The Role of Trading Frictions in Real Asset Markets

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November, 2008

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.

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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. In this paper, I investigate how trading frictions vary with the thickness of the asset market, analyzing patterns of asset utilizations 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, 2007).

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.

Assets with a thin market imply that firms on each side of the market do not search exhaustively for the best matches (Ramey and Shapiro, 2001). In turn, this affects owners' decision over whether or not to sell when their idiosyncratic profitability changes over time. Instead, the matching between buyers and sellers becomes easier in a thicker asset market. In this sense, assets with a thicker market are more "liquid." When assets have a very thick market, they transfer immediately to the highest-profitability firms. Instead, it is optimal for inefficient firms to keep assets with a thin market rather than selling them. The reason is that assets with a thin market are more difficult to sell, and they have higher option values: Firms choose to hold on to them for longer periods in case their profitability rises in the future. Hence, when assets have a thin market, the average profitability of firms is

[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 (forthcoming) 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.

lower, and, at the same time, the dispersion of their profitability is higher. In summary, asset turnover is lower in thinner markets, and assets with a thin market are less efficiently allocated than assets with a thick market.

The effects of trading frictions on asset allocations transmits to asset prices. Market thinness decreases the level of asset prices and increases the dispersion of transaction prices. The reason is that when firms bargain over the price, the transaction price depends on each firm's ability to generate cash-flow from the asset.[3] Because trading frictions are lower for assets with a thicker market, assets with a thick market generate a high level of firms' profitability and a small dispersion of profitability. Hence, transaction prices are high and the dispersion of transaction prices is low. Conversely, when the asset market is thin, the low equilibrium level and high dispersion of firm profitabilities translate into a low average price and high dispersion of transaction prices. Asset prices reflect how active the market is and how efficiently assets are allocated.

In this paper, I use a simple model of trading in decentralized markets with two-sided search and bilateral bargaining to formalize the effects of the size of asset markets on asset allocations and prices. I then test a rich number of empirical predictions 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 models to financial markets. In particular, the setup shares a number of features with the recent contributions by Vayanos and Wang (forthcoming) and Weill (forthcoming), but with an important difference.[4] The distribution of agents' ability to generate cash-flow from an asset is continuous rather than discrete. This departure allows the characterization of the equilibrium distribution of buyers' and sellers' profitabilities and the equilibrium distribution of transaction prices that can be mapped into their empirical counterparts.

The key economic mechanism is that, under a standard assumption on the meeting rate between buyers and sellers,[5] the trading technology exhibits increasing returns to scale. Thus, as the mass of assets increases, the 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.[6,7]

[3]Pulvino (1998) empirically establishes that sellers in worse financial conditions sell assets at a lower price. In Section 4.7, I discuss in more detail the relationship between this paper and Pulvino (1998).

[4]See, also, Duffie, Gârleanu and Pedersen (forthcoming), Miao (2006), Lagos and Rocheteau (2007), Vayanos and Weill (forthcoming), and Weill (forthcoming).

[5]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 forthcoming), Vayanos and Wang (forthcoming), and Weill (forthcoming) for a sample of recent papers adopting this assumption.

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

[7]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

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." Thus, assets trade more frequently in a thicker market.

Through the trading technology just described, the size of the asset market has important implications for allocations and prices. Specifically, assets with a larger 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.

In the empirical section, I combine four distinct datasets concerning the aircraft market to empirically investigate the above implications. 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 how trading frictions vary with thickness of the asset market and, thus, of the effects of asset market thickness on input allocations and prices. Moreover, the aircraft market provides an ideal candidate for general investigation of a search model of trading in decentralized markets and, in particular, of scale effects. First, secondary markets for aircraft are the typical example of decentralized markets. Aircraft is the only form of capital equipment that can be redeployed to an operator anywhere in the world within a day, and this characteristic means that there are global markets for aircraft. Second, aircraft are differentiated products, designed to serve different markets and different ranges. Thus, the differential number of different airline markets imply that some aircraft are more popular than others. Third, commercial aircraft are registered goods with all major "life" events (date of first flight, maintenance, scrappage, etc.) recorded, so very detailed data are available. Thus, the richness of the data allows me to use two related 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.[8] Moreover, the richness of the data also 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. For example, 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, 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 to identify the effect of market thickness on asset allocations.

The empirical analysis confirms all theoretical predictions. Moreover, the analysis reveals

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.

[8]The empirical results are very similar across the two measures.

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.

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.[9] 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 also contributes to the literature on productivity dispersion. Capacity utilization is closely related to firm productivity.[10] 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, forthcoming), 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).[11,12]

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

[10] Indeed, the model shows that more-productive firms choose a higher level of capacity utlization.

[11] In independent work, Balasubramanian and Sivadasan (forthcoming) construct an index of sunkenness of capital investments for US 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.

[12] 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

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 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 empirical predictions of the model on the effect of market thickness on asset allocations and prices. Section 5 concludes. Appendices B and C contain some mathematical derivations.

2 Commercial Aircraft Markets

The market for used commercial aircraft might seem relatively active compared to the market for other more specialized equipment. All airlines in the world use the same types of aircraft, and there are relatively few types. Also, 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. Thus, the secondary market for aircraft is a single, worldwide market.

However, several other facts suggests that trading frictions may be important. In particular, compared to financial markets and to other equipment markets, the absolute number of transactions in the aircraft market remains very 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.[13]

Moreover, the market is organized around privately negotiated transactions.[14] Most major carriers have staff devoted to the acquisition and disposition of aircraft, which suggests that trade is not frictionless. Also, independent brokers are sometimes used to match buyers and sellers, which again indicates the importance of frictions. Moreover, 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 aircraft sold from the 35 offered for sale. Subsequent auctions ended even without a single sale. Hence, prices are very sensitive to party's 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.

Furthermore, aircraft are differentiated products, and product differentiation generates

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.

[13]The comparison with other capital goods is complicated because of the heterogeneity of capital goods. In a cross-industry study of corporate asset sales, Schilngemann 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.

[14]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.

economic rents. Each type of aircraft requires human-capital investments in specific skills for pilots, crew and mechanics that increase the degree of physical differentiation. Product differentiation also implies that aircraft are imperfect substitutes for one another, as different types are designed to serve different markets and different ranges. For example, a Boeing 747 is suited to serve markets in which both demand and distance are large. Thus, the differential size and number of different airline markets imply that different aircraft types have differential popularity, and a carrier could choose to operate an aircraft with a rather thin market if it suits its route structure better. For a given type, the number of annual transactions may be small. For example, 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,[15] Wachovia Securities (2005) states: "From a lessor's 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....' "[16]

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.[17] Hence, the number of current operators of an aircraft type captures well the number of potential buyers (Benmelech and Bergman, forthcoming A and B; Gavazza, 2008). A larger number

[15]Leasing is very popular in the aircraft market, with about 50 percent of the current stock of commercial aircraft being leased. Gavazza (2007) explores the effect of leasing on aircraft turnover. Gavazza (2008) explores how the liquidty/redeployability of aircraft affects whether aircraft are leased or not, the equilibrium maturity and pricing of lease contracts.

