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An Empirical Equilibrium Model of a Decentralized Asset Market^{*}

Alessandro Gavazza¶

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Abstract

I estimate a search-and-bargaining model of a decentralized market to quantify the effects of trading frictions on asset allocations, asset prices and welfare, and to quantify the effects of intermediaries that facilitate trade. Using business-aircraft data, I find that, relative to the Walrasian benchmark, 18.3 percent of the assets are misallocated; prices are 19.2-percent lower; and the aggregate welfare losses equal 23.9 percent. Dealers play an important role in reducing trading frictions: In a market with no dealers, a larger fraction of assets would be misallocated, and prices would be higher. However, dealers reduce aggregate welfare because their operations are costly, and they impose a negative externality by decreasing the number of agents' direct transactions.

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1 Introduction

How large are trading frictions? How do they affect the allocations and prices of assets, and the welfare of market participants? What is the role of intermediaries in reducing trading frictions? Do they increase welfare? This paper estimates a structural model of a decentralized market to provide quantitative answers to these questions.

Many assets trade in decentralized markets. Classic examples are financial assets such as bonds and derivatives, consumer durable goods such as cars and houses, and firms' capital assets such as plants and equipment. The fundamental characteristics of decentralized markets are that agents must search for trading partners and that, once a buyer and a seller meet, they must bargain to determine a price. Moreover, in response to trading frictions, almost all decentralized markets have intermediaries. Indeed, starting with Demsetz (1968), trading frictions have been used to explain the existence of intermediaries. The key role of intermediaries in such markets is to improve allocations by reducing frictions, but, since their operations are costly, intermediaries' effect on aggregate welfare may be ambiguous (Hsieh and Moretti, 2003; Budish, Cramton, and Shim, 2014; Leslie and Sorensen, 2014; Pagnotta and Philippon, 2011).

In this paper, I lay out a model of trading in decentralized markets with two-sided search and bilateral bargaining to study the effects of trading frictions on asset allocations, asset prices and welfare, as well as the role of intermediaries in these markets. I then quantify the role of frictions and of dealers, estimating this model using data on business jet aircraft.

The theoretical framework combines elements from Rubinstein and Wolinsky (1987) and Duffie, Gârleanu, and Pedersen (2005), extending them to capture key features of real asset markets, such as the heterogeneity of assets due to depreciation. Gains from trade arise from heterogeneous valuations of holding an aircraft: A flow of agents enters the market in every period, seeking to acquire an aircraft, whereas aircraft owners wish to sell their assets when their valuations drop. Buyers contact sellers at a rate that depends on the mass of aircraft for sale and on agents' search ability, and they contact dealers at another rate that reflects dealers' inventories and search ability. Trading frictions generate profitable opportunities for dealers, since they can gain arbitrage revenues by shortening the time that agents have to wait in order to trade (Grossman and Miller, 1988; Rubinstein and Wolinsky, 1987); however, dealers' entry imposes a negative externality on agents by lowering their direct meeting rates.¹ When agents meet or meet dealers, they bargain over the terms of

¹Thus, the paper focuses on dealers' advantage over direct exchange in lowering trading delays; see

trade.

Equilibrium allocations and prices depend in an intuitive way on agents' and dealers' search abilities, bargaining powers and valuations. Specifically, while in a first-best Wal-rasian market with no delays, only high-valuation agents own aircraft and dealers are not active, trading frictions imply that some low-valuation agents own aircraft and dealers hold inventories, depressing asset prices, as well. Moreover, while dealers increase welfare by facilitating the reallocation of assets from low-valuation sellers to high-valuation buyers, in a free-entry equilibrium, dealers' entry may be excessive from a social point of view, and this excessive entry is more likely to arise when dealers enjoy greater bargaining power (Von Weizsacker, 1980; Mankiw and Whinston, 1986).

I estimate the model by using data on the secondary market of business jet aircraft a typical decentralized market. The data are well-suited to studying the effects of search frictions and the role of intermediaries. In particular, they report the number of aircraft for sale and number of aircraft transactions in each month, and their ratio is informative on the magnitude of trading delays. Similarly, the data report dealers' inventories and dealers' transactions, and their ratio is informative on the role of dealers in reducing delays. In addition, the data report two series of prices: retail prices between final users of the aircraft; and wholesale prices between aircraft owners (as sellers) and dealers (as buyers). Their differences are useful in understanding how much dealers are able to command by supplying immediacy of trade.

The estimation reveals that trading delays are non-trivial: On average, aircraft stay on the market approximately eight months before a seller is able to finalize a sale. The quantitative importance of these delays depends on how frequently agents seek to trade, determined by a drop in their valuations; this happens, on average, every five years. The estimation further implies that the dealers enjoy strong bargaining power, capturing almost the entire surplus of transactions.

I use the estimated parameters to simulate two counterfactual scenarios. In the first one, I quantify the effects of trading frictions on asset allocations, asset prices and aggregate welfare by computing a Walrasian market equilibrium, in which the highest-valuations agents always own all assets. The estimates imply that trading frictions generate moderate inefficiencies. Compared to the Walrasian benchmark, new-aircraft prices are 19.26-percent lower, and

Section 4.2 for empirical evidence on this. Intermediaries may also increase the match-specific value between buyers and goods (Shevchenko, 2004) and may also ameliorate the consequences of asymmetric information (Biglaiser, 1993). However, intermediaries feature prominently in several markets, such as financial markets, in which match-specific values and asymmetries of information between parties play a minor role.

18.3 percent of all business aircraft are misallocated: 13.2 percent are on the market for sale, whereas, for 5.1 percent of all aircraft, the trading frictions are larger than sellers' expected gross gains from trade; thus, their low-valuation owners prefer to keep them rather than put them on the market for sale. Moreover, aggregate welfare in the estimated model is 23.98-percent lower than that in the Walrasian market. The decomposition of this welfare loss indicates that 13.38 percent of the welfare difference is due to the misallocation of assets to lower-valuation users; 10.32 percent is due to dealers' costs, and only 0.28 percent is due to the agents' search costs.

In the second counterfactual, I examine the quantitative effect of dealers on the decentralized market equilibrium, comparing it to a decentralized market with no dealers. This comparison indicates that dealers have a sizable effect on asset allocations and asset prices: In a market without them, 20.6 percent of the assets would be misallocated, and prices would increase by 2.88 percent. Overall, the net effect of dealers is a welfare *loss* equal to 9.66 percent of aggregate welfare of the estimated model. The reason for this result is that, while dealers improve the allocation of assets, they extract almost all gains from trade. Many dealers enter the market to capture these arbitrage profits and, in a free-entry equilibrium, their aggregate costs become larger than their aggregate benefits, since they appropriate surplus that would be created by agents trading directly. Hence, an interesting conclusion of this counterfactual analysis is that it may be incorrect to make aggregate welfare statements by looking exclusively at asset allocations.

This paper makes two main contributions. First, it provides a framework suited to empirically analyzing decentralized asset markets with intermediaries. Search models have proved useful in understanding key features of labor markets, and, more recently, researchers have started to apply search models to financial markets. To my knowledge, this paper is the first to estimate a bilateral search model that investigates the microstructure of the market for a capital asset/durable good, quantifying the effects of trading delays and of intermediaries. Second, the empirical findings suggest that, even within a well-defined asset class such as business aircraft, trading frictions are a non-trivial impediment to the efficient allocation of assets and have significant effects on asset prices. Thus, the paper innovates on recent works that study the process of asset reallocation (Ramey and Shapiro, 1998, 2001; Maksimovic and Phillips, 2001; Eisfeldt and Rampini, 2006; Gavazza, 2011a,b) by quantifying its inefficiencies. Moreover, the empirical results highlight that the costs of intermediation can be larger than the aggregate gains from a more-efficient allocation, since intermediaties expend resources to capture the rents that trading frictions generate.

The paper proceeds as follows. Section 2 reviews the literature. Section 3 presents some institutional details on the business-aircraft market. Section 4 introduces the data. Section 5 presents the theoretical model, and Section 6 estimates it. Section 7 performs the counterfactual analysis. Section 8 concludes. Appendix A reports on patterns of trade in the data, and Appendix B contains details of the calculations of the standard errors and of the confidence intervals. The Online Appendix provides the analytical solution of the model with the assumption of no depreciation.

2 Related Literature

This paper contributes to the important literature that analyzes decentralized markets. The theoretical literature is vast. The most closely related papers examine bilateral search markets, in which both buyers and sellers search for a trading counterpart, and prices are determined through bilateral bargaining (Rubinstein and Wolinsky, 1985, 1987; Gale, 1987; Mortensen and Wright, 2002; Duffie, Gârleanu, and Pedersen, 2005, 2007; Miao, 2006). The main focus of these theoretical papers is to investigate whether the equilibrium converges to the competitive outcome as frictions vanish. To my knowledge, this paper is the first to estimate a bilateral search model of a real asset market to quantify the effects of trading frictions—i.e., the focus of the theoretical literature.

The paper further contributes to the literature on intermediaries. Several papers investigate the role of brokers/dealers in financial markets and their inventory-management policies; for a survey, see O'Hara (1995). Spulber (1999) provides a thorough analysis of intermediaries between customers and suppliers. Weill (2007) presents a search-and-bargaining model to understand how intermediaries provide liquidity by accumulating inventories when selling pressure is great, and then dispose of those inventories after that selling pressure has subsided. Recent empirical analyses of non-financial intermediaries include Hall and Rust (2000), who focus on the inventory investment of a single steel wholesaler, and Gavazza (2011a), who focuses on the role of lessors in reallocating commercial aircraft. To my knowledge, this paper presents the first structural empirical analysis of the role of intermediaries in a search-and-bargaining framework, quantifying their effects on asset allocations, asset prices, and aggregate welfare. The empirical results complement those of other papers that, in different settings, find that intermediaries' entry may be excessive from a welfare point

of view: See, among others, Hsieh and Moretti (2003), Budish, Cramton, and Shim (2014), Leslie and Sorensen (2014), and Pagnotta and Philippon (2011).

This paper is also related to the empirical literature on the structural estimation of search models. Most applications focus on labor markets. Eckstein and Wolpin (1990) pioneered this literature by estimating the model of Albrecht and Axell (1984). Eckstein and Van den Berg (2007) provide an insightful survey of this literature. One key difference between the current paper and previous research is that this paper seeks to understand how search frictions affect the *level* of asset prices and of asset allocations (and the role of intermediaries), while most papers that structurally estimate labor-market search models focus on how search frictions affect wage *dispersion* across workers (notable exceptions are Gautier and Teulings, 2006, forthcoming). Search models have also been applied to housing markets, with Carrillo (2012) being the closest empirical paper.

Finally, this paper is related to a few that investigate aircraft transactions. Using data on commercial-aircraft transactions, Pulvino (1998) finds that airlines under financial pressure sell aircraft at a 14-percent discount, and that distressed airlines experience higher rates of asset sales than non-distressed airlines do. Using data on business jets similar to the data that I use in this paper, Gilligan (2004) finds empirical evidence consistent with the idea that leasing ameliorates the quality of used aircraft traded on secondary markets. Gavazza (2011b) empirically investigates whether trading frictions vary with the size of the asset market in commercial-aircraft markets. However, none of these papers quantifies the magnitudes and the welfare effects of trading frictions by estimating a structural model.

3 Business-Aircraft Markets

For several reasons, the business-aircraft market is an interesting context in which to investigate the effects of search frictions and the role of intermediaries.

First, used business aircraft trade in decentralized markets, organized around privatelynegotiated transactions. Almost all buyers (and sellers) are either wealthy individuals or corporations that use the aircraft to fly their executives. To initiate a transaction, a prospective seller must contact multiple potential buyers or sell its aircraft to a dealer. For buyers, comparing two similar aircraft is costly since aircraft sales involve the material inspection of the aircraft, which could be in two different locations. Thus, aircraft markets share many features with other over-the-counter markets for financial assets (mortgage-backed securities, corporate bonds, bank loans, derivatives, etc.) and for real assets (real estate), in which trading involves material and opportunity costs (Duffie, Gârleanu, and Pedersen, 2005, 2007). Moreover, compared to financial markets and other equipment markets, business-aircraft markets are "thin": Slightly more than 17,000 business jet aircraft were operated worldwide in December 2008. In thin markets, the search costs to find high-value buyers are usually large (Ramey and Shapiro, 2001; Gavazza, 2011b).

Second, intermediaries play an important role in mediating transactions. Most intermediaries operate as brokers who match buyers and sellers. Some intermediaries operate also as dealers, acquiring aircraft for inventories. To the best of my knowledge, in the U.S., there is no regulation preventing a potential dealer from entering the market and competing with the incumbents. For example, most U.S. states require an 'aircraft dealer' license, but that is simply a license that allows dealers to acquire aircraft for inventory without paying sales tax. Most foreign jurisdictions have similar regulations.

Finally, business aircraft are registered goods with all major "life" events (date of first flight, maintenance, scrappage, etc.) recorded, so detailed data are available. In the next section, I describe them.

4 Data

Patterns in the data suggest that trading delays are an important feature of aircraft markets. Moreover, the available data dictate some of the modeling choices of this paper. Hence, I describe the data before presenting the model. This description also introduces some of the identification issues that I discuss in more detail in Section 6.

4.1 Data Sources

I combine two distinct datasets. The first is an extensive database that tracks the history of business-aircraft transactions. The second reports the average values of several aircraft models, similar to "Blue Book" prices. I now describe each dataset in more detail.

