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Endogenous Rigidities and Capital Misallocation: Evidence from Containerships^{*}

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Abstract

We investigate how endogenous rigidities inhibit physical capital reallocation. We focus on the role of contract duration - a classic example of an adjustment rigidity. We argue that when agents sign longer contracts in booms when markets are thin, they generate a contracting externality which further amplifies thinness and impedes the adjustment of markets to shocks. We develop a dynamic spatial framework with booms and busts where agents search and choose match duration. Applying the framework to the containership leasing market, we find substantial misallocation from endogenous rigidities, particularly in the transition after a crash.

JEL Classification: D22, D23, L14, L22, L91, R40

Keywords: capital misallocation, contract duration, contracting externalities, container shipping, search frictions

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1 Introduction

Physical capital reallocation between firms is a central channel by which the aggregate economy adjusts to booms and busts.¹ For many forms of physical capital — like ships, drilling rigs, heavy equipment, and aircraft — capital reallocation occurs in decentralized leasing markets where agents need to search for and match with trading partners. As a result, adjustment rigidities and frictions in these markets may be a cause of misallocation across the business cycle. However, due to limited data, less is known about the exact process of capital reallocation in specific settings.

In this paper we focus on rigidities in the form of fixed-term contracts in these leasing markets, which prevent immediate reallocation of capital to its optimal use after a shock. The key mechanism we explore is that these rigidities may emerge endogenously from how agents choose contract duration over the business cycle. The choice of duration balances the cost of lock-in to a match that turns bad (which favors a shorter contract) against the assurance value of avoiding search frictions associated with renewing a match (which favors a longer contract). In booms, as frictional leasing markets become thinner and it becomes more difficult to find a match, contracts may get longer. This then generates a contracting externality where even fewer assets are available and equilibrium contracts are too long in booms. The resulting contract overhang can inhibit efficient reallocation of capital in response to future shocks (e.g., if the boom turns into a bust).²

Our main research question is: what are the implications of endogenous rigidities for capital misallocation? We focus on the leased containership market, an excellent example of a decentralized market with fluctuations, and also important in its own right for global trade. We answer our research question in three steps.

First, we construct a novel dataset of firm-to-firm contracts and information about the underlying capital allocations, and use these data to show descriptive evidence consistent with the main mechanism we propose.³ Second, based on this evidence, we develop a new empirical dynamic matching framework with booms and busts, where spatially differentiated agents choose for *how long* to match. Third, using the framework, we quantify the extent of misallocation from the contracting externality.

The majority of world trade in goods takes place via containerships and about half of these ships are rented

¹For example, although aggregate data typically do not contain information on capital leasing markets (the focus of this paper), [Eisfeldt and Rampini \(2006\)](#) document that reallocation through sales of physical capital alone accounts for one quarter of total investment, and is pro-cyclical.

²Note that whether pro-cyclical contract duration is inefficient is ultimately an empirical question, as we discuss later, since how firms need to allocate their physical capital could systematically change in a way that favors a longer duration in booms.

³Unlike many firm-to-firm markets where individual contracts and other key data are often confidential (which has limited research progress), in our setting we have a rich dataset of contracts and allocations, including the exact location and amount of cargo that each ship is carrying.

under fixed-term contracts (UNCTAD, 2018). In this market charterers (such as ‘COSCO’) need to lease physical capital — the containerships — from shipowners (such as ‘Seaspan’). The leasing market is decentralized and fragmented on both sides, and several features point to the presence of search frictions: sizable price dispersion across observationally equivalent matches, ships simultaneously reallocating into and out of the same region, the widespread use of brokers, and the emergence of e-procurement. Charterers who lease ships allocate them to fixed scheduled routes, and transact with downstream exporters for container slots on their routes. Demand in the industry is cyclical, reflecting the global business cycle.

Shipowners and charterers use time-charter contracts, which involve a negotiated ‘day-rate’ for a given duration. Charterers specialize both geographically and in their relationships with downstream exporters, and so face idiosyncratic demand shocks which create opportunities for reallocation (especially following aggregate fluctuations). However, contract lock-in as well as search frictions impede reallocation.

We assemble a dataset of contracts and port calls from 2006-2015.⁴ Using these data we present four key empirical observations. First, we show that contract duration is pro-cyclical. This causes a substantial contract overhang after a crash, with charterers and ships locked into matches formed years previously in the boom. As well, we document that pro-cyclical contract duration is a feature across other physical capital markets where contract data are available, including drilling rigs, bulk shipping, and (anecdotally) aircraft.

Second, we show that reallocation is valuable because charterers are geographically specialized and face heterogeneous demand shocks that vary both across and within trade regions. Consistent with this mechanism, ships increase output after reallocating across routes, including during the downturn.

Third, we provide evidence consistent with the contract overhang impeding reallocation and generating misallocation. We find that observationally equivalent ships carry systematically different amounts of cargo — measured in both volume and value — within the same time period. This dispersion in ship utilization suggests misallocation; i.e., there are unexploited gains from reallocating ships to different firms.⁵ We then link these patterns to contract rigidities. Specifically, reallocations are significantly more likely to occur when a ship starts a new contract, suggesting longer contracts inhibit reallocation. In the 2008-2010 crash and transition, when the contract overhang is highest, dispersion jumps sharply. Furthermore, this rise in dispersion is largely concentrated among ships under contracts signed at least a year earlier.

⁴The year 2006 is the first time that systematic data are available on both ship positions and ship draft, while after 2015 there was consolidation of the industry into alliances; during the 2006-2015 period the global market was unconcentrated on both sides. Furthermore, in this period we observe fluctuations in market conditions.

⁵As we discuss in our counterfactuals, however, we need to estimate a model to say so conclusively because some dispersion may be consistent with (constrained) efficient contracts in the presence of search frictions.

Finally, we show that longer contracts are associated with thinner local markets in the cross-section, suggesting market thickness shapes contract duration. Consistent with local market thickness mattering for the matching process, we also find that charterers are more likely to match with nearby ships.

Based on this descriptive evidence, we build and estimate a spatial, dynamic model of the market. Charterers operate in different regions of the world and need to search and match with shipowners. In each region, charterers enter the market with a valuation of a match and a probability that this value expires idiosyncratically (i.e., falls to zero) in each period, both of which depend on the regional demand state. Thus charterers are subject to demand shocks that vary both across and within regions, consistent with the descriptive evidence. During booms there is a higher entry rate of charterers. Charterers target ships across regions, with the likelihood of matching with any given ship a function of distance. Matching depends on local market thickness and is subject to search frictions.

Upon meeting, agents choose a contract length to maximize the total surplus of the match, given their types and the demand states. Longer contracts avoid agents having to search again (and risk not being matched), but may cause lock-in if the match value expires before the end of the contract. After matching, the ship and charterer are removed from the market for the duration of the contract. Contracts generate externalities since the contract durations chosen by agents shape market thickness in future periods.

We estimate the model in two steps. In the first step we estimate demand for shipping services and recover the demand process in each region. In the second step we use simulated method of moments to estimate the structural parameters. The large state space (which includes the distribution of all matches under contract in each region of the world) in the second step results in a curse of dimensionality. We solve this by using a solution concept similar to a Moment-Based Markov Equilibrium ([Ifrach and Weintraub, 2017](#)). A key empirical challenge here that we overcome is disentangling time-varying match-specific factors that drive agents to sign longer contracts, from market thinness considerations.

We use the estimated model to quantify misallocation in the decentralized equilibrium. We solve for a constrained social planner who can set the optimal contract length for the entire market in each period to maximize the joint profits of the firms. This planner is still subject to search frictions and cannot predict the exact future realizations of demand shocks. The planner's tradeoff is similar to that faced by an individual pair, except they also internalize a thin/thick market externality. When a pair signs a longer contract, they delay their return to the search pool. In a frictional matching market, these duration choices change future market thickness and therefore the matching probabilities faced by other agents. While the private pair takes those future search pools as given, the planner internalizes them. This is the contract duration analogue of

the standard thin/thick market externality in search models ([Hosios, 1990](#); [Brancaccio et al., 2023](#)).

We find that, in booms, the planner would prefer to thicken the market with a shorter contract length than we see in the data. A shorter contract (in our estimated model) generates a negative ‘quantity effect’: agents return to the frictional search market more often and risk spending time unmatched, which reduces the total number of matches.⁶ On the other hand, a shorter contract also generates a positive ‘quality effect’ that reduces lock-in to bad matches. During a boom, when there are many available charterers, the risk of a ship being unmatched is low, so the quality effect dominates. As a result, the optimal contract length is counter-cyclical, in stark contrast to the decentralized equilibrium.⁷

Overall, misallocation due to the contracting externality is 12.9% on average, measured in lost joint profits to the firms. This average number masks substantial changes over the cycle. Misallocation rises in a boom and is highest (19.6%) at the start of the 2008 crash, when the market transitions from a boom to a bust but agents are locked into long contracts. In other words, the supply chain rigidities that result from the observed long contract overhang in booms are also inefficient.

We also simulate an intermediary (in the form of a centralized platform) that can eliminate search frictions. This induces agents to sign much shorter contracts, by lowering the risk of remaining unmatched once a contract ends. As a result, the intermediary raises welfare by 32.9%, whereas the welfare gain would be only 7.0% if contract duration were held fixed. The value of intermediation thus comes primarily from its indirect effect of shortening equilibrium contracts and thereby reducing the contracting externality, rather than through direct reductions in search frictions.

1.1 Related literature and contributions

This paper is related to several strands of literature. The first is about the inner workings of decentralized asset markets. Some of these papers highlight the role of search frictions and market thinness in determining efficient allocations (e.g., [Gavazza \(2011a\)](#), [Gavazza \(2011b\)](#), [Gavazza \(2016\)](#)). Other papers study how capital reallocation determines efficient allocations (e.g., [Lanteri and Rampini \(2023\)](#), and [Vreugdenhil \(2026\)](#)); and the role of adjustment costs in capital reallocation more generally (e.g., [Asker et al. \(2014\)](#)). Our main contribution here is that we are the first (to our knowledge) to shed light on the role of equilibrium contract duration in causing capital misallocation.

⁶ With increasing returns to scale in matching, a shorter contract could in theory thicken the market enough to raise ship match rates. Our baseline analysis employs a constant returns matching technology, but we show in Appendix [D.3](#) that our results are robust to increasing returns.

⁷ Note that this is ultimately an empirical finding, since we also allow for time-varying match-specific factors that could (in principle) have caused the optimal contract length to increase in booms.

The second strand is the literature that investigates the empirical determinants and effects of contractual form (e.g., [Hubbard \(2001\)](#), [MacKay \(2022\)](#), [Darmouni et al. \(2026\)](#)). Our paper aims to understand the complete equilibrium effect of contract duration, which operates through a contracting externality, whereas this literature has primarily focused on partial equilibrium analyses.

There are two main exceptions which consider the broader equilibrium effects of organizational form. First, [Harris and Nguyen \(2025\)](#) explore how long-term relationships in the trucking industry increase spot market frictions. Our results are complementary, but the economics of our paper are different. Concretely, unlike relationships — where there is no commitment — we focus on the choice of contract duration with two-sided commitment in booms and busts. With commitment, long contracts formed in a boom can persist well into a bust, inhibiting reallocation when one party is locked in to the match. The second exception is [Zahur \(2025\)](#), which incorporates contracting externalities in a downstream spot market and studies the role of contracts in mitigating under-investment. Our focus is different: we study a cyclical decentralized market with search frictions, and quantify how the choice of contract duration causes misallocation in booms and busts.

More broadly, models of contract duration in search and matching frameworks in labor economics consider settings where there is one-sided commitment, since employees cannot be forced to work.⁸ Physical capital markets involve agreements between two firms, and so can operate quite differently with two-sided commitment and explicit agreements over duration.

Third, this paper is related to the literature in industrial organization that studies search-and-matching markets, particularly in the transportation sector. Recent examples include [Fréchette et al. \(2019\)](#), [Brancaccio et al. \(2020\)](#), [Buchholz \(2022\)](#), [Gaineddenova \(2022\)](#), [Brancaccio et al. \(2023\)](#), [Castillo \(2025\)](#), [Rosaia \(2025\)](#), and [Yang \(2026\)](#). Many of these papers are centered on markets like taxis or bulk shipping, where a match typically involves a single trip of a specific duration. By contrast, in markets such as air transport or container shipping, matches last longer, and so agents use fixed-term contracts. In these markets, the choice of match duration – which is the central choice of agents in our framework – is first-order.

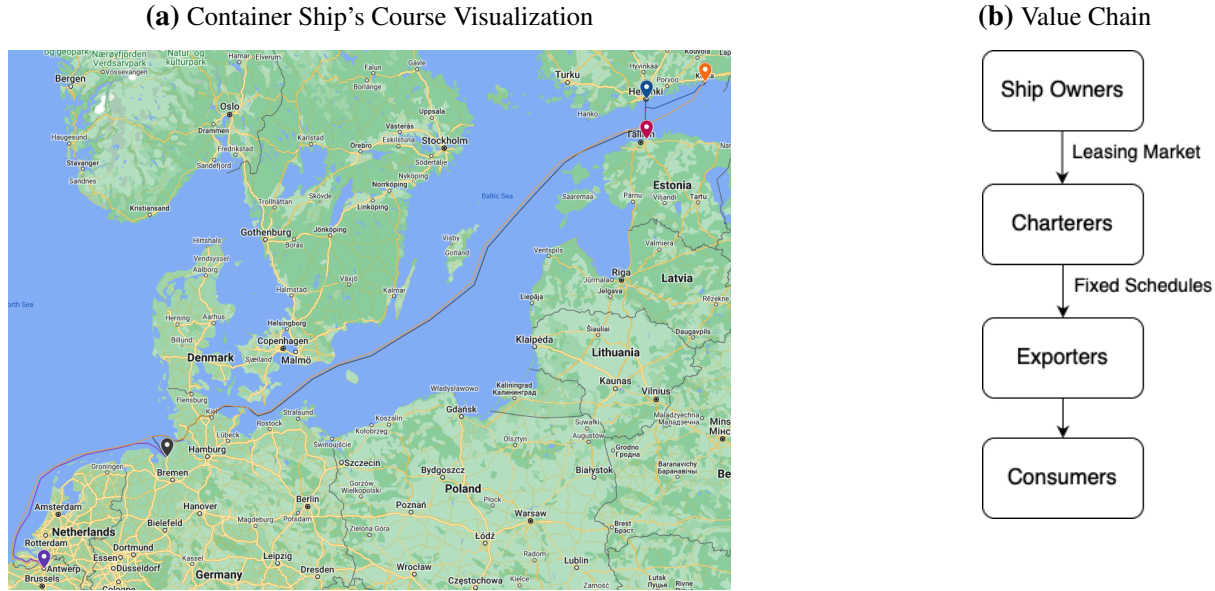
Finally, the paper extends the literature that studies shipping markets. These papers include [Kalouptside \(2014\)](#), [Kalouptside \(2018\)](#), [Jeon \(2022\)](#), [Ganapati et al. \(2024\)](#), [Brancaccio et al. \(2024\)](#), among others. Our paper incorporates key institutional details of these markets (like search frictions), but our focus is quite different in that we study trade in the fixed-term leasing market in booms and busts.

⁸Therefore, contracts must be carefully designed to retain workers with one-sided commitment in mind (e.g., [Balke and Lamadon, 2022](#)).

2 Container shipping industry

Our analysis focuses on the global container shipping industry. Containerships can be thought of as the ‘buses of the ocean’, typically operating on fixed schedules where they pass through a designated set of ports.⁹ At each port a ship drops off and picks up a portion of its containerized cargo. Figure 1a presents a map with the route for one of the containerships in our sample.

Figure 1: Container Shipping Industry Structure



Note: Panel (a): This shows a geographical map of a ship in our data performing its scheduled stops. The ship has the following schedule: Antwerp - Bremerhaven - Muuga - Helsinki - Kotka - Antwerp. Panel (b): One component not pictured (but mentioned in the text) is that charterers can also own ships (in addition to leasing them) and allocate them to fixed schedules downstream.

The value chain of the maritime shipping industry can be visualized in Figure 1b. Cargo owners (or exporters) are the enterprises that use maritime transport providers and other suppliers of services to import/export their cargo. Containerships are operated by carriers (also known as liner companies) that specialize in the transport of containerized goods across the world (for example, COSCO). Carriers compete by setting up shipping schedules along a series of ports. As we document later, carriers typically specialize geographically.

About half the containerships in the world are owned by the carriers themselves; these “owner-operated ships” are rarely leased out to other companies, and form the core of the fleet of carriers. As we show in Figure C.3 in the Appendix, this share has remained relatively stable over time.¹⁰ The remaining “charter-

⁹This is in contrast to the dry bulk shipping industry, where ships operate more like taxi cabs and make voyage decisions on a trip-by-trip basis, often travelling in “ballast” without any cargo at all (Brancaccio et al., 2020).

¹⁰Similarly, this roughly even split persists even if we split ships by size, in terms of below/above the median capacity (the leasing share is 48% and 51% respectively), or in terms of below/above the median age (here the leasing share is 53% and 47% respectively). The stability of the leased share over time as well as within these subsets motivates our choice to not include the decision to own versus lease a ship as a margin for adjustment in the model.

operated ships" are owned by shipping companies (who we refer to as "shipowners") that do not themselves provide container shipping services, but instead specialize in leasing out these ships to the carriers (or "charterers"). It is this leasing market that we focus on.¹¹

Since containerships are a highly movable form of capital, practitioners treat the leasing market as global. Consistent with this, prices of new leasing contracts are highly correlated across regions (Appendix Figure C.5). However, this does not mean that every ship is equally easy to lease at every point in time. For example, a ship that is more distant from the charterer's intended route must reposition farther before starting the contract, losing time in transit. Thus, we treat the leasing market as globally connected but locally imperfectly integrated: agents can search across regions, but local availability still affects match probabilities.

The market is unconcentrated and fragmented, with a large number of agents searching on both sides of the market.¹² During our 2006–2015 study period, we compute the charterer and shipowner Herfindahl–Hirschman Indices (HHIs) from each firm's annual share of active contracts. The HHI is 365 for charterers and 75 for shipowners that lease out their ships. Note that since 2015 — outside the period of our study — many charterers have consolidated into alliances. So, in order to focus on a period during which the market structure was relatively constant, we limit the scope of our analysis to before this period.¹³

2.1 Leasing contracts

Shipowners lease to charterers using time-charter contracts. These contracts are relatively simple and follow a standard template called 'Boxtime 2004' (BIMCO, 2004). Each contract specifies a 'dayrate' (the price per day to lease the ship that the charterer pays the shipowner) for a specified duration. Shipowners pay the operating costs of the vessel (i.e. the crew, maintenance and repair), while charterers pay voyage expenses (i.e. bunker fuel, port charges, canal dues, and cargo-handling costs). Note that contracts do not restrict the routes to which charterers can allocate the ship.

¹¹ The leasing market emerged over the 1980s and 1990s; by around the mid-1990s, 40 percent of container ship capacity was chartered. This expansion reflected both demand- and supply-side forces: on the demand side, carriers turned to chartering to scale capacity beyond their balance sheet constraints (Stopford, 2009); on the supply side, German tax policy attracted substantial private capital into ship ownership (Johns and Sturm, 2014). During our sample period, which carriers charter largely reflects stable differences in their business models. For example, some simply specialize in selling transport services to downstream exporters; under a time charter, vessel financing, crewing, and maintenance remain with the owner (Stopford, 2009).

¹² This is in contrast to downstream container shipping markets, which are regionally segmented and therefore more concentrated. In these markets, carriers are able to exercise significant market power when transacting with exporting firms, as shown by Hummels et al. (2009) and Ardelean and Lugovskyy (2023).

¹³ There did exist alliances in the 2006–2015 period (e.g., the G6 alliance formed in 2012), but these were relatively small. Re-computing the HHI for the charterers based on alliances only increases the index to 425 from 365. Furthermore, in Appendix A.11 we show that charterer concentration (accounting for alliances) remains low throughout the sample period. We also show that concentration remains low when we segment by ship size, age, and region. As a result, we abstract away from these alliances or market power considerations in our analysis.

Subleasing is rare In theory, charterers can sublet leased ships to other carriers. In practice, subleases are rare and account for only 2.5 percent of all contracts (Appendix A.10). Three institutional factors suggest why subleasing is not widely used. First, the point in the cycle where charterers would most like to sublease the ship — when a boom transitions to a bust and they are locked into a match — is exactly the point where other charterers do not need a ship. Second, even if the market is currently in a boom, charterers are generally unwilling to sublease to their competitors in the downstream shipping market (see, for example, Wackett (2021)). Third, subleasing requires charterers to operate on the other side of the leasing market, with which they may not be experienced.

Extensions Contracts can be extended. However, contracts typically do not have explicit options for extensions: only 2.9% of contracts provide charterers a formal option to renew (Appendix A.9).¹⁴ Instead, these extensions are negotiated on an individual basis by the charterer and the owner if the ship does not have a subsequent contract. Similarly, contracts almost always do not include clauses for re-negotiation; any re-negotiations (such as an early termination) must be agreed to by both the shipowner and charterer, and are reportedly rare.¹⁵

2.2 Reallocations

There are two types of reallocation in this industry. The first is the reallocation of a ship between different charterers, which occurs across contracts. The second is the physical reallocation of a ship to different routes, which, in theory, could happen within or across contracts. However, as we later show in Section 4.3, the physical reallocation of a ship often coincides with a contractual reallocation. This is not surprising since charterers typically follow fixed shipping itineraries that they only infrequently adjust (Stopford, 2009). We discuss further in Section 4.2 what generates profitable opportunities for reallocation in this industry. Reallocating a ship incurs an adjustment cost in the form of lost time as the ship moves to its new schedule.

3 Data

We use two main data sources. The first is a dataset on containership time-charter contracts from Clarksons. Our full dataset covers the period from 1999 to 2022. Importantly, we only observe a subset of all the contracts in the market. However, these contract data are obtained broadly from the market and so are arguably

¹⁴In direct correspondence, Clarksons confirmed that in the containership sector it is “much more common for consecutive fixture periods to be negotiated as an extension at a later date rather than included as an optional period initially,” suggesting the low incidence of recorded options is a feature of the market rather than a data limitation.

¹⁵We are only aware of a handful of cases of early termination by mutual consent where the charterer was faced with financial difficulties: see Miller (2023).

representative.¹⁶ Furthermore, in Appendix Section [A.1.1](#) we show that we observe 82 percent of ships in the contract subsample and that ship covariates are similar between the subsample and the population. We provide more details about how Clarksons collects these contracts, the dataset construction, and how we merge contracts with shipping movement data, in Appendix [A.1](#).

In the data we use for analysis, we exclude 4.2% of ships that are Post-Panamax or larger (i.e., above 5,000 twenty-foot equivalent unit (TEU) in capacity), so that the resulting sample is relatively homogeneous in terms of ship size. Post-Panamax vessels are commonly analyzed as a distinct segment of the containership market by industry practitioners ([U.S. Maritime Administration, 2013](#)). We also exclude 6.2% of the contracts that are by newly built ships, since we do not model the use of contracts as collateral to obtain cheaper financing terms (we discuss this further in Section [4.1.1](#)). Likewise, we exclude a very small number of contracts longer than 10 years (about 0.06% of the sample), as some of them may be “capital leases” where the charterer acquires the ship upon contract expiry ([Gavazza, 2010](#)). In the contract dataset there are 1,354 unique ships, out of a total population of 1,643 leased ships (excluding new and large ships), and we observe around 2 contracts per ship. The resulting sample features ships that are relatively substitutable, as further evidenced by the fact that individual charterers lease ships of different sizes and ages rather than confining themselves to a single segment.¹⁷

Around 42.0 percent of contracts are extensions, which is a similar number to [Vreugdenhil \(2026\)](#), who studies another frictional capital market. We explain how we identify extensions in Appendix Section [A.9](#); our procedure considers cases where we observe sequential contracts for the same ship and measures the fraction of contracts that retain the same charterer.

The other key dataset we utilize in our analysis is port call data from the second quarter of 2006 (which is the earliest date for which systematic data on “draft” are available) through 2015 provided by Lloyd’s List Intelligence. This dataset contains the universe of port calls, including the dates of arrival and sailing, and the ports visited on each call. For a subset of port calls, we also observe the ship’s “draft”: the vertical distance between the waterline and the bottom of the hull. A ship that is carrying more cargo will sink deeper into the water, so we use draft data to measure capacity utilization (following [Heiland et al. \(2025\)](#)). Specifically,

¹⁶Clarksons also acts as a contract broker. Therefore, one may be concerned that they only report contracts from their own brokerage. However, we emailed Clarksons: they confirmed this is not the case and the contract data are “...not limited to [Clarksons’] own fixtures”.

¹⁷We run regressions of the ship size/build year on charterer fixed effects using the contract-level data, and find that charterer fixed effects explain only 25.9% of the variation in leased ship size and 16.5% of the variation in build year in our contract sample. Consistent with this, we find that 58.2% of charterers lease both small and large ships, and 74% lease both newer and older ships (where we divide ships into small/large using the median capacity, and old/new ships based on the median age); these estimates are likely conservative since we only observe a subset of contracts for each charterer.

we normalize the observed draft by the ship’s draft when empty and its draft when fully loaded, yielding a utilization measure that ranges from 0 (empty) to 1 (fully loaded) (see Appendix A.3 for details). We also compute the share of ships not under contract using the port call data and the sample of contracts. We classify a ship as idle when it stays in port beyond the time needed to unload and load; we then back out the share of ships without a contract from the overall idle share, adjusting for the fact that ships under contract may also occasionally be idle (Appendix A.4 provides details).¹⁸

Similarly to the contract dataset, we exclude large and newly built ships from the port call dataset. For consistency, we also exclude any port calls for ships not matched at least once in our contracts subsample. Overall, our port call dataset includes 989,272 port calls, with 187,966 of them matched with contract data.¹⁹ In addition, as a proxy for aggregate demand, we use the containership time-charter rate index, a monthly index published by Clarksons based on their assessments of the rates of newly negotiated time-charters. We provide more details about how this index is constructed in Appendix Section A.1.2. Table 1 provides descriptive statistics on the duration of the contracts, dayrates (contract price), age of the ships contracted, and capacity utilization from our sample period that runs from the third quarter of 2006 through 2015 (with the second quarter of 2006 serving as a burn-in period in order to calculate dispersion in utilization, as we explain further below in Section 3.3).

3.1 Reallocations

We use the port call data to identify when a ship reallocates from one itinerary to another. This is challenging since we do not directly observe shipping itineraries in our raw data. Instead, what we observe are repeated sequences of port calls. We identify reallocations as large deviations across space from old port call sequences to a new set of port call sequences, using a threshold of 1000 km to define large deviations. Because a move to a new schedule often generates several such deviations in quick succession, we count only the first deviation and exclude any subsequent deviations that happen within three months of an initial reallocation.

We describe the algorithm for detecting reallocations in Appendix A.5. The threshold of 1000 km is not especially restrictive as ships are often moved across large geographical distances when they begin a new itinerary. The average distance when a ship is reallocated is 3436 km, and 26.7% of reallocations involve a deviation of more than 4000 km.

¹⁸We also compute idle rates for a subset of the owned ship market in Appendix A.4. We find that this idle rate is relatively similar to that for leased ships.

¹⁹ As we discuss further in Appendix Section A.1 this matched share of port calls is relatively similar to the share of time a non-idle ship appears in the contracts subsample.

Table 1: Summary statistics for the dataset

Variable	Obs	Mean	SD	Min	Q25	Q50	Q75	Max
Panel A: Contract-level variables								
Duration (months)	2704	7.4	6.6	0.2	3.0	6.0	10.0	84.0
Dayrate (thousands \$/day)	2701	8.8	4.6	2.8	6.0	7.4	10.4	33.0
Ship age (years)	2704	9.2	5.5	1.0	5.0	9.0	13.0	29.0
Panel B: Port-call variables								
Capacity utilization	676837	0.53	0.23	0.00	0.37	0.55	0.71	1.00
Reallocation	989272	0.01	0.08	0.00	0.00	0.00	0.00	1.00
Panel C: Aggregate variables								
Time-charter rate index	114	62.0	26.2	32.0	43.9	47.6	75.1	116.3
Share of ships under contract	114	0.94	0.03	0.86	0.93	0.95	0.96	0.98
Dispersion - quantity measure	114	12.3	1.7	10.1	11.2	11.7	13.7	16.5
Dispersion - revenue measure	114	14.2	2.1	10.5	12.7	13.9	15.3	19.7

Note: Panel A reports summary statistics for the contract data, where each observation is a leasing contract. Panel B reports port call summary statistics, where each observation is a single port call for a ship. We measure capacity utilization only for the subset of port calls that report the ship’s draft. Finally, Panel C reports summary statistics for aggregate variables, with each observation a year-month. We describe how we construct the quantity and revenue-based measures of dispersion in Section 3.3; we multiply the quantity dispersion measure by 100 to ensure it is in comparable units to the revenue measure which uses an index normalized to 100 in the baseline year.

3.2 Routes and Trade Regions

The algorithm for detecting reallocations also identifies which schedule a ship is on, since all port calls between successive reallocations must belong to the same schedule. We group together schedules that are geographically very similar into *routes*. We count the top 3 countries that are most visited by the ship during the schedule; schedules that share the same set of top 3 countries are defined as having the same route.²⁰

We then further aggregate routes to *trade regions*. A trade region is a collection of routes that are close to each other geographically. In practice, we classify all the routes into eight trade regions: Asia - Europe, Europe - North America, Asia - North America, Intra-Asia, Intra-Europe, Americas, Middle East and Africa, and Others (see Appendix A.6).

We make the distinction between routes and trade regions to capture different spatial levels at which demand shocks may materialize. A bilateral tariff shock, for example, will primarily affect routes connecting the two countries involved; whereas a broader regional economic shock may affect all routes in a trade region.

²⁰In practice, two ships that cycle through the same countries may visit different ports (e.g. Shanghai - Brisbane - Seattle vs. Shanghai - Melbourne - LA), but we abstract from such heterogeneity to keep the definition of a route relatively tractable.

3.3 Dispersion in capacity utilization and misallocation

We provide evidence consistent with misallocation by considering cross-sectional dispersion in capacity utilization for observationally equivalent ships. If a ship leased to charterer A is systematically under-utilized compared to an otherwise equivalent ship leased to a different charterer B, this is arguably indicative of misallocation – industry output would increase if the first ship were reallocated from charterer A to B. This is similar to how practitioners view fleet efficiency in the industry e.g., [Adland et al. \(2018\)](#) and [UNCTAD \(2010\)](#).

We address three issues to operationalize this argument empirically. First, due to cargo imbalances, the amount of cargo a ship is carrying may differ across port calls depending on which direction of the route the ship is traveling on and which port it is visiting.²¹ This is known as the ‘round trip effect’ ([Wong, 2022](#)). To deal with this, we aggregate utilization by calculating a 90-day moving average of each ship’s utilization: while a ship’s utilization on a given port call may vary due to cargo imbalances, these cargo imbalances average out when we aggregate over a sufficiently high number of port calls, and across a 90-day period, each ship will have completed at least one round trip.²² Furthermore, the allocation decision for charterers is really about which sequence of port calls to allocate a ship to, rather than an individual trip, and our more aggregated measure reflects this choice.

Second, ships may differ in capacity utilization due to underlying characteristics such as size and fuel efficiency. Therefore, we residualize the capacity utilization of each ship by ship fixed effects. Third, capacity utilization varies over time with aggregate demand. As a result, we compute the cross-sectional standard deviation of residualized capacity utilization in each month. This nets out the effect of any time-varying changes in the aggregate demand. As such, dispersion within a time period in this measure indicates that there are more productive matches available, but ships are not matched to them, which is consistent with misallocation.

Revenue dispersion We also obtain a revenue-based measure of dispersion in utilization because downstream exporter prices may be heterogeneous across routes. Therefore, in theory, it may be efficient to deploy ships on routes where these prices are high, regardless of physical utilization. To construct our measure

²¹For instance, on the Trans-Pacific trade region, there is typically considerably more demand when ships are traveling from Asia to North America than in the reverse direction.

²²As a robustness check, we also aggregate utilization by looking at dispersion in the top quartile of the utilization of the ship in its previous 90 days. This is motivated by the idea that if a ship is traveling fully loaded on one leg of its schedule, it might be efficiently deployed even if it is underutilized on the other legs of its residual itinerary. We report results for the top-quartile measure in Appendix Table D.4 and find they are qualitatively similar to our baseline results; using maximum utilization over the previous 90 days yields the same conclusion.

we multiply residualized capacity utilization by the freight rate of the itinerary the ship is currently operating on (Appendix Section A.7 provides more details). We then measure dispersion in the revenue across ships within the same time period. As we discuss further in Section 4.3, our results are similar regardless of whether we use physical or revenue-based dispersion in residualized capacity utilization.

Interpretation as misallocation Although dispersion in utilization for observationally equivalent ships is suggestive of misallocation, note that later we also consider other explanations for this dispersion that would be consistent with an efficient market. For example, in Section 4 we consider whether dispersion is driven by regional shocks and there are high adjustment costs to reallocating ships, as well as other possible explanations. Furthermore, since our framework in Section 5 allows for adjustment costs and search frictions, it is an empirical question about whether longer contracts that generate dispersion are socially optimal. Based on this idea we quantify the degree of “inefficient” dispersion later in the counterfactuals in Section 8.

3.4 Search frictions

Five features point to significant search frictions in the containership leasing market.²³ The first is substantial price dispersion for observationally equivalent matches in the same region, which we document in detail in Appendix Section A.15. The logic is that in the absence of search frictions, the ‘law of one price’ should hold, so we should observe relatively little price dispersion for similar matches.