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

[17]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.

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.[18] 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 these observations suggests that trading frictions can 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 setup 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.

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), and, for simplicity, let us assume that all aircraft are homogenous. 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 the use of an aircraft, with more productive carriers choosing a higher level of utilization.[19]

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

[18] 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.

[19] 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 utlization. Moreover, equilibrium profits are an increasing function of productivity. Hence, profits and productivity move one-to-one with capacity utilization.

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 with a fixed arrival rate. 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 (and reduced form) 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 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.[20]

[20]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

Moreover, 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 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 equilibrium distribution of firms' profitabilities transmit to the distribution of transaction prices. As a result, assets with a thicker market have a higher average level of asset prices and, simultaneously, a lower dispersion of transaction prices.

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; 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" 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 was compiled by a producer of aviation-market information systems and 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 was compiled by the producer of the aircraft history dataset and 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

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 US carriers, and that capacity utilization is substantially lower before a carrier enters into bankruptcy.

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.[21]

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.[22]

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 one is by counting the total stock outstanding of aircraft of type i in year t, and I call this variable $\textsc{Airtype}_{it}$. 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 variable $\textsc{Optype}_{it}$. 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.[23]

I then match $\textsc{Airtype}_{it}$ and $\textsc{Optype}_{it}$ to the dataset on aircraft utilization and the two datasets on prices to investigate the effects of market thickness on asset allocations and prices. More precisely, to investigate the effect of market thickness on allocations, I match $\textsc{Airtype}_{it}$ and $\textsc{Optype}_{it}$ to each aircraft's holding duration to study whether aircraft with a thicker market have higher turnover. Further, I match $\textsc{Airtype}_{it}$ and $\textsc{Optype}_{it}$ to the annual flying

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

[22] For further details about these data, see Pulvino (1998).

[23] 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.

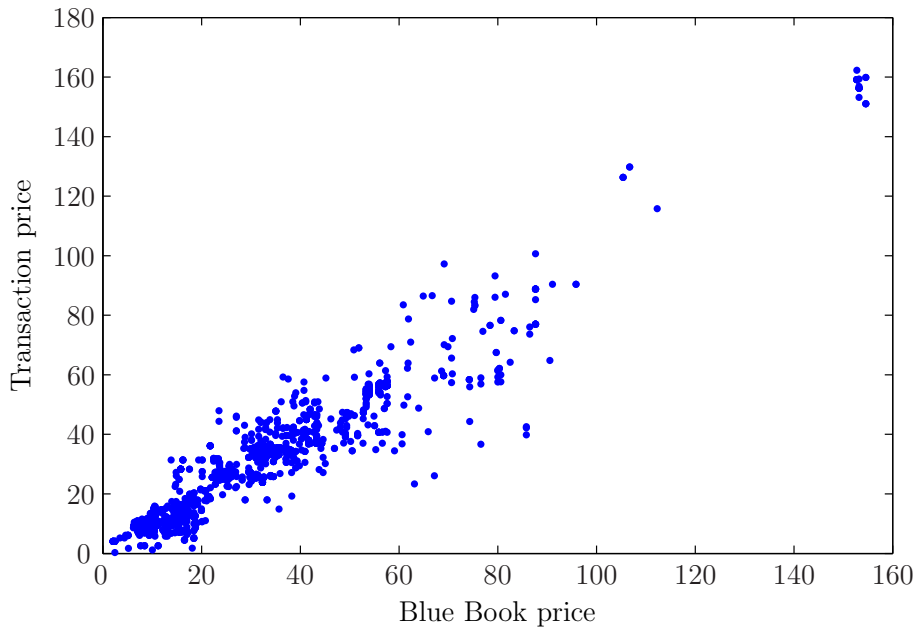

FIG. 1: Transaction price vs. Blue Book price

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 touples, $\overline{fh}_{akit}$. 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., $\left|\frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}}\right|$.

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 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 touple 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 very well the average price of a specific aircraft. 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.[24]

[24] 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 several disadvantages to this procedure:

Table 1: Summary statistics

Panel A: Asset Turnover	Mean	St. Dev.
Holding duration	7.02	6.46
Types of aircraft	26	
Aircraft per type—Airtype	1167.6	1007.1
Operators per type—Optype	96.13	85.61
Panel B: Aircraft Utilization		
Flying hours fh_{jkit}	2741.13	1097.02
Absolute percentage deviation $\left\lvert \frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}} \right\rvert$	.1883	.2644
Parked aircraft	.041	.198
Types of aircraft	26	
Aircraft per type—Airtype	1434.58	1100.88
Operators per type—Optype	122.78	100.84
Age	11.80	7.89
Panel C: Blue Book Prices		
Average price $\bar{p}_{jkit}$	32.32	27.55
Types of aircraft	18	
Aircraft per type—Airtype	1019	944
Operators per type—Optype	86.97	81.09
Age	9.44	7.50
Panel D: Transaction Prices		
Transaction price p_{jkit}	30.60	24.47
Absolute percentage deviation $\left\lvert \frac{p_{jkit}-\bar{p}_{akit}}{\bar{p}_{akit}} \right\rvert$	.171	.193
Types of aircraft	13	
Aircraft per type—Airtype	960.6	612.2
Operators per type—Optype	74.45	46.75
Age	7.35	6.94

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. 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, 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 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.

1) the dataset would no longer be a panel dataset; thus, the Arellano and Bond procedure described below cannot be employed; 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.

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.

4.3 Some Suggestive Evidence on Trading Frictions

Before turning to a more formal analysis, I would like to present some simple conditional correlations that speak directly to the importance of 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.[25] Lessors appear to be more sophisticated than carriers at turning their aircraft over (Gavazza, 2007). Hence, delays between two consecutive lessees can be interpreted as a lower bound on average delays. Clearly, if there were no frictions, we would expect no delay at all between any two 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.[26] 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).[27] As the table clearly shows, aircraft with a larger market are redeployed faster to

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

[26] 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.

[27] 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

Table 2: Delays before Leasing Transactions: Negative Binomial Regressions

Days between two lessees	(1)	(2)	(3)	(4)
Log(Airtype)	−.20638		−.25078	
	(.02087)		(.04050)	
Log(Optype)		−.13902		−.16737
		(.02411)		(.04649)
Age	.06795	.06410	.04029	.03633
	(.00782)	(.00779)	(.01310)	(.01305)
Age squared	−.00054	−.00041	−.00034	−.00019
	(.00024)	(.00023)	(.00039)	(.00039)
Log-Likelihood	−30637.14	−30667.57	−7782.05	−7793.91
# Obs	9358	9358	4396	4396

Notes—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).

