NBER WORKING PAPER SERIES

DELAYED CREATIVE DESTRUCTION:
HOW UNCERTAINTY SHAPES CORPORATE ASSETS

Murillo Campello
Gaurav Kankanhalli
Hyunseob Kim

Working Paper 28971
http://www.nber.org/papers/w28971

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2021, Revised January 2024

We are grateful to Kevin Aretz, Nick Bloom, Jason Faberman, Alex Fakos, Huseyin Gulen (discussant), Charlie Hadlock, Candace Jens, Andrea Lanteri (discussant), Howard Kung, RoniMichaely, Ryan Peters (discussant), Roberto Pinto (discussant), Frederik Schlingemann, Toni Whited, as well as conference and seminar participants at the 2020 ASU Sonoran Winter Finance Conference, Auburn University, Bayes Business School, Baylor University, Boston University, 2019 Bristol Corporate Finance Conference, Cornell University, 2022 EFA, Federal Reserve Bank of Chicago, Frankfurt School of Finance & Management, 2020 ITAM Finance Conference, 2023 LUBRAFIN Conference, Michigan State University, Seoul National University, University of Cambridge, University of Florida, University of Glasgow, University of Illinois at Urbana-Champaign, University of Notre Dame, University of Pittsburgh, and 2020 WFA for helpful comments. We thank David Jordan and Darren Liew at Clarksons Research for data support and Byung-Ryul Ahn at Hyundai Samho Heavy Industries for helpful discussions on the shipping industry. This research was funded in part by the Cornell Center for the Social Sciences and Smith Family Business Initiative at Cornell University. Heewon Ahn, Ikchan An, Penghao Chen, Eric Kim, Jason Lee, Phillip Lee, Boyao Li, Yao Lu, Youngjun Song, and George Sun provided excellent research assistance. Any views expressed are those of the authors and not those of the Federal Reserve System or the National Bureau of Economic Research.

Delayed Creative Destruction: How Uncertainty Shapes Corporate Assets
Murillo Campello, Gaurav Kankanhalli, and Hyunseob Kim
NBER Working Paper No. 28971
June 2021, Revised January 2024
JEL No. D22,D25,G31

ABSTRACT

We show how uncertainty shapes corporate asset allocation, composition, and productivity using data from the shipping industry. Firms curtail both ship acquisitions and disposals when uncertainty increases, primarily through cuts in new ship orders and ship demolitions—decisions that are costlier to reverse vis-à-vis secondary market transactions. Uncertainty also prompts firms to concentrate their fleets into narrower, less productive portfolios. We corroborate our findings using the 2009-2011 spike in Somali pirate attacks as an uncertainty shock to shipping activity. Uncertainty hampers "creative destruction," slowing both the adoption of innovation embodied in new capital and the disposal of old capital.

Murillo Campello
Johnson Graduate School of Management
Cornell University
114 East Avenue
369 Sage Hall
Ithaca, NY 14853-6201
and NBER
campello@cornell.edu

Gaurav Kankanhalli
Joseph M. Katz Graduate School of Business
University of Pittsburgh
226 Mervis Hall
Pittsburgh, PA 15260
gkankanhalli@katz.pitt.edu

Hyunseob Kim
Federal Reserve Bank of Chicago
230 South LaSalle St.
Chicago, IL 60604
United States
hyunseob.kim@chi.frb.org

1 Introduction

Recent macroeconomic models emphasize the role of asset allocation in shaping the impact of uncertainty on aggregate productivity and growth (see, e.g., Bloom (2009) and Bloom et al. (2018)). This body of research stresses that investigating the link between uncertainty and firms' capital adjustment decisions at a micro-level is key to understanding the dynamics at work. In a similar fashion, vintage capital models emphasize the importance of firm investment in new, efficient assets in fostering productivity (Solow (1960) and Hsieh (2001)). In this paper, we show how uncertainty affects corporate asset allocation, composition, and productivity through the lens of capital-intensive firms' decisions to invest and disinvest. We do so by looking at firms in the shipping industry. In this industry, investment and disinvestment decisions (buying, selling, and demolishing ships) are discrete, well-defined, and fully documented. The industry's singularly most important capital input, the ship vessel, is actively traded in worldwide markets.

Our study uses ship-level data over the 2006–2019 period from Clarksons Research (the "Clarksons data"), the world-leading maritime research firm. The Clarksons data cover the near-universe of commercial vessels in the global market, encompassing both public and private firms across over one hundred countries. The data are unique in allowing us to measure three distinct, but related, concepts: asset allocation, asset composition, and asset productivity. On the dimension of asset allocation, the Clarksons data contain detailed information (including quantities and prices) on four key margins along which shipping firms can alter their asset base: new ship orders, secondary market purchases and sales, and demolitions. Regarding asset composition, the database records individual ships with identifiers linked to owner firms, allowing us to track the evolution of shipping firms' asset portfolios (fleets) over time. The data also contain several measures of asset productivity, such as ship age, dead-weight tonnage, and engine revolutions per minute. Using the ownership and transactions information, we further measure the liquidity of the secondary market for ships at a detailed level, which we demonstrate is a key factor modulating the effect of uncertainty on firms' asset-level decisions. Finally, the database provides information that allows us to infer the maritime routes that different ships travel, enabling us to develop an empirical approach that plausibly identifies the impact of uncertainty on shipping firms' asset allocation.

We lay out our priors on the links between uncertainty and firms' decisions to alter their asset portfolios through investment in and disinvestment of ships using a real-options conceptual framework. As in standard models, it predicts a negative relation between uncertainty and both investment and disinvestment activities. The framework additionally implies that these relations are stronger when decisions are costlier to reverse (see Bernanke (1983) and Leahy and Whited (1996)). The costly reversibility arises from two primary sources: secondary asset market illiquidity (Gavazza (2011)) and the fixed costs of investing and disinvesting (Hackbarth and Johnson (2015)).

Under this framework, a liquid secondary market modulates the negative uncertainty–investment (–disinvestment) relation, as market liquidity makes it easier for firms to undo their investment (disinvestment) decisions by selling (buying) ships. Importantly, because new ship orders and ship demolitions entail high fixed costs, firms will exhibit a more pronounced response to uncertainty along these two decision margins, relative to decisions involving the straight-up purchase or sale of ships in secondary markets.[1] These fixed costs imply that uncertainty hinders "creative destruction:" it delays firms' acquisition of new, technologically-advanced capital and disposal of old, obsolete capital. The resulting uncertainty-driven misallocation of corporate resources across young and old assets has not been explored in prior work.

We begin our empirical analysis by showing how uncertainty generally shapes shipping firms' investment and disinvestment decisions. We measure investment using the total number of ships a firm orders new or purchases used in the secondary market in a given subsector. Analogously, we measure disinvestment as the number of ships the firm demolishes or sells. Our specifications incorporate forward-looking metrics of a shipping firm's expected investment opportunities in each of the subsectors in which it operates based on forward freight agreement prices ("first moment").[2] As discussed in detail below, we operationalize the concept of business uncertainty faced by a shipping firm ("second moment") using the equity option-implied volatility of firms in each of the subsectors the firm operates. Our base empirical results show a negative relation between uncertainty and *both* investment and disinvestment decisions (measured independently). These base results are new and revealing since papers in the literature largely report the "combined, net effect" of investment and disinvestment. We further show that asset liquidity (measured by the secondary market price premium and price dispersion) plays a central role in modulating the impact of uncertainty on firm investment and disinvestment.

In our main tests, we leverage our asset-level data to shed new light on the role that uncertainty plays in capital allocation at a granular level. We begin this examination by decomposing investment and disinvestment into new ship orders, used ship purchases, ship demolitions, and used ship sales; alternatives that entail different fixed costs and thus different degrees of irreversibility. In this analysis, it is particularly informative to focus on ship age since it serves as a convenient proxy for a wide range of technological advances in the shipping industry. Consistent with irreversibility being higher for new-vintage capital investment, we find that the negative relation between uncertainty and investment is almost entirely driven by new ship orders. In stark contrast, used ship purchases are largely unaffected by uncertainty. Analogously, among the two margins of disinvestment, the

[1] New ship orders incur additional fixed costs due to time-to-build, customization, and financing frictions. Concurrently, demolition entails higher search costs when replacing a demolished ship in the future (that ship cannot be later reacquired and reintegrated into the fleet), high environmental costs, and losses from asset disassembling (very few components of a demolished ship find alternative uses).

[2] Derivatives on shipping rate indexes, such as the Baltic Dry Index (BDI), trade on the Baltic Exchange, and we obtain their prices from Bloomberg. Kellogg (2014) uses a similar proxy for expected investment opportunities in the oil industry.

negative effect of uncertainty is driven in large part by demolition, with sales playing a marginal role. Notably, the negative relation between uncertainty and new ship orders and ship demolitions is amplified when asset liquidity is low. These results point to a novel effect of uncertainty on firms' asset composition and vintage. In particular, the irreversibility-driven asset-level responses to increased uncertainty that we document may lead to a deterioration in the portfolio of assets firms retain.

We strive to provide more causal evidence for the link between business uncertainty and firm investment and disinvestment using a quasi-experimental test design. Specifically, we examine shipping firms' responses to a sudden increase in uncertainty caused by the escalation in Somali pirate attacks between 2009 and 2011. That local piracy activity introduced considerable uncertainty to shipping routes that cross the Suez Canal by increasing the likelihood of both very negative (being attacked) and very positive (high profits from reduced competition) outcomes. Our discontinuity-based strategy exploits pre-determined vessel size limitations imposed by the Suez Canal to identify ships that are likely exposed to the heightened risk of Somali pirates and others that are similar in size and type of service, but unlikely affected. In a matched-sample difference-in-differences analysis, we find that firms significantly reduce both their investment in ships (particularly new orders) and disinvestment of ships (particularly demolition) belonging to the affected group, relative to the control group, during the period of heightened uncertainty in the Suez Canal route, but not before or afterwards. Complementary tests employing synthetic control units provide additional corroborating evidence.

We next study the impact of uncertainty on asset productivity. We show that the negative effect of uncertainty on investment is more pronounced for the purchase of high-productivity ships (those that are newer, carry bigger loads, and have more efficient engines). At the same time, firms cut back more on demolishing their less productive ships (older, smaller, with inefficient engines). We further show that low asset liquidity amplifies these uncertainty-led declines in investment and disinvestment along the lines of asset productivity. Our analysis demonstrates that uncertainty adversely affects the overall productivity of shipping firms' asset base by disproportionately reducing investments in new technology and more productive equipment, as well as the disposal of outdated, less productive assets.

We supplement our *asset-level* (firm-by-ship subsector) analyses with a host of *firm-level* tests to characterize the economic implications of the decisions we document for firms' asset composition. We first show that firms reduce their exposure across different markets when uncertainty is high: they consolidate their ship holdings into fewer subsectors in response to increased uncertainty, and the average productivity of assets kept in their portfolios declines. Notably, low asset liquidity is associated with more pronounced firm-level responses along these margins. In addition to their novelty, these results show that our inferences do not simply reflect firms reallocating investment and disinvestment from less liquid into more liquid segments without altering the overall productivity of their fleets when uncertainty rises. That is, firms' asset-level ("marginal") allocation decisions in the face of uncertainty do not "offset" each other; rather, these decisions cumulatively affect their firm-level ("overall") asset composition. Our results show that high uncertainty, combined with low asset liquidity, has a particularly deleterious effect on the efficiency of firms' asset mix.

Our paper contributes to the literature on the effect of uncertainty on economic activity on several fronts. Existing empirical work primarily examines the effects of uncertainty on aggregate output (Baker and Bloom (2013)) and firm investment, often conditional on the degree of irreversibility (e.g., Julio and Yook (2012), Gulen and Ion (2016), and Jens (2017)). This paper is the first to empirically show that uncertainty slows down firms' asset allocation across both the investment and disinvestment margins, particularly through cuts in purchases of new, productive assets and in the demolition of older assets. Our findings imply that increased economic uncertainty has negative consequences for corporate productivity and growth by deteriorating the quality of the firm's asset base, consistent with theoretical work showing that uncertainty reduces economic efficiency by slowing down capital allocation (e.g., Bloom (2009) and Bloom et al. (2018)). This contribution is made possible by the detailed asset-level data we use, which provide information on asset ownership, transactions, prices, and productivity. We also contribute to the literature by developing empirical measures of asset liquidity that closely resemble the theoretical definition of investment (and disinvestment) irreversibility.

Our findings are also related to the literature on the cyclical fluctuations of investment. Existing studies establish relations between these dynamics and learning (Fajgelbaum et al. (2017) and Jeon (2022)) and extrapolative expectations (Greenwood and Hanson (2015)), among other factors. Relative to these papers, our work emphasizes the real-options effects of uncertainty on asset allocation and mix, encompassing both investment and disinvestment across several margins. At the same time, our paper is complementary to this literature since alternative mechanisms (such as learning) may be consistent with some of our findings (particularly on investment). Our paper is also related to the theoretical (Benhabib and Rustichini (1991) and Hsieh (2001)) and empirical (Benmelech and Bergman (2011) and Ma et al. (2022)) literature on vintage capital. Existing theories posit that investing in new capital while scrapping old capital ("creative destruction") is key to promoting productivity and growth. Our paper is the first to provide micro-level evidence that uncertainty adversely affects productivity by hampering the adoption of technological progress embodied in newer-vintage capital.[3] In doing so, we shed light on a novel dimension of uncertainty's deleterious impacts on the *nature of assets* firms invest in and dispose of, in addition to the quantity of investment.

[3]Models that relate uncertainty to misallocation (e.g., Bloom et al. (2018)) may capture some of the forces that drive the uncertainty–technological progress link we explore.

2 Conceptual Framework

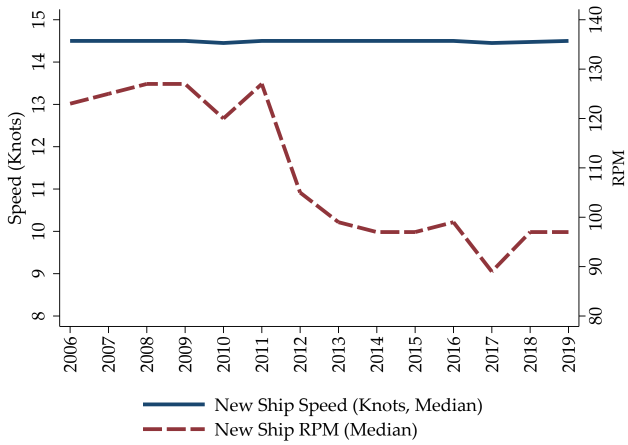
We use a simple, real-options-based conceptual framework to guide our analysis of the impact of uncertainty on the capital allocation decisions of shipping firms. Appendix A provides a formal analysis of the framework, in which we explicitly derive the optimal investment and disinvestment decisions of a representative shipping firm. In what follows, we describe the framework's underlying economic intuition and use it to motivate several empirical predictions that we subsequently take to the data.

Consider a firm that operates a fleet of ships across eight "subsectors." These subsectors correspond to four size-based categories of the two key sectors of the shipping industry: dry bulk carrier ships, or "bulkers," and tanker ships, or "tankers" (Section 3.1 provides details on shipping subsectors). Within each subsector, the firm makes capital allocation decisions along four margins, two corresponding to investment and two corresponding to disinvestment. Specifically, the firm may invest by ordering a new ship or buying a used ship in the secondary market, and it may disinvest by demolishing a ship or selling a ship in the secondary market. The firm incurs different costs and benefits from investing and disinvesting along these margins.

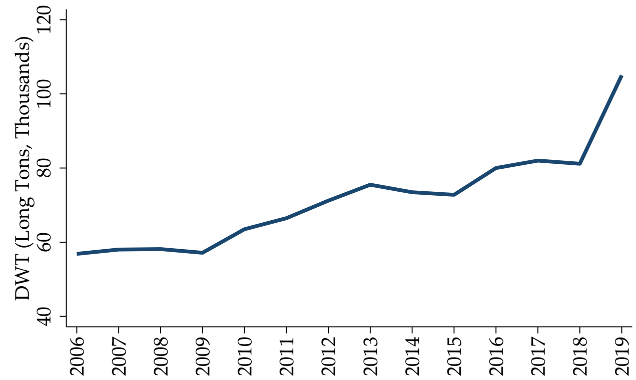
We first discuss the costs and benefits associated with investing and disinvesting; either through trade in the secondary ship market or through new ship orders and ship demolition. Assuming the secondary ship market is segmented by subsectors, the price paid (received) by the buyer (seller) of a used ship in the market is a function of two attributes. The first is a ship's productivity, which determines the present value of cash flows that the firm can generate from it, or its "fundamental value." The second determinant is the time-varying "liquidity" of the secondary ship market corresponding to the ship's subsector. Secondary market liquidity, in turn, is a function of market thickness, motivated by the idea that search frictions between buyers and sellers are smaller in "thicker" (or larger) asset resale markets (see Gavazza (2011)). Accordingly, more liquid used ship markets are characterized by higher resale prices due to the increased likelihood of finding matches between buyers and sellers in a given time window. Appendices A and B, respectively, analyze the microfoundations for, and empirical validity of, our notion of secondary market liquidity.

The costs and benefits associated with ordering a new ship may differ from those corresponding to purchasing a used ship primarily along two dimensions.[4] First, the firm incurs fixed costs when ordering a new ship. The fixed costs arise from time-to-build, customization, and financing frictions, among others. See Chapter 15 of Stopford (2009) for a discussion of the fixed costs associated with ordering new ships, as well as demolishing existing ships. Second, new ships are likely more productive (i.e., generate greater cash flows for a given investment) than used ones. We can use our data to illustrate that newly ordered ships are more productive. Figure 1 shows that while the speed of new

[4]The prices of new and used ships may also be affected by common factors like liquidity in the used ship market, albeit with potentially different sensitivities.



(A) Speed and RPM



(B) DWT

Figure 1. Speed, RPM, and DWT of New Ships. Panel A shows the median speed (in knots, primary Y-axis) and engine revolutions per minute (RPM, secondary Y-axis), and Panel B shows the median dead-weight tonnage (DWT, in thousands of long tons) for new ships ordered in each year in our sample period.

ships ordered in each year remained constant between 2006 and 2019, their engines' revolutions per minute (RPM) declined by over 20% over that same period (Panel A). Average dead-weight tonnage (DWT) per ship also increased over time (Panel B). These trends reflect the ongoing technological development in maritime engineering towards vessels with more fuel-efficient and powerful (more productive) engines and greater cargo capacity.

The costs and benefits associated with demolishing a ship differ from those involved with selling a ship in the secondary market along three dimensions. First, the scrap value is determined by supply and demand in the broader scrap metal market. Second, demolishing ships incurs fixed costs, arising from environmental costs and legal exposures, as well as the loss in value from disassembling a ship into its components and raw materials. Third, demolished ships are likely less productive than ships sold in the secondary market.