Second, in an exercise inspired by Brancaccio et al. (2023), we show evidence of simultaneous arrivals and departures of ships reallocating as they begin new contracts. Specifically, we document in Appendix Section A.15 that a sizable share of regions simultaneously experience ships arriving to begin new contracts and ships departing to start contracts elsewhere. Furthermore, we also show the existence of *reallocation cycles*. The most common such cycles are two-way cycles where during the same month, some ships reallocate from region A to region B while others reallocate in the opposite direction ($A \rightarrow B \rightarrow A$); but other types of cycles also exist (such as $A \rightarrow B \rightarrow C \rightarrow A$, or $A \rightarrow B \rightarrow C \rightarrow D \rightarrow A$). These patterns are unlikely to be compatible with a frictionless matching process and suggest the presence of search frictions.

The third is the presence of specialized ship brokers, such as Bertling, Clarksons, and Maersk Broker. Since the market is fragmented with a large number of agents searching on both sides, these brokers undertake matching on behalf of their shipowner and charterer clients. Typical commission fees equal 1.25% of the total payment made under the contract (i.e., the dayrate times the duration of the contract).²⁴ While the

²³Similar details have been documented as evidence for search frictions in other markets for maritime vessels like bulk shipping (Brancaccio et al., 2020), and oil and gas rigs (Vreugdenhil, 2026).

²⁴See, for example, Smith (2019) and Seaspan Corporation (2014).

empirical model that we develop later abstracts from broker commissions, Appendix D.2 reports a robustness check that incorporates these commissions into the model.²⁵

A fourth feature is that the matching process is unstructured — that is, there is no centralized platform — leading to instances where matches do not form despite searching agents on both sides of the market. Information about available ships and searching charterers is usually shared via e-mail, and brokers receive a large number of e-mails each day.²⁶ As one manager in the industry observed: “Many shipping companies face e-mail overload - literally hundreds or thousands of e-mails each day. Failing to catch key operational information or an urgent e-mail from a broker can have a toll on a business” ([The Maritime Executive, 2014](#)).

Finally, since the end of our study period in 2015, there have been attempts to use technology to improve matching. Participants have begun to create online centralized platforms (sometimes marketed as an ‘Uber for ships’) to better connect ships and charterers.²⁷ The development of these platforms suggests inefficiencies in the matching process during the study period. Such platforms have yet to be widely adopted in the container shipping industry, however.²⁸ In our counterfactual analysis, we simulate the welfare gains from a centralized platform that can eliminate search frictions.

4 Descriptive evidence

We describe four key empirical observations that underlie our analysis.

4.1 Observation 1: New contract duration increases in booms, leading to substantial contract overhang after a market crash.

Figure 2 shows how the average duration of newly signed leasing contracts changes over time. In the same figure, we also plot the containership ‘timecharter rate index’, which is a measure used within the industry to index whether the market is in a boom or a bust.²⁹ The market is highly cyclical and firms sign significantly longer contracts during booms. This effect is especially pronounced during the boom in the mid-2000s, when the average duration of newly signed contracts increases from 8 months to more than 24 months.

²⁵While brokers may have incentives to influence contract terms, analogous to the steering documented in residential real estate brokerage ([Barwick et al., 2017](#)), this concern is limited in our setting for two reasons. First, unlike homebuyers who transact infrequently and have limited market knowledge, charterers and shipowners are sophisticated repeat players who negotiate these contracts regularly and are unlikely to be steered into suboptimal arrangements. Second, brokers rely on repeat business from these same experienced counterparties, so reputation concerns further align broker incentives with those of their clients.

²⁶This is not unique to the container shipping leasing market: [Brancaccio et al. \(2023\)](#) discuss how brokers in the dry bulk industry report receiving many thousands of emails every day.

²⁷See [Smith \(2019\)](#) for a description of these platforms and the connection with Uber’s marketplace.

²⁸Consistent with this, utilization rates for the ships in our sample did not increase after 2015: the average utilization rate was 0.53 from 2011-2015 and 0.51 between 2016-2019. Furthermore, mean utilization does not trend upward towards the end of our sample (Appendix Figure C.6), which is also consistent with other institutional details like the market remaining relatively unconsolidated during our sample period which ends in 2015 (Appendix A.11).

²⁹Note that later in the model we directly estimate the demand process rather than use the price index.

Furthermore, the correlation in Figure 2 is robust to controls (Appendix Table A.13), and is not driven by a few unusually long contracts, since we see the same pattern if we plot the median contract duration over time (Appendix Figure C.1). The correlation is also robust to alternative measures of demand in the industry (Appendix Figure A.1). Lastly, it is not driven by longer contracts simply fetching higher prices and therefore leading to a higher time-charter index in booms (Appendix Section A.2).

Figure 2: Average duration over the cycle: new vs existing contracts

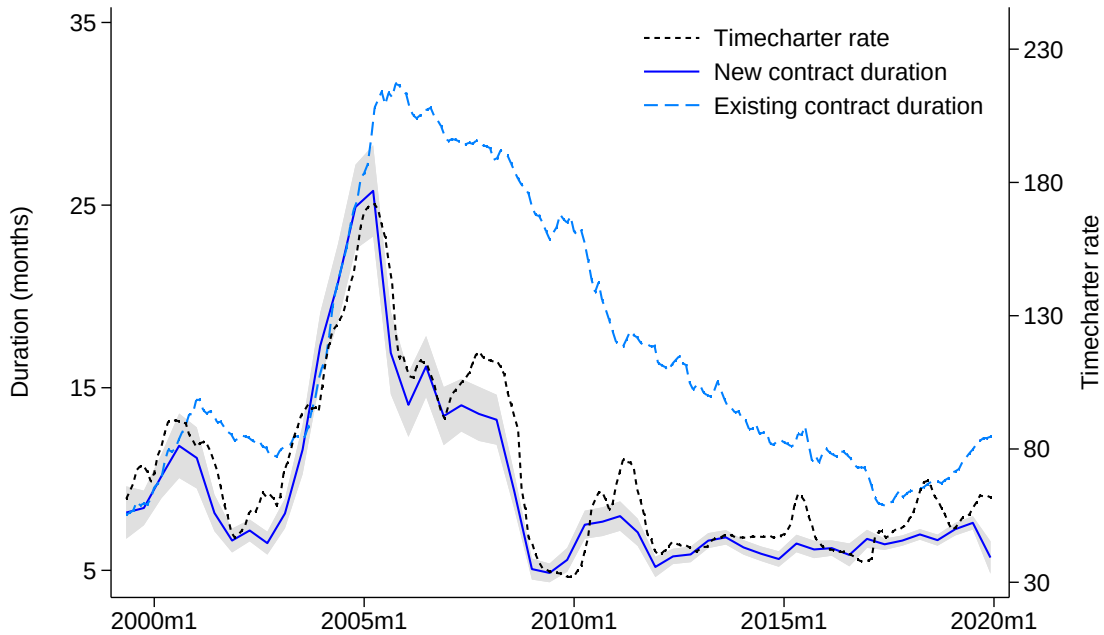


Figure 2 also plots the duration of all existing contracts at each time period. This illustrates the long-run effects of a boom when there is pro-cyclical contract duration. Concretely, the boom causes an overhang of existing contracts (and the corresponding matches) that persists for years after the market crashes. The difference between new versus existing contracts is most pronounced during the “Great Trade Collapse” of 2008 - 2010.³⁰ We discuss below how this contract overhang affected the reallocation of physical capital in the market.

4.1.1 Alternative explanations for pro-cyclical contract duration

Insurance motives Firms may prefer longer lease contracts to manage risk. Longer contracts guard against the risk of not being able to find another match upon contract expiry, which is a core mechanism that we focus on and explicitly model. In addition, longer contracts may also be used to hedge against price risk,

³⁰One may ask how the existing contract duration can be above the maximum value of the mean contract duration. This is due to (i) dispersion in contract duration around the mean and (ii) mechanical effects where short-term contracts expire sooner but longer contracts persist. We provide a numerical example of this phenomenon in Appendix A.17.1. This dispersion in contract durations is also why the overhang from 2005 partially lasts until at least 2010.

a channel not present in our model, since we assume risk-neutral firms. We make this assumption since shipping firms have ready access to financial derivatives (such as forward freight agreements) for price risk mitigation (Adland et al., 2020). Furthermore, if hedging against price risks were a central driver of pro-cyclical duration, we would expect prices of longer contracts to be less cyclical (and less volatile) than prices of shorter contracts; as Appendix Figure C.4 shows, however, the prices of long and short contracts are similarly pro-cyclical.

Obtaining finance for new ships Some shipowners sign long-term leasing contracts with charterers when they acquire new ships, since the guaranteed contract revenue allows them to obtain external finance at a cheaper cost.³¹ This suggests a potential alternative explanation for pro-cyclical contract duration: during booms, demand for new ships rises, and lease contracts lengthen to facilitate financing. However, as previously discussed in Section 3, we drop contracts for new ships from our sample. Furthermore, the pro-cyclical lengthening of contracts is of the same magnitude even if we control for ship age (Appendix Table A.13).

4.1.2 Evidence for pro-cyclical contract duration in other physical capital markets

In Figure 3 we document that pro-cyclical contract duration is a feature of a wider range of physical capital markets than just our primary setting of containerships. We choose these markets (bulk shipping, drilling rigs) because they have systematic time-series data on contracts (which are usually confidential in firm-to-firm markets) and are important markets in their own right. In Appendix A.16 we also provide anecdotal evidence from other markets (e.g. aircraft), as well as data sources and further details for this Figure.

4.2 Observation 2: Reallocation is valuable because of geographic specialization and heterogeneous demand shocks

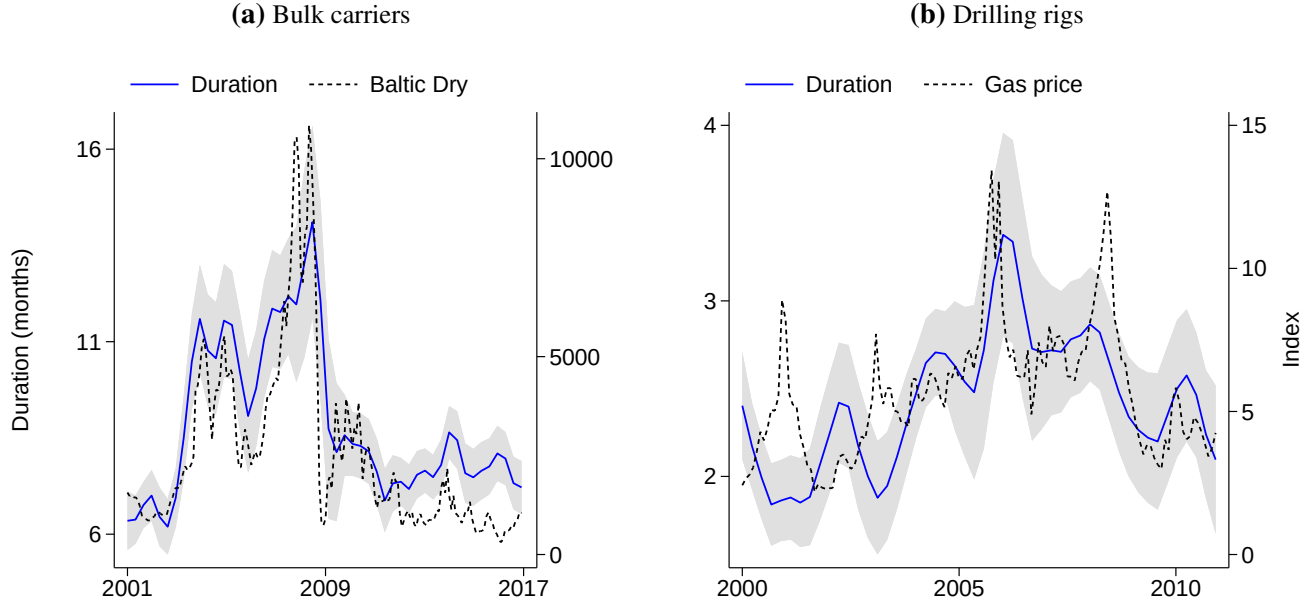
A key reason across-firm reallocations are valuable is that charterers are geographically specialized. In Appendix Section A.12, we document that most charterers only operate in a single trade region, and further specialize to a limited set of routes within that region. This is consistent with the industry feature that it is costly to establish new liner services (Haralambides, 2019).

This geographic specialization exposes different firms to different local shocks. As we demonstrate in Appendix B.3, demand shocks are heterogeneous across trade regions, and even more so across routes. Global shocks explain 13.6% of the monthly variation in regional demand shocks, and just 4.6% at the route level. As a result, reallocation is valuable when a ship moves from a charterer with a bad shock who no longer needs a ship, to a charterer who does need a ship.³² As well, even within a route, charterers have heteroge-

³¹One example is described in Jiang (2018).

³²We show in Appendix Section A.14 that most new contracts are generated from existing charterers entering new

Figure 3: Contract duration over the business cycle for other physical capital markets



Note: See Appendix A.16 for data sources and more details. In the left-hand-side panel, the ‘Baltic Dry Index’ is the most commonly used shipping freight rate index for bulk shipping and is indicative of whether the market is in a boom or bust. In the right-hand-side panel, the natural gas price is a commonly-used indicator for the business cycle in the market for offshore shallow-water drilling rigs, with higher prices corresponding to a ‘boom’.

neous relationships with downstream exporters (Ardelean and Lugovskyy, 2023) which can further expose them to idiosyncratic shocks.³³ On the other hand, Appendix Section A.19 shows that charterer scale has little relationship with ship utilization, and so is unlikely to be a source of gains from reallocation.

We provide direct evidence that reallocation of ships is valuable in Appendix Table D.5. We find that reallocations of ships across routes significantly increase output, even during the downturn. This finding is robust to measuring output in terms of physical quantity as well as total revenue.

4.3 Observation 3: Evidence consistent with contract overhang inhibiting reallocation

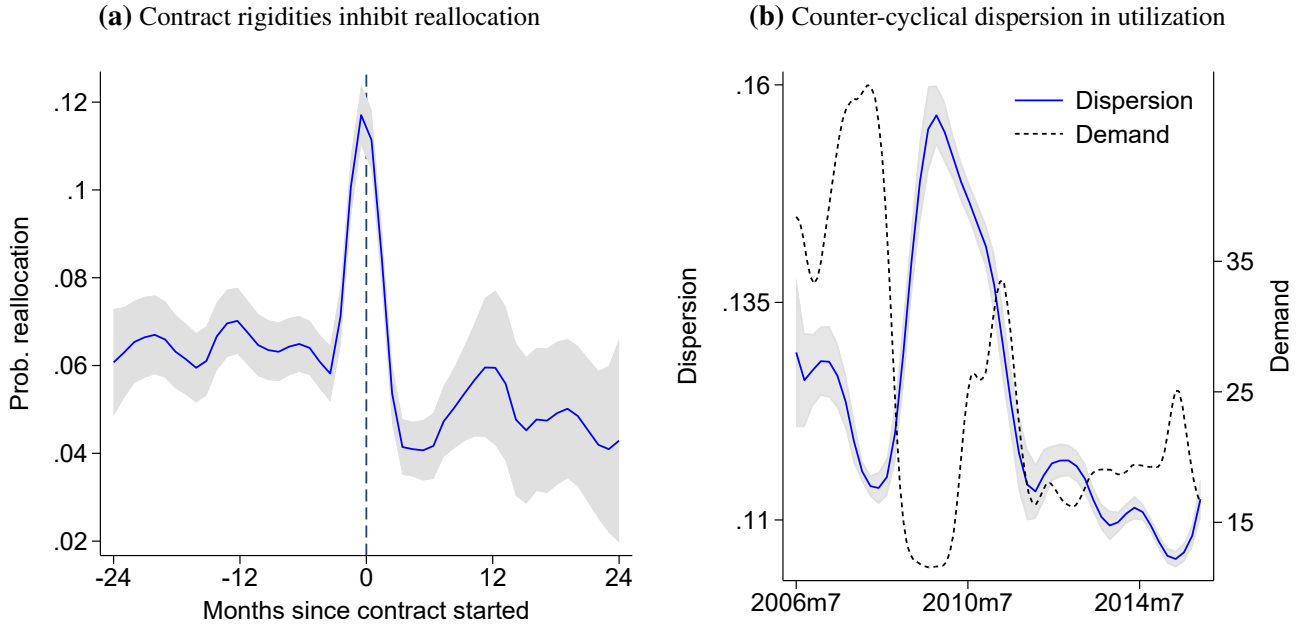
Contract rigidities inhibit reallocation We document evidence that contracting rigidities prevent the immediate reallocation of ships. To do this, we look at how the probability that a ship is reallocated to a different itinerary changes over the lifetime of a contract. If contracts did not inhibit reallocation, one would expect reallocations to happen more or less independently of which stage of the contract the ship happens to be in. Figure 4a shows, however, that the probability of reallocation jumps at the start of the contract (controlling for ship fixed effects and a time trend). Within-contract reallocation is limited because charterers specialize

routes/chartering additional ships, rather than entirely new charterers.

³³The fragmented market structure and lack of subleasing amplify the importance of such across-firm reallocation. Since charterers are geographically specialized, they cannot easily smooth idiosyncratic demand shocks through internal fleet reallocation and must rely on the external leasing market.

geographically and it is costly for them to establish a new liner service.³⁴

Figure 4: Evidence consistent with contract overhang inhibiting reallocation



Note: Panel (a): The figure plots the share of containerships reallocated every month in a 4 year window around the month when the ship begins a new contract, after controlling for ship fixed effects and a time trend. Panel (b): Plots dispersion in residualized utilization across containerships every month, where residualized utilization is obtained by regressing a 90-day moving average of utilization on ship fixed effects and a time trend. Note that we start the plot from 2006Q3 rather than the beginning of the utilization data in 2006Q2 to ensure that the full band is available at each time period.

Counter-cyclical dispersion in ship utilization Figure 4b shows that dispersion in capacity utilization is counter-cyclical, rising significantly during the “Great Trade Collapse” when charterers were locked into long contracts. Table 2 documents that dispersion in revenue is similarly counter-cyclical (Panel A).³⁵ When we decompose the dispersion in utilization into its within-charterer and between-charterer components (similar to Kehrig and Vincent (2026)), we find that dispersion *across* charterers increases during the crash, while dispersion *within* charterers remains similar (Panel B of Table 2), suggestive of misallocation of ships across charterers.

Why does dispersion in utilization rise during the 2008 - 2010 period? We argue this is firstly because the impact of the crisis was highly heterogeneous across different parts of the world. Consistent with that, Panel C illustrates that most of the increase in dispersion is generated by dispersion *between* routes rather than *within* routes. Furthermore, we show in Appendix Section A.18.1 that this increase in dispersion is not

³⁴Note that we do observe instances of within-contract reallocation in the data, and in Section 5 we discuss how our framework accommodates these events.

³⁵Note that dispersion being lower during the boom is not a mechanical consequence of capacity utilization being bounded above at 1, since capacity utilization equalled 1 for only 0.3% of ship-year month observations during the boom, and was higher than 0.95 for just 1.1% of observations.

Table 2: Dispersion in Utilization Rises Following the Bust

Panel A: Dispersion in Utilization, All Ships				
	(1)		(2)	
	S.d., utilization		S.d., revenue	
Great Trade Collapse	1.917		2.293	
(July 2008 - End-2010)	(0.339)		(0.420)	
R-squared	0.477		0.497	

Panel B: Dispersion in Utilization: Between and Within Charterer				
	Between Charterer		Within Charterer	
	(1)	(2)	(3)	(4)
	S.d., utilization	S.d., revenue	S.d., utilization	S.d., revenue
Great Trade Collapse	1.959	2.525	0.498	0.547
(July 2008 - End-2010)	(0.366)	(0.421)	(0.260)	(0.383)
R-squared	0.522	0.537	0.314	0.290

Panel C: Dispersion in Utilization: Between and Within Route				
	Between Route		Within Route	
	(1)	(2)	(3)	(4)
	S.d., utilization	S.d., revenue	S.d., utilization	S.d., revenue
Great Trade Collapse	1.953	2.480	0.625	0.504
(July 2008 - End-2010)	(0.299)	(0.357)	(0.202)	(0.264)
R-squared	0.529	0.586	0.262	0.201

Panel D: Dispersion in Utilization by Contract Vintage				
	Signed $\geq$ 12 months prior		Signed $<$ 12 months prior	
	(1)	(2)	(3)	(4)
	S.d., utilization	S.d., revenue	S.d., utilization	S.d., revenue
Great Trade Collapse	3.278	4.218	0.581	0.960
(July 2008 - End-2010)	(0.611)	(0.704)	(0.353)	(0.459)
R-squared	0.419	0.475	0.512	0.490

Note: Each observation is a year-month, and there are 114 observations. The regressions also include a constant and a fixed effect for the post-2010 period. We obtain residualized utilization by regressing a 90-day moving average of utilization on ship fixed effects and a time trend and recovering the residuals; residualized revenue is calculated in the same fashion. "S.d., utilization" is the standard deviation of residualized capacity utilization (with utilization normalized to range from 0 to 100). "S.d., revenue" is the standard deviation of residualized revenue, where revenue is the product of utilization and the freight rate index.

In Panel A, we measure dispersion across all ships. In Panel B, we document how between-charterer dispersion in utilization and revenue (Columns (1) and (2)), and within-charterer dispersion (Columns (3) and (4)), change during the bust. In Panel C, we document how between-route dispersion in utilization and revenue (Columns (1) and (2)), and within-route dispersion (Columns (3) and (4)), change during the bust. In Panel D, we measure dispersion separately for ships where the contract was signed at least 12 months prior (Columns (1) and (2)), and for ships where the contract was signed within the last 12 months (Columns (3) and (4)).

generated simply by all ships decreasing their utilization, but at different rates. Rather, a significant share of ships exhibit higher capacity utilization in July 2008-End 2010 compared to their pre-crisis baseline. Finally, in Appendix Section A.18.2 we show that these results are robust to combining ships within the same route using a matching simulation.³⁶

Second, Panel D of Table 2 provides a direct test of the contract overhang mechanism. If contract overhang drives the counter-cyclical rise in dispersion, the increase should be concentrated among ships still under contracts signed further in the past. Consistent with this prediction, we find that the rise in dispersion during the bust was large among ships under contracts signed at least 12 months earlier; among ships with more recently signed contracts, the increase is much smaller.³⁷

The above patterns are consistent with contract overhang during the downturn preventing the reallocation of ships toward more efficient charterers operating on routes with more favorable demand conditions. One may ask whether the lack of reallocation in the downturn is simply due to all firms operating well below capacity during this period. Here, it may not be individually optimal for firms to reallocate capital since adding a ship to a route does not increase output. However, as discussed earlier, we find that reallocations of ships across routes — even in the downturn — significantly increase output (Appendix Table D.5).

4.4 Observation 4: Longer contracts are associated with market thinness

A key idea we explore in this paper is that market thinness is a central driver of the choice of contract duration. Table 3 presents evidence consistent with this: longer contracts are associated with thinner local markets. Here, local thinness captures the ease of finding a suitable nearby ship within a globally connected leasing market; it does not define a separate closed market.

Why might local market thinness influence the choice of contract duration? As we show in Appendix A.13, geographically specialized charterers are more likely to match with nearby ships. Two mechanisms may contribute to this pattern, both of which we allow for in the model. First, matching with a nearby ship reduces the distance the ship must travel to begin the new contract and therefore lowers the adjustment cost. Second, charterers may direct their search toward nearby ships because of these distance costs or other factors, such as information. Consequently, when fewer nearby ships are available, the charterer's expected return to continued search falls, favoring longer contracts. We formalize this mechanism in the model in

³⁶This addresses the potential concern that consolidating ships within a route, by moving load from low- to high-utilization ships and reallocating the empty ships elsewhere, could raise measured dispersion while also increasing efficiency. In our matching simulation, we implement exactly this exercise and find that the resulting gain in efficiency is small, while the rise in dispersion during the bust is quantitatively unchanged.

³⁷While subleasing could theoretically reduce inefficiencies from long contracts, recall that these are rare for the reasons discussed in Section 2.

Section 5.3, and target the relationship in Table 3 directly when estimating the model.

We construct Table 3 in three steps. First, we construct a measure for geographical market thinness for each match by counting the number of alternative ships nearby. We discuss the details about how we construct this measure in Appendix A.8. Intuitively, the thinness measure traces out different areas across the earth, with geographically isolated markets producing lower measures than trading hubs.

Next, we regress duration on the total number of ships nearby. We include granular year-month time fixed effects in this regression. Therefore, we isolate the relationship between thinness and duration in the cross-section, controlling for time-varying factors that might also affect contract duration.

Finally, we convert the elasticity of duration on total ships nearby, to an elasticity of duration on *available* ships (i.e. ships nearby that are unemployed or in the final month of a non-extended contract, consistent with our model in Section 5). Table 3 reports this recovered elasticity. Our conversion leverages a mapping which relates the total number of ships to the predicted number of available ships, and explicitly corrects for the mechanical feedback loop where increased contract duration reduces availability.³⁸ We provide formal details on this Indirect Least Squares method in Appendix Section A.8.3.

The results across the columns in Table 3 show that thinner markets (with fewer nearby available ships) are associated with longer contracts. One may be concerned that different types of charterers operate in thinner markets, and that these charterers sign contracts of different durations. To address this concern we include controls for a range of key observable charterer characteristics that could affect contract duration across columns (1)-(4), such as charterer scale and experience.³⁹ We also control for ship heterogeneity by including ship size fixed effects. Overall our results are robust to including these controls and we provide a detailed discussion in Appendix Section A.8.2. As well as being statistically significant, these results are also economically meaningful: moving from the minimum to the maximum of market thinness is associated with about a 27% increase in contract duration using our preferred specification in column (4).

³⁸Concretely, we use two components. First, the laws of motion in a setting where ships can search on the job in the final period of a non-extended contract, consistent with the setup later in the model. Second, an accounting assumption that the age distribution of contracts, by remaining duration, is constant. Under this setup, $a = nf(\tau)$ where $f(\tau) = u + (1 - u) \frac{1 - \mathbb{P}_{\text{extend}}}{\tau}$. Here, a is the total number of available ships, n is the total number of ships, u is the idle rate, $\mathbb{P}_{\text{extend}}$ is the probability of extending a contract, and τ is the prevailing contract duration. All of the objects on the right-hand-side can be constructed from the data. Appendix Section A.8.3 provides further details.

³⁹A natural approach would be to include charterer fixed effects. However, the market is very fragmented with the median number of contracts per charterer equal to 3, and the modal number equal to 1. Estimation using these short panels would potentially lose precision, especially given the inclusion of granular time fixed effects.

Table 3: Longer contracts are associated with thinner markets

	(1)	(2)	(3)	(4)
	Log(duration)	Log(duration)	Log(duration)	Log(duration)
Log(# available ships nearby)	-0.088 (0.032)	-0.078 (0.033)	-0.079 (0.033)	-0.079 (0.033)
Year-month FEs	Yes	Yes	Yes	Yes
Ship controls	Yes	Yes	Yes	Yes
Charterer scale control - # contracts	Yes	Yes	Yes	Yes
Charterer scale control - total TEU	No	Yes	Yes	Yes
Charterer experience control	No	No	Yes	Yes
Charterer utilization control	No	No	No	Yes
Observations	2,692	2,692	2,692	2,692
Adjusted R^2	0.187	0.190	0.189	0.190

Note: The reported coefficient is the elasticity with respect to available ships, recovered through Indirect Least Squares via the three-step procedure described in the main text and in more detail in Appendix Section A.8.3. Standard errors in parentheses are computed by the delta method. Note that a small number of observations are dropped due to the granular time fixed-effects. We also include controls for ship heterogeneity (ship-size fixed effects). Controls for charterer scale are the total number of contracts the charterer has signed and the charterer’s total contract ship capacity (TEU). We also include controls in some regressions for charterer experience (whether the charterer has operated within the same area), and a control for charterer average ship utilization. We provide a detailed discussion about charterer controls in Appendix Section A.8.2.

5 Model

5.1 Setup

Time is discrete with each period (a month) denoted by t . Agents are risk-neutral and forward-looking, and have discount factor β . There are two types of agents in our model, shipowners and charterers. We assume that each shipowner owns a single ship, and so refer interchangeably to ships and shipowners.⁴⁰ There are n_t homogeneous ships. Shipowners lease out ships to charterers and we assume that each charterer requires a single ship.⁴¹

Let R denote the set of regions.⁴² Each charterer has a fixed home region; each ship has a current region, which updates each time the ship signs a new contract. We use r for the focal region and use j and k as additional region indices when distinguishing partner regions or summing across regions. For pair-specific objects, the first region is the ship’s current region and the second is the charterer’s region.

⁴⁰This is a relatively innocuous assumption as shipowner market power is very limited in this market (with an HHI of 75). Moreover, a shipowner very rarely negotiates over more than one ship with the same charterer in the same year (only 1.6% of contracts), so owning several ships is unlikely to confer bargaining power.

⁴¹Note that, in practice, charterers may own or lease other ships, and so one may be concerned that this could generate a more complicated portfolio problem. To keep the focus on the contract length decision we choose to not explicitly model this complex decision. Rather, the charterer’s value of a match and idiosyncratic shock (described later) embeds such considerations.

⁴²We define the regions in Section 3.2; in our empirical implementation $|R| = 7$ (we drop “Others”).

Payoffs Agents choose for how long to match; we denote the contract length (in months) by τ . In any region r , a match generates flow value $v_{r,t}$ if the charterer is alive, and zero value if the charterer is dead. The shipowner pays the operating cost c each period.⁴³ The alive/dead state is stochastic: a charterer that is “alive” in period t remains alive in period $t + 1$ with probability $\eta_{r,t}$; with probability $1 - \eta_{r,t}$ the charterer becomes “dead” forever.

The parameters $v_{r,t}$ and $\eta_{r,t}$ in each region r are largely determined by demand conditions in the downstream market, where the charterer schedules a ship and sells the container slots to exporters. We summarize the match-relevant component of these conditions with a region-level demand state which enters directly into $\eta_{r,t}$ and $v_{r,t}$. We provide more details about this demand state in Section 5.4 and describe its construction in Section 6.3.

The fact that the alive/dead shocks are idiosyncratic across charterers, even within the same region, generates profitable reallocation opportunities both within and across regions. Concretely, this generates situations where a ship is contracted under a dead match but could be profitably re-matched to another charterer. As discussed in Section 4.2, charterers specialize to a limited set of routes and have heterogeneous relationships with downstream exporters, leaving them differentially exposed to demand shocks (e.g., at the route level).

Adjustment cost When a ship in region r signs a new contract with a charterer in region j , the ship is relocated from r to j , and the charterer pays a one-time adjustment cost $c_{r,j,t}^{\text{adj}}$ that depends on the distance between the two regions. The cost can be non-zero even within the same region ($r = j$), since within-region moves may still involve distance adjustments. It is paid only for a new match; contract extensions in place incur no adjustment cost. We specify the functional form for $c_{r,j,t}^{\text{adj}}$ in Section 6.1.

Let $\hat{\eta}_{j,t,h} = \prod_{\ell=0}^{h-1} \eta_{j,t+\ell}$ denote the probability that a charterer in region j is alive h periods ahead. The expected total value of a τ -period contract by a ship with a charterer in region j at time t is:

$$V_{j,t,\tau} = (v_{j,t} - c) + \mathbb{E}_t \sum_{h=1}^{\tau-1} \beta^h (\hat{\eta}_{j,t,h} v_{j,t+h} - c). \quad (1)$$

The expectation is taken over the industry state s_t . The adjustment cost $c_{r,j,t}^{\text{adj}}$ does not enter $V_{j,t,\tau}$; it is paid once by the charterer at the start of the contract and appears separately in the value functions of Section 5.2.

Heterogeneity in the model The model accommodates heterogeneity across charterers, ships, and matches

⁴³In practice, shipowners pay vessel operating costs (e.g., crew), which are part of c . Charterers pay all voyage expenses (e.g., bunker fuel) and cargo-handling costs; these costs therefore affect $v_{r,t}$. More generally, $v_{r,t}$ embeds anything that would affect a charterer’s net benefits to leasing a ship. This includes demand in the downstream market and a charterer’s ability to reallocate a ship within a contract.

through three channels. First, there is region-level differentiation: each agent is located in a region $r \in R$ that faces heterogeneous demand, generating differences in match surplus, match probabilities, prices, and durations across pairs. Second, even within a region, charterers face idiosyncratic match-survival risk: a match remains alive with probability $\eta_{r,t}$. As discussed in Section 3.2, demand shocks can materialize at both the route and regional levels. Since we track regions rather than individual routes in the model, we interpret the idiosyncratic realization of the alive-or-dead state as a reduced-form representation of route- and charterer-specific demand shocks within a region. Third, a contract duration shock ϵ_r (drawn iid across matches and durations, as we discuss in Section 5.2) introduces idiosyncratic variation in contract duration across observationally similar pairs, rationalizing the cross-sectional dispersion in duration observed in the data.

