potential endogeneity of AIRTYPE and OPTYPE.

TABLE 3: Market Thickness and Aircraft Turnover: Hazard Model Estimates of Trading

HAZARD	(1)	(2)	(3)	(4)
AGE AT THE BEGINNING OF SPELL	.04451 (.00453)	.04344 (.00448)	.00027 (.00487)	−.00015 (.00479)
LOG(AIRTYPE)	.25517 (.09215)		.19042 (.09835)	
LOG(OPTYPE)		.37810 (.12095)		.33125 (.13469)
LOG-LIKELIHOOD	−136760.3	−136704.9	−132836.8	−132793.8
# OBS	241622	241622	241622	241622
AIRCRAFT	17398	17398	17398	17398

Notes—This table presents maximum likelihood estimates of Cox proportional hazard models that investigate the effect of market thickness on the probability of trading aircraft. AGE AT THE BEGINNING OF THE SPELL is the age of the aircraft (in years) at the time of the acquisition. AIRTYPE is the total stock of aircraft of a given aircraft type in a given year. OPTYPE is the total number of carriers operating a given aircraft type in a given year. Standard errors clustered at the aircraft-type–year level in parentheses. All equations allow the baseline hazard to vary by aircraft-type. The equations estimated in all columns also contain year fixed effects (not reported). The equations estimated in columns (3) and (4) additionally contain carrier fixed effects (not reported).

ber of engines, the maximum take-off weight, and the number of years since the release date); the average number of days of strike per worker in the manufacturing sector in the country of the aircraft manufacturer and its lags, and the interactions with aircraft characteristics (the number of seats, the number of engines, the maximum take-off weight, and the number of years since the release date).

Table 3 presents the results of the second stage. I measure the size of the market with AIRTYPE in columns (1) and (3), and with OPTYPE in columns (2) and (4). The specification of columns (1) and (2) does not include carrier fixed effects, while the specification of columns (3) and (4) includes them. The results indicate that aircraft with a thicker market have shorter holding durations. These results are robust across the two ways of measuring market thickness, and to the inclusion of carrier fixed effects. The point estimates mean that an increase of AIRTYPE by ten percent increases the hazard rate of trading by about 1.9-2.5 percent, a sizable magnitude. Similarly, an increase of OPTYPE by ten percent increases the hazard rate of trading by about 3.3-3.7 percent. To understand the economic magnitude of these elasticities, a ten-percent increase in the market thickness of the Boeing 737—the most popular aircraft—corresponds to about 190 aircraft in the year 1990, and this is similar to the average annual production of *new* Boeing 737. Such increase in market thickness decreases each holding duration by about two to three months. Since the Boeing 737 is the aircraft type with the thickest market, the elasticities imply that an equivalent increase of 190 aircraft in the market size of any other aircraft type decreases holding durations by a larger amount—i.e., the magnitudes reported for the Boeing 737 are the lowest bound of the magnitudes of all

aircraft types.[38]

Overall, the results reported here provides strong evidence in favor of prediction 1: Assets with a thicker market have higher turnover.

4.5.2 Capacity Utilization

The previous analysis shows that aircraft trade more frequently as their market gets thicker, suggesting that aircraft with a thinner market are more illiquid. This has potential implications for the allocation of the assets. In fact, the model implies that aircraft that trade more frequently are allocated more efficiently. I now investigate another aspect of asset allocations, testing prediction 2 that capacity utilization of aircraft operators should be higher as the aircraft market gets thicker.

The theoretical model with endogenous capacity utilization developed in Appendix A indicates that capital utilization is an increasing function of the firm's underlying productivity, as other papers in the literature also suggest (e.g., Burnside and Eichenbaum, 1996). Moreover, most of the extensive empirical literature on productivity cannot precisely distinguish productivity from capacity utilization (see Jorgenson and Griliches, 1967, for an early discussion). Hence, these theory-driven considerations imply that we can infer something about carriers' productivity by studying utilization rates, and the link between aircraft AIRTYPE or OPTYPE and capacity utilization indicates whether assets with a thicker market are more efficiently allocated. To this end, I estimate equation (1) with $\text{LOG}(fh_{jkit})$ as a dependent variable, where fh_{jkit} is the total annual flying hours of aircraft j of model k type i in year t.

The estimation of equation (1) with $\text{LOG}(fh_{jkit})$ as the dependent variable faces a few econometric challenges, in addition to the ones already outlined in Section 4.4. The first challenge is that aircraft are frequently parked inactive in the desert. Technically, parked aircraft imply that the dependent variable is censored at zero. I could deal with this complication generically—estimating a Tobit model via maximum likelihood—but in the data, censoring acts in a slightly more subtle way. In particular, all parked aircraft have zero flying hours, but the non-parked aircraft have flying hours that start at around 1,000 hours per year. This gap implies that the effects of the independent variables on the extensive and the intensive margins are likely to be different. Moreover, unobserved heterogeneity in the extensive margin is likely correlated with unobserved heterogeneity in the intensive margin, implying that $E(\epsilon_{jkit}|Q_{jkit}, fh_{jkit} > 0) \neq 0$ and simple regressions on the sample of aircraft with positive

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[38]One potential issue with the previous analysis is the role of replacement purchases of aircraft. If carriers sell old aircraft when they acquire new ones of the same type, then, mechanically, we would observe more frequent trading of existing aircraft when more new units of the same type are produced. The quantity-based measure AIRTYPE includes new units, and, thus, the observed correlation between turnover and AIRTYPE could be simply due to replacement purchases. In reality, the use of the instruments described in the text eliminates this concern. Moreover, the evidence reported in Gavazza (2009) shows that aircraft replacement accounts for a minority of aircraft trades, and most trades are, instead, due to profitability shocks to carriers. In addition, the observed correlations would still imply that one motive for trade (replacement) is stronger for more popular aircraft, which is perfectly consistent with the idea put forth in this paper that market thickness matters for asset allocations and prices. In short, even if all trades were due to replacement, we should still conclude that replacement is more frequent for more-popular aircraft, indicating that trading frictions are lower for more-popular aircraft.

TABLE 4: Market Thickness and Aircraft Utilization: difference-GMM estimates

	(1) FLY_{jkit}	(2) FLY_{jkit}	(3) $\text{LOG}(fh_{jkit})$	(4) $\text{LOG}(fh_{jkit})$
AGE	−.01497 (.00232)	−.01279 (.00281)	−.03437 (.00383)	−.03521 (.00361)
LOG(AIRTYPE)	.09842 (.04861)		.18996 (.08998)	
LOG(OPTYPE)		.08586 (.02413)		.09105 (.03845)
# OBS	64279	64279	60139	60139
AIRCRAFT	11596	11596	11240	11240

Notes—This table presents Arellano and Bond GMM estimates of the effect of market thickness on capacity utilization. The dependent variable in columns (1) and (2) is a binary indicator equal to one if the aircraft had positive flying hours in a given year, and zero otherwise. The dependent variable in columns (3) and (4) is the log of annual flying hours. The sample is restricted to aircraft with strictly positive flying hours in the specifications of columns (3) and (4). AGE is the age of the aircraft. AIRTYPE is the total stock of aircraft of a given aircraft type in a given year. OPTYPE is the total number of carriers operating a given aircraft type in a given year. Standard errors clustered at the aircraft-type–year level in parentheses. All equations also contain year fixed effects (not reported).

flying hours provide inconsistent estimates. However, in practice, all parameters can be consistently recovered using only aircraft with positive flying hours by estimating equation (1) in the first-difference specification—equation (5). Thus, I estimate two separate equations: one for the extensive margin, and one for the intensive margin.[39]

The difference-GMM procedure outlined in section 4.4 relies on the linearity of the estimating equation. Hence, I use a linear probability model also in the extensive-margin equation, since the difference-GMM procedure allows me to deal with many econometric complexities. In particular, in addition to endogeneity issues previously discussed, it is useful to highlight that the difference-GMM procedure also allows me to difference out any selection effect that may induce different carriers with different business models (e.g., hub-and-spoke versus point-to-point; scheduled airlines versus charter airlines) to choose different aircraft types, and affect the average level of capacity utilization.

Table 4 presents the coefficients of the difference-GMM.[40] Columns (1) and (2) present the results of the extensive-margin equation, and columns (3) and (4) of the intensive margin. According to the estimates in column (1), a ten-percent increase in AIRTYPE is associated with a 0.9 percentage point increase in the probability that the aircraft is flying, a considerable

[39]Aircraft also have a maximum utilization rate, as they cannot fly more than 24 hours per day. However, in the data, we do not observe any mass point in the upper tail of the utilization distribution, which suggests that the upper bound is never achieved.

[40]The number of observations in columns (1) and (2) differs from the number of observations in columns (3) and (4) because the regressions on the intensive margin (columns (3) and (4)) use only aircraft that have positive flying hours in periods t and $t-1$.

magnitude. The results reported in column (2) using OPTYPE are very similar: a ten-percent increase in OPTYPE is associated with a 0.8 percentage point increase in the probability that the aircraft is flying. According to the estimates in column (3), conditional on flying, a ten-percent increase in AIRTYPE is associated with a 1.9-percent increase in capacity utilization. The results obtained using OPTYPE in column (4) are slightly smaller: a ten-percent increase in OPTYPE is associated with a 0.9-percent increase in capacity utilization. These elasticities imply, for example, that a ten-percent increase in market thickness of the Boeing 737 (either 190 aircraft per type or 17 operators in the year 1990, at the beginning of this sample period) increases annual flying hours by about 30 to 60 hours, a non-trivial number. As I previously pointed out, since the Boeing 737 is the aircraft type with the thickest market, the magnitudes for the Boeing 737 are the lowest bound of the magnitudes for all aircraft types.