In our framework, the firm evaluates whether to "invest now" (alternatively, "disinvest now") or "invest later" (alternatively, "disinvest later") in its capital allocation decisions. It does so by comparing the aforementioned costs and the expected cash flows generated by its fleet of ships based on current and future demand conditions. The irreversible costs of investment and disinvestment arise from two sources: relevant fixed costs and illiquidity in secondary markets. Together, they imply negative relationships between uncertainty and *both* firm investment and disinvestment. We test this more standard prediction using our data, noting that the existing empirical literature does not investigate the impact of uncertainty on disinvestment, nor on capital composition — decisions that are critical for replacing outdated assets with those that embed new technology — using micro data. We state our first testable prediction as follows.

Prediction 1. *Shipping firms will reduce their investment and disinvestment in response to increases in uncertainty.*

The economic intuition for Prediction 1 relies on the optionality inherent in the firm's investment and disinvestment decisions when they are costly to reverse. The option to delay investment (disinvestment) represents a call (put) option from the firm's perspective (see, e.g., Pindyck (1991) and Abel and Eberly (1996) for classical contributions to the theoretical real-options literature). Naturally, the value of these options to "wait-and-see" increases in uncertainty. The framework also implies that because fixed, irreversible costs are higher for new ship purchases and ship demolition (relative to used ship purchases and sales), the negative effects of uncertainty arising from increased "wait-and-see" option values should be more pronounced along these action margins. Our second prediction below summarizes this intuition, which is novel to the literature in illuminating the link between uncertainty and various dimensions of investment and disinvestment.

Prediction 2. *Shipping firms will reduce their relatively irreversible investment and disinvestment (new ship purchases and ship demolition) more than they will reduce their relatively reversible investment and disinvestment (used ship purchases and sales) in response to increases in uncertainty.*

Our analysis further implies that the negative relationship between uncertainty and investment and disinvestment is modulated by asset liquidity. The probability of successfully finding a trading counterparty is lower in thinner — and therefore less liquid — markets. Accordingly, the option to "wait-and-see" is more valuable in less liquid markets, as investment (disinvestment) decisions taken now are more costly to reverse in the future, should shipping demand be lower (higher) than expected. We state our third prediction.

Prediction 3. *Shipping firms will reduce their investment and disinvestment in response to increases in uncertainty by a larger degree when the secondary ship market liquidity is lower.*

Relatedly, because investing in more productive assets or disinvesting less productive assets is associated with a greater degree of irreversibility, the framework implies that the effects of increases in uncertainty will differ along the lines of asset productivity. This leads to our fourth prediction.

Prediction 4. *Shipping firms will reduce their investment (disinvestment) in more (less) productive ships by a larger degree in response to increases in uncertainty.*

We set out to test these empirical predictions in the remainder of the paper.

3 Data and Empirical Methodology

3.1 Ship-Level Data

We obtain near-universal data on shipping firms' ownership and transactions of ships over the 2006–2019 period from Clarksons Research. We use four databases compiled by Clarksons. The first is a panel dataset on ship ownership. This dataset allows us to observe characteristics of each ship, including unique ship identifiers (e.g., the International Maritime Organization, or IMO, number), the date the ship was built, the identity and country of its builder, and engine characteristics such as speed (nautical miles per hour) and revolutions per minute (RPM). We also observe a ship's dead-weight tonnage (DWT), which specifies how much weight the ship can carry, including primarily cargo, but also fuel, crew, passengers, food, and water. DWT is expressed in long tons and is customarily used in the industry to define ship size. The dataset also contains point-in-time information on the identity of a ship's owning firm, allowing us to construct a firm-quarter panel of ship holdings. The Clarksons dataset covers 3,966 unique firms, both public and private, domiciled in 109 countries.[5] These firms own on average seven ships in a given quarter, worth $412 million (in average purchase price terms). The average aggregate value of the ship holdings across our sample firms in a given year is $378 billion.

The second dataset provides information on new vessel orders and allows us to observe firms' investment in new ships. The third dataset contains records on secondary market ship transactions; i.e., purchases and sales of used ships. We observe the ship identifiers, buyer and seller identities, transaction date, and resale price, and calculate firms' investment in used ships and disinvestment of existing ships through sales. The final dataset contains information on ship demolition activity, including the ship identifiers, owner identity, demolition date, and scrap value.

Following the industry standard, we classify ships into two sectors, dry bulkers and tankers, and eight size-based subsectors (four within each sector). The four subsectors within dry bulkers are: Handysize (DWT < 40,000), Handymax (DWT 40,000–59,999), Panamax (DWT 60,000–109,999), and Capesize (DWT ≥ 110,000). The four subsectors within tankers are: Medium Range (or MR, DWT < 45,000), Long Range 1 (or LR1, DWT 45,000–79,999), Long Range 2 (or LR2, DWT 80,000–159,999), and Very Large Crude Carriers (or VLCC, DWT ≥ 160,000). Ships within each of these subsectors are operated for specialized purposes and routes due to physical size limitations and economic viability. Dry bulker ships, by design, hold dry cargo such as iron ore, coal, other minerals and grains. Tankers, on the other hand, hold liquid cargo, primarily crude oil and its refined derivatives. Further, ships in

[5] As state-owned enterprises may have different objectives than private-sector firms, in Table C.1 we verify that our results are robust to the exclusion of any shipping firm with ownership of over 51% attributable to state-owned entities. We obtain data on firms' ownership structure from Orbis and conduct manual searches to verify whether each owner is a state-owned entity.

different subsectors generally operate different routes and carry different subsets of dry or wet cargo. For instance, within tankers, the largest ships (VLCC) tend to exclusively carry crude oil, whereas the smaller ships tend to carry a wider variety of refined products (e.g., propane, automobile fuel, and jet fuel). In addition, ships are limited in the routes they can navigate due to their size. For example, Panamax ships are so named because they are the largest bulkers that are able to traverse the Panama Canal. Capesize ships must navigate around the Cape of Good Hope as they are too large to transit through the Suez or Panama Canals. As a result, markets for shipping services and used ships are segmented between these subsectors. We define the unit of our analysis at the firm-subsector-quarter level. Our final panel of ship holdings consists of approximately 100,000 observations.

The aforementioned features of the shipping market lead to segmentation in the types of ships a firm operates. We show this by plotting our sample firms' ship ownership by subsector in Appendix Figure C.1. Panel A plots the number of firms operating in each subsector, with subsectors within the bulker or tanker sectors shown in ascending order of ship size. The panel indicates that there are a relatively large number of firms that operate smaller ships. Panel B plots the distribution of firms by the number of subsectors in which they operate ships. The vast majority of firms operate ships in one to four subsectors. Most shipping firms operate ships within just the bulker or tanker sector, with 24% of firms operating across both of those two sectors.

3.2 Variable Construction and Measurement

3.2.1 Ship Investment and Disinvestment

We construct three measures of investment at the firm-subsector-quarter level. First, we compute the new ship investment rate as the number of new ships a given firm orders in a given subsector in a given quarter, scaled by the number of ships the firm owns in that subsector in the previous quarter. We calculate the used ship investment rate in a similar fashion, by summing the number of used ships in each subsector that a given firm purchases in a given quarter in the secondary market, scaled by the number of ships the firm owns in each subsector in the previous quarter. We calculate the total investment rate as the sum of the new and used ship investment rates in a given firm-subsector-quarter.

We construct measures of firm disinvestment in an analogous fashion. The first is the demolition rate, defined as the number of ships a given firm demolishes in a given subsector and quarter, scaled by the number of ships the firm owns in that subsector in the previous quarter. Firms can also disinvest ships through sales in the secondary market. We calculate the used ship sale rate as the number of ships a given firm sells in each subsector in a given quarter, scaled by the number of ships the firm owns in each subsector in the previous quarter. We calculate the total disinvestment rate as the sum of the demolition and used ship sale rates in a given firm-subsector-quarter.

3.2.2 Uncertainty in the Shipping Industry

We construct an *ex-ante* measure of uncertainty in shipping at the subsector-quarter level for our tests. We do so using implied volatilities from publicly-traded options for shipping firms' stocks taken from OptionMetrics. This measure is constructed according to the following steps. First, for each shipping firm with publicly-traded options, we identify for each day in a given quarter the nearest-to-money American call option expiring at the end of the next quarter. Second, we obtain the annualized implied volatility for this option on each day of the quarter. Third, this daily implied volatility is averaged across all days in a quarter for each firm. Fourth, we identify all the subsectors in which each firm operates in a given quarter. For each subsector-quarter, we finally take the average of the quarterly implied volatility across all firms operating in that subsector-quarter, weighted by the number of ships each firm operates in the subsector-quarter. The resulting metric is our baseline measure of subsectoral-quarter uncertainty (labeled *Uncertainty*).[6] In later tests, we aggregate the subsector-quarter *Uncertainty* measure to the firm level using the number of ships a firm operates in each subsector-quarter as the weight.

In robustness tests reported in Table 9, we employ the realized (*ex-post*) volatility of the subsectoral forward freight agreement price changes (defined in Section 3.2.4) as an alternate proxy for uncertainty in the shipping subsector, which we label *Volatility*(Δ*Subsectoral BDI*). Reassuringly, and consistent with rational expectations among options-market investors, the correlation between the *ex-ante* and *ex-post* uncertainty measures is very high, on the order of 0.82. This high correlation suggests that our preferred, *ex-ante* measure based on the subset of firms with publicly-traded options in a shipping subsector is representative of uncertainty in the subsector as a whole. Notably, the firms with publicly-traded options, whose implied volatilities form the basis for our *Uncertainty* measure, represent 38% of the aggregate shipping fleet in dead-weight tonnage. We further address the possibility that heterogeneity in the representativeness of firms with publicly-traded options across subsectors may influence our results in Section 7.6.

3.2.3 Secondary Ship Market Liquidity

We compute two key measures of secondary ship market liquidity, i.e., the ease at which ships sell in the secondary market. Our first liquidity measure aims to directly capture investment irreversibility as in Arrow (1968), defined as the difference between the purchase and resale prices of capital. Specifically, we define *Price Premium* as the resale price minus the purchase price divided by the purchase price, averaged across all secondary market transactions in a subsector and year-quarter.

[6] We also consider an alternative weighting scheme that decomposes each firm's implied volatility across subsectors based on the distribution of its own fleet across the subsectors, as opposed to the fraction of total ships in a subsector made up by its own ships as we do in our baseline *Uncertainty* measure (see Appendix D.1). We further replicate our baseline results under various alternative option maturities in Appendix D.2.

Our second (reverse) measure of liquidity is *Price Dispersion*, defined as the year-quarterly mean absolute deviation of resale prices divided by the mean resale price of all transactions in a given subsector and year-quarter. The idea behind this measure is that the dispersion of transaction prices is lower when it is easier to find a counterparty for transactions.

We validate our secondary ship market liquidity proxies by examining whether variation in these liquidity measures is driven by differences in the thickness of asset resale markets.[7] To do so, we construct three measures of market thickness. The first (*# Ships*) is the log total stock of ships in each subsector-quarter. The second measure (*# Firms*) is the log total number of firms in each subsector-quarter. These two proxies are motivated by our conceptual framework as well as Gavazza (2011). The second measure, in particular, captures the number of potential buyers in the secondary market (as in Benmelech (2009)). The third measure (*# Transactions*) is the number of secondary market transactions completed in a given subsector-quarter divided by the lagged stock of ships in that subsector-quarter. This last measure captures *ex-post* trading frequency (or turnover) in the used ship market (see also Schlingemann et al. (2002)).

Verifying the relation is important as it directly builds on the conceptual link between trading frictions and investment irreversibility. To wit, our framework implies that the incentive to "wait-and-see" before investing or disinvesting under uncertainty is heightened when these decisions are costlier to reverse through trade in less liquid secondary markets. For this validation analysis, we regress each of our two liquidity measures, *Price Premium* and *Price Dispersion*, on each of our three measures of market thickness, *# Ships*, *# Firms*, and *# Transactions*, along with controls for demand conditions and ship-level determinants of secondary market prices. Appendix B reports the results. The estimates in Table B.1 imply that secondary ship markets are more liquid — and thus, investment and disinvestment decisions are less costly to reverse — when secondary markets are thicker.

3.2.4 Control Variables

We control for a number of variables that are likely to influence shipping firms' demand for capital. First, we proxy for the expected shipping demand using a forward-looking measure of shipping rates at the subsector level. Specifically, Δ*Subsectoral BDI* is the quarterly return on the shipping rate indices derived from forward freight agreement prices for commonly-served routes in a given subsector. Forward freight agreements (FFAs) are derivatives that allow to lock in a price for a given freight shipping route at some future date. The Baltic Dry Index (BDI) is an example of a shipping index constructed from FFA prices that is widely used as a proxy for business prospects in the shipping industry. We obtain the forward rates quoted on the Baltic Exchange from Bloomberg. Second,

[7] The notion that the thickness of a market affects transaction prices dates back to Diamond (1982). His search-and-bargaining model has been adapted to real asset (e.g., Gavazza (2011)), financial (e.g., Duffie et al. (2005)), and labor markets (e.g., Rogerson et al. (2005)).

Cash Flow is the quarterly income before extraordinary items plus depreciation and amortization divided by lagged total assets, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector. To construct this variable, we manually match firms in the Clarksons data to public and private firms in Compustat and Orbis. We also construct controls for lagged fleet characteristics at the firm-subsector-quarter level. Specifically, we calculate the average log of age, DWT, and RPM, across all ships that a firm holds in a given subsector-quarter.

3.3 Descriptive Statistics

Table 1 presents descriptive statistics for our investment and disinvestment measures as well as other variables described above. The average total quarterly investment rate for our sample of shipping firms is around 1.4%, whether calculated using number of ships acquired or their DWT. New ship orders account for approximately 82% of the average firm's total investment, and used ship purchases account for the rest. Firms in our sample have average quarterly total disinvestment rates of 1.3%. About 51% of disinvestment occurs through ship sales in the secondary market, the rest is via demolition. Translating these rates into numbers of ships per firm-year implies that the average firm invests in 5.5 ships per year, out of which new ship orders account for 4.5. The average firm disinvests around 5.1 ships a year, out of which 2.5 ships are demolished. The annualized implied equity volatility, our base measure of uncertainty in a subsector, has a mean of 9% and a standard deviation of 2.9%.

TABLE 1 ABOUT HERE.

3.4 Empirical Specification

We use an empirical model that relates firms' capital allocation decisions with uncertainty and asset liquidity to test the predictions outlined in Section 2. We do so controlling for other drivers of firm investment and disinvestment, including proxies for expected shipping demand and cash flows. Our base specification takes the form:

$$\begin{aligned} Y_{i,j,t} = &\beta_1 Uncertainty_{j,t} + \beta_2 Liquidity_{j,t} + \beta_3 Uncertainty_{j,t} \times Liquidity_{j,t} \\ &+ \theta \boldsymbol{Controls}_{i,j,t} + FEs + \epsilon_{i,j,t}, \end{aligned} \tag{1}$$

where $Y_{i,j,t}$ refers to the investment and disinvestment measures described in Section 3.2.1 for firm i, in subsector j, and year-quarter t. $Uncertainty_{j,t}$ is subsectoral-quarter uncertainty measured by average implied equity volatility, and $Liquidity_{j,t}$ is one of the two subsectoral-quarter ship market liquidity measures (*Price Premium* and *Price Dispersion*). The vector $\boldsymbol{Controls}_{i,j,t}$ contains proxies for the first moment of investment opportunities, Δ*Subsectoral BDI* and *Cash Flow* at the subsector-quarter level, as well as lagged fleet characteristics, including the average log age, log DWT, and log

RPM in the firm-subsector-quarter. We estimate several variants of Eq. (1) controlling for unobservables at multiple levels by including fixed effects for: firm, subsector, (headquarter) country, year-quarter, country × year-quarter, and firm × subsector. Standard errors are double-clustered at the firm-subsector and year-quarter levels. Our results are robust to clustering at various levels including at the subsector level and double-clustering at the subsector and year-quarter levels, corresponding to the level of variation in our key variables of interest (see Tables C.2 and C.3). We stress that our inferences continue to obtain when we recalculate t-statistics based on standard errors obtained by applying the wild bootstrap method of resampling clusters at either the subsector or subsector and year-quarter levels. This final check is particularly relevant in our setting in light of work by Cameron et al. (2008) showing that bootstrap-based resampling of clusters provides asymptotic refinement to inferences when the number of clusters is small. Such concerns could arise with respect to the aforementioned subsector-level clustering in which there are eight clusters corresponding to the eight shipping subsectors (see Section 7.6 for more details).

4 Uncertainty, Investment, and Disinvestment

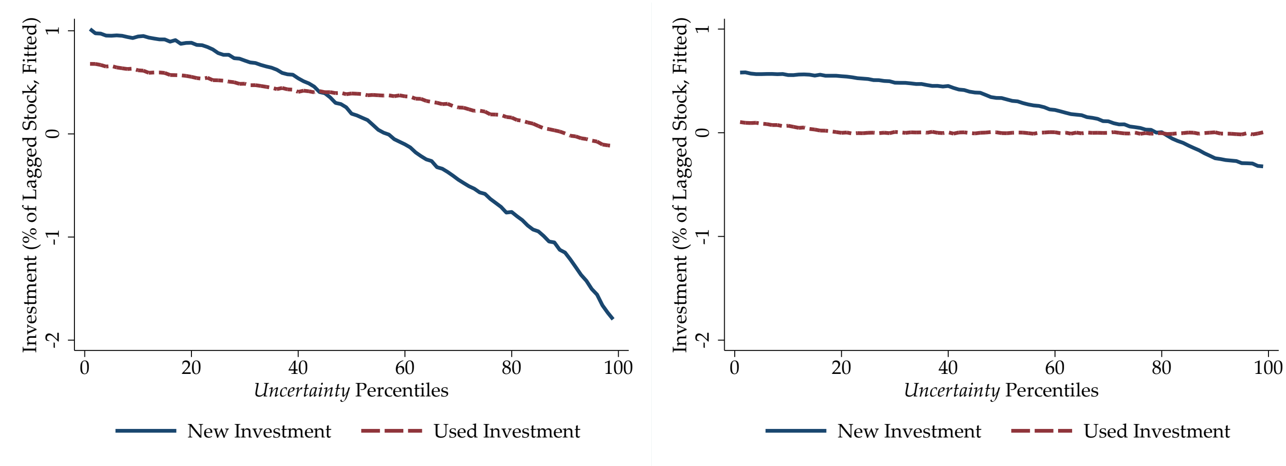
4.1 Total Investment, New Ship Orders, and Used Ship Purchases

We estimate Eq. (1) first using total investment and then its disaggregated components (new ship orders and used ship purchases) as dependent variables. We report the results in Table 2, Panel A.

TABLE 2 ABOUT HERE.