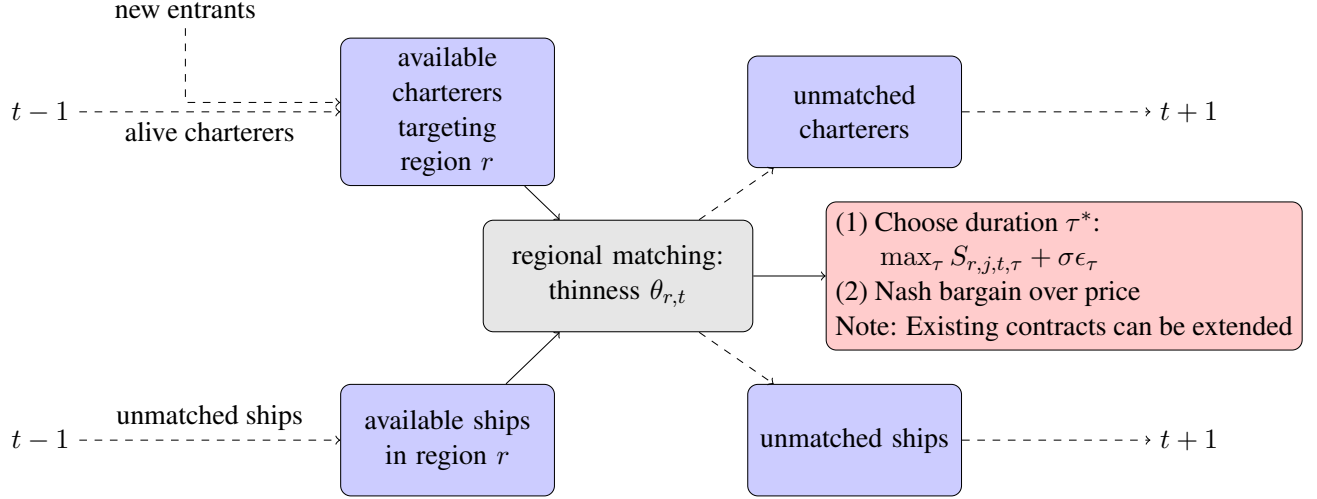
Timing In each period, the timing is as follows (see also Figure 5):

1. *Match expiry and charterer exit:* The valuation $v_{r,t}$ remains positive with probability $\eta_{r,t-1}$. If a charterer is not under contract and no longer alive, then they will exit.
2. *Contract extensions and entry:* Existing contracts that are ending are potentially extended with probability $\mathbb{P}_{\text{extend}}$ if the charterer is still alive. Otherwise the ship, and the charterer (if alive), are added to the pools of available ships and available charterers. As well, there is a pool of $e_{r,t}$ potential charterer entrants in each region. A potential entrant enters if $U_{r,t}^{\text{chart}} > c_{\text{entry}}$, where c_{entry} is a vacancy posting cost.⁴⁴
3. *Search and matching:* Available charterers target search across ship regions, weighting nearby ships more heavily; matches form according to the spatial protocol described below.
4. *Choice of contract duration and price:* If agents are matched, they choose for how long to match (the contract duration), as well as a fixed price paid by the charterer to the ship.⁴⁵ The ship and the charterer choose the contract duration to maximize their joint surplus from matching. Prices are then determined by Nash bargaining where $\delta \in [0, 1]$ is the Nash bargaining weight of the ship.
5. *Output:* The per-period output of the match (i.e., the sum of realized match values net of operating costs, minus adjustment costs) is realized.

⁴⁴Note that, in the estimated model, we find that this entry condition always holds, so all potential entrants enter and entry is determined by $e_{r,t}$. Nevertheless, it is still important to include it in the model.

⁴⁵This assumption is consistent with the fact that in practice, at the time of contract, the parties agree to a daily charter rate that is fixed over the duration of the contract.

Figure 5: Timing within each period and region



Spatial matching Available charterers search across ships which are located in different regions.⁴⁶ Our matching protocol shares features with the approaches in e.g., [Eaton et al. \(2026\)](#) and [Manning and Petrongolo \(2017\)](#). Throughout, let $a_{r,t}^{ship}$ and $a_{j,t}^{chart}$ denote the masses of searching ships in region r and searching charterers in region j .

A charterer in region j targets ships in region r with probability $\mu_{r|j,t}$. Targeting is proportional to the mass of available ships, weighted by the distance kernel $w_{r,j} = \exp(-\alpha_1 x_{r,j})$, where $\alpha_1 \geq 0$ is the targeting parameter, and $x_{r,j}$ is the distance between r and j . The distance kernel captures the fact that ships must reposition before beginning a new contract, and so charterers may prefer to target nearby ships. If $\alpha_1 = 0$, distance does not affect targeting and matching is global; as $\alpha_1 \rightarrow \infty$, markets become fully segmented across regions. Aggregating these targeting probabilities across searching regions gives local market thinness $\theta_{r,t}$ in each region r :

$$\mu_{r|j,t} = \frac{a_{r,t}^{ship} w_{r,j}}{\sum_k a_{k,t}^{ship} w_{k,j}}, \quad \theta_{r,t} = \frac{\sum_k a_{k,t}^{chart} \mu_{r|k,t}}{a_{r,t}^{ship}}. \quad (2)$$

Higher $\theta_{r,t}$ means more searching charterers per available ship in region r , so the market is thinner from the charterer side. We use a constant returns to scale matching function to characterize the outcome of the matching process in each region.⁴⁷ The resulting per-ship and per-charterer match rates therefore depend on

⁴⁶We abstract from unmatched ships repositioning before securing a new contract. This is consistent with our finding in Section 4.3 that physical reallocations often coincide with the start of a new contract. Moreover, the model does not prevent a ship from finding a distant use: charterers can target ships globally, after which the ship repositions and incurs the associated adjustment cost. We therefore consolidate search and physical repositioning into the beginning of the next contract. Finally, ship idle rates are low empirically across the sample, so repositioning without a contract is unlikely to be first-order.

⁴⁷We show in Appendix D.3 that our results are robust to allowing for increasing returns to scale in the matching technology.

thinness alone, $q_{r,t}^{ship}(\theta_{r,t})$ and $q_{r,t}^{chart}(\theta_{r,t})$; we specify their functional form later in Section 6.1.

Let $\pi_{r|j,t}^{chart}$ denote the probability a charterer in j is matched to a ship in r and $\pi_{j|r,t}^{ship}$ the probability a ship in r is matched to a charterer in j . Combining the above targeting probabilities with the match rates yields these match probabilities:

$$\pi_{r|j,t}^{chart} = q_{r,t}^{chart}(\theta_{r,t})\mu_{r|j,t}, \quad \pi_{j|r,t}^{ship} = q_{r,t}^{ship}(\theta_{r,t}) \frac{a_{j,t}^{chart}\mu_{r|j,t}}{\sum_k a_{k,t}^{chart}\mu_{r|k,t}}. \quad (3)$$

Discussion of assumptions We discuss two main assumptions in the model setup. First, we assume that agents do not reject matches. While in principle agents might wish to reject a match in order to wait for a higher quality match (e.g. a match involving a smaller adjustment cost), we confirm later that at the estimated parameters, the match surplus is always positive.

Second, we model the idiosyncratic state of the match as a binary variable. In reality, this process may be more continuous, with the value of a match falling over time until it is below a critical value where the charterer would prefer to dissolve the match. Modeling the state of a match as a binary variable can be viewed as an approximation of this more complicated process that allows us to keep the model tractable. This approximation retains the empirical content of our key descriptive fact regarding dispersion in utilization: as we show in Appendix A.20, if we replace the continuous utilization measure by a binary counterpart that mirrors the model's dead-or-alive structure, we find a similar increase in dispersion during the collapse.

5.2 Contract duration choice

Match surplus An important component to the contract duration choice is the match surplus $S_{r,j,t,\tau}$, the joint value to a charterer in region j and a ship in region r from a τ -period contract at time t , minus their outside options. Note that a contract can be either an initial contract or an extension, and for the initial contract the net match surplus also incorporates the distance-dependent adjustment cost, i.e., it is $-c_{r,j,t}^{\text{adj}} + S_{r,j,t,\tau}$. Here, $S_{r,j,t,\tau}$ is:

$$\begin{aligned} S_{r,j,t,\tau} = & \underbrace{V_{j,t,\tau}}_{\text{Expected value during contract}} + \underbrace{\beta^\tau \mathbb{E}_t \left(\hat{\eta}_{j,t,\tau} (M_{j,t+\tau}^{ship} + M_{j,t+\tau}^{chart}) + (1 - \hat{\eta}_{j,t,\tau}) U_{j,t+\tau}^{ship} \right)}_{\text{Continuation values after being matched}} \\ & - \underbrace{\beta \mathbb{E}_t \left(U_{r,t+1}^{ship} + \eta_{j,t} U_{j,t+1}^{chart} \right)}_{\text{Outside options}} \end{aligned} \quad (4)$$

Here, $M_{j,t}^{ship}$ and $M_{j,t}^{chart}$ denote the value functions for the ship and charterer at the end of the initial contract if the charterer is still alive. These are evaluated at region j , the region where the ship is located after matching

with the charterer. As we discuss further below, these values embed that the match may be extended if the charterer is still alive. Therefore, $S_{r,j,t,\tau}$ accounts for the fact that the total match duration may extend beyond the initial contract τ . Note that in an extension, the new contract duration and price are *not* simply a repetition of the initial contract; rather they are chosen optimally given the updated state.

The components $U_{r,t}^{ship}$ and $U_{j,t}^{chart}$ are unmatched value functions evaluated at the ship's initial region r and the charterer's region j . In the event of disagreement, both the charterer and ship need to wait until the next period, when they may enter the pool of searching agents.

Choice of contract duration After matching, agents choose the contract duration based on the match surplus and an idiosyncratic shock to the value of signing a τ -period contract, ϵ_τ , which is drawn from a standard i.i.d type-1 extreme value distribution. The ϵ_τ shocks are idiosyncratic across matches and across contract lengths τ , and enter the surplus scaled by $\sigma > 0$.

Denote $W_{r,j,t}$ as the ex-ante surplus (the expected value of the surplus before the ϵ_τ are drawn), which can be written as the inclusive value formula:

$$W_{r,j,t} = \mathbb{E}_\epsilon \left[\max_{\tau \in \{1,2,\dots,\tau_{max}\}} \{S_{r,j,t,\tau} + \sigma \epsilon_\tau\} \right] = \sigma \log \left(\sum_{\tau \in \{1,2,\dots,\tau_{max}\}} \exp(S_{r,j,t,\tau}/\sigma) \right) + \sigma \gamma^{euler} \quad (5)$$

where γ^{euler} is Euler's gamma and τ_{max} is the maximum possible contract duration (in practice, 48 months).⁴⁸ For the initial contract, since Equation (5) is the inclusive value and the adjustment cost is an additive value, the ex-ante surplus is $-c_{r,j,t}^{adj} + W_{r,j,t}$. The probability that a matched charterer-ship pair chooses a contract of length τ is:

$$\frac{\exp(S_{r,j,t,\tau}/\sigma)}{\sum_{\tau'} \exp(S_{r,j,t,\tau'}/\sigma)} \quad (6)$$

Note that it is individually rational for both ships and charterers to choose the contract duration that maximizes the surplus of a match, since Nash bargaining implies perfectly transferable utility. Furthermore, since the adjustment cost enters additively into all duration options for the initial contract, this choice probability is the same both for initial contracts and extensions.

Other value functions Let $\Psi_{r,t}^{ship} \equiv \sum_j \pi_{j|r,t}^{ship} (W_{r,j,t} - c_{r,j,t}^{adj})$ denote the expected net surplus a ship in region r would generate if it were in the pool of searching ships in period t ; $\Psi_{r,t}^{chart} \equiv \sum_j \pi_{j|r,t}^{chart} (W_{j,r,t} - c_{j,r,t}^{adj})$ is analogously defined for charterers. In Appendix B.1 we prove that the value of unmatched ships and

⁴⁸Only 0.30% of contracts in our estimation sample exceed 48 months in duration.

charterers (i.e., their outside options) can be written as:

$$U_{r,t}^{chart} = (1 - \delta) \Psi_{r,t}^{chart} + \beta \eta_{r,t} \mathbb{E}_t U_{r,t+1}^{chart}, \quad (7)$$

$$U_{r,t}^{ship} = \delta \Psi_{r,t}^{ship} + \beta \mathbb{E}_t U_{r,t+1}^{ship}. \quad (8)$$

A searching charterer in region r earns share $(1 - \delta)$ of the expected net surplus $\Psi_{r,t}^{chart}$ in period t ; the ship's equation is similar. The final term in each line is the discounted unmatched value, which for charterers is multiplied by the survival probability $\eta_{r,t}$. Since market thickness and therefore the probability of finding a match vary over the business cycle, these outside options $U_{r,t}^{chart}$ and $U_{r,t}^{ship}$ also change over the cycle, which affects the choice of contract duration: a point we discuss further in Section 5.3.

The value functions $M_{r,t}^{ship}$ and $M_{r,t}^{chart}$ have a similar structure but incorporate the possibility of contract extension. At the end of a contract, if the charterer is still alive, with probability $\mathbb{P}_{\text{extend}}$ the partners extend in place—the ship is already with the charterer, so no new adjustment cost is paid. With probability $1 - \mathbb{P}_{\text{extend}}$ the contract ends and the agents return to the unmatched pool. This gives the form:

$$M_{r,t}^{chart} = \mathbb{P}_{\text{extend}} ((1 - \delta) W_{r,r,t} + \beta \eta_{r,t} \mathbb{E}_t U_{r,t+1}^{chart}) + (1 - \mathbb{P}_{\text{extend}}) U_{r,t}^{chart} \quad (9)$$

$$M_{r,t}^{ship} = \mathbb{P}_{\text{extend}} (\delta W_{r,r,t} + \beta \mathbb{E}_t U_{r,t+1}^{ship}) + (1 - \mathbb{P}_{\text{extend}}) U_{r,t}^{ship} \quad (10)$$

Note that $\mathbb{P}_{\text{extend}}$ is the probability of the *opportunity* to extend, conditional on the charterer being alive; the realized extension probability is endogenous. For a τ -period contract signed at time t , the realized extension probability equals $\hat{\eta}_{j,t,\tau} \mathbb{P}_{\text{extend}}$, and therefore varies over the business cycle through charterer survival.

Our formulation for extensions allows for the possibility that alive matches are not always extended (i.e. $\mathbb{P}_{\text{extend}} < 1$).⁴⁹ Doing so is important in the context of our model: for example, consider the extreme case of $\mathbb{P}_{\text{extend}} = 1$ and $\sigma \rightarrow 0$. Here, it is optimal for agents to sign single period contracts and extend them month-to-month if and only if the match is alive each period. This is clearly rejected by the data because we observe very few single-period contracts (only 4.4% of all contracts).

A further justification for our formulation of extensions is that it approximates a model with the following properties. First, agents make an endogenous extension choice. Second, unmatched charterers can contact ships who are finishing their contract. Third, information about whether charterers will be alive arises independently and continuously across charterers. Here, there are two possibilities for what might happen if

⁴⁹Recall as well that pre-negotiated options to extend are rarely used, as documented in Section 2.

the charterer is still alive at the end of a contract.⁵⁰ The ship may be contacted by an alternative unmatched alive charterer, before information has arrived that the current matched charterer will be alive. In this case, if the value of matching with the new charterer is sufficiently high, it is optimal for the ship to switch to the new charterer (rather than wait and risk unemployment), so an extension will not take place. Alternatively, good information may arrive that the current match will be alive, before the ship is contacted by a sufficiently attractive alternative match; in this case, the agents will extend the contract. We approximate the probability of this second case by $\mathbb{P}_{\text{extend}}$.

Prices Prices are determined by the standard Nash bargaining form: the ship and charterer split the joint surplus, with the ship's bargaining weight equal to $\delta \in [0, 1]$. Appendix B.1 details the formal equations.

5.3 Key theoretical mechanisms in the model

We now describe the key forces at work in the model. For parsimony, we do this in the special case where $\mathbb{P}_{\text{extend}} = 0$ in the main paper. In Appendix B.1 we provide corresponding derivations for $\mathbb{P}_{\text{extend}} > 0$ and show that the intuition carries over to this more complicated case.

Decentralized contract duration choice To understand how optimal duration is determined, consider how the match surplus changes when duration is increased by one period $\Delta S_{r,j,t,\tau} \equiv S_{r,j,t,\tau+1} - S_{r,j,t,\tau}$. Substituting Equations (1) and (7)–(10) (with $\mathbb{P}_{\text{extend}} = 0$) into Equation (4), and leaving the formal derivation to Appendix B.1, results in:

$$\Delta S_{r,j,t,\tau} = \beta^\tau \mathbb{E}_t \left[\underbrace{-c - \delta \Psi_{j,t+\tau}^{\text{ship}}}_{\text{lock-in cost}} + \hat{\eta}_{j,t,\tau} \underbrace{\left(v_{j,t+\tau} - (1 - \delta) \Psi_{j,t+\tau}^{\text{chart}} \right)}_{\text{assurance premium}} \right]. \quad (11)$$

Therefore, increasing duration by one period creates the following tradeoff. There is a ‘lock-in cost’ which pushes agents towards shorter contracts: regardless of whether the match is alive or dead, the ship's expenses c must still be paid. As well, the ship gives up the option to search one period earlier at the end of a contract and this opportunity cost is $\delta \Psi_{j,t+\tau}^{\text{ship}}$. On the other hand, there is an ‘assurance premium’ which incentivizes agents to sign longer contracts. If the match is alive at the end of the contract (which happens with probability $\hat{\eta}_{j,t,\tau}$), then increasing duration by one period assures the charterer of receiving the match value, $v_{j,t+\tau}$, versus continued search which would result in $(1 - \delta) \Psi_{j,t+\tau}^{\text{chart}}$. The assurance premium is the gap between the secured match value and the return to search without the contract.

This trade-off is governed by several features of the underlying environment. For example, if matches die

⁵⁰If the charterer is ‘dead’ at the end of the contract, agents will optimally not extend the contract and the ship will return to the searching pool; this choice is incorporated into the match surplus in Equation 4.

quickly (low $\hat{\eta}_{j,t,\tau}$), the lock-in effect dominates, leading to shorter contracts. Conversely, when search frictions are large (making it difficult to find a match) or adjustment costs $c_{r,j,t}^{\text{adj}}$ are large (making it more costly to match), the returns to search fall on both sides of the market. The decline in $\Psi_{j,t+\tau}^{\text{chart}}$ increases the assurance premium, while the decline in $\Psi_{j,t+\tau}^{\text{ship}}$ reduces the ship's opportunity cost of lock-in; both forces favor longer contracts.

Cyclicalities in duration How then does the contract duration choice change in booms and busts? When a bust turns to a boom there are two effects. The first is a ‘match effect’, where match quality changes across the cycle. A boom can change the value of the match, $v_{j,t+\tau}$, and the probability that the match is still alive at the end of the contract, $\hat{\eta}_{j,t,\tau}$. If, for example, the boom increases downstream demand from exporters, this increases the match value, amplifying the assurance premium and favoring a longer contract.

The second effect is a ‘market thinness effect’ that arises because of increased charterer entry. To make this comparative static precise, let ε index a counterfactual increase in local market thinness at the end of the contract, $\theta_{j,t+\tau}^\varepsilon = \theta_{j,t+\tau} + \varepsilon$, holding fixed $v_{j,t+\tau}$, $\hat{\eta}_{j,t,\tau}$, and the conditional distribution of other states. Then, the market thinness effect is:

$$\left. \frac{d \Delta S_{r,j,t,\tau}(\varepsilon)}{d\varepsilon} \right|_{\varepsilon=0} = -\beta^\tau \mathbb{E}_t \left[\delta \frac{\partial \Psi_{j,t+\tau}^{\text{ship}}}{\partial \theta_{j,t+\tau}} + \hat{\eta}_{j,t,\tau} (1 - \delta) \frac{\partial \Psi_{j,t+\tau}^{\text{chart}}}{\partial \theta_{j,t+\tau}} \right]. \quad (12)$$

Here, an increase in market thinness means ships are scarcer relative to charterers. This increases the ship's payoff from being able to search again $\Psi_{j,t+\tau}^{\text{ship}}$ (which favors shorter contracts) but decreases the charterer's payoff $\Psi_{j,t+\tau}^{\text{chart}}$ (which favors longer contracts). Therefore, the overall effect is theoretically ambiguous. Ultimately, the bargaining parameter δ governs this asymmetry: when δ is small, as we find in Section 7, the charterer effect dominates, leading to longer contracts in booms.

Cyclicalities in utilization dispersion The cyclicalities of contract duration underpins one mechanism via which the model can generate cyclical changes in cross-sectional dispersion in utilization. For example, if contracts lengthen during a boom, and a downturn arrives with ships still bound by the long contracts, some ships will remain locked into matches that turn dead, increasing dispersion. However, dispersion may also increase during the downturn because of physical adjustment costs ($c_{r,j,t}^{\text{adj}}$), or because search is partly local. Here, either of these forces may keep ships from reallocating away from regions where demand has collapsed, even if they are not locked in to contracts. Ultimately, which of these channels explains the observed counter-cyclical rise in dispersion (Observation 3) is an empirical question.

Social planner While individual agents choose duration to maximize their individual match surplus, a social planner chooses duration to maximize total output of the entire market. Here, to build intuition, we focus on the special case where ships match only with charterers in the same region and there are no extensions. We discuss more general results in Appendix B.1. We show in the appendix that the marginal social value of raising duration by one period is:

$$\Delta S_{r,j,t,\tau}^{\text{planner}} = \beta^\tau \mathbb{E}_t \left[-c - \omega_{j,t+\tau} \Psi_{j,t+\tau}^{\text{ship}} + \hat{\eta}_{j,t,\tau} (v_{j,t+\tau} - (1 - \omega_{j,t+\tau}) \Psi_{j,t+\tau}^{\text{chart}}) \right]. \quad (13)$$

Here, $\omega_{j,t+\tau}$ denotes the elasticity of the matching function with respect to the number of ships. Note that this is identical to Equation (11) except that the bargaining weight δ is replaced by the matching elasticity $\omega_{j,t+\tau}$. Therefore, by similar arguments to the cyclical comparative statics for the individual agents, whether the social planner will choose pro-cyclical or counter-cyclical duration is partially a function of $\omega_{j,t+\tau}$. Specifically, if $\omega_{j,t+\tau}$ is sufficiently high, the social planner will choose shorter contracts during booms (the opposite of the pro-cyclical contracts chosen in the decentralized equilibrium when δ is low). Intuitively, when match creation is highly sensitive to the supply of ships (high ω), releasing scarce ships back to search becomes especially socially valuable as the market thins during the boom.

We also isolate the wedge between the planner's solution and the decentralized equilibrium in this special case:

$$\Delta S_{r,j,t,\tau}^{\text{planner}} - \Delta S_{r,j,t,\tau} = \beta^\tau \mathbb{E}_t \left[(\delta - \omega_{j,t+\tau}) (\Psi_{j,t+\tau}^{\text{ship}} - \hat{\eta}_{j,t,\tau} \Psi_{j,t+\tau}^{\text{chart}}) \right]. \quad (14)$$

The above expression identifies the contract externality. When $\delta = \omega_{j,t+\tau}$, the wedge is zero; this is the contract duration analogue of the Hosios condition in Hosios (1990), where the private bargaining weight equals the matching elasticity. Intuitively, the planner and private agents agree on the operating cost of the ship and the flow value of the match, so these terms cancel. However, they disagree on how to value the option of returning to search. For instance, ships value their continuation option according to their bargaining weight δ ; whereas the planner instead values the same option according to $\omega_{j,t+\tau}$, which accounts for how returning a ship to the search pool affects match creation for other agents. Thus, the wedge arises from a thin/thick market externality operating through contract duration: private pairs choose how long to remove themselves from future search pools based on their private value from doing so, while the planner values the social effect of releasing agents back into the market.

In Appendix B.1 we show that with across-region targeting, the same intuition applies, but the analogue of

Equation (14) also includes a spatial adjustment term. Hence, $\delta = \omega_{j,t+\tau}$ may not fully eliminate the wedge.

5.4 States and computation

Demand Let $z_{r,t}$ denote total demand in region r at time t , which directly governs entry $e_{r,t}$. We assume that match-specific factors (i.e., $\eta_{r,t}$ and $v_{r,t}$) are determined by a normalized index of this demand, $\tilde{z}_{r,t}$, which adjusts for size differences across regions.⁵¹ Finally, $z_t^G = \sum_r z_{r,t}$ denotes the aggregate global demand state. We describe the construction of the demand states and the exact normalization in Section 6.3.

States The state for each agent consists of both its own state, and a detailed industry state in period t , s_t .⁵² The detailed industry state consists of the demand states, the distributions of searching agents, and current matches in each region of the world. Since the market is relatively fragmented, we assume each agent takes the industry state as given.

The detailed industry state is high-dimensional.⁵³ Computing value functions with such a state space is infeasible due to the curse of dimensionality. Instead, we employ an approximation method similar to a Moment-Based Markov-Equilibrium (Ifrach and Weintraub, 2017). Specifically, we assume that agents approximate the industry state by only keeping track of the normalized demand state $\tilde{z}_{r,t}$ and the market thinness $\theta_{r,t}$ in their particular region, together with the aggregate global demand state z_t^G , acting as if this low-dimensional summary is a sufficient statistic for their decisions.⁵⁴

This assumption shows up in two places. First, agents believe that $\tilde{z}_{r,t}$ and z_t^G follow log AR(1) processes, and forecast market thinness $\theta_{r,t}$ using a deterministic log AR(1) rule. Note that this deterministic rule describes agents' forecasts, not the model's law of motion. The model's realized process for market thinness evolves endogenously through contract duration choices and charterer entry and exit, which respond to the stochastic demand shocks. As we describe below, the outer loop of our computational algorithm enforces consistency between the forecasting rule and this realized process. Second, as shown in Appendix B.4.1, the value functions $U_{r,t}^{ship}$ and $U_{r,t}^{chart}$ split into two components: the expected payoff from matching within the agent's own region, and a 'cross-region adjustment' from the expected payoff of matching in every alternative region. This cross-region adjustment component depends on demand in every alternative region $j \neq r$, which

⁵¹The components $\eta_{r,t}$ and $v_{r,t}$ are defined at the match level, but $z_{r,t}$ increases mechanically with region size. For example, a region with 100 charterers and 100 ships will have higher $z_{r,t}$ than a region with 10 charterers and 10 ships, even if demand per ship is the same. Therefore, we normalize $z_{r,t}$ before using it in $\eta_{r,t}$ and $v_{r,t}$.

⁵²For a matched ship and charterer, their own state is the number of periods remaining on the contract, their region, and whether the match is alive or dead. For an unmatched ship and (alive) charterer, their own state includes the current region.

⁵³For example, the distribution of current matches includes, for each match, a state for the number of remaining periods and a state for whether the match is still alive.

⁵⁴Raw demand $z_{r,t}$ (which affects charterer entry) also matters for continuation values, but only indirectly through the distribution of searching agents, which we assume agents approximate by tracking local market thinness $\theta_{r,t}$.

is relatively high-dimensional. We assume agents approximate this term as a function of $(\tilde{z}_{r,t}, \theta_{r,t}, z_t^G)$ only.

Computation The computational algorithm involves an inner loop and an outer loop. In the inner loop we compute the value functions given the current iteration of the demand transition processes, market thinness forecasting rule (i.e., log AR(1) process for $\theta_{r,t}$), and cross-region adjustment terms. In an outer loop we update the market thinness forecasting rule and the cross-region adjustment terms so that they are consistent with the detailed state evolution generated by forward simulation using the value functions computed in the inner loop. We estimate the log AR(1) processes for the demand realizations “offline” (since they depend on global economic conditions and are arguably exogenous to the containership leasing market). We provide more information about the computational algorithm in Appendix Section B.4. We plot the evolution of market thinness in the estimated model in Appendix Section B.4.3.

5.5 Equilibrium

A dynamic equilibrium is characterized by a mass of searching agents in each region r ($a_{r,t}^{chart}, a_{r,t}^{ship}$), a distribution of current matches (including how many periods remain on each contract, and whether or not each match is still “alive”), contract duration choice probabilities, prices, and agents’ beliefs about state transitions, such that at each state of the industry s_t , the following conditions are satisfied:

1. Agents optimally choose contract duration, according to equations (1)-(10).
2. Equilibrium prices are determined by Nash bargaining.
3. The mass of searching ships and charterers and the distribution of current matches evolve as described in Section 5.1.
4. Agents have expectations over $(\tilde{z}_{r,t}, \theta_{r,t}, z_t^G)$ that are consistent with the transition processes described in Section 5.4.

Equilibrium uniqueness One may be concerned about multiple equilibria because actions are strategic complements: it is better to choose a longer contract when others are also choosing a longer contract. The complexity of the model does not allow us to provide a formal proof that the equilibrium is unique. However, we carefully initialize the model from a variety of starting points both in estimation and counterfactuals. Ultimately we find that regardless of the initial point, the model converges to the same equilibrium, consistent with the idea that multiple equilibria do not seem to be an issue empirically.

6 Estimation and identification

6.1 Overview and parameterization

We estimate the model in two steps. In the first step we recover raw region-level demand shifters “offline”. We then estimate the rest of the parameters by simulated method of moments. Note that for the total number of ships n_t we use the empirical value in each period.⁵⁵ Table 4 provides an overview of the parameters and in which step they are estimated.

Table 4: Overview of parameters

Name	Object	Parameters	Stage
Discount factor		β	Calibrated
Ship operating cost		c	Calibrated
Adjustment cost	$c_{r,j,t}^{\text{adj}}$	ν	Calibrated
Maximum contract length		$\tau_{\max}$	Calibrated
Entry cost		c_{entry}	Calibrated
Demand objects	$z_{r,t}, \tilde{z}_{r,t}, z_t^G$		Stage 1
Charterer potential entrants	$e_{r,t}$	$\gamma_{0,e,r}, \gamma_{1,e}$	Stage 2
Charterer value	$v_{r,t}$	$\gamma_{0,v}, \gamma_{1,v}$	Stage 2
Charterer survival process	$\eta_{r,t}$	$\gamma_{0,\eta}, \gamma_{1,\eta}$	Stage 2
Targeting parameter	$w_{r,j}$	α_1	Stage 2
Matching parameter	$q_{r,t}^{\text{ship}}, q_{r,t}^{\text{chart}}$	α_2	Stage 2
Duration-specific shock		σ	Stage 2
Bargaining parameter		δ	Stage 2
Extension probability		$\mathbb{P}_{\text{extend}}$	Stage 2

Calibrated parameters A period in the model is one month. We calibrate the discount factor, $\beta = 0.99$. Since global interest rates vary over the sample period, Appendix D.1 reports a robustness check where we replace the constant discount factor with a time-varying discount factor fitted to 3-month Treasury bill rates; the welfare gain from removing the contracting externality in our main counter-factual is qualitatively unchanged. We calibrate the per-period cost of operating a ship $c = \$2,500$ per day, based on [Stopford \(2009\)](#); Appendix B.2 has details.

We calibrate adjustment costs $c_{r,j,t}^{\text{adj}}$: these come in the form of lost time when a ship is empty but traveling to its new match. A ship moving from its region r to a charterer’s region j forgoes the match value over the time required to sail the distance $x_{r,j}$ between them at a representative speed ν . Thus, $c_{r,j,t}^{\text{adj}} = v_{j,t} x_{r,j} / \nu$. We calibrate ν to 22 thousand km/month based on additional data from Clarksons for containerships of the size

⁵⁵ We treat the fleet size as exogenous to the leasing market, motivated by the long time-to-build and the long operational lifespan of containerships. Shipbuilding involves substantial construction lags and capacity constraints, implying that the fleet size at any point in time largely reflects investment decisions made years earlier (see, e.g., [Kalouptzidi \(2014\)](#), for evidence from bulk shipping, a closely related market). Fleet composition and size are therefore plausibly predetermined in the medium-term with respect to current leasing market conditions.

we focus on between 2008 (the earliest the series is available) and 2015.⁵⁶ Note that a within-region rematch still incurs an adjustment cost since $x_{r,r} > 0$.

Recall that charterer entry has two components: a pool of potential entrants $e_{r,t}$ and an entry condition. A potential charterer in region r enters when $U_{r,t}^{chart} > c_{\text{entry}}$, where c_{entry} is akin to a ‘vacancy posting cost’ in labor search models (Pissarides, 2000). We estimate the number of potential entrants and calibrate the cost. Specifically, the closest counterpart to this posting cost in our setting is the brokerage commission a charterer pays to secure a ship. Therefore, we set c_{entry} to a conservative upper bound: the expected commission, which equals $q_{r,t}^{chart}$ times a fee of 1.25% of contract value (HandyBulk, 2025).⁵⁷ At the estimated payoffs, $U_{r,t}^{chart} > c_{\text{entry}}$ in every region-month, and this remains true if we double c_{entry} . Therefore, realized entry in the estimated model is disciplined primarily by the pool of potential entrants $e_{r,t}$ rather than by a binding entry cost.

Parametric forms Section 5 defines the spatial matching protocol. Here we specify the matching function. Following den Haan, Ramey and Watson (2000), the per-ship and per-charterer match rates, as functions of market thinness $\theta_{r,t}$, are

$$q_{r,t}^{ship} = \frac{\theta_{r,t}}{(1 + \theta_{r,t}^{\alpha_2})^{1/\alpha_2}}, \quad q_{r,t}^{chart} = \frac{q_{r,t}^{ship}}{\theta_{r,t}} = (1 + \theta_{r,t}^{\alpha_2})^{-1/\alpha_2}, \quad (15)$$

where the larger the parameter α_2 is, the lower search frictions are: in the limit, as $\alpha_2 \rightarrow \infty$, matching becomes frictionless. We show that our counterfactual results are robust to alternative parametric forms for this matching function in Appendix D.3.