Overall, the results support prediction 2 that aircraft capacity utilization increases as the aircraft market gets thicker. Since the model indicates that capacity utilization and productivity are directly related (are a one-to-one function), the evidence, thus, suggests that assets are more efficiently allocated when their market gets thicker.

4.5.3 Dispersion of Capacity Utilization

As highlighted by the discussion in Section 3, the same economic forces that increase capacity utilization when the market gets thicker imply that the equilibrium dispersions of carriers' capacity utilization is lower as the asset market gets thicker. Thus, I now turn to the empirical investigation of the dispersion of utilization rates, directly testing prediction 3.

I analyze the link between the size of the aircraft market and dispersion of capacity utilization, investigating whether the absolute percentage deviation of flying hours $\left|\frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}}\right|$ described in subsection 4.2 is lower for aircraft with a thicker market. More precisely, I specify equation (1) with $\left|\frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}}\right|$ as the dependent variable. I then employ difference-GMM to estimate equation (5) with $\Delta \left|\frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}}\right|$ as the dependent variable, with instruments for the potentially endogenous variable market thickness.[41] As previously noted, the difference-GMM procedure is particularly well suited to difference out any selection effect that may induce different carriers with different business models to choose different aircraft types, and generate dispersion of capacity utilization.

Table 5 reports the estimated coefficients. Market size is measured with AIRTYPE in columns (1) and (3), and with OPTYPE in columns (2) and (4). The negative coefficients of the market-size variables show that as the aircraft market gets thicker, the dispersion of capacity utilization decreases. The coefficients reported in column (1) imply that a ten-percent increase in the stock of aircraft decreases dispersion of utilization by 2.2 percent. The coefficients reported in column (2) imply that a ten-percent increase in the number of operators decreases dispersion by approximately one percent. At the average value of the

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[41]I also undertook the same procedure calculating the average for each age a-type i-year t tuple—i.e., $\overline{fh}_{ait}$, and using $\left|\frac{fh_{jkit}-\overline{fh}_{ait}}{\overline{fh}_{ait}}\right|$ as a dependent variable. The results are very similar to those reported in Table 5 and, thus, are omitted.

TABLE 5: Market Thickness and Dispersion of Capacity Utilization: difference-GMM estimates

	(1) $\left|\frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}}\right|$	(2) $\left|\frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}}\right|$	(3) $\left|\frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}}\right|_{fh_{jkit}>0}$	(4) $\left|\frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}}\right|_{fh_{jkit}>0}$
AGE	.03102 (.00559)	.03717 (.00521)	.01672 (.00267)	.01687 (.00271)
LOG(AIRTYPE)	−.22892 (.09246)		−.17437 (.06521)	
LOG(OPTYPE)		−.10631 (.04163)		−.05421 (.02861)
# OBS	63886	63886	60139	60139
AIRCRAFT	11582	11582	11240	11240

Notes—This table presents Arellano and Bond's GMM estimates of the effect of market thickness on the dispersion of capacity utilization. The dependent variable is the absolute percentage deviation of flying hours of a given aircraft from the average flying hours of all aircraft of the same age and model in the same year. The equations estimated in specifications (3) and (4) use only observations with strictly positive flying hours. AGE is the age of the aircraft. AIRTYPE is the total stock of aircraft of a given aircraft type in a given year. OPTYPE is the total number of carriers operating a given aircraft type in a given year. Standard errors clustered at the aircraft-type–year level in parentheses. All equations also contain year fixed effects (not reported).

variables, these elasticities imply that a ten-percent increase in market thickness of the Boeing 737 (either 190 aircraft per type or 17 operators in the year 1990, at the beginning of this sample period) decreases the absolute value of the deviation of individual annual flying hours from the mean—i.e., $|fh_{jkit} - \overline{fh}_{akit}|$—by about five to ten hours.

In columns (3) and (4), I perform the same regressions as in columns (1) and (2), but I consider only observations with positive flying hours. More precisely, I calculate the average $\overline{fh}_{akit}$ only using observations with $fh_{jkit} > 0$, and then calculate $\left|\frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}}\right|_{fh_{jkit}>0}$. The reason for this choice is that aircraft with zero flying hours mechanically increase the dispersion of utilization levels, and it is instructive to understand whether the dispersion is driven exclusively by parked aircraft. The coefficients reported in columns (3) and (4) show that, as expected, the magnitude of the effect of market thickness on dispersion is smaller when only active aircraft are considered. However, the size of the aircraft market still has a considerable effect: A ten-percent increase in AIRTYPE$_{it}$ decreases dispersion of utilization by 1.7 percent, and a ten-percent increase in OPTYPE$_{it}$ decreases dispersion of utilization by 0.5 percent. These elasticities imply, for example, that a ten-percent increase in market thickness of the Boeing 737 (either 190 aircraft per type or 17 operators in the year 1990, at the beginning of this sample period) decreases the absolute value of the deviation of individual annual flying hours from the mean—i.e., $|fh_{jkit} - \overline{fh}_{akit}|_{fh_{jkit}>0}$—by about two to six hours. Moreover, the magnitudes for all other aircraft types are larger, since the Boeing 737 is the aircraft type with the largest market.

These regressions confirm that market thickness affects both the intensive and the extensive

margins of utilization.[42,43]

4.6 Results: the Effect of Market Thickness on Aircraft Prices

This subsection investigates the effect of market thickness on asset prices. I present two sets of results, directly testing predictions 1 and 2 related to the first and second moments of the cross-sectional price distribution.[44]

4.6.1 Average Prices

To test prediction 4 on the effect of market thickness on aircraft prices, I specify equation (1) with $\log \bar{p}_{jkit}$ as the dependent variable, where $\bar{p}_{jkit}$ is the Blue Book price of an aircraft of vintage j model k type i in year t.[45] I then estimate the first-difference version (5) with $\Delta \log \bar{p}_{jkit}$ as the dependent variable using GMM, instrumenting for the potentially endogenous variable $\Delta \text{LOG}(\text{AIRTYPE}_{it})$ and $\Delta \text{LOG}(\text{OPTYPE}_{it})$.

Table 6 reports the estimated coefficients. The table shows that aircraft prices increase as their market gets thicker, confirming prediction 4. Moreover, the magnitude of the economic effect is sizable: A ten-percent increase in AIRTYPE is associated with a 2.7-percent increase in the price of the aircraft. This magnitude is equivalent to the effect on price of around six months of AGE. Similarly, a ten-percent increase in OPTYPE is associated with a 2.0-percent increase in the price of the aircraft. To get a better sense of the economic significance of the results, these elasticities imply that the price of a new Boeing 737 aircraft—whose average price was approximately 36 million dollars in 1990—increases by approximately 700,000 to 970,000 dollars after a one-off ten-percent increase in its market size Boeing 737 (either 190

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[42]I have also employed a second empirical strategy that follows directly from the previous analysis of the effect of market thickness on the level of capacity utilization. More precisely, based on the estimates reported in columns (3) and (4) of Table 4, I obtain the residuals $\hat{\epsilon}_{jkit}$ of the utilization equation. I then calculate the variance $\text{VAR}(\hat{\epsilon}_{jIt})$ of these residuals for each type-year pair, and I regress $\text{VAR}(\hat{\epsilon}_{jIt})$ on the corresponding measure of market thickness $\text{LOG}(\text{AIRTYPE})$ or $\text{LOG}(\text{OPTYPE})$, aircraft-type fixed effects and year fixed effects. The results confirm that aircraft with a thicker market have a lower variance $\text{VAR}(\hat{\epsilon}_{jIt})$, which corroborates the results reported in Table 5.

[43]A potential concern with the regressions in Table 5 is that the dependent variable has the average utilization in the denominator, and the regressions reported in Table 5 indicate that average utilization increases as the asset market gets thicker. Hence, to check the robustness of the results, I have run all regressions with $\left| fh_{jkit} - \overline{fh}_{akit} \right|$ as the dependent variable. The results are robust to this alternative way of measuring dispersion.

[44]The regression reported in the subsequent Tables 6 and 7 are designed to investigate how market thickness affects the first and second moment of the cross-sectional distribution of prices—i.e., the *level* and *dispersion* of prices. A related question is how market thickness affects the time-series of prices—i.e., the *volatility* of prices. Duffie, Gârleanu and Pedersen (2007) show that shocks have a bigger effects on prices when search frictions are larger. To investigate this issue, I run a regression similar to equation (1) with $|\Delta \log \bar{p}_{jkit}|$ as the dependent variable—i.e., the absolute value of the difference between the (log of the) Blue Book price $\bar{p}_{jkit}$ of an aircraft of vintage j model k type i in year t and the (log of the) price $\bar{p}_{jkit-1}$ of the same aircraft—i.e., same vintage j model k type i—in year $t-1$. The regressions (available from the author) confirm that the volatility of aircraft prices decreases as their market gets thicker, providing further evidence on the empirical importance of trading frictions due to market thinness. I am grateful to an anonymous referee for raising this point.

[45]Note that the panel variable is, thus, a model-vintage pair. I have also estimated the price equation using model-age as a panel variable. The results are identical and, thus, are omitted.