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, so that the magnitudes of the conditional correlations are non-trivial. For example, 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.

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. This is for two 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

individual aircraft fixed effects in the specifications of columns (3) and (4) substantially reduces the number of observations compared 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.)

[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 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. Hence, the evidence suggests that market thinness is able to generate frictions that delay transactions. I next turn to a more formal empirical analysis of the causal effects of asset market thickness on asset allocations and prices.

4.4 Empirical Framework and Identification

To test for the effect of market thickness on allocations and prices, I specify the following reduced-form equation:

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

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. $\textsc{Thickness}_{it}$ is either Airtype or Optype. X_{jkit} is specific to each individual aircraft—i.e., $\textsc{Age}_{jit}$. ζ_k is an aircraft-model fixed effect, η_t is a year fixed effect and ϵ_{jkit} is an idiosyncratic unobserved component.

The use of the quantity-based measures Airtype and Optype creates a few potential challenges to the 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 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

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.

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. Moreover, the inclusion of year dummies 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 should 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:

$$y_{jkit} = \beta Z_{jkit} + \zeta_k + \eta_t + \epsilon_{jkit}, \tag{2}$$

$$\epsilon_{jkit} = \rho\epsilon_{jkit-1} + \nu_{jkit}. \tag{3}$$

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:

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

Taking first-differences, the following equation obtains:

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

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 $E\left(\Delta\nu_{jkit} * W\right)$, 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} 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 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.[30] 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 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 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[31] and the one-year and two-year lags, each interacted with aircraft characteristics (the number of seats, the number of enigines, the maximum take-off weight, and the number of years since the release date);[32] and the average number of days of

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

[30] For simplicity, the discussion here focuses on AIRTYPE as the measure of market thickness. The argument for OPTYPE is very similar.

[31] 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`

[32] 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

strike per worker in the manufacturing sector in the country of the aircraft manufacturer[33] and the lags up to three years, and their interactions with aircraft characteristics (the number of seats, the number of enigines, 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 should be lower if the number of strikes in the manufacturing sector in the country where the aircraft is assembled is higher.

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 are not very persistent. Similarly, the two main shifters of AIRTYPE and OPTYPE (production of new aircraft and retirement of old aircraft) exhibit substantial year-to-year variation.

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 it 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 enigines, 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 enigines, 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.

restriction needed for the validity of the instruments.

[33]The strike data are obtained from the Laborsta database operated by the International Labour Office, Bureau of Statistics. Available at `http://laborsta.ilo.org/`.

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 on 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:

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

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; $\textsc{Thickness}_{it}$ 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.[34,35] 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

[34] 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).

[35] 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.

across aircraft types.[36] 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.[37]

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).[38] 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 number of enigines, 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 enigines, 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

[36] 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:

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

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

[37] 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.

[38] 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	.04344	.00027	−.00015
	(.00453)	(.00448)	(.00487)	(.00479)
Log(Airtype)	.25517		.19042	
	(.09215)		(.09835)	
Log(Optype)		.37810		.33125
		(.12095)		(.13469)
Log-Likelihood	−136760.3	−136704.9	−132836.8	−132793.8
# Obs	241622	241622	241622	241622
Aircraft	17398	17398	17398	17398

Notes—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).

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.[39]

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

[39]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 eliminate this concern. Moreover, the evidence reported in Gavazza (2007) 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 for more popular aircraft.

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 should be 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 $\log(fh_{jkit})$ 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 $\log(fh_{jkit})$ 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 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.[40]

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 allows me also to difference out any

[40] 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.

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

	(1)	(2)	(3)	(4)
	Fly_{jkit}	Fly_{jkit}	$\log(fh_{jkit})$	$\log(fh_{jkit})$
Age	−.01497	−.01279	−.03437	−.03521
	(.00232)	(.00281)	(.00383)	(.00361)
Log(Airtype)	.09842		.18996	
	(.04861)		(.08998)	
Log(Optype)		.08586		.09105
		(.02413)		(.03845)
# Obs	64279	64279	60139	60139
Aircraft	11596	11596	11240	11240

Notes—Standard errors clustered at the aircraft-type–year level in parentheses. All equations also contain year fixed effects (not reported).

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.[41] 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 of Airtype is associated with a 0.9 percentage point increase in the probability that the aircraft is flying, a considerable magnitude. The results reported in column (2) using Optype are very similar: a ten-percent increase of 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 of 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 of Optype is associated with a 0.9-percent increase in capacity utilization.

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.

[41] 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 $t-1$.

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.[42] As previously noticed, 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.

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 sizable 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 regressions confirm that market thickness affects both the intensive and the

[42] 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) $\left\lvert\frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}}\right\rvert$	(2) $\left\lvert\frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}}\right\rvert$	(3) $\left\lvert\frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}}\right\rvert_{fh_{jkit}>0}$	(4) $\left\lvert\frac{fh_{jkit}-\overline{fh}_{akit}}{\overline{fh}_{akit}}\right\rvert_{fh_{jkit}>0}$
Age	.03102	.03717	.01672	.01687
	(.00559)	(.00521)	(.00267)	(.00271)
Log(Airtype)	−.22892		−.17437	
	(.09246)		(.06521)	
Log(Optype)		−.10631		−.05421
		(.04163)		(.02861)
# Obs	63886	63886	60139	60139
Aircraft	11582	11582	11240	11240

Notes—Standard errors clustered at the aircraft-type–year level in parentheses. All equations also contain year fixed effects (not reported). The equations estimated in columns (3) and (4) uses only observations with positive flying hours.

extensive margins of utilization.[43,44]

4.6 Results: the Effect of Market Thickness on Aircraft Prices

Having investigated the effect of market thickness on asset allocations, in this subsection, I investigates the effects on prices. I present two sets of results, directly testing predictions 4 and 5 related to the first and second moments of the price distribution.

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

[43] 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 Table 4, I obtain the residuals $\hat{\epsilon}_{jkit}$ of the utilization equation. I then calculate the variance $\text{Var}(\hat{\epsilon}_{jkit})$ of these residuals, and I regress $\text{Var}(\hat{\epsilon}_{jkit})$ on Airtype or Optype, aircraft-type fixed effects and year fixed effects. I find that aircraft with a larger market have a lower variance $\text{Var}(\hat{\epsilon}_{jkit})$, which is consistent with the results reported in Table 5,

[44] 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.

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—Standard errors clustered at the aircraft-type–year level in parentheses. The equation estimated also contains year fixed effects (not reported).

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 an increase in the price of the aircraft by 2.7 percent. This magnitude is equivalent to the effect on price of around six months of Age. Similarly, a ten-percent increase of Optype is associated with an increase in the price of the aircraft by 2.0 percent.