We next map demand into match quality and entry. Match quality depends on the normalized demand index $\tilde{z}_{r,t}$, which we construct from the first-stage demand estimates below. We parameterize the match survival process as $\eta_{r,t} = \Lambda(\gamma_{0,\eta} + \gamma_{1,\eta} \log(1 + \tilde{z}_{r,t}))$, where $\Lambda(\cdot)$ is the logistic function, and the match value as $v_{r,t} = \gamma_{0,v} + \gamma_{1,v} \log(1 + \tilde{z}_{r,t})$.

By contrast, the per-region pool of potential charterer entrants depends on raw demand, $e_{r,t} = \text{softplus}(\gamma_{0,e,r} + \gamma_{1,e} \log(1 + z_{r,t}))$, where $\text{softplus}(x) = \log(1 + e^x)$ is a smooth counterpart to $\max\{0, x\}$. The number of potential entrants responds to demand through the common slope $\gamma_{1,e}$ and shifts

⁵⁶We obtain similar results if we double or halve ν (halving or doubling the implied adjustment costs). This insensitivity is not surprising in this setting, since containerhips are designed to be relatively movable forms of capital and adjustment costs are paid only when a ship begins a new match. By contrast, the core duration tradeoff is governed by — as we discuss in Section 5.3 — components such as match survival $\eta_{r,t}$, match value $v_{r,t}$, bargaining δ , and the elasticity of the matching function.

⁵⁷This overstates the entry cost, since the commission is only paid ex post upon a match, and we assign its full incidence to the charterer; discussions with Clarksons indicate that much of the upfront effort is borne by the broker rather than the charterer.

across regions through the region-specific intercept $\gamma_{0,e,r}$.

6.2 Identification

We discuss how we identify the stage 2 parameters in the simulated method of moments. To capture cyclicity, we split the sample into three periods when defining many of the moments. These are the *collapse* period (July 2008–December 2010, capturing the main bust in the data); the *pre-collapse* period before July 2008; and the *post-collapse* period from January 2011 onward.

Charterer survival process $\eta_{r,t}$ and charterer value $v_{r,t}$ The parameters $\gamma_{0,v}, \gamma_{1,v}$, which underpin the level of match values and how they change with the cycle, are identified from the average contracted price in the pre-collapse period and its change during the collapse. Similarly, the parameters $\gamma_{0,\eta}, \gamma_{1,\eta}$, which underpin the charterer survival process $\eta_{r,t}$, are identified by matching the counter-cyclical pattern of dispersion in capacity utilization documented in [Observation 3](#) (Figure 4b and Table 2). Concretely, we include two moments: the average dispersion in the pre-collapse period and its change between the pre-collapse and collapse periods. The model’s binary dead-or-alive states need not correspond to empirical utilization rates of exactly zero and one. To express model-implied dispersion in units comparable to the empirical measure, we therefore assign dead and alive matches the 10th and 90th percentiles of the empirical residualized utilization distribution, respectively, when computing dispersion.

Bargaining parameter δ Intuitively, the model allows for two reasons for lengthening contracts in booms. The first is that the match value may systematically change in the boom — the ‘match effect’ from the comparative static in Section 5.3. This is already pinned down through the estimates for $\gamma_{0,\eta}, \gamma_{1,\eta}, \gamma_{0,v}, \gamma_{1,v}$. The second is the bargaining parameter δ , which governs the ‘market thinness effect’ from the same comparative static (Equation 11). A smaller bargaining parameter gives charterers a higher share of the match surplus, and this tends to amplify differences in the charterer’s outside option in booms versus busts (Equation 12). This then makes differences in the match surplus between a long and short contract more procyclical, and the corresponding contract duration choice is also more procyclical.

Thus, δ is identified by the residual cyclicity of contract duration, once match-specific factors are controlled for. So, we include moments for the mean contract duration in the pre-collapse period and its change between the pre-collapse and collapse periods. We emphasize that this identification procedure could potentially result in either a high δ or a low δ , depending on the cyclicity of the match-specific factors ($\eta_{r,t}$ and $v_{r,t}$).

Extension and duration-specific shock parameters The extension probability $\mathbb{P}_{\text{extend}}$ is identified by matching the average probability of an extension in the data. The scale parameter of the logit shock σ in the

contract duration choice is identified through a moment for within-period dispersion of contract duration.

Matching function and targeting parameter The matching parameter α_2 governs how easily agents can rematch after separating, which affects contract duration choice through the assurance premium discussed in Section 5.3. We therefore identify α_2 by matching the cross-sectional elasticity of contract duration with respect to the number of available ships (the equilibrium relationship documented in Observation 4). We match the regression in Column (4) of Table 3 using the corresponding regression in our model, which leverages across-region thinness within a time period (a thinner market corresponds to a lower number of available ships). Intuitively, a higher α_2 makes matching more efficient. This causes contract duration to fall in every region. It also compresses how responsive duration is to cross-sectional differences in thinness. For example, consider a very high α_2 . Here, even agents in a thin market can find new matches quickly, and so the duration-thinness relationship becomes flatter.

The targeting parameter α_1 is identified separately by a moment capturing how far ships travel when they reallocate. Here, a larger α_1 makes ships rematch closer to their current location, lowering the average reallocation distance. Specifically, we include a moment for the ‘relative’ reallocation distance: among ships that move to a different region ($j \neq r$), we take the flow-weighted average of the distance traveled normalized by the within-region distance, $x_{r,j}/x_{r,r}$. This normalization strips out baseline differences in distance across regions. Appendix Section B.5.1 provides a diagnostic sensitivity exercise showing how these two identifying moments move with α_2 and α_1 .

Charterer entry process With the matching and survival processes identified, the proportion of ships under contract in a region maps one-to-one into the (unobserved) number of searching charterers there. We identify the per-region entry intercepts $\gamma_{0,e,r}$ from the region-level shares of ships under contract, and the common slope $\gamma_{1,e}$ from how the aggregate share of ships under contract changes between the pre-collapse and collapse periods.

6.3 Estimation

First stage: demand estimation Since the raw demand shifters are not directly observed, we recover them “offline”, similar to Jeon (2022). We assume that demand for container shipping services in each trade region takes a constant-elasticity form:

$$d_{r,t} = z_{r,t} \cdot P_{r,t}^{\gamma_{1,z}} \quad (16)$$

where $d_{r,t}$ is the total cargo carried on trade region r during period t , $P_{r,t}$ is the price of hiring container-ships in that region, and $z_{r,t}$ is the raw demand shifter for region r . Summing across regions, aggregate demand inherits the same constant-elasticity form, $d_t = z_t^G \cdot P_t^{\gamma_{1,z}}$, where $z_t^G \equiv \sum_r z_{r,t}$ is the aggregate demand state and P_t is an aggregate price index that we approximate using the time-charter rate index (see Appendix B.3 for details).

We parametrize aggregate demand as $\ln(z_t^G) = \gamma_{0,z} + \gamma_{2,z}X_t + \xi_t$, where X_t denotes observed demand shifters (a time trend and an OECD industrial production index) and ξ_t denotes idiosyncratic shocks to aggregate demand. To estimate the demand elasticity $\gamma_{1,z}$, we take logs of the aggregate demand expression and substitute this parametrization:

$$\ln(d_t) = \gamma_{0,z} + \gamma_{1,z} \ln(P_t) + \gamma_{2,z}X_t + \xi_t \quad (17)$$

Following Jeon (2022), we instrument for the price $\ln(P_t)$ using the average size and age of ships, and the share of ships older than 20 years: these are all cost shifters since larger and newer ships are more cost-efficient.⁵⁸

Having estimated $\gamma_{1,z}$, we recover the aggregate raw demand shifter as $z_t^G = d_t \cdot P_t^{-\hat{\gamma}_{1,z}}$, and the region-level raw demand shifters as $z_{r,t} = d_{r,t} \cdot P_{r,t}^{-\hat{\gamma}_{1,z}}$. We then smooth these series and construct the normalized demand index used for match quality as $\tilde{z}_{r,t} = z_{r,t} / [\kappa_r (n_t/\bar{n})]$, where $\kappa_r = T^{-1} \sum_t d_{r,t}$ is the region's average cargo volume, and $n_t/\bar{n}$ is aggregate fleet size relative to its sample mean. We use this normalized index for $v_{r,t}$ and $\eta_{r,t}$ because these primitives describe the quality and survival of an individual match, rather than the size of the regional market. We then estimate the log AR(1) processes for $\tilde{z}_{r,t}$ and z_t^G (see Appendix B.4).

Second stage: simulated method of moments We use the moments described above in Section 6.2 using a diagonal weight matrix. We scale the weights on the diagonal so that the moments enter into the objective function with a common scale and detail the specific weights in Appendix Section B.5. Note that, when constructing the moments, we residualize the data to control for ship heterogeneity, as described further in Appendix Section B.5. Each evaluation of the objective requires solving the model's dynamic spatial equilibrium, which we compute by iterating on agents' forecasting rules and the simulated state evolution. We compute standard errors via the bootstrap. Appendix Table B.3 reports a Monte Carlo exercise verifying that this moment structure recovers the second-stage parameters.

⁵⁸ The instruments plausibly satisfy the exclusion restriction, since fleet composition reflects shipbuilding decisions made several years prior to delivery due to long construction lags. For example, the global fleet continued to grow in 2009 despite the collapse in demand. Consequently, variation in average ship size and age is plausibly predetermined with respect to current demand shocks.

7 Results and model fit

First-stage demand estimates Appendix Table B.1 reports demand estimates. Our estimated demand elasticity is around -1.45. Appendix Figure B.1 shows how the aggregate demand state z_t^G evolves over time.

Second-stage parameters Table 5 shows the estimated parameters. Appendix Section B.5 provides a comparison between the empirical moments and the simulated moments, and we find that the model fits the data well. As an additional check, Appendix Table B.4 shows a close fit to the monthly time series for price, contract duration, utilization, and dispersion.

Table 5: Parameter estimates

Parameter	Estimate	SE	Region, $\gamma_{0,e,r}$	Estimate	SE
Targeting parameter, α_1	0.344	0.174	Americas	-13.825	2.617
Matching parameter, α_2	0.545	0.055	Asia–Europe	-15.776	3.127
Ship bargaining weight, δ	0.074	0.012	Asia–North America	-14.189	1.516
Std. dev. of logit shock, σ	0.675	0.069	Intra-Asia	-11.515	1.813
Survival intercept, $\gamma_{0,\eta}$	1.579	0.097	Intra-Europe	-5.248	2.353
Survival slope, $\gamma_{1,\eta}$	1.269	0.121	Middle East and Africa	-7.065	1.282
Match-value intercept, $\gamma_{0,v}$	1.919	0.168	Europe–North America	-8.445	1.963
Match-value slope, $\gamma_{1,v}$	0.394	0.139			
Entry slope, $\gamma_{1,e}$	7.404	0.611			
Extension parameter, $\mathbb{P}_{\text{extend}}$	0.755	0.041			

We find a matching parameter α_2 of 0.55, indicating sizeable search frictions. The equilibrium object relevant for the planner in Section 5.3 and for our identification argument in Section 6.2 is the elasticity of the matching function with respect to ships. In the estimated dynamic equilibrium, the average ship-side matching elasticity is 0.693; although we study a physical capital market, this value is within the standard range of unemployment-side elasticities in matching models in labor market settings (Petrongolo and Pissarides, 2001).

We next turn to the bargaining parameter δ . We again emphasize that the magnitude of δ is an empirical question and a high value of δ that favors ships is consistent with procyclical contract duration if the match-specific factors in the model (v_t, η_t) are also sufficiently procyclical. In our context, we find a $\delta = 0.07$, which implies that charterers capture most of the match surplus.⁵⁹ However, it is hard to interpret δ in isolation. This is because there are two channels in the Nash bargaining solution that generate negotiation asymmetries: differences in the outside options and δ . For example, an arguably more interpretable measure of the outcome of the negotiation process is the ship’s share of expected discounted contract profit (rather

⁵⁹We also test whether bargaining parameters change over time with boom-bust outside options, but do not find evidence of a time-varying bargaining parameter; see Appendix D.4.

than the surplus, which also includes the outside options). This value, averaged over the sample, is 0.35, which implies that charterers still do well in the negotiation process but — because ships have a strong outside option — not as well as one might expect looking at the raw magnitude of δ .

Furthermore, the low δ for ships is consistent with institutional characteristics of the industry. The market for leasing containerships is relatively new compared to our sample period: it did not exist before the 1980s (Stopford, 2009). However, the firms that charter ships have been around for decades offering liner services using their own ships. Therefore, these shipowners who specialize in leasing out ships are relatively inexperienced and potentially less sophisticated at negotiating. This pattern of higher bargaining power for charterers is consistent with evidence from other industries where pro-cyclical contract duration is also observed: in bulk shipping, Brancaccio et al. (2023) find that exporters capture a larger share of the surplus than shipowners, and in offshore drilling rigs, Vreugdenhil (2026) estimates a rig owner bargaining weight of 0.37. Across these markets, charterers' stronger bargaining position may contribute to the pro-cyclicality of contract duration.

8 Counterfactuals

We begin by documenting how the decentralized equilibrium contract length changes with the business cycle in our model and the implications for misallocation. We compare the results to a constrained social planner, who still faces search frictions and no information about the realization of future shocks, but is able to coordinate firms to set a contract length each period that optimally maximizes total welfare (measured in total joint profits) of the market.⁶⁰

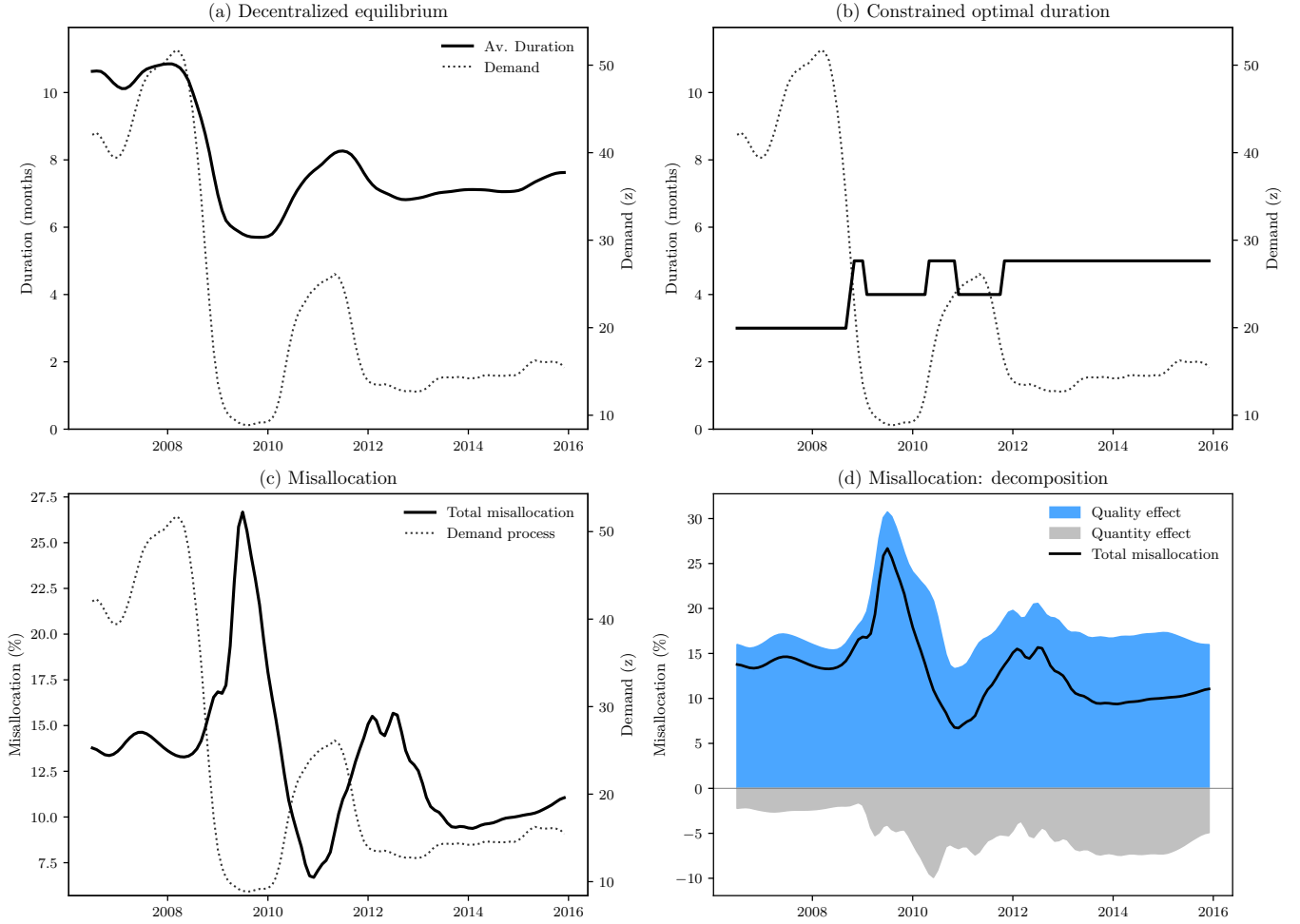
We present the results in Figure 6, with additional numerical results in Table 6. In Panel (a) of Figure 6 we plot the decentralized contract duration in the solid black line and the demand process in the dotted line. Consistent with the data, it is pro-cyclical.

We compute the constrained optimal duration in Panel (b). We find, strikingly, that the optimal contract length is actually counter-cyclical and *decreases* in the boom. We provide more intuition for this later through a decomposition exercise.

The difference in total profits of the firms (misallocation) moving from the decentralized contract to the optimal duration is pictured in Panel (c). The level of misallocation follows the level of the demand realization but with a lag. The lag occurs because it takes time for the stock of existing contracts to accumulate (or

⁶⁰To compute the social planner's duration for any given state, we iterate over all possible contract durations, compute the equilibrium total welfare for each selection via forward simulation, and then choose the contract duration with the corresponding highest total welfare.

Figure 6: Misallocation across the boom-bust cycle



Note: Panel (a): This shows the average duration in the baseline case (in the solid line) versus the demand shifter (in the dashed line). Panel (b): Shows the optimal duration for a social planner that is constrained to not have information about future shocks, and where search frictions are still present. There is a single monthly optimal duration at each time and so there are discrete jumps between time periods. Panel (c): Misallocation between the decentralized vs optimal duration, measured in terms of total joint profits.

de-accumulate in a crash). As a result, the corresponding effects on market thinness and misallocation can take time to appear.⁶¹

Overall, misallocation from the contracting externality results in a 12.9% reduction in industry profits. Misallocation is cyclical and is especially high during the transition from the boom to the bust (because of the contract overhang generated in the boom). Indeed, in the transition in 2009, misallocation jumps to 19.6%.

These results illustrate a second implication of the efficient contract: it also allows the market to flexibly respond to aggregate shocks across booms and busts. To put it another way, the supply chain rigidities that result from the long decentralized contract overhang in booms — which are a striking feature of the

⁶¹This also highlights an advantage of our framework, which is that it is *not* simply a comparison between a steady-state boom and a steady-state bust. Rather, we accommodate that the market is constantly in transition.

descriptive results — are inefficient.

Table 6: Misallocation and utilization dispersion results for various counterfactuals

	(a) Duration (months)			(b) Dispersion in utilization		
	<i>Pre-collapse</i>	<i>Collapse</i>	<i>Overall</i>	<i>Pre-collapse</i>	<i>Collapse</i>	<i>Overall</i>
Baseline	10.6	6.7	7.6	0.11	0.13	0.12
Optimal contract	3.0	4.2	4.2	0.06	0.10	0.09
Intermediary - baseline duration	10.6	6.7	7.6	0.11	0.13	0.12
Intermediary	1.8	2.2	2.2	0.05	0.08	0.08

	(c) Total welfare (percent change from baseline)					
	(i) Transition			(ii) Overall		
	<i>Quality</i>	<i>Quantity</i>	<i>Total</i>	<i>Quality</i>	<i>Quantity</i>	<i>Total</i>
Optimal contract	23.4	-3.8	19.6	17.9	-5.0	12.9
Intermediary - baseline duration	1.1	4.3	5.4	0.5	6.5	7.0
Intermediary	30.7	5.8	36.5	24.7	8.2	32.9

Note: Panel (a) and (b): The pre-collapse period is July 2006–June 2008; the collapse period is July 2008–December 2010, when dispersion in utilization spikes in the data. Panel (c): Total welfare is measured in terms of the joint profits of the firms. ‘Quality effect’ is determined by keeping the number of matches constant and measuring the change in total profit moving to the counterfactual. ‘Quantity effect’ is then the remaining effect determined by changing the number of matches holding the average profit of each match constant. We define the ‘transition’ as May 2009–December 2009, the months in which misallocation spikes after demand crashes.

Decomposition We develop intuition for these results by decomposing total misallocation into a *quantity effect* and a *quality effect* in Panel (d) of Figure 6. To do so we begin with the decentralized contract duration. We then measure the change in total welfare keeping the number of matches fixed, but changing the profit per match to equal the level at the optimal contract duration (quality effect). This will be positive if the probability of an alive match is higher under the optimal duration. We then allow the number of matches to vary, and the resulting change in welfare is the quantity effect.

Recall from Section 5.3 that the key trade-off the planner faces is between a lock-in cost (that favors shorter contracts) and an assurance premium (that favors longer contracts). The decomposition in Panel (d) quantitatively illustrates this tradeoff. On the one hand, if contracts are too long then there may be lock-in of matches that have “died” but are still under contract. These contracted ships could be reallocated to alive charterers who are unmatched. This is the quality effect.

On the other hand, if contracts are too short, ships who are matched to charterers who are still alive at the end of the contract will need to search again. But searching involves frictions where they risk being unmatched; ex-post they would rather have remained under contract, which would have assured them of the match value. This is the quantity effect.⁶²

⁶²Although shorter contracts lead to a larger search pool, this does not raise match rates under constant returns to scale in

Note that — as we discuss in Section 5.3 — the planner’s trade-off is somewhat similar to the trade-off individual agents face when choosing the optimal contract length. The key difference is that the planner internalizes a thin/thick market externality. Specifically, individual agents value the option of returning to search according to the bargaining weight δ , whereas the planner values it according to the matching elasticity, which captures a searching ship’s marginal contribution to total match creation (Equation 14).

With the above trade-off in mind, consider the market in the boom when it is unbalanced with more searching charterers than ships. Here, the probability that a searching ship will find a match is high. The planner therefore prefers a shorter contract, knowing ships will quickly rematch with alive charterers, rather than risk lock-in with a longer contract. Conversely, in a bust, the number of searching agents on both sides of the market is more balanced. In this case, a searching ship is less likely to find a match, so the planner prefers a longer contract, which is why the optimal contract duration is counter-cyclical.

Effects on dispersion in ship utilization Table 6(b) illustrates dispersion in ship utilization across the counterfactuals. In the presence of search frictions, some dispersion is still efficient, as illustrated by the results for the optimal contract. Concretely, dispersion would be 0.12 under the decentralized contract baseline, but significantly lower at 0.09 under the optimal contract. Therefore, approximately 73.1 percent of dispersion is efficient and 26.9 percent is inefficient.

This comparison also helps disentangle the mechanisms discussed in Section 5.3. The planner continues to face regional demand shocks, distance-dependent adjustment costs, and distance-dependent search. Thus, the decline in dispersion under the optimal contract comes only from reducing the inefficient contract overhang generated by decentralized duration choices.

The intuition behind these findings is similar to the intuition behind the optimal contract. Dispersion rises due to contract lock-in which creates more dead matches. However, some risk of lock-in (and therefore some dispersion) is optimal because a contract that is too short means that agents have to search more frequently. In the presence of search frictions, this can generate an inefficiently high number of unmatched agents.

Role of search frictions/an intermediary The above findings all consider a constrained planner that still faces search frictions. What is the role of search frictions in the results? To answer this question we implement an intermediary in the form of a centralized platform — intuitively, an Uber for containerships — which eliminates search frictions. We operationalize this by implementing a ‘frictionless’ matching function of $\min\{a_{r,t}^{ships}, a_{r,t}^{chart}\}$ and also setting $\mathbb{P}_{extend} = 1$. Agents then choose their privately optimal contract.

matching. With increasing returns, shorter contracts could in theory thicken the market in a way that raises overall match rates. Appendix D.3 shows, however, that our results are robust to incorporating increasing returns to scale in matching.

The results in Table 6 show that an intermediary would result in an extremely short contract in equilibrium (in part due to agents' ability to continuously extend the contract), and substantially reduce dispersion in utilization. Overall, an intermediary would increase welfare by 32.9%. Strikingly, if contract duration is held fixed at baseline levels, the intermediary raises welfare by only 7.0%. The vast majority of the gain is instead driven by the equilibrium response of contract duration to the removal of search frictions. By eliminating the risk of remaining unmatched, the intermediary removes agents' incentive to use long contracts as insurance against failed future searches (so that the assurance premium goes down). Equilibrium contract duration therefore falls sharply, mitigating the contracting externality. The value of intermediation thus comes primarily through its indirect effect on contract length, rather than through direct improvements in matching efficiency.

9 Conclusion

This paper shows how endogenous rigidities — in the form of agents' choice of contract duration — affect physical capital reallocation in decentralized markets with search frictions. To do so we exploit rich data on contracts and allocations in the market for leased containerships; a market that is also important by itself as a key part of the supply chain. Using these data and an empirical model, we argue that agents choose longer contracts in booms when the market becomes thin, and that this results in a contracting externality that implies contracts are too long in booms, leading to misallocation.

Using the model, we find that there is significant misallocation from endogenous contracting rigidities, particularly when the market transitions from a boom to a bust. Overall, given that contract duration also rises during booms across a range of other capital markets, our paper suggests that accounting for endogenous rigidities is important for understanding the process of capital reallocation in booms and busts.

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A Appendix

A.1 Data construction

The Clarksons contract data includes a number of key contract details, most notably the charter period (or duration), and the contracted charter rate (in \$/day); as well as the charterer name. For some contracts, we

also observe the “delivery location”, which is the location where the ship is transferred from the shipowner to the charterer. The contract data also includes information on ship characteristics, such as vessel type, name, twenty-foot equivalent unit (TEU), deadweight tonnage, and year of build.

We match each ship in our dataset to a comprehensive dataset of containerships collected from Vessel Finder, which includes a variety of additional ship-level information (e.g., ownership information), as well as (crucially) the International Maritime Organization (IMO) number for each ship. We use these IMO numbers (unique to each ship) in order to merge the Clarksons contract data with port call information from Lloyd’s. We find that 19 percent of port calls are matched to a contract. This is relatively similar to the share of time a ship appears in the contract subsample (16 percent), where we compute the total time a ship is in the port call data as the time between the earliest port call to the final port call.

Some contract records from Clarksons lack precise charter durations but provide approximate ranges (e.g., “20-40 days” or “5-7 months”). For the empirical analysis, we compute two measures of contract duration: mean values (e.g., 6 months for “5-7 months”) and the maximum period (e.g., 7 months for “5-7 months” or the period until the next contract for the ship starts, whichever comes first). Our baseline analysis is carried out using the maximum period of each contract as the contract duration; all our results, however, are robust to using the other measure instead.

Our full dataset of contracts includes over 16,000 time-charter contracts from 1999 - 2022. Our analysis focuses on the period of 2006 - 2015. After implementing the sample cuts described in Section 3 (e.g., removing very large ships or brand-new ships), we are left with 2,704 contracts in our main estimation sample.

A.1.1 Representativeness of the contract subsample

In our contract sample, we observe 82 percent of the ‘full sample’ of ships, which is the universe of leased containerships that satisfy our standard data cleaning steps i.e. removing large ships above 5,000 TEU capacity as well as brand-new ships. For each ship, we observe contracts covering about 16 percent of the time between its first and last port call during the sample period. Thus, our sample covers about 13 percent of eligible fleet ship-time.

In Table A.1 we show additional evidence that the sample of contracts is not selected along important dimensions. To do so we compare the year the ship is built and the ship size (two key ship covariates) between the matched vs the full sample (i.e. the population of chartered ships that satisfy our data cleaning criteria). We find that these covariates are similar in the matched sample and the full sample.

We also compare how the idle ship rate computed using our contract data for the full sample period (using the procedure in Section A.4) matches the idle rate published by Clarksons (which is calculated using the universe of all containerships); the two series overlap in 2014-2015. We find that the mean value of these two series is similar during this 2014-2015 period, further evidence that our sample of contracts is representative.

Table A.1: Representativeness of the contract subsample

(a) Comparing ships in the contract dataset vs the full set of ships

	Contract sample	Full sample	Percent similarity
Number of unique ships	1,354	1,643	82
Median ship size (1000s TEU)	1.6	1.7	97
Median ship year built	2003	2007	91

(b) Comparing idle ship rates computed with contract dataset vs Clarksons' measure (for 2014-2015)

	Contract sample	Clarkson's
Ship idle rate (percent)	5.92	5.05

Note: Panel (a): Percent similarity is computed, for 'ship size', and 'ship year built', as $100 \times (1 - \Delta/\text{Range})$, where Δ is the difference in medians and *Range* is the range of the covariate in the full sample. For the 'number of unique ships' row, this measure is the number of matched ships in the contract sample as a percent of the full sample. Data on the full sample of containerships is obtained from Clarksons fleet register data, which covers all containerships in the world. Panel (b): This panel uses data from 2014-2015, which is the overlap of our idle measure (which is constructed from the contract sample using the procedure in Section A.4) and the data we have directly on ship idleness from Clarksons.

A.1.2 Clarkson's indexes

In addition to the contract data, Clarksons' Shipping Intelligence Network provides aggregate indexes such as the containership time-charter rate index, China Containerized Freight Index (CCFI), and other freight price indices. The most important one for our analysis is the containership time-charter rate index, an index published by Clarksons based on daily rates of newly negotiated time-charter contracts. In correspondence with Clarksons they told us that the containership time-charter rate index is "a weighted average (normalised for TEU) of the timecharter rate benchmarks that we publish each week". According to Clarksons, these benchmarks are formed by: "requesting brokers to fill in a weekly pro-forma with the latest rate for each ship type or by estimating the likely rate acceptable to an owner in the absence of any fixtures" (Clarkson Research Services, 2015). Therefore, this index does not simply aggregate the reported contracts, but is rather based on broader market conditions.

The China Containerized Freight Index (CCFI) is an index of container freight rates based on the price of containers leaving from all major ports in China. We use this, as well as other freight indices, when

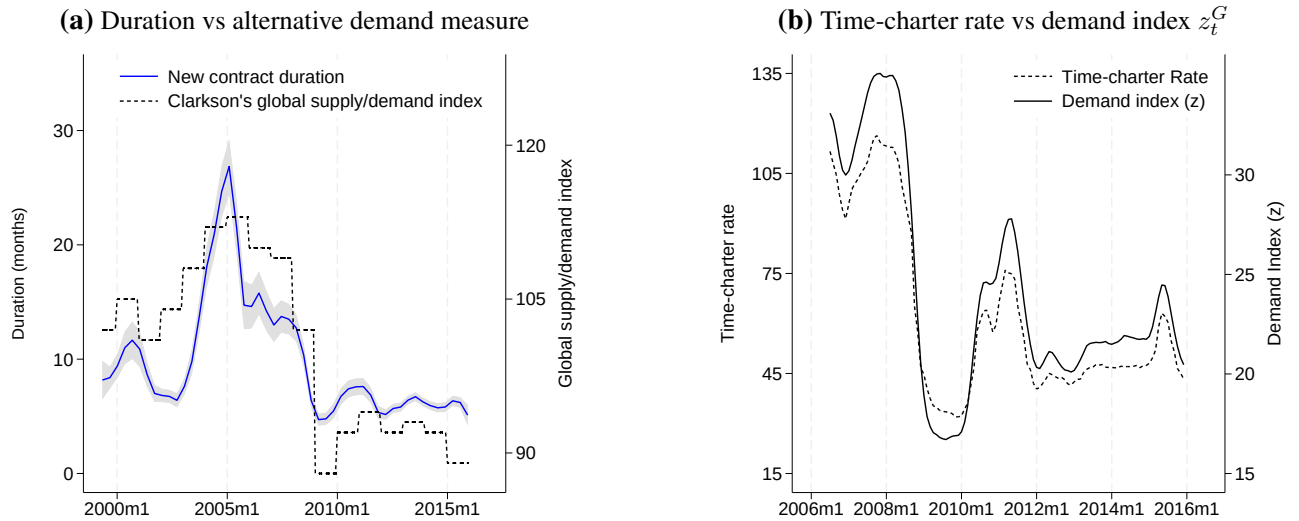
measuring revenue earned by ships (Section A.7).

A.2 Pro-cyclical duration: robustness checks

In Figure A.1a we show the robustness of the correlation in Figure 2 to an alternative demand measure: Clarkson's global supply/demand index. We collect the annual values of this index from Clarkson's Container Intelligence Quarterly.⁶³ The two series are highly correlated, implying that Observation 1 (that new contract duration increases in booms) is robust to alternative measures of demand. Note that we choose to not use this as our main demand measure in Figure 2 because it is only an annual measure, whereas contract duration is defined over a more granular time-series.

Figure A.1b provides additional evidence that the time-charter rate index is a good proxy for overall demand conditions in the market. Here we plot it against the demand index (z_t^G) that we construct in the paper and show the two series are highly correlated. Note, however, that we cannot use z_t^G as the demand index in Figure 2 because it requires utilization data which is only available from 2006 onwards.