Aircraft Transactions—This database is compiled by AMSTAT, a producer of aviationmarket information systems.² It provides summary reports that track business-aircraft market transactions. For each month from January 1990 to December 2008 and for each model

²http://www.amstatcorp.com/pages/pr_stat.html.The website states: "AMSTAT's customers are aircraft professionals, whose primary business is selling, buying, leasing and/or financing business aircraft, as well as providers of related services and equipment."

(e.g., Cessna Citation V or VI), the dataset reports information on the active fleet (e.g., the number of active aircraft; the number of new deliveries); information on aircraft for sale (e.g., the number of aircraft for sale, by owners and by dealers; the average vintage); and information on completed transactions (e.g., the total number of transactions; the number of retail-to-retail, retail-to-dealer, dealer-to-dealer and dealer-to-retail transactions). The dataset also reports the main characteristics of each aircraft model (e.g., average number of seats, maximum range, fuel consumption). I restrict the analysis to business jets, thus excluding turbo-propellers.

Aircraft Prices—I obtained business-aircraft prices from the Aircraft Bluebook Historical Value Reference.³ This dataset is an unbalanced panel, reporting quarterly historic values of different vintages for the most popular business-aircraft models during the period 1990-2008. Two series are reported: average retail prices and average wholesale prices. Average retail prices report prices between final users of the aircraft, and average wholesale prices report average transaction prices between an aircraft owner (as a seller) and a dealer (as a buyer). All prices are based on the company's experience in consulting, appraisal and fleet evaluation. All values are in U.S. dollars, and I have deflated them using the GDP Implicit Price Deflator, with 2005 as the base year.

It is important to note that the construction of the Aircraft Bluebook Historical Value Reference implies that the retail and wholesale price series are free of several biases. First, wholesale prices refer to sales to dealers—thus before dealers could make any improvement to the aircraft. Second, the database reports historical retail and wholesale prices, even for those model-vintage pairs for which only one unit (i.e., one serial number) exists, suggesting that the price series are not affected by sellers' selection based on aircraft quality (observable or unobservable to both trading parties) or on their valuations.

4.2 Data Description

Table 1 provides summary statistics of the main variables used in the empirical analysis. Panel A refers to the Aircraft Transactions Dataset, a sample containing 161 models (the definition of a model is quite fine in this dataset) comprising a total of 26,125 aircraft modelmonth observations.⁴ For each model, the stock of ACTIVE AIRCRAFT equals approximately

³The dataset is available at http://www.aircraftbluebook.com. The website describes the dataset as: "The Aircraft Bluebook Historical Value Reference is specifically designed for lease companies, bankers, aircraft dealers, or anyone who needs to know the pricing history of an individual aircraft."

⁴The quantitative analysis in Section 6 does not exploit the cross-sectional differences across models.

PANEL A: TRANSACTIONS (N=26, 125)	Mean	St. Dev.	Median	Min.	MAX.
Models of Aircraft	161				
ACTIVE AIRCRAFT	90.13	107.45	49	1	593
AIRCRAFT FOR SALE	10.95	15.13	6	0	140
-by Owners	7.77	11.95	4	0	112
-by Dealers	3.18	4.78	2	0	50
AVERAGE AGE, AIRCRAFT FOR SALE	18.48	11.06	19	0	43
RETAIL-TO-RETAIL TRANSACTIONS	0.59	1.12	0	0	14
RETAIL-TO-DEALER TRANSACTIONS	0.83	1.48	0	0	16
Dealer-to-Dealer Transactions	0.28	0.78	0	0	16
DEALER-TO-RETAIL TRANSACTIONS	0.84	1.50	0	0	18
TOTAL NUMBER OF TRANSACTIONS	1.43	2.30	0	0	23
PANEL B: PRICES (N=30,706)					
Models of Aircraft	72				
Retail Price (in \$1,000)	7,978	8,523	4,702	308	55,800
Wholesale Price (in \$1,000)	7,070	7,577	4,172	258	49,500
Age (in Years)	12.70	8.20	12	0	30

TABLE 1: Summary statistics

Notes—This table provides summary statistics of the variables used in the empirical analysis. Panel A presents summary statistics for the Aircraft Transactions dataset. Each observation represents a model-month pair. Panel B presents summary statistics for the Blue Book prices dataset. Each observation represents a model-vintage-quarter tuple. Aircraft prices are in thousands of U.S. dollars and have been deflated using the GDP Implicit Price Deflator, with 2005 as the base year.

90 units. In a given month, approximately 11 out of these 90 aircraft are for sale: eight by owners and three by dealers. The number of transactions is small relative to the number of aircraft for sale: On average, there are 0.59 RETAIL-TO-RETAIL TRANSACTIONS and 0.83 DEALER-TO-RETAIL TRANSACTIONS per model-month pair (I include lease transactions in DEALER-TO-RETAIL TRANSACTIONS). There are also a few DEALER-TO-DEALER TRANS-ACTIONS—0.28 per month, on average—suggesting that dealers smooth their inventories by trading with other intermediaries. The TOTAL NUMBER OF TRANSACTIONS, defined as the sum of RETAIL-TO-RETAIL TRANSACTIONS and DEALER-TO-RETAIL TRANSACTIONS, and DEALER-TO-RETAIL TRANSACTIONS, indicates that, on aggregate, approximately 1.5 aircraft per model trade in a given month and that a dealer is the seller to the final retail user in approximately 60 percent of these

transactions.

Panel B provides summary statistics for the Aircraft Prices dataset. This sample contains 72 models (indicating that the definition of a model is coarser than in the Aircraft Transactions Dataset), comprising a total of 30,706 aircraft model-vintage-quarter observations. The average RETAIL PRICE of an aircraft in the sample is 7.9 million (year 2005) dollars, and the average WHOLESALE PRICE is 7.0 million (year 2005) dollars. Moreover, there is substantial variation in both prices, reflecting both across-model and across-vintage variation: The standard deviation of retail prices is 8.5 million dollars and of wholesale prices is 7.5 million dollars. Nonetheless, the difference between RETAIL PRICE and WHOLESALE PRICE is always positive within observations.

The two datasets provide a rich description of the business-aircraft market, providing insights into the motives for trade in this market. Specifically, Appendix A reports on three related patterns that indicate that the main determinant of secondary-markets transactions is changes in owners' valuations of the assets—versus the alternative that these transactions are due to replacements of depreciated units with higher-quality ones, as in, for example, the car market; see Stolyarov (2002) and Gavazza, Lizzeri, and Roketskiy (2014).

- 1. In asset markets in which replacement is the main motive for trade, comparative statics across different models imply that assets with faster depreciation have higher resale rates. The argument is as follows. Agents with heterogeneous willingness-to-pay for vertically-differentiated vintages wish to replace their durables when they depreciate, but trading frictions are an impediment to instantaneous (100 percent) trade. When there are transaction costs in the secondhand market, the volume of trade is higher when different vintages are more imperfect substitutes. A faster rate of depreciation increases the vertical differentiation between vintages, thereby increasing the volume of trade. Instead, when valuation shocks are the main motives for trade, resale rates are uncorrelated with assets' depreciation rates. See Table 6 in Appendix A.
- 2. A similar cross-sectional comparative static of a framework in which replacement is the main motive for trade is that assets with greater depreciation should be traded earlier "in their life." Since a faster rate of depreciation increases the vertical differentiation between vintages, owners replace assets with faster depreciation rates at younger ages than they replace assets with slower depreciation rates. Instead, when valuation shocks are the main motives for trade, the age of traded used assets is uncorrelated with assets'

depreciation rates. See Table 7 in Appendix A.

3. Many vintages are on the market simultaneously, including the youngest ones; see Figure 7 in Appendix A. This pattern contrasts with the evidence from other asset markets in which replacement purchases are the main motives for trade, such as the car market. In particular, in the car market, the fraction of cars sold is lowest for the youngest vintages (Porter and Sattler, 1999; Stolyarov, 2002). The reason is that, because of transaction costs, few households sell their cars one year after purchasing them.

The data present additional patterns that are suggestive of the nature of these valuation shocks. Specifically, aggregate trading volume and prices are positively correlated, and time on the market is negatively correlated, with the value of the S&P 500 index. These correlations are consistent with the ideas that corporate demand for aircraft depends on the stock-market valuation of the corporation; and that wealthy individuals face significant exposure to aggregate stock-market fluctuations, thereby affecting their demand—an idea consistent with broader evidence on their consumption reported in, among others, Mankiw and Zeldes (1991) and Parker and Vissing-Jørgensen (2009).

Overall, these empirical patterns inform the model to focus on valuations' shocks as the main motive for trade.⁵ Moreover, the data are well-suited to investigating the importance of frictions and the role of dealers. Specifically, three key patterns suggest that trading delays may be non-trivial and that dealers reduce them. First, the difference between the number of AIRCRAFT FOR SALE (on average, 11 aircraft per model-month) and the TOTAL NUMBER OF TRANSACTIONS (on average, 1.5 per model-month) means that aircraft stay on the market for several months before selling, indicating that trading delays are substantial. Second, the ratio between RETAIL-TO-DEALER TRANSACTIONS and AIRCRAFT FOR SALE BY DEALERS is higher than the ratio between TOTAL NUMBER OF TRANSACTIONS and AIRCRAFT FOR SALE, suggesting that dealers are faster than owners at turning aircraft over. Third, the difference between the RETAIL PRICE and the WHOLESALE PRICE is quite large (on average, 13 percent), corroborating that frictions are relevant in this market and that dealers are able to command a substantial markup by supplying immediacy of trade.

⁵Several newspaper articles provide anecdotal evidence that several young aircraft trade exactly because of valuations shocks. For example, the *Financial Times* reports on October 20, 2014: "Tesco took delivery of the aircraft [...] this month. Yet, when the Financial Times reported the aircraft's delivery at the beginning of October, it heightened shareholders' unease about how the struggling retailer was managed. Tesco was quick to announce that the new jet and the rest of the company's fleet were all up for sale."

With all their advantages, however, the datasets pose some challenges. In my view, the main limitation is that both datasets provide aggregate statistics of the market for different models. This limitation implies that a model with rich heterogeneity of agents and dealers, while theoretically feasible, would not be identified with these aggregated data. For example, the aircraft-price dataset does not allow the identification of rich heterogeneity in asset valuations, which would be possible if transaction prices were available.⁶ Therefore, the model admits a parsimonious binary distribution of valuations, high and low, and focuses on valuations' shocks as the main motive for trade. Similarly, the aircraft-transaction dataset reports only aggregate dealers' inventories, limiting the possibilities of identifying heterogeneity for the interpretation of the empirical results. Finally, an additional limitation is that the aircraft-transaction dataset does not report whether retail buyers or sellers hired a broker to search for trading counterparts, although these intermediaries are popular in business-aircraft markets.

5 Model

In this section, I lay out a model of a decentralized market with two-sided search to theoretically investigate the effects of search frictions on asset allocations, prices and welfare. The model combines elements from Rubinstein and Wolinsky (1987) and Duffie, Gârleanu, and Pedersen (2005), extending them to capture key features of real asset markets, such as the depreciation of assets.

I explicitly model frictions of reallocating assets. In particular, each agent contacts another agent randomly, and this is costly for two reasons: 1) There is an explicit cost c_s of searching; and 2) there is a time cost, in that all agents discount future values by the discount rate $\rho > 0$.

5.1 Assumptions

Time is continuous and the horizon infinite. A mass μ of risk-neutral agents enters the economy at every instant. All entrants have a valuation $z = z_h > 0$ for an aircraft. This valuation parameter is a Markov chain, switching from z_h to $z_l < z_h$ with intensity λ ; z_l is

⁶Some of this heterogeneity may depend on whether the aircraft owner is a corporation or an individual. Specifically, agency conflicts between managers and shareholders may generate a wedge between the valuation of the user of the aircraft versus the financier in the case of corporate-owned aircraft.

an absorbing state. The valuation processes of any two agents are independent. Hence, the steady-state mass of high-valuation agents equals $\frac{\mu}{\lambda}$.

A constant flow $x < \mu$ of new aircraft enters the economy at every instant, and x high-valuation agents entering the economy purchase them at the (endogenous) price p^* . Aircraft depreciate continuously over time and become worthless when they reach age T, but they could be endogenously scrapped earlier. Thus, the endogenous total mass A of aircraft is, at most, equal to xT. I assume that $\frac{\mu}{\lambda} > xT$, implying that $\frac{\mu}{\lambda} > A$, which means that the "marginal" owner in a Walrasian market is a high-valuation agent. An aircraft of age a generates an instantaneous flow of utility equal to $\pi(z, a)$ to its owner with valuation z. The function $\pi(z, a)$ satisfies the following: 1) It is increasing in the valuation z, $\pi(z_h, a) > \pi(z_l, a)$; 2) it is decreasing in the age a of the asset, $\frac{\partial \pi(z_l, a)}{\partial a} < 0$; and 3) it exhibits negative complementarity between the valuation z and the age a of the asset, $\frac{\partial \pi(z_l, a)}{\partial a} < \frac{\partial \pi(z_l, a)}{\partial a}$.

Each agent can own either zero or one aircraft.⁷ Agents can trade aircraft: A given agent wishing to trade (either a buyer or a seller) pays a flow cost c_s while searching for a counterparty.⁸ While searching, he makes contact with other agents pairwise independently at Poisson arrival times with intensity $\gamma > 0$. Thus, given that matches are determined at random, the arrival rate γ_s for a seller (the rate at which he meets buyers) is $\gamma_s = \gamma \mu_b$, and the arrival rate $\gamma_b(a)$ for a buyer (the rate at which he meets sellers of an age-*a* aircraft) is $\gamma_b(a) = \gamma \mu_s(a)$, where μ_b and $\mu_s(a)$ are the endogenous equilibrium masses of buyers and sellers of an age-*a* aircraft, respectively. Thus, the aggregate matching function exhibits increasing returns to scale. I further assume that agents cannot both use an asset and search for a new one at the same time.⁹

In addition, there is an endogenous mass μ_d of independent used-aircraft dealers that meets agents also through a search process. Each dealer has a flow cost equal to k and has, at most, one unit of inventory.¹⁰ An agent wishing to trade meets dealers pairwise

⁷Hence, I do not consider quantity decisions, as do Duffie, Gârleanu, and Pedersen (2005, 2007); Miao (2006); Vayanos and Wang (2007); Vayanos and Weill (2008); and Weill (2007). See Lagos and Rocheteau (2009) for a model that considers quantity decisions.