4.6.2 Price Dispersion

The previous results showed that there exists a clear parallel between the increase in the aircraft price levels and the increase in the level of capacity utilization as the aircraft 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.

[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.

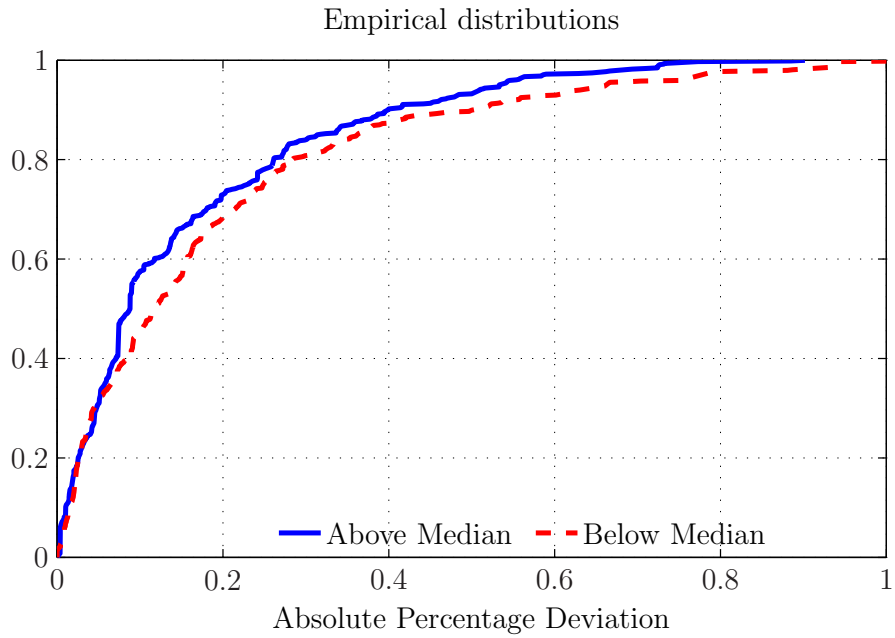

FIG. 2: Empirical distributions of deviations of transaction price from Blue Book price for above- and below-median liquidity.

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 AIRTYPE above and below the median: Figure 2 plots these two empirical distributions.[46] 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 2 clearly shows that the dispersion of 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 further investigate 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 enigines, 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 enigines, the maximum take-off

[46] The figure using OPTYPE is very similar.

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—Standard errors clustered at the aircraft-type–year level in parentheses. 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).

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 reduce endogeneity concerns to a minimum, and the 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 of Airtype is associated with a decrease in the absolute value of the percentage difference between transaction price and Blue Book price by 1.3-1.5 percent. Similarly, a ten-percent increase of Optype is associated with a decrease in the absolute value of the percentage difference between transaction price and Blue Book price by 1.0-1.1 percent.[47,48]

4.7 Discussion of Empirical Results

The empirical analysis provides quite 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

[47]Similar to the remark in footnote 44, a potential concern with the regressions of Table 5 is that the dependent variable has the average price in the denominator, and the regressions reported in Table 5 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.

[48]It may seem puzzling that, in some tables, the coefficients of Airtype is 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.

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 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 exclude the possibility that the quantity-based measures Airtype or Optype capture the effect of unobserved demand shocks. I now discuss in detail the difference between my paper and a few closely related empirical papers, and I present evidence against some alternative hypotheses.

Related papers - The empirical patterns documented in this paper share some similarities with the patterns uncovered by a few papers in the literature. Syverson (2004, forthcoming) investigates the determinants of firms' average productivity and the dispersion of productivity levels. However, the precise economic forces behind Syverson's papers and that behind my paper are rather different. Syverson focuses on a demand-side effect: In his model, consumers can more easily switch between suppliers in a denser market. As a result, suppliers' average productivity is higher, and the dispersion of productivities is lower in denser markets. Instead, this paper focuses on a supply-side effect: the thickness of the input market.[49] 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).

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.

Alternative Hypotheses - The literature on durable goods highlights the role of depreciation (quality differentials) in explaining patterns of trade. The literature makes different predictions if parties have symmetric versus asymmetric information on the depreciation (quality) of the asset. Under symmetric information, the literature (Hendel and Lizzeri, 1999; Stolyarov, 2002) predicts that lower-quality goods should trade more frequently. In my setting, since assets with a thicker market trade more frequently, we must conclude that these assets are of lower quality. Clearly, this conclusion is inconsistent with the fact that assets with a thicker market have higher capacity utilizations and command higher prices. Thus,

[49] See, also, Balasubramanian and Sivadasan (forthcoming).

theories of quality differentials under symmetric information cannot explain the observed patterns.

Under asymmetric information, higher-quality durable goods trade more frequently (Hendel and Lizzeri, 1999), in contrast with Akerlof's (1970) original analysis. Hence, we must conclude that assets with a thicker market are of higher quality. This explanation might seem to explain a number of patterns. However, several institutional features of the aircraft market and a closer look at the data show that this explanation is unlikely to account for all observed patterns. First, the aviation authorities regulate aircraft maintenance: After a certain number of hours flown, 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 observed dispersion of transaction prices is exactly the *opposite* of that predicted by asymmetric-information models. In particular, under information asymmetries, we should expect a lower dispersion of transaction prices for assets with more severe information asymmetries, as prices do not depend on unobserved quality differences.

An alternative hypothesis for assets' patterns of trade, suggested by the finance literature, is that firms sell assets to reduce the degree of firm diversification (e.g., John and Ofek, 1995). This motivation for trade implies that firms tend to sell their marginal assets. However, the evidence is inconsistent with the idea that the majority of assets sold are marginal assets. The reason is that assets that trade more frequently are more popular, so they cannot be marginal assets for all carriers. Moreover, the evidence shows that assets that trade more frequently fetch higher prices. If they were marginal assets, we should expect them, instead, to fetch lower prices.

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 by investigating how market thickness affects asset prices and asset allocations. I setup a model of a bilateral search market to investigate how trading frictions vary as asset markets get thicker, and what implications market thickness has for asset allocations and prices. The key economic mechanism in the model is that the trading technology fundamentally 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 working 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. This finding has several potential implications. 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 way that the cost of firing labor acts in the general equilibrium model of Hopenhayn and Rogerson (1993).

This paper further contributes to the literature on productivity and productivity dispersion. Most of the explanations for the large and persistent productivity dispersion observed within industries focus on technological differences between firms. Here, in the model, I show in a simple way how productivity and capacity utilization are related, and in the empirical analysis, how the dispersion of capacity utilization decreases when the asset market gets larger by reducing the costs of selling inputs.