In line with our conceptual framework, the coefficient estimates on our subsector-level uncertainty measure, *Uncertainty*, in columns (1) and (4) show that total investment is negatively related to uncertainty in a given industry subsector. As expected, investment in ships is positively associated with Δ*Subsectoral BDI* and *Cash Flow*. However, only the former variable is statistically significant, suggesting that the industry-specific, forward-looking measure of shipping rates better captures first-moment expectations for shipping firms' investment opportunities.

Importantly, our real-options framework predicts that the effect of uncertainty on investment should be particularly strong for ordering new ships — as opposed to buying used ships — given the associated fixed costs. We test this prediction by estimating Eq. (1) with investment rates in new and used ships as separate dependent variables. Results in columns (2), (3), (5), and (6) of Table 2, Panel A show that the effect of uncertainty on total investment is driven almost entirely by new ship investments (columns (2) and (5)), rather than used ships acquisitions (columns (3) and (6)). New to the literature, this finding suggests that sunk costs lead firms to respond to increased uncertainty by reducing investment in the newest-vintage capital the most. In Section 5, we further investigate



(A) Low *Liquidity*

(B) High *Liquidity*

Figure 2. Relationship between Uncertainty and Investment for Low and High Secondary Market Liquidity. Each panel depicts the fitted investment rate from the specification in Eq. (1) estimated at the 25$^{\text{th}}$ ("Low") and 75$^{\text{th}}$ ("High") percentiles of *Liquidity* measured as the resale price premium of secondary ship transactions in a subsector-quarter.

how measures of asset productivity — including vintage — affect firms' capital allocation decisions when uncertainty varies.

One advantage of our setting is that we are able to examine the role of secondary asset market liquidity in shaping the dynamics of investment under uncertainty. For narrative purposes, we transform all liquidity measures such that higher values indicate higher liquidity. Using the resale price premium in a subsector as a proxy for liquidity, we find that the negative relation between uncertainty and total investment is significantly mitigated by secondary market liquidity; see column (1) of Panel A. When liquidity is at its 25$^{\text{th}}$ percentile, a one-standard-deviation increase in *Uncertainty* decreases investment by 41% relative to mean rates, which translates into 2.3 fewer ships invested per year. In contrast, when secondary market liquidity is at its 75$^{\text{th}}$ percentile, it has virtually no effect on investment.[8] We observe similar dynamics when employing the dispersion of resale prices as a measure of liquidity (see column (4) of Panel A) or other measures motivated by market thickness (see Section 7.2 and Appendix E). These results verify our prediction that heightened uncertainty increases firms' incentives to delay investment, particularly when the decisions are costly to reverse due to low asset market liquidity. They are also consistent with prior literature examining these dynamics in different settings (see, e.g., Gulen and Ion (2016) and Kim and Kung (2017)).

Figure 2 provides a graphical illustration of our findings. In it, we plot regression-fitted investment rates, disaggregated across new and used ship purchases, against percentiles of *Uncertainty* at

[8]These magnitudes are calculated using the marginal effect of *Uncertainty* assuming liquidity measured by the price premium is at its 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles, –5.34 and 3.02, respectively. The marginal effects of *Uncertainty* at these percentiles are $-0.081+0.021\times-5.34=-0.193$ and $-0.081+0.021\times3.02=-0.018$, respectively. Multiplying these marginal effects with the standard deviation of *Uncertainty* (2.893), we obtain $-0.193\times2.893=-0.56$ and $-0.018\times2.893=-0.05$. Finally, dividing by the average investment rate of 1.36%, we get $-0.56/1.36=-41\%$ and $-0.05/1.36=-4\%$.

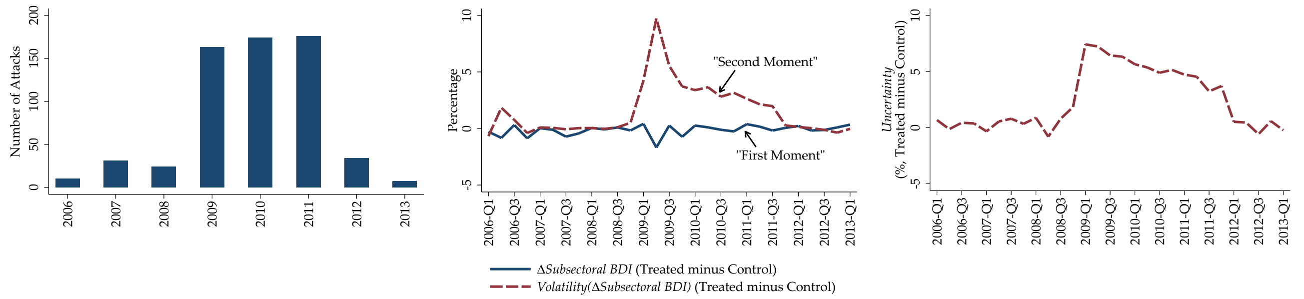
low (25th percentile, Panel A) and high (75th percentile, Panel B) levels of *Liquidity*. The figure shows that new ship orders (blue solid line) respond more pronouncedly to variation in uncertainty than used ship purchases (red dashed line). A comparison of the two panels shows that the response is considerably stronger when asset market liquidity is low. The figure also reveals a non-linear effect of uncertainty on new investment: an effect that is pronounced at the highest levels of uncertainty.

4.2 Total Disinvestment, Demolition, and Used Ship Sales

We next examine the effect of uncertainty on disinvestment; both total disinvestment, as well as disaggregated into its components, demolition and sales. Our framework predicts that when disinvestment decisions are costly to reverse, uncertainty increases firms' incentive to delay them and that this effect is mitigated by asset market liquidity. The estimates in Table 2, Panel B confirm this prediction. In particular, the results in columns (1) and (4) show that uncertainty is negatively associated with total disinvestment. They also show that the first-moment proxies are generally negatively associated with disinvestment. In accordance with our framework, the negative uncertainty–disinvestment relation is mitigated by asset market liquidity, indicating that when disinvestment decisions are less costly to reverse, uncertainty has only a limited impact on disinvestment. The associated economic magnitudes are significant. According to the estimates in column (1), when asset liquidity is at its 25th percentile, a one-standard-deviation increase in uncertainty is associated with a 70% decline in disinvestment rates, relative to the mean. In contrast, when liquidity is at its 75th percentile, it is associated with a more modest 35% decline from the mean.

Our framework further implies that the impact of uncertainty on disinvestment is particularly high for ship demolitions (the more irreversible margin) compared to ship sales. Accordingly, we study disinvestment in the forms of demolition and sales separately in columns (2) and (3) (alternatively, columns (5) and (6)) of Panel B. We find that the negative effect of uncertainty is far more pronounced for demolition: the magnitude of the effect on demolition is 72% of the total disinvestment effect, with sales making up the balance. These results are consistent with greater sunk costs making firms more cautious about demolishing relative to selling ships when uncertainty is high in the relevant industry subsector.

In all, the results in Table 2 confirm several of our framework's predictions. Further, they provide early insight into an important result that uncertainty bears a *compositional effect* on shipping firms' asset base: when uncertainty rises, firms invest less in new vessels (which likely embody new technology) and dispose less of ships intended for demolition (containing old-vintage technology). We study this effect in further depth in Section 5.



(A) Number of Attacks per Year **(B)** Δ*Subsectoral BDI* Levels and Volatilities **(C)** *Uncertainty*

Figure 3. Frequency of Somali Attacks, Shipping Demand Levels, and Uncertainty. Panel A depicts the number of Somali pirate attacks per year based on statistics compiled by the International Maritime Bureau. Panel B shows the differences in the levels and volatilities of Δ*Subsectoral BDI* between treated and control subsectors. Panel C shows the differences in *Uncertainty* between treated and control subsectors. Treated subsectors consist of Panamax bulkers and LR2 tankers. Control subsectors consist of Capesize bulkers and VLCC tankers.

4.3 A Quasi-Natural Experiment: The Somali Piracy Wave

The evidence so far is consistent with shipping firms delaying their capital allocation in the face of uncertainty. In this section, we employ a design-based empirical approach to support that assertion (Card (2022)). Specifically, we use the escalation of piracy off the coast of Somalia between 2009 and 2011 as a quasi-natural experiment. The event represented a significant, positive innovation to uncertainty in particular shipping subsectors for three reasons. First, the escalation in piracy increased the downside risk (costs from being attacked) as well as the potential upside from successfully passing through (due to a reduction in competition), acting as a mean-preserving spread. Second, the increase in uncertainty affected some subsectors of ships, while leaving others largely unaffected, generating plausible "treated" and "control" groups for testing. To wit, the waters surrounding Somalia are traversed primarily by ships entering and exiting the Suez Canal, whose physical features limit the size of ships that can pass through it. Accordingly, the increase in uncertainty only affected ships that could pass through the Canal. Using this discontinuity, we define treated and control subsectors as those falling immediately below (Panamax bulkers and LR2 tankers) and above (Capesize bulkers and VLCC tankers) the size thresholds for using the Canal, respectively.[9]

Third, there was a clear period of heightened risk of pirate attacks, providing a discrete, identifiable shock to uncertainty in the industry. Panel A of Figure 3 shows that the number of attacks dramatically increased from 24 in 2008 to 163 in 2009, and remained high at 174 and 176 in 2010 and 2011, respectively. Contemporary accounts suggest that the escalation in attacks was viewed as potentially long-lasting.[10] Due to historical ambiguities of maritime jurisdictions in the area and

[9]The large-scale disruption caused by an incident involving a single ship, the *Ever Given*, made explicit the importance of this route for the global economy, as well as its fragility to extraneous factors. See *The Wall Street Journal*, March 24, 2021, "*Suez Canal Is Blocked by Container Ship Causing Huge Traffic Jam.*"

[10]See the testimony by the Acting Deputy Administrator of the U.S. Department of Transportation's Maritime Administration, James Caponiti, before the U.S. Senate Armed Services Committee on May 5, 2009. Mr. Caponiti states that the

the lack of a functional government in Somalia, the international community had to coordinate a response to the heightened risk of pirate attacks (Weitz (2009)). These efforts led to an increase in multi-lateral law enforcement in the area, which virtually ended the pirate attacks by 2012, a full three years after the escalation began.

To verify that the escalation in Somali piracy represents a differential shock to uncertainty in shipping demand for the treated versus control subsectors, we examine changes in shipping rate volatility around the event period. Panel B of Figure 3 shows a marked increase in the difference in the volatility of Δ*Subsectoral BDI* for treated relative to control subsectors during the 2009–2011 window. Panel C shows a similar dynamic using our option-implied measure, *Uncertainty*. Importantly, Panel B shows that the difference in Δ*Subsectoral BDI* between treated and control subsectors is largely flat around zero, suggesting that the escalation did not embed a concurrent first-moment shock for treated subsectors (see Figure F.2 for dynamics of the first-moment proxy separately for the two subsectors).

We analyze the effect of the increase in uncertainty due to the rise in piracy by comparing the investment and disinvestment rates of treated and matched control firm-subsectors. In particular, for each treated firm-subsector, we assign a matched control firm-subsector as its nearest neighbor in terms of treatment propensity. We estimate the propensity score as a function of firm-subsector fleet characteristics, including the average log age, log DWT, and log RPM. This matching ensures that we compare firm-subsectors that are otherwise similar in fleet characteristics, except that they lie on either side of the pre-defined size threshold. Consequently, ships belonging to the treated and control groups are likely to be similar in the commodities they carry and the destinations they serve, differing only in the routes taken. We perform detailed checks in Appendix Table F.1 and Figure F.1 to verify that the matched treated and control firm-subsectors are comparable along fleet characteristics, ownership, and common origin–destination pairs served. The observed similarity across these various dimensions implies that demand conditions across the treated and control subsectors are likely to be driven by common trends in commodity prices (such as iron ore and crude oil). Importantly for our experiment, these trends were unrelated to the emergence of piracy in Somalia, which was driven by domestic political conflicts. As we test explicitly, the common demand conditions (see Panel B of Figure 3 and Figure F.2) lend credibility to our identifying assumption that the trends in outcomes for treated and control firm-subsectors would have evolved in parallel absent the unexpected increase in Somali piracy. Using the matched sample, we estimate

"*serious threat stemming from the ongoing piracy problem in the waters off of Somalia [...] has grown substantially worse.*" Supporting the view that there was no reason to expect the threat to naturally subside, Mr. Caponiti notes, "*One reason for the success of seajackings and ransom taking is that the government in Somalia is ineffective and this has enabled pirates to operate with virtual impunity.*" On the topic of piracy mitigation efforts, Mr. Caponiti's testimony outlines several current and planned U.S.-led initiatives that would require the coordination of international bodies, concluding that "*Combating international piracy is no small effort. [...] much remains to be done, before international piracy can be eliminated.*"

the following difference-in-differences model:

$$Y_{i,j,t} = \beta_1 Treat_j \times Piracy_t + \theta \boldsymbol{Controls}_{i,j,t} + FEs + \epsilon_{i,j,t}, \tag{2}$$

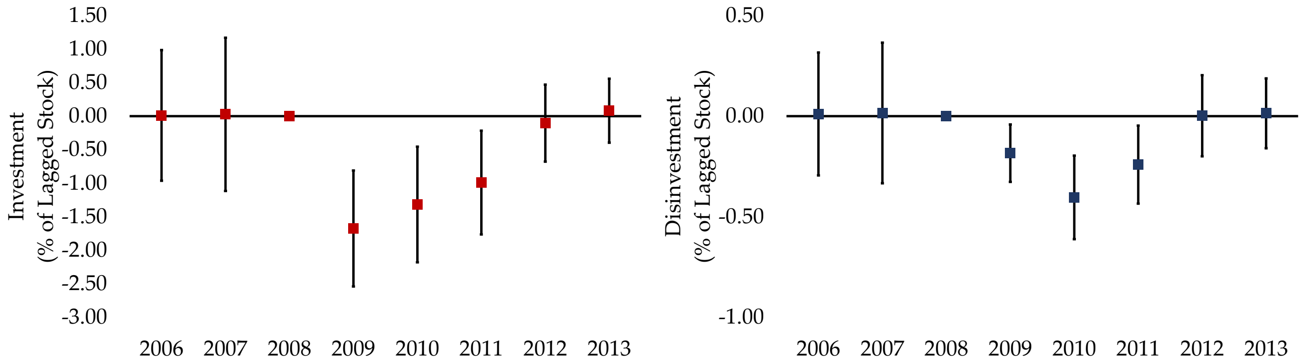
where $Y_{i,j,t}$ refers to the investment and disinvestment measures for firm i, in subsector j, and year-quarter t. $Treat_j$ is an indicator equal to one for the Panamax bulker and LR2 tanker subsectors, and zero for the Capesize bulker and VLCC tanker subsectors. $Piracy_t$ is an indicator equal to one during 2009–2011, and zero for all other years from 2006 through 2013. The vector $\boldsymbol{Controls}_{i,j,t}$ is defined as in Eq. (1). We include the firm's headquarter country × year-quarter and firm × subsector fixed effects. Standard errors are clustered at the match level (cf. Abadie and Spiess (2022)). The coefficient of interest is β_1, which represents the difference in investment or disinvestment rates between affected and control firm-subsectors during the period of heightened uncertainty due to Somali piracy relative to all other years between 2006 and 2013.

Table 3, Panel A reports the results from estimating Eq. (2). While piracy risk is heightened, treated firms cut both their investment and disinvestment in subsectors exposed to the risk, relative to the unaffected subsectors. The economic magnitude of the effects is significant. In the three years of heightened uncertainty, the cut in quarterly investment rates implied by the estimate in column (1) is 1.30 percentage points, which represents 38% of the mean investment rate of 3.43% for treated firm-subsectors during the pre-event period (2006–2008). Likewise, treated firms cut their disinvestment rates by 18% of the pre-event mean. These cuts are more pronounced among new ship purchases and demolition, where the degree of irreversibility is likely to be higher.

TABLE 3 ABOUT HERE.

Figure 4 shows the dynamic effects of the escalation in piracy on investment and disinvestment by plotting annual coefficients from a variant of Eq. (2). Notably, the figure provides evidence of parallel pre-trends in investment and disinvestment, a key assumption underlying our experiment. We further verify that our results are not driven by differential pre-trends using a synthetic difference-in-differences approach in which control units are reweighted to achieve parallel pre-trends in outcome variables with treated units (cf. Arkhangelsky et al. (2021)). The investment and disinvestment dynamics depicted in Figure F.3 resemble those in Figure 4. Reassuringly, both Figures 4 and F.3 show significant drops in investment and disinvestment coinciding with the event window.

In order to compare the magnitude of the effect of uncertainty from the quasi-natural experiment with our baseline results, we estimate a version of Eq. (1) (without *Liquidity*) using $Treat_j \times Piracy_t$ as an instrument for $Uncertainty_{j,t}$. Table 3, Panel B reports the second-stage estimates (first-stage estimates are in Table F.5). A comparison of the economic magnitudes implied by the coefficients on *Uncertainty* in columns (1) and (4) of Panel B in Table 3 with those under column (1) of Panels A and B in Table 2 indicates that they are of similar orders of magnitudes. The escalation in



(A) Investment Dynamics

(B) Disinvestment Dynamics

Figure 4. Investment and Disinvestment Dynamics around the Escalation in Somali Piracy. This figure displays coefficient estimates and 95% confidence intervals for $Treat_j$ interacted with yearly indicators estimated from a modified version of the specification in Eq. (2) (coefficients are taken from Table F.4). The modified specification replaces the single treatment period indicator ($Piracy_t$) with annual indicator variables and the country × year-quarter fixed effects with country × year fixed effects. The dependent variables are investment (Panel A) and disinvestment (Panel B).

piracy is a strong instrument for *Uncertainty* (first-stage F-ratio of 153.23, see Table F.5), and thus the inferences drawn from the second-stage estimates are likely valid (Lee et al. (2022)). Overall, our quasi-natural experiment provides evidence supporting a causal argument that uncertainty dampens corporate capital allocation across both investment and disinvestment.

One caveat for the external validity of our empirical design is that the escalation in piracy took place during a period of somewhat declining first moments across shipping subsectors (see Figure F.2). Accordingly, our estimates should be interpreted as representing local average treatment effects (LATE) of increased uncertainty on investment and disinvestment when first moments are declining. Nevertheless, the fact that we continue to find a strong, negative uncertainty–*disinvestment* relationship in the quasi-natural experimental design is reassuring for the validity of our inferences. Specifically, this relationship would be, if anything, attenuated during periods of declining first moments as firms would have greater incentives to disinvest under such conditions. Our unique data on firms' granular disinvestment decisions enable us to shed light on the dynamics of capital allocation under uncertainty even conditional on first-moment shocks.

5 Uncertainty and Asset Productivity

In this section, we test the prediction that uncertainty disproportionately affects firms' investment in (disinvestment of) more (less) productive assets. The analysis provides insight into the impact of uncertainty on the productivity of firms' *entire asset base* (fleets). We study the asset composition dynamics in further detail in the next section.