⁸The main role of the search cost c_s is to avoid swaps of assets. For example, a low-valuations agent with a young aircraft and a high-valuation agent with an old aircraft may want to swap their assets. However, a positive flow cost of search c_s eliminates these transactions with small gains from trade.

⁹This assumption greatly simplifies the derivation of the equilibrium allocations and prices, and the quantitative and welfare implications of allowing agents to use the old aircraft and look for a new one should be small.

¹⁰The assumption of constant-returns and unit inventory is useful to gain tractability, but it does not

independently at Poisson arrival times with intensity $\gamma' > 0$. Thus, a buyer meets a dealer with a vintage-*a* aircraft to sell at rate $\gamma_{bd}(a) = \gamma' \mu_{do}(a)$, and a dealer with an aircraft to sell meets a buyer at rate $\alpha_{ds} = \gamma' \mu_b$, where $\mu_{do}(a)$ is the endogenous mass of dealers with a vintage-*a* aircraft to sell. The rates $\gamma_{bd}(a)$ and α_{ds} represent the sum of the intensity of buyers' search for dealers and dealers' search for buyers. A seller meets a dealer willing to buy an aircraft at rate $\gamma_{sd} = \gamma' \mu_{dn}$, and a dealer willing to buy an aircraft meets a seller of an aircraft of age *a* at rate $\alpha_{db}(a) = \gamma' \mu_s(a)$, where μ_{dn} is the endogenous mass of dealers with an aircraft to sell. There is free entry into the dealers' market.

Once a buyer and a seller meet, or one of them meets a dealer, parties negotiate a price to trade. I assume that a buyer and a seller negotiate a price according to generalized Nash bargaining, with $\theta_s \in [0, 1]$ denoting the bargaining power of the seller. Similarly, when an agent meets a dealer, they negotiate a price, and $\theta_d \in [0, 1]$ denotes the dealer's bargaining power.¹¹

5.2 Solution

There are four types of agents in the model economy and two types of dealers: high- and low- valuation owners and non-owners, and dealers with and without an aircraft for sale. I denote their types ho, lo, hn, ln, do, dn, respectively.

The owner of an age-*a* aircraft with valuation *z* can keep operating it, put it up for sale, or scrap it. In the first case, he enjoys the utility flow $\pi(z, a)$. In the second case, he meets potential trading partners at rate γ_s and a dealer at rate γ_{sd} . In the last case, he becomes an agent with no aircraft. Owners prefer to sell their assets when their valuations are low and the assets are relatively young since the complementarity between valuation *z* and age *a* in the flow utility $\pi(z, a)$ means that the gains from trade between buyers and sellers are larger for younger aircraft. Moreover, high-valuation owners scrap their old aircraft, seeking to purchase newer ones. Similarly, an agent with no aircraft can meet active sellers of age-*a* aircraft at rate $\gamma_b(a)$ and a dealer at rate $\gamma_{bd}(a)$, or he can exit the market. Non-owners choose to search when their valuation is high, and they purchase only relatively young assets.

affect the main welfare results of the papers, since dealers' free-entry condition implies that dealers' expected margins equal their average costs. Aircraft prices allow me to compute dealers' margins and, thus, obtain an estimate of average dealers' costs, which holds irrespective of the assumption of dealers' level of inventories.

¹¹The model assumes symmetry of information about the quality of the asset. Several institutional features of aircraft markets support this assumption. First, the aviation authorities often regulate aircraft maintenance. Second, maintenance records are frequently available, and all parties can observe the entire history of owners of each aircraft. Finally, all transactions involve a thorough material inspection of the aircraft.

Dealers without inventories operate similarly to buyers, and dealers with inventories operate similarly to sellers, with the key difference that dealers do not enjoy utility from holding assets, and their opportunity costs differ from buyers' and sellers'; thus, their choice of which assets (i.e., vintages) to purchase differs.

I now formally derive the value functions for all agents in the economy and the transaction price at which trade occurs. These value functions allow me to pin down the equilibrium conditions and derive the endogenous distribution of owners' valuations. This distribution describes how frictions generate allocative inefficiencies and affect aircraft prices.

5.2.1 Agents' Value Functions

Let $U_{ho}(a)$ be the value function of an agent with valuation z_h who owns an aircraft of age a and is not seeking to sell it. $U_{ho}(a)$ satisfies:

$$\rho U_{ho}(a) = \pi (z_h, a) + \lambda (V_{lo}(a) - U_{ho}(a)) + U'_{ho}(a).$$
(1)

Equation (1) has the usual interpretation of an asset-pricing equation. An agent with valuation z_h enjoys the flow utility $\pi(z_h, a)$ from an aircraft of age a. At any date, one possible event, at most, might happen to him: At rate λ , his valuation drops to z_l , in which case he chooses between continuing to operate the aircraft (enjoying the value $U_{lo}(a)$) and actively seeking to sell it (enjoying value $S_{lo}(a)$). Thus, the agent obtains a value $V_{lo}(a) = \max \{U_{lo}(a), S_{lo}(a)\}$ and a capital loss equal to $V_{lo}(a) - U_{ho}(a)$. Moreover, the aircraft depreciates continuously, so that the agent has a capital loss equal to $U'_{ho}(a)$.

Similarly, the value function $S_{ho}(a)$ of an agent with valuation z_h who owns an aircraft of age a and is actively seeking to sell it satisfies:

$$\rho S_{ho}(a) = \pi (z_h, a) - c_s + \lambda (V_{lo}(a) - S_{ho}(a)) + \gamma_s \max \{ p(a) + V_{hn} - S_{ho}(a), 0 \} + \gamma_{sd} \max \{ p_B(a) + V_{hn} - S_{ho}(a), 0 \} + S'_{ho}(a).$$
(2)

An agent with valuation z_h enjoys the flow utility $\pi(z_h, a)$ from an aircraft of age a, but he pays the flow cost c_s while actively seeking to sell it. At any date, one of three possible events might happen to him: 1) At rate λ , his valuation drops to z_l . In this case, the agent chooses between keeping the aircraft (enjoying the value $U_{lo}(a)$) and actively seeking to sell it (enjoying value $S_{lo}(a)$). Hence, the agent obtains a capital loss equal to $V_{lo}(a) - S_{ho}(a)$. 2) At rate γ_s , the agent meets a potential buyer and chooses between trading the aircraft or keeping it. If he trades it at price p(a), he becomes a high-valuation non-owner with value V_{hn} , thus obtaining a capital gain equal to $p(a) + V_{hn} - S_{ho}(a)$. If he keeps it, he obtains a capital gain of zero. 3) At rate γ_{sd} , he meets a dealer and chooses between trading the aircraft or keeping it. If he trades it at price $p_B(a)$, he then chooses between actively searching for another aircraft or not, thus obtaining a capital gain equal to $p_B(a) + V_{hn} - S_{ho}(a)$. If he keeps it, he obtains a capital gain of zero. Moreover, the aircraft depreciates continuously, so that the agent has a capital loss equal to $S'_{ho}(a)$.

The value functions $U_{lo}(a)$ and $S_{lo}(a)$ of an agent with valuation z_l who owns an aircraft of age *a* satisfy the following Bellman equations, respectively:

$$\rho U_{lo}(a) = \pi (z_l, a) + U'_{lo}(a), \qquad (3)$$

$$\rho S_{lo}(a) = \pi (z_l, a) - c_s + \gamma_s \max \{ p(a) + V_{ln} - S_{lo}(a), 0 \} + \gamma_{sd} \max \{ p_B(a) + V_{ln} - S_{lo}(a), 0 \} + S'_{lo}(a).$$
(4)

The interpretation of equations (3) and (4) is now straightforward. An agent with valuation z_l enjoys the flow utility $\pi(z_l, a)$ from an aircraft of age a. If he does not seek to sell the aircraft, the only event that affects his utility is the depreciation of the aircraft, with capital loss $U'_{lo}(a)$. If he seeks to sell the aircraft, the search cost c_s reduces his flow utility. Then, at any date, he meets a potential buyer at rate γ_s , in which case he chooses between selling the aircraft at price p(a)—thus obtaining a capital gain equal to $p(a) + V_{ln} - S_{lo}(a)$, where $V_{ln} = \max\{U_{ln}, S_{ln}\}$ —or keeping it—thus obtaining a capital gain of zero. Similarly, he meets a dealer at rate γ_{sd} , in which case he chooses between trading the aircraft at price $p_B(a)$ —thus, obtaining a capital gain equal to $p_B(a) + V_{ln} - S_{lo}(a)$ —or keeping it—thus obtaining a capital gain of zero. Moreover, the aircraft depreciates continuously, so that the agent has a capital loss equal to $S'_{lo}(a)$.

The value functions of high- and low-valuation agents with no aircraft satisfy:

$$\rho S_{hn} = -c_s + \lambda \left(V_{ln} - S_{hn} \right) + \int \gamma_b \left(a \right) \max \left\{ V_{ho} \left(a \right) - p \left(a \right) - S_{hn}, 0 \right\} da +$$
(5)

$$\int \gamma_{bd}(a) \max \{ V_{ho}(a) - p_A(a) - S_{hn}, 0 \} da,$$

$$\rho U_{hn} = 0,$$
(6)

$$\rho S_{ln} = -c_s + \int \gamma_b(a) \max \{ V_{lo}(a) - p(a) - S_{ln}, 0 \} da +$$
(7)

$$\int \gamma_{bd}(a) \max \{ V_{lo}(a) - p_A(a) - S_{ln}, 0 \} da,$$

$$\rho U_{ln} = 0.$$
(8)

Equation (5) says that a high-valuation agent with no aircraft who is paying the search cost c_s has a capital loss equal to $V_{ln} - S_{hn}$ when, at rate λ , his valuation drops from high to low; has a capital gain equal to max $\{V_{ho}(a) - p(a) - S_{hn}, 0\}$ when, at rate $\gamma_b(a)$, he meets a seller of an aircraft of age a; and has a capital gain equal to max $\{V_{ho}(a) - p_A(a) - S_{hn}, 0\}$ when, at rate $\gamma_{bd}(a)$, he meets a dealer selling an aircraft of age a, where $V_{ho}(a) = \max\{U_{ho}(a), S_{hn}\}$. Since the hn-agent does not know the age of the aircraft that the counterparty will have, he takes expectation over the possible capital gains that arise from the different vintages. Similarly, equation (7) says that a low-valuation agent with no aircraft, who is paying the search cost c_s to search for a counterparty, has an expected capital gain equal to max $\{V_{lo}(a) - p(a) - S_{ln}, 0\}$ when he meets a potential seller of an aircraft of age a, and an expected capital gain equal to max $\{V_{lo}(a) - p_A(a) - S_{ln}, 0\}$ when he meets a dealer. Equations (6) and (8) say that agents without aircraft who are not searching have a zero value.

5.2.2 Dealers' Value Functions

As in Rubinstein and Wolinsky (1987), dealers can extract surplus by shortening the time that buyers and sellers have to wait in order to trade. They are capacity-constrained and cannot hold more than one aircraft. Thus, the value functions $J_{do}(a)$ and J_{dn} of dealers with and without an aircraft for sale, respectively, satisfy:

$$\rho J_{do}(a) = \max \left\{ -k + \alpha_{ds} \left(p_A(a) + J_{dn} - J_{do}(a) \right) + J'_{do}(a) , \rho J_{dn} \right\},$$
(9)

$$\rho J_{dn} = -k + \int \alpha_{db}(a) \max \{ J_{do}(a) - p_B(a) - J_{dn}, 0 \} da.$$
(10)

Equation (9) says that a dealer who owns an aircraft of age a pays the flow cost k and chooses between two alternatives: 1) He can actively seek to sell it, meeting a potential buyer at rate α_{ds} . In this case, the dealer trades the aircraft at a negotiated price $p_A(a)$, obtaining a capital gain equal to $p_A(a) + J_{dn} - J_{do}(a)$. Moreover, the dealer has a capital loss equal to $J'_{do}(a)$ because the aircraft depreciates continuously; or 2) he can scrap the aircraft, thereby becoming a dealer without an aircraft for sale.

Similarly, equation (10) says that a dealer without an aircraft pays the flow cost k while he actively seeks to purchase one. At rate $\alpha_{db}(a)$, this dealer meets a potential seller of an aircraft of age a, in which case the dealer decides whether or not to trade, thus enjoying a capital gain equal to max $\{J_{do}(a) - p_B(a) - J_{dn}, 0\}$. Since the *dn*-dealer does not know the age of the aircraft that the counterparty will have, he takes expectation over the possible capital gains that arise from the different vintages.

Dealers' free entry requires that $J_{dn} = 0$ —i.e., dealers' expected capital gain is exactly equal to their fixed operating cost.