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

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 is 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

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

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

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 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 profitability $\pi(z)$ 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 z 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

$$\begin{aligned} rV_B(b) &= -c + \gamma S \int \max\{W_S(b) - p(b,s) - V_B(b), 0\} dG_S(s) \\ &\quad + \lambda \int (\max\{V_B(z), W_B(z)\} - V_B(b)) dF(z) \end{aligned} \tag{7}$$

where $G_S(s)$ is the endogenous equilibrium distribution of active sellers (which is derived below).

Equation (7) 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:

$$\begin{aligned} rV_S(s) &= -c + \pi(s) + \gamma B \int \max\{p(b,s) + W_B(s) - V_S(s), 0\} dG_B(b) \\ &\quad + \lambda \int (\max\{V_S(z), W_S(z)\} - V_S(s)) dF(z). \end{aligned} \tag{8}$$

where $G_B(b)$ is the endogenous equilibrium distribution of active buyers (which, again, is derived below).

The interpretation of equation (8) 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 z, 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:

$$rW_B(b) = \lambda \int (\max\{V_B(z), W_B(z)\} - W_B(b))\, dF(z) \tag{9}$$

$$rW_S(s) = \pi(s) + \lambda \int (\max\{V_S(z), W_S(z)\} - W_S(s))\, dF(z). \tag{10}$$

Equations (9) and (10) 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.[52]

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

$$p(b,s) = \theta(V_S(s) - W_B) + (1-\theta)(W_S(b) - V_B(b)) \tag{11}$$

is the solution to the following symmetric-information bargaining problem:[53]

$$\max_p [W_S(b) - p - V_B(b)]^{\theta} [p + W_B - V_S(s)]^{1-\theta}$$

$$\text{subject to:} \quad W_S(b) - p \geq V_B(b) \text{ and } p + W_B \geq V_S(s).$$

Using the equilibrium price (11), the value function of an active buyer b becomes

$$\begin{aligned} rV_B(b) + c &= \gamma S\theta \int \max\{-V_S(s) + W_B + W_S(b) - V_B(b), 0\}\, dG_S(s) \\ &\quad + \lambda \int (\max\{V_B(z), W_B(z)\} - V_B(b))\, dF(z). \end{aligned} \tag{12}$$

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

$$\begin{aligned} rV_S(s) + c &= \pi(s) + \gamma B(1-\theta) \int \max\{-V_S(s) + W_B + W_S(b) - V_B(b), 0\}\, dG_B(b) \\ &\quad + \lambda \int (\max\{V_S(z), W_S(z)\} - V_S(s))\, dF(z). \end{aligned} \tag{13}$$

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

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

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

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

[52] Thus, the value of an inactive buyer is independent of his profitability.

[53] The characteristics of aircraft markets described in section 4.7 support the assumption of symmetric information.

When r is small, it can be shown that $-V_S(s)+V_B(s)+V_S(b)-V_B(b) \geq 0$ for all possible meetings of active buyers and sellers.[54] Hence, Appendix B shows that we can rewrite the value function of an active buyer as

$$V_B(b) = k(\pi(b) - \pi(R_B)) + \frac{\lambda \int \max\{V_B(z), W_B\} dF(z)}{r+\lambda} \tag{14}$$

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

$$V_S(s) = \frac{\pi(s) - \pi(R_S)}{\delta} + \frac{\pi(R_S) + \lambda \int \max\{V_S(z), W_S(z)\} dF(z)}{r+\lambda} \tag{15}$$

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

$$\begin{aligned} p(b,s) \;=\; & \theta\left(\frac{\pi(s)-\pi(R_S)}{\delta} + \frac{\pi(R_S)}{r+\lambda}\right) + (1-\theta)\left(\frac{\pi(b)}{r+\lambda} - k(\pi(b)-\pi(R_B))\right) + \\ & \int_{R_S} \frac{\lambda\pi(z)}{r(r+\lambda)} dF(z) + \frac{\lambda}{r}\int^{R_S}\left(\frac{\pi(z)-\pi(R_S)}{\delta} + \frac{\pi(R_S)}{r+\lambda}\right) dF(z) - \\ & \int_{R_B} \frac{\lambda k(\pi(z)-\pi(R_B))}{r} dF(z). \end{aligned} \tag{16}$$

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.

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. Appendix C shows the exact calculations. Moreover, it is easy to show that for c sufficiently large, $R_B > R_S$. Thus, 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 simply

$$g_S(z) = \begin{cases} 0 & \text{for } R_S \leq z \\ \frac{f(z)}{F(R_S)} & \text{for } z < R_S \end{cases} \tag{17}$$

[54] See Mortensen and Wright (2002).

and active buyers is

$$g_B(z) = \begin{cases} \frac{f(z)}{1-F(R_B)} & \text{for } R_B \leq z \\ 0 & \text{for } z < R_B. \end{cases} \tag{18}$$

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:*[55]

$$c = \gamma S\theta \int \left(\frac{\pi(R_S) - \pi(s)}{\delta} - \frac{\pi(R_S) - \pi(R_B)}{r+\lambda} \right) dG_S(s) \tag{19}$$

$$c = \gamma B(1-\theta) \int \left(\frac{\pi(b) - \pi(R_S)}{r+\lambda} - k(\pi(b) - \pi(R_B)) \right) dG_B(b) \tag{20}$$

   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 (17) and (18);

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.[56] 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.

[55] The conditions are obtained by combining equations (12), (14) and (9), and equations (13), (15) and (10), respectively.

[56] 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.