TABLE 6: Market Thickness and Aircraft Prices: difference-GMM estimates

$\text{LOG}(\bar{p}_{jkit})$	(1)	(2)
AGE	−.01326	−.03776
	(.01862)	(.01439)
LOG(AIRTYPE)	.27736	
	(.1418)	
LOG(OPTYPE)		.20668
		(.08842)
# OBS	4398	4398
AIRCRAFT (VINTAGE-MODEL)	332	332

Notes—This table presents Arellano and Bond's GMM estimates of the effect of market thickness on aircraft prices. The dependent variable is the log of the deflated aircraft price. AGE is the age of the aircraft. AIRTYPE is the total stock of aircraft of a given aircraft type in a given year. OPTYPE is the total number of carriers operating a given aircraft type in a given year. Standard errors clustered at the aircraft-type–year level in parentheses. All equations also contain year fixed effects (not reported)

aircraft per type or 17 operators in the year 1990). Since the Boeing 737 is the aircraft type with the thickest market, the prices of all other aircraft types increase by an even larger amount after the same absolute increase in the size of the market.

4.6.2 Price Dispersion

The previous results showed that there exists a clear parallel between the increase in the level of capacity utilization and the increase in the level of aircraft prices as the market gets thicker. I now investigate if the same parallel exists for dispersion. In particular, the dispersion of transaction prices should be the mirror image of the dispersion of utilization levels previously documented. Thus, I now test prediction 5 on the effect of market thickness on the dispersion of transaction prices.

As reported in subsection 4.1, I measure price dispersion using the absolute percentage deviation $\left|\frac{p_{jkit}-\bar{p}_{akit}}{\bar{p}_{akit}}\right|$ of the transaction price from the Blue Book price, where p_{jkit} is the transaction price of aircraft j of age $\text{AGE}_{jkit} = a$ model k type i in year t, and $\bar{p}_{akit}$ is the Blue Book price of aircraft of age a model k type i in year t. Figure 1 showed that the two price series are highly correlated, so that $\left|\frac{p_{jkit}-\bar{p}_{akit}}{\bar{p}_{akit}}\right|$ seems a reasonable way to measure the dispersion of transaction prices.

It is instructive to have a sense of the data by simply looking at the empirical distributions of $\left|\frac{p_{jkit}-\bar{p}_{akit}}{\bar{p}_{akit}}\right|$ corresponding to values of market thickness of AIRTYPE above and below the median: Figure 3 plots these two empirical distributions (The figure using OPTYPE is very similar). The solid line is the empirical c.d.f. of absolute percentage deviation $\left|\frac{p_{jkit}-\bar{p}_{akit}}{\bar{p}_{akit}}\right|$ when the corresponding value of AIRTYPE is above the sample median, while the dotted line is the empirical c.d.f. of the same variable when AIRTYPE is below the sample median. The comparison of the two empirical distributions in Figure 3 clearly shows that the dispersion of
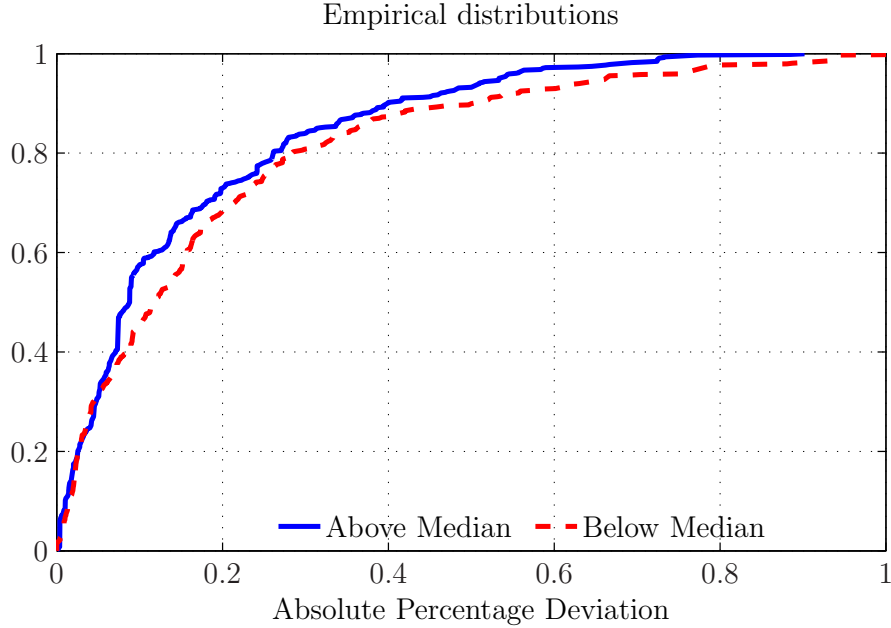
FIG. 3: Empirical distributions of deviations of transaction price from Blue Book price for above- and below-median liquidity.

transaction prices is higher for aircraft with a thicker market. The Kolmogorov-Smirnov test clearly rejects equality of two distributions (the p-value is 1.7422×10^{-6}).

In order to investigate more formally the effects of market thickness on the dispersion of transaction prices, I estimate equation (1) using the absolute percentage deviation $\left| \frac{p_{jkit} - \bar{p}_{akit}}{\bar{p}_{akit}} \right|$ as the dependent variable. As the dependent variable is based on transaction prices, no panel-data are available, and the difference-GMM procedure cannot be used. Thus, I can simply instrument market thickness using the instruments described in section 4.4: cumulative production in year $t-5$; the stock of aircraft of the same type produced more than 25 years ago; the (deflated) price of aluminum and its lags, interacted with aircraft characteristics (the number of seats, the number of engines, the maximum take-off weight, and the number of years since the release date); and the average number of days of strike per worker in the manufacturing sector in the country of the aircraft manufacturer and its lags, and their interactions with aircraft characteristics (the number of seats, the number of engines, the maximum take-off weight, and the number of years since the release date). As already highlighted, this IV strategy is a weaker procedure than difference-GMM. Nonetheless, the use of very distant lags of cumulative production reduces endogeneity concerns to a minimum, and the other *supply-side* instruments are clearly uncorrelated with *demand-side* shocks.

Table 7 reports the estimated coefficients. The table clearly shows that the dispersion of transaction prices is lower for aircraft with a thicker market, thus verifying prediction 5. According to the estimates, a ten-percent increase in AIRTYPE is associated with a 1.3-1.5-percent decrease in the absolute value of the percentage difference between transaction price and Blue Book price. Similarly, a ten-percent increase in OPTYPE is associated with a 1.0-1.1-percent decrease in the absolute value of the percentage difference between transaction price

TABLE 7: Market Thickness and Aircraft Price Dispersion: IV estimates

$\frac{p_{jkit}-\bar{p}_{akit}}{\bar{p}_{akit}}$	(1)	(2)	(3)	(4)
AGE	.00179	.00265	.00285	.00393
	(.00365)	(.00377)	(.00595)	(.00618)
LOG(AIRTYPE)	−.13635		−.15692	
	(.04372)		(.04116)	
LOG(OPTYPE)		−.10401		−.11208
		(.04365)		(.04204)
R^2	.419	.413	.494	.486
# OBS	1570	1570	1570	1570

Notes—This table presents IV estimates of the effect of market thickness on the dispersion of transaction prices. The dependent variable is the absolute percentage deviation of the transaction price of a given aircraft from the Blue Book price of an aircraft of the same age and model in the same year. AGE is the age of the aircraft. AIRTYPE is the total stock of aircraft of a given aircraft type in a given year. OPTYPE is the total number of carriers operating a given aircraft type in a given year. Standard errors clustered at the aircraft-type–year level in parentheses. All equations also contain year fixed effects (not reported). The equation estimated in columns (1) and (2) also contains aircraft-model, year and noise-stage fixed effects (not reported). The equation estimated in columns (3) and (4) also contains aircraft-model, year, noise-stage and engine-type fixed effects (not reported).

and Blue Book price. These elasticities imply that a ten-percent increase in market thickness of the Boeing 737 (either 190 aircraft per type or 17 operators in the year 1990, towards the end of this sample period) decreases the absolute value of the deviation of the transaction price from the Blue Book price—i.e., $|p_{jkit} - \bar{p}_{akit}|$—by about 22,000 to 33,000 dollars. Again, since the Boeing 737 is the aircraft type with the thickest market, these magnitudes represent the lowest bound on the decrease in the dispersion of prices following an equivalent increase in the absolute size of the market.[46],[47]

4.7 Robustness Checks and Alternative Hypotheses

The empirical analysis provides strong evidence that trading frictions are lower for more-popular aircraft. The results suggest that aircraft become more "liquid" as their market gets thicker, increasing the lower bound of operators' equilibrium productivity levels and resulting in higher utilization rates, as well as less dispersion of capacity utilization rates. In turn, the effects of market thickness on utilization transmit to prices, increasing the average

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[46]Similar to the remark in footnote 43, a potential concern with the regressions of Table 7 is that the dependent variable has the average price in the denominator, and the regressions reported in Table 7 indicate that the average price increases as the asset market gets thicker. Hence, to check the robustness of the results, I have run all regressions with $|p_{jkit} - \bar{p}_{akit}|$ as the dependent variable. The results (unreported) are robust to this alternative way of measuring price dispersion.

[47]It may seem puzzling that, in some tables, the coefficients of AIRTYPE are larger in absolute value than the coefficients of OPTYPE, while, in others, the opposite is true. As emphasized in Section 4.1, it is important to remember that, sometimes, the data used in the different regressions correspond to different time periods.

level and decreasing the dispersion of transaction prices. Moreover, the richness of the data allowed me to control for a number of unobservable factors that could have made it difficult to cleanly identify the effect of market thickness on prices and allocations. The use of difference-GMM and instruments excludes the possibility that the quantity-based measures AIRTYPE or OPTYPE capture the effect of unobserved demand shocks.[48]

This Section reports on robustness checks that control for the role of leasing and for carriers' financial positions. Finally, it discusses alternative hypotheses that focus on resale costs, and on observed or unobserved quality differences across aircraft. The analysis confirms and strengthens the previous findings.