5.2.3 Prices

When a buyer and a seller meet and agree to trade, the negotiated price,

$$p(a) = (1 - \theta_s) \left(S_{lo}(a) - V_{ln} \right) + \theta_s \left(U_{ho}(a) - S_{hn} \right), \tag{11}$$

is the solution to the following symmetric-information bargaining problem:

subject to:

$$\max_{p(a)} \left[U_{ho}(a) - p(a) - S_{hn} \right]^{1-\theta_s} \left[p(a) + V_{ln} - S_{lo}(a) \right]^{\theta_s} \\
= 0 \text{ and } p(a) + V_{ln} - S_{lo}(a) \ge 0.$$

Similarly, the ask and bid prices $p_A(a)$ and $p_B(a)$ satisfy:

$$p_A(a) = (1 - \theta_d) \left(J_{do}(a) - J_{dn} \right) + \theta_d \left(U_{ho}(a) - S_{hn} \right), \tag{12}$$

$$p_B(a) = (1 - \theta_d) \left(J_{do}(a) - J_{dn} \right) + \theta_d \left(S_{lo}(a) - V_{ln} \right).$$
(13)

Finally, the price p^* of new assets is such that new entrants are indifferent between paying the price p^* and searching on the secondary market:

$$U_{ho}\left(0\right) - p^* = S_{hn}$$

Hence, new assets trade at a premium relative to all used assets because of differential frictions between the primary market and secondary markets.

5.2.4 Agents' and Dealers' Policies

We can simplify the value functions of all types of agents $\{ho, lo, hn, ln\}$ recognizing that gains from trade may arise only when high-valuation non-owners meet low-valuation owners. Moreover, since the flow utility $\pi(z, a)$ exhibits complementarity between agents' valuation z and the age a of the asset, the gains from trade are larger for younger assets. In turn, this implies that, depending on parameters, it is possible that not all assets trade in equilibrium. Indeed, Section 6 will show that not all assets trade in the estimated model, so I focus on this case.

Specifically, since $U_{ho}(a)$ is decreasing in a, there exists a cutoff age a_{ho}^* such that hoagents scrap their asset when it reaches age a_{ho}^* —i.e., a_{ho}^* satisfies $U_{ho}(a_{ho}^*) = S_{hn}$. Moreover, a cutoff age a_{hn}^* determines whether or not hn-agents purchase an age-a asset. Trading frictions generate a wedge that implies that $a_{hn}^* \leq a_{ho}^*$. Thus, high-valuation owners' value functions are:

$$V_{ho}(a) = \begin{cases} U_{ho}(a) & \text{for } a < a_{ho}^*, \\ S_{hn} & \text{for } a \ge a_{ho}^*. \end{cases}$$

The policy of *lo*-owners satisfies a cutoff rule, as well. Specifically, since the flow utility $\pi(z_l, a)$ is decreasing in the age a of the asset, whereas the flow search cost c_s is constant, there exists a cutoff age a_l^* such that *lo*-agents sell their aircraft if it is younger than a_l^* , but keep it if it is older—i.e., $U_{lo}(a) > S_{lo}(a)$ if $a < a_l^*$, $U_{lo}(a_{lo}^*) = S_{lo}(a_{lo}^*)$ and $U_{lo}(a) < S_{lo}(a)$ if $a > a_l^*$. Equilibrium requires that *lo*-agents sell assets that hn-agents are willing to purchase—thus, $a_l^* \leq a_{hn}^*$. Moreover, since *lo*-agents enjoy positive utility from these old assets, they keep them until they reach the scrappage age T. Thus, the low-valuation owners' value functions are:

$$V_{lo}(a) = \begin{cases} S_{lo}(a) & \text{for } a < a_l^*, \\ U_{lo}(a) & \text{for } a \le a_l^* < T, \\ V_{ln} & \text{for } a = T. \end{cases}$$

Non-owners' value functions are:

$$V_{hn} = S_{hn},$$
$$V_{ln} = 0.$$

Similar arguments also apply to dealers. Their value function $J_{do}(a)$ is decreasing in a because younger aircraft sell at greater margins, as the gains from trade are larger. Thus, since dealers' fixed cost k is independent of the age of the asset, there exist two cutoff ages a_{dn}^* and a_{do}^* such that dealers do not purchase aircraft older than a_{dn}^* and scrap aircraft when they reach age a_{do}^* . Since the asset purchase price is sunk at the time of scrapping it, but not at the time of buying it, $a_{dn}^* < a_{do}^*$. Moreover, equilibrium requires that dealers sell assets that buyers are willing to purchase. Hence, $a_{do}^* \leq a_{hn}^*$.

5.2.5 Distribution of Agents

Let $\mu_i(a)$ be the masses of owners of age-*a* aircraft whose state is $i \in \{ho, lo, do\}$, and let μ_i be the masses of non-owners whose state is $i \in \{hn, ln, dn\}$. The masses of owners evolve over time according to the following system of differential equations:

$$\dot{\mu}_{ho}\left(a\right) = \left(\gamma_{b}\left(a\right)\mu_{hn} + \gamma_{bd}\left(a\right)\mu_{hn}\right) - \lambda\mu_{ho}\left(a\right) \text{ for } a < a_{ho}^{*},\tag{14}$$

$$\dot{\mu}_{lo}(a) = \lambda 1 \left(a < a_{ho}^* \right) \mu_{ho}(a) - \gamma_s 1 \left(a < a_l^* \right) \mu_{lo}(a) +$$
(15)

$$-\gamma_{sd} 1 (a < \min\{a_l^*, a_{dn}^*\}) \mu_{lo}(a) \text{ for } a < T,$$

$$\dot{\mu}_{do}(a) = \alpha_{db}(a) 1 (a < a_{dn}^*) \mu_{dn} - \alpha_{ds} \mu_{do}(a) \text{ for } a < a_{do}^*,$$
(16)

with initial conditions $\mu_{ho}(0) = x$ and $\mu_{lo}(0) = \mu_{do}(0) = 0$, and terminal conditions $\mu_{ho}(a) = 0$ for $a_{ho}^* \leq a < T$ and $\mu_{do}(a) = 0$ for $a_{do}^* \leq a < T$. The notation 1 (Y) represents an indicator function equal to one if the event Y is true, and zero otherwise.

The intuition for these equations is as follows. Equation (14) states that the mass of high-valuation agents with an age-*a* asset is the result of flows of three sets of agents: 1) the inflow of high-valuation non-owners that found a seller of an age-*a* aircraft—the term $\gamma_b(a) \mu_{hn}$; 2) the inflow of high-valuation non-owners that found a dealer selling an age-*a* aircraft—the term $\gamma_{bd}(a) \mu_{hn}$; and 3) the outflow of high-valuation age-*a* aircraft owners whose valuation just dropped—the term $\lambda \mu_{ho}(a)$. Equation (14) already incorporates the equilibrium outcomes that low-valuation owners of an age-*a* aircraft are willing to sell it rather than keep it (i.e., $\gamma_b(a) > 0$) and that dealers have inventories of age-*a* aircraft (i.e., $\gamma_{bd}(a) > 0$) only if high-valuation non-owners are willing to buy them (i.e., $a < a_{hn}^*$).

Equation (15) states that the mass of low-valuation agents with an age-a asset is the result of flows of three sets of agents: 1) the inflow of high-valuation agents whose valuation just dropped. Since high-valuation agents scrap the oldest assets, this inflow applies only to

owners of assets younger than a_{ho}^* —hence the term $\lambda 1 (a < a_{ho}^*) \mu_{ho}(a)$; 2) the outflow of lowvaluation aircraft owners who prefer to sell their aircraft rather than keep it (i.e., an aircraft of age $a < a_l^*$) and who have found a buyer (this buyer is willing to purchase it because $a_l^* \leq a_{hn}^*$)—hence the term $\gamma_s 1 (a < a_l^*) \mu_{lo}(a)$; and 3) the outflow of low-valuation aircraft owners who prefer to sell their aircraft rather than keep it (i.e., an aircraft of age $a < a_l^*$) and who have found a dealer willing to purchase it (i.e., an aircraft of age $a < a_{dn}^*$)—hence the term $\gamma_{sd} 1 (a < \min \{a_l^*, a_{dn}^*\}) \mu_{lo}(a)$. The intuition for equation (16) is similar.

Moreover, the masses of high-valuation non-owners and dealers without inventories evolve over time according to:

$$\dot{\mu}_{hn} = (\mu - x) + \mu_{ho} (a_{ho}^*) - \lambda \mu_{hn} - \mu_{hn} \int_0^{a_l^*} \gamma_b (a) \, da - \mu_{hn} \int_0^{a_{dn}^*} \gamma_{bd} (a) \, da,$$

$$\dot{\mu}_{dn} = \alpha_{ds} \int_0^{a_{do}^*} \mu_{do} (a) \, da - \mu_{dn} \int_0^{\min\{a_l^*, a_{dn}^*\}} \alpha_{db} (a) \, da + \mu_{do} (a_{dn}^{**}),$$

whereas, in each instant, the mass of ln-agents equals:

$$\mu_{ln} = \lambda \mu_{hn} + \gamma_s \int_0^{a_l^*} \mu_{lo}(a) \, da + \gamma_{sd} \int_0^{\min\left\{a_l^*, a_{dn}^*\right\}} \mu_{lo}(a) \, da + \mu_{lo}(T) \, .$$

Steady state imposes the following constraints on the evolution of these masses: 1) The aggregate masses of owners $\int_0^T \mu_i(a) da$ for $i \in \{ho, lo, do\}$ and the aggregate masses μ_{hn} and μ_{dn} are constant over time; 2) the mass μ_{ln} of exiters equals the mass μ of new entrants; 3) the total mass of agents with high valuation $\mu_{hn} + \int_0^T \mu_{ho}(a) da$ equals $\frac{\mu}{\lambda}$; 4) the total mass of dealers μ_d equals $\int_0^T \mu_{do}(a) da + \mu_{dn}$; 5) the aggregate masses of assets sold and purchased by dealers equal the aggregate masses of assets purchased from and sold to dealers: $\mu_{hn} \int_0^{a^*_{do}} \gamma_{bd}(a) da = \alpha_{ds} \int_0^{a^*_{do}} \mu_{do}(a) da$ and $\mu_{dn} \int_0^{\min\{a^*_l, a^*_{dn}\}} \alpha_{db}(a) da = \gamma_{sd} \int_0^{\min\{a^*_l, a^*_{dn}\}} \mu_{lo}(a) da$; and 6) dealers' aggregate inventories do not change over time: $\mu_{hn} \int_0^{a^*_{do}} \gamma_{bd}(a) da = \mu_{dn} \int_0^{\min\{a^*_l, a^*_{dn}\}} \alpha_{db}(a) da$. In addition, equilibrium requires that the total mass of owners of age-a aircraft $\mu_{ho}(a) + \mu_{lo}(a) + \mu_{do}(a) = \min\{a^*_{do}, a^*_{ho}\}$.

All these steady-state equalities and the equilibrium condition $\mu_{ho}(a) + \mu_{lo}(a) + \mu_{do}(a) \leq x$ allow us to solve for the endogenous masses as a function of the exogenous parameters x, T, μ and λ , and the exogenous parameters of the matching functions.

Letting γ increase, $\lim_{\gamma \to +\infty} \mu_{lo}(a)$ converges to 0: When frictions vanish, no low-valuation agent owns an aircraft. Similarly, $\lim_{\gamma' \to +\infty} \mu_{do}(a)$ converges to 0. Thus, the masses $\int_0^T \mu_{lo}(a) da$

and $\int_0^T \mu_{do}(a) da$ —i.e., the masses of low-valuation agents and dealers with inventories—are measures of assets inefficiently allocated in the economy. Based on the parameters estimated from the data, in Section 7.1, I compute these measures to quantify the effects of trading frictions on asset allocations.

6 Quantitative Analysis

The model does not admit an analytic solution for the asset allocations and asset prices as a function of all the model primitives, except in the special case when assets are homogeneous i.e., $\frac{\partial \pi(z,a)}{\partial a} = 0$; the Online Appendix reports this special case. Hence, the goal of the quantitative analysis is to choose the parameters that best match moments of the data with the corresponding moments computed from the model's numerical solution. Since the analytic solution of the model under the assumption that $\frac{\partial \pi(z,a)}{\partial a} = 0$ (presented in the Online Appendix) provides an approximation of the general model, it helps to build intuition for the identification of some parameters.

6.1 Estimation

I estimate the model using the data on business aircraft described in Section 4, assuming that they are generated from the model's steady state. I set the unit of time to be one quarter.

Unfortunately, the data lack some detailed information for identifying all parameters. Therefore, I fix some values. Specifically, the discount rate ρ is traditionally difficult to identify, and I fix it to $\rho = .015$. Moreover, since aircraft prices seem to reach the value of zero at the age of 40, I fix the useful lifetime of an aircraft to be equal to T = 160 quarters. I also fix the total mass of aircraft to be equal to the sample median A = 9,687, and I use a directory of aircraft dealers to calibrate total dealers' capacity to equal $\mu_d = 1000$. Furthermore, I assume that aircraft owners' flow payoff equals:

$$\pi(z,a) = z\delta_1 e^{-\delta_2 a},\tag{17}$$

further imposing that $\delta_1 = 1$, as this parameter is not separately identified from the baseline valuation z_l (this is just a normalization).

I estimate the vector $\psi = \{\lambda, \gamma_s, \gamma_{sd}, \alpha_{ds}, z_h, z_l, \delta_2, c_s, \theta_s, \theta_d\}$ composed of the exogenous

parameters $\{\lambda, z_h, z_l, \delta_2, c_s, \theta_s, \theta_d\}$ and of the endogenous contact rates $\{\gamma_s, \gamma_{sd}, \alpha_{ds}\}$ using a minimum-distance estimator that matches key moments of the model with their sample analog. While $\gamma_s, \alpha_{ds}, \gamma_{sd}$ are endogenous rates, I can infer them directly from the data, and this inference allows me to identify other primitives of the model, as I explain in more detail in the next subsection.