Figure A.1: Robustness: using the time-charter rate index as a measure of demand



Finally, we address a specific concern: if longer duration contracts are more expensive, then the time-charter index might ‘mechanically’ increase through changes in duration. To address this concern we run two regressions in the form: $dayrate_t \sim \beta_0 + \beta_1 \widehat{time_charter}_t$ where $\widehat{time_charter}_t$ is the de-meaned time-charter index and $dayrate_t$ is the average (smoothed) contract dayrate in month t . The first regression is for contracts with below-median duration and the second regression is for contracts with above-median

⁶³This index is constructed for the global containership market using the following methodology, described in the Container Intelligence Quarterly. “In each case end 1996 = 100. From that point in time onwards, increases in demand are divided by increases in supply to create an annual factor, which is multiplied by the previous annual index value to create the index value for the current year.”

duration. We present the regressions in Table A.2.

In the extreme case where changes in the cross-sectional distribution of contracts are responsible for changes in the time-charter index, we would expect large differences in the average price (captured in the intercept β_0) across the two groups, and $\beta_1 \approx 0.0$. However, we observe the opposite: prices are only slightly higher for longer contracts (around 14 percent). Therefore, cross-sectional changes in the distribution of contract durations cannot explain the large swings in the time-charter index on the order of 600% across the 1999-2016 period. Rather, the similar estimates for β_1 , as well as the high R^2 measures, show that prices are highly correlated with the time-charter rate index *within* each duration group. Overall, this indicates that it is price increases for *all* contract durations that are largely responsible for changes in the time-charter index, in contrast to the specific concern.

Table A.2: Relationship between contract price and the time-charter rate index for different durations

	(1) $\leq$ Median duration	(2) $>$ Median duration
β_1	119.8 (4.59)	111.8 (3.47)
β_0	9806.2 (157.05)	11363.8 (118.76)
R^2	0.77	0.84
N	201	201

A.3 Measuring utilization

To measure utilization, we exploit the fact that for many port calls, we observe the draft of the ship, which is indicative of how much cargo the ship is carrying. We then define utilization as the percentage of the ship’s capacity that is used for carrying cargo; if this number is low, it suggests the ship is not being fully utilized. While we do not directly observe this in the data, we can infer utilization from draft data following the approach in Heiland et al. (2025), as we describe below.

Each ship has a “scantling draft” (H_S), also referred to as the design draft, which represents the ship’s draft when fully loaded and is a constant value since the ship is constructed to operate at this specific draft. While we don’t observe the scantling draft, we proxy for it by choosing the observed maximum draft for the specific ship in the data.

A ship that is sailing without cargo is sailing “in ballast”. In practical terms, a ship is considered to be sailing in ballast if its draft is less than a specified threshold value known as the “ballast draft” (H_B). In the maritime engineering literature, a weight of 0.55 (relative to the scantling draft) is employed to establish the

ballast draft (Heiland et al., 2025). Following this literature, we define the ballast draft (H_B) as 55% of the ship's scantling draft (H_S). We then compute utilization, defined as the percentage of the ship's capacity that is being utilized on a specific voyage, using the following formula:

$$\text{Utilization} = (H_A - H_B) / (H_S - H_B) \quad (18)$$

where H_A is the draft reported in the port call data. Note that in the analysis we always account for ship heterogeneity when using this measure (e.g., by including ship fixed effects), in order to ensure that the measure is comparable across vessels.

Finally, since ships only report draft information when they arrive at or depart from a port, this measure of utilization only captures the intensive margin (i.e., how full the ship is, conditional on being non-idle). We separately measure the extensive margin by using the port call data to identify idle ships, as we discuss in the next section.

A.4 Measuring idleness

Identifying whether or not a ship is idle We use the port call data to identify whether or not a ship is idle. If a ship is not being utilized at all, it will typically stay moored at a single port for a longer period than is needed for the ship to unload and load.⁶⁴ We assume conservatively that it takes a maximum of 7 days for a ship to unload and load at a port (taking into account port congestion), and that any length of time it stays beyond that time is idle time. Based on this measure, we are able to calculate, for each ship, the number of days it is idle each month. Aggregating this across ships allows us to measure the overall share of idle ships at any point in time.

Measuring proportion of ships under contract The most direct way to measure the proportion of ships under contract at any point in time would be to simply count the number of ships in port call data with active contracts; however, this is likely to be an underestimate since we do not see the universe of contracts.

Instead, we leverage our measure of idleness in order to calculate the proportion of ships under contract. When we do this, we allow for the possibility that ships may be idle even when they are under contract: this could be because they are undergoing repairs, or because the match has low value and the charterer is not able to find a productive use for the ship. As Figure A.2 shows, while the share of ships under contract that are idle is substantially smaller than the overall share of idle ships, it is still higher than zero.

⁶⁴Note that a ship's draft is not reported except on days the ship arrives at a port or departs from it, which is why draft data itself is not enough to identify idleness.

Let u denote the share of ships that are not under contract (or unemployed). Let $i_{overall}$ denote the overall share of idle ships, and $i_{contract}$ the share of ships with a contract that are idle. Assuming that a ship without a contract is necessarily idle, we can decompose $i_{overall}$ as follows:

$$i_{overall} = u + (1 - u)i_{contract}$$

Re-arranging this yields the following equation for u , the share of ships without a contract:

$$u = \frac{i_{overall} - i_{contract}}{1 - i_{contract}}$$

Figure A.3 plots the share of ships under contract (i.e., $(1 - u)$) over time, which (as expected) is procyclical. Notice, however, that even during the bust, a very high share of ships (around 90%) is under contract.

Figure A.2: Share of idle ships

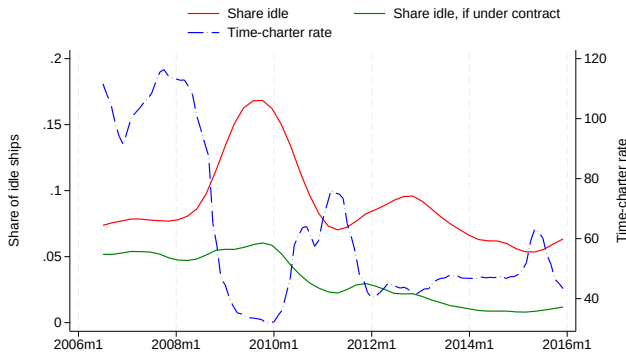
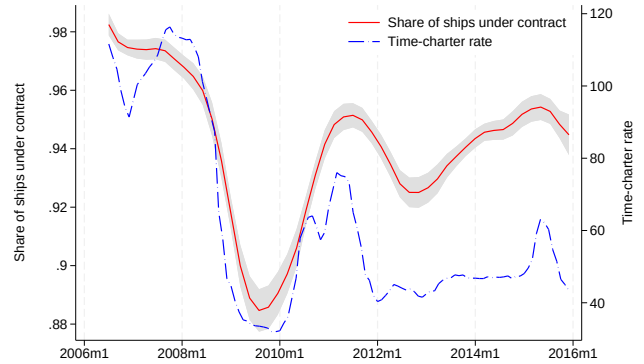


Figure A.3: Share of ships under contract



Since our procedure also leverages the contract dataset (which is a sample of the total contracts), one may also be concerned about selection. As we show in Table A.1b, our constructed idleness measure matches well Clarkson's measure based on the universe of containerships, during the time periods where the samples overlap.

Comparing idleness of owner-operated and leased ships We have also collected port call data for a sample of about 220 owner-operated ships from the top ten carriers in the world. We are therefore able to compare idleness for these owner-operated ships with leased ships (with the caveat that our sample of owner-operated ships may not be fully representative of the overall global fleet). During our sample period between the middle of 2006 and the end of 2015, owner-operated ships were idle 6.9% of the time, compared to 9.0% for leased ships (Table A.3). So, the difference in the share of idle ships is relatively small at (accounting for

rounding) 2.1%. Therefore, the relative idleness of leased vs owned ships is unlikely to amplify or dampen the results of endogenous rigidities.

Table A.3: Share of idle ships: leased ships vs. owner-operated ships

	Mean	SD	N
Share of idle ships, leased	0.0900	0.0340	114
Share of idle ships, owner-operated	0.0692	0.0331	114

A.5 Measuring reallocations

We use the port call data to measure ship reallocations. The key challenge is that since containerships are operated like “buses”, they may travel very long distances and stop at a large number of ports while remaining within a fixed schedule.⁶⁵

We develop an algorithm for identifying when a ship is reallocated. The idea behind the algorithm is that if a ship is reallocated, it is likely to stop at a new set of ports compared to those that were on its original schedule. Thus, when we observe a ship visit a new port that it has not visited in recent months, we can infer that the ship has been spatially reallocated. To fix ideas, we provide an example of a reallocation in our dataset between two schedules in Table A.4, showing both the raw data and generated ‘constructed data’ that the algorithm produces. (Note that in our raw data we also have a lot more information e.g. the ship name, the arrival and departure dates, and the spatial coordinates of each port, but we remove them from Table A.4 since our data are proprietary.)

One challenge with identifying reallocations and schedules is that a containership may visit a new port that involves a minimal deviation from its existing itinerary. An example of this would be a ship that is on an itinerary involving regular round-trips between Tokyo and Singapore, which at some point decides to make a stop at Manila along the way. These are unlikely to be true reallocations of the ship, and instead may simply represent extra voyages the carrier/charterer has decided to make while largely sticking to their original route. Thus, in order to not classify such minor deviations as reallocations, we also require that it is not a one-off stop but rather part of a new repeated schedule, and that the new port that is visited be a sufficiently large distance away from any of the existing ports that the ship visited.

We now describe the algorithm we use to formalize this idea. For every port call, we calculate the *minimum* distance between coordinates of the current port call and all the other port calls in the last 6 months. The

⁶⁵For example, one containership in the data was observed to first stop at several ports in New Zealand, make its way up to North America (stopping at several Canadian and American ports), then travel to Western Europe, then return back to New Zealand (stopping in Colombia along the way). This sequence was repeated several times.

Table A.4: Example of schedules and a reallocation between schedules in our data

Raw data		Constructed data	
Port call order	Port name	Schedule ID	Schedule stop number
1	Ulsan	1	1
2	Ningbo	1	2
3	Shanghai	1	3
4	Busan	1	4
5	Ulsan	1	1
6	Shanghai	1	2
7	Ningbo	1	3
8	Busan	1	4
9	Hong Kong	2	1
10	Cebu	2	2
11	Saipan Is.	2	3
12	Guam	2	4
13	Hong Kong	2	1
14	Cebu	2	2
15	Saipan Is.	2	3
16	Guam	2	4

metric is assigned a value of 0 if the vessel has made a prior call at that port within the preceding 6 months. Conversely, when the port represents a new visit, the metric assumes a positive value, with its magnitude increasing proportionally as the port’s distance from the current location grows, indicating a more significant alteration to the voyage schedule.

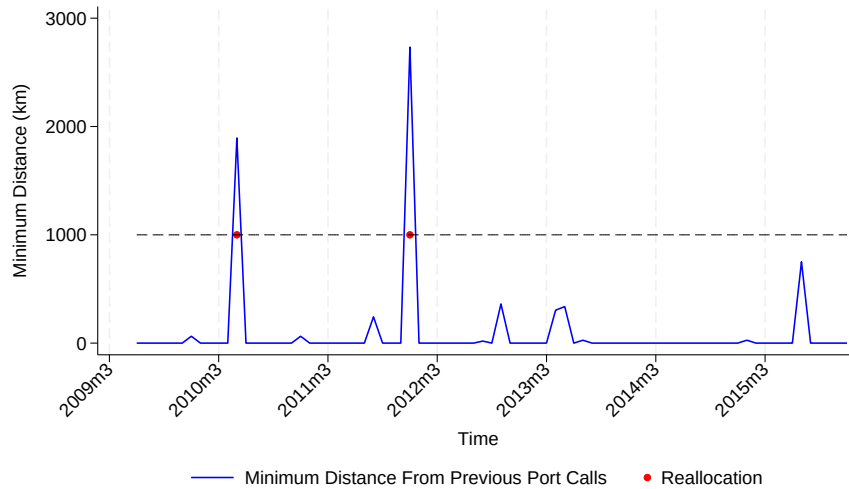
To rule out “false positives” caused by minor deviations from a set route, we classify the ship as having reallocated in a given time period only if the minimum distance metric exceeds a threshold value of 1,000 km. As well, we require that the port responsible for the “large deviation” from the current schedule is repeated at least once in the following three months. This ensures that the ship has genuinely moved to a new schedule as opposed to, for example, a one-off stop so that the crew can return home with the ship then returning to its regular schedule afterwards. In terms of the Manila example, although it is further than 1,000 km from its adjacent stops, a one-off stop would not count as a reallocation. We also do not allow ships to be reallocated again within three months of an initial reallocation (since there may be more than one jump of 1,000km as the ship moves to a new schedule).

We found this algorithm to work well in practice; the episodes it identifies as reallocations match well with what appear in the data to be true reallocations.⁶⁶ An example of how we identify reallocations is depicted in Figure A.4, which plots the minimum distance over time for a single ship: there are two instances when the

⁶⁶We recognize that the choice of 1000 km as a threshold is somewhat arbitrary. Our results on reallocation are robust to other choices of the threshold.

minimum distance from ports visited in the last six months exceeds 1000 km (in May 2010 and December 2011), and in both cases the ship would go on to visit the same port again. Therefore, the algorithm classifies both these deviations as reallocations.

Figure A.4: Example of how we identify reallocations



Note: This figure plots the minimum distance from all ports visited in the previous six months, for an example ship. The horizontal line is the threshold of 1,000 km: if the minimum distance exceeds 1,000 km, and if that port is visited again in the next three months, we identify that as an episode of reallocation. In the above figure, this criterion is satisfied by the port calls in May 2010, and December 2011.

We provide further evidence that this definition connects well with the industry setting in Table A.5. Here, we document summary statistics for the ‘deviation distance,’ which is the distance between a port call and any other port call visited within the previous six months and is an input into how we define reallocations. The sum of this deviation distance per trip (i.e. per iteration of each schedule) is typically 0.0, indicating that once a new schedule starts, it is relatively predictable. Excluding the first iteration — which has large deviations by construction since it is where the ship is reallocated — we also document the deviation distance in the second row. Here we see that the total deviation distance is typically small, except in rare cases, especially considering the median number of port calls each trip is 4.0. As well, we document the deviation distance between port calls in the last row of Table A.5, which is directly used to construct reallocations. Here we see that this variable is typically 0.0 but jumps to very large values in a small number of cases. Thus, this variable appears to capture the pattern that ships move on fixed schedules and then make large discrete jumps across space when moving to a new schedule.

One natural alternative definition for classifying reallocations would be to consider whether there are multiple deviations within a certain period (e.g. whether there are two new port calls in a schedule where each port call is 1000km away from an existing port call). However, this alternative definition would result in

relatively similar measures of reallocation: 94.8 percent of port call deviations greater than 1000km are combined with an additional 1000km port call deviation within three months. As well, this high percentage motivates us to exclude large port call deviations within three months of an initial deviation from our definition of reallocation, as previously mentioned, since they likely correspond to the same original reallocation.

Table A.5: Information about schedules and reallocations

	N	Mean	1%	5%	50%	95%	99%
Deviation distance per trip (km)	341468	923.4	0.0	0.0	0.0	3159.2	24129.6
Deviation distance per trip, except first (km)	319823	321.5	0.0	0.0	0.0	884.5	6816.5
Port calls per trip	341468	4.6	1.0	1.0	4.0	10.0	17.0
Deviation distance between port calls (km)	1585370	200.2	0.0	0.0	0.0	712.4	6476.1

Note: The metric ‘deviation distance’ is defined as the distance between a port call and any other port call visited within the last six months, consistent with the metric used to define reallocations in Section A.5. The first row provides the sum of this metric for each iteration of a schedule (a ‘trip’). The second row reports the same metric but without the first iteration (which typically includes large jumps that define a reallocation). Overall, the results highlight that our method of defining reallocations using large deviations from existing schedules connects well with the institutional setting. For example, most port calls are similar to those in the last few months, and deviations tend to come in groups, consistent with systematic changes in schedules.

A.6 Classifying schedules into routes and trade regions

In this section, we discuss how we classify all the observed schedules (or itineraries) into *routes* and *trade regions*.⁶⁷

Routes Our first step is to group together schedules that are geographically very similar to one another into trade routes. In general, no two schedules are completely alike: on an average schedule, a ship visits around 14.6 distinct ports, and there are 1857 unique ports. However, many different schedules share a common geography, involving ships visiting the same countries repeatedly at broadly similar intervals. We group together similar schedules in the following fashion: for each ship in a given schedule, we count the number of port calls made in each country and identify the three countries visited most frequently over the course of the schedule. Schedules that share the same set of top three countries are classified as belonging to the same *route*.⁶⁸

This approach allows us to aggregate schedules in a tractable way while still preserving much of the rich spatial heterogeneity of the raw itineraries. For example, a trade shock affecting a bilateral country pair (e.g., due to tariffs) would be expected to have a large effect on demand on schedules connecting those two countries, but much less so on other nearby schedules that do not involve a stop at both the affected

⁶⁷See Section A.5 for the algorithm we use to identify schedules from observed sequences of port calls by each ship. Note that throughout the paper, we use ‘schedules’ and ‘itineraries’ interchangeably.

⁶⁸Thus a ship that is on a schedule that primarily alternates between Shanghai, Brisbane, and San Francisco is considered as belonging to the same route as one that primarily alternates between Shanghai, Melbourne and Los Angeles, even though the exact ports visited may differ.

countries. Our granular definition of a route allows us to capture such idiosyncratic demand shocks (which are important for our analysis), which a more aggregated definition might miss.

Trade regions We further aggregate routes into *trade regions*, which is helpful for two reasons. First, although each route is potentially subject to idiosyncratic demand shocks, these demand shocks may be spatially correlated, as we show in Appendix B.3. Second, many routes are spatially quite close to one another, so that once a contract ends, a ship can be easily reallocated to another route nearby (whereas it may be more costly to reallocate the ship to a distant route). Therefore, it is logical to suppose that matching takes place at a more aggregated spatial level (that we call a *trade region*), even if different ships within that region are subject to different demand shocks depending on which route they are on.⁶⁹

We aggregate all the routes in our data into eight trade regions using the criteria listed below:

- *Asia - North America (Trans-Pacific)*: port calls to Asian and North American ports account for at least 70% of all port calls on the route, and each of the individual zones (Asia, North America) must separately account for at least 10% of the port calls.⁷⁰
- *Asia - Europe*: port calls to Asian and European ports account for at least 70% of all port calls on the route, and each of the individual zones (Asia, Europe) must separately account for at least 10% of the port calls.
- *Europe - North America (Trans-Atlantic)*: port calls to European and North American ports account for at least 70% of all port calls on the route, and each of the individual zones (Europe, North America) must separately account for at least 10% of the port calls.
- *Intra - Asia*: at least 70% of the port calls on the route are visits to Asian ports.
- *Intra - Europe*: at least 70% of the port calls on the route are visits to European ports.
- *Americas*: at least 70% of the port calls on the route are visits to North American or South American ports.
- *Middle East and Africa*: We classify two types of routes into this trade region. Firstly, we include any route where at least 70% of the port calls are visits to Middle Eastern and African ports. Second, we include routes that do not belong to any previously defined trade region and primarily connect the

⁶⁹Our approach also reflects how practitioners think about how container trade is spatially organized. For example, [Stopford \(2009\)](#) describes how there are over 1,000 different potential trade routes, but classifies them into three main groups (though he does not use the terminology of trade regions to describe such groups).

⁷⁰The latter criterion is meant to exclude ships that are primarily on an intra-regional trade region with occasional trips made to a different region.

Middle East and Africa with another major trading area (Asia, Europe, or the Americas). Specifically, we include routes where the combined share of port calls to the Middle East, Africa, and one of these partner regions is at least 70%, and where at least 10% of port calls are to Middle Eastern and African ports (with the same rule applied for Asia, Europe, or the Americas).

- *Others*: any route that cannot be classified into one of the above trade regions.⁷¹

Table A.6 shows the resulting classification of our estimation sample (where each observation is a single ship at the year-month level) into the different routes.

Table A.6: Classification of routes into trade regions

Routes	Year-Month Observations
Asia - North America	4,194
Asia - Europe	2,355
Europe - North America	3,873
Intra-Asia	38,998
Intra-Europe	25,581
Americas	14,951
Middle East and Africa	14,307
Others	2,300

Reallocation distance between trade regions We now discuss how we measure how far a ship has to travel when it reallocates from one trade region to another. A complication is that a ship in trade region r may, at different points in time, be visiting ports in very different parts of the world; and therefore the distance that it must travel in order to reallocate to trade region j depends on where it happens to be just prior to the reallocation.⁷²

We therefore work with the *expected* reallocation distance $x_{r,j}$, which is the average distance a ship can be expected to travel when it reallocates between regions r and j (including within-region reallocations, for which $r = j$). We compute this using the empirical distribution of reallocation distances. Specifically, we identify all observed reallocations between trade regions r and j in our sample, measure the distance the ship travels between its last port call in the original route on the previous trade region and its first port call in the new route on the new trade region, and average these distances across all observed reallocations.⁷³

⁷¹In practice, only 2.2% of ship - month observations end up being classified to this region.

⁷²For example, consider a ship reallocating from the North America–Asia trade region to the Intra-Asia trade region. If the ship’s last port call was in North America, the reallocation distance may be substantial; but if it happened to be calling at an Asian port, the reallocation distance would be much shorter.

⁷³We have also tried an alternative approach where we compute $x_{r,j}$ as a probability-weighted average of port-to-port distances. Specifically, let $f_r(p)$ denote the empirical probability that a ship in trade region r is visiting port p , and let $d(p, p')$ denote the distance between ports p and p' . Then $x_{r,j}^{\text{alt}} = \sum_{p,p'} f_r(p) f_j(p') d(p, p')$, where we take the sum across port pairs where port p belongs to region r and p' belongs to region j . Our results are robust to using this alternative measure.

A.7 Measuring dispersion in revenue

As we discussed in Section 3.3, we use cross-sectional dispersion in physical capacity utilization (residualized of ship heterogeneity) as our primary metric for inferring misallocation. However, dispersion in *physical* utilization may not necessarily imply an inefficient allocation of ships, if the prices of shipping services are heterogeneous across ships. For example, some charterers may operate on routes where the amount of cargo that needs to be moved each period is relatively limited (so that the charterer will have to operate at low physical utilization), but the value of moving that cargo is high.

As an alternative, therefore, we also construct a revenue-based dispersion measure. We multiply residualized capacity utilization by the freight rate of the itinerary the ship is operating on to obtain the revenue of the ship each month, and then calculate the standard deviation of the revenue each month. In this section, we discuss how we measure freight prices.

Our raw dataset does not include a direct measure of the freight price. In general, due to the confidentiality of the contractual agreements between charterers/shippers and downstream exporting firms, granular data on freight prices are impossible to obtain, except for a few specific importing countries.⁷⁴ Instead, our approach takes two steps. First, we collect data on average freight rates from various industry sources, and construct a quarterly freight price index for each of the trade regions. Second, we match these freight rate indices to the specific trade region that each charterer is operating on at each time, which we identify by utilizing port call information (as discussed above in Section A.6).

The most detailed data we have on freight rates is for the 3 major inter-regional trade regions: Asia - North America, Asia - Europe, and Europe - North America, as well as for intra-regional routes where ships travel via China. We normalize all the freight rate indices so they equal 100 in the first quarter of 2003 (which is the first year for which we have complete freight rate data).

For the Asia - North America trade region, we use the average of the CCFI (China Containerized Freight Index) for the China-US West Coast and China-East Coast trade routes. For Asia-Europe, we take the average of the CCFI for the China-Europe and China-Mediterranean routes.⁷⁵ For Europe-North America, we use the freight rate reported in UNCTAD up until 2009, and impute the freight rate from 2010 onwards.⁷⁶

⁷⁴For example, [Ardelean and Lugovskyy \(2023\)](#) collect transaction-level data for the Chilean import market in order to study price discrimination in liner shipping.

⁷⁵An alternative approach for these two routes is to use freight rates reported in UNCTAD's annual reports, similar to [Jeon \(2022\)](#); this yields a very similar measure of the Asia-North American freight rate.

⁷⁶The imputation is needed as UNCTAD stopped reporting Europe - North America freight rates from 2010. We first regress the Europe-North America freight rate on CCFI freight rates in other routes (namely, China-Europe, China-US West Coast, China-West Africa, China-South America) in the pre-2009 period. Then from 2010 onwards, when we only observe the CCFI

The freight rate for the Intra-Asia trade region is the average of the CCFI indices for the China-Hong Kong, China-Japan, China-Korea, and China-Southeast Asia routes. The freight rate for the Intra-Europe trade region is constructed as the average of the Asia - Europe freight rate and the US - Europe freight rate: the idea being that these freight rates for ships that travel between Europe and other regions should broadly reflect freight rates for ships that stay within Europe. In a similar fashion, the freight rate for the Americas trade region is constructed as the average of the Asia - North America freight rate, US - Europe freight rate, and the China-South America CCFI freight rate; while the freight rate for Middle East and Africa is constructed as the average of the CCFI freight rate for the China-South America and China-Mediterranean routes. Finally, for all other trade regions, we assume their freight rate index equals CCFI's overall global freight rate index.

A.8 Market thinness regressions

A.8.1 Measurement

In order to construct a market thinness measure we need to take a stand on how to define a “market”. We define the relevant market for each contract as the number of unique ships that were within 5000 kilometers of the first port call on the contract, and were in this radius within 15 days on either side of the date the contract began.⁷⁷ This measure proxies for market thinness by tracing out different areas across the earth, with geographically isolated markets (such as the west coast of Australia) producing lower measures than trading hubs (for example, ships located in a radius around Singapore).

A.8.2 Robustness of regressions to charterer types

Here we provide more information about how the four separate charterer controls in Table 3 affect the estimates. In columns (1) and (2) we include charterer scale controls. The motivation is that larger charterers may prefer longer contracts because they can more reliably use vessels over time. We measure scale both in terms of the number of other contracts the same charterer has signed (across the full sample) in column (1), and in terms of the total ship capacity contracted by the charterer in column (2). The results are robust to the inclusion of these controls.

In column (3) we include a charterer experience control, which is a binary indicator for whether we observe the charterer signing any other contract within the same area (defined as within a 5000 kilometer radius of

indices, we use the estimated regression equation to impute the Europe - North America freight rate.

⁷⁷The distance of 5000 kilometers is approximately the distance from the west coast to the east coast of the US. One limitation of this measure of market thickness is that we would like to also look at ships that were not just traveling in this market, but also were close to the end of their contract. Unfortunately our data, which only contain a subset of the total contracts, do not allow for this. Nevertheless, as we argue in the text, this measure is likely to still be a good *relative* proxy for thin and more geographically isolated markets, versus thicker markets.

the port call) at any point during the sample period. This control captures the idea that charterers who tend to operate within a specific area may prefer to sign longer contracts, and that such specialized charterers might locate in thinner markets. Again, the results are robust to this control.

In column (4) we include a charterer utilization control, which is the charterer's average utilization of all ships it ever has under contract. This addresses the concern that some charterers are more efficient at using their ships, leading to longer contracts. Including this control does not affect the results.

A.8.3 Recovering the effect of availability on contract duration

In this section we formally describe how we identify the elasticity of contract duration with respect to available ships, using observed variation in the total number of ships nearby. Contracts are indexed by i , and t denotes time.

We assume that the contract duration τ_{it} is determined by the number of nearby available ships, a_{it} , via the following equation:

$$\ln \tau_{it} = \beta_{a,0} + \beta_{a,1} \ln a_{it} \quad (19)$$

There are two key challenges in estimating the elasticity, $\beta_{a,1}$. First, a_{it} is not directly observed. Second, even if availability were observed, a direct regression of τ_{it} on a_{it} would be biased. This is due to equilibrium feedback effects: an increase in contract duration (τ_{it}) mechanically reduces the number of available ships a_{it} in that market, which would lead a simple regression to overstate the direct causal effect.

To overcome these challenges, we use an Indirect Least Squares strategy that leverages (exogenous) variation in the total number of nearby ships n_{it} . Availability is related to n_{it} by the identity $a_{it} = n_{it}f(\tau_{it})$, where $f(\tau_{it}) = u_{it} + \frac{(1-u_{it})(1-\mathbb{P}_{\text{extend},it})}{\tau_{it}}$, τ_{it} is the average duration, u_{it} is the idle rate, n_{it} is the total number of ships, and $\mathbb{P}_{\text{extend},it}$ is the probability of extending a contract. This accounting identity rests on two assumptions. First, ships can search on the job in the final period of a non-extended contract, consistent with how we set up the model. Second, we assume for simplicity that active contracts are uniformly distributed across remaining durations, so that at any point in time, the fraction of ships that are in their final contract period equals $1/\tau_{it}$. Under these assumptions, the share of all ships that are available, $f(\tau_{it})$, equals the share of unemployed ships u_{it} plus the share of employed ships that are in their final period and whose contracts are not extended. We can construct $f(\tau_{it})$ from objects directly observed in the data.⁷⁸

⁷⁸Although u_{it} and τ_{it} are equilibrium outcomes, we use them only to evaluate the accounting identity $a_{it} = n_{it}f(\tau_{it})$, not as sources of identifying variation; identification relies on (exogenous) variation in n_{it} , as we explain below.

We begin by estimating the (reduced-form) relationship between duration and n_{it} :

$$\ln \tau_{it} = \beta_{n,0} + \beta_{n,1} \ln n_{it} + \Gamma_s X_{ship} + \Gamma_c X_{charterer} + \delta_t + \epsilon_{it} \quad (20)$$

Note that the empirical specification is richer than equation (19): we include X_{ship} and $X_{charterer}$ to control for heterogeneity across ships and charterers, and we include granular year-month fixed effects, δ_t , in order to isolate the relationship between duration and n_{it} in the cross-section. We can then recover the structural parameter $\beta_{a,1}$ from the reduced-form elasticity $\beta_{n,1}$ using the following relationship which we prove below:

$$\beta_{a,1} = \frac{\beta_{n,1}}{1 + \beta_{n,1} \cdot \eta_{a,\tau}} \quad (21)$$

where $\eta_{a,\tau} = \frac{f'(\tau)\tau}{f(\tau)}$ is the elasticity of availability with respect to duration ($f'(\tau) < 0$), which we evaluate at the sample means of u , τ , and $\mathbb{P}_{\text{extend}}$. Intuitively, the denominator of equation (21) (which exceeds 1, since $\beta_{n,1} < 0$ and $\eta_{a,\tau} < 0$) adjusts for equilibrium feedback effects: an increase in the number of nearby ships n shortens duration, which mechanically releases ships back into the available pool faster, further increasing availability. As a result, the reduced-form elasticity $\beta_{n,1}$ overstates the structural effect of availability on duration in magnitude, and the denominator corrects for this.

Proof of Equation (21) Substitute $a = nf(\tau)$ into Equation (19):⁷⁹

$$\ln \tau = \beta_{a,0} + \beta_{a,1}(\ln n + \ln f(\tau)) \quad (22)$$

Then:

$$\frac{d \ln \tau}{d \ln n} = \beta_{a,1} \left(1 + \frac{d \ln f(\tau)}{d \ln n} \right) \quad (23)$$

Also note that:

$$\frac{d \ln f(\tau)}{d \ln n} = \frac{d \ln f(\tau)}{d \tau} \frac{d \tau}{d \ln n} = \frac{f'(\tau)}{f(\tau)} \frac{d \tau}{d \ln n} = \frac{f'(\tau)\tau}{f(\tau)} \frac{d \ln \tau}{d \ln n} \quad (24)$$

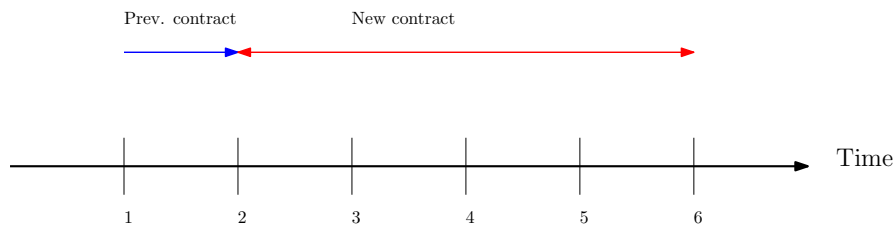
Substituting Equation (24) into Equation (23), rearranging, and noting that $\beta_{n,1} = \frac{d \ln \tau}{d \ln n}$, yields Equation (21).

⁷⁹For simplicity, we drop the i and t subscripts in what follows.

A.9 Contract extensions

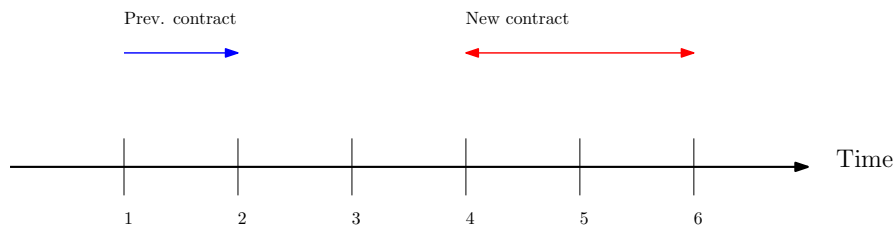
Identifying extensions To measure the share of contracts that are extensions, we look for *consecutive contracts* by the same ship and ask how often the charterer is unchanged across the pair. Ideally, if our data had no measurement error, we should expect the extended contract to begin as soon as the original contract ends. An example of this is depicted in Figure A.5, where the original contract ends in period 2 and the new contract begins right after: in such a case, as long as the charterer for the ship is the same, the new contract is very likely to be an agreed upon extension of the original contract.