4.7.1 The Role of Leasing

Gavazza (2009) documents that the role of aircraft leasing has increased rapidly since the mid-1980s, up to the point that, in the year 2003, about half of all commercial aircraft were leased. Gavazza (2010) further shows that aircraft with a thicker market are more likely to be leased. Thus, a natural question is whether the previously documented empirical patterns of the effects of market thickness on allocations and prices are robust to the inclusion of additional variables that control for the number of leased aircraft across aircraft types and years.

To investigate this issue, from the Aircraft History database, I construct the number of aircraft leased for each type i year t, AIRTYPE LEASED$_{it}$. Then, I re-estimate most of the specifications in Tables 3-7 with this additional control variable. To save space, I report in Table 8 only the specifications that use AIRTYPE as a measure of market thickness.

Table 8 shows that the results are robust to this potential concern. The magnitudes of the coefficients of LOG(AIRTYPE) in Table 8 are very similar to the magnitudes reported in Tables 3-7. Surprisingly, the signs of the coefficients of LOG(AIRTYPE LEASED) are opposite of the signs of the coefficients of LOG(AIRTYPE), although they are often insignificant. In particular, the coefficients of LOG(AIRTYPE LEASED) indicate that a larger number of leased aircraft does not systematically generate direct spillovers to other aircraft of the same type.[49]

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[48]For example, consider resale costs that vary across aircraft types and over time. An unobserved increase in the level of these resale costs could simulatenously decrease aircraft demand (and, thus, AIRTYPE), and lower turnover, capacity utilization and prices. The empirical model addresses these demand shocks explicitly in the following way. Aircraft type-specific resale costs are factors that go into the unobservable ϵ_{jit} of equation (1). Substracting the lagged endogenous variable removes the persistent component of the unobservable (equation (4)), leaving only the current period innovation in the unobservable ν_{jit} (i.e., the innovation in resale costs from period $t-1$ to period t). Taking first-differences further removes the fixed effect $(1-\rho)\zeta_i$. The differenced innovation $\Delta\nu_{jit}$ could be correlated with changes in market thickness, thus instruments are required. The supply-side instruments listed in Section 4.4 are plausibly predetermined at the time the innovation to the current period unobservable is realized, such as the innovation/change in resale costs from period $t-1$ to period t. Hence, the empirical results are unlikely to be due to demand factors, like changes in resale costs.

[49]The results reported in Table 8 are not inconsistent with the empirical results in Gavazza (2009), that shows that leased aircraft trade more frequently and fly more, suggesting that trading frictions are lower on leased aircraft than on owned aircraft. In particular, Table 8 investigates whether leased aircraft generate spillovers to *other* aircraft, while Gavazza (2009) investigates cross-sectional differences between leased and owned aircraft. First-differencing the data eliminates these cross-sectional differences in Table 8.

TABLE 8: Robustness Check I: the Role of Leasing

	(1) $h_{jkit}(s)$	(2) FLY_{jkit}	(3) $\text{LOG}(fh_{jkit})$	(4) $\left\|\frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}}\right\|$	(5) $\left\|\frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}}\right\|_{fh_{jkit}>0}$	(6) $\text{LOG}(\bar{p}_{jkit})$	(7) $\left\|\frac{p_{jkit}-\bar{p}_{akit}}{\bar{p}_{akit}}\right\|$
AGE	.04247	−.01591	−.03321	.03913	.01931	−.03441	.00293
	(.00410)	(.00214)	(.00420)	(.00485)	(.00207)	(.01605)	(.00277)
LOG(AIRTYPE)	.57798	.11515	.23179	−.11944	−.07478	.17021	−.18889
	(.24396)	(.04256)	(.07137)	(.05541)	(.03767)	(.09234)	(.06215)
LOG(AIRTYPE LEASED)	−.22148	−.02962	−.01146	.03692	.02350	−.06856	.04671
	(.16254)	(.01226)	(.02149)	(.01220)	(.00957)	(.03536)	(.03152)
# OBS	241622	64279	60139	63886	60139	4398	1570
AIRCRAFT	17398	11596	11240	11582	11240	332	1570

Notes—This table presents the results of robustness checks on the role of leasing. Column (1) reports the estimates of a Cox proportional hazard model, equivalent to specification (1) of Table 3. Columns (2) and (3) report Arellano and Bond GMM estimates equivalent to specifications (1) and (3) in Table 4. Columns (4) and (5) report Arellano and Bond GMM estimates equivalent to specifications (1) and (3) in Table 5. Column (6) reports Arellano and Bond GMM estimates equivalent to specification (1) in Table 6. Column (7) reports IV estimates equivalent to specification (3) in Table 7. AIRTYPE is the total stock of aircraft of a given aircraft type in a given year. Standard errors clustered at the aircraft-type–year level in parentheses. All equations also contain year fixed effects (not reported).

4.7.2 Carriers' Financial Position

In an insightful paper, Pulvino (1998) investigates the determinants of aircraft transaction prices and finds that carriers in worse financial conditions sell aircraft at bigger discounts. Two key predictions of the theoretical framework of my paper are that sellers' profitabilities are *endogenously* lower when assets have a thinner market, and that the dispersion of transaction prices is *endogenously* bigger for assets with a thinner market. Clearly, firms' financial conditions and profitabilities are very closely related—economic and financial distress are often two sides of the same coin—and the dispersion of transaction prices is also very closely related to price discounts. Hence, my paper elucidates Pulvino's results by describing an economic mechanism that *simultaneously* implies that sellers are, on average, in worse financial condition and that price discounts are bigger when aircraft have a thinner market. In light of Pulvino's results, I now perform an additional robustness check by investigating whether carriers in worse financial conditions also have lower capacity utilization.

Unfortunately, the dataset described in Section 4.1 does not report any operators' financial information. However, U.S. carriers (publicly-listed and privately-owned) with annual operating revenues of $20 million or more are required to report their operating balance sheet statements on a quarterly basis to the Department of Transportation. These statements (Form 41) are available at `http://www.transtats.bts.gov`. Thus, I follow Pulvino (1998) and use the LEVERAGE RATIO (defined as book value of debt plus capitalized lease obligations divided by the sum of book value of debt, capitalized lease obligations and book value of equity) and the CURRENT RATIO (defined as current assets divided by current liabilities) as measures of an operator's financial position. To match these financial ratios to annual aircraft utilization, I use financial data for the fourth quarter of each year, and I include in the sample only aircraft that have been operated by a U.S. carrier for the entire year (thus, aircraft acquired or relinquished by a U.S. carrier are excluded in the year when the transactions occurred).

Table 9 reports the results of several specifications that include carriers' financial positions as explanatory variables. Columns (1) and (2) presents the results for the intensive-margin equation of whether to fly the aircraft or not. Columns (3) to (4) presents the results for the extensive-margin equation of how many hours to fly the aircraft. Odd-numbered columns use LOG(AIRTYPE) as the measure of market thickness, and even-numbered columns use LOG(OPTYPE). All regressions are equivalent to the regressions reported in Table 4, with only the difference that they include carriers' financial ratios and, thus, are also restricted to U.S. operators. In all regressions, the measures of market thickness LOG(AIRTYPE) and LOG(OPTYPE) are instrumented with the same instruments described in Section 4.4.

The Table shows that the results on the effects of market thickness on capacity utilization are robust to the inclusion of carriers' financial ratios. Carriers' leverage ratio is negatively correlated with capacity utilization. Instead, the current ratio does not add any significant explanatory power to the regressions. Overall, these regressions confirm that market thickness has important effects on aircraft allocations. They also reinforce the idea that firms' financial conditions and productivities are closely related, although the direction of causality between productivity and financial conditions is difficult to establish in these regressions.

TABLE 9: Robustness Check II: Carriers' Financial Position and Aircraft Utilization

| | (1) | (2) | (3) | (4) |
	FLY_{jkit}	FLY_{jkit}	$\text{LOG}(fh_{jkit})$	$\text{LOG}(fh_{jkit})$
AGE	−.00747	−.03422	−.02900	−.03469
	(.00245)	(.00297)	(.00804)	(.00920)
LEVERAGE RATIO	−.01474	.01718	−.07965	−.07240
	(.00747)	(.00615)	(.01595)	(.01862)
CURRENT RATIO	−.00118	.01202	.00447	−.00235
	(.00131)	(.00239)	(.00787)	(.00945)
LOG(AIRTYPE)	.07934		.26031	
	(.03984)		(.13363)	
LOG(OPTYPE)		.07800		.15076
		(.01226)		(.04251)
# OBS	29566	29566	28343	28343
AIRCRAFT	6320	6320	6210	6210

Notes—This table presents Arellano and Bond's GMM estimates of the effect of market thickness and carriers' financial position on capacity utilization. The dependent variable in columns (1) and (2) is a binary indicator equal to one if the aircraft had positive flying hours in a given year, and zero otherwise. The dependent variable in columns (3) and (4) is the log of annual flying hours. The sample is restricted to aircraft with strictly positive flying hours in the specifications of columns (3) and (4). AGE is the age of the aircraft. The LEVERAGE RATIO is equal to the book value of debt plus capitalized lease obligations divided by the sum of book value of debt, capitalized lease obligations and book value of equity. The CURRENT RATIO is equal to current assets divided by current liabilities. AIRTYPE is the total stock of aircraft of a given aircraft type in a given year. OPTYPE is the total number of carriers operating a given aircraft type in a given year. Standard errors clustered at the aircraft-type–year level in parentheses. All equations also contain year fixed effects (not reported).