We consider a number of individual ship characteristics as proxies for asset productivity. We do so utilizing widely accepted industry standards. We start by estimating a battery of hedonic pricing regressions to identify ship attributes that attract higher secondary-market prices, reflecting their greater productivity (see Appendix Table B.1). These attributes are: *DWT* (larger ships carry a greater volume of goods per trip), *RPM* (ships with lower RPM are more fuel-efficient), and *Age* (new ships incorporate an array of technological advancements, ranging from safety to automation, to navigational and docking capabilities). We then adopt two approaches to gauging the productivity of ships firms invest in. First, we identify whether a given ship's productivity proxies are above or below its subsector-median numbers for two metrics: (1) *DWT* and (2) $-1\times RPM$. A ship is classified as "high-productivity" if it is above the median on at least one of those two metrics, and "low-productivity" otherwise. Second, we consider ship *Age* separately as it captures a collection of technological advances in shipping. We compute investment rates separately for high- and low-productivity ships based on each of the two classifications and gauge the impact of uncertainty on these types of investment. We report the results of this analysis in Table 4.

TABLE 4 ABOUT HERE.

The estimates in Panel A show that uncertainty most negatively impacts investment in *high-productivity* ships, as captured by ship size (*DWT*) and engine efficiency (*RPM*), particularly when these ships are new (see column (1)). In contrast, investments in new but low-productivity ships and used ships in general are largely unaffected by uncertainty. These results are consistent with the prediction that firms delay investment in high-productivity ships more when faced with higher uncertainty. Importantly, they point to a slowdown in firms' upgrading of their fleets under uncertainty. We next focus on ship age in Panel B. The estimates show that the negative effect of uncertainty on investment becomes monotonically weaker as age increases. New ship orders and purchases of used ships with ages less than 16 years are significantly negatively affected by increases in uncertainty, while purchases of older ships are not at all impacted. Our results flesh out in great detail the deleterious effect of uncertainty on the productivity of firms' asset base: it operates through delayed investment in larger, more fuel-efficient ships, as well as newer ships with the latest technological advances.

We conclude this section by examining whether uncertainty differently affects firms' disinvestment of ships of different productivity. To condense this analysis, we classify a ship as "high-productivity" if it satisfies at least two of the following three criteria in its subsector-quarter: (1) above median *DWT*, (2) below median *RPM*, and (3) below median *Age*; and "low-productivity" otherwise. Table 5 reports results for the demolition and sales of high- and low-productivity ships.

TABLE 5 ABOUT HERE.

The estimates in Table 5 show that the negative effect of uncertainty on disinvestment, and its interactive effect with asset liquidity, are driven by the demolition and sales of *low-productivity* ships (see columns (3) and (4)). Our framework would predict this exact result if the costs of reversing demolition and sales of low-productivity ships are higher than those of high-productivity ships. Although we cannot directly test this sensible conjecture, we find evidence that sunk costs are indeed higher for disinvestment of low-productivity ships. For demolition, we calculate an analogue to the resale price premium as the scrap value minus the most recent purchase price scaled by the purchase price. The higher this variable, the lower the degree of irreversibility. The average is –67% for low-productivity ships and only –42% for high-productivity ones. Similarly, the price premium conditional on sale is lower for low-productivity (–5%) than for high-productivity ships (22%). Firms appear to incur a greater loss from demolishing or selling low-productivity ships. The greater costs of demolishing these ships are likely due to their poorer conditions and environmental and regulatory restrictions on where and how they can be demolished (see Stopford (2009) for a detailed discussion).

6 Uncertainty and Firm Asset Composition

The firm-subsector-level analyses in the previous sections reveal considerable heterogeneity in firms' investment and disinvestment responses to changes in uncertainty based on the vintage and productivity of the assets they operate. The differential responses across individual assets suggest that uncertainty may significantly affect firms' overall asset composition. In this section, we explicitly test how firms alter their asset portfolios when uncertainty in the industry changes.

We first investigate whether firms alter the concentration of their asset holdings in response to uncertainty. Assuming the existence of fixed costs associated with operating different ships across multiple subsectors at the same time (e.g., arising from informational frictions and coordination of fleets with specific cargo-route combinations), our framework would imply that a firm will concentrate its fleet into fewer subsectors in the face of higher uncertainty. We employ the (log) number of distinct market subsectors the firm operates in during a given quarter as an (inverse) measure a firm's fleet concentration and use it as the dependent variable in a firm-level variant of Eq. (1). We also use the Herfindahl-Hirschman Index (HHI) of the number of ships a given firm-quarter operates across subsectors as a complementary measure. The coefficient on uncertainty, therefore, captures the extent to which firms concentrate their fleets into a smaller number of market subsectors when uncertainty increases. Table 6 reports the results.

TABLE 6 ABOUT HERE.

The results in Panel A show that firms reduce the number of subsectors they operate in when faced with heightened uncertainty; or equivalently, firms expand into new subsectors in periods of lower uncertainty. This finding suggests that the effects of uncertainty on firms' capital allocation are in part driven by changes in *extensive margin* exposures to market subsectors (Williamson (1975, 1985) and Teece (1980)). In addition, Panel B shows that the coefficient on uncertainty is significantly positive and the coefficient on its interaction with liquidity is significantly negative when the dependent variable is the HHI, indicating that firms' holdings become more concentrated as uncertainty rises, particularly when asset liquidity is low. These results are consistent with fixed costs associated with operating ships across multiple markets, which lead firms to concentrate their ship portfolios in subsectors with greater importance when uncertainty rises. Low asset liquidity accentuates this effect as it makes the *ex-post* retreat from subsectors more costly. Viewed together, these results show that firms' *asset-level* allocation decisions in the face of heightened uncertainty do not "offset" each other; rather, these decisions cumulatively affect their *firm-level* asset composition and, ultimately, the boundaries of the firm.

We next explore how the productivity of a firm's ship portfolio changes during periods of heightened uncertainty. Building upon the analysis of Section 5, we gauge whether firms' *marginal* asset allocation decisions along the lines of productivity (see Tables 4 and 5) translate into significant changes in the *average* productivity of their fleets. We do so by estimating a firm-level version of Eq. (1) in which the dependent variables are the average log *Age*, log *DWT*, and log *RPM* across all ships held by a given firm-quarter. We also consider three composite measures of technical efficiency: the average ratios of *Speed/RPM*, *DWT/RPM*, and *DWT/Speed*. Table 7 reports the results.

TABLE 7 ABOUT HERE.

The within-firm estimates point to a significant worsening in the average firm-level productivity of assets when uncertainty increases, and particularly so when secondary ship markets are illiquid. Column (1) shows that the average log *Age* of ship holdings increases substantially with heightened uncertainty. The economic magnitude of this effect is large: a one-standard-deviation increase in *Uncertainty* (2.90) is associated with a 23-log point increase in average fleet age when liquidity is at its 25$^{\text{th}}$ percentile (–5.34). Translating into years, this would imply a 25.9% increase ($= e^{0.23} - 1$) or 5.2 years relative to a mean fleet age of 20.1 years. Likewise, columns (2) and (3) show that firms hold smaller ships (lower log *DWT*) with less fuel-efficient engines (higher log *RPM*) in the face of higher uncertainty. Their fleets also exhibit lower technical efficiency, with lower speed-per-revolution, weight-per-revolution, and weight-per-speed ratios (columns (4) through (6)). The overall results imply that firms' asset portfolios experience a tangible deterioration in productivity when uncertainty increases.

In our final set of firm-level tests, we aggregate our investment and disinvestment measures at the firm-quarter level across all subsectors firms operate in. The results in Table 8 confirm that our micro-level findings on asset allocation (at the firm-subsector level) ultimately translate into firm-level changes in fleets. For example, firms as a whole predominantly cut back on new ship orders when uncertainty increases, whereas used ship purchases are unaffected (see Panel A).

The firm-level results on disinvestment in Panel B also closely resemble their firm-subsector-level counterparts in Table 2, Panel B.

TABLE 8 ABOUT HERE.

The results of this section show that firms' subsector-level responses to increased uncertainty "add up" to measurable changes in firm-wide capital allocation, negatively affecting the productivity of firms' assets and reducing their exposure to different markets.[11] These results are new to the literature. They imply that uncertainty may lead to diminished competition and innovation incentives at the industrial sector level, features commonly associated with healthy entry-exit dynamism (see, e.g., Foster et al. (2019)). In light of recent evidence of both rising uncertainty (Baker et al. (2014)) and declining business dynamism (Decker et al. (2016)), our results point to a mechanism connecting these two phenomena.

7 Robustness and Alternative Explanations

7.1 Alternative Measures of Uncertainty

We examine the robustness of our baseline results to various alternative measures of uncertainty. We do so for two reasons. First, it is important to understand whether the effects of uncertainty that we show are driven by broad, macroeconomic uncertainty rather than shipping sector-specific uncertainty. This analysis is informative on the role of unobserved changes in first moments as fluctuations in macroeconomic uncertainty are often confounded with business-cycle movements (see Storesletten et al. (2004)). To this end, we augment our main specification in Eq. (1) with the following macroeconomic uncertainty measures: (1) the VIX index from the Chicago Board Options Exchange, (2) the Jurado et al. (2015) measure of macroeconomic uncertainty, (3) the Baker et al. (2016) economic policy uncertainty (EPU) index, and (4) the dispersion of GDP forecasts from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. Second, it is crucial to ensure that our baseline *Uncertainty* measure, constructed from option-implied volatilities of shipping firms with publicly-traded options, reflects the uncertainty facing the population of shipping firms at large. We capture shipping sector-specific uncertainty using the realized volatility of the forward freight agreement prices used to calculate our Δ *Subsectoral BDI* measure.[12]

[11] We repeat our main analysis in the subsample of "pure-play" firms that operate ships only in a single subsector. Such firms, by definition, do not substitute investment or disinvestment across subsectors. The results are similar to those observed for the full sample (see Appendix Table C.4).

[12] We find similar results using the *Uncertainty* measure computed using shipping firms' implied equity volatilities. We report results using *Volatility(ΔSubsectoral BDI)* in this analysis because it is constructed from publicly available data, similar to the macroeconomic uncertainty measures employed.

Table 9 reports results for investment and disinvestment rates. Across both columns, the only uncertainty measure that attracts statistically significant both main and interaction (with *Liquidity*) effects is our own shipping sector-specific measure, *Volatility(ΔSubsectoral BDI)*. This result is reassuring, suggesting that the ex-ante *Uncertainty* measure we use in the main analysis represents uncertainty encompassing all firms, both publicly-traded and private, in the shipping market. The estimates further suggest that the source of uncertainty specific to shipping, as opposed to broader macroeconomic uncertainty, drives our results on shipping firms' investment and disinvestment.

TABLE 9 ABOUT HERE.

As an additional robustness check, in Appendix D.1, we show that our inferences are robust to the use of alternative weights in the construction of the *Uncertainty* measure. Finally, in Appendix D.2, we examine the dynamics of the uncertainty–(dis)investment relationships, and verify the robustness of our results to changing the maturity of the options used to calculate our *Uncertainty* measure.

7.2 Alternative Measures of Liquidity and Irreversibility

In Appendix E, we examine the robustness of our baseline results to alternative, theoretically-motivated measures of secondary market liquidity and irreversibility. First, we employ the ratio of the number of unique buyer firms to the number of ships available in a given subsector-quarter as a measure of liquidity. This measure is analogous to the vacancy-to-unemployment ratio commonly used in the macro-labor literature to gauge labor market tightness (e.g., Mortensen and Pissarides (1994)) and is similar to a measure employed in product market contexts (e.g., Gourio and Rudanko (2014)). As such, higher values of this measure indicate a more liquid secondary market in which it is easier to sell ships. Results utilizing this measure are reported under columns (1) through (3) in Table E.1. They confirm that the negative association between uncertainty and investment (particularly new ship orders) is significantly dampened in more liquid markets as measured by this alternative proxy. Results in columns (1) through (3) in Table E.2 demonstrate that our findings on the modulating effect of asset liquidity on firms' disinvestment, particularly through ship demolition, also obtain under this alternative liquidity metric.

Second, we verify that our results hold for alternative proxies for liquidity that capture market thickness. We discuss in Section 3.2.3 and demonstrate in Appendix B how these measures are closely related to the market price-based liquidity measures. Consistent with this tight link, the results in Table E.3 show that our main findings continue to obtain when we use the measures of market thickness in place of the main liquidity measures.

Third, following Gulen and Ion (2016), we conjecture that assets with a shorter useful life (or higher depreciation rate) are likely to have a lower degree of irreversibility. The theory underlying this conjecture argues that sunk costs, and thus the degree of irreversibility, decrease in the depreciated component of capital (e.g., Kessides (1990) and Farinas and Ruano (2005)). We, therefore, include the reverse of useful life as our *Liquidity* variable in Eq. (1). We construct a subsector-level measure of useful life by computing the average age at which ships in a given subsector are demolished. Results in Table E.1, columns (4) through (6) show that uncertainty increases are associated with a significantly less negative investment response in firm-subsectors with a shorter useful life of assets, consistent with the findings of Gulen and Ion (2016). Likewise, the negative relationship between uncertainty and disinvestment of ships is mitigated in firm-subsectors with a shorter useful life (see Table E.2, columns (4) through (6)). In all, the baseline results reported in Table 2 are robust to a host of measures of irreversibility capturing its various dimensions, including the thickness of the secondary ship market and assets' useful life.

7.3 Financing Constraints

We next investigate whether the negative relation between uncertainty and corporate asset allocation could be ascribed to a concurrent tightening of firms' financing constraints. Prior work has shown that higher uncertainty is associated with increased credit spreads, which may lead financially constrained firms to curtail investment (see, e.g., Gilchrist et al. (2014), Kaviani et al. (2020), and Alfaro et al. (2022)). We account for this channel by including two common proxies for firms' financing constraints, together with their interactions with *Uncertainty*, as additional controls: (1) the size-age index as in Hadlock and Pierce (2010) and (2) an indicator for whether the firm is private.

Table C.5 shows that our findings continue to hold when accounting for financing constraints. For instance, column (1) shows that the size-age index of financing constraints is negatively related to investment and that more constrained firms disproportionately cut their investment when uncertainty increases. However, the effects of uncertainty, both standalone and interacted with liquidity, remain significant. Columns (2) and (4) show that private firms are less likely to invest and more likely to disinvest, both unconditionally and when uncertainty increases, but most of these effects are insignificant. Again, both the standalone and interactive effects of uncertainty on disinvestment remain significant. These checks suggest that financing constraints do not explain the observed relationships between investment (and disinvestment) and uncertainty.

7.4 Lumpiness of Investment and Disinvestment

We address potential estimation issues arising from the lumpiness of shipping firms' investment and disinvestment decisions in two ways. First, we re-estimate Eq. (1) at semi-annual and annual horizons, instead of the quarterly horizon used in our baseline tests. In addition to reducing the lumpiness by aggregating the dependent variables at a lower frequency, this test accounts for potentially lagged responses of capital allocation decisions to changes in uncertainty. Appendix Table G.1, Panel A confirms that the associations between uncertainty, liquidity, and capital allocation that we report in our baseline tests hold at the longer horizons.

Second, we verify that our main results are robust to statistical issues owing to a large fraction of the dependent variable taking zero values. Specifically, we employ the continuous investment and disinvestment rates that we bound from above at one as dependent variables in zero–one inflated beta regressions. These regressions explicitly allow for an inflated rate of zero and one values in the outcome variables (see Ospina and Ferrari (2012) and Staub and Winkelmann (2013)). Columns (3) and (6) in Panel B of Appendix Table G.1 show that the results using this alternative specification are similar to the baseline results. We also estimate linear probability and conditional logit models using indicator variables for positive (dis)investment rates. Our results continue to hold in these specifications as well (see columns (1), (2), (4), and (5) in Panel B of Appendix Table G.1).

7.5 Investment and Disinvestment Tonnage

Our baseline investment and disinvestment measures are calculated using numbers of ships. To address the possibility that the main results may be disproportionately influenced by decisions involving small ships, we re-run our main tests using investment and disinvestment measures computed with dead-weight tonnage in place of the number of ships. Table C.6 shows that our inferences continue to hold: high uncertainty is associated with both lower total investment and disinvestment, which is more pronounced when asset market liquidity is low.

7.6 Additional Robustness Tests

We conduct several additional robustness tests and report the results in Appendix C. First, Table C.1 examines whether our results hold after excluding state-owned shipping firms (such as COSCO Group) from our sample. To the extent that state-owned firms may have different objectives than maximizing profits, they may not represent an ideal sample to test the real-options predictions. We obtain information on shipping firms' ownership from Orbis and manually inspect the identity of their owners. We exclude firms with at least 51% ownership attributable to state-owned entities. The results reported in Table C.1 confirm our baseline findings.

Second, given that several of our key variables of interest (such as *Uncertainty* and *Liquidity*) vary at the subsector and year-quarter level, in Tables C.2 and C.3 we show that our inferences are robust to clustering standard errors at the subsector level or double-clustering at the subsector and year-quarter level. In addition, we show that our inferences hold under standard errors computed by resampling subsector and year-quarter clusters using Cameron et al.'s (2008) wild bootstrap-c method. This alternative approach addresses the issue that clustering may underestimate standard errors when the number of clusters (subsectors in our case) is relatively small (eight). The resulting t-statistics {in curly parentheses} are virtually identical to those produced under the regular clustering [in square parentheses]. Third, we re-estimate our baseline specifications with the firm-level uncertainty measure (as in Tables 6 through 8) and subsector × year-quarter fixed effects. This specification addresses the possibility that unobservable, time-varying subsector-level factors not captured by our subsector-level controls may explain our main findings. The results in Table C.7 confirm the base results.

Finally, we address the possibility that relying on *Uncertainty* calculated from the implied volatilities of shipping firms with publicly-traded options may influence our results. Notably, the results in Table 9 based on the ex-post volatility of shipping derivative prices (reflecting all firms operating in a given subsector) already suggest that these firms represent the broad sample of shipping firms. Nevertheless, in Table C.8 we show that weighting each observation by the fraction of ships in that subsector-quarter operated by firms with publicly-traded options does not materially alter our inferences. This shows that our baseline estimates are robust to measurement issues that could arise from the heterogeneous presence of firms with publicly-traded options across subsector-quarters.

8 Concluding Remarks

Using near-universal data on shipping firms' capital allocation decisions across new orders, secondary-market transactions, and demolition of ships, combined with subsector-specific measures of uncertainty, we show that shipping firms delay both the purchase and disposal of ships in response to heightened uncertainty. These dynamics are more pronounced for less liquid secondary ship markets and for new ship orders and demolition, relative to secondary market purchases and sales. New to the literature, we also show that investment (disinvestment) reductions are concentrated among more (less) productive ships.