For any value of the vector ψ , I solve the model of Section 5 to find agents' and dealers' policy functions and agents' and dealers' distributions { $\mu_{ho}(a), \mu_{lo}(a), \mu_{do}(a), \mu_{hn}, \mu_{ln}, \mu_{dn}$ } that are consistent with each other. Based on the model's solution, I calculate the vector $m(\psi)$ composed of two sets of moments.

A. The first set, $m_1(\psi)$, includes moments based on transactions:

1. The fraction of aircraft for sale, which, in the model, equals:

$$\frac{\int_{0}^{a_{l}^{*}} \mu_{lo}\left(a\right) da + \int_{0}^{a_{do}^{*}} \mu_{do}\left(a\right) da}{A}.$$
(18)

2. The fraction of aircraft for sale by dealers (i.e., aggregate dealers' inventories), which equals:

$$\frac{\int_0^{a_{do}^*} \mu_{do}\left(a\right) da}{A}.$$
(19)

3. The fraction of retail-to-retail transactions to total aircraft, which equals:

$$\frac{\gamma_s \int_0^{a_l^*} \mu_{lo}\left(a\right) da}{A}.$$
(20)

4. The fraction of dealer-to-retail transactions to total aircraft, which equals:

$$\frac{\alpha_{ds} \int_0^{a^*_{do}} \mu_{do}\left(a\right) da}{A}.$$
(21)

5. The average age of aircraft for sale, which equals:

$$\frac{\int_{0}^{a_{l}^{*}} a\mu_{lo}\left(a\right) da + \int_{0}^{a_{do}^{*}} a\mu_{do}\left(a\right) da}{\int_{0}^{a_{l}^{*}} \mu_{lo}\left(a\right) da + \int_{0}^{a_{do}^{*}} \mu_{do}\left(a\right) da}.$$
(22)

B. The second set, $m_2(\psi)$, includes moments based on prices, obtained from the following indirect inference procedure. Using the aircraft price data, I estimate via non-linear

least squares the coefficients $\{\beta_0; \beta_1; \beta_2; \beta_3; \beta_4; \beta_5\}$ of the following auxiliary equations:

$$p(a) = \beta_0 + \beta_1 e^{-\beta_2 a}, \qquad (23)$$

$$p_B(a) = \beta_3 + \beta_4 e^{-\beta_5 a}. \tag{24}$$

I simulate the model and use the simulated prices to estimate the corresponding coefficients $\{\beta_{0,sim}; \beta_{1,sim}; \beta_{2,sim}; \beta_{3,sim}; \beta_{4,sim}; \beta_{5,sim}\}$ of equations (23) and (24). I then match the vector of coefficients obtained from simulated prices and the one obtained from the aircraft price data.

I follow Hansen (1982), who shows that the optimal (two-step) estimator takes the form

$$\hat{\psi} = \arg\min_{\psi\in\Psi} \left(m\left(\psi\right) - m_S\right)' \Omega\left(\tilde{\psi}\right) \left(m\left(\psi\right) - m_S\right),$$

where $m(\psi) = \begin{bmatrix} m_1(\psi) \\ m_2(\psi) \end{bmatrix}$ is the vector of moments computed from the model evaluated at the parameter vector ψ ; $m_S = \begin{bmatrix} m_{S_1} \\ m_{S_2} \end{bmatrix}$ is the vector of corresponding sample moments; and $\Omega\left(\tilde{\psi}\right)$ is a consistent estimate of the inverse of the asymptotic variance-covariance matrix of the moments, obtained using a preliminary consistent estimate $\tilde{\psi}$ of ψ . In practice, to have a similar scale, I use moments in percentage deviation from their targets—i.e., $\frac{m(\psi)-m_S}{m_S}$. Moreover, in the first step, I use the identity matrix to weight the (rescaled) moments. In the second step, since I combine two different datasets with two independent sampling processes, I use a block-diagonal weighting matrix with two blocks, each containing the inverse of the variance-covariance matrix of the moments $\frac{m_i(\tilde{\psi})-m_{S_i}}{m_{S_i}}$ i = 1, 2, obtained using the first-step consistent estimate $\tilde{\psi}$ to compute $m_i\left(\tilde{\psi}\right)$ and the corresponding dataset to compute m_{S_i} .

6.2 Identification

The identification of the model shares several similarities with that of structural search models of the labor market; see Eckstein and Van den Berg (2007). Specifically, although the model is highly nonlinear, so that (almost) all parameters affect all outcomes, the identification of some parameters relies on some key moments in the data. The data on transactions identify the transition rates between states: λ , γ_s , α_{ds} , γ_{sd} . The inference of the endogenous contact rates γ_s , α_{ds} , γ_{sd} allows me to identify the mass of entrants μ and the efficiency parameters γ and γ' of the matching functions. More precisely, the fraction of aircraft for sale by owners that trades as retail-to-retail transactions identifies the rate γ_s at which a seller meets a direct buyer. Similarly, the fraction of dealers' inventories that trades as dealer-to-retail transactions identifies the rate α_{ds} at which a dealer with an aircraft to sell meets a buyer. Table 1 reports that dealers are faster than owners at selling aircraft, and the model captures this difference through differences between their corresponding trading rates α_{ds} and γ_s . Moreover, since owners wish to sell their assets when their valuations drop, the fraction of aircraft for sale identifies the parameter λ that governs these changes. Finally, aggregate dealers' inventories identify the rate γ_{sd} at which a seller meets a dealer willing to buy an aircraft.

The estimates of these rates λ , γ_s , γ_{sd} , α_{ds} , together with A, μ_d and the steady-state condition $\frac{\mu}{\lambda} = \mu_{hn} + \int_0^T \mu_{ho}(a) da$, allow me to recover the mass of entrants μ and the efficiency parameters γ and γ' of the matching functions by solving the differential equations (14)-(16) that characterize the evolution of the endogenous distributions of agents $\mu_{ho}(a)$, $\mu_{lo}(a)$ and $\mu_{do}(a)$.

The data on prices, along with the average age of assets on the market—i.e., equation (22)—jointly identify the remaining parameters: the aircraft depreciation δ_2 , the valuations z_h and z_l , the bargaining parameters θ_s and θ_d , and the search cost c_s . Specifically, the price variation across vintages identifies the parameter δ_2 that governs the depreciation of aircraft.

Moreover, Nash Bargaining implies that equilibrium prices depend on buyers' outside option, which is the value of continuing to search S_{hn} . However, since buyers do not know the age of the asset in their next meeting with a seller or a dealer, the value S_{hn} does not vary with the age of the asset traded and, thus, it affects the prices of all vintages—i.e., through the intercepts β_0 and β_3 in the price equations (23) and (24). The value of searching S_{hn} obviously depends on buyers' valuations z_h and z_l , as well as on their bargaining parameters: It is negative if sellers and dealers leave no surplus to buyers—i.e., $\theta_s = \theta_d = 1$ —and increases with buyers' bargaining powers $1 - \theta_s$ and $1 - \theta_d$. Hence, the intercepts β_0 and β_3 in equations (23) and (24) contribute to identifying the valuations and the bargaining parameters. Similarly, the utility flow (17) and the negotiated prices (23) and (24) suggest that the coefficients β_1 and β_4 also contribute to the identification of the valuations z_h and z_l , and of the bargaining parameters θ_s and θ_d .

To further help explain the separate identification of bargaining parameters and valua-



FIG. 1: This figure displays the results of numerical comparative statics of retail prices p(a) (solid line) and wholesale prices $p_B(a)$ (dashed line) with respect to dealers' bargaining parameter θ_d and to agents' valuation z_h ; the vertical dash-dot line corresponds to the estimated parameter, reported in Table 2. The left panels display the prices of age-a = 0 aircraft, which correspond to the parameters $\beta_0 + \beta_1$ in equation (23) and $\beta_3 + \beta_4$ in equation (24), respectively; the right panels display the intercepts β_0 and β_3 . All other parameters are fixed at their calibrated/estimated value.

tions, Figure 1 displays the numerical comparative statics of retail (solid line) and wholesale prices (dashed line) with respect to dealers' bargaining parameter θ_d (first row) and to agents' valuation z_h/z_l (second row), in the neighborhood of the estimated parameters (the vertical dotted line): the left panels display the prices of age-a = 0 aircraft, which correspond to the parameters $\beta_0 + \beta_1$ in equation (23) and $\beta_3 + \beta_4$ in equation (24), respectively; the right panels display the intercepts β_0 and β_3 . These panels show that bargaining parameters and valuations have a differential effect on prices. Most notably, both top panels show that dealers' bargaining parameter has a greater effect on wholesale prices than on retail prices, and the right panel indicates that the ranking of the intercepts rules out certain combinations of bargaining parameters { θ_s , θ_d }. Hence, these panels suggest that the differences between retail and wholesale prices identify the bargaining parameters—i.e., the differences between the intercepts $\beta_0 - \beta_3$ and between the coefficients $\beta_1 - \beta_4$ —whereas the level of these prices identifies the valuations.¹²

Furthermore, the average age of assets on the market is a decreasing function of the search cost c_s . When deciding whether or not to put the asset on the market, sellers anticipate that they have to pay the flow cost c_s while searching for a counterparty. This cost is sunk at the time of the negotiation, but ex-ante, when deciding whether to put their assets on the market, sellers will be unwilling to do so if the search cost c_s is large. As this cost decreases, sellers will be more willing to put their assets on the market, but only if it makes sense from an ex-ante point of view. Since the gains from trade are larger for younger assets, sellers are more likely to sell older aircraft if search costs are low. Thus, the average age of assets on the market is informative about c_s .

Finally, the free-entry condition $J_{dn} = 0$ implies that I can recover dealers' fixed costs k from dealers' bid-ask spread and their trading rates.

6.3 Estimates

Table 2 reports estimates of the parameters and of the contact rates γ_s , α_{ds} , and γ_{sd} . The top part of the table reports the parameters and contact rates that are estimated directly, while the bottom part reports the parameters μ , γ , γ' , and k that are derived from the estimated contact rates γ_s , α_{ds} , and γ_{sd} . I calculate asymptotic standard errors for the direct estimates and 95-percent confidence intervals obtained by bootstrapping the data for the parameters μ , γ , γ' , and k. As a compromise between accuracy and computation burden, I use 100 replications. Appendix B provides more detail about the computation of the standard errors and the bootstrap simulations.

The magnitude of the parameter λ indicates that, on average, valuations switch from high to low approximately every five years. The magnitude of the sum $\gamma_s + \gamma_{sd}$ indicates that an aircraft stays on the market approximately eight months before a low-valuation owner is able to sell it. The magnitude of the parameter α_{ds} indicates that, on average, it takes slightly more than four months for a dealer to find a buyer. On average, each dealer trades

¹²To my knowledge, this identification of the bargaining parameters is novel in the literature. A few recent papers in the labor-search literature estimate workers' and firms' bargaining parameters; see Cahuc, Postel-Vinay, and Robin (2006) and Flinn (2006). Those papers use additional information on labor demand or on firms' production function, together with observed wages, to infer workers' bargaining parameter. In the current setting, it would correspond to having additional information on aircraft demand that could be used to infer agents' valuations z_h and z_l . Instead, in the absence of this information, I identify the bargaining parameters by exploiting the difference between retail and dealer prices, and the vertical heterogeneity of the assets.

λ	0.0457	<i>7</i> ,	695, 610
Λ	(0.0035)	$\sim h$	(41, 258)
γ_s	0.1825	~,	114,060
	(0.0015)	\sim_l	(16, 250)
γ_{sd}	0.1737	0	1,622.7
	(0.0447)	C_{S}	(486.23)
~	0.7021	ρ	0.3925
α_{ds}	(0.0054)	v_s	(0.0923)
8	0.0167	Δ.	0.9732
02	$(0.1346 * 10^{-3})$	v_d	(0.0054)
~	$5.9717 * 10^{-5}$		482.3
γ	$[3.823; 6.225] * 10^{-5}$	μ	[475.7; 733.0]
~′	$2.2973 * 10^{-4}$	k	244,767
γ	$[1.444; 2.333] \ast 10^{-4}$		$\left[232, 810; 303, 120\right]$

TABLE 2: Estimates

Notes—This table reports the estimates of the parameters. Asymptotic standard errors, in parentheses. 95-percent confidence intervals in brackets are obtained by bootstrapping the data using 100 replications.

one aircraft every $\frac{1}{\int_0^{a_{do}^*} \alpha_{db}(a) da} + \frac{1}{\alpha_{ds}} \simeq 6$ quarters. These parameters, γ_s , γ_{sd} and α_{ds} , imply that trading delays are non-trivial in this market and that dealers play an important role in reducing them: their pairwise-meeting rate γ' is almost four times the agents' direct meeting rate γ .

The parameter δ_2 indicates that business aircraft depreciate by approximately seven percent every year, a decline comparable to that of larger commercial aircraft. The valuations z_h and z_l indicate that the difference between buyers' and sellers' valuations are large i.e., gains from trade are large. The parameter c_s indicates that the flow search costs are small, implying that the average search costs of completing a transaction $\frac{c_s}{\gamma_s + \gamma_{sd}}$ are trivial: approximately \$5,000.

The bargaining parameter θ_s implies that buyers and sellers split the surplus almost equally, with buyers capturing a slightly large share. Dealers' bargaining parameter θ_d , however, implies that they capture almost all the surplus of their transactions. The difference between these bargaining parameters is, perhaps, suggestive of the fact that intermediaries, who trade frequently, are more sophisticated in negotiations than agents, who trade occasionally (Green, Hollifield, and Schürhoff, 2007a,b). In turn, free entry implies that the costs of "market-making" are large, and Table 2 reports that dealers' costs k equal \$244,767 per quarter.