4.7.3 Observable Quality

The literature on durable goods highlights the role of depreciation (quality differentials) in explaining patterns of trade and makes different predictions if parties have symmetric versus asymmetric information on the depreciation (quality) of the asset. Hendel and Lizzeri (1999), Porter and Sattler (1999) and Stolyarov (2002) predict that, under symmetric information, lower-quality goods: 1) trade more frequently; and 2) command *lower* prices. Clearly, these predictions are inconsistent with the fact that assets with a thicker market trade more frequently and command *higher* prices. Thus, theories of quality differentials under symmetric information cannot explain the observed patterns.

In addition, a faster improvement in new goods is theoretically equivalent to a faster depreciation rate, since we can rescale all available qualities in terms of the highest available quality in the market. Thus, the same theoretical considerations discussed by Hendel and Lizzeri (1999), Porter and Sattler (1999) and Stolyarov (2002) apply to a model with different rates of innovations across assets. In particular, a model in which assets with a thicker market exhibit a faster rate of product innovation (and, thus, higher turnover) cannot explain the

empirical results.

4.7.4 Unobservable Quality

Hendel and Lizzeri (1999) show that, under asymmetric information, durable goods with higher information asymmetries: 1) trade less frequently; and 2) command lower prices. Moreover, *any* asymmetric-information model implies that goods with more-severe information asymmetries exhibit a lower dispersion of transaction prices, as transaction prices do not depend on unobserved quality differences. Several institutional features of the aircraft market, and a close look at the data show that asymmetric information is unlikely to account for all observed patterns.

First, the aviation authorities regulate aircraft maintenance: After an aircraft has flown a certain number of hours, carriers undertake compulsory maintenance. This suggests that quality differences cannot be too high. Moreover, Pulvino (1998) rejects the hypothesis that, conditional on observable characteristics such as age, quality differentials between aircraft explain trade patterns. Furthermore, maintenance records are readily available, and all parties can observe the entire history of each aircraft. This suggests that asymmetries of information cannot be too strong. Second, it is important to reiterate that panel data techniques mean that the effect of market thickness on prices is identified from variations in market thickness through the life of a given vintage-type combination, and the effect of market thickness on utilization is identified from variations in market thickness through the life of a given aircraft serial number. Thus, if the patterns were explained by asymmetries of information, then we would have to conclude that the quality of a given vintage (of a given serial number) improves over its lifespan in the case of prices (in the case of utilization), which seems very unlikely. In the specific case of prices, moreover, it is not clear why such improvements over the life of the vintage are not capitalized immediately in prices. Third, the aforementioned predictions of models with asymmetric informations are inconsistent with the fact that assets with a thinner market trade less frequently, command lower prices, and exhibit a *higher* price dispersion.

In summary, these reasonable alternative hypotheses (and several others) do not explain *all* empirical patterns documented. Therefore, I conclude that trading frictions vary with market thickness, and that they have considerable effects on allocations and prices in the market for capital equipment, as predicted by the theoretical framework.

5 Conclusions

In this paper, I have investigated whether trading frictions vary with the size of the asset market. I set up a model of a bilateral search market to investigate what implications market thickness has for asset allocations and prices. The key economic mechanism is that the trading technology exhibits increasing returns to scale, so that, as the mass of assets increases, the flow of meetings increases more than proportionally. As a result, assets with a thicker market: 1) trade more frequently; 2) have higher average capacity utilizations; 3) have lower dispersion

of capacity utilization levels; 4) fetch higher average prices; and 5) have lower dispersion of transaction prices.

Detailed microdata on assets allow a study of the workings of one specific decentralized market, the market for commercial aircraft. The empirical analysis uncovers a number of robust empirical findings, confirming all predictions of the theoretical framework. A ten-percent increase in the stock of aircraft of a given type implies: 1) a 1.9-percent increase in the hazard of trading the aircraft; 2) a 1.9-percent increase in the average capacity utilization; 3) a 2.2-percent decrease in the absolute percentage deviation of utilizations from the mean utilization; 4) a 2.7-percent increase in the average price; and 5) a 1.5-percent decrease in the absolute percentage deviation of transaction prices from the mean price.

This paper shows that the thickness of the asset market reduces frictions in input markets, thereby increasing the aggregate efficiency of output markets. Aircraft are among the easiest assets to redeploy across users. Nonetheless, differences between aircraft with a thin market and a thick market are still non-negligible. These differences indicate that market thinness acts like a sunk cost of investment, and the literature on irreversible investment finds that sunk costs have a first-order effect on firms' investment decisions. Abel and Eberly (1996) show that even small degrees of irreversibility matter a lot for establishment-level dynamics. However, the aggregate effects of irreversibility are more ambiguous. For example, Veracierto (2002) suggests that investment irreversibilities do not play a significant role for aggregate fluctuations. This paper does not consider aggregate shocks and aggregate fluctuations, but finds that one aggregate effect of the expansion of asset markets is to raise the equilibrium efficiency of the firms that operate these assets. In this sense, market thinness acts, here, in much the same way as the entry cost in the general equilibrium models of Hopenhayn (1992) and Asplund and Nocke (2006), and as the cost of firing labor in Hopenhayn and Rogerson (1993).

The mechanism identified in this paper potentially applies to the economy as a whole. Investigating whether the market for corporate assets has become larger and more liquid over time, and whether this has affected aggregate productivity, seems an interesting question for future research.

APPENDICES (Not for Publication)

A   Model

In this section, I lay out a model of a decentralized market with two-sided search (Mortensen and Wright, 2002) to theoretically investigate the effects of market thickness on asset allocations and prices. As in the recent literature on search in financial markets, the model adapts the framework introduced by Diamond's (1982) seminal paper.

I model frictions of reallocating assets explicitly. In particular, each agent contacts another agent randomly, and this is costly for two reasons: 1) there is an explicit search cost c that an agent pays in order to actively meet another (random) active agent; and 2) there is a time cost in that all agents discount future values by the discount rate $r > 0$.

A.1   Assumptions

Time is continuous and the horizon infinite. There are a total mass $S' > 0$ of assets (i.e., the thickness of the asset market), and a mass $A = S' + B'$ of agents, with $B' > S'$. All agents are risk-neutral and discount the future at the positive rate $r > 0$.

Agents are differentiated by the exogenous productivity parameter $z \geq 0$. The exogenous productivity z is distributed in the population according to the cumulative distribution function $F(z)$ and follows an independent stochastic process: Each agent receives a new draw from $F(z)$ at the instantaneous rate λ

Each agent can own either zero or one asset.[50] An agent z who owns an asset chooses the endogenous utilization h of the asset to maximize the instantaneous payoff given by the difference between revenue zh and costs $\frac{h^2}{2}$ from operating the asset:

$$\pi(z) = \max_h zh - \frac{h^2}{2}.$$

Hence, the optimal capacity utilization is equal to productivity (i.e., $h^* = z$), and $\pi(z) = \frac{1}{2}z^2$ are the instantaneous profits.[51]

Agents can trade assets, and an agent who wants to trade an asset pays a search cost c. An agent who wants to trade makes contacts with other traders pairwise independently at Poisson arrival times with intensity $\gamma > 0$. Given a contact, because of the random-matching assumption, the probability that a buyer (seller) makes contact with a seller (buyer) is $S(B)$, where S and B are the stocks of active sellers and active buyers. In other words, the mass of

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[50]Hence, I do not consider quantity decisions, like Duffie, Gârleanu and Pedersen (2005 and 2007), Miao (2006), Vayanos and Wang (2007), Vayanos and Weill (2008), and Weill (2007 and 2008). It will be clear that the intuition applies more generally. See Lagos and Rocheteau (2009) for a model that considers quantity decisions.

[51]Under more general forms of complementarity between productivity z and capacity utilization h, the optimal capacity utilization is still an increasing function of productivity.

active sellers S (active buyers B) is the subset of the mass of potential sellers S' (potential buyers B') that has paid the search cost c. Thus, conditional on making contact, all traders are "equally likely" to be contacted. On aggregate, contacts between sellers and buyers occur continually at a total (almost sure) rate of γBS.

Once an active buyer and an active seller meet, they negotiate a price to trade. I assume that an active buyer and an active seller negotiate a price according to generalized Nash bargaining, where $\theta \in (0, 1)$ denotes the bargaining power of the buyer.

A.2 Solution

The potential seller of an aircraft with productivity z can put it up for sale or keep operating it. In the former case, he pays the search cost c and meets potential trading partners at rate γB. In the latter case, he enjoys the flow profit $\pi(z)$. Similarly, a potential buyer can pay the search cost c and meet active sellers at rate γS, or can wait to search later when his profitability changes. We, thus, have four categories of agents: active and non-active buyers and sellers. I denote by $V_B(z)$ the value function of an active buyer, and by $W_B(z)$ the value function of a non-active buyer. Similarly, $V_S(z)$ and $W_S(z)$ are the value functions of an active and non-active seller, respectively.

Intuitively, a potential buyer prefers to be an active buyer when his productivity z is sufficiently high, and a potential seller prefers to be an active seller when her productivity is sufficiently low. Moreover, an active buyer that has just bought an aircraft does not immediately become (i.e., before z changes) an active seller since he would have been better off not buying the aircraft and not paying the search cost. Thus, when an active buyer and active seller meet and trade, they become a non-active seller and a non-active buyer, respectively.

I now derive formally the value functions for active and inactive agents, and the transaction prices at which trade occurs. These value functions allow me to pin down the equilibrium conditions and to characterize the endogenous distribution of productivities and capacity utilizations of active firms and the endogenous distribution of transaction prices.