Major recent geo-political developments, such as the escalation of trade tensions between the U.S. and China and the U.K.'s Brexit, have raised concerns about the effects of heightened economic uncertainty among managers and investors. The Covid-19 pandemic has only exacerbated those concerns. Our results uniquely suggest that such developments, indicative of heightened global uncertainty, may impose additional economic costs through their impact on the efficiency of firms' capital allocation decisions, particularly those that are costlier to reverse. Uncertainty appears to play an important role in decelerating "creative destruction" dynamics by impeding the adoption of new technologies embodied in new capital, the disposal of obsolete technologies in old-vintage capital, and discouraging firm entry into new market segments. Critically, this dampened capital allocation can have an adverse effect on productivity and growth. While our work provides new insights into these dynamics, more research on this important topic is needed.

References

Abadie, Alberto, and Jann Spiess, 2022, Robust Post-Matching Inference, *Journal of the American Statistical Association* 117, 983–995.

Abel, Andrew, and Janice Eberly, 1996, Optimal Investment with Costly Reversibility, *The Review of Economic Studies* 63, 581–593.

Alfaro, Ivan, Nicholas Bloom, and Xiaoji Lin, 2022, The Finance Uncertainty Multiplier, Technical report, National Bureau of Economic Research.

Arkhangelsky, Dmitry, Susan Athey, David Hirshberg, Guido Imbens, and Stefan Wager, 2021, Synthetic Difference-in-Differences, *American Economic Review* 111, 4088–4118.

Arrow, Kenneth, 1968, Optimal Capital Policy with Irreversible Investment, in "Value, Capital and Growth, Essays in Honor of Sir John Hicks" (JN Wolfe, Ed.).

Baker, Scott, and Nicholas Bloom, 2013, Does Uncertainty Reduce Growth? Using Disasters as Natural Experiments, Technical report, National Bureau of Economic Research.

Baker, Scott, Nicholas Bloom, Brandice Canes-Wrone, Steven Davis, and Jonathan Rodden, 2014, Why Has US Policy Uncertainty Risen Since 1960?, *American Economic Review* 104, 56–60.

Baker, Scott, Nicholas Bloom, and Steven Davis, 2016, Measuring Economic Policy Uncertainty, *The Quarterly Journal of Economics* 131, 1593–1636.

Benhabib, Jess, and Aldo Rustichini, 1991, Vintage Capital, Investment, and Growth, *Journal of Economic Theory* 55, 323–339.

Benmelech, Efraim, 2009, Asset Salability and Debt Maturity: Evidence from Nineteenth-Century American Railroads, *The Review of Financial Studies* 22, 1545–1583.

Benmelech, Efraim, and Nittai Bergman, 2011, Vintage Capital and Creditor Protection, *Journal of Financial Economics* 99, 308–332.

Bernanke, Ben, 1983, Irreversibility, Uncertainty, and Cyclical Investment, *The Quarterly Journal of Economics* 98, 85–106.

Bloom, Nicholas, 2009, The Impact of Uncertainty Shocks, *Econometrica* 77, 623–685.

Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen Terry, 2018, Really Uncertain Business Cycles, *Econometrica* 86, 1031–1065.

Cameron, A Colin, Jonah Gelbach, and Douglas Miller, 2008, Bootstrap-based Improvements for Inference with Clustered Errors, *The Review of Economics and Statistics* 90, 414–427.

Card, David, 2022, Design-based Research in Empirical Microeconomics, *American Economic Review* 112, 1773–81.

Decker, Ryan, John Haltiwanger, Ron Jarmin, and Javier Miranda, 2016, Declining Business Dynamism: What We Know and the Way Forward, *American Economic Review* 106, 203–207.

Diamond, Peter, 1982, Aggregate Demand Management in Search Equilibrium, *Journal of Political Economy* 90, 881–894.

Duffie, Darrell, Nicolae Gârleanu, and Lasse Heje Pedersen, 2005, Over-the-Counter Markets, *Econometrica* 73, 1815–1847.

Fajgelbaum, Pablo, Edouard Schaal, and Mathieu Taschereau-Dumouchel, 2017, Uncertainty Traps, *The Quarterly Journal of Economics* 132, 1641–1692.

Farinas, Jose, and Sonia Ruano, 2005, Firm Productivity, Heterogeneity, Sunk Costs and Market Selection, *International Journal of Industrial Organization* 23, 505–534.

Foster, Lucia, Cheryl Grim, John Haltiwanger, and Zoltan Wolf, 2019, Innovation, Productivity Dispersion, and Productivity Growth, in *Measuring and Accounting for Innovation in the 21st Century* (University of Chicago Press).

Gavazza, Alessandro, 2011, The Role of Trading Frictions in Real Asset Markets, *American Economic Review* 101, 1106–1043.

Gilchrist, Simon, Jae Sim, and Egon Zakrajšek, 2014, Uncertainty, Financial Frictions, and Investment Dynamics, Technical report, National Bureau of Economic Research.

Gourio, Francois, and Leena Rudanko, 2014, Customer Capital, *The Review of Economic Studies* 81, 1102–1136.

Greenwood, Robin, and Samuel Hanson, 2015, Waves in Ship Prices and Investment, *The Quarterly Journal of Economics* 130, 55–109.

Gulen, Huseyin, and Mihai Ion, 2016, Policy Uncertainty and Corporate Investment, *The Review of Financial Studies* 29, 523–564.

Hackbarth, Dirk, and Timothy Johnson, 2015, Real Options and Risk Dynamics, *The Review of Economic Studies* 82, 1449–1482.

Hadlock, Charles, and Joshua Pierce, 2010, New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index, *The Review of Financial Studies* 23, 1909–1940.

Hsieh, Chang-Tai, 2001, Endogenous Growth and Obsolescence, *Journal of Development Economics* 66, 153–171.

Jens, Candace, 2017, Political Uncertainty and Investment: Causal Evidence from US Gubernatorial Elections, *Journal of Financial Economics* 124, 563–579.

Jeon, Jihye, 2022, Learning and Investment under Demand Uncertainty in Container Shipping, *The RAND Journal of Economics* 53, 226–259.

Julio, Brandon, and Youngsuk Yook, 2012, Political Uncertainty and Corporate Investment Cycles, *The Journal of Finance* 67, 45–83.

Jurado, Kyle, Sydney Ludvigson, and Serena Ng, 2015, Measuring Uncertainty, *American Economic Review* 105, 1177–1216.

Kaviani, Mahsa, Lawrence Kryzanowski, Hosein Maleki, and Pavel Savor, 2020, Policy Uncertainty and Corporate Credit Spreads, *Journal of Financial Economics* 138, 838–865.

Kellogg, Ryan, 2014, The Effect of Uncertainty on Investment: Evidence from Texas Oil Drilling, *American Economic Review* 104, 1698–1734.

Kessides, Ioannis, 1990, Market Concentration, Contestability, and Sunk Costs, *The Review of Economics and Statistics* 614–622.

Kim, Hyunseob, and Howard Kung, 2017, The Asset Redeployability Channel: How Uncertainty Affects Corporate Investment, *The Review of Financial Studies* 30, 245–280.

Leahy, John, and Toni Whited, 1996, The Effect of Uncertainty on Investment: Some Stylized Facts, *Journal of Money, Credit and Banking* 28, 64–83.

Lee, David, Justin McCrary, Marcelo Moreira, and Jack Porter, 2022, Valid t-ratio Inference for IV, *American Economic Review* 112, 3260–3290.

Lee, Jaewoo, and Kwanho Shin, 2000, The Role of a Variable Input in the Relationship between Investment and Uncertainty, *American Economic Review* 90, 667–680.

Ma, Song, Justin Murfin, and Ryan Pratt, 2022, Young Firms, Old Capital, *Journal of Financial Economics* 146, 331–356.

Mortensen, Dale, and Christopher Pissarides, 1994, Job Creation and Job Destruction in the Theory of Unemployment, *The Review of Economic Studies* 61, 397–415.

Ospina, Raydonal, and Silvia Ferrari, 2012, A General Class of Zero-or-one Inflated Beta Regression Models, *Computational Statistics & Data Analysis* 56, 1609–1623.

Pindyck, Robert, 1991, Irreversibility, uncertainty, and investment, *Journal of Economic Literature* 29, 1110–1148.

Rogerson, Richard, Robert Shimer, and Randall Wright, 2005, Search-theoretic Models of the Labor Market: A Survey, *Journal of Economic Literature* 43, 959–988.

Schlingemann, Frederik, René Stulz, and Ralph Walkling, 2002, Divestitures and the Liquidity of the Market for Corporate Assets, *Journal of Financial Economics* 64, 117–144.

Solow, Robert, 1960, Investment and Technical Progress, *Mathematical Methods in the Social Sciences* 1, 48–93.

Staub, Kevin, and Rainer Winkelmann, 2013, Consistent Estimation of Zero-Inflated Count Models, *Health Economics* 22, 673–686.

Stopford, Martin, 2009, *Maritime Economics 3rd Edition* (Routledge).

Storesletten, Kjetil, Chris Telmer, and Amir Yaron, 2004, Cyclical Dynamics in Idiosyncratic Labor Market Risk, *Journal of Political Economy* 112, 695–717.

Teece, David, 1980, Economies of Scope and the Scope of the Enterprise, *Journal of Economic Behavior & Organization* 1, 223–247.

Weitz, Richard, 2009, Countering the Somali Pirates: Harmonizing the International Response, *Journal of Strategic Security* 2, 1–12.

Williamson, Oliver, 1975, *Markets and Hierarchies, Analysis and Antitrust Implications: A Study in the Economics of Internal Organization* (Free Press).

Williamson, Oliver, 1985, *The Economic Institutions of Capitalism* (Free Press).

Table 1. Descriptive Statistics

This table presents descriptive statistics for the main variables used in our empirical analyses over the 2006–2019 period. Dependent variables are indicated in normal-type font and independent variables are denoted in italics. The investment measures are calculated at the firm-subsector-quarter level by dividing the number (alternatively, dead-weight tons) of new, used, and the sum of new and used ships acquired by the lagged number (alternatively, dead-weight tons) of ships held, and are obtained from Clarksons Research. The disinvestment measures are calculated at the firm-subsector-quarter level by dividing the number (alternatively, dead-weight tons) of ships demolished, sold, and the sum of ships demolished and sold by the lagged number (alternatively, dead-weight tons) of ships held, and are obtained from Clarksons Research. *Age* is the average of the logarithm of the years since a ship was built, calculated across all ships in a given firm-subsector-quarter. *DWT* is the average of the logarithm of dead-weight tons of a ship, calculated across all ships in a given firm-subsector-quarter. *RPM* is the average of the logarithm of ship engine's revolutions per minute, calculated across all ships in a given firm-subsector-quarter. Δ*Subsectoral BDI* is the quarterly percentage change in the sectoral indices derived from forward freight agreement prices for routes commonly served by ships in each subsector quoted on the Baltic Exchange, and is obtained from Bloomberg. *Cash Flow* is the quarterly income before extraordinary items plus depreciation and amortization divided by lagged total assets, averaged across all firms operating in a given subsector weighted by the number of ships they operate in the subsector, and is obtained from Compustat and Orbis. *Uncertainty* is the quarterly average of the annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector, and is obtained from OptionMetrics. The *Liquidity* measures are defined as the price premium, which is the quarterly average resale price minus the purchase price divided by the purchase price, across all used ship transactions in a given subsector, and the (reverse of the) price dispersion, which is the quarterly mean absolute deviation of resale prices divided by the mean resale price of all transactions involving ships of a given subsector. All variables are winsorized at the 1% and 99% levels.

Variable	N	Mean	SD	Median	IQR
Investment Measures (Quarterly)					
Investment (Ships)/Lagged Number of Ships (%)	99,928	1.360	9.712	0	0
Investment (DWT)/Lagged DWT of Ships (%)	99,928	1.378	9.988	0	0
Investment (New Ships)/Lagged Number of Ships (%)	99,928	1.115	9.317	0	0
Investment (New DWT)/Lagged DWT of Ships (%)	99,928	1.128	8.614	0	0
Investment (Used Ships)/Lagged Number of Ships (%)	99,928	0.245	2.534	0	0
Investment (Used DWT)/Lagged DWT of Ships (%)	99,928	0.250	2.540	0	0
Disinvestment Measures (Quarterly)					
Disinvestment (Ships)/Lagged Number of Ships (%)	99,928	1.262	7.994	0	0
Disinvestment (DWT)/Lagged DWT of Ships (%)	99,928	1.257	8.004	0	0
Disinvestment (Ships Sold)/Lagged Number of Ships (%)	99,928	0.642	5.167	0	0
Disinvestment (DWT Sold)/Lagged DWT of Ships (%)	99,928	0.639	5.198	0	0
Disinvestment (Ships Demolished)/Lagged Number of Ships (%)	99,928	0.620	6.128	0	0
Disinvestment (DWT Demolished)/Lagged DWT of Ships (%)	99,928	0.618	5.218	0	0
Firm Fleet Characteristics (Quarterly)					
Age (Log # Years)	99,928	2.873	0.886	2.929	1.387
DWT (Log)	99,928	11.436	0.795	11.422	1.033
RPM (Log)	99,928	4.769	0.386	4.742	0.284
Control Variables (Quarterly)					
Δ*Subsectoral BDI* (%)	99,928	0.215	24.947	–0.144	28.173
Cash Flow (%)	99,928	1.065	2.516	1.091	1.719
Uncertainty (%)	99,928	9.039	2.893	8.234	3.628
Liquidity (*Price Premium*, %)	99,928	–0.711	2.486	–2.182	8.360
Liquidity (*Price Dispersion*, %)	99,928	4.545	2.388	2.412	7.198

Table 2. Uncertainty, Asset Liquidity, and Investment and Disinvestment

This table reports output from Eq. (1). The dependent variable in Panel A is the investment rate, both the total rate and disaggregated into its components. The investment rate is calculated at the firm-subsector-quarter level by dividing the number of ships acquired (total, new ships acquired, or used ships acquired) by the lagged number of ships held. The dependent variable in Panel B is the disinvestment rate, both the total rate and disaggregated into its components. The disinvestment rate is calculated at the firm-subsector-quarter level by dividing the number of ships disinvested (total, ships demolished, or ships sold) by the lagged number of ships held. Δ*Subsectoral BDI* is the quarterly percentage change in the sectoral indices derived from forward freight agreement prices for routes commonly served by ships in each subsector quoted on the Baltic Exchange. *Cash Flow* is the quarterly income before extraordinary items plus depreciation and amortization divided by lagged total assets, averaged across all firms operating in a given subsector weighted by the number of ships they operate in the subsector. *Uncertainty* is the quarterly average of annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector. The *Liquidity* measures are defined as the price premium, which is the quarterly average resale price minus the purchase price divided by the purchase price, across all used ship transactions in a given subsector, and the (reverse of the) price dispersion, which is the quarterly mean absolute deviation of resale prices divided by the mean resale price of all transactions involving ships of a given subsector. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Fixed effects for headquarter country, firm, subsector, and year-quarter are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm-subsector and year-quarter.

	Panel A: Investment (Ships Acquired)					
	Total	New	Used	Total	New	Used
	(1)	(2)	(3)	(4)	(5)	(6)
Δ *Subsectoral BDI*	0.006***	0.006***	0.001	0.012***	0.009***	0.003
	(4.18)	(3.82)	(1.58)	(4.21)	(4.91)	(1.22)
Cash Flow	0.318	0.281	0.037	0.481	0.299	0.182
	(1.47)	(1.37)	(1.11)	(0.72)	(1.18)	(0.64)
Uncertainty	–0.081***	–0.078***	–0.004	–0.143***	–0.142***	–0.001
	(–3.23)	(–3.64)	(–0.17)	(–4.99)	(–5.17)	(–0.12)
Liquidity	0.221***	0.208***	0.013**	0.072***	0.049***	0.023***
	(3.77)	(3.85)	(2.11)	(5.88)	(6.76)	(7.92)
Uncertainty × *Liquidity*	0.021***	0.018***	0.002	0.014***	0.011***	0.003
	(3.56)	(3.84)	(0.20)	(4.24)	(5.16)	(1.15)
Liquidity Measure	Price Premium	Price Premium	Price Premium	Price Dispersion	Price Dispersion	Price Dispersion
Controls						
Firm-Subsector Fleet	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Country × Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99,928	99,928	99,928	99,928	99,928	99,928
Adjusted R^2	0.049	0.052	0.024	0.062	0.077	0.041

	Panel B: Disinvestment (Ships Disinvested)					
	Total	Demolished	Sold	Total	Demolished	Sold
	(1)	(2)	(3)	(4)	(5)	(6)
Δ *Subsectoral BDI*	–0.010*	–0.008**	–0.002*	–0.037*	–0.024*	–0.013*
	(–1.81)	(–2.10)	(–1.65)	(–1.91)	(–1.82)	(–1.80)
Cash Flow	–0.708	–0.687	–0.021	–0.897	–0.581	–0.316
	(–0.12)	(–0.78)	(–0.25)	(–0.65)	(–0.31)	(–0.96)
Uncertainty	–0.208***	–0.149***	–0.059*	–0.268***	–0.227***	–0.041
	(–3.99)	(–3.77)	(–1.73)	(–3.87)	(–4.31)	(–0.91)
Liquidity	0.142***	0.095**	0.047	0.124	0.129**	–0.005
	(2.82)	(2.46)	(1.46)	(1.40)	(2.00)	(–0.18)
Uncertainty × *Liquidity*	0.018***	0.013***	0.005*	0.014**	0.010**	0.004
	(4.05)	(3.75)	(1.83)	(2.41)	(2.28)	(0.49)
Liquidity Measure	Price Premium	Price Premium	Price Premium	Price Dispersion	Price Dispersion	Price Dispersion
Controls						
Firm-Subsector Fleet	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Country × Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99,928	99,928	99,928	99,928	99,928	99,928
Adjusted R^2	0.048	0.077	0.025	0.048	0.077	0.025

Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3. Uncertainty, Investment, and Disinvestment: A Quasi-Natural Experiment

This table reports output from Eq. (2) in a matched sample in Panel A. In Panel B, we report the second stage output from a simplified version of Eq. (1) estimated using instrumental variables. The dependent variable is the investment (disinvestment) rate. The investment rate is calculated at the firm-subsector-quarter level by dividing the number of ships acquired (disinvested) by the lagged number of ships held. *Treat* is an indicator that takes the value of one for the Panamax and LR1 subsectors and zero for the Capesize and VLCC subsectors. *Piracy* is an indicator that takes the value of one for the years 2009–2011, and zero for all other years from 2006–2013. Subsector controls are Δ*Subsectoral BDI* and *Cash Flow*, and are defined in Table 2. *Uncertainty* is the quarterly average of annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Each treated firm-subsector is matched to one control firm-subsector (with replacement) which is its nearest neighbor in terms of treatment propensity. The propensity score is a function of the firm-subsector fleet controls. In Panel B, *Uncertainty* is instrumented by *Treat* × *Piracy*. Fixed effects for headquarter country, firm, subsector, and year-quarter are included as indicated. All regressions are estimated over the 2006–2013 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by match in Panel A and by firm-subsector and year-quarter in Panel B.