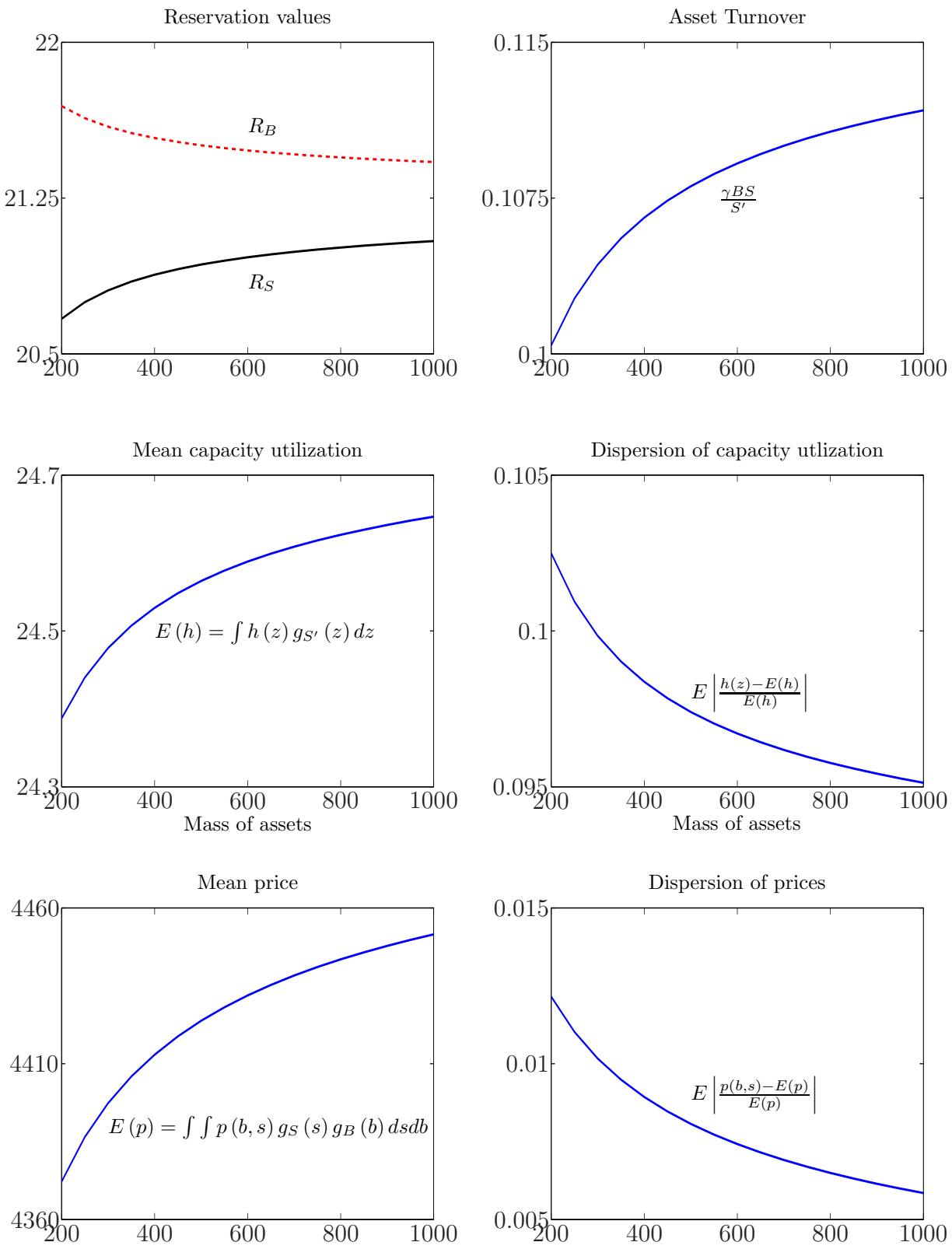

FIG. 3: Numerical solutions

Figure 3 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. Moreover, 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 $1 - F(R^*) = \frac{S'}{S'+B'}$.[57]

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. In the third plot (second row, first column), I plot 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 suggests 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 $\phi(\cdot)$ and $\Phi(\cdot)$ denote the standard normal p.d.f. and c.d.f., respectively.[58] In the fourth plot (second row, second column) I plot the dispersion of capacity utilization $E\left|\frac{h(z)-E(h)}{E(h)}\right|$, which is identical to the dispersion of productivity $E\left|\frac{z-E(z)}{E(z)}\right|$, and the plot shows that the dispersion of capacity utilization and productivity decrease 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 3 documents that the average asset price $E(p) = \int\int p(b,s)\, g_S(s)\, g_B(b)\, dsdb$ increases when the asset market becomes thicker. Moreover, the price converges to the Walrasian price equal to $\frac{\pi(R^*)}{r}$.[59] 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.[60]

[57]Given the numerical values assumed, the Walrasian limit R^* of R_S and R_B is equal to 21.26.

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

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

[60]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.

B Value Functions and Transaction Prices

To obtain the value functions, first note that $\frac{\partial V_B(x)}{\partial \pi(x)}$ 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. Moreover, we can use the conditions on the marginal traders $V_S(R_S)$ and $V_B(R_B)$ to find the intercepts. Thus, we have

$$V_B(b) = k(\pi(b)-\pi(R_B)) + \frac{\lambda\int \max\{V_B(z), W_B(z)\}\,dF(z)}{r+\lambda} \tag{21}$$

$$V_S(s) = \frac{\pi(s)-\pi(R_S)}{\delta} + \frac{\pi(R_S)+\lambda\int \max\{V_S(z), W_S(z)\}\,dF(z)}{r+\lambda} \tag{22}$$

where $k = \frac{\gamma S\theta}{(r+\lambda)(r+\lambda+\gamma S\theta)}$ and $\delta = r+\lambda+\gamma B(1-\theta)$.

Moreover, define EB and ES as follows:

$$EB = \int \max\{V_B(z), W_B(z)\}\,dF(z) \quad ; \quad ES = \int \max\{V_S(z), W_S(z)\}\,dF(z)$$

and note that we can calculate

$$\begin{aligned} EB &= \int^{R_B} W_B(z)\,dF(z) + \int_{R_B} V_B(z)\,dF(z) \\ &= \frac{\lambda EB}{r+\lambda} + \int_{R_B} k(\pi(z)-\pi(R_B))\,dF(z) = \frac{(r+\lambda)\int_{R_B} k(\pi(z)-\pi(R_B))\,dF(z)}{r} \end{aligned}$$

and

$$\begin{aligned} ES &= \int^{R_S} V_S(z)\,dF(z) + \int_{R_S} W_S(z)\,dF(z) \\ &= \int^{R_S}\left(\frac{\pi(z)-\pi(R_S)}{\delta} + \frac{\pi(R_S)+\lambda ES}{r+\lambda}\right)dF(z) + \int_{R_S}\frac{\pi(z)+\lambda ES}{r+\lambda}dF(z) \\ &= \frac{r+\lambda}{r}\int^{R_S}\left(\frac{\pi(z)-\pi(R_S)}{\delta} + \frac{\pi(R_S)}{r+\lambda}\right)dF(z) + \frac{r+\lambda}{r}\int_{R_S}\frac{\pi(z)}{r+\lambda}dF(z) \end{aligned}$$

Thus, when seller s and buyer b meet, the transaction price satisfies

$$\begin{aligned}
p(b,s) &= \theta\left(V_S(s)-W_B(s)\right)+(1-\theta)\left(W_S(b)-V_B(b)\right) \\
&= \theta\left(\frac{\pi(s)-\pi(R_S)}{\delta}+\frac{\pi(R_S)+\lambda ES}{r+\lambda}-\frac{\lambda EB}{r+\lambda}\right)+ \\
&\quad (1-\theta)\left(\frac{\pi(b)+\lambda ES}{r+\lambda}-k\left(\pi(b)-\pi(R_B)\right)-\frac{\lambda EB}{r+\lambda}\right) \\
&= \theta\left(\frac{\pi(s)-\pi(R_S)}{\delta}+\frac{\pi(R_S)}{r+\lambda}\right)+(1-\theta)\left(\frac{\pi(b)}{r+\lambda}-k\left(\pi(b)-\pi(R_B)\right)\right)+ \\
&\quad \int^{R_S}\frac{\lambda}{r}\left(\frac{\pi(z)-\pi(R_S)}{\delta}+\frac{\pi(R_S)}{r+\lambda}\right)dF(z)+\int_{R_S}\frac{\lambda\pi(z)}{r(r+\lambda)}dF(z)- \\
&\quad \int_{R_B}\frac{k\lambda}{r}\left(\pi(z)-\pi(R_B)\right)dF(z)
\end{aligned}$$

C Steady State Distributions of Buyers B' and 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 distributions of potential sellers $g_{S'}(\cdot,t)$ evolves from time t to time $t+\epsilon$ according to:

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

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

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

Rearranging and taking the limit for $\epsilon\to 0$, the steady-state distributions (17) and (18) are obtained.