Numerical solutions shows that the key element affecting the first two moments of the productivity/capacity utilization and transaction price distributions is how potential sellers' and buyers' cutoff values—the values at which potential sellers and buyers are indifferent between being active or inactive—change with the thickness of the market—that is, with S'. In particular, the higher the sellers' cutoff value and the lower the buyers' cutoff value, the higher is the average and the lower is the variance of potential sellers' productivity. A higher average z, then, translates into a higher average transaction price, and a lower variance of valuation into a lower variance of transaction prices. In turn, sellers' and buyers' cutoff values are determined by the (endogenous) total number of meetings γBS.

As spelled out in more detail in Section 3, the key economic force is that the trading technology exhibits increasing returns to scale. Hence, sellers' reservation value increases and buyers' reservation value decreases as the asset market gets thicker. In turn, as the mass of assets increases: 1) assets have a higher turnover; 2) the average productivity z and average capacity utilization h of firms increase; 3) the dispersion of firms' productivity and the dispersion of firms' capacity utilizations decrease; 4) assets have a higher average price;

and 5) assets have a lower dispersion of transaction prices.

A.2.1   Value Functions

Consider an agent with productivity b and no asset. The agent can choose to pay the search cost c and search, or he can decide to stay inactive.

If the agent decides to be an active buyer, his value function $V_B(b)$ satisfies

$$
\begin{aligned}
rV_B(b) \;=\; & -c + \gamma S \int \max\left\{W_S(b) - p(b,s) - V_B(b), 0\right\} dG_S(s) \\
& + \lambda \int \left(\max\left\{V_B(z), W_B(z)\right\} - V_B(b)\right) dF(z)
\end{aligned}
\tag{A1}
$$

where $G_S(s)$ is the endogenous equilibrium distribution of active sellers (which is derived below). Equation (A1) has the usual interpretation of an asset-pricing equation. An active buyer with productivity b pays the search cost c. At any date, at most, one of two possible events might happen to him: 1) At rate γS, he meets an active seller. If he trades, he becomes an inactive seller and, thus, obtains a capital gain equal to $W_S(b) - p(b,s) - V_B(b)$. If he doesn't trade, he has no capital gain. 2) At rate λ, he receives a new productivity draw. After learning his new productivity, he decides whether to remain an active buyer (in which case he has a capital gain/loss equal to $V_B(z) - V_B(b)$) or to become an inactive buyer (in which case he has a capital gain/loss equal to $W_B(z) - V_B(b)$).

Similarly, the value function $V_S(s)$ of an active seller with productivity s satisfies the following Bellman equation:

$$
\begin{aligned}
rV_S(s) \;=\; & -c + \pi(s) + \gamma B \int \max\left\{p(b,s) + W_B(s) - V_S(s), 0\right\} dG_B(b) \\
& + \lambda \int \left(\max\left\{V_S(z), W_S(z)\right\} - V_S(s)\right) dF(z).
\end{aligned}
\tag{A2}
$$

where $G_B(b)$ is the endogenous equilibrium distribution of active buyers (which, again, is derived below). The interpretation of equation (A2) is now straightforward. An active seller receives an instantaneous payoff flow equal to the difference between her profitability $\pi(s)$ and the search cost c. At rate γB, she meets an active buyer. If she trades, she obtains a capital gain equal to $p(b,s) + W_B(s) - V_S(s)$. If she does not trade, she has no capital gain. At rate λ, she receives a new productivity draw. After learning her new productivity, she decides whether to remain an active seller (in which case she has a capital gain/loss equal to $V_S(z) - V_S(s)$) or to become an inactive seller (in which case she has a capital gain/loss equal to $W_S(z) - V_S(s)$).

The value functions W_B and $W_S(s)$ of an inactive buyer and of an inactive seller with

productivity s satisfy:

$$rW_B = \lambda \int \left(\max \left\{ V_B(z), W_B \right\} - W_B \right) dF(z) \tag{A3}$$

$$rW_S(s) = \pi(s) + \lambda \int \left(\max \left\{ V_S(z), W_S(z) \right\} - W_S(s) \right) dF(z). \tag{A4}$$

Equations (A3) and (A4) say that the flow value of an inactive trader is equal to the instantaneous profits (0 for a buyer, $\pi(s)$ for a seller) plus the expected capital gain/loss. Thus, the value of an inactive buyer is independent of his profitability.

When an active buyer b and an active seller s meet, if they trade, the negotiated price

$$p(b, s) = \theta \left(V_S(s) - W_B \right) + (1 - \theta) \left(W_S(b) - V_B(b) \right) \tag{A5}$$

is the solution to the following symmetric-information bargaining problem:[52]

$$\max_p \left[W_S(b) - p - V_B(b) \right]^\theta \left[p + W_B - V_S(s) \right]^{1-\theta}$$
$$\text{subject to:} \quad W_S(b) - p \geq V_B(b) \ \text{ and } \ p + W_B \geq V_S(s).$$

Using the equilibrium price (A5), the value function of an active buyer b becomes

$$rV_B(b) + c = \gamma S\theta \int \max \left\{ -V_S(s) + W_B + W_S(b) - V_B(b), 0 \right\} dG_S(s)$$
$$+ \lambda \int \left(\max \left\{ V_B(z), W_B(z) \right\} - V_B(b) \right) dF(z). \tag{A6}$$

Similarly, a value function of an active seller s is:

$$rV_S(s) + c = \pi(s) + \gamma B(1 - \theta) \int \max \left\{ -V_S(s) + W_B + W_S(b) - V_B(b), 0 \right\} dG_B(b)$$
$$+ \lambda \int \left(\max \left\{ V_S(z), W_S(z) \right\} - V_S(s) \right) dF(z). \tag{A7}$$

Since $V_B(b)$ is increasing in b, there exists a reservation value R_B such that only buyers with productivity $b \geq R_B$ (and, hence, profits $\pi(b) \geq \pi(R_B)$) have positive gains from trade. R_B satisfies

$$V_B(R_B) = \frac{\lambda \int \left(\max \left\{ V_B(z), W_B \right\} \right) dF(z)}{r + \lambda}.$$

Similarly, there exists reservation value R_S such that only sellers with productivity $s \leq R_S$ (profits $\pi(s) \leq \pi(R_S)$) have positive gains from trade. R_S satisfies

$$V_S(R_S) = \frac{\pi(R_S) + \lambda \int \max \left\{ V_S(z), W_S(z) \right\} dF(z)}{r + \lambda}.$$

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[52]The characteristics of aircraft markets described in Section 2 support the assumption of symmetric information.

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It is easy to show that for c sufficiently large, $R_B > R_S$.

When r is small, $-V_S(s) + V_B(s) + V_S(b) - V_B(b) \geq 0$ for all possible meetings of active buyers and sellers (Mortensen and Wright, 2002). Moreover, $\frac{\partial V_B(x)}{\partial \pi(x)}$ satisfies

$$(r + \lambda + \gamma S\theta)\frac{\partial V_B(x)}{\partial \pi(x)} = \frac{\gamma S\theta}{r + \lambda}.$$

Similarly, $\frac{\partial V_S(x)}{\partial \pi(x)}$ satisfies

$$\frac{\partial V_S(x)}{\partial \pi(x)} = \frac{1}{r + \lambda + \gamma B(1 - \theta)}.$$

Thus, both $V_B(x)$ and $V_S(x)$ are linear in $\pi(x)$, with slopes given by $\frac{\partial V_B(x)}{\partial \pi(x)}$ and $\frac{\partial V_S(x)}{\partial \pi(x)}$, respectively. Furthermore, we can use the conditions on the marginal traders $V_S(R_S)$ and $V_B(R_B)$ to find the intercepts. Thus, we can rewrite the value function of an active buyer as

$$V_B(b) = k_B(\pi(b) - \pi(R_B)) + \frac{\lambda \int \max\{V_B(z), W_B\} dF(z)}{r + \lambda} \tag{A8}$$

where $k_B = \frac{\gamma S\theta}{(r + \lambda)(r + \lambda + \gamma S\theta)}$. Similarly, the value function of an active seller is

$$V_S(s) = k_S(\pi(s) - \pi(R_S)) + \frac{\pi(R_S) + \lambda \int \max\{V_S(z), W_S(z)\} dF(z)}{r + \lambda} \tag{A9}$$

where $k_S = \frac{1}{r + \lambda + \gamma B(1 - \theta)}$. Thus, the transaction price when seller s and buyer b meet is equal to:

$$\begin{aligned}
p(b, s) &= \theta\left(k_S(\pi(s) - \pi(R_S)) + \frac{\pi(R_S)}{r + \lambda}\right) + (1 - \theta)\left(\frac{\pi(b)}{r + \lambda} - k_B(\pi(b) - \pi(R_B))\right) + \\
&\quad \int_{R_S} \frac{\lambda\pi(z)}{r(r + \lambda)} dF(z) + \frac{\lambda}{r}\int^{R_S}\left(k_S(\pi(z) - \pi(R_S)) + \frac{\pi(R_S)}{r + \lambda}\right) dF(z) - \\
&\quad \int_{R_B} \frac{\lambda k_B(\pi(z) - \pi(R_B))}{r} dF(z). \tag{A10}
\end{aligned}$$

A.2.2 Distributions of Buyers and Sellers

I now derive the endogenous equilibrium distribution of potential buyers B' and potential sellers S' and the endogenous distribution of active buyers B and active sellers S.