Panel A: Matched Sample Difference-in-Differences						
	Investment (Ships Acquired)			Disinvestment (Ships Disinvested)		
	Total	New	Used	Total	Demolish	Sale
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × *Piracy*	–1.299***	–1.197***	–0.102	–0.252***	–0.166***	–0.086
	(–2.97)	(–3.41)	(–0.89)	(–3.28)	(–3.44)	(–1.17)
Controls						
Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Subsector Fleet	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Country × Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,651	14,651	14,651	14,651	14,651	14,651
Adjusted R^2	0.045	0.055	0.043	0.066	0.085	0.053

	Investment (Ships Acquired)			Disinvestment (Ships Disinvested)		
Panel B: Instrumental Variables Regression (Second Stage)						
	Total	New	Used	Total	Demolish	Sale
	(1)	(2)	(3)	(4)	(5)	(6)
Uncertainty	–0.187***	–0.168***	–0.019	–0.038**	–0.025**	–0.013
	(–2.80)	(–2.88)	(–0.91)	(–2.14)	(–2.29)	(–1.58)
Controls						
Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Subsector Fleet	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Country × Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Lee et al. (2022) Diagnostics						
First Stage F-ratio	153.23					
5% Adjustment Factor	1.00					
1% Adjustment Factor	1.00					
Observations	14,651	14,651	14,651	14,651	14,651	14,651

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4. Uncertainty and Productivity – Investment

This table reports output from Eq. (1). The dependent variable is the investment rate conditioning on measures of productivity. The investment rate is calculated at the firm-subsector-quarter level by dividing the number of ships acquired (high- or low-productivity) by the lagged number of ships held. Panel A reports results on investment (new or used) conditioning on a ship's productivity. High-productivity ships are defined as ships that are above (below) the median on at least one out of two characteristics: *DWT* (*RPM*). Low-productivity ships are analogously defined. Panel B reports results on investment conditioning on a ship's *Age* at the time of investment. Subsector controls are Δ*Subsectoral BDI* and *Cash Flow*, and are defined in Table 2. *Uncertainty* is the quarterly average of annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector. The *Liquidity* measure is the price premium, and is defined in Table 2. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Fixed effects for headquarter country, firm, subsector, and year-quarter are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm-subsector and year-quarter.

Panel A: Investment (Ships Acquired) by Productivity (DWT and RPM)

	New		Used	
	High-Productivity (1)	Low-Productivity (2)	High-Productivity (3)	Low-Productivity (4)
Uncertainty	–0.055***	–0.022	–0.004*	–0.002
	(–4.15)	(–1.44)	(–1.74)	(–0.19)
Liquidity	0.143**	0.064*	0.026*	0.006*
	(2.35)	(1.72)	(1.94)	(1.76)
Uncertainty × *Liquidity*	0.013***	0.005	0.002	0.000
	(4.45)	(1.34)	(0.15)	(0.69)
Liquidity Measure	Price Premium	Price Premium	Price Premium	Price Premium
Controls				
Subsector	Yes	Yes	Yes	Yes
Firm-Subsector Fleet	Yes	Yes	Yes	Yes
Fixed Effects				
Country × Year-Quarter	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	Yes	Yes	Yes
Observations	99,928	99,928	99,928	99,928
Adjusted R^2	0.055	0.055	0.045	0.044

Panel B: Investment (Ships Acquired) by Age					
	New (1)	1-5 Years (2)	6-15 Years (3)	16-25 Years (4)	26+ Years (5)
Uncertainty	–0.078***	–0.003**	–0.001**	–0.000	–0.000
	(–3.64)	(–2.92)	(–1.79)	(–0.63)	(–1.04)
Liquidity	0.208***	0.007**	0.004	0.001	0.001
	(3.85)	(2.04)	(1.25)	(1.57)	(0.35)
Uncertainty × *Liquidity*	0.018***	0.001	0.001	0.000	0.000
	(3.84)	(1.06)	(0.18)	(0.39)	(0.46)
Liquidity Measure	Price Premium	Price Premium	Price Premium	Price Premium	Price Premium
Controls					
Subsector	Yes	Yes	Yes	Yes	Yes
Firm-Subsector Fleet	Yes	Yes	Yes	Yes	Yes
Fixed Effects					
Country × Year-Quarter	Yes	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	Yes	Yes	Yes	Yes
Observations	99,928	99,928	99,928	99,928	99,928
Adjusted R^2	0.052	0.051	0.055	0.053	0.050

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table 5. Uncertainty and Productivity – Disinvestment

This table reports output from Eq. (1). The dependent variable is the disinvestment rate conditioning on measures of productivity. The disinvestment rate is calculated at the firm-subsector-quarter level by dividing the number of ships disinvested (high- or low-productivity) by the lagged number of ships held. High-productivity ships are defined as ships that are above (below) the median on two out of three characteristics: *DWT* (*Age*, *RPM*). Low-productivity ships are analogously defined. Subsector controls are Δ*Subsectoral BDI* and *Cash Flow*, and are defined in Table 2. *Uncertainty* is the quarterly average of annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector. The *Liquidity* measure is the price premium, and is defined in Table 2. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Fixed effects for headquarter country, firm, subsector, and year-quarter are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm-subsector and year-quarter.

	High-Productivity Ships		Low-Productivity Ships	
	Demolition	Sale	Demolition	Sale
	(1)	(2)	(3)	(4)
Uncertainty	–0.024	–0.013	–0.125***	–0.046*
	(–0.46)	(–0.29)	(–4.89)	(–1.83)
Liquidity	0.018	0.021	0.077*	0.026
	(1.24)	(1.50)	(1.84)	(0.54)
Uncertainty × *Liquidity*	0.002	0.001	0.011***	0.004*
	(0.16)	(0.70)	(4.40)	(1.66)
Liquidity Measure	Price Premium	Price Premium	Price Premium	Price Premium
Controls				
Subsector	Yes	Yes	Yes	Yes
Firm-Subsector Fleet	Yes	Yes	Yes	Yes
Fixed Effects				
Country × Year-Quarter	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	Yes	Yes	Yes
Observations	99,928	99,928	99,928	99,928
Adjusted R^2	0.075	0.022	0.077	0.021

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table 6. Uncertainty, Asset Liquidity, and Concentration of Firm Asset Holdings

This table reports output from a variant of Eq. (1) estimated at the firm-quarter level. The dependent variable in Panel A is the natural logarithm of the distinct number of subsectors a firm is exposed to, calculated at the firm-quarter level. The dependent variable in Panel B is the HHI of a firm's ship holdings across the subsectors it operates in, calculated at the firm-quarter level. Firm controls are *Cash Flow* and Δ*Subsectoral BDI*, and are defined in Table 2, except that they are averaged across all subsectors that a firm operates in weighted by the number of ships it operates in the subsector. *Uncertainty* is the quarterly average of annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector, averaged across all subsectors that a firm operates in weighted by the number of ships it operates in the subsector. The *Liquidity* measures are defined as the price premium, which is the quarterly average resale price minus the purchase price divided by the purchase price, across all used ship transactions in a given subsector, and the (reverse of the) price dispersion, which is the quarterly mean absolute deviation of resale prices divided by the mean resale price of all transactions involving ships of a given subsector. Both are averaged across all subsectors that a firm operates in weighted by the number of ships it operates in the subsector. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm in the lagged quarter. Fixed effects for headquarter country, firm, and year-quarter are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm and year-quarter.

Panel A: Log Number of Subsectors at the Firm Level			
	(1)	(2)	(3)
Uncertainty	–0.006***	–0.005***	–0.002***
	(–7.39)	(–3.69)	(–3.60)
Liquidity		0.011	0.028
		(1.33)	(1.63)
Uncertainty × *Liquidity*		0.014**	0.008***
		(3.68)	(4.38)
Liquidity Measure	NA	Price Premium	Price Dispersion
Controls			
Firm	Yes	Yes	Yes
Firm Fleet	Yes	Yes	Yes
Fixed Effects			
Country × Year-Quarter	Yes	Yes	Yes
Firm	Yes	Yes	Yes
Observations	42,206	42,206	42,206
Adjusted R^2	0.741	0.801	0.804

Panel B: HHI of Ship Holdings at the Firm Level			
	(1)	(2)	(3)
Uncertainty	0.007***	0.002***	0.008***
	(3.64)	(5.12)	(5.23)
Liquidity		0.706***	0.429***
		(6.75)	(4.83)
Uncertainty × *Liquidity*		–0.012***	–0.014***
		(–7.73)	(–6.60)
Liquidity Measure	NA	Price Premium	Price Dispersion
Controls			
Firm	Yes	Yes	Yes
Firm Fleet	Yes	Yes	Yes
Fixed Effects			
Country × Year-Quarter	Yes	Yes	Yes
Firm	Yes	Yes	Yes
Observations	42,206	42,206	42,206
Adjusted R^2	0.644	0.698	0.698

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table 7. Uncertainty, Asset Liquidity, and Productivity of Firm Asset Holdings

This table reports output from a variant of Eq. (1) estimated at the firm-quarter level. The dependent variables are the average logarithm of *Age*, logarithm of *DWT*, logarithm of *RPM*, *Speed/RPM*, *DWT/RPM*, and *DWT/Speed* ratios of ships held by a firm in a given quarter. Firm controls are *Cash Flow* and Δ*Subsectoral BDI*, and are defined in Table 2, except that they are averaged across all subsectors that a firm operates in weighted by the number of ships it operates in the subsector. *Uncertainty* is the quarterly average of annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector, averaged across all subsectors that a firm operates in weighted by the number of ships it operates in the subsector. The *Liquidity* measure is defined as the price premium, which is the quarterly average resale price minus the purchase price divided by the purchase price, across all used ship transactions in a given subsector. Both are averaged across all subsectors that a firm operates in weighted by the number of ships it operates in the subsector. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm in the lagged quarter. Note that in columns (1) through (3), we omit the lagged firm fleet control corresponding to the respective outcome variable. Fixed effects for headquarter country, firm, and year-quarter are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm and year-quarter.

	Average Asset Characteristics at the Firm Level					
	Log Age	*Log DWT*	*Log RPM*	*Speed/RPM*	*DWT/RPM*	*DWT/Speed*
	(1)	(2)	(3)	(4)	(5)	(6)
Uncertainty	0.005***	–0.006***	0.002**	–0.538***	–0.025***	–0.462***
	(3.51)	(–2.81)	(2.15)	(–6.71)	(–3.37)	(–8.30)
Liquidity	–0.039***	0.004	–0.002	–2.426***	–0.227	–1.976***
	(–5.60)	(0.12)	(–0.51)	(–7.04)	(1.50)	(–8.49)
Uncertainty × *Liquidity*	–0.014***	0.018**	–0.009**	5.375***	0.248***	4.619***
	(–3.25)	(2.27)	(–2.22)	(6.71)	(3.37)	(8.30)
Liquidity Measure	Price Premium	Price Premium	Price Premium	Price Premium	Price Premium	Price Premium
Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fleet	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Country × Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,206	42,206	42,206	42,206	42,206	42,206
Adjusted R^2	0.751	0.740	0.696	0.449	0.537	0.444

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 8. Uncertainty, Asset Liquidity, and Asset Allocation at the Firm Level

This table reports output from a variant of Eq. (1) estimated at the firm-quarter level. The dependent variables are the investment and disinvestment rates. The investment rate is calculated at the firm-quarter level by dividing the number of ships acquired (new, used, and total) by the lagged number of ships held. The disinvestment rate is calculated at the firm-quarter level by dividing the number of ships disinvested (demolished, sold, and total) by the lagged number of ships held. Δ*Subsectoral BDI* is the quarterly percentage change in the sectoral indices derived from forward freight agreement prices for routes commonly served by ships in each subsector quoted on the Baltic Exchange, averaged across all subsectors that a firm operates in weighted by the number of ships it operates in the subsector. *Cash Flow* is the quarterly income before extraordinary items plus depreciation and amortization divided by lagged total assets, averaged across all firms operating in a given subsector weighted by the number of ships they operate in the subsector, averaged across all subsectors that a firm operates in weighted by the number of ships it operates in the subsector. *Uncertainty* is the quarterly average of annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector, averaged across all subsectors that a firm operates in weighted by the number of ships it operates in the subsector. The *Liquidity* measure is defined as the price premium, which is the quarterly average resale price minus the purchase price divided by the purchase price, across all used ship transactions in a given subsector. Both are averaged across all subsectors that a firm operates in weighted by the number of ships it operates in the subsector. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm in the lagged quarter. Fixed effects for headquarter country, firm, and year-quarter are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm and year-quarter.

Panel A: Investment (Ships Acquired) at the Firm Level

	Total		New		Used	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ *Subsectoral BDI*	0.005***	0.006***	0.004***	0.003***	0.001***	0.003**
	(3.55)	(3.93)	(3.07)	(4.10)	(3.37)	(2.02)
Cash Flow	0.012*	0.004***	0.009**	0.002***	0.003**	0.001**
	(1.66)	(4.75)	(2.38)	(4.74)	(2.24)	(2.40)
Uncertainty	–0.067**	–0.119**	–0.051***	–0.099***	–0.016	–0.020
	(–2.64)	(–2.39)	(–3.12)	(–3.48)	(–1.08)	(–0.66)
Liquidity		2.607***		2.490***		0.117
		(3.47)		(3.67)		(1.34)
Uncertainty × *Liquidity*		0.202**		0.184**		0.018
		(2.33)		(2.53)		(1.44)
Liquidity Measure	NA	Price Premium	NA	Price Premium	NA	Price Premium
Controls						
Firm Fleet	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Country × Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,206	42,206	42,206	42,206	42,206	42,206
Adjusted R^2	0.071	0.120	0.069	0.117	0.038	0.038

Panel B: Disinvestment (Ships Disinvested) at the Firm Level						
	Total		Demolition		Sale	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ *Subsectoral BDI*	–0.003***	–0.004***	–0.002**	–0.003*	–0.001**	–0.001*
	(–3.73)	(–3.00)	(–5.89)	(–1.95)	(–2.49)	(–1.83)
Cash Flow	–0.005*	–0.003	–0.002	–0.002	–0.002	–0.002
	(–1.81)	(–0.82)	(–1.14)	(–1.45)	(–1.49)	(–0.42)
Uncertainty	–0.051***	–0.063***	–0.026***	–0.038**	–0.025	–0.025**
	(–3.13)	(–3.59)	(–4.99)	(–2.24)	(–1.78)	(–2.38)
Liquidity		0.387		0.352		0.035
		(1.13)		(0.55)		(1.34)
Uncertainty × *Liquidity*		0.015**		0.012**		0.003
		(2.16)		(2.00)		(0.77)
Liquidity Measure	NA	Price Premium	NA	Price Premium	NA	Price Premium
Controls						
Firm Fleet	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Country × Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,206	42,206	42,206	42,206	42,206	42,206
Adjusted R^2	0.052	0.054	0.059	0.061	0.035	0.038

Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9. Aggregate *versus* Sectoral Uncertainty and Investment and Disinvestment

This table reports output from Eq. (1). The dependent variables are the investment and disinvestment rates. The investment (disinvestment) rate is calculated at the firm-subsector-quarter level by dividing the number of ships acquired (disinvested) by the lagged number of ships held. *VIX* is the quarterly Volatility Index from the CBOE. *JLN Uncertainty* is the quarterly uncertainty index from Jurado et al. (2015). *EPU* is the quarterly US Economic Policy Uncertainty Index from Baker et al. (2016). *GDP Dispersion* is the quarterly GDP forecast dispersion from the Survey of Professional Forecasters compiled by the Federal Reserve Bank of Philadelphia. *Volatility*(Δ*Subsectoral BDI*) is the quarterly realized volatility of Δ*Subsectoral BDI*. Subsector controls consist of Δ*Subsectoral BDI* and *Cash Flow*. See Table 2 for definitions of these variables. The *Liquidity* measure is defined as the price premium, which is the average resale price minus the purchase price divided by the purchase price, across all used ship transactions in a given subsector. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Fixed effects for firm and subsector are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm-subsector and year-quarter.

	Investment	Disinvestment
	(1)	(2)
Liquidity	0.366***	–0.044
	(3.40)	(–0.45)
VIX	–0.057	–0.018
	(–0.85)	(–0.28)
VIX × *Liquidity*	0.018	0.002
	(0.85)	(1.45)
JLN Uncertainty	–0.184	–0.125
	(–0.63)	(–1.22)
JLN Uncertainty × *Liquidity*	0.355	0.058
	(0.63)	(0.50)
EPU	–0.005	–0.001
	(–1.22)	(–0.41)
EPU × *Liquidity*	0.004	0.002
	(0.95)	(0.91)
GDP Dispersion	–1.198	–1.240
	(–0.97)	(–1.01)
GDP Dispersion × *Liquidity*	4.877	6.585
	(0.42)	(0.71)
Volatility(Δ*Subsectoral BDI*)	–0.163***	–0.039***
	(–8.32)	(–3.51)
Volatility(Δ*Subsectoral BDI*) × *Liquidity*	0.014***	0.021***
	(3.15)	(3.90)
Liquidity Measure	Price Premium	Price Premium
Controls		
Subsector	Yes	Yes
Firm-Subsector Fleet	Yes	Yes
Fixed Effects		
Firm × Subsector	Yes	Yes
Observations	99,928	99,928
Adjusted R^2	0.128	0.144

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Appendix A Theoretical Framework

A.1 Set Up

In our theoretical analysis, we characterize increases in uncertainty using the concept of mean-preserving spread (MPS). An uncertainty-increasing MPS only requires that a zero-mean, non-degenerate random variable is added to the outcome distribution. This approach allows us to derive results that hold with generality, while remaining agnostic about the functional forms governing the distribution and moments of the outcomes (see also Lee and Shin (2000)).

A.1.1 The Firm and the Ship Market

The firm is endowed with ships $\omega_{\mathbf{t}} \in \mathbb{R}^8_+$ across eight "subsectors" at time t. Subsectors correspond to four size categories of two of the largest sectors of the shipping industry: dry bulk carrier ships ("bulkers") and tanker ships ("tankers"). The representative firm is a price-taker in the market for ships. We begin by characterizing three price processes corresponding to the three sets of capital allocation decisions the firm can take: (1) trade (buy or sell) a used ship in the secondary market, (2) order a new ship in the primary market, and (3) demolish a ship.

Trading Used Ships

Let $\mathbf{p_t}$ be the vector of the secondary market prices of ships in each subsector, with $\mathbf{p_t} = \left(p_{1t}, \ldots, p_{8t}\right)'$, where:

$$p_{it} = \lambda_i(N_{it}) \times Seller_{it} + \gamma_{it}^{\alpha_i}, \tag{A.1}$$

$i = 1, ..., 8$ indexes the shipping subsectors, N_{it} represents the number of ships in subsector i at time t, and γ_{it} captures productivity, or the cash flow generated by a ship in subsector i at time t (defined shortly in Section A.1.2). The elasticity parameter, α_i, is positive. The function $\lambda(\cdot)$ is increasing in N and can be interpreted as the probability of successfully finding a trading counterparty. $Seller_{it}$ takes the value of 1 (−1) if the transacting party is a seller (buyer).