References

[1] Abel, A.B. and J.C. Eberly, "Optimal Investment with Costly Reversibility," *The Review of Economic Studies*, Vol. 63, No. 4 (Oct., 1996), pp. 581–593.

[2] Akerlof, G.A., "The Market for "Lemons": Quality Uncertainty and the Market Mechanism," *The Quarterly Journal of Economics*, Vol. 84, No. 3 (Aug., 1970), pp. 488–500.

[3] Alchian, A., "Reliability of Progress Curves in Airframe Production," *Econometrica*, Vol. 31, No. 4, (Oct., 1963), pp. 679–694.

[4] Amihud, Y., H. Mendelson and J. Uno, "Number of Shareholders and Stock Prices: Evidence from Japan," *The Journal of Finance*, Vol. 54, Issue 3, (June, 1999), pp. 1169–1184.

[5] Arellano, M. and S. Bond, "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies*, Vol. 58, No. 2 (Apr., 1991), pp. 277–297.

[6] Arellano, M. and O. Bover, "Another look at the instrumental variable estimation of error-components models," *Journal of Econometrics*, Vol. 68, Issue 1 (July, 1995), pp. 29–51.

[7] Argote, L. and D. Epple, "Learning Curves in Manufacturing," *Science*, Vol. 247, (Feb., 1990), pp. 920–924.

[8] Asher, H., *Cost-Quantity Relationships in the Airframe Industry.* Santa Monica, CA, The Rand Corporation, (1956).

[9] Asplund, M., "What Fraction of a Capital Investment Is Sunk Costs?", *The Journal of Industrial Economics,* Vol. 48, No. 3 (Sep., 2000), pp. 287–304.

[10] Balasubramanian, N. and J. Sivadasan, "Capital Resalability, Productivity Dispersion and Market Structure," *Review of Economics and Statistics*, (forthcoming).

[11] Bartelsman, E.J. and M. Doms, "Understanding Productivity: Lessons from Longitudinal Microdata," *Journal of Economic Literature*, Vol. 38, No. 3 (Sept., 2000), pp. 569–594.

[12] Benkard, C.L., "Learning and Forgetting: The Dynamics of Aircraft Production," *The American Economic Review,* Vol. 90, No. 4 (Sep., 2000), pp. 1034–1054.

[13] Benmelech, E. and N. Bergman, "Collateral Pricing," *Journal of Financial Economics*, forthcoming A.

[14] Benmelech, E. and N. Bergman, "Liquidation Values and the Credibility of Financial Contract Renegotiation: Evidence from U.S. Airlines," *Quarterly Journal of Economics*, forthcoming B.

[15] Benmelech, E., M.J. Garmaise and T.J. Moskowitz, "Do Liquidation Values Affect Financial Contracts? Evidence from Commercial Loan Contracts and Zoning Regulation," *Quarterly Journal of Economics*, Vol. 120, No. 3 (Aug., 2005), pp. 1121–1154.

[16] Bleakley, H. and J. Lin, "Thick-Market Effects and Churning in the Labor Market: Evidence from U.S. Cities," mimeo, University of Chicago, (2006).

[17] Blundell, R. and S. Bond, "Initial conditions and moment restrictions in dynamic panel data models," *Journal of Econometrics*, Volume 87, Issue 1 (Aug., 1998), pp. 115–143.

[18] Blundell, R. and J. Powell, "Endogeneity in Nonparametric and Semiparametric Regression Models," *Advances in Economics and Econometrics: Theory and Applications*, ed. by M. Dewatripont, L.P. Hansen and S. Turnovsky, Vol. 2, Econometric Society Monograph #36, Cambridge University Press, Cambridge, (2003).

[19] Burnside, C. and M. Eichenbaum, "Factor-Hoarding and the Propagation of Business-Cycle Shocks," *The American Economic Review*, Vol. 86, No. 5 (Dec., 1996), pp. 1154–1174.

[20] Caballero, R.J. and M.L. Hammour, "The Macroeconomics of Specificity," *The Journal of Political Economy,* Vol. 106, No. 4 (Aug., 1998), pp. 724–767.

[21] Demsetz, H., "The Cost of Transacting," *The Quarterly Journal of Economics,* Vol. 82, No. 1 (Feb., 1968), pp. 33–53.

[22] Diamond, P., "Aggregate Demand Management in Search Equilibrium," *Journal of Political Economy*, Vol. 90, No. 5 (Oct., 1982), pp. 881–894.

[23] Dixit, A.R and R.S. Pindyck, *Investment under Uncertainty,* Princeton, N.J.: Princeton Univ. Press, (1994).

[24] Duffie, D., N. Gârleanu and L.H. Pedersen, "Over-the-Counter Markets," *Econometrica,* Vol. 73, No. 6 (Nov., 2005), pp. 1815–1847.

[25] Duffie, D., N. Gârleanu, and L.H. Pedersen, "Valuation in Over-the-counter Markets," *Review of Financial Studies,* (forthcoming).

[26] Eisfeldt, A. and A. Rampini, "Capital reallocation and liquidity," *Journal of Monetary Economics,* Vol. 53, Issue 3 (April, 2006), pp. 369–399.

[27] Fleming, M.J., "The round-the-clock market for U.S. Treasury securities," *FRBNY Economic Policy Review,* (July, 1997).

[28] Gan, L. and Q. Zhang, "The thick market effect on local unemployment rate fluctuations," *Journal of Econometrics*, Vol. 133, Issue 1, (July, 2006), pp. 127–152.

[29] Garbade, K.D. and W.L. Silber, "Price Dispersion in the Government Securities Market," *The Journal of Political Economy,* Vol. 84, No. 4, Part 1 (Aug., 1976), pp. 721–740.

[30] Gavazza, A., "Leasing and Secondary Markets: Theory and Evidence from Commercial Aircraft," mimeo, New York University, (2007).

[31] Gavazza, A., "Asset Liquidity and Financial Contracts: Evidence from Aircraft Leases," mimeo, New York University, (2008).

[32] Hart, O., *Firms, Contracts and Financial Structure.* Oxford, Oxford University Press, (1995).