6.4 Model Fit

Before considering some broader implications of our results, I examine the fit of the estimated model. Table 3 contains the moments calculated from the data, as well as from the numerical solutions of the model. To appreciate how different weighting of the moments affects the estimation, I report the numerical values of the moments calculated from the model using the first-step parameters in column (4) and the second-step parameters in column (5).

Overall, Table 3 reports that the model evaluated at the first-step parameters matches the data quite precisely, with an average absolute percentage deviation between the empirical moments and the simulated moments of 3.8 percent. The weighting of the moments in the second step pushes the estimation to match the price moments more precisely than the transaction moments, since they have a relatively lower variance. The average absolute percentage deviation between the actual and simulated data slightly increases as a consequence of the differential weighting.

Nonetheless, the number of moments is larger than the number of estimated parameters they equal 11 and 10, respectively; thus, I can test the over-identifying restriction by constructing the *J*-statistic, which is asymptotically distributed as a χ^2 with one degree of freedom under the null hypothesis that $m(\hat{\psi}) - m_S = 0$. With the value of the *J*-statistic being 2.9, I cannot reject the null hypothesis that the over-identifying restriction holds at the standard 95-percent confidence level, thus indicating that the fit of the estimated model is quite good.

To further demonstrate how the model fits the price data in a, perhaps, more-intuitive way, Figure 2 displays the empirical average retail prices by vintage, along with their theoretical counterparts p(a), showing that the model fits them well. Similarly, the theoretical dealers' bid prices $p_B(a)$ fit the empirical average wholesale prices almost perfectly.¹³ Section 6.2 argued that prices play a key role in the identification of the bargaining parameters, and Section 7 will show that the bargaining parameters play a key role in the welfare results of the counterfactual analyses; thus, it is instructive that the empirical and theoretical prices are almost identical. Of course, the model focuses on a market with homogeneous assets in steady state, whereas the price data exhibit both cross-sectional variability across heteroge-

¹³The estimates imply that dealers' ask prices $p_A(a)$ are approximately 30-percent larger than $p_B(a)$. Unfortunately, the aircraft prices dataset does not report their empirical analog.

(1)	(2)	(3)	(4)	(5)		
Empirical Moment	Empirical Value	Theoretical Moment	Simulated Value	SIMULATED VALUE		
	LMI IIIOAL VALUE	THEORETICAL MOMENT	First Step	Second Step		
		* *				
$E\left(\frac{\text{Aircraft for Sale}}{\text{Active Aircraft}}\right)$	0.1223	$\frac{\int_0^{a_l^*} \mu_{lo}(a) da + \int_0^{a_d^* o} \mu_{do}(a) da}{A}$	0.1266	0.1324		
$E\left(\frac{\text{Aircraft for Sale by Dealers}}{\text{Active Aircraft}}\right)$	0.0357	$\frac{\int_0^{a_{do}^*} \mu_{do}(a) da}{A}$	0.0362	0.0264		
$E\left(\frac{\text{Retail-to-Retail Transactions}}{\text{Active Aircraft}} ight)$	0.0196	$\frac{\gamma_s \int_0^{a_l^*} \mu_{lo}(a) da}{A}$	0.0188	0.0193		
$E\left(\frac{\text{Dealer-to-Retail Transactions}}{\text{Active Aircraft}}\right)$	0.0279	$\frac{\alpha_{ds} \int_0^{a_{do}^*} \mu_{do}(a) da}{A}$	0.0268	0.0186		
E (Average Age, Aircraft for Sale)	57.2148	$\frac{\int_{0}^{a_{l}^{*}}a\mu_{lo}(a)da + \int_{0}^{a_{do}^{*}}a\mu_{do}(a)da}{\int_{0}^{a_{l}^{*}}\mu_{lo}(a)da + \int_{0}^{a_{do}^{*}}\mu_{do}(a)da}$	61.3937	76.0232		
$\beta_0+\beta_1$	17,656,300	$\beta_{0,sim}+\beta_{1,sim}$	17,051,000	17,549,000		
β_1	19,414,500	$\beta_{1,sim}$	18,213,600	19,499,000		
eta_2	0.0161	$\beta_{2,sim}$	0.0160	0.0158		
$\beta_3+\beta_4$	15, 593, 700	$\beta_{3,sim}+\beta_{4,sim}$	16,636,000	15,579,000		
eta_4	17,281,400	$\beta_{4,sim}$	17,853,200	17,469,000		
β_5	0.0159	$\beta_{5,sim}$	0.0162	0.0157		

TABLE 3: Model Fit

Notes—This table reports the values of the empirical moments and of the simulated moments calculated at the estimated parameters. Column (4) reports the simulated moments calculated using the first-step estimates (not reported), and column (5) reports the simulated moments calculated using the second-step estimates reported in Table 2. The coefficients β_0 , β_1 and β_2 are obtained from a non-linear least squares regression using RETAIL PRICES; the coefficients β_3 , β_4 and β_5 are obtained from a non-linear least squares regression using WHOLESALE PRICES; the coefficients $\beta_{0,sim}$, $\beta_{1,sim}$ and $\beta_{2,sim}$ are obtained from a non-linear least squares regression using simulated retail-to-retail prices p(a); the coefficients $\beta_{3,sim}$, $\beta_{4,sim}$ and $\beta_{5,sim}$ are obtained from a non-linear least squares regression using simulated retail-to-dealer prices $p_B(a)$.



FIG. 2: Model fit: average retail prices in the data (dashed line) and prices in the model (solid line) as a function of aircraft age.

neous aircraft and time-series variability due to business cycles. Thus, the empirical average prices by vintage, displayed in Figure 2, remove the cross-sectional and time-series variability. Other measures of fit, such as the R^2 of the non-linear least squares regressions (24), preserve the variability in the data and, indeed, exhibit larger differences between actual and simulated price data: they equal 0.31 and 1, respectively.

7 Counterfactual Analyses

I now perform two counterfactuals to answer the questions of how frictions and dealers affect asset allocations, prices and welfare. In both cases, I compute the equilibrium in these counterfactual scenarios using the parameter estimates reported in Table 2.

7.1 Quantifying the Effects of Frictions

The estimates of the parameters allow me to quantify the effect of trading frictions on the allocation and the prices of assets, as well as on welfare. Specifically, I compare asset allocations, asset prices and welfare with the Walrasian efficient benchmark, which is a special case of the model presented in Section 5 when trade is frictionless—i.e., $\gamma \to +\infty$ and $c_s = 0$.

In the Walrasian market, as soon as high-valuation agents enter the market, they immediately meet low-valuation sellers or dealers. Hence, in a frictionless market, no low-valuation agents and no dealers have aircraft—i.e., $\mu_{lo}^w(a) = \mu_{do}^w(a) = 0$ for any a. Thus, the sum $\int_0^T (\mu_{lo}(a) + \mu_{do}(a)) da$ measures the total mass of assets misallocated due to search frictions. Of these misallocated assets, the mass $\int_0^{a_l^*} \mu_{lo}(a) da + \int_0^{a_{do}^*} \mu_{do}(a) da$ is on the market for sale, and the mass $\int_0^T (\mu_{lo}(a) + \mu_{do}(a)) da - \int_0^{a_l^*} \mu_{lo}(a) da - \int_0^{a_{do}^*} \mu_{do}(a) da = \int_{a_l^*}^T \mu_{lo}(a) da$ corresponds to the mass of aircraft older than a_l^* that low-valuation owners are keeping rather than selling since sellers' expected surplus is lower than their transaction costs.¹⁴

Walrasian prices are equal to:

$$p^{w}(a) = \int_{a}^{T} e^{-\rho(t-a)} z_{h} e^{-\delta_{2}t} dt$$

= $\frac{z_{h} e^{\rho a}}{\rho + \delta_{2}} \left(e^{-a(\delta_{2}+\rho)} - e^{-T(\delta_{2}+\rho)} \right).$

Instead, in the estimated model with frictions, prices are equal to $p(a) = (1 - \theta_s) (S_{lo}(a) - V_{ln}) + \theta_s (U_{ho}(a) - S_{hn})$, as in equation (11).

The top parts of columns (1) and (2) in Table 4 report the calculations of these magnitudes for the model and the Walrasian benchmark, respectively. The first row reports that trading frictions cause the misallocation of 1,681 aircraft, corresponding to 18.3 percent of all aircraft. The third row reports that 1,215 aircraft are on the market for sale, whereas for the remaining 1,681-1,215 = 466 aircraft, the trading costs of selling them are larger the sellers' expected gains from trade; thus, these aircraft are not even on the market for sale. Table 4 further shows that trading frictions decrease the price of new aircraft by $\frac{p(0)-p^w(0)}{p^w(0)} = -19.26$ percent (corresponding to \$4, 201, 000) relative to the Walrasian benchmark. The percent decrease of a ten-year-old aircraft is similar.

The bottom part of Table 4 calculates welfare in the estimated model and in the Walrasian market, decomposing it into three components: allocations, search costs and dealers' costs. Hence, the differences in these components between the estimated model and the Walrasian market account for the welfare effects of trading frictions, with key model parameters affecting each of them. Specifically:

1. Allocations.

¹⁴The estimates imply that the age cutoff a_l^* equals 138 quarters, whereas dealers' age cutoff a_{do}^* equals 125 quarters.

	(1)	(2)	(3)	
	ESTIMATED MODEL	WALRASIAN MARKET	$c_s = 0$	
$\int T \left(\left(\right) \right) + \left(\left(\right) \right) $	1,681	0	1,698	
$\int_0 \left(\mu_{lo}\left(a\right) + \mu_{do}\left(a\right) \right) da$	[1, 646; 2, 399]	[0; 0]	[1, 683; 2, 480]	
$\int_{0}^{T} (\mu_{I_0}(a) + \mu_{J_0}(a)) da$	0.183	0	0.183	
$\frac{50}{A}$	[0.179; 0.256]	[0; 0]	[0.182; 0.264]	
$\int a_1^* \dots \langle a \rangle da = \int a_d^* \dots \langle a \rangle da$	1,215	0	1,218	
$J_0^{*} \mu_{lo}(a) aa + J_0^{*} \mu_{do}(a) aa$	[1, 202; 1, 755]	[0; 0]	[1, 152; 1, 742]	
$\int_{a}^{a_l^*} \mu_{a,l}(a) da + \int_{a}^{a_{do}^*} \mu_{a,l}(a) da$	0.132	0	0.132	
$\frac{f_0}{A} = \frac{p_{lo}(\alpha)\alpha\alpha + f_0}{A}$	[0.130; 0.187]	[0; 0]	[0.125; 0.184]	
m(0)	17,611,151	21, 812, 709	17,648,470	
p(0)	$[17, 253; 17, 969] * 10^3$	$[21, 532; 22, 145] * 10^3$	$[17, 249; 18, 097] * 10^3$	
m(10)	8,437,910	11,008,194	8,475,461	
p(10)	$[8, 366; 8, 531] * 10^3$	$[10, 633; 11, 221] * 10^3$	$[8, 148; 8, 672] * 10^3$	
ALLOCATIONS	$2.054 * 10^9$	$2.371 * 10^9$	$2.057 * 10^9$	
ALLOCATIONS	$[1.942; 2.060] * 10^9$	$[2.324; 2.397] * 10^3$	$[1.941; 2.062] * 10^3$	
SEADCH COSTS	$6.534 * 10^6$	0	0	
SEARCH COS15	$[4.817; 14.182] * 10^6$	[0; 0]	[0; 0]	
DEALEDS COSTS	$244 * 10^6$	0	$255 * 10^6$	
DEALERS COSIS	$[232.8; 303.1] * 10^6$	[0; 0]	$[206.5; 311.6] * 10^6$	
WELEADE	$1.802 * 10^9$	$2.371 * 10^9$	$1.801 * 10^9$	
VV ELFARE	$[1.614; 1.803] * 10^9$	$[2.324; 2.397] * 10^3$	$[1.632; 1.828] * 10^3$	

TABLE 4: Comparison with Walrasian Market

Notes—This table reports counterfactual allocations and prices. 95-percent confidence intervals in brackets are obtained by bootstrapping the data using 100 replications.

These equal the equilibrium utility flows: $\int_0^T (\mu_{ho}(a) z_h + \mu_{lo}(a) z_l) e^{-\delta_2 a} da$ in the estimated model and $xT \int_0^T z_h e^{-\delta_2 a} da$ in the Walrasian market.

Hence, this component of the aggregate welfare costs is determined by: a) the mass of misallocated assets. In turn, these depend on the trading delays, captured by the contact rates γ_s , γ_{sd} and α_{ds} ; and on how frequently agents seek to trade, captured by the parameter λ . b) the difference between the utility flows of buyers, sellers and dealers. These flows depend on their valuations z_h , z_l and 0, respectively, and on the age of the asset through $e^{-\delta_2 a}$.

At the estimated parameters, the welfare loss equals \$317, 220, 000 per quarter, or 13.38 percent of the total potential welfare $xT \int_0^T z_h e^{-\delta_2 a} da$ of the Walrasian market.

2. Buyers' and sellers' search costs.

These equal the costs that buyers and sellers incur while searching for a counterparty in the estimated model, and they correspond to $c_s \left(\int_0^{a_h^*} \mu_{lo}(a) \, da + \mu_{hn} \right)$. They equal zero in the Walrasian market.

Hence, this component of the aggregate welfare costs depends on the search cost c_s and on the masses of agents that seek to trade—which, again, depend on the trading delays (captured by the contact rates γ_s , γ_{sd} and α_{ds}) and on how frequently agents seek to trade (captured by the parameter λ).