Figure A.5: Consecutive contracts with no gap



But in practice, we often see consecutive contracts (for the ship with the same charterer), but with a gap in between the two contracts: for example, the situation depicted in Figure A.6. In such cases, provided the gap between the contracts is fairly small, it is still quite likely that the original contract was extended, but due to measurement error, the start date of the extended contract is not recorded as beginning right after the end of the original contract. Of course if the gap is sufficiently long, then it is more likely that the ship and/or charterer were searching for interim matches in the period, before deciding on a brand-new contract, which is therefore not just a continuation or renewal of the previous contract.

Figure A.6: Consecutive contracts with a gap



We therefore measure the fraction of contracts that are extended as follows. We first identify all cases where we see consecutive contracts by the same ship, with at most a gap of four months between them. Within this sample, we define a contract extension as any contract where the charterer is unchanged from that of the most recent contract by the same ship. Using this approach, we find that the share of extensions is 42.0 percent. This share is quite robust to the choice of the maximum gap, ranging from 41.0% - 46.5% as we vary it from 1 to 6 months.

Identifying options to extend Contracts occasionally have a built-in option to renew, where the charterer reserves the right to extend the contract. These options are recorded in the data in two ways. In some contracts, Clarksons records the exercise of a renewal option in the delivery location field.⁸⁰ In other contract records, the raw variable recording the contract duration will include not just the duration of the first contract, but also the duration of the subsequent contract if the charterer were to exercise the option to renew.⁸¹ We combine both types of information in order to measure the prevalence of such options: as mentioned in Section 2.1, these account for 2.9% of all contracts.

Note that even if a contract does not have a built-in option to renew (as is the case for the vast majority of contracts), the shipowner and charterer can and often do agree to extend the original contract, as discussed previously.

A.10 Identifying subleases

We identify subleases as contracts that satisfy the following criteria:

- The lease period is nested within the lease period of a previous contract for the same ship. We impose this criterion since a charterer cannot sublet beyond the period for which they have the ship.
- The charterer/lessee for the sublease must be different from that of the original lease (since one cannot sublet to oneself).

We also need to adjust the observed share of subleases $\hat{s}$ by the fact that we only observe a random sample of the total contracts p . The true share of subleases in the population is $s = \hat{s}/p$.⁸² In practice, $\hat{s} = 0.33\%$, and we set $p = 0.13$ (which is the proportion of contracts we observe, as detailed in Appendix Section A.1). This leads to $s = 2.5$ percent.

A.11 Market Concentration Accounting for Alliances

Evolution of Charterer Concentration Over Time Figure A.7 plots the annual HHI for the charterer side of the leasing market, taking into account alliances: when computing market shares, we treat each alliance as a single firm. The HHI rises over time as charterers begin consolidating into alliances, especially starting

⁸⁰Normally, the delivery location records the location where the shipowner is expected to deliver the ship to the charterer. But if a contract is an extension of a previous contract with the same charterer that had an option to renew, there is of course no delivery required (since the charterer already has possession of the ship). In such cases, instead of keeping this variable blank, Clarksons sometimes uses it to record whether the contract is based on an exercise of a previous renewal option.

⁸¹For example, a contract with a 6-month duration and an option to renew for another 6 months might be recorded as having a duration of “6/6 months”.

⁸²This is because a sublease is identified only if its original lease is also observed. An observed contract is a sublease with probability s , and its original lease appears in the sample with probability p . Therefore, the expected fraction of observed contracts that are identified subleases is $\hat{s} = sp$. Rearranging for s then produces the result.

from 2012.⁸³ However, the HHI always remains well below the 1,000 threshold used by the FTC to classify markets as moderately concentrated, reaching a maximum of 661 in 2015. As a result, the leasing market is best characterized as unconcentrated throughout the sample period even after accounting for alliances.

Charterer Concentration by Ship Age and Size In Table A.7 (second and third panels), we report charterer concentration segmented by both ship age and ship size, both for the 2006 - 2011 and the 2012 - 2015 periods. We divide ships into small/large ships using the median capacity, and divide them into old/new ships using the median age. HHI increased after 2012 across all segments, consistent with some increase in market concentration as alliances emerged. Nevertheless, the HHI in each segment remains below 1,000, suggesting that the leasing market remains unconcentrated by the end of the sample period regardless of segmentation.

Figure A.7: Charterer Concentration Accounting for Alliances (HHI)

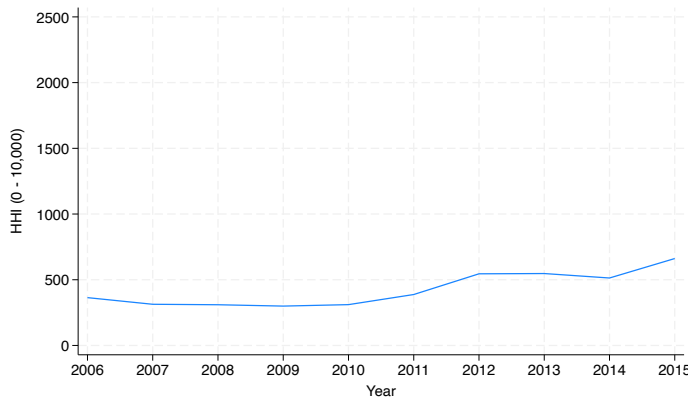


Table A.7: Charterer Concentration (HHI) Accounting for Alliances, Pre- and Post-2012 by Ship Age, Size, and Region

	2006–2011	2012–2015
<i>Global</i>		
Global HHI	331	567
<i>By Ship Age</i>		
1–9 years	379	630
10 years and more	374	584
<i>By Ship Size</i>		
<1,600 TEU	275	475
>1,600 TEU	578	721
<i>By Region</i>		
Americas	570	698
Asia–Europe	338	594
Asia–North America	503	864
Intra-Asia	336	580
Intra-Europe	449	852
Middle East and Africa	470	836
Europe–North America	469	726

Note: Figure A.7 plots the annual HHI for the charterer side of the leasing market. In each year, we compute each charterer's market share as its share of active contracts and treat members of a shipping alliance as a single entity. Table A.7 reports averages of annual HHIs for 2006–2011 and 2012–2015, overall and by ship age, ship size, and region segments. Within each segment and year, we compute HHI as $\sum_j s_j^2 \times 10,000$, where s_j is charterer j 's share of active contracts, again treating alliance members as a single entity. For the regional HHIs in Table A.7, we calculate localized charterer shares using empirical ship transition probabilities, following Equation (26).

Charterer Concentration by Region Since different charterers operate in different regions (see Appendix A.12), and there may be adjustment costs in moving ships from one region to another, we also measure

⁸³In 2012, the New World Alliance (consisting of APL, NOL, HMM & MOL) and the Grand Alliance (consisting of Hapag-Lloyd, NYK and OOCL) combined to form the G6 alliance (Merk et al., 2018), with a leasing market share of 10.4%.

concentration separately by region. In doing so, however, we need to account for the fact that regions are not isolated markets: a ship located in a given region may be leased not just by the charterers operating in that region, but also by charterers operating elsewhere. Thus, the charterers in one region compete for ships with charterers in other regions, with the extent of competition governed by the likelihood that a ship transitions to a different region upon the start of a new contract.

We therefore construct a region-level HHI that explicitly takes competition across regions into account, following an idea proposed by [Ellickson et al. \(2020\)](#). Formally, let s_{irt} denote charterer i 's share of active contracts on route r at time t , and let $\pi_{r'|r}$ denote the empirical transition probability that a ship moves from region r to region r' once their contract ends, estimated from the sequence of contracts observed for each vessel.⁸⁴ We then define the *localized market share* of charterer i in region r as:

$$\tilde{s}_{irt} = \sum_{r'} \pi_{r'|r} \cdot s_{ir't} \quad (25)$$

The localized market share can be interpreted as the probability that a ship ending a contract in region r ends up being leased by charterer i . If regional markets were strictly segmented, and ships never reallocated across regions (i.e., $\pi_{r'|r} = 0$ when $r' \neq r$), then the localized market share is just equal to charterer i 's share of contracts in that region. By contrast, if regional markets were unsegmented, and the ship's previous region has no bearing on the next region, then the localized market share would be approximately equal to the charterer's global market share.

The regional HHI for region r is then calculated using the localized market share for each charterer i :

$$\widetilde{\text{HHI}}_r = \sum_i \tilde{s}_{irt}^2 \times 10,000 \quad (26)$$

The final panel of Table [A.7](#) shows these regional HHIs for each region, separately for both the 2006 – 2011 and 2012 – 2015 periods. Overall, while the regional HHI increases somewhat in the latter part of the sample (consistent with the overall increase in concentration), each regional market remains unconcentrated.

⁸⁴In principle, we could also have calculated a time-varying transition probability $\pi_{r'|r,t}$, but there are not enough contracts in each period to make this practical.

A.12 Charterer geographic specialization

Specialization to trade regions We provide evidence here that charterers specialize across trade regions.⁸⁵ Table A.8 shows that for the average charterer, 84% of all of its schedules are concentrated within a single trade region.

One might wonder if this is driven by lumpiness of ships: if a charterer is only observed to lease a small number of ships, then they may end up allocating a high share of their ships to one region by random chance (akin to the “dartboard” problem associated with measuring regional specialization in the urban economics literature: see [Ellison and Glaeser \(1997\)](#)). To address this, we simulate trade region shares for each charterer assuming that they randomly allocate each of their leased ships across trade regions in proportion to the overall share of schedules allocated to each trade region. We then report summary statistics for the simulated top-region share under random allocation as the second column (“Simulated”) in Table A.8. As we can see, the observed top-region share is significantly larger than the simulated top-region share that would be generated by random allocation alone. For example, random allocation predicts that the median charterer would allocate only 52% of its schedules to its primary trade region, whereas the median charterer in practice allocates *all* of its schedules to its primary trade region. This pattern suggests charterers mostly specialize in particular trade regions.

Table A.8: Share of each charterer’s schedules allocated to their most visited trade region

	Observed	Simulated
Mean	0.84	0.62
5th Percentile	0.37	0.39
25th Percentile	0.67	0.43
Median	1.00	0.52
75th Percentile	1.00	1.00
95th Percentile	1.00	1.00

Note: For each charterer, we calculate the observed share of its schedules allocated to its top trade region. We compare this to simulated shares obtained under the assumption that schedules are randomly allocated across trade regions according to the overall market distribution. The table reports both the mean of the observed and simulated top-region share across charterers, as well as various percentiles.

Specialization to routes Furthermore, as we document here, charterers also specialize to a limited number of routes within their most favored trade regions. This is consistent with the institutional feature that it is costly for charterers to establish new liner services on a new route (as discussed in, for example, [Haralambides \(2019\)](#)).

⁸⁵The eight trade regions are Intra-Asia, Intra-Europe, Middle East & Africa, Americas, Asia - North America, Asia - Europe, North America - Europe, and others.

To show that charterers specialize to routes, we proceed as follows. For each charterer, we restrict attention to their most visited trade region (e.g., Asia - Europe) and compute the share of port calls on its *top* route within that trade region, as well as the share on its top two routes. Table A.9 shows that on average, a charterer concentrates 66% of its port calls within a single route, and 82% within its top two routes. To put this into context, there are many possible routes within a region: indeed, the average charterer operates in only 3% of all possible routes available in their most visited region.

This narrow footprint extends to other measures of geographic specialization: the average charterer visits only 11% of the countries and 7% of the ports served by ships in the same region. Together, these patterns suggest that charterers specialize in particular routes within a region, rather than operating broadly across the trade region.

Table A.9: Share of each charterer’s port calls in their top routes (within most visited trade region)

	Top 1	Top 2
Mean	0.66	0.82
5th Percentile	0.18	0.32
25th Percentile	0.40	0.61
Median	0.66	1.00
75th Percentile	1.00	1.00
95th Percentile	1.00	1.00

Note: For each charterer, we restrict to port calls on their most visited trade region and compute the share of port calls allocated to each route within that trade region. Routes are defined by the top three countries visited (as discussed in Section A.6). “Top 1” reports the share of port calls on the charterer’s single most visited route; “Top 2” reports the cumulative share in the top two routes. The table reports the mean across charterers as well as various percentiles.

A.13 Reallocation distance and match probability

In this section, we examine whether shipowners and charterers are more likely to match when they are geographically closer to one another. To do this, we estimate a conditional logit regression of the trade region (e.g., Asia - Europe) to which a ship is allocated upon signing a new contract, as a function of (i) the distance between the ship’s previous region and new region (ii) an indicator equal to one if the ship remains in the same region as before. Table A.10 shows that ships are more likely to be matched with charterers located in nearby regions rather than faraway ones. The effect of distance is economically meaningful in magnitude: in our preferred specification in Column (2), a 10% decrease in the reallocation distance to a given trade region is associated with an increase of 18.7% in the probability that the ship will be allocated to that region. Moreover, ships are more likely to be matched with charterers that are in the same region, above and beyond the impact of distance alone.

We obtain similar results if we do this analysis at the route level instead, with the ship “choosing” between

Table A.10: Conditional logit regression of the trade region a ship is allocated to upon signing a new contract

	(1)	(2)
Reallocation distance (1000 km)	-1.253 (0.0241)	-0.374 (0.0372)
Same region as before		2.555 (0.106)
Observations	19,296	19,296
Log-likelihood	-2,144	-1,767
Distance elasticity	-6.25	-1.87
Standard errors in parentheses		

Note: Each observation corresponds to a ship-region pair at the start of a new contract (we do not include extensions in this regression). The dependent variable equals 1 for the trade region to which the ship is allocated upon starting a new contract, and is 0 for all other regions. We define the ship's trade region upon beginning a new contract as the region that the ship is allocated to in the 3 months following the start of a contract. The ship's trade region prior to the new contract is defined as the region the ship is allocated to in the 3 months before the start of a new contract. The reallocation distance is the distance between the ship's previous region and new region. The distance elasticity reported in the final row of the table can be interpreted as the percentage change in the probability that a ship is allocated to a trade region if the distance to that region increases by 1%.

different routes, rather than between different trade regions. The relevant distance is then the distance between the ship's previous route and its new route. Because there are a large number of possible routes, we follow an approach suggested by [McFadden \(1978\)](#) and allow the choice set for each ship to include the route actually chosen as well as 15 alternatives randomly selected from all the remaining routes. We find that a 10% decrease in the reallocation distance to a given route is associated with an increase of 29.3% in the probability that the ship will be allocated to that route.

Why are charterers and shipowners more likely to match when they are closer to one another? First, reallocation incurs an adjustment cost in the form of time lost in transit: the further the ship has to travel to reallocate, the greater this adjustment cost. Second, charterers (who are geographically specialized) may have superior information about matches nearby: for example, they may work with brokers specializing in the region where they operate.

One might wonder if an additional reason why shipowners match with nearby charterers is in order to minimize crew change costs, given that the shipowner is legally obligated to cover the costs of repatriating crew members to their home countries.⁸⁶ However, crew travel costs are a relatively small portion (significantly less than 10%) of overall crew costs ([Drewry, 2007](#)).⁸⁷ Moreover, container ship crews tend to be highly

⁸⁶Crew members will typically work in a ship on contracts lasting four to twelve months (depending on rank and nationality), after which they take time off ([Drewry, 2007](#)). The shipowner incurs all crew change costs, and crew travel costs are a standard component of shipowner operating expenses ([Stopford, 2009](#)); the shipowner is legally obligated to bear these travel costs regardless of where the vessel is located ([International Labour Organization, 2006](#)).

⁸⁷For a typical containership, wages and victualling (i.e., the supply of food and provisions for the crew) alone account for around 90-92% of total crew costs, with all other costs (which include not just crew travel costs but also insurance, agent fees etc.) together accounting for the remaining 8-10% ([Drewry, 2007](#)).

multinational in nature, and it is typical for shipowners to hire crew members from many parts of the world (UNCTAD, 2016), often through manning agencies (Drewry, 2007). Thus it is unlikely that the costs of repatriating crew members vary substantially depending on where the ship is operating.

A.14 Charterer entry statistics

In Table A.11 we show that most new contracts are from existing charterers entering new routes/chartering more ships. For example, a charterer may decide to add another ship if there is a positive demand shock on an existing route. The finding that contracts typically come from existing charterers is the case both during the Great Trade Collapse as well as the rest of the sample, and is consistent with past literature discussing entry in the container shipping industry (Haralambides, 2007).

To construct the table we use the full contract dataset which begins in 1999. We define an ‘existing charterer’ as one which is present both in our final sample period (starting 2006Q3) and the earlier period. Otherwise we define the charterer as ‘new’. Our procedure is conservative in terms of detecting existing charterers because we observe only a random sample of contracts, as detailed in Section 3, and so it is possible that some existing charterers might simply not be observed in the earlier period.⁸⁸

Table A.11: Are new contracts from new charterers or existing charterers?

Period	New	Existing
Great Trade Collapse	15.3%	84.7%
Other Periods	11.1%	88.9%

A.15 Evidence of search frictions

Price dispersion Table A.12 documents substantial cross-sectional dispersion in prices within trade regions for observationally equivalent matches, suggestive of search frictions. We first demean contract prices by the average price in each trade region and month, to account for differences in demand and other market conditions both across regions and over time. We then regress demeaned prices on a set of controls and fixed effects, and report both the unexplained variation $1 - R^2$, as well as $1 - \text{Adjusted } R^2$. In Column (1), we control for ship fixed effects, while in Column (2), we additionally control for a 3rd-order polynomial in contract duration, a 3rd-order polynomial in the distance reallocated, as well as trade region-by-time fixed effects. Despite the inclusion of these granular fixed effects and controls, there is sizable unexplained price variation, with about 20% of the within-region-time price variation unexplained in the most granular specification (2). These magnitudes are comparable to other papers that have documented price dispersion

⁸⁸We also attempted to further disentangle whether existing charterers either enter new routes or charter more ships on existing routes. However, we only observe charterer names in our contracts data, not in the port call dataset. Therefore — given the relatively large number of potential routes — it is challenging to precisely measure entry of charterers at the route level.

as motivating evidence of search frictions e.g. [Brancaccio et al. \(2023\)](#), [Salz \(2022\)](#), [Vreugdenhil \(2026\)](#).

Table A.12: Contract Price Dispersion

	(1)	(2)
1 - R-squared	0.381	0.204
1 - Adj. R-squared	0.598	0.489
Ship FE	Yes	Yes
Region-by-Time FE	No	Yes
Controls	No	Yes

Note: This table documents cross-sectional dispersion in prices within trade regions. The dependent variable is the contract price (in USD/day) demeaned by the average contract price in the same region and year-month. In column (1), we regress the demeaned contract price on ship fixed effects and report the R^2 and the adjusted R^2 from that regression. In Column (2), we report the R^2 and adjusted R^2 after regressing demeaned prices on ship fixed effects, region-by-time fixed effects and a set of controls that includes a 3rd-order polynomial in the contract duration, and a 3rd-order polynomial in the distance reallocated at the start of the contract.

Simultaneous arrivals and departures of ships beginning new contracts Here we provide evidence that during the same period, trade regions experience simultaneous arrivals and departures of ships that are re-allocating as they start new contracts.⁸⁹ Among all trade region-by-month observations with at least one ship reallocation, 25.4% feature both arriving ships (ships arriving to that trade region from elsewhere) and departing ships (ships departing that trade region to begin a contract elsewhere) in the same month.⁹⁰ Even restricting to long-distance reallocations (where the distance reallocated exceeds the median reallocation distance), 12.3% of region-by-month observations feature simultaneous arrivals and departures. We interpret this as evidence of search frictions: had search frictions not been present, one might have expected ships to either reallocate away from a trade region or reallocate towards a trade region, but not both.⁹¹

One might wonder if this pattern is driven by a small fraction of errant reallocations. However, 20.5% of all ship reallocations are either arrivals to or departures from a region experiencing simultaneous flows. Furthermore, if we zoom in on region-by-month observations featuring simultaneous arrivals and departures, we see that in trade regions that primarily experience an outflow of ships, the average ratio of incoming ships to outgoing ships is 0.446. Likewise in trade regions that primarily experience an inflow of ships, the

⁸⁹This exercise is similar in spirit to (and inspired by) [Brancaccio et al. \(2023\)](#), who document evidence of simultaneous arrivals and departures of empty ships in the market for bulk shipping to motivate the presence of search frictions.

⁹⁰This is likely to be a lower bound of the true share of the sample with simultaneous arrivals and departures, given that we observe a subset of all contracts: as discussed in Section A.1, 19 percent of port calls are matched to a contract.

⁹¹As previously discussed, we take several data cleaning steps to ensure that ships are relatively substitutable in our sample. However, even if we split up the sample further we see similar patterns. For example, among region-by-month observations with at least one reallocation, 18.6% feature both arrivals and departures of ships in the same size group (above-average or below-average size). Similarly, 17.5% feature simultaneous arrivals and departures of ships in the same age group (above-average or below-average age).

average ratio of outgoing ships to incoming ships is 0.450. In the absence of search frictions, we would expect these ratios to be close to zero.

Cycles An alternative explanation for simultaneous arrivals and departures (that does not rely on there being search frictions) is a chain of reallocations. Suppose demand shifts from region A to region C, and region B lies between them. Rather than one ship reallocating the full distance from A to C, it may be efficient for one ship to reallocate from A to B and for another ship to reallocate from B to C, since each ship then repositions a shorter distance. Such a chain involves region B experiencing simultaneous arrivals and departures, even though the allocation is efficient. However, a set of reallocations that together constitute a *cycle* (e.g., some ships reallocating from A to B, others from B to C, and still others from C to A) is unlikely to be compatible with an efficient allocation: canceling the flows around the cycle would leave each region’s net change in ships unchanged while saving reallocation costs.

We find evidence of such cycles in the data. Overall, 13.4% of ship reallocations form part of at least one cycle. The most common is a 2-cycle, where ships reallocate from A to B while other ships simultaneously reallocate from B to A; 11.4% of reallocations are part of such 2-cycles. We also observe longer cycles: 1.9% of reallocations are part of 3-cycles ($A \rightarrow B \rightarrow C \rightarrow A$) and 2.2% are part of 4-cycles ($A \rightarrow B \rightarrow C \rightarrow D \rightarrow A$).⁹² The existence of such reallocation cycles is suggestive of the presence of search frictions.

A.16 Evidence on pro-cyclical contract duration from other leasing markets

Figure 3 showed that contract duration is pro-cyclical not just for containerships, but also in the leasing markets for bulk carriers and drilling rigs. We describe here how we document this for other leasing markets.

Bulk carriers Bulk carriers are primarily leased via “trip-charters” (i.e., for one single voyage at a time), but about 10% of contracts for leasing bulk carriers are time-charter contracts where the owner and charterer decide in advance on the contract duration, similar to the contracts used for leasing container-ships (Brancaccio et al., 2020). We collected data on 10,629 bulk leasing contracts from past issues of the *Shipping Intelligence Weekly* published by Clarksons, covering the period from 2001 to 2016. We also collected monthly data on the Baltic Dry Index (the most commonly used shipping freight rate index for bulk shipping markets), from Clarksons’ Shipping Intelligence Network. In the first panel of Figure 3, we plot both the average contract duration (smoothed using a local polynomial regression), as well as the Baltic Dry Index.

⁹²Note that a single reallocation can be part of multiple cycle types simultaneously. For example, if ships reallocate $A \rightarrow B \rightarrow C \rightarrow A$, the flow $A \rightarrow B$ is part of the 3-cycle, but if there is also a flow $B \rightarrow A$ in the same period, then $A \rightarrow B$ is additionally part of a 2-cycle. Because of this, the shares across cycle types (e.g., 2-cycles, 3-cycles, 4-cycles etc.) sum to more than the overall share of reallocations in any cycle.

Drilling rigs We obtain data on leasing contracts for drilling rigs from Rigzone. We focus on jackup rigs used to drill wells in the Gulf of Mexico during the 2000 - 2010 period, prior to the Deepwater Horizon oil spill that triggered a drilling moratorium. Each contract specifies both a “dayrate” and a duration (typically 2 - 4 months). [Vreugdenhil \(2026\)](#) contains a further discussion of the industry and details of the dataset. Similar to [Vreugdenhil \(2026\)](#), we use movements in the natural gas price to capture booms and busts, since wells drilled in the Gulf of Mexico contain more natural gas than oil. In the last panel of Figure 3, we plot both the average contract duration for rigs used in the Gulf of Mexico (again, smoothed using a local polynomial regression), as well as the Henry Hub natural gas price, finding that new contract duration is pro-cyclical. (Note that the estimation strategy in [Vreugdenhil \(2026\)](#) allows for contract duration to potentially change with the cycle since the policy functions for contract duration are a flexible function of the state.)

Anecdotal evidence from other markets There is anecdotal evidence to suggest that lease duration is pro-cyclical in other markets as well, beyond the three markets for which we have detailed data. In the leasing market for aircraft, for example, the use of shorter leases increased after the Covid-19 pandemic-induced collapse of demand for air travel ([Yeomans, 2020](#)). Commercial office lease lengths also follow a pro-cyclical pattern ([Avison Young, 2023](#)).

A.17 Pro-cyclical contract duration: robustness checks

Table [A.13](#) reports various regressions of contract duration on the logarithm of the time charter index (to capture pro-cyclicality of new contract duration) and the logarithm of the number of nearby ships (to account for the role of market thickness, as in Observation 4), as well as various controls. Column (1) shows that the contract duration is highly pro-cyclical, consistent with the pattern depicted in Figure 2, while contract duration decreases as the market becomes thicker.

In Column (2), we control for the contract dayrate (i.e., the daily price paid to the owner). Longer contracts have a higher dayrate, but even after controlling for the contract dayrate, duration is pro-cyclical, meaning that similarly priced contracts tend to have a longer duration when signed during a boom. The correlation between contract duration and the time-charter index remains very similar when we control for ship age (Column 3). Across all specifications, the relationship between market thickness and contract duration is similar.

Table A.13: Further evidence for pro-cyclical contract duration in containership leasing

	(1) Log(duration)	(2) Log(duration)	(3) Log(duration)
Log(time charter index)	0.83*** (0.043)	0.37*** (0.082)	0.41*** (0.083)
Log(# ships nearby)	-0.13*** (0.035)	-0.12*** (0.035)	-0.12*** (0.035)
Log(contract dayrate)		0.47*** (0.072)	0.44*** (0.072)
Age of ship			-0.01*** (0.003)
1[mid-size ship]	0.13*** (0.035)	0.00 (0.040)	0.02 (0.041)
1[large-size ship]	0.36*** (0.041)	0.14*** (0.054)	0.15*** (0.054)
Observations	2,693	2,690	2,690
Adjusted R-squared	0.147	0.160	0.162

Note: Standard errors in parentheses. In Column (2), we control for the contract dayrate. In Column (3), we control for ship age.

A.17.1 Numerical example: why the mean duration of existing contracts can exceed that of new contracts

Consider the case where there are two possible contract durations τ_1, τ_2 and $\tau_1 > \tau_2$. Suppose that N contracts are signed each period and a share p of them are of τ_1 duration. Then the steady-state average duration of existing contracts is:

$$\bar{\tau} = \frac{p\tau_1^2 + (1-p)\tau_2^2}{p\tau_1 + (1-p)\tau_2}$$

To understand this equation, first note that the number of active contracts in any period is $N(p\tau_1 + (1-p)\tau_2)$. Also note that the sum of the durations over the active stock of contracts in the steady state is: $(Np\tau_1)\tau_1 + (N(1-p)\tau_2)\tau_2$. Dividing this sum of durations by the number of active contracts results in $\bar{\tau}$.

The average duration of existing contracts is weakly higher than the average duration of new contracts. To see this, note that average duration of new contracts is given by $E[\tau] = p\tau_1 + (1-p)\tau_2$, while $E[\tau^2] = p\tau_1^2 + (1-p)\tau_2^2$, so that (using the equation above) the average duration of existing contracts can be written

as $\bar{\tau} = E[\tau^2]/E[\tau]$. Then:

$$\bar{\tau} - E[\tau] = \frac{E[\tau^2] - E[\tau]^2}{E[\tau]} = \frac{\text{Var}(\tau)}{E[\tau]} \geq 0,$$

with the inequality strict whenever there is dispersion in contract duration.

The intuition behind this result relates to the selection on the type of contracts included in the existing contract duration measure. Here, shorter contracts expire sooner; therefore, they are more likely to be removed from the average existing contract duration measure. By contrast, longer contracts remain in this average. Overall, this increases the average existing contract duration above the average duration for new contracts. For example, if $\tau_1 = 24$, $\tau_2 = 6$, and $p = 0.5$, the average duration of new contracts is 15 months, while the average duration of existing contracts is 20.4 months.

In the model, we allow for dispersion in contract duration within each period. Finally — as we explain in the main text in Section 4.1 — although there is cross-sectional dispersion in contract duration, the increases in contract duration in booms are not simply driven by the presence of very long contracts. Rather, the entire distribution shifts, as exhibited by a plot of the median duration across time in Appendix Figure C.1.

A.18 Connection between dispersion in residualized utilization and misallocation

A.18.1 How ship-level changes in utilization contributed to the dispersion increase in July 2008–End 2010

One concern with using changes in dispersion in residualized utilization as a proxy for misallocation is the following counterexample. Consider two scenarios. In scenario 1, during a boom, charterer A’s utilization increases from 20% to 30% and charterer B’s utilization increases from 60% to 80%. In scenario 2, suppose that instead A’s utilization drops from 20% to 10% and B’s utilization increases from 60% to 80%. While dispersion increases in both scenarios, it is only in scenario 2 that it appears to be a good proxy for misallocation. Specifically, in scenario 1, utilization increases for both charterers but at different rates. In scenario 2, utilization ‘fans out’ in different directions, suggesting an additional increase in the benefits of reallocation.

We therefore investigate how ship-level changes in utilization contributed to dispersion in the collapse period (July 2008–December 2010). This is a useful exercise because (i) we focus on dispersion in this period in our descriptive analysis, and (ii) the crisis represents a plausibly unexpected shock that shifted ex-post rather than ex-ante match values.

We present the results in Table A.14. To construct the first column we test whether the utilization of each ship increased or decreased in the collapse period compared to its baseline pre-collapse utilization. In the case, as in scenario 1, where the increase in dispersion is driven by all ships decreasing utilization in the same direction but at different rates, the ‘percent of ships with a positive change’ should be small. If utilization fans out, as in scenario 2, this metric should be positive.⁹³ Consistent with the scenario 2 case, we see that a sizeable percentage of ships actually increased their utilization in this period: 41.8 percent in the case of the capacity-based utilization measure and this is robust if we use the revenue-based measure. These positive changes are economically meaningful: the mean increase in capacity utilization for ships with a positive change is 12.5 percent compared to a 16.2 percent decrease for ships with a negative change. In the second column we decompose the total variance in utilization in the collapse period (subscript ‘c’) into positive and negative changes compared to each ship’s pre-collapse baseline (subscript ‘p’). Concretely, we consider:

$$\text{Var}(u_{i,c}) = \underbrace{\frac{1}{N} \sum_i (u_{i,c} - u_c)^2 \cdot \mathbf{1}[u_{i,c} \geq u_{i,p}]}_{\text{Improved ships}} + \underbrace{\frac{1}{N} \sum_i (u_{i,c} - u_c)^2 \cdot \mathbf{1}[u_{i,c} < u_{i,p}]}_{\text{Declined ships}} \quad (27)$$

We report the ‘improved ships’ component as a proportion of total $\text{Var}(u_{i,c})$ in the final column of Table A.14. This share should be small in the scenario 1 case but economically meaningful in the scenario 2 case. Again, we see that improved ships contribute a large share of the variance, consistent with the ‘fanning out’ scenario where increases in dispersion are suggestive of misallocation.

Table A.14: How changes in utilization generated dispersion during July 2008-End 2010

	Pct Ships with Positive Change	Share of Variance from Improved Ships
Capacity-based	41.8%	45.0%
Revenue-based	43.1%	49.3%

A.18.2 Within vs across route dispersion, and consolidating ships

Another case where a higher level of dispersion would be efficient is the following counterexample. Suppose that on an individual route one ship has 80% utilization and one ship has 20% utilization. Here, the more efficient outcome would be the former ship carrying everything (100% utilization) and the latter ship being used on other routes, but such an outcome need not reduce dispersion and may in fact increase it.

⁹³Note that the two example ‘scenarios’ considered the case where a bust turns to a boom, whereas here we have a boom turning to a bust. The economic idea is similar, however.

We illustrate that this counterexample is unlikely to be important in our setting in two ways. First, recall from Panel C of Table 2 that during July 2008-End 2010, which is the key period in which we analyze dispersion, over three-quarters of the rise in dispersion is generated by dispersion *between* routes rather than *within* routes. Therefore, the exercise in the counterexample (combining ships *within* routes) cannot feasibly account for most of the increase in dispersion.

Matching simulation Second, to make this point even more explicit, we implement the counterexample using a matching simulation with the following algorithm. We begin by combining ships within a route/month. Specifically, starting with the lowest-utilized ships within a route/month in the data, we counterfactually consolidate their observed load to the highest-utilized ships within the route/month, up to capacity. We continue this process until no more consolidation can take place. Next, we take these empty ships and reallocate them (efficiently) to alternative routes with the highest utilization. To prevent unrealistic scenarios where these empty ships ‘flood’ a single alternative route, we assume that at most an alternative route can accept a 20% increase in the number of ships.

We then run the same regressions in Panel A of Table 2 and present them in Appendix Table A.15a. Our key result about dispersion increasing in the transition period July 2008-End-2010 has a similar quantitative magnitude regardless of whether we combine ships within a route/month. Again, this indicates little scope for efficiently combining ships *within* a route in a way that would account for the rise in dispersion in this period.