[33] Hausman, J., B.H. Hall and Z. Griliches, "Econometric Models for Count Data with an Application to the Patents-R & D Relationship," *Econometrica*, Vol. 52, No. 4 (Jul., 1984), pp. 909–938.

[34] Hendel, I. and A. Lizzeri, "Adverse Selection in Durable Goods Markets," *The American Economic Review*, Vol. 89, No. 5 (Dec., 1999), pp. 1097–1115.

[35] Hopenhayn, H. and R. Rogerson, "Job Turnover and Policy Evaluation: A General Equilibrium Analysis," *The Journal of Political Economy*, Vol. 101, No. 5 (Oct., 1993), pp. 915–938.

[36] House, C.L. and E. Ozdenoren, "Durable Goods and Confirmity," *RAND Journal of Economics,* (forthcoming).

[37] John, K. and E. Ofek, "Asset sales and increase in focus," *Journal of Financial Economics*, Volume 37, Issue 1 (Jan., 1995), pp. 105–126.

[38] Jorgenson, D.W. and Z. Griliches, "The Explanation of Productivity Change," *The Review of Economic Studies*, Vol. 34, No. 3 (Jul., 1967), pp. 249–283.

[39] Kim, C.E., "The Effects of Asset Liquidity: Evidence from the Contract Drilling Industry," *Journal of Financial Intermediation*, Vol. 7, Issue 2 (Apr., 1998), pp. 151–176.

[40] Lagos, R. and G. Rocheteau, "Liquidity in Asset Markets with Search Frictions," mimeo, New York University, (2007).

[41] Lehman Brothers, "Aircraft Securitisation", *Aircraft Financing, Third Edition*, ed. by A. Littlejohns and S. McGairl, Euromoney Books, London, UK, (1998).

[42] Lippman, S.A. and J.J. McCall, "An Operational Measure of Liquidity," *The American Economic Review*, Vol. 76, No. 1 (Mar., 1986), pp. 43–55.

[43] Littlejohns, A., and S. McGairl, eds., *Aircraft Financing (Third Edition).* Euromoney Books, London, UK, (1998).

[44] Maksimovic, V. and G. Phillips, "The market for corporate assets: who engages in mergers and asset sales and are there efficiency gains?", *Journal of Finance,* Vol 56, No. 6 (Dec., 2001), pp. 2019–2065.

[45] Melitz, M. "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, Vol. 71, Issue 6, (Nov., 2003), pp. 1695–1725

[46] Miao, J., "A Search Model of Centralized and Decentralized Trade," *Review of Economic Dynamics*, Vol. 9, Issue 1 (Jan., 2006), pp. 68–92.

[47] Mortensen, D. and R. Wright, "Competitive Pricing and Efficiency in Search Equilibrium," *International Economic Review,* Vol. 43, No. 1 (Feb., 2002), pp. 1–20.

[48] Neyman, J. and E. Scott, "Consistent Estimates Based on Partially Consistent Observations," *Econometrica*, Vol. 16, No. 1 (Jan., 1948), pp. 1–32.

[49] Petrongolo, B. and C. Pissarides, "Scale effects in markets with search," *Economic Journal,* Vol. 116, Issue 508 (Jan., 2006), pp. 21–44.

[50] Pulvino, T., "Do Asset Fire Sales Exist? An Empirical Investigation of Commercial Aircraft Transactions," *The Journal of Finance*, Vol. 53, No. 3 (Jun., 1998), pp. 939–978.

[51] Ramey, V. and M. Shapiro, "Costly capital reallocation and the effects of government spending," *Carnegie-Rochester Conference Series on Public Policy,* Vol. 48, (June, 1998), pp. 145–194.

[52] Ramey, V. and M. Shapiro, "Displaced Capital: A Study of Aerospace Plant Closings," *The Journal of Political Economy,* Vol. 109, No. 5 (Oct., 2001), pp. 958–992.

[53] Rauch, J.E., "Networks versus markets in international trade," *Journal of International Economics*, Vol. 48, Issue 1 (Jun., 1999), pp. 7–35.

[54] Rogerson, R., R. Shimer and R. Wright, "Search-Theoretic Models of the Labor Market: A Survey," *Journal of Economic Literature*, Vol. 43, No. 4 (Dec., 2005), pp. 959-988.

[55] Schlingemann, F.P., R.M. Stulz and R.A. Walkling, "Divestitures and the liquidity of the market for corporate assets," *Journal of Financial Economics*, Volume 64, Issue 1 (April, 2002), pp. 117–144.

[56] Shleifer, A. and R. Vishny, "Liquidation Values and Debt Capacity: A Market Equilibrium Approach," *The Journal of Finance,* Vol. 47, No. 4 (Sep., 1992), pp. 1343–1366.

[57] Stolyarov, D., "Turnover of Used Durables in a Stationary Equilibrium: Are Older Goods Traded More?", *Journal of Political Economy,* Vol. 110, No. 6 (Dec., 2002), pp. 1390–1413.

[58] Syverson, C., "Market Structure and Productivity: A Concrete Example," *Journal of Political Economy,* Vol. 112, No. 6 (Dec., 2004), pp. 1181–1222.

[59] Syverson, C., "Prices, Spatial Competition, and Heterogeneous Producers: An Empirical Test," *Journal of Industrial Economics*, (forthcoming).

[60] Tanner, J.E. and L.A. Kochin, "The Determinants of the Difference Between Bid and Ask Prices on Government Bonds," *The Journal of Business,* Vol. 44, No. 4 (Oct., 1971), pp. 375–379.

[61] Teulings, C.N. and P. A. Gautier, "The Right Man for the Job," *Review of Economic Studies,* Vol. 71, Issue 2, (April, 2005), pp. 553–580.

[62] Vayanos, D. and T. Wang, "Search and endogenous concentration of liquidity in asset markets," *Journal of Economic Theory*, (forthcoming).

[63] Vayanos, D. and P.O. Weill, "A Search-Based Theory of the On-the-Run Phenomenon," *Journal of Finance,* (forthcoming).

[64] Veracierto, M.L., "Plant-Level Irreversible Investment and Equilibrium Business Cycles," *The American Economic Review*, Vol. 92, No. 1 (Mar., 2002), pp. 181–197.

[65] Weill, P.O., "Leaning Against the Wind," *Review of Economic Studies,* Vol. 74, Issue 7, (Oct., 2007), pp. 1329–1354.

[66] Weill, P.O., "Liquidity Premia in Dynamic Bargaining Markets," *Journal of Economic Theory*, (forthcoming).

[67] Williamson, O., *Markets and Hierarchies: Analysis and Antitrust Implications*. New York: Free Press, (1975).

[68] Wright, T.P., "Factors Affecting the Cost of Airplanes," *Journal of Aeronautical Sciences*, Vol. 3, (Feb., 1936), pp. 122–128.