Let $g_{S'}(\cdot, t)$ and $g_{B'}(\cdot, t)$ be the distributions of potential sellers and potential buyers, respectively. Consider a small interval of time of length ϵ. Up to terms in $o(\epsilon)$, the distribution of potential sellers $g_{S'}(\cdot, t)$ evolves from time t to time $t + \epsilon$ according to:

$$g_{S'}(z, t + \epsilon) = \begin{cases} \gamma S\frac{B'}{S'}\epsilon g_{B'}(z, t) + \lambda\epsilon f(z, t) + (1 - \lambda\epsilon) g_{S'}(z, t) & \text{for } R_B \leq z \\ \lambda\epsilon f(z, t) + (1 - \lambda\epsilon) g_{S'}(z, t) & \text{for } R_S \leq z < R_B \\ \lambda\epsilon f(z, t) + (1 - \lambda\epsilon - \gamma B\epsilon) g_{S'}(z, t) & \text{for } z < R_S. \end{cases}$$

Similarly, the distribution of potential buyers $g_B(\cdot, t)$ evolves over time according to:

$$g_{B'}(z, t+\epsilon) = \begin{cases} \lambda \epsilon f(z,t) + (1 - \lambda\epsilon - \gamma S\epsilon) g_{B'}(z,t) & \text{for } R_B \leq z \\ \lambda \epsilon f(z,t) + (1 - \lambda\epsilon) g_{B'}(z,t) & \text{for } R_S \leq z < R_B \\ \gamma B \frac{S'}{B'} \epsilon g_{S'}(z,t) + \lambda \epsilon f(z,t) + (1 - \lambda\epsilon) g_{B'}(z,t) & \text{for } z < R_S. \end{cases}$$

Steady state requires that traders' flows for each interval of the distribution functions of potential buyers B' and potential sellers S' are equal to traders' flows out. Thus, rearranging and taking the limit for $\epsilon \to 0$, the endogenous distribution of potential sellers S' satisfies

$$g_{S'}(z) = \begin{cases} \frac{B'}{S'} \frac{\gamma S}{\lambda + \gamma S} f(z) + f(z) & \text{for } R_B \leq z \\ f(z) & \text{for } R_S \leq z < R_B \\ \frac{\lambda}{\lambda + \gamma B} f(z) & \text{for } z < R_S. \end{cases}$$

Similarly, the endogenous distribution of potential buyers satisfies

$$g_{B'}(z) = \begin{cases} \frac{\lambda}{\lambda + \gamma S} f(z) & \text{for } R_B \leq z \\ f(z) & \text{for } R_S \leq z < R_B \\ \frac{S'}{B'} \frac{\gamma B}{\lambda + \gamma B} f(z) + f(z) & \text{for } z < R_S. \end{cases}$$

Hence, the distribution of active sellers is

$$g_S(z) = \begin{cases} 0 & \text{for } R_S \leq z \\ \frac{f(z)}{F(R_S)} & \text{for } z < R_S \end{cases} \tag{A11}$$

and of active buyers is

$$g_B(z) = \begin{cases} \frac{f(z)}{1 - F(R_B)} & \text{for } R_B \leq z \\ 0 & \text{for } z < R_B. \end{cases} \tag{A12}$$

A.3 Equilibrium

The equilibrium conditions determine the four endogenous variables (R_S, R_B, S, B).

Definition 1 *A steady-state equilibrium is a set of reservation values (R_S, R_B), and a stock of active buyers and sellers (B, S) satisfying the following conditions:*

1. *The reservation values (R_S, R_B) satisfy the following indifference conditions:*[53]

$$c = \gamma S\theta \int \left(k_S (\pi(R_S) - \pi(s)) - \frac{\pi(R_S) - \pi(R_B)}{r + \lambda} \right) dG_S(s) \tag{A13}$$

$$c = \gamma B (1 - \theta) \int \left(\frac{\pi(b) - \pi(R_S)}{r + \lambda} - k_B (\pi(b) - \pi(R_B)) \right) dG_B(b) \tag{A14}$$

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[53]The conditions are obtained by combining equations (A6), (A8) and (A3), and equations (A7), (A9) and (A4), respectively.

where $G_S(s)$ and $G_B(b)$ are the cumulative distribution functions of active sellers and active buyers, respectively. $G_S(s)$ and $G_B(b)$ are derived from the probability density functions $g_S(s)$ and $g_B(b)$ defined in (A11) and (A12);

2. *Active buyers are all potential buyers with productivity above R_B, and active sellers are all potential sellers with productivity below R_S:*

$$B = (1 - G_{B'}(R_B))B' = B'(1 - F(R_B))\frac{\lambda}{\lambda + \gamma S}$$

$$S = G_{S'}(R_S)S' = S'\frac{\lambda}{\lambda + \gamma B}F(R_S).$$

A.4 A Numerical Illustration

Unfortunately, the equilibrium conditions do not admit an explicit solution of the endogenous variables (R_S, R_B, S, B) as a function of the exogenous parameters. Thus, in order to understand how market thickness S' affects the equilibrium distribution of productivity and prices, I fix values of the exogenous parameters and the exogenous distribution $F(z)$, and then solve the model numerically.[54] More precisely, the numerical solutions illustrate how moments of the distributions of productivities and prices change as the thickness of the asset market S' increases, while holding the ratio of potential sellers (and, thus, assets) S' and potential buyers B' constant.

Figure 4 illustrates several features of the equilibrium. The behavior of the endogenous variables (R_S, R_B) plotted in the first plot (first row, first column) is the key to understanding the effects of market thickness on asset allocations and asset prices. The plot shows that sellers' reservation value R_S increases and buyers' reservation value R_B decreases as the number of assets increases. This is intuitive: When the asset market is thin, trading frictions are high. Thus, sellers rationally choose to hold on to assets with a thin market for longer periods of time in case their productivity z rises in the future. As market thickness increases, frictions vanish. Hence, the reservation values R_S and R_B converge, and their common limit is given by the Walrasian benchmark R^* that solves $1 - F(R^*) = \frac{S'}{S'+B'}$.[55]

The second plot (first row, second column) shows that the turnover of assets $\frac{\gamma BS}{S'}$ increases as the mass of assets increases. This is due to two reasons: 1) Sellers' cutoff value is higher, so the probability that assets are put on the market for sale is higher; and 2) the meeting rate is higher, so conditional on being on the market, assets trade faster.

The plots in the second row document the effects of market thickness on capacity utilization. The third plot (second row, first column) shows how the average capacity utilization $E(h) = \int h(z)g_{S'}(z)dz$ varies with the mass of assets. Moreover, since each agent chooses the capacity utilization h to be equal to its productivity parameter z, the distribution $g_{S'}(z)$ reflects the efficiency of the allocation of assets. The plot clearly shows that average capacity utilization and average productivity increase as the asset market becomes thicker. This sug-

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[54]The numerical values of the exogenous parameters are: $\theta = .5$; $c = 150$; $r = .05$; $\gamma = .2$; $\lambda = .2$; $B' = 1.5S'$ and $F(z)$ is the normal distribution with mean μ equal to 20 and standard deviation σ equal to 5.

[55]Given the numerical values assumed, the Walrasian limit R^* of R_S and R_B is equal to 21.26.
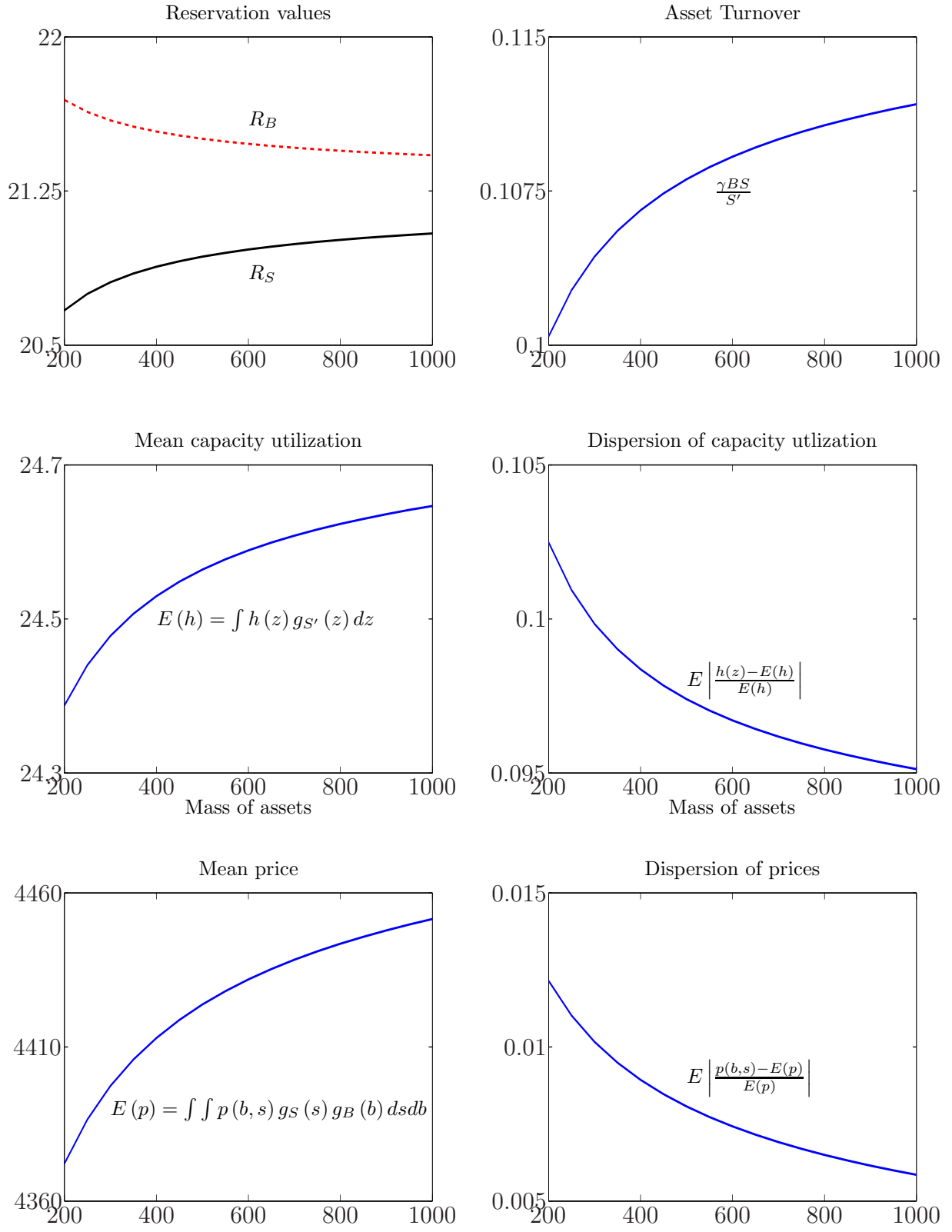
FIG. 4: Numerical solutions