In Table A.15b we implement the matching simulation by accounting for different ship capacities in terms of TEU. This exercise examines whether moving load from a smaller to a bigger ship might affect dispersion (as opposed to reallocation across charterers/routes). We find here that this would not qualitatively affect our key regressions in Panel A of Table 2, and the quantitative effects are very small. These numbers are similar to Appendix Table A.15a, which may not be surprising because our data construction and analysis remove large ships (>5000 TEU), and so our analysis focuses on dispersion in ships that have relatively similar capacities. As an additional measure beyond these sample cuts, recall that all our results residualize utilization by ship fixed effects and therefore control for ship size characteristics.

A.19 Charterer Size Differences and Utilization

In this section, we investigate whether charterer size differences are important in determining ship utilization. Table A.16 reports regressions of utilization (residualized of ship fixed effects) on charterer scale, as

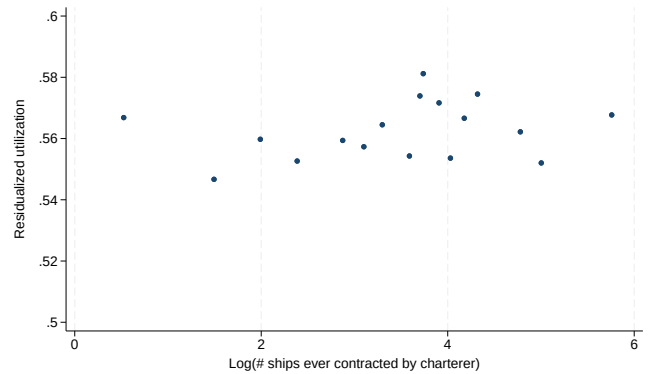
Table A.15: Change in dispersion in July 2008-End-2010: baseline vs combining ships within route

(a) Actual vs simulated			(b) Actual vs TEU-adjusted simulation		
	Capacity-based	Revenue-based		Capacity-based	Revenue-based
Actual	1.917 (0.339)	2.293 (0.420)	Actual	1.917 (0.339)	2.293 (0.420)
Simulated	1.838 (0.308)	2.593 (0.350)	Simulated	1.921 (0.322)	2.686 (0.363)

measured by the logarithm of the total number of ships contracted by the charterer in our sample.⁹⁴ Each observation is a ship - year month. In Column (1), we do not include any other controls; in Column (2), we control for the time-charter rate index; while in Column (3), our preferred specification, we include year-month fixed effects. While we find that larger charterers have higher utilization, the effect is tiny in magnitude: based on the results in Column (3), doubling a charterer's size is associated with an increase in utilization of only 0.0012, compared to a mean utilization of 0.562. Figure A.8 plots a binscatter of utilization (residualized) against charterer scale, providing further confirmation that there is only a weak positive relationship between charterer scale and ship utilization. Overall, our results therefore suggest that charterer size differences play a relatively minor role in explaining dispersion in ship utilization.

Table A.16: Residualized Utilization and Charterer Scale

	(1) Utilization	(2) Utilization	(3) Utilization
Log(# ships ever contracted)	0.0012** (0.0006)	0.0023*** (0.0006)	0.0017*** (0.0006)
Time-charter rate index		0.0005*** (0.0000)	
Year-month FE	No	No	Yes
Observations	20,664	20,664	20,664
Adj. R^2	0.000	0.013	0.031
Mean utilization	0.562	0.562	0.562

Figure A.8: Binscatter plot of utilization (residualized) against charterer scale

A.20 Dispersion in Binary Utilization

The model treats the idiosyncratic state of a match as binary (a match is either “dead” or “alive”), whereas the utilization data are continuous. To verify that the binary approximation used in the model is reasonable, we construct a binary utilization variable that mirrors the model's structure: ship-months in the bottom

⁹⁴All our results are very similar if we instead measure charterer scale by the logarithm of the total ship capacity (TEU) contracted by the charterer.

decile of the residualized utilization distribution are classified as dead matches, while all other observations are considered alive matches. We then construct dispersion in this binary measure and re-run the regressions of Table 2.

Table A.17 reports the results. Our key finding of an increase in dispersion during the Great Trade Collapse is unchanged under the binary measure, for both physical and revenue utilization. The dead-or-alive approximation therefore retains the empirical content of this descriptive finding.

Table A.17: Robustness: binary utilization

	Baseline (Continuous)		Binary	
	(1)	(2)	(3)	(4)
	S.d., utilization	S.d., revenue	S.d., utilization	S.d., revenue
Great Trade Collapse (July 2008 - End-2010)	1.917 (0.339)	2.293 (0.420)	1.825 (0.293)	2.203 (0.660)
N	114	114	114	114
R-squared	0.477	0.497	0.397	0.225

Note: Columns (1) and (2) are the baseline results and are identical to those reported in Panel A of Table 2, where dispersion is based on a continuous measure of utilization. In columns (3) and (4), we report results from a robustness check where we instead use a binary utilization measure. Specifically, each ship-month is classified as a “dead match” if its residualized utilization falls in the bottom decile of the utilization distribution, and is “alive” otherwise. We then construct dispersion in these binary utilization measures and run the same regressions as in Table 2.

B Additional proofs and results

B.1 Model details

Value of unmatched charterers and ships Here we prove that the value function of unmatched charterers takes the form given in Equation (7). We begin by showing that, conditional on matching with a ship from region r , a previously unmatched, searching charterer in region j has expected payoff $(1 - \delta)(W_{r,j,t} - c_{r,j,t}^{\text{adj}}) + \beta \eta_{j,t} \mathbb{E}_t U_{j,t+1}^{\text{chart}}$. Recall that the generalized Nash bargaining solution can be written such that each player gets their disagreement payoff/outside option plus a share of the match surplus proportional to their bargaining weight (Corollary 2.3, Muthoo (1999)). Using the notation and components from our model, and focusing on the charterer side of the market, results in the following equation for the payoff of a charterer in region j that matches with a ship from region r and chooses a duration equal to τ :

$$\Pi_{r,j,t,\tau}^{\text{chart}} = \beta \eta_{j,t} \mathbb{E}_t U_{j,t+1}^{\text{chart}} + (1 - \delta) (S_{r,j,t,\tau} - c_{r,j,t}^{\text{adj}} + \sigma \epsilon_\tau). \quad (28)$$

Denote $\tilde{S}_{r,j,t,\tau} = S_{r,j,t,\tau} - c_{r,j,t}^{\text{adj}} + \sigma \epsilon_\tau$. Note that once ϵ_τ is drawn, τ is optimally chosen to maximize $\tilde{S}_{r,j,t,\tau}$.

Then, the charterer's *expected* payoff (before the ϵ_τ have been drawn) from the match is:

$$\mathbb{E}_\epsilon[(1 - \delta) \max_\tau \tilde{S}_{r,j,t,\tau} + \beta \eta_{j,t} \mathbb{E}_t U_{j,t+1}^{chart}] = (1 - \delta) \mathbb{E}_\epsilon[\max_\tau \tilde{S}_{r,j,t,\tau}] + \beta \eta_{j,t} \mathbb{E}_t U_{j,t+1}^{chart} \quad (29)$$

$$= (1 - \delta) (W_{r,j,t} - c_{r,j,t}^{\text{adj}}) + \beta \eta_{j,t} \mathbb{E}_t U_{j,t+1}^{chart}, \quad (30)$$

which proves the result. To obtain Equation (7), note that an unmatched charterer in region j matches with a ship from region r with probability $\pi_{r|j,t}^{chart}$, receiving the payoff above, and with the remaining probability matches no ship and receives only the disagreement payoff $\beta \eta_{j,t} \mathbb{E}_t U_{j,t+1}^{chart}$. Since the disagreement payoff is received in every outcome, it enters with total weight one, and:

$$U_{j,t}^{chart} = (1 - \delta) \sum_r \pi_{r|j,t}^{chart} (W_{r,j,t} - c_{r,j,t}^{\text{adj}}) + \beta \eta_{j,t} \mathbb{E}_t U_{j,t+1}^{chart} = (1 - \delta) \Psi_{j,t}^{chart} + \beta \eta_{j,t} \mathbb{E}_t U_{j,t+1}^{chart},$$

which is Equation (7). A similar result can be derived for the value function of an unmatched ship (Equation (8)).

Equilibrium prices Prices for a new τ -period contract at time t , $p_{r,j,t,\tau}$, are determined by Nash bargaining between the charterer (in region j) and ship (from region r), with the surplus split as follows:

$$\begin{aligned} & \sum_{h=0}^{\tau-1} \beta^h (p_{r,j,t,\tau} - c) + \beta^\tau \mathbb{E}_t \left(\hat{\eta}_{j,t,\tau} M_{j,t+\tau}^{ship} + (1 - \hat{\eta}_{j,t,\tau}) U_{j,t+\tau}^{ship} \right) - \beta \mathbb{E}_t U_{r,t+1}^{ship} \\ &= \delta \left(S_{r,j,t,\tau} - c_{r,j,t}^{\text{adj}} + \sigma \epsilon_\tau \right) \end{aligned} \quad (31)$$

The left-hand side is the ship's value of being in the match minus its outside option (the ship pays no adjustment cost). The right-hand side is the ship's share δ of the joint surplus, which includes the iid contract quality draw ϵ_τ and is net of the adjustment cost $c_{r,j,t}^{\text{adj}}$ paid by the charterer at the time of the match.⁹⁵ The equation for an extension is identical except the adjustment cost is omitted, since the ship is already with the charterer.

Derivation of Equation (11) We derive $\Delta S_{r,j,t,\tau} \equiv S_{r,j,t,\tau+1} - S_{r,j,t,\tau}$ for arbitrary $\mathbb{P}_{\text{extend}} \in [0, 1]$, and then obtain Equation (11) as a special case. Let $T \equiv t + \tau$ denote the original expiration date. Neither the outside options in Equation (4) nor the initial adjustment cost $c_{r,j,t}^{\text{adj}}$ varies with τ , so these both drop out of $\Delta S_{r,j,t,\tau}$ (which therefore does not depend on the initial ship region r). The only components of

⁹⁵We assume that these draws and the adjustment cost directly affect the payoff of the charterer, so they enter into the surplus on the right-hand side but not directly into the ship's payoff on the left-hand side.

the match surplus in Equation (4) that change with duration are therefore $V_{j,t,\tau}$ (the expected value during contract), and the sum of continuation values after being matched, which we denote by $\mathcal{C}_{j,t,\tau}$. Note that $\mathcal{C}_{j,t,\tau} = \beta^\tau \mathbb{E}_t \left(\hat{\eta}_{j,t,\tau} (M_{j,T}^{ship} + M_{j,T}^{chart}) + (1 - \hat{\eta}_{j,t,\tau}) U_{j,T}^{ship} \right)$.

From Equation (1), we directly obtain how the expected value during contract changes as duration is increased by one period: $V_{j,t,\tau+1} - V_{j,t,\tau} = \beta^\tau \mathbb{E}_t [\hat{\eta}_{j,t,\tau} v_{j,T} - c]$.

Next, rearranging Equations (8) and (7) at any date s gives

$$\beta \mathbb{E}_s U_{j,s+1}^{ship} - U_{j,s}^{ship} = -\delta \Psi_{j,s}^{ship}, \quad \beta \eta_{j,s} \mathbb{E}_s U_{j,s+1}^{chart} - U_{j,s}^{chart} = -(1 - \delta) \Psi_{j,s}^{chart}. \quad (32)$$

Summing Equations (9) and (10) and applying Equation (32) gives $M_{j,s}^{ship} + M_{j,s}^{chart} = U_{j,s}^{ship} + U_{j,s}^{chart} + \mathbb{P}_{\text{extend}} X_{j,s}$, where $X_{j,s} \equiv W_{j,j,s} - \delta \Psi_{j,s}^{ship} - (1 - \delta) \Psi_{j,s}^{chart}$ is the net value of the extension option. Substituting this identity into the expression for the continuation value term $\mathcal{C}_{j,t,\tau}$ yields:

$$\mathcal{C}_{j,t,\tau} = \beta^\tau \mathbb{E}_t \left[U_{j,T}^{ship} + \hat{\eta}_{j,t,\tau} U_{j,T}^{chart} + \mathbb{P}_{\text{extend}} \hat{\eta}_{j,t,\tau} X_{j,T} \right]. \quad (33)$$

When duration is increased by a period, we then obtain (using $\hat{\eta}_{j,t,\tau+1} = \hat{\eta}_{j,t,\tau} \eta_{j,T}$):

$$\begin{aligned} \mathcal{C}_{j,t,\tau+1} - \mathcal{C}_{j,t,\tau} = \beta^\tau \mathbb{E}_t \left[(\beta U_{j,T+1}^{ship} - U_{j,T}^{ship}) + \hat{\eta}_{j,t,\tau} (\beta \eta_{j,T} U_{j,T+1}^{chart} - U_{j,T}^{chart}) \right. \\ \left. + \mathbb{P}_{\text{extend}} \hat{\eta}_{j,t,\tau} (\beta \eta_{j,T} X_{j,T+1} - X_{j,T}) \right]. \end{aligned} \quad (34)$$

Substituting Equation (32) into the above expression (applying the law of iterated expectations) and adding the change in the expected contract value yields:

$$\begin{aligned} \Delta S_{r,j,t,\tau} = \beta^\tau \mathbb{E}_t \left[-c - \delta \Psi_{j,T}^{ship} + \hat{\eta}_{j,t,\tau} (v_{j,T} - (1 - \delta) \Psi_{j,T}^{chart}) \right. \\ \left. + \mathbb{P}_{\text{extend}} \hat{\eta}_{j,t,\tau} (\beta \eta_{j,T} \mathbb{E}_T X_{j,T+1} - X_{j,T}) \right]. \end{aligned} \quad (35)$$

Setting $\mathbb{P}_{\text{extend}} = 0$ and restoring $T = t + \tau$ yields Equation (11). For $\mathbb{P}_{\text{extend}} > 0$, the final term captures the value of deferring the extension option by one period. Intuitively, as Equation (35) illustrates, extensions can be thought of as dampening the assurance premium term in the agents' contract duration tradeoff.

Derivation of Equation (13) Let m index a match, with $r(m)$ denoting the ship's initial region and $j(m)$ the charterer's region. For any contract duration policy at time t , social welfare is given by the following

expression:

$$\begin{aligned} \mathcal{W}_t = \mathbb{E}_t \sum_{\ell=0}^{\infty} \beta^\ell \left[\sum_{\substack{m \text{ active} \\ \text{at } t+\ell}} (\mathbf{1}\{m \text{ alive}\} v_{j(m),t+\ell} - c) \right. \\ \left. + \sum_{\substack{m \text{ newly matched} \\ \text{at } t+\ell}} (\sigma \epsilon_{\tau(m)} - c_{r(m),j(m),t+\ell}^{\text{adj}}) - \sum_{\substack{\text{charterers entering} \\ \text{at } t+\ell}} c_{\text{entry}} \right]. \end{aligned} \quad (36)$$

To understand the above expression, note that a match active in period $t + l$ (which could be either a brand-new contract or an existing contract) produces a net flow payoff of $(\mathbf{1}\{m \text{ alive}\} v_{j(m),t+\ell} - c)$, but newly formed matches also incur a one-time adjustment cost of $c_{r(m),j(m),t+\ell}^{\text{adj}}$ and earn an idiosyncratic duration-specific value $\sigma \epsilon_{\tau(m)}$.

To derive the marginal social value of raising duration by one period, we begin with the case where there are no extensions, and ships only match with charterers in the same region. We obtain Equation (13) by starting at the decentralized equilibrium; holding fixed the continuation policy, entry, aggregate states, and targeting probabilities; and raising the contract duration in a single region j from τ to $\tau + 1$ before returning to the fixed policy. We evaluate what happens to social welfare $\mathcal{W}_t$ when we perturb duration in this fashion.

Increasing the contract duration by one period generates a net flow payoff of $\hat{\eta}_{j,t,\tau} v_{j,t+\tau} - c$ at the original expiration date, but prevents the ship and (conditional on survival) the charterer from searching then. Under constant returns to scale, an additional searching ship and an additional searching charterer create $\omega_{j,t+\tau} q_{j,t+\tau}^{\text{ship}}$ and $(1 - \omega_{j,t+\tau}) q_{j,t+\tau}^{\text{chart}}$ matches, respectively. The expected discounted net surplus from a new local match equals $W_{j,j,t+\tau} - c_{j,j,t+\tau}^{\text{adj}}$. The marginal social search values are therefore $\omega_{j,t+\tau} \Psi_{j,t+\tau}^{\text{ship}}$ and $(1 - \omega_{j,t+\tau}) \Psi_{j,t+\tau}^{\text{chart}}$.⁹⁶ Putting all this together yields Equation (13):

$$\Delta S_{r,j,t,\tau}^{\text{planner}} = \beta^\tau \mathbb{E}_t \left[-c - \omega_{j,t+\tau} \Psi_{j,t+\tau}^{\text{ship}} + \hat{\eta}_{j,t,\tau} (v_{j,t+\tau} - (1 - \omega_{j,t+\tau}) \Psi_{j,t+\tau}^{\text{chart}}) \right]. \quad (13)$$

Here $S_{r,j,t,\tau}^{\text{planner}}$ is the net change in $\mathcal{W}_t$ from perturbing duration by one period. Subtracting Equation (11) from Equation (13) gives Equation (14). Thus, when $\delta = \omega_{j,t+\tau}$, the wedge between the planner's solution and decentralized equilibrium disappears.

Additional cases Next, we consider the case where contracts can be extended (as in the full model), but matching is still within-region. Let $T \equiv t + \tau$. Subtracting Equation (35) from its planner analogue and

⁹⁶This is because in the single-region case, $\Psi_{j,t+\tau}^{\text{ship}} \equiv q_{j,t+\tau}^{\text{ship}} (W_{j,j,t+\tau} - c_{j,j,t+\tau}^{\text{adj}})$ and $\Psi_{j,t+\tau}^{\text{chart}} \equiv q_{j,t+\tau}^{\text{chart}} (W_{j,j,t+\tau} - c_{j,j,t+\tau}^{\text{adj}})$.

collecting the contemporaneous terms shows that the wedge $\Delta S_{r,j,t,\tau}^{\text{planner}} - \Delta S_{r,j,t,\tau}$ equals

$$\begin{aligned} & \beta^\tau \mathbb{E}_t \left[(\delta - \omega_{j,T}) \left\{ \Psi_{j,T}^{\text{ship}} - \hat{\eta}_{j,t,\tau} \Psi_{j,T}^{\text{chart}} - \mathbb{P}_{\text{extend}} \hat{\eta}_{j,t,\tau} (\Psi_{j,T}^{\text{ship}} - \Psi_{j,T}^{\text{chart}}) \right\} \right. \\ & \quad \left. + \mathbb{P}_{\text{extend}} \hat{\eta}_{j,t,\tau} \beta \eta_{j,T} \mathbb{E}_T \left[(\delta - \omega_{j,T+1}) (\Psi_{j,T+1}^{\text{ship}} - \Psi_{j,T+1}^{\text{chart}}) \right] \right]. \end{aligned} \quad (37)$$

Thus, contract extensions add a correction term to the planner wedge, which reflects that if contract duration is raised by one period at period T , with some probability the contract is extended and therefore the marginal social costs of foregone search are incurred further in the future. Note that the wedge is now zero when $\delta = \omega_{j,s}$ at both $s = T$ and $s = T + 1$, very similar to the Hosios-like condition in Equation (14).

Finally, we consider the case where charterers can search across regions; for simplicity, we go back to assuming that contracts cannot be extended. Holding across-region targeting probabilities μ fixed, the wedge $(\Delta S^{\text{planner}} - \Delta S)_{r,j,t,\tau} \big|_{\mu \text{ fixed}}$ equals

$$\begin{aligned} & \beta^\tau \mathbb{E}_t \left[(\delta - \omega_{j,T}) (\Psi_{j,T}^{\text{ship}} - \hat{\eta}_{j,t,\tau} \Psi_{j,T}^{\text{chart}}) \right. \\ & \quad \left. + \hat{\eta}_{j,t,\tau} \left\{ (1 - \omega_{j,T}) \Psi_{j,T}^{\text{chart}} - \sum_{\ell,k} \mu_{\ell|j,T} (1 - \omega_{\ell,T}) q_{\ell,T}^{\text{chart}} \frac{a_{k,T}^{\text{chart}} \mu_{\ell|k,T}}{\sum_h a_{h,T}^{\text{chart}} \mu_{\ell|h,T}} (W_{\ell,k,T} - c_{\ell,k,T}^{\text{adj}}) \right\} \right], \end{aligned} \quad (38)$$

where the fraction is the share of region- ℓ contacts coming from region k , as in Equation (3).

Equation (38) follows from two steps. First, we differentiate $\mathcal{W}_t$ with respect to the masses of searching ships and charterers (a^{ship} and a^{chart}), holding μ fixed. Second, we subtract $\Delta S_{r,j,t,\tau}$. The first term is the same wedge as in Equation (14), which arises from differences in how private agents and the planner value the option of returning to search. The term in braces is a spatial correction: intuitively, it accounts for the fact that when a charterer in region j ends a contract, they search for ships across regions, which affects matches formed in other regions as well (an effect the private agents do not internalize).⁹⁷

B.2 Calibration of ship operating costs

Industry measures of container-ship “operating costs” borne by the shipowner include both the crew cost, as well as maintenance and repair costs.⁹⁸ According to [Stopford \(2009\)](#), the total operating cost of a container-

⁹⁷Note that the planner’s full solution that we compute in the counterfactuals (where the duration policy is chosen to maximize $\mathcal{W}_t$) additionally allows μ to respond to changes in the masses of searching agents as contract duration is adjusted.

⁹⁸These are the only variable costs incurred by shipowners; other voyage expenses (such as bunker costs or port charges) are borne by the charterer.

ship with capacity of 2,000 TEU (which is close to a median ship in our sample) is around \$5,000/day. A very similar number is reported by [Greiner \(2017\)](#), who moreover finds that operating costs of container-ships were fairly stable from year to year; therefore, when calibrating ship operating costs, we assume they do not change over time.⁹⁹

When calibrating c based on these industry estimates, we have to account for the fact that only crew costs are true operating costs, in the sense that they are borne only when the ship is in use (for example, when it is under lease to a charterer). By contrast, a shipowner will likely have to incur costs of maintenance and repair even if the ship is idle, and therefore these are better thought of as fixed costs that are borne regardless of whether the ship is in operation. Since crew costs typically account for half of the total cost of operating a ship, we set c to be equal to \$2,500/day; this is consistent with typical industry estimates of the cost of crew ranging from \$2,000-\$3,000/day.

B.3 Estimation of demand for shipping services

Here we provide more details on how we estimate demand (equation (17)) and construct the aggregate demand state z_t^G as well as the region-level demand states $z_{r,t}$.

Aggregation of region-level demand We begin by describing how we aggregate region-level demand ($d_{r,t}$) to global demand. Summing equation (16) across regions yields:

$$d_t = \sum_r z_{r,t} \cdot P_{r,t}^{\gamma_{1,z}}. \quad (39)$$

Defining $z_t^G \equiv \sum_r z_{r,t}$ and weights $\phi_{r,t} \equiv z_{r,t}/z_t^G$, this can be written as

$$d_t = z_t^G \cdot P_t^{\gamma_{1,z}} \quad (40)$$

where P_t is an aggregate price index defined by $P_t^{\gamma_{1,z}} \equiv \sum_r \phi_{r,t} \cdot P_{r,t}^{\gamma_{1,z}}$. Aggregate demand thus inherits the same elasticity $\gamma_{1,z}$ as region-level demand.

Variable construction We use our port call data to construct d_t and $d_{r,t}$. To do so, we first calculate how much cargo each ship carries each month, using information on idleness (i.e., the number of days the ship is not carrying cargo) and utilization (i.e., the total proportion of the ship's capacity that is utilized on non-idle days).¹⁰⁰ We aggregate this across ships to calculate total cargo volume transported by containerships

⁹⁹Bunker costs may vary substantially over time as a function of fuel prices, but recall those are borne by the charterer, not by the shipowner, and as such are not part of c . Instead, they are embedded in the flow value to the charterer, $v_{r,t}$.

¹⁰⁰See Appendix A.3 for how we measure utilization, and Appendix A.4 for how we measure idleness.

every month, both at the aggregate level (d_t) as well as separately by trade region ($d_{r,t}$). All prices and price indexes are deflated. Region-level prices $P_{r,t}$ are constructed by averaging observed contract prices across each region; we interpolate a small number of missing values using lagged region-level prices and the time-charter rate index.

Demand estimation and results Since our controls and instruments are available at the aggregate level, we estimate $\gamma_{1,z}$ from equation (17), using the time-charter rate index (the most granular price index available to us) as a proxy for P_t . Table B.1 reports demand estimates. Once we have estimated demand, we validate the above approximation by verifying that the model-implied price index (defined implicitly by $P_t^{\gamma_{1,z}} \equiv \sum_r \phi_{r,t} \cdot P_{r,t}^{\gamma_{1,z}}$) and the time-charter rate index are very close to one another: in particular, they have the same mean and a correlation of 0.9879.

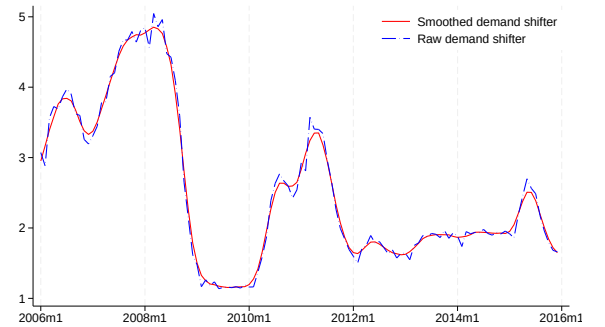
Given $\hat{\gamma}_{1,z}$, we recover the aggregate demand state as $z_t^G = d_t \cdot P_t^{-\hat{\gamma}_{1,z}}$. We then smooth z_t^G by carrying out a local polynomial regression using an Epanechnikov kernel and a bandwidth of 3 months. Our results are very similar with other choices of bandwidth. Figure B.1 shows how z_t^G (both the raw measure, and the smoothed version we use in our structural model estimation) evolves over time. As expected, demand is high in the period prior to the financial crisis, but collapses during the crisis, before partially rebounding towards the end of 2010.

Table B.1: Estimates of demand for container-ship services

	First-stage Log(Price)	2SLS Log(Quantity)
Log(Price)		-1.449 (0.657)
Share of ships older than 20 years	-0.012 (0.033)	
Average ship age	0.087 (0.053)	
Average ship size	0.000 (0.001)	
Log of Industrial Production Index (OECD)	5.787 (0.348)	9.010 (4.016)
Time Trend	-0.014 (0.002)	-0.012 (0.007)
N	120	120
Demand elasticity (mean)		-1.45

Note: In Table B.1, we approximate prices using the time-charter index. Figure B.1 plots the raw aggregate demand state and the smoothed series used in the structural estimation; we smooth the raw series using a local-polynomial regression with an Epanechnikov kernel and a three-month bandwidth.

Figure B.1: Estimated aggregate demand state z_t^G , before and after smoothing



In a similar fashion, we recover the regional demand states using the equation $z_{r,t} = d_{r,t} \cdot P_{r,t}^{-\hat{\gamma}_{1,z}}$. We also recover route-level demand states using the equation $z_{s,t} = d_{s,t} \cdot P_{s,t}^{-\hat{\gamma}_{1,z}}$, where $d_{s,t}$ is the total cargo volume

transported by containerships in route s during year-month t . Because our contract price data are sparse at the route level, we assume that all routes within the same region share the same price; that is, $P_{s,t} = P_{r,t}$ for all routes s that belong to region r .

B.3.1 Regional and route-level demand innovations

A natural question is how much of the variation in demand at the regional and route level is driven by aggregate versus local shocks. Note that the demand shock that matters for lock-in is the innovation that arrives *after* conditioning on the information agents use to forecast future match values. Therefore, for each local market j , where j is either a trade region or a route, we first recover these unexpected shocks by estimating the following AR(1) process:

$$\log z_{j,t} = a_j + \rho_j \log z_{j,t-1} + \lambda_j \log z_{t-1}^G + \varepsilon_{j,t} \quad (41)$$

We also estimate an aggregate AR(1), $\log z_t^G = a + \rho \log z_{t-1}^G + \varepsilon_t$.

We then project each local innovation $\varepsilon_{j,t}$ on the aggregate innovation ε_t and report the average share of local innovation variance explained by the aggregate demand innovation. We compute the exercise for both regional and route level shocks, and at both monthly and quarterly frequencies.

Table B.2: Decomposition of local demand innovations

	Region	Route
Quarterly	55.6%	18.4%
Monthly	13.6%	4.6%

Note: The table reports the share of regional and route-level shocks explained by aggregate demand shocks.

Table B.2 shows that regional and route-level demand shocks are relatively idiosyncratic. In terms of regional shocks, only 55.6% of the variation is explained by global shocks at the quarterly level, and even less, 13.6%, at the monthly level (which is the frequency used in our model). The values for route-level shocks are lower still at 18.4% and 4.6%.

This pattern is directly connected to the lock-in effect in the model. A longer contract insulates a match from repeated search, but it also keeps the ship tied to a local market whose realized demand may evolve differently from aggregate demand. If local demand innovations were mostly aggregate, then the value of being in one region would move closely with the value of being available elsewhere. Instead, Table B.2 shows that a large share of regional innovations are local, and even more so at the route level. Consequently, a ship can be locked into a route after a negative local shock while other routes receive positive demand

shocks, which is exactly the margin on which endogenous contract duration affects reallocation.

B.4 Computing the equilibrium in the second stage

B.4.1 Cross-region adjustment terms

The unmatched value functions (7)–(8) are functions of the sum of surplus across regions, weighted by the average probability of matching an agent in each region. We split these sums into a component for the expected value from matching in the current region and a cross-region adjustment:¹⁰¹

$$\Psi_{r,t}^{ship} = \sum_j \pi_{j|r,t}^{ship} [W_{r,j,t} - c_{r,j,t}^{adj}] = q_{r,t}^{ship} (W_{r,r,t} - c_{r,r,t}^{adj}) + \xi_{r,t}^{ship}, \quad (42)$$

$$\Psi_{j,t}^{chart} = \sum_r \pi_{r|j,t}^{chart} [W_{r,j,t} - c_{r,j,t}^{adj}] = q_{j,t}^{chart} (W_{j,j,t} - c_{j,j,t}^{adj}) + \xi_{j,t}^{chart}, \quad (43)$$

Intuitively, $\xi_{r,t}^{ship}$ measures the extra value to a ship at r from access to charterers in other regions, and $\xi_{j,t}^{chart}$ the analogous gain to a charterer in region j from targeting ships elsewhere. Both adjustments are positive when alternative regions offer better net surplus than the local one.

To see why the above formulation is useful, substitute (42) into (8):

$$U_{r,t}^{ship} = \delta [q_{r,t}^{ship} (W_{r,r,t} - c_{r,r,t}^{adj}) + \xi_{r,t}^{ship}] + \beta \mathbb{E}_t U_{r,t+1}^{ship}. \quad (44)$$

The first term on the right-hand-side, $q_{r,t}^{ship} (W_{r,r,t} - c_{r,r,t}^{adj})$, depends directly only on the state in the agent's current region $(\tilde{z}_{r,t}, \theta_{r,t})$, as well as future values of $U_{r,t}^{ship}$, $M_{r,t}^{ship}$, $U_{r,t}^{chart}$, and $M_{r,t}^{chart}$ (which all affect $W_{r,r,t}$). The cross-region adjustments $\xi_{r,t}^{ship}$ and $\xi_{r,t}^{chart}$ collect everything else. Therefore, if we could approximate $\xi_{r,t}^{ship}$ and $\xi_{r,t}^{chart}$ as functions of a reduced state space (e.g., $(\tilde{z}_{r,t}, \theta_{r,t}, z_t^G)$), then the value functions $U_{r,t}^{ship}$, $U_{r,t}^{chart}$, $M_{r,t}^{ship}$, and $M_{r,t}^{chart}$ are also only functions of the reduced state space if the transitions are known. We build upon this idea in the detailed algorithm in the next section.

B.4.2 Detailed algorithm

We compute the equilibrium of the model for fixed parameters via a nested algorithm with an inner and outer loop. The inner loop computes the value functions and duration choice within each region given current beliefs. In the outer loop, we iterate over two perceived objects so they are consistent with equilibrium behavior: (i) agent beliefs over the transition of the region-level market thinness $\theta_{r,t}$, and (ii) a regression

¹⁰¹Recall from Equation (3) that $\pi_{j|r,t}^{ship} = q_{r,t}^{ship} \times$ (the share of region- r contacts coming from region j). The residuals are defined implicitly as: $\xi_{r,t}^{ship} = \sum_j \pi_{j|r,t}^{ship} (W_{r,j,t} - c_{r,j,t}^{adj}) - q_{r,t}^{ship} (W_{r,r,t} - c_{r,r,t}^{adj})$ and $\xi_{j,t}^{chart} = \sum_r \pi_{r|j,t}^{chart} (W_{r,j,t} - c_{r,j,t}^{adj}) - q_{j,t}^{chart} (W_{j,j,t} - c_{j,j,t}^{adj})$.

approximation of the cross-region adjustment terms ξ^{ship}, ξ^{chart} (defined above in Section B.4.1) in the value functions. At each iteration we simulate the model over the sample period, and update both perceived objects from simulated data, continuing this process until the outer loop converges.