The intuition for modeling the price is straightforward and found in prior literature (see, e.g., Gavazza (2011)). As N increases, the ship's secondary market price increases from a seller's perspective (decreases from a buyer's perspective) due to improvement in liquidity driven by reduced search costs, holding γ constant. The use of N, or the stock of ships, as a proxy for secondary market liquidity is motivated by the idea that search frictions between buyers and sellers are smaller in "thicker" (or larger) asset resale markets. Likewise, holding market thickness, N constant, higher productivity γ is associated with higher resale prices. A plausible microfoundation for Eq. (A.1) is that the "spread" charged by a market maker (e.g., a ship broker) is decreasing in the likelihood of finding a match between a potential buyer and a seller in a given time window, assuming buyer and seller arrivals are driven by a Poisson process whose arrival rate increases with N.

In Figure A.1 we provide evidence supporting the link between market thickness, N, and our main measures of liquidity, the resale price premium and price dispersion, using data on the resale market for tankers. The figure shows a positive cross-sectional association between the number of ships N (blue vertical bars) and resale price premium (red solid line), defined as the difference between the resale and purchase prices of a ship, divided by the purchase price. This positive relation is consistent with our model in that the theoretical counterpart to the resale price premium from a seller's perspective, $\left(p - q\right)/q$ in which q is defined below, is increasing in N due to reduced search costs. Figure A.1 also reveals a negative association between N and the dispersion of resale

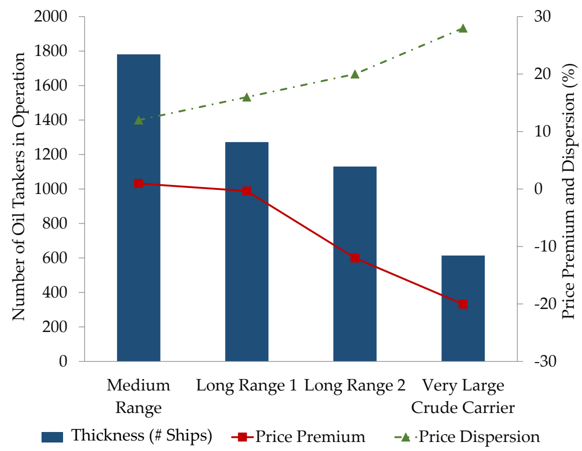


Figure A.1. Asset Market Thickness and Liquidity. This figure shows the thickness of the secondary ship market, measured by the average number of ships in each subsector of Oil Tankers (blue vertical bars, primary Y-axis), and the liquidity, measured by the average percentage resale price premium (red connected squares, secondary Y-axis) and the resale price dispersion (green connected triangles, secondary Y-axis). Resale price dispersion is defined as the mean absolute deviation of resale prices divided by the mean resale price.

prices (green dashed line), implying that improved liquidity that arises from lower search costs reduces variability in resale prices (see also Gavazza (2011)).

Ordering New Ships

If the firm orders a new ship, the primary market price is denoted by $\mathbf{q_t} = \left(q_{1t}, \ldots, q_{8t}\right)'$, where:

$$q_{it} = F + \widetilde{\gamma}_{it}^{\alpha_i}. \tag{A.2}$$

Our modeling of the new ship price assumes a competitive shipbuilding sector (i.e., aggregate supply is elastic). Naturally, this assumption may not hold in some subsectors due to capacity adjustment costs at shipyards. The price at which a firm may order a new ship differs from the price at which it buys a ship in the secondary market along three dimensions. First, the new ship order price may be independent of N, the stock of existing ships, and the measure of secondary market thickness. This assumption is introduced for analytical simplicity. However, it is not critical for our model results, as long as the sensitivity of the secondary market price to N is greater than that of the new ship order price. Second, the firm incurs fixed costs, $F > 0$, when ordering a new ship. Third, new ships are, on average, more productive than ships purchased in the secondary market (i.e., $\widetilde{\gamma}_{it} = \widetilde{\delta}_i \gamma_{it}$, $\widetilde{\delta}_i \geq 1$). Our model allows the price of a new ship to be higher or lower than the price of a used ship according to the relative magnitudes of fixed costs (F), secondary market thickness (N), and the productivity differential ($\widetilde{\delta}$).

Demolishing Ships

The final course of action the firm can implement is to demolish a ship in its fleet, receiving the scrap value in return. Scrap values are given by $\mathbf{r_t} = (r_{1t}, \ldots, r_{8t})'$, where:

$$r_{it} = G + \widehat{\gamma}_{it}^{\alpha_i}. \tag{A.3}$$

The scrap value a firm receives when demolishing a ship differs from the price at which it sells a ship in the secondary market along three dimensions. First, the demolition value is independent of N, the secondary market thickness. Second, the firm incurs fixed costs, $G < 0$, when demolishing a ship. Third, demolished ships are likely less productive than ships sold in the secondary market (i.e., $\widehat{\gamma}_{it} = \widehat{\delta}_i \gamma_{it}$, $\widehat{\delta}_i \leq 1$). The scrap value of a used ship may be higher or lower than the secondary market price of a comparable used ship depending on the relative magnitudes of associated fixed costs (G), secondary market thickness (N), and the productivity differential ($\widehat{\delta}$).

A.1.2 The Firm Investment Problem

The firm operates for three periods, $t = 0$, 1, and 2. The cash flow from each ship at each time t is given by $\pi_\mathbf{t} \circ \omega_\mathbf{t}$, where $\pi_{it} = \gamma_i V_t + \epsilon_{it}$. The source of sectoral uncertainty is represented by V_t, whose distribution can be characterized as an MPS with degree x; i.e., $V_t \sim H(\cdot, x)$. Thus, the total cash flow of the firm is $\pi_\mathbf{t} \cdot \omega_\mathbf{t}$. The firm's endowment vector, $\omega_\mathbf{t}$, evolves over time. At $t = 2$, its endowment is $\omega_\mathbf{2} = \omega_\mathbf{1} + \mathbf{i_1} - \mathbf{d_1}$, where $\mathbf{i_1} = \mathbf{n_1} + \mathbf{u_1}$ is the vector of new and used ships purchased (investment), and $\mathbf{d_1} = \mathbf{s_1} + \mathbf{de_1}$ is the vector of ships sold and demolished (disinvestment) at $t = 1$. The firm's investment set is limited at $\mathbf{I} = \mathbf{N} + \mathbf{U}$. Its disinvestment set is naturally limited by its endowment of ships.[13]

The firm makes investment and disinvestment decisions as follows. If the firm makes no new investment at $t-1$, then its income is $\pi_\mathbf{t} \cdot \omega_\mathbf{t}$ in t. If it invests, then its income is $-\mathbf{n_{t-1}} \cdot \mathbf{q_t} - \mathbf{u_{t-1}} \cdot \mathbf{p_t} + \pi_\mathbf{t} \cdot (\omega_\mathbf{t} + \mathbf{i_{t-1}})$. The first term, $-\mathbf{n_{t-1}} \cdot \mathbf{q_t}$, is the cost of the new ships it orders, while the second term, $-\mathbf{u_{t-1}} \cdot \mathbf{p_t}$, is the cost of the used ships it purchases in secondary markets. The third term, $\pi_\mathbf{t} \cdot (\omega_\mathbf{t} + \mathbf{i_{t-1}})$, is the operating cash flow the firm earns from its stock of ships, consisting of existing and newly invested ones.

If the firm disinvests in $t-1$, then its income is $\mathbf{s_{t-1}} \cdot \mathbf{p_t} + \mathbf{de_{t-1}} \cdot \mathbf{r_t} + \pi_\mathbf{t} \cdot (\omega_\mathbf{t} - \mathbf{d_{t-1}})$ at t. The first term, $\mathbf{s_{t-1}} \cdot \mathbf{p_t}$, is the amount the firm receives from selling its ships in the secondary market. The second term, $\mathbf{de_{t-1}} \cdot \mathbf{r_t}$, is the amount it receives from demolishing its ships. The third term, $\pi_\mathbf{t} \cdot (\omega_\mathbf{t} - \mathbf{d_{t-1}})$, is the cash flow the firm earns from its stock of ships, consisting of existing ships minus disinvested ones.

A.2 Analysis

We first analyze the firm's investment problem building on standard real-options arguments relating uncertainty and investment. We do so in order to frame the economic environment in which we advance our new results. The firm chooses its investment levels $\mathbf{i_0}$ (invest now) and $\mathbf{i_1}$ (invest later) based on Eq. (A.4). It prefers to invest now if the expected cash flow from doing so exceeds the expected cash flow from waiting to invest later, contingent on demand conditions evolving favorably. We state this condition via the following inequality:

$$\underbrace{\mathbb{E}[\pi_\mathbf{1} + \pi_\mathbf{2}] \cdot \mathbf{i_0} - \mathbf{n_0} \cdot \mathbf{q_1} - \mathbf{u_0} \cdot \mathbf{p_1}}_{\textit{Invest Now}} \geq \underbrace{\mathbb{E}[\max(\pi_\mathbf{2} \cdot \mathbf{i_1} - \mathbf{n_1} \cdot \mathbf{q_2} - \mathbf{u_1} \cdot \mathbf{p_2}, 0)]}_{\textit{Invest Later}}. \tag{A.4}$$

The breakeven levels of investment, $\mathbf{i_0^*} = \mathbf{n_0^*} + \mathbf{u_0^*}$ and $\mathbf{i_1^*} = \mathbf{n_1^*} + \mathbf{u_1^*}$, are such that:

$$\mathbb{E}[\pi_\mathbf{1} + \pi_\mathbf{2}] \cdot \mathbf{i_0^*} - \mathbf{n_0^*} \cdot \mathbf{q_1} - \mathbf{u_0^*} \cdot \mathbf{p_1} = \mathbb{E}\Big[\max\Big(\pi_\mathbf{2} \cdot \mathbf{i_1^*} - \mathbf{n_1^*} \cdot \mathbf{q_2} - \mathbf{u_1^*} \cdot \mathbf{p_2}, 0\Big)\Big]. \tag{A.5}$$

We first establish the existence of $\mathbf{i_0^*}$ and $\mathbf{i_1^*}$ in Lemma 1.

Lemma 1. *The optimal investment levels $\mathbf{i_0^*}$ and $\mathbf{i_1^*}$ are given by Eq. (A.5).*

[13] We assume an arbitrary $\omega_\mathbf{0}$. The constraint on the investment set implies that $\mathbf{i_0} + \mathbf{i_1} \leq \mathbf{I}$, $\mathbf{n_0} + \mathbf{n_1} \leq \mathbf{N}$, and $\mathbf{u_0} + \mathbf{u_1} \leq \mathbf{U}$.

Analogously, the firm chooses its disinvestment levels $\mathbf{d_0}$ (disinvest now) and $\mathbf{d_1}$ (disinvest later) based on Eq. (A.6). It prefers to disinvest now if the expected cash flow from doing so exceeds the expected cash flow from disinvesting later only upon observing that demand conditions have evolved unfavorably. Formally:

$$\underbrace{\mathbb{E}[-\pi_1-\pi_2]\cdot\mathbf{d_0}+\mathbf{s_0}\cdot\mathbf{p_1}+\mathbf{de_0}\cdot\mathbf{r_1}}_{\textit{Disinvest Now}}\geq\underbrace{\mathbb{E}[\max(-\pi_2\cdot\mathbf{d_1}+\mathbf{s_1}\cdot\mathbf{p_2}+\mathbf{de_1}\cdot\mathbf{r_2},0)]}_{\textit{Disinvest Later}}. \tag{A.6}$$

The breakeven levels of disinvestment, $\mathbf{d_0^*}=\mathbf{s_0^*}+\mathbf{de_0^*}$ and $\mathbf{d_1^*}=\mathbf{s_1^*}+\mathbf{de_1^*}$, are such that:

$$\mathbb{E}[-\pi_1-\pi_2]\cdot\mathbf{d_0^*}+\mathbf{s_0^*}\cdot\mathbf{p_1}+\mathbf{de_0^*}\cdot\mathbf{r_1}=\mathbb{E}\big[\max\big(-\pi_2\cdot\mathbf{d_1^*}+\mathbf{s_1^*}\cdot\mathbf{p_2}+\mathbf{de_1^*}\cdot\mathbf{r_2},0\big)\big]. \tag{A.7}$$

As with the case of investment, the existence of $\mathbf{d_0^*}$ and $\mathbf{d_1^*}$ is established in Lemma 2.

Lemma 2. *The optimal disinvestment levels $\mathbf{d_0^*}$ and $\mathbf{d_1^*}$ are given by Eq. (A.7).*

Explicitly writing the breakeven conditions in terms of V_t, and therefore, as a function of x (the mean-preserving spread parameter), we can show that $D_x\mathbf{i_0^*}<0$ and $D_x\mathbf{d_0^*}<0$.

Proposition 1. *Increased uncertainty leads to less investment and disinvestment. For $x'>x$, namely when $H(.,x')$ is obtained by a mean-preserving spread of $H(.,x)$, $\mathbf{i_0^*}(x')<\mathbf{i_0^*}(x)$ and $\mathbf{d_0^*}(x')<\mathbf{d_0^*}(x)$.*

We next characterize the effect of uncertainty on various margins of the investment and disinvestment action space.

Proposition 2. *The negative effect of uncertainty on investment is more pronounced for purchases of new ships relative to used ships, and the effect of uncertainty on disinvestment is more pronounced for demolition of ships than for ship sales; namely, $D_x\mathbf{n_0^*}<D_x\mathbf{u_0^*}$ and $D_x\mathbf{de_0^*}<D_x\mathbf{s_0^*}$.*

Next, we show the moderating role of asset market thickness on the effects of uncertainty.

Proposition 3. *The effect of uncertainty on investment and disinvestment is mitigated in thicker resale markets (with higher N); namely, $D_{xN}\mathbf{i_0^*}>0$ and $D_{xN}\mathbf{d_0^*}>0$.*

A.3 Proof of Lemma 1

Proof. Let us take a representative element of the investment vector in Eq. (A.5) and define a function

$$H(i_0^*,i_1^*)=\mathbb{E}[\pi_1+\pi_2]\,i_0^*-n_0^*q_1-u_0^*p_1-\mathbb{E}\big[\max\big(\pi_2 i_1^*-n_1^*q_2-u_1^*p_2,0\big)\big].$$

We can rewrite the function $H(\cdot)$ purely in terms of i_0^* given that the constraint $i_0^*+i_1^*\leq I$ will bind for some I.

$$H(i_0^*)=\mathbb{E}[\pi_1+\pi_2]\,i_0^*-n_0^*q_1-u_0^*p_1-\mathbb{E}\big[\max\big(\pi_2\big(I-i_0^*\big)-\big(N-n_0^*\big)q_2-\big(U-u_0^*\big)p_2,0\big)\big].$$

To guarantee the existence of i_0^* (and, equivalently, i_1^*) as characterized by Eq. (A.5), it suffices to show that $H(i_0^*)=0$ for some $i_0^*\in[0,I]$. Since $H(\cdot)$ is a sum of continuous functions, it is itself continuous. Since $\pi_1>0$ and $\pi_2>0$, it follows that:

$$H(0)=-\mathbb{E}\big[\pi_2 I-Nq_2-Up_2\big]<0.$$

Finally, for $I\to\infty$, we have that:

$$\begin{aligned}\lim_{I\to\infty}H(I)&=\lim_{I\to\infty}\big(\mathbb{E}[\pi_1+\pi_2]I-Nq_1-Up_1\big)+\lim_{I\to\infty}\big(\mathbb{E}\big[\max\big(\pi_2(I-I)-(N-N)q_2-(U-U)p_2,0\big)\big]\big)\\&=\infty-0=\infty.\end{aligned}$$

Thus, there must exist an $\bar{I} \in \mathbb{R}$ such that, for $I > \bar{I}$, $H(\bar{I}) > 0$. Putting these conditions together with the continuity of $H(\cdot)$ over $[0, I]$, the Intermediate Value Theorem guarantees that there exists an $i_0^* \in [0, I]$ and $i_1^* \in [0, I]$ such that $H(i_0^*, i_1^*) = 0$. □

A.4 Proof of Lemma 2

Proof. Symmetric to the case of investment. □

A.5 Proof of Proposition 1

Proof. Let us, once again, consider a representative element of the investment vector in Eq. (A.5) and define

$$H(i_0^*; r) = \mathbb{E}[\pi_1 + \pi_2]\, i_0^* - n_0^* q_1 - u_0^* p_1 - \mathbb{E}\left[\max\left(\pi_2\left(I - i_0^*\right) - \left(N - n_0^*\right) q_2 - \left(U - u_0^*\right) p_2, 0\right); r\right].$$

By the Implicit Function Theorem,

$$\frac{d i_0^*}{d r} = -\frac{\partial H / \partial i_0^*}{\partial H / \partial r}.$$

Considering first the derivative of H with respect to i_0^*, we have:

$$\begin{aligned}
\frac{\partial H(i_0^*; r)}{\partial i_0^*} &= \mathbb{E}[\pi_1 + \pi_2] - q_1 - p_1 - \frac{\partial}{\partial i_0^*}\mathbb{E}\left[\max\left(\pi_2\left(I - i_0^*\right) - \left(N - n_0^*\right) q_2 - \left(U - u_0^*\right) p_2, 0\right); r\right] \\
&= \mathbb{E}[\pi_1 + \pi_2] - q_1 - p_1 - \mathbb{E}\left[\frac{\partial}{\partial i_0^*}\max\left(\pi_2\left(I - i_0^*\right) - \left(N - n_0^*\right) q_2 - \left(U - u_0^*\right) p_2, 0\right); r\right] \\
&= \mathbb{E}[\pi_1 + \pi_2] - q_1 - p_1 - \mathbb{E}\left[-\max\left(\pi_2 - (q_2 + p_2), 0\right); r\right] \\
&< 0.
\end{aligned}$$

Next, considering the derivative of H with respect to r, we have:

$$\frac{\partial H(i_0^*; r)}{\partial r} = -\frac{\partial}{\partial r}\mathbb{E}\left[\max\left(\pi_2\left(I - i_0^*\right) - \left(N - n_0^*\right) q_2 - \left(U - u_0^*\right) p_2, 0\right); r\right].$$

Because $G(\cdot, r')$ is a MPS of $G(\cdot, r)$, for any convex function $J(\cdot)$,

$$\begin{aligned}
\mathbb{E}\left[J(\pi_2); r'\right] &= \int J(\pi_2) dG(\pi_2, r') \\
&\geq \int J(\pi_2) dG(\pi_2, r) \\
&= \mathbb{E}[J(\pi_2); r].
\end{aligned}$$