At the estimated parameters, this welfare loss equals \$6,534,000 per quarter, or 0.28 percent of total potential welfare of the Walrasian market.

3. Dealers' costs.

These equal the costs that dealers incur to provide intermediation, and they correspond to $k\mu_d$ in the estimated model. They are equal to zero in the Walrasian market.

Hence, this component of the aggregate welfare costs is determined by dealers' aggregate capacity μ_d and by dealers' costs k. In a free-entry equilibrium, dealers' costs depend on their bid-ask spread, which, in turn, depends on their bargaining parameter θ_d .

At the estimated parameters, this welfare loss equals \$244,770,000 per quarter, or 10.32 percent of total potential welfare of the Walrasian market.

Overall, the aggregate welfare loss due to trading frictions equals \$568, 520,000 per quarter, or 23.98 percent of welfare in the Walrasian market.

Two frictions affect allocations, prices and welfare in the estimated model relative to the Walrasian market: trading delays and search costs. We can assess the relative contribution of search costs by computing the equilibrium when $c_s = 0$; column (3) in Table 4 reports these calculations. In general, the elimination of search costs directly affects parties' outside options in bargaining, thereby changing agents' policies and the negotiated prices. In addition, this reduction in search costs affects dealers' margins. Thus, dealers' free-entry condition implies that their mass changes, as well. Since dealers' mass determines agents' buying and selling rates, the elimination of search costs has general-equilibrium effects on allocations, further affecting equilibrium prices. In the specific case reported in Table 4, dealers' margins increase, thereby increasing their mass μ_d and their aggregate inventories. Overall, column



FIG. 3: Actual prices (solid line), Walrasian prices (dashed line) and prices without search costs (dash-dotted line) as a function of aircraft age.

(3) says that the mass of misallocated aircraft increases and that asset prices increase when $c_s = 0$.

The bottom part of column (3) calculates welfare, also decomposing it into its different components. It shows that aggregate welfare *decreases* relative to the case in which search costs are positive, indicating that inefficiencies may *increase* when search costs vanish—i.e., in contrast to the findings of a large search literature. The reason is that more dealers enter the market, but since they mainly appropriate surplus that other agents and other dealers would create, the private benefits of new entrants outweigh the social benefits (Von Weizsacker, 1980; Mankiw and Whinston, 1986). However, the magnitude of this welfare decrease is small, as the search costs are small.

Figure 3 plots the estimated and counterfactual prices, confirming that actual prices (the solid line) are always lower than Walrasian prices (the dashed line) and prices without search costs (the dash-dotted line). Moreover, the figure displays an additional interesting pattern: Walrasian prices decline at a faster rate than actual prices. The reason is that the willingness to pay for a marginally younger—i.e., better—aircraft is higher if there are no frictions.

Overall, these counterfactuals imply non-trivial effects on allocations, prices and welfare, clearly illustrating the importance of frictions in this decentralized market.

7.2 Quantifying the Effects of Dealers

The estimates of the parameters allow me to quantify the effects of dealers on asset allocation, asset prices and welfare. Specifically, I compare asset allocations and asset prices with the counterfactual of no dealers—i.e., $\gamma' = 0$ or $k \to +\infty$ —and then compare aggregate welfare and its components: allocations, search costs and dealers' costs.

If dealers are not active, buyers' and sellers' meeting rates change, thus changing their distributions over the states. Specifically, the distributions of agents evolve according to:

$$\begin{split} \dot{\mu}_{ho}(a) &= \gamma_b(a) \,\mu_{hn} - \lambda \mu_{ho}(a) \text{ for } a < a_{ho}^{**}, \\ \dot{\mu}_{lo}(a) &= \lambda 1 \left(a < a_{ho}^{**} \right) \mu_{ho}(a) - \gamma_s 1 \left(a < a_l^{**} \right) \mu_{lo}(a) \text{ for } a < T, \\ \dot{\mu}_{hn} &= (\mu - x) + \mu_{ho}(a_{ho}^{**}) - \lambda \mu_{hn} - \mu_{hn} \int_0^{a_l^{**}} \gamma_b(a) \, da, \end{split}$$

with initial conditions $\mu_{ho}(0) = x$ and $\mu_{lo}(0) = 0$ and terminal conditions $\mu_{ho}(a) = 0$ for $a_{ho}^{**} < a < T$. Similarly, at each instant, the mass of *ln*-agents equals:

$$\mu_{ln} = \lambda \mu_{hn} + \gamma_s \int_0^{a_l^{**}} \mu_{lo}\left(a\right) da + \mu_{lo}\left(T\right).$$

The cutoff ages a_{ho}^{**} and a_l^{**} may differ from a_h^* and a_l^* , defined in Section 5.2.4, as agents' value functions and policies depend on whether or not dealers are active. Moreover, the counterfactual steady-state distributions of agents have to be consistent with the counterfactual trading probabilities $\gamma_b(a)$ and γ_s , which are also key components of the counterfactual prices.

Table 5 reports the calculations of these magnitudes for the model and the counterfactual market with no dealers, and Figure 4 plots the prices. The table and the figure show interesting features. The first row of the table reports that the number of misallocated assets increases to 2,013 units, or 20.6 percent of all aircraft. This 2.3-percentage-point increase in misallocated assets corresponds to a 12.5-percent increase in misallocated assets relative to the estimated model. The third row reports that 2,000 of these 2,013 misallocated aircraft would be for sale in a market without dealers. This mass is larger than in the estimated model for two reasons: 1) the longer trading delays increase the mass of assets on the market for a given volume of trade; and 2) low-valuation owners are more likely to sell their older assets—i.e., their cutoff increases: $a_l^{**} > a_l^*$ —since they capture a greater share of the surplus: sellers' bargaining power is now always equal to $\theta_s = .3756$, whereas it was equal

	Estimated Model	NO DEALER MARKET			
$\int T$ () I () I () I	1,681	2,013			
$\int_0 \mu_{lo}(a) aa + \int_0^{ab} \mu_{do}(a) aa$	[1, 646; 2, 399]	[1, 979; 2, 634]			
$\int_{a}^{T} u_{1}(a) da + \int_{a}^{a} \int_{a}^{a} u_{2}(a) da$	0.183	0.206			
$\frac{f_0}{A} \frac{\mu_{lo}(\omega)\omega\omega + f_0}{A}$	[0.179; 0.256]	[0.203; 0.270]			
$\int a_l^* \cdots (a) da + \int a_{da}^* \cdots (a) da$	1,215	2,000			
$J_0^* \mu_{lo}(a) aa + J_0^* \mu_{do}(a) aa$	[1, 202; 1, 755]	[1, 979; 2, 616]			
$\int_{a}^{a_l^*} u_{\lambda}(a) da + \int_{a}^{a_l^*} u_{\lambda}(a) da$	0.132	0.205			
$\frac{J_0 - \mu_{lo}(\alpha) \alpha \alpha + J_0 - \mu_{do}(\alpha) \alpha \alpha}{A}$	[0.130; 0.187]	[0.203; 0.268]			
m(0)	17,611,151	18, 118, 803			
$p\left(0\right)$	$[17, 253; 17, 969] \ast 10^3$	$[17,791;18,738]*10^3$			
n(10)	8,437,910	9,086,250			
p(10)	$[8, 366; 8, 531] \ast 10^3$	$[8, 836; 9, 295] * 10^3$			
ALLOCATIONS	$2.054 * 10^9$	$1.984 * 10^9$			
ALLOCATIONS	$[1.942; 2.060] * 10^9$	$[1.859; 1.990] * 10^9$			
SEADCH COSTS	$6.534 * 10^6$	$7.817 * 10^6$			
SEARCH COSTS	$[4.817; 14.182] * 10^6$	$[5.631; 16.368] * 10^6$			
DEALEDS COSTS	$244 * 10^6$	0			
DEALERS COSTS	$[232.8; 303.1] * 10^6$	[0;0]			
WELFARE	$1.802 * 10^9$	$1.977 * 10^9$			
VV ELFARE	$[1.614; 1.803] * 10^9$	$[1.844; 1.983] * 10^9$			

TABLE 5: Comparison with a Market with No Dealers

Notes—This table reports counterfactual allocations and prices in a market without dealers. 95percent confidence intervals in brackets are obtained by bootstrapping the data using 100 replications.

to $1 - \theta_d = 1 - .9732 = .0268$ when they sold to a dealer. This second effect dominates the opposing effect that total search costs are greater because delays are longer, since the flow search cost c_s is small.

The bottom part of Table 5 calculates the different components of welfare in the counterfactual market with no dealers—i.e., allocations, search costs and dealers costs—and, thus, the differences of these components between the estimated model and the counterfactual market account for the welfare effects of dealers. Specifically:

1. Allocations.

At the estimated parameters, dealers improve the allocation, and this welfare gain equals \$69, 261,000 per quarter, corresponding to 3.84 percent of aggregate welfare of the estimated model.



FIG. 4: Actual (solid line) and counterfactual (dashed line) aircraft prices if there were no dealers as a function of aircraft age.

2. Buyers' and sellers' search costs.

With dealers, agents trade faster, incurring lower cumulative search costs. The welfare gain due to lower agents' search costs equals \$1, 282, 600 per quarter, corresponding to 0.07 percent of aggregate welfare of the estimated model.

3. Dealers' costs.

Dealers' costs to provide intermediation equal $k\mu_d$. Using the estimated parameters, the welfare loss due to dealers' costs equals \$244, 443, 693 per quarter, corresponding to 13.57 percent of aggregate welfare of the estimated model.

The net effect of dealers is a welfare *loss* of \$174, 220,000 per quarter, or 9.66 percent of aggregate welfare of the estimated model. The reason for this result is that, while dealers improve the allocation of assets, they impose a negative externality on agents by lowering their direct meeting rates and, thus, appropriate surplus that agents would create. Moreover, since dealers appropriate almost all the transaction surplus, many enter to capture arbitrage profits, but these profits are competed away in a market with free entry (Von Weizsacker, 1980; Mankiw and Whinston, 1986). Hence, dealers' aggregate costs outweigh the social benefits that they generate in terms of a more efficient asset allocation.

Table 5 also shows that prices of new aircraft increase by approximately \$500,000, a 2.88percent increase. The reason for this increase is that, without dealers, the volume of trade is lower. Therefore, at any point in time, the mass of high-valuation agents seeking to buy an aircraft is larger—i.e., $\mu_{hn}^{nd} > \mu_{hn}$. Hence, it is easier for sellers to find a high-valuation buyer—i.e., $\gamma_s^{nd} > \gamma_s$ —thereby increasing their value function $V_{lo}(a)$ and their outside option in bargaining. This effect dominates the opposite effects of higher search costs and slower trade on asset prices.

7.3 Sensitivity Analysis

The main result reported in Table 5 is, perhaps, striking: that is, at the estimated parameter values, dealers decrease aggregate welfare. Hence, I now perform additional analyses to investigate the ranges of the parameters for which this result holds. In turn, these analyses should shed further light on the key mechanism behind the result, as well as on the empirical moments that underpin it.

Figure 5 displays the results of numerical comparative statics with respect to key parameters of the model. Each row displays equilibrium outcomes of a numerical solution of the model in which one parameter differs from its estimated value, while all other parameters are fixed at their calibrated/estimated values. For example, the plots of the first row obtain as the valuation z_h varies from its lower bound z_l to un upper bound of $20z_l$; the vertical dashed line indicates the estimated value of the parameter. All other parameters $\{\rho, T, A, z_l, \delta_2, \gamma, \gamma', \lambda, \mu, \theta_s, \theta_d, c_s, k\}$ are kept at their calibrated/estimated values. Using these parameters, I compute the numerical solution of the model by imposing dealers' freeentry condition $J_{dn} = 0$, which results in a different value of the mass of dealers μ_d , displayed in the left column. I further compute the resulting welfare, as well as the welfare in the market with no dealers (i.e., following the same calculations reported in Section 7.2) at these parameters, and the right column displays their ratio.

The figure shows several interesting findings. First, the main result, that dealers decrease welfare, appears very robust to individual changes in parameter values: a different value of the high-valuation z_h , of the switching rate λ , of dealers' bargaining power θ_d , of agents' search cost c_s , and of dealers' cost k does not bring about a welfare increase. Welfare increases exclusively when the ratio of meeting rates $\frac{\gamma'}{\gamma}$ —i.e., a ratio that captures dealers' trading efficiency relative to agents'—exceeds the value of 94, which is approximately 25 times larger than its estimated value of 3.8. Second, for several values of the parameters,



FIG. 5: This figure displays the results of comparative statics with respect to key parameters. Each row displays the equilibrium mass of dealers (left column), as well as the corresponding welfare relative to the market with no dealers (right column), obtained from a numerical solution of the model. The vertical dash-dot line displays the estimated value of the parameter that varies in in each plot. All other parameters are fixed at their calibrated/estimated value.

dealers do not enter, as their costs k are larger than the revenues that they can earn; thus, aggregate welfare equals the value of aggregate welfare in a market with no dealers. More specifically, if the valuation z_h (which captures the gain from trade) is sufficiently low, or the switching rate λ (which captures the frequency of trade) is sufficiently low, or dealers' bargaining power θ_d is sufficiently low, or dealers' costs k are sufficiently high, then no dealer enters the market. Third, when dealers enter, welfare is lower than in the market with no dealers, but welfare does not necessarily decrease as more dealers enter: for example, the left panel in the bottom row of Figure 5 shows that dealers' mass is a monotonic function of their cost k, whereas the right panel shows that welfare is a non-monotonic function of dealers' costs. In practice, these patterns imply that welfare would decrease for a large range of lower costs than those reported in Table 2.