gests that, on average, assets are more efficiently allocated when their market becomes thicker. The plot also shows that the average capacity utilization and productivity converge to the Walrasian benchmark given by $\mu + \sigma \frac{\phi\left(\frac{R^*-\mu}{\sigma}\right)}{1-\Phi\left(\frac{R^*-\mu}{\sigma}\right)}$, where $\phi\left(\cdot\right)$ and $\Phi\left(\cdot\right)$ denote the standard normal p.d.f. and c.d.f., respectively.[56] The fourth plot (second row, second column) shows that the dispersion of capacity utilization $E\left|\frac{h(z)-E(h)}{E(h)}\right|$—which is identical to the dispersion of productivity $E\left|\frac{z-E(z)}{E(z)}\right|$—decreases as asset markets become thicker.

The plots in the third row document the effects of market thickness on asset prices. The fifth plot (third row, first column) of Figure 4 documents that the average asset price $E\left(p\right) = \int\int p\left(b,s\right)g_S\left(s\right)g_B\left(b\right)dsdb$ increases when the asset market becomes thicker. Moreover, the price converges to the Walrasian price equal to $\frac{\pi(R^*)}{r}$.[57] The sixth plot (third row, second column) shows that the dispersion of transaction prices $E\left|\frac{p(b,s)-E(p)}{E(p)}\right|$ decreases as the size of the asset market increases.[58]

B   Calibration

The goal of this Appendix is to calibrate the model to assess the magnitude of trading frictions. To this end, I proceed in two steps: 1) I describe the additional assumptions that I need to impose given the available data; and 2) I calibrate a slightly modified version of the model to match moments of the data.

1. The model says that the profits that the asset generates are an increasing function of the productivity of a carrier, and utilization is an increasing function of the productivity of the carrier, as well. Thus, profits generated by an aircraft are an increasing function of utilization, and the data confirm this necessary step (see footnote 18).

   However, calculating the magnitude of trading frictions requires us to understand the exact way in which aircraft utilization translates into aircraft prices—i.e., we need to know the exact functional form that links utilization and profits. Important missing pieces of information, for example, are the revenues and the costs generated by one hour of utilization for each aircraft. This information is not readily available in the data.

   Moreover, the separate identification of many parameters is problematic. Although the model is highly non-linear, so that all parameters affect all outcomes, intuitively revenues and costs parameters determine aircraft prices, and trading parameters determine turnover rates. More precisely, revenues/profits $\pi\left(h\right)$ and trading cost parameter c affect one single outcome—i.e., aircraft prices. Thus, there is one equation in two unknown

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[56]The numerical value of the Walrasian limit is equal to 24.83.

[57]The numerical value of the Walrasian limit is equal to 4522.7.

[58]I am reporting the quantities $E\left|\frac{h(z)-E(h)}{E(h(z))}\right|$ and $E\left|\frac{p(b,s)-E(p)}{E(p)}\right|$ to measure the dispersion of capacity utilizations and prices, rather than the more common variances, because the empirical analysis is based on these quantities $E\left|\frac{h(z)-E(h)}{E(h)}\right|$ and $E\left|\frac{p(b,s)-E(p)}{E(p)}\right|$. The variances of capacity utilizations and prices display identical qualitative patterns—i.e., they decrease as the number of assets increases.

parameters. Similarly, the parameters λ—the persistence of carriers' profitability—and γ—the rate of traders' pairwise meetings—determine the turnover rate.

In addition, one additional important piece of information that determines turnover, utilizations and prices is the ratio of buyers to sellers $\frac{B'}{S'}$. The paper keeps it constant, and the qualitative results do not depend on how much larger B' is than S'. The ratio $\frac{B'}{S'}$ determines the ratio of active buyers to active sellers $\frac{B}{S}$, and $\frac{B}{S}$ determines the aggregate number of transactions γBS and the individual trading rates. Potentially, I could recover the magnitude of the ratio $\frac{B'}{S'}$ if I knew how long it takes for a seller to sell an aircraft and for a buyer to buy an aircraft. Unfortunately, as described in Section 4.3, the data offer little indication of the magnitudes of these delays and, hence, no indication of what the ratio $\frac{B'}{S'}$ is. Thus, the Poisson rate γ and the ratio $\frac{B'}{S'}$ cannot be separately identified.

2. With the previous caveats in mind, I proceed by fixing some parameters, and by imposing some assumptions on the functional form that links utilization and profits. Then, I use the model to infer the magnitudes of transaction costs by calibrating the key parameters to match some moments of the data.

Specifically, I fix the bargaining power to $\theta = .5$ and the interest rate $r = .05$. It is well known that the bargaining power and the discount factor/interest rate are difficult parameters to calibrate in the data. In addition, I fix $\gamma = .1$, $\frac{B'}{S'} = 1.5$, and $c = 500,000$. Moreover, I assume that the profit function takes the following form:

$$\pi(h) = \alpha h,$$

where α is a parameter to be calibrated. The above expression arises, for example, if the profit function is

$$\pi(z) = \max_h \alpha\left(zh^{1/2} - h\right)$$

so that the optimal $h = \left(\frac{z}{2}\right)^2$ and $\pi(z) = \alpha\left(\frac{z}{2}\right)^2 = \alpha h$. I further assume that $F(z)$ is normal with mean μ and standard deviation σ to be calibrated.

Further, I select the more popular aircraft type—the Boeing 737—to reduce the heterogeneity across aircraft types, and compute some moments from the data. More precisely, I take the average number of Boeing 737s during the period 1990-2002—equal to 2,700 units—and calculate the corresponding average flying hours, the standard deviations of flying hours, the average price from the "Blue Book" dataset, and the average turnover of Boeing 737s (I am not using any moment on the dispersion of transaction prices since the sample of transaction prices refer to earlier years.) Then, I take a ten-percent increase in the number of Boeing 737s, and apply the elasticities estimated in Tables 4 and 6 to the average flying hours and average price. Columns (1) and (2) in Panel A-Table B1 report the exact numeric value of the moments.

Then, I then calibrate the parameters $(\alpha, \lambda, \mu, \sigma)$ so that the moments computed from the model are as close as possible to the moments in the data, as reported in Table B1. Panel B of Table B1 reports the implied parameters, and columns (3) and (4) of Panel

TABLE B1: Moments and Parameters of the Calibration

PANEL A: MOMENTS

	(1)	(2)	(3)	(4)
	DATA	DATA	MODEL	MODEL
NUMBER OF AIRCRAFT (AIRTYPE)	2700	3000	2700	3000
AVERAGE FLYING HOURS $E(h)$	2724	2780	2751	2752
STANDARD DEVIATION OF FLYING HOURS	239		239	
AVERAGE PRICE ($1,000)	32,950	33,930	33,433	33,445
TURNOVER	.11	.12	.114	.115

PANEL B: PARAMETERS

γ	0.05
$\frac{B'}{S'}$	1.5
c	500,000
α	672.63
λ	0.217
μ	98.24
σ	7.17

Notes—This table contains details of the calibration of model parameters. Columns (1) and (2) in Panel A report the moments of the data that the model seeks to match. Columns (3) and (4) in Panel A report the corresponding moments computed from the model with the parameters reported in Panel B.

A report the moments computed from the model at those parameters.

Overall, the model matches the data moderately well. Moreover, the magnitudes of parameters seem reasonable. The parameter λ implies that the productivity of a carrier varies, on average, every five years $(\approx 1/\lambda)$. The parameter α means that one flying hour translates into approximately \$672 of profits. More interestingly, the Poisson rate γ of the trading technology—fixed at .05—along with the endogenous mass of buyers implies that the individual rate of selling (buying) an aircraft is equal to $\gamma B \approx 3.98$ $(\gamma S \approx 3.87)$, so that it takes approximately $\frac{12}{\gamma B} \approx 3$ months to sell a Boeing 737 when the size of the market is 2,700 units. Since the annual search cost parameter c is fixed to \$500,000 and it takes approximately three months to sell a Boeing 737, the total transaction costs are equal to approximately $\frac{c}{\gamma B} \approx \$125,000$ (in year-2000 values), or $\frac{\frac{c}{\gamma B}}{\alpha E(h)} \approx 6.7$ percent of the annual flow of profits from operating the aircraft.

As mentioned, these parameters and the implied transaction costs rely on several assumptions. Unfortunately, some of these assumptions are not directly testable with the available data. For these reasons, I view these parameters as suggestive. Moreover, the magnitudes that these parameters imply do not seem unreasonable, and they conform fairly well with some estimates reported in industry publications (Airfinance Journal, several issues)

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