The full set of AR(1) and regression specifications is:

$$\log z_{t+1}^G = \rho_0^g + \rho_1^g \log z_t^G + \varepsilon_{t+1}^g, \quad (45)$$

$$\log \tilde{z}_{r,t+1} = \rho_0^r + \rho_1^r \log \tilde{z}_{r,t} + \rho_2^r \log z_t^G + \varepsilon_{r,t+1}^r, \quad r \in R, \quad (46)$$

$$\log \theta_{r,t+1} = \rho_0^\theta + \rho_1^\theta \log \theta_{r,t}, \quad (47)$$

$$\hat{\xi}_{r,t}^i = \rho_0^{\xi,i} + \rho_1^{\xi,i} \log \theta_{r,t} + \rho_2^{\xi,i} \Delta z_{r,t} + \rho_3^{\xi,i} z_t^G + \rho_4^{\xi,i} (\Delta z_{r,t})^2, \quad i \in \{ship, chart\}, \quad (48)$$

where $\Delta z_{r,t} \equiv z_{r,t} - z_t^G$ is the difference between the region's demand and aggregate demand (which is intuitive because the ξ components define the differences in expected surplus accruing from across-region matches, which is primarily a function of $\Delta z_{r,t}$).

The first two equations are estimated offline from the data, since they depend on overall economic conditions and are arguably exogenous to the containership leasing market. Concretely, we fit $(\rho_0^r, \rho_1^r, \rho_2^r)$ per region $r \in R$, as well as (ρ_0^g, ρ_1^g) for the global demand process. We also estimate the standard deviation of the normal shocks in these processes: a single σ^g for ε^g , and per-region standard deviations σ^r (one for each r) for ε^r .

The final two equations (the perceived θ process and the cross-region adjustment coefficients) are updated in the outer loop of the algorithm. Note that, to simplify the algorithm, we pool coefficients in the last two equations across regions; however, the input states (and therefore the predicted $\xi_{r,t}^{ship}, \xi_{r,t}^{chart}, \theta_{r,t}$) are still region-specific.

Recall that in the model we compute two different objects for the θ process: agents' perceived evolution of this state (which they use to compute their value functions), and the full simulation of this state over the 2006–2015 time series (which we use to discipline the perceived evolution and to compute the simulated moments). For the perceived evolution, to reduce the computational burden, we do not include an innovation term in the process for market thinness in (47). Note that stochastic variation still enters agents' perceived evolution of the state through the demand shocks in (45)–(46).

However, the model still allows θ to evolve endogenously and stochastically in the full simulation of the time series. In particular, θ depends on the accumulated duration choices of all agents (i.e., removing a

marginal ship and marginal charterer changes the ratio of available charterers to ships), together with entry and charterer exit, which respond to the demand shocks. The outer loop of the computational algorithm enforces consistency between the perceived rule and this realized process.

The detailed algorithm is as follows:

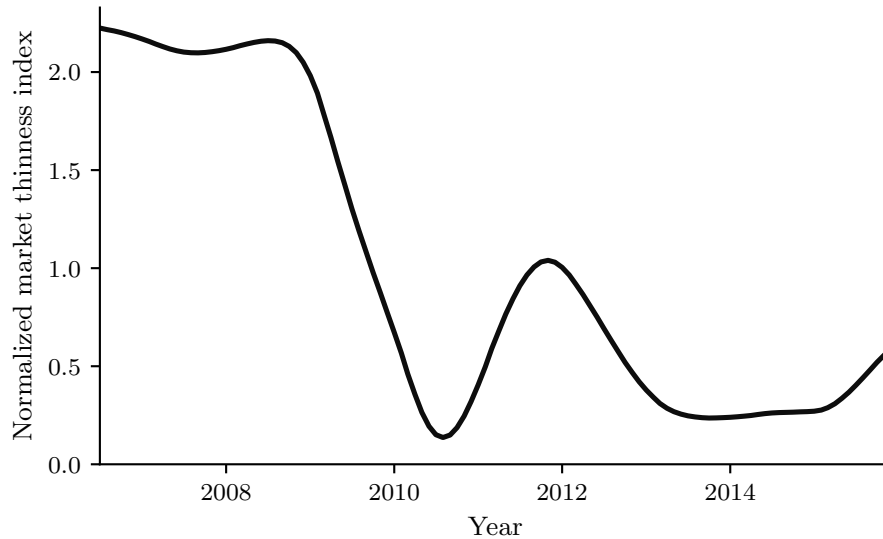
1. Estimate the offline AR(1) coefficients $(\rho_0^g, \rho_1^g, \sigma^g)$ in (45) and $(\rho_0^r, \rho_1^r, \rho_2^r, \sigma^r)$ in (46) from the data. The perceived outer-loop coefficients $(\rho_0^\theta, \rho_1^\theta)$ in (47) and $(\rho_0^{\xi,i}, \rho_1^{\xi,i}, \rho_2^{\xi,i}, \rho_3^{\xi,i}, \rho_4^{\xi,i})$ in (48) are then updated in the loop below.
2. Given the current guess of the perceived transitions, compute five different value functions $(W_{r,t}, U_{r,t}^{chart}, U_{r,t}^{ship}, M_{r,t}^{chart}, M_{r,t}^{ship})$, for each region $r \in R$, via value function iteration:
 - (a) Initialize these value functions as a set of nodes of the three states $(\tilde{z}_{r,t}, \theta_{r,t}, z_t^G)$ (we compute intermediate values via linear interpolation).
 - (b) Using forward simulation, compute the (expected) match surplus at each node, for each contract length $\{1, 2, \dots, \tau_{max}\}$.
 - In this step, we aggregate over 30 forward simulations at each node. Randomness comes from two sources: the global demand shocks ε_t^g in (45) and the region-specific demand shocks $\varepsilon_{r,t}^r$ in (46), drawn independently each period.
 - (c) Compute the ex-ante surplus value at each node using the inclusive value formula (equation (5)).
 - (d) Update the value functions and return to (b) until the value functions converge.
3. Simulate the industry evolution over the sample period, using the empirical demand shock processes. This includes simulating the spatial position of each ship across regions, and the distribution of matches within each region.
4. Based on the simulated industry evolution, update the perceived coefficients $(\rho_0^\theta, \rho_1^\theta)$ in (47) and $(\rho_0^{\xi,i}, \rho_1^{\xi,i}, \rho_2^{\xi,i}, \rho_3^{\xi,i}, \rho_4^{\xi,i})$ in (48) by OLS on the simulated panel.
5. Return to step 2. Keep iterating until all coefficients converge.

B.4.3 Evolution of market thinness

Figure B.2 plots the evolution of market thinness in the estimated model over the sample period. We plot the series in logs because the log of market thinness is the state over which agents form beliefs in the forecasting rule (equation (47)). Since average thinness differs across regions, we normalize each region's log thinness

by its own sample mean, which makes the series comparable across regions and better shows the evolution over time. We then aggregate by averaging the normalized series across regions in each month.

Figure B.2: Evolution of market thinness over the sample period



Note: The figure plots normalized log market thinness averaged across regions, computed from the baseline simulation of the estimated model. For each region r , we compute market thinness $\theta_{r,t}$ from the simulated masses of searching charterers and available ships, take logs, and divide by the region's sample-mean log thinness before averaging across regions in each month.

B.5 Simulated method of moments: additional details

We provide details here on how we construct the moments described in Section 6.2 and estimate the parameters via simulated method of moments. The full set of moments we use is listed in Table B.5.

Moment construction Several of our moments capture the cyclicity of key outcome variables. To keep these moments comparable across outcomes, we use the three-period split described in Section 6.2: the pre-collapse period before July 2008, the collapse period from July 2008 through December 2010, and the post-collapse period from January 2011 onward. The moments therefore use a common timing convention; identification comes from how the model matches different outcomes (e.g., prices, duration, and utilization) across the same periods.

The duration, price and extension moments are all computed based on contract data. In order to account for ship heterogeneity, we residualize each of these variables before computing the moments. We residualize contract duration and price controlling for ship fixed effects. We residualize extensions controlling for ship size (in TEU) and the square of ship size.¹⁰²

Note that our contract price data enter the estimation as two empirical price moments which we match to the

¹⁰²Since extensions are relatively sparse (and many ships never have an extended contract), we chose not to control for ship fixed effects when residualizing extensions, in order to avoid discarding a significant portion of the data.

model-computed price moments. We ultimately find that the model provides a close fit to the empirical price moments. An alternative approach would be to construct these price moments using the time-charter index, which is computed using a confidential algorithm from Clarksons. This would make similar predictions: using our approach, the average contract price (before residualizing) in the collapse period is 47 percent of its level in the pre-collapse period; the corresponding ratio (had we instead used the time-charter index) is similar at 46 percent.

Weights We use a diagonal weighting matrix. We choose the diagonal entries by first specifying economically interpretable tolerances tol_m for each moment and then setting the weight equal to $1/\text{tol}_m^2$. Thus, a moment that misses its target by one tolerance unit contributes one unit to the objective function in the simulated method of moments.

For duration, we use a tolerance of 0.5 months for the pre-collapse duration level; 0.1 months for the change in duration during the collapse period; and 0.05 months for the cross-sectional standard deviation of duration. We use a tolerance of 0.005 for the duration-thickness elasticity. For the dispersion moments and the moments for the share of ships under contract, which are measured in shares, we use percentage-point tolerances. We use a tolerance of 1 percentage point for the pre-collapse aggregate share of ships under contract (as well as for the share of ships under contract in each region), and 0.2 percentage points for the moment measuring how the aggregate share changes during the collapse period. For dispersion, the tolerance is 0.2 percentage points for the pre-collapse dispersion level, and 0.1 percentage points for how dispersion changes during the collapse. For prices we use a tolerance of 0.05 for both the pre-collapse level and the change during the collapse period. Finally, we use tolerances of 1 percentage point for the extension probability moment, and 0.02 for the normalized (i.e., relative) reallocation distance moment.

Overall, the weighting choices are not designed to force a narrow fit to one subset of moments. In practice, as we can see from Table B.5, the model matches all of the targeted moments closely.

Table B.5 also shows that the model fits idle rates relatively well, since the idle rate measure is one minus the share of ships under contract. In particular, the table illustrates a very close fit in terms of the average share under contract by each region, and also in the time series moment for the change in the share under contract after the collapse.

Finally, below we report the Monte Carlo exercise referenced in Section 6.3. Table B.3 reports statistics for how well we recover all 17 second-stage parameters; the table notes describe the design of the exercise.

Table B.3: Monte Carlo check: recovery of the second-stage parameters

Parameter	Description	Truth (mean)	Estimate (mean)	Corr.	Norm. RMSE (%)
$\gamma_{0,v}$	Match value: intercept	1.934	1.933	0.999	0.39
$\gamma_{1,v}$	Match value: slope	0.393	0.394	0.996	0.93
$\gamma_{0,\eta}$	Match survival: intercept	1.582	1.582	1.000	0.26
$\gamma_{1,\eta}$	Match survival: slope	1.272	1.272	0.999	0.35
$\gamma_{1,e}$	Entrant pool: slope	7.375	7.384	0.998	0.49
α_1	Targeting parameter	0.349	0.350	0.995	0.79
α_2	Matching parameter	0.551	0.550	0.999	0.36
δ	Bargaining parameter	0.073	0.073	0.999	0.47
σ	Duration shock scale	0.670	0.670	0.999	0.39
$\mathbb{P}_{\text{extend}}$	Extension probability	0.756	0.756	0.999	0.11
<i>Entrant pool: region intercepts $\gamma_{0,e,r}$</i>					
	Americas	-13.846	-13.863	0.998	0.55
	Asia–Europe	-15.890	-16.094	0.988	1.89
	Asia–North America	-14.087	-14.108	0.997	0.63
	Intra-Asia	-11.484	-11.521	0.998	0.70
	Intra-Europe	-5.243	-5.249	0.997	0.68
	Middle East and Africa	-7.158	-7.185	0.997	0.79
	Europe–North America	-8.481	-8.493	0.992	1.18

Note: This table shows the results from a Monte Carlo exercise for the second-stage estimation. Each of 100 replications draws a “true” parameter vector uniformly within $\pm 15\%$ of the baseline estimates, simulates the model at that vector to construct the targeted moments, and re-estimates all 17 second-stage parameters. “Truth (mean)” and “Estimate (mean)” are the means of the drawn true values and of the estimated values across replications. “Corr.” is the correlation between the true and estimated values across replications; “Norm. RMSE” is the root mean squared error divided by the absolute value of the baseline estimate, in percent. Overall, the results show that the estimation routine closely recovers the parameters.

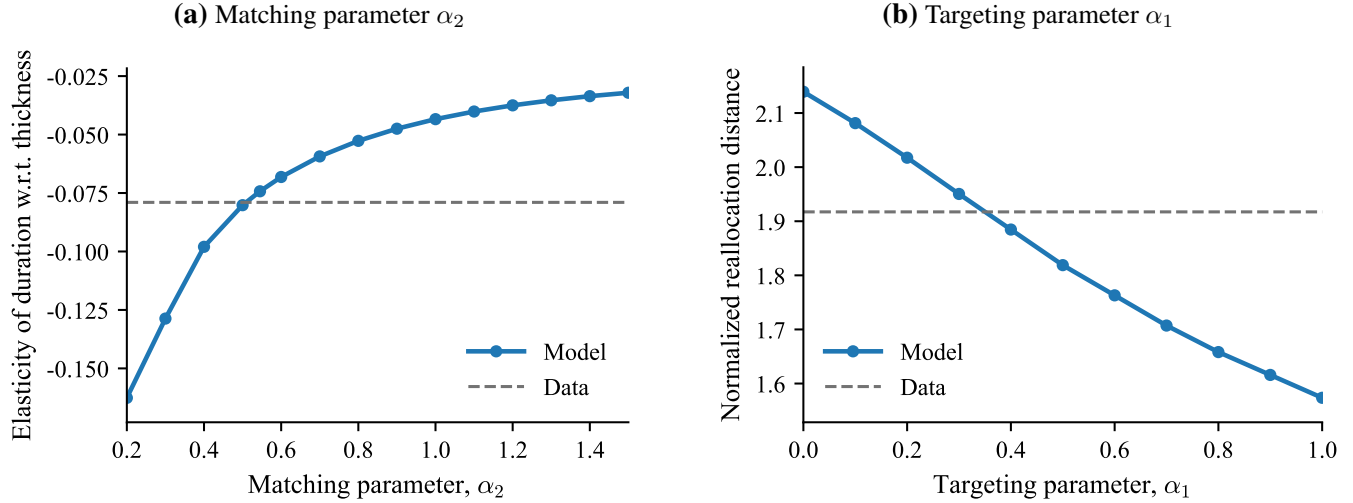
B.5.1 Identification of the matching function parameters

Figure B.3 reports a sensitivity exercise for the two parameters that govern matching. Panel (a) varies the matching parameter α_2 , holding the other estimated parameters fixed, and recomputes the model-implied elasticity of contract duration with respect to market thickness. Panel (b) varies the targeting parameter α_1 and recomputes the relative reallocation distance moment. These are the two moments that directly discipline the matching process: the duration-thickness elasticity disciplines the matching parameter, while the reallocation distance moment disciplines the targeting parameter. The corresponding empirical targets are the horizontal gray lines. The results of this exercise are consistent with the heuristic discussion of identification in Section 6.2: a lower matching parameter α_2 strengthens the elasticity of duration with respect to market thickness, while higher α_1 lowers the distance traveled by reallocating ships.

B.5.2 Time-series fit

We also evaluate model fit using monthly time-series paths for the key variables: contract prices, duration,

Figure B.3: Identification of matching-function parameters

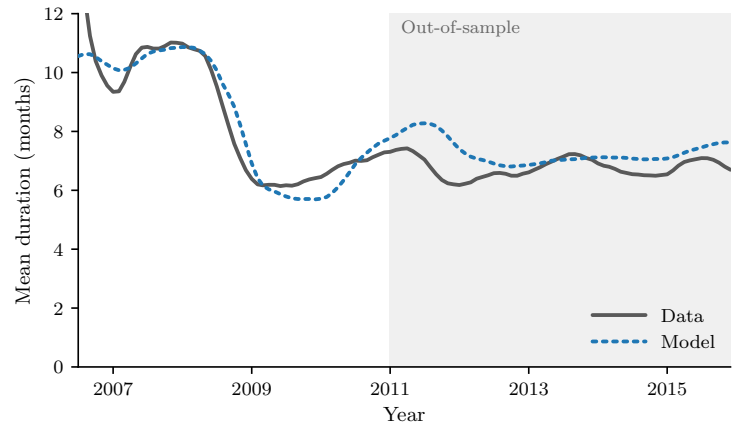


Note: Panel (a) varies the matching parameter α_2 and plots the model-implied elasticity of contract duration with respect to market thickness. Panel (b) varies the targeting parameter α_1 and plots the relative reallocation distance moment. In both panels, the blue line is the model moment and the gray dashed line is the empirical target. All other structural parameters are held fixed at their baseline estimates.

utilization, and dispersion. The targeted moments (Table B.5) discipline their period averages, differences, and regression coefficients, but do not directly target the month-to-month movements in the individual series. Matching the time-series movements therefore provides a more demanding check of model fit than reproducing the targeted moments. Table B.4 reports the root mean squared error (RMSE), i.e., the square root of the average squared distance between the empirical and simulated monthly series, and the normalized RMSE, which divides this quantity by the empirical average, for each variable over July 2006–December 2015. Figure B.4 plots the duration component of the same exercise; the shaded region begins in January 2011 and marks the out-of-sample region for the duration series (since the post-collapse duration is not directly targeted in estimation).

Table B.4: Monthly time-series fit

	Full-sample monthly fit	
	<i>RMSE</i>	<i>Normalized RMSE</i>
Price (\$000/day)	1.35	15.0%
Duration (months)	0.75	9.8%
Utilization	0.041	4.4%
Dispersion	0.016	13.1%

Figure B.4: Empirical and simulated contract duration

Note: Table B.4 reports root mean squared errors for prices, contract duration, utilization, and dispersion over July 2006–December 2015; normalized RMSE divides each RMSE by its empirical average over the same period. Figure B.4 plots mean contract duration over the same sample. For both Table B.4 and Figure B.4, we smooth the empirical series using a local-polynomial smoother with a six-month bandwidth and use unsmoothed monthly simulations for the model series. The gray shaded region in Figure B.4 marks January 2011 onward, the post-collapse period. We do not directly target the monthly post-collapse duration path in estimation.

Table B.5: Model fit: comparison of empirical and simulated moments

Panel A: Aggregate moments			Panel B: Share under contract, by region		
	Model	Data		Model	Data
Share under contract, pre-collapse	0.99	0.97	Americas	0.95	0.96
Δ share under contract	-0.059	-0.061	Asia–Europe	0.96	0.97
Dispersion, pre-collapse	0.11	0.12	Asia–North America	0.95	0.95
Δ dispersion	0.020	0.019	Intra-Asia	0.96	0.97
Duration, pre-collapse (months)	10.6	10.7	Intra-Europe	0.97	0.97
Δ duration (months)	-3.9	-3.9	Middle East and Africa	0.96	0.94
Price, pre-collapse	1.2	1.2	Europe–North America	0.95	0.98
Δ price	-0.49	-0.47			
SD of duration (months)	3.8	3.8			
Duration–thickness elasticity	-0.078	-0.079			
Extension probability	0.43	0.43			
Normalized reallocation distance	1.9	1.9			

Note: Panel A reports aggregate targeted moments; Panel B reports average shares of ships under contract by region. The pre-collapse period ends in June 2008, the collapse period is July 2008–December 2010, and Δ denotes collapse minus pre-collapse.

C Additional figures and tables

Figure C.1: Median contract duration for container-ship time-charter contracts and time-charter index, 1999–2019

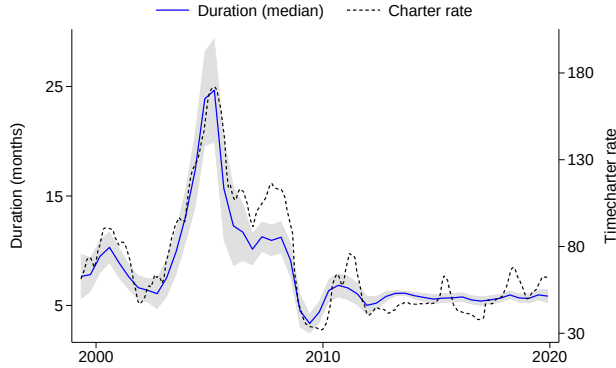


Figure C.2: Average contract duration for container-ship time-charter contracts and time-charter index, 1999–2022

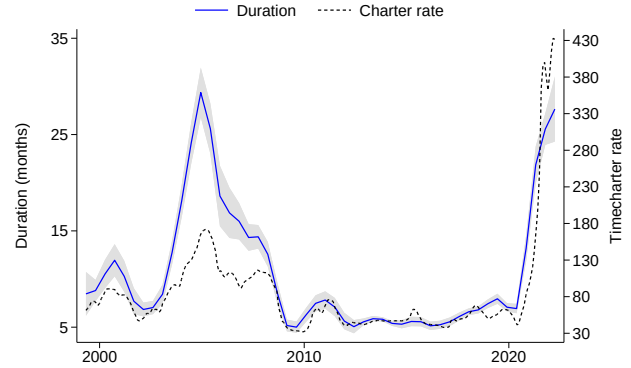


Figure C.3: The share of owned vs. leased ships is relatively stable over time

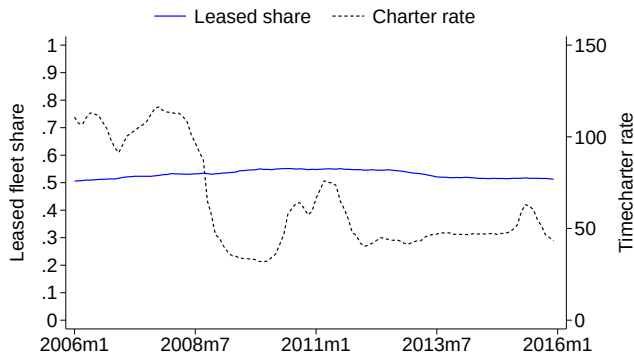


Figure C.4: Contract price, long vs. short contracts

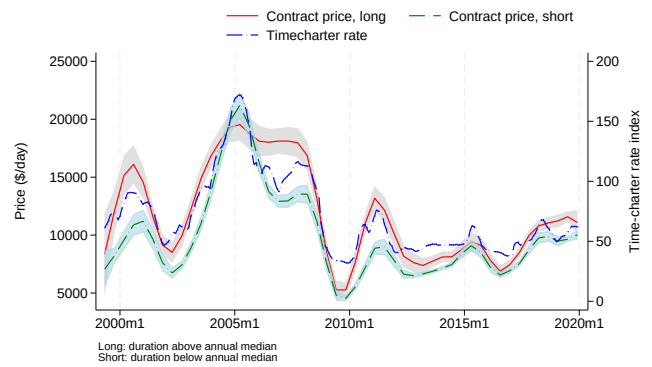


Figure C.5: Contract prices (residualized) across trade regions

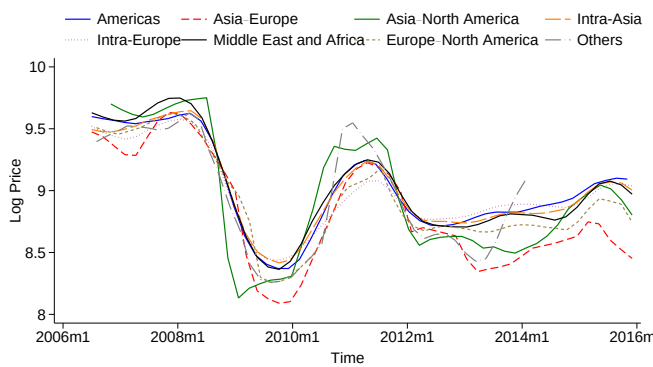
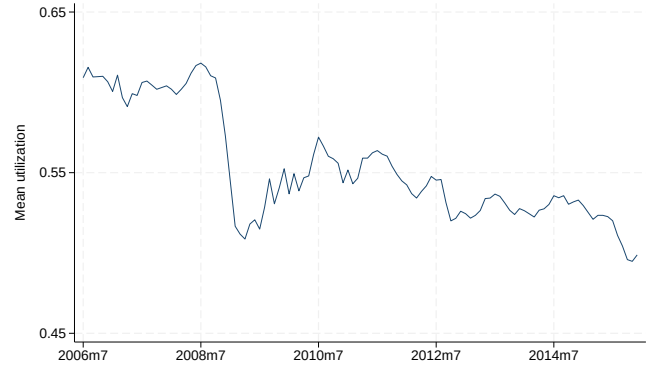


Figure C.6: Average ship utilization



Notes: Figure C.3 plots the share of leased ships alongside the charter rate, which indexes the business cycle in the market. Around 50% of ships are leased, and this share is relatively stable over the business cycle. For Figure C.5, we regress the logarithm of price on ship size, ship age, and region fixed effects and recover the residuals. The figure plots smoothed average residuals over time for each trade region. See Appendix A.6 for how we identify each ship's trade region. Figure C.6 plots the 90-day moving average of utilization, averaged across ships by month.

D Robustness

D.1 Robustness to time-varying discount factors

We test whether the planner output gain from eliminating the contracting externality changes when discounting varies with interest rates. We implement this by incorporating state-dependent discount factors. For each month t , we convert the annualized 3-month Treasury bill rate into a monthly discount factor, $\beta_t^{TB} = 1/(1 + r_t)$, where r_t is the monthly equivalent of the annualized rate, and estimate

$$\beta_t^{TB} = \beta_0 + \beta_1 z_t^G + \varepsilon_t,$$

where z_t^G is the aggregate demand state in the model. We then replace the constant discount factor with the fitted deterministic rule $\beta(z_t^G) = \beta_0 + \beta_1 z_t^G$ and recompute both the decentralized equilibrium and the planner’s problem. Since discounting is a deterministic function of the state, the model can still be solved on the same state space; both the decentralized agents and the planner value future payoffs using the product of the one-period fitted discount factors along the simulated state path. Table D.1 reports the results. Overall, the results are qualitatively unchanged, and our main finding that the contracting externality is substantial is preserved.

Table D.1: Robustness of the planner output gain to time-varying interest rates

	Baseline	Time-varying interest rates
Total planner output gain	12.86%	15.05%

Note: The robustness specification converts 3-month Treasury bill rates into monthly discount factors, fits $\beta(z_t^G) = \beta_0 + \beta_1 z_t^G$, where $\beta_1 = -1.2 \times 10^{-4}$, and recomputes the planner’s time-varying contract duration schedule using the fitted state-dependent discount factor.

D.2 Robustness to broker fees

We test whether the planner output gain from eliminating the contracting externality changes when agents pay a broker fee at signing. Table D.2 reports the results. We add a 1.25% broker commission to the decentralized contract length choice, and hold the planner’s time-varying contract duration schedule at its no-fee baseline. Overall, the planner output gain is essentially unchanged.

Table D.2: Robustness of the planner output gain to a ship-side broker fee

	Baseline	Broker fee
Total planner output gain	12.86%	12.77%

Note: The robustness specification charges a broker commission of 1.25% of contract value at signing, which enters the decentralized agents’ contract duration choice.

Table D.3: Robustness to alternative parametric forms of the matching function

Matching function	Total gain from social planner
Baseline	12.9%
Cobb–Douglas	15.8%
Increasing returns (Cobb–Douglas)	17.1%

D.3 Robustness to alternative matching functions

The strength of the contracting externality depends on the shape of the matching function, as discussed in Section 5. We therefore re-solve the model under alternative parametric forms for the matching technology and recompute the planner’s output gain. We consider a Cobb–Douglas matching technology that nests both constant and increasing returns to scale. For the constant returns specification, we hold the remaining structural parameters at their baseline estimates. For the increasing returns specification, since it is a larger change to the model, we also re-estimate the full vector of structural parameters. For both specifications, we re-optimize the planner’s time-varying contract duration schedule τ_t^* under the alternative matching technology. Table D.3 reports the results.

With a Cobb–Douglas matching technology, total matches in region r are $\hat{\alpha}_1 (n_{r,t}^{ship})^{\hat{\alpha}_3 - \hat{\alpha}_2} (n_{r,t}^{chart})^{\hat{\alpha}_2}$, where $n_{r,t}^{ship}$ and $n_{r,t}^{chart}$ are the searching ships and charterers, and $\hat{\alpha}_1$ and $\hat{\alpha}_2$ are parameters. The parameter $\hat{\alpha}_3$ is the degree of homogeneity, which governs returns to scale. In both our robustness tests we calibrate $\hat{\alpha}_1$ to exactly match the baseline average matching rate for ships (given the other parameters), and estimate $\hat{\alpha}_2$.

First, we impose constant returns ($\hat{\alpha}_3 = 1$) and estimate the parameter $\hat{\alpha}_2$ to target the same cross-sectional elasticity of contract duration with respect to market thinness used in estimation. We keep all other parameters at their baseline. This yields an output gain of 15.8%, close to the baseline.

Second, we allow increasing returns. As documented by [Castillo and Mathur \(2023\)](#), constant returns to scale may not be well justified in a spatial setting. We therefore fix the degree of homogeneity to $\hat{\alpha}_3 = 1.35$, with the caveat that this number comes from the setting of Uber, which is likely quite different from our market; we use it in the spirit of a robustness test. Also note that our model goes beyond a simple global matching function and instead allows space to matter in terms of how charterers and ships match, reflecting the emphasis of [Castillo and Mathur \(2023\)](#) on using detailed data to “approximate the matching function well.” When we re-estimate the structural parameters, we find that $\hat{\alpha}_2 = 0.41$. The output gain from the planner’s solution is 17.1%. Overall, the finding that the contracting externality is substantial is qualitatively robust across these robustness tests.

D.4 Time-varying bargaining parameter

We also test whether the bargaining parameter could change over time. Specifically, holding the baseline structural parameters fixed, we set $\delta_t = \delta + \delta_1(z_t^G - \bar{z}^G)$ in the model, where $\bar{z}^G$ is the average value of z_t^G in the sample period, and δ_1 governs how the bargaining parameter changes over time. Compared to the baseline estimation, we include an extra moment to identify δ_1 : the average duration during the post-collapse period (2011 - 2015). The choice of this moment is motivated by our argument that the bargaining parameter is identified by matching the empirical contract duration once other factors are pinned down.

We find that $\delta_1 \approx 0.000$, which is approximately the constant bargaining parameter baseline. Furthermore, our quantification of the contracting externality is quantitatively unchanged. We therefore do not find evidence of a time-varying bargaining parameter.

D.5 Additional robustness checks

Table D.4: Robustness: residual itineraries

	Baseline		Top-Quartile Utilization	
	(1) S.d., utilization	(2) S.d., revenue	(3) S.d., utilization	(4) S.d., revenue
Great Trade Collapse (July 2008 - End-2010)	1.917 (0.339)	2.293 (0.420)	2.289 (0.368)	2.713 (0.438)
Mean Dispersion	12.32	14.16	13.33	15.42
% change during Great Trade Collapse	15.55	16.20	17.17	17.59
N	114	114	114	114
R-squared	0.477	0.497	0.409	0.457

Note: We illustrate the robustness of our results to the residual itineraries in a schedule in the dispersion measure. For example, suppose that two ships are traveling between port X and Y and are fully utilized in one direction; their relative utilizations on the way back do not matter in terms of efficiency. To capture this idea, we construct an alternative measure of dispersion that is based on the top quartile of utilization of each ship in its previous 90 days; the idea is that the upper quartile of utilization is less likely to be influenced by lower utilization on backhaul legs.

In the case of the example, the dispersion using this alternative measure would be zero (since both ships are fully utilized on one leg), consistent with the non-existence of efficient reallocations. We find that the results using this alternative measure of dispersion are qualitatively robust compared to the estimates in the main text.

Table D.5: Reallocations increase output even in a downturn

Dependent Variable	(1)	(2)	(3)	(4)
	Total Trade (quantity)		Total Trade (revenue)	
	Great Trade Collapse	Other Periods	Great Trade Collapse	Other Periods
Reallocation	0.235 (0.115)	0.544 (0.118)	0.434 (0.136)	0.506 (0.116)
Route-Pair FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Bins for Number of Ships	✓	✓	✓	✓
Observations	1,149,262	3,899,705	1,149,262	3,899,705
R-squared	0.894	0.801	0.876	0.803
Mean of Dep. Var. (Normalized)	0.424	0.408	0.450	0.443

Note: We construct the dependent variable in two steps. First, we measure trade volume on each route (e.g., Japan - China - Singapore) as the total cargo carried by the ships operating on that route. Second, for each pair of routes, we compute the total trade volume combined across routes. Note that an increase in this measure therefore reflects an increase in total output across the pair, rather than a redistribution of output between routes. Using this dependent variable, we focus our analysis on route-pairs where at most a single reallocation took place, to avoid issues relating to multiple treatments. We also compute a revenue-based output measure by multiplying trade volume by the freight rate (similarly to how we construct this measure in the other parts of the paper).

We estimate the effects of reallocation using a difference-in-differences specification, restricting attention to a 12-month window around each reallocation. We include route-pair fixed effects and time fixed effects. We also include 10 fixed-effect bins for the number of ships on the two routes to control for time-varying changes in fleet size (for instance, from entry of newly built ships into these routes). Overall, we use within-route-pair variation to estimate the change in output that occurs due to the reallocation. For comparison, in the final row of the table we report the mean of the dependent variable normalized by the number of ships on the route (i.e. the per-ship output). We find that reallocations increase output even in a downturn and that the magnitude is economically and statistically significant. This result holds regardless of whether we use a revenue- or physical-quantity-based measure of output.