More generally, these comparative statics highlight that the model allows intermediaries to increase or decrease welfare, depending on parameters. Dealers' entry generates a trade-off for aggregate efficiency. The aggregate benefits are the improvement in asset allocations and the reduction in cumulative search costs; both benefits increase as the difference between the meeting rates $\gamma' - \gamma$ becomes larger. The aggregate costs are dealers' costs $k\mu_d$, which, in a free-entry equilibrium, equal their revenues and, thus, depend on the share θ_d of the surplus that they capture.

Figure 6 focuses on this trade-off. Specifically, it displays the numerical results of additional comparative statics in which I simultaneously vary the benefits due to dealers, measured by the ratio $\frac{\gamma'}{\gamma}$, and their costs, measured by their bargaining power θ_d .

Figure 6 clearly identifies three separate regions: 1) dealers do not enter, if their bargaining power is so low that they cannot recoup their costs; 2) dealers enter and decrease welfare, if their relative trading efficiency is not large, but they capture a large share of aggregate surplus (which is competed away in a free-entry equilibrium); and 3) dealers enter and increase welfare, if their relative trading efficiency is large and they do not capture all transaction surplus.

While Figure 6 highlights that intermediaries' welfare effects are ambiguous in the model, the star in the bottom-right corner of Figure 6 shows that the estimated parameters are unambiguously in the region in which dealers decrease welfare. It is important to remember which features of the data determine these estimates. The estimates of the trading efficiency parameters γ' and γ obtain from the relative trading speed of dealers and agents: the transaction data in Table 1 indicate that dealers' inventories stay on the market for approximately



FIG. 6: The figure displays the combinations of the ratio between the pairwise meeting rates γ'/γ and of dealers' bargaining parameter θ_d for which dealers do not enter (white area); dealers enter and increase welfare (light-shaded area); dealers enter and decrease welfare (dark-shaded area). The star corresponds to values of the estimated parameters.

four months, whereas agents' assets stay on the market for about eight months; thus, dealers, indeed, meet counterparties at a faster rate than agents, but their relative efficiency is limited. The bargaining power obtains from the price data, most notably from the large difference between RETAIL PRICE and WHOLESALE PRICE reported in Table 1. Together, these different data suggest that dealers extract a larger share of the surplus than the social benefits that they generate; however, dealers' private benefits are competed away in a market with free entry and, thus, welfare decreases (Mankiw and Whinston, 1986).

Overall, these data on asset trades and on asset prices, along with the numerical results reported in Figures 5 and 6, seem to refute the main factors that could adversely affect the finding that dealers decrease welfare—i.e., a greater efficiency or a smaller bargaining power of dealers.

8 Concluding Remarks

This paper provides a framework for empirically analyzing decentralized asset markets. I use this framework to investigate the effects of trading frictions and of intermediaries on asset allocations, asset prices and welfare in the business-aircraft market. The model fits the data well. The estimates imply that trading frictions generate moderate allocative inefficiencies in such markets: Compared to the Walrasian benchmark, 18.3 percent of all business aircraft are misallocated, and aircraft prices are 19.2-percent lower. Moreover, dealers play an important role in reducing frictions: In a market with no dealers, 20.6 percent of the assets would be misallocated, and prices would increase by 2.88 percent. However, the net effect of dealers is a welfare *loss* equal to 9.66 percent of aggregate welfare of the estimated model. This is because dealers impose a negative externality by decreasing agents' direct transactions, and the estimate of dealers' bargaining power implies that they appropriate almost all gains from trade. Thus, many dealers enter to capture these arbitrage profits, but their profits are competed away in a market with free entry.

While these empirical results complement those of other papers that, in different settings, find that intermediaries' entry may be excessive from a welfare point of view (e.g., Hsieh and Moretti, 2003; Budish, Cramton, and Shim, 2014; Leslie and Sorensen, 2014; Pagnotta and Philippon, 2011), they obtain in a model with some important limitations. First, the supply x of new assets is exogenous. This modeling assumption is common in many other models that focus on secondary markets and on trading frictions. Second, information on buyers is unavailable: The mass of new buyers μ is exogenous, and their meeting rates are derived from the model. Hence, the identification of trading frictions relies exclusively on the sellers' side of the market. Many equilibrium search models share this feature, and one objective of this paper is to show that, under the same assumptions, it is possible to quantify the effect of trading delays on allocations, prices and welfare. Third, there are no aggregate shocks. In reality, the business-aircraft market, like most other asset markets, exhibits fluctuations in prices and trading volume, corresponding to fluctuations in supply and demand. The key advantage of a stationary framework is that the numerical solution of the model is quite fast to compute, thereby facilitating the estimation and the counterfactual analyses. Nonetheless, a potential concern is how sensitive the estimation results are to this stationarity assumption. The fact that the estimates of the parameters are quite precise (the standard errors are small; see Section 6.3) may suggest that aggregate shocks do not greatly affect the empirical moments and, thus, the results. Fourth, price is the only characteristic over which parties bargain, and no other characteristics, such as financing, are taken into consideration.

Finally, the model allows for parsimonious heterogeneity among agents and among dealers. As explained in Section 4, the aggregate nature of the data makes a model with richer heterogeneity difficult to identify. One important consequence of agents' limited heterogeneity is that the model focuses on negative shocks to valuations as the motive for selling assets, and agents replace their aircraft only when they reach the scrappage age. Similarly, dealers' limited heterogeneity contributes to the close substitutability of all transactions. Hence, while providing immediacy to agents, dealers simultaneously impose a negative externality on them by lowering their direct meeting rates, and this accounts, in part, for the negative welfare effects of dealers' free entry.

For these main reasons, I view this paper as a first step in quantifying the role of trading frictions and of intermediaries in asset markets. The empirical application clarifies the data requirements to estimate such a model and how the parameters are identified, and the estimation delivers a sense of the magnitudes involved, allowing me to assess which forces dominate and their welfare effects. Nonetheless, I hope that the future availability of richer data will allow me to incorporate additional features of these markets and, most notably, to study the role of intermediaries in greater detail.

APPENDICES

A Motives for Trade

The goal of this Appendix is to document patterns of trade in the data. These patterns are inconsistent with the idea that most secondary-market transactions are due to replacements of depreciated units with higher-quality ones. Instead, they favor the idea that the main motive for trade in the secondary market is the change in owners' valuations of the assets.

More specifically, Hendel and Lizzeri (1999), Porter and Sattler (1999), and Stolyarov (2002) develop models in which agents with heterogeneous willingness-to-pay for verticallydifferentiated vintages wish to replace their durables after they depreciate, but transaction costs are an impediment to instantaneous trade. In these models, a faster rate of depreciation increases the vertical differentiation between vintages, thereby leading to more-frequent replacements. Thus, these theoretical arguments lead to the following implications:

1. Assets with faster depreciation should have higher resale rates.

To investigate whether the data are consistent with this prediction, I proceed in two steps: 1) I obtain an annual DEPRECIATION RATE of each aircraft-model i in year tin the data by fitting the following regression on the different vintages a within model i in year t:

$$\log p\left(a\right) = \varphi_{0it} + \varphi_{1it}a,\tag{25}$$

where p(a) is the RETAIL PRICE of the vintage-*a* aircraft. The absolute value of φ_{1it} (note that it is negative) is the estimate of the DEPRECIATION RATE.

2) I construct the variable VOLUME OF TRADE of aircraft-model i and year t as the ratio $\frac{\text{Total Number of Transactions}}{\text{Active Aircraft}}$ and investigate whether it is correlated with the DEPRECIATION RATE.

Table 6 reports the results of several specifications. Columns (1)-(4) report coefficients of OLS regressions that pool all model-year pairs; columns (5)-(8) report coefficients of random-effects panel regressions; and columns (9)-(12) report coefficients of fixedeffects panel regressions. The DEPRECIATION RATE has no significant effect on the VOLUME OF TRADE in any of the specifications (1)-(12), suggesting that replacement is not the main motive for trade.

	TABLE 6: The Effect of Depreciation on Volume of Trade												
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	DEPRECIATION RATE	.0492	.1532	.0659	.1733	2453	0058	1800	.0243	2867	0843	2043	0173
		(.1758)	(.1887)	(.1784)	(.1965)	(.1420)	(.1458)	(.1310)	(.1462)	(.1534)	(.1372)	(.1380)	(.1324)
	I og (Active Aidedaet)			.0087	.0094			.0274	.0206			.0355	.0356
6	LOG(ACTIVE AIRCRAFT)			(.0044)	(.0044)			(.0038)	(.0046)			(.0044)	(.0051)
	Year Fixed Effects	No	Yes										
	Model Effects	None	None	None	None	Random	Random	Random	Random	Fixed	Fixed	Fixed	Fixed
	Observations	861	861	861	861	861	861	861	861	861	861	861	861

Notes—Standard errors in parentheses are clustered at the model level.

2. Assets with faster depreciation should trade earlier "in their life."

To investigate whether the data are consistent with this prediction, I investigate whether the AVERAGE AGE, AIRCRAFT FOR SALE of aircraft-model i in year t is correlated with the DEPRECIATION RATE.

Table 7 reports the results of several specifications.¹⁵ Columns (1)-(4) report coefficients of OLS regressions that pool all model-year pairs; columns (5)-(8) report coefficients of random-effects panel regressions; and columns (9)-(12) report coefficients of fixed-effects panel regressions. Overall, specifications (1)-(12) indicate that the DEPRE-CIATION RATE has no effect on the AVERAGE AGE, AIRCRAFT FOR SALE, reinforcing the idea that replacement is not the main motive for trade in the business-aircraft market.¹⁶

3. The fraction of aircraft sold should be lowest for the youngest vintages.

The reason is that, because of transaction costs, few households sell their assets one year after purchasing them.

The Aircraft Transaction database reports the AVERAGE AGE, AIRCRAFT FOR SALE, and I use it to investigate this prediction. However, the data are not ideally suited to investigate it because, as described in Section 4, they are aggregated at the modelquarter level. Hence, this aggregation could mask some important age heterogeneity between different aircraft for sale within each model-quarter pair. Nonetheless, I provide suggestive evidence by restricting the analysis to model-quarter pairs for which AIRCRAFT FOR SALE equals one: For this restricted sample, there is obviously no age heterogeneity within a model-year pair. Figure 7 plots the histogram of the age of aircraft for sale of this restricted sample, showing that the youngest vintages are frequently for sale. This pattern contradicts the evidence from other asset markets in which replacement purchases are the main motives for trade. For example, in the car market, the fraction of cars sold is lowest for the youngest vintages (Porter and Sattler, 1999; Stolyarov, 2002). Thus, while the sample restriction recommends some caution in putting too much weight on this evidence, Figure 7 further corroborates that replacement is not the main motive for trade.

¹⁵The number of observations in Table 7 is lower than those in Table 6 because AVERAGE AGE, AIRCRAFT FOR SALE is missing in years in which there are no aircraft for sale.

¹⁶The negative coefficient of LOG(ACTIVE AIRCRAFT) in the more-saturated specifications (8) and (12) is due to the fact that out-of-production aircraft are progressively scrapped as they age, thereby simultaneously decreasing ACTIVE AIRCRAFT and increasing the average age of the stock of aircraft.

	TABLE 7: The Effect of Depreciation on the Age of Aircraft for Sale												
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
7.	DEPRECIATION RATE	38.445	49.005	40.098	51.949	-34.172	5.347	-29.205	2.953	-37.154	5.223	-32.032	2.757
		(38.222)	(41.626)	(37.371)	(41.101)	(21.489)	(3.761)	(20.683)	(3.179)	(21.911)	(3.788)	(21.316)	(3.157)
	Log(Active Aircraft)			.9452	.8864			2.318	-1.390			2.359	-1.457
öo				(1.124)	(1.139)			(.477)	(.235)			(.529)	(.247)
	Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
	Model Effects	None	None	None	None	Random	Random	Random	Random	Fixed	Fixed	Fixed	Fixed
	Observations	851	851	851	851	851	851	851	851	851	851	851	851

Notes—Standard errors in parentheses are clustered at the model level.



FIG. 7: Histogram of the age of aircraft for sale.

B Computation of Standard Errors and Confidence Intervals

Section 4 reports that the two datasets are unbalanced panels: The transaction dataset includes $N_1 = 161$ models over $T_1 = 228$ months; the aircraft prices dataset includes $N_2 =$ 72 models over $T_2 = 57$ quarters. The aircraft price dataset also includes one additional dimension of variation: different vintages a of model i in year t.

For ease of comparability between the two datasets, I aggregate the transaction dataset at the quarterly level; hence, the estimation samples cover $T_2 = 57$ quarters. Overall, I have 8,737 observations about transactions and 30,706 observations about prices (i.e., 30,706 retail prices and 30,706 transaction prices). The numbers of observations, models and time periods indicate that the cross-sectional variability is larger than the time-series variability.

I assume that all of these observations are independent. Hence, from the transaction datasets, I compute the moments reported in Section 6.1 of the paper by aggregating the individual observations; for example, the aggregate fraction of aircraft for sale is computed as $\frac{\sum \text{AIRCRAFT FOR SALE}}{\sum \text{ACTIVE}}$. I compute the variance-covariance matrix of the empirical moments of each dataset correspondingly.

Moreover, in each of the 100 bootstrap replications, I draw with replacement 8,737 observations from the transaction dataset and 30,706 observations from price dataset. I estimate the parameters separately for each replication sample, and perform the counterfactuals with

these parameters. The reported confidence intervals consist of the third and the 98th percentiles of the distributions of these parameters.

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