Since $\max\left(\pi_2\left(I - i_0^*\right) - \left(N - n_0^*\right) q_2 - \left(U - u_0^*\right) p_2, 0\right)$ is convex in π_2, it follows that:

$$\mathbb{E}\left[\max\left(\pi_2\left(I - i_0^*\right) - \left(N - n_0^*\right) q_2 - \left(U - u_0^*\right) p_2, 0\right); r'\right] \geq \mathbb{E}\left[\max\left(\pi_2\left(I - i_0^*\right) - \left(N - n_0^*\right) q_2 - \left(U - u_0^*\right) p_2, 0\right); r\right] \forall r' > r.$$

This implies

$$\frac{\partial}{\partial r}\mathbb{E}\left[\max\left(\pi_2\left(I - i_0^*\right) - \left(N - n_0^*\right) q_2 - \left(U - u_0^*\right) p_2, 0\right); r\right] \geq 0.$$

Thus,

$$\frac{\partial H(i_0^*;r)}{\partial r} = -\frac{\partial}{\partial r}\mathbb{E}\left[\max\left(\pi_2\left(I-i_0^*\right)-\left(N-n_0^*\right)q_2-\left(U-u_0^*\right)p_2,0\right);r\right]$$
$$\leq 0.$$

Putting these conditions together, we have:

$$\frac{d i_0^*}{dr} = -\frac{\partial H/\partial i_0^*}{\partial H/\partial r} < 0.$$

The disinvestment case is symmetric. □

A.6 Proof of Propositions 2 and 3

Proof. Considering, once again, a representative element of the investment vector in Eq. (A.5), we must show that:

$$\frac{d n_0^*}{dr} < \frac{d u_0^*}{dr}.$$

Using the Implicit Function Theorem, this is equivalent to showing:

$$-\frac{\partial H/\partial n_0^*}{\partial H/\partial r} < -\frac{\partial H/\partial u_0^*}{\partial H/\partial r},$$

or, since $\frac{\partial H}{\partial r} \leq 0$, we must show that:

$$\frac{\partial H}{\partial n_0^*} < \frac{\partial H}{\partial u_0^*}.$$

Simplifying the above, it is clear that:

$$\frac{\partial H}{\partial n_0^*} < \frac{\partial H}{\partial u_0^*} \Leftrightarrow F + \tilde{\gamma}_{it}^{\alpha_i} > \lambda_i(N_{it}) \times Seller_{it} + \gamma_{it}^{\alpha_i}.$$

Simplifying further, and noting that $\tilde{\gamma}_{it}^{\alpha_i} = (\tilde{\delta}_i \gamma_{it})^{\alpha_i}$ with $\tilde{\delta}_i > 1$ and $\alpha_i > 0$, we have:

$$F - \lambda_i(N_{it}) \times Seller_{it} > \gamma_{it}^{\alpha_i} - (\tilde{\delta}_i \gamma_{it})^{\alpha_i},$$

since $F > 0$, $N > 0$, $Seller_{it} = -1$. The disinvestment case is symmetric. It immediately follows that the cross-partial derivatives $\frac{\partial^2 i_0^*}{\partial r \partial N}$ and $\frac{\partial^2 d_0^*}{\partial r \partial N}$ are positive as $\lambda(\cdot)$ is differentiable for $N > 0$ and $\lambda'(\cdot) > 0$.

□

Delayed Creative Destruction: How Uncertainty Shapes Corporate Assets

Internet Appendix

MURILLO CAMPELLO
Cornell University & NBER

GAURAV KANKANHALLI
University of Pittsburgh

HYUNSEOB KIM
Federal Reserve Bank of Chicago

Appendix B Asset Liquidity and Market Thickness

We validate our liquidity measures by examining whether they reflect market thickness in the ship resale market. We estimate secondary ship market transaction-level regressions of the form:

$$Liquidity_{i,j,t} = \beta_1 Market\ Thickness_{j,t} + \theta\, \boldsymbol{Controls}_{i,j,t} + FEs + \epsilon_{i,j,t}, \tag{B.1}$$

where $Liquidity_{i,j,t}$ represents our two liquidity measures. First, we consider $Price\ Premium_{i,j,t}$. This variable is a (reverse) measure of irreversibility, defined as the resale price minus the purchase price divided by the purchase price for transaction i involving a ship in subsector j in year-quarter t. As an alternate measure of liquidity, we also consider $Price\ Dispersion_{j,t}$, defined as the quarterly mean absolute deviation of resale prices divided by the mean resale price of all transactions involving ships in subsector j in year-quarter t. The variable of interest in the above regression, $Market\ Thickness_{j,t}$, refers to one of the three subsectoral ship market thickness measures, *# Ships*, *# Firms*, and *# Transactions*. The vector $\boldsymbol{Controls}_{i,j,t}$ includes $\Delta Subsectoral\ BDI_{j,t}$ as a subsector-quarter-level proxy for changes in expected shipping demand, and ship-level characteristics that affect their secondary market pricing. These include the log of the ship's age, DWT, RPM, as well as indicator variables for whether the ship was built in Korea, Japan, or China. These three shipbuilding nations account for 95% of new ship deliveries in our sample. We do not include engine speed as a control due to collinearity with RPM. Engines in larger ships have both lower RPM and lower speed. We estimate Eq. (B.1) with both subsector and year-quarter fixed effects. Standard errors are double-clustered at the subsector and year-quarter levels. We further verify (in unreported checks) that the results are robust to resampling clusters at the subsector and year-quarter levels, following the wild bootstrap-c clustering method proposed by Cameron et al. (2008). Table B.1 reports the results.

TABLE B.1 ABOUT HERE.

The estimates for *Market Thickness* in columns (1) through (6) show that thicker markets are associated with higher resale relative to purchase prices and lower price dispersion, indicative of greater liquidity. The economic magnitude of these relations is large. Estimates in column (1) suggest that a one-standard-deviation increase in market thickness measured by the log number of ships in the subsector-quarter (0.41) is associated with a 10.7-percentage point (= 0.41 × 26.12) increase in the resale price premium. Likewise, the estimated coefficient on *Market Thickness* in column (2) indicates that a one-standard-deviation increase in the transaction-based thickness measure (0.89) is associated with a 6-percentage point (= 0.89 × 6.79) increase in resale price premia. The positive relationship between market thickness and price premia suggests that investment decisions are less costly to reverse when secondary markets are thicker. This finding provides important support for our conceptual framework by showing that the incentive to forego investment and disinvestment in the face of heightened uncertainty is particularly acute when the secondary ship market is thin. The negative relationship between market thickness and price dispersion (columns (4) through (6)) suggests a more "stable" match quality between buyers and sellers in thicker markets (Gavazza (2011)).

Table B.1 also sheds light on general pricing determinants in the secondary ship market. The estimates in column (1), for instance, show that resale price premia are strongly related to shipping demand, evident from the positive and significant coefficient on $\Delta Subsectoral\ BDI$. Younger and larger ships, and those with lower-RPM engines attract significantly higher resale prices relative to their purchase prices. To the extent that ship prices reflect their productivity, the estimates in columns (1) through (3) indicate that ships with lower age, higher DWT, and lower RPM engines tend to be more productive. We exploit these *ex ante* proxies for ship productivity in our analyses examining investment and disinvestment measures conditional on productivity.

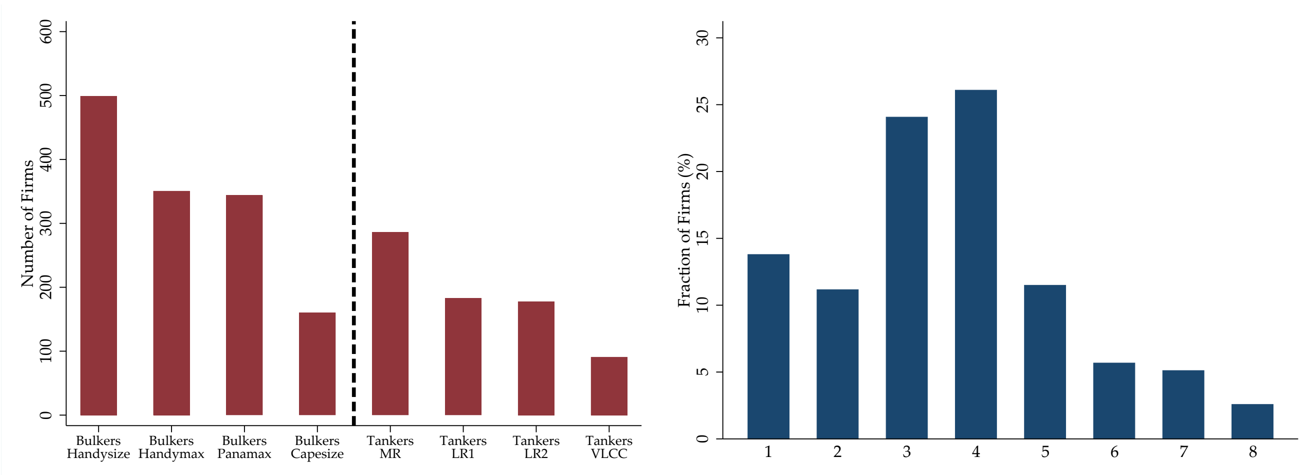
Table B.1. Asset Liquidity and Market Thickness

This table reports output from Eq. (B.1). The dependent variables are the price premium and the price dispersion. Price Premium is the resale price minus the purchase price divided by the purchase price. Price Dispersion is the quarterly mean absolute deviation of resale prices divided by the mean resale price of all transactions involving ships of a given subsector. The *Market Thickness* measures are defined as the quarterly logarithm of the number of ships, number of transactions divided by the lagged number of ships, and logarithm of the number of firms in a given subsector. *Age* is the logarithm of the years since the ship was built, *DWT* is the logarithm of dead-weight tons of the ship, and *RPM* is the logarithm of the ship engine's revolutions per minute. *Korea*, *Japan*, and *China* are indicator variables that take the value of one if the ship was constructed by a builder based in each respective country. Subsector and year-quarter fixed effects are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by subsector and year-quarter.

	Price Premium (1)	Price Premium (2)	Price Premium (3)	Price Dispersion (4)	Price Dispersion (5)	Price Dispersion (6)
Market Thickness	26.118***	6.788**	34.397***	–6.491**	–1.845*	–7.396***
	(4.18)	(2.10)	(4.12)	(–2.12)	(–1.76)	(–2.73)
Δ *Subsectoral BDI*	0.453***	0.182***	0.487***	0.193**	0.594***	0.792**
	(5.36)	(4.08)	(4.09)	(2.22)	(2.58)	(2.54)
Age	–14.555***	–14.137***	–14.787***	1.199**	2.485***	0.822**
	(–7.00)	(–11.61)	(–7.23)	(2.41)	(2.82)	(2.32)
DWT	17.704***	0.448**	17.662***	–5.812	–1.929	–7.039
	(3.98)	(2.09)	(3.35)	(–1.07)	(–0.59)	(–1.55)
RPM	–19.730***	–12.439*	–11.127***	2.403	7.127	2.181
	(–2.97)	(–1.80)	(–3.33)	(0.74)	(0.93)	(0.28)
Korea	–5.928	–9.518*	–6.112	13.483	10.181	14.122
	(–1.04)	(–1.79)	(–0.81)	(0.86)	(0.95)	(0.61)
Japan	3.885	3.682	2.404	–0.378	–0.540	–0.201
	(0.67)	(0.77)	(0.46)	(–0.30)	(–0.05)	(–0.02)
China	–1.918	–1.109	–2.146	5.589	7.624	5.364
	(–0.71)	(–0.17)	(–0.34)	(0.10)	(0.68)	(0.49)
Market Thickness Measure	# Ships	# Trans.	# Firms	# Ships	# Trans.	# Firms
Fixed Effects						
Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,489	3,489	3,489	372	372	372
R-squard	0.488	0.471	0.480	0.208	0.220	0.224

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Appendix C Additional Figures and Tables



(A) Number of Firms per Subsector

(B) Number of Subsectors per Firm

Figure C.1. Shipping Firms' Operating Activities by Subsector. Panel A plots the number of firms operating ships in each of the eight subsectors we analyze. Panel B plots the share of firms operating ships in one through eight subsectors.

Table C.1. Uncertainty, Asset Liquidity, and Investment and Disinvestment without State-Owned Enterprises

This table reports output from Eq. (1) estimated on the sample excluding state-owned enterprises. The dependent variables are the investment and disinvestment rates. The investment (disinvestment) rate is calculated at the firm-subsector-quarter level by dividing the number of ships acquired (disinvested) by the lagged number of ships held. *Uncertainty* is the quarterly average of the annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector. The *Liquidity* measure is defined as the price premium, which is the average resale price minus the purchase price divided by the purchase price, across all used ship transactions in a given subsector. Subsector controls are Δ*Subsectoral BDI* and *Cash Flow*, and are defined in Table 2. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Fixed effects for headquarter country, firm, subsector, and year-quarter are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm-subsector and year-quarter.

	Investment	Disinvestment
	(1)	(2)
Uncertainty	–0.074***	–0.206***
	(–4.13)	(–3.88)
Liquidity	0.216***	0.139**
	(3.50)	(2.79)
Uncertainty × *Liquidity*	0.028***	0.013***
	(3.51)	(4.02)
Liquidity Measure	Price Premium	Price Premium
Controls		
Subsector	Yes	Yes
Firm-Subsector Fleet	Yes	Yes
Fixed Effects		
Firm	Yes	Yes
Subsector × Year-Quarter	Yes	Yes
Observations	92,126	92,126
Adjusted R^2	0.051	0.049

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table C.2. Uncertainty, Asset Liquidity, and Investment with Alternative Levels of Clustering

This table reports output from Eq. (1). The variables and fixed effects are as described in Table 2. Three sets of t-statistics are reported below the coefficient estimates. First, in (regular) parentheses, t-statistics are computed using robust standard errors clustered by subsector. Second, in [square] parentheses, t-statistics are computed using robust standard errors clustered by subsector and year-quarter. Third, in {curly} parentheses, t-statistics are computed using standard errors calculated by resampling subsector and year-quarter clusters under the wild bootstrapping-c method described in Cameron et al. (2008).

	Investment (Ships Acquired)					
	Total	New	Used	Total	New	Used
	(1)	(2)	(3)	(4)	(5)	(6)
Δ *Subsectoral BDI*	0.006	0.006	0.001	0.012	0.009	0.003
	(13.44)***	(12.87)***	(3.01)***	(10.52)***	(7.12)***	(2.84)***
	[12.52]***	[11.64]***	[2.26]**	[9.97]***	[6.76]***	[2.11]**
	{11.17}***	{10.54}***	{1.99}**	{9.12}***	{5.88}***	{2.01}**
Cash Flow	0.318	0.281	0.037	0.481	0.299	0.182
	(2.09)**	(1.88)*	(1.95)*	(2.44)**	(1.88)*	(1.81)*
	[1.98]**	[1.74]*	[1.89]*	[1.99]**	[1.84]*	[1.60]
	{1.86}*	{1.51}	{1.33}	{1.84}*	{1.32}	{1.10}
Uncertainty	–0.081	–0.078	–0.004	–0.143	–0.142	–0.001
	(–14.55)***	(–12.87)***	(–1.64)	(–13.88)***	(–12.40)***	(–1.12)
	[–13.82]***	[–11.15]***	[–1.48]	[–13.16]***	[–11.33]***	[–0.80]
	{–12.77}***	{–10.29}***	{–0.87}	{–11.98}***	{–9.71}***	{–0.73}
Liquidity	0.221	0.208	0.013	0.072	0.049	0.023
	(7.80)***	(7.96)***	(9.75)***	(7.98)***	(5.82)***	(6.99)***
	[7.76]***	[6.29]***	[9.25]***	[7.52]***	[5.41]***	[5.52]***
	{6.61}***	{5.12}***	{8.84}***	{6.49}***	{4.78}***	{5.19}***
Uncertainty × *Liquidity*	0.021	0.018	0.002	0.014	0.011	0.003
	(11.20)***	(9.57)***	(0.94)	(6.81)***	(9.34)***	(1.42)
	[10.09]***	[8.66]***	[0.70]	[6.14]***	[8.67]***	[1.09]
	{9.40}***	{7.21}***	{0.15}	{5.87}***	{7.96}***	{0.83}
Liquidity Measure	Price Premium	Price Premium	Price Premium	Price Dispersion	Price Dispersion	Price Dispersion
Controls						
Firm-Subsector Fleet	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Country × Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99,928	99,928	99,928	99,928	99,928	99,928
Adjusted R^2	0.049	0.052	0.024	0.062	0.077	0.041

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table C.3. Uncertainty, Asset Liquidity, and Disinvestment with Alternative Levels of Clustering

This table reports output from Eq. (1). The variables and fixed effects are as described in Table 2. Three sets of t-statistics are reported below the coefficient estimates. First, in (regular) parentheses, t-statistics are computed using robust standard errors clustered by subsector. Second, in [square] parentheses, t-statistics are computed using robust standard errors clustered by subsector and year-quarter. Third, in {curly} parentheses, t-statistics are computed using standard errors calculated by resampling subsector and year-quarter clusters under the wild bootstrapping-c method described in Cameron et al. (2008).

	Disinvestment (Ships Disinvested)					
	Total	Demolished	Sold	Total	Demolished	Sold
	(1)	(2)	(3)	(4)	(5)	(6)
Δ *Subsectoral BDI*	–0.010	–0.008	–0.002	–0.037	–0.024	–0.013
	(–3.53)***	(–3.51)***	(–1.56)	(–3.18)***	(–2.22)**	(–1.25)
	[–2.73]***	[–2.89]***	[–1.44]	[–2.55]**	[–1.68]*	[–1.12]
	{–2.56}**	{–2.76}***	{–1.12}	{–2.21}**	{–1.50}	{–1.09}
Cash Flow	–0.708	–0.687	–0.021	–0.897	–0.581	–0.316
	(–1.89)*	(–1.40)	(–1.76)*	(–1.35)	(–0.73)	(–1.41)
	[–1.56]	[–1.23]	[–1.37]	[–1.32]	[–0.14]	[–0.87]
	{–1.34}	{–1.22}	{–1.18}	{–1.21}	{–0.12}	{–0.74}
Uncertainty	–0.208	–0.149	–0.059	–0.268	–0.227	–0.041
	(–4.78)***	(–3.04)***	(–1.99)**	(–3.75)***	(–6.10)***	(–1.24)
	[–3.89]***	[–2.51]**	[–1.63]	[–3.38]***	[–5.89]***	[–1.09]
	{–3.21}***	{–2.43}**	{–1.64}	{–3.14}***	{–5.28}***	{–0.89}
Liquidity	0.142	0.095	0.047	0.124	0.129	–0.005
	(5.71)***	(4.34)***	(1.37)	(2.41)**	(4.11)***	(–0.57)
	[4.81]***	[2.66]***	[1.22]	[2.12]**	[3.84]***	[–0.43]
	{4.36}***	{2.44}**	{1.08}	{1.99}**	{3.17}***	{–0.33}
Uncertainty × *Liquidity*	0.018	0.013	0.005	0.014	0.010	0.004
	(5.44)***	(3.91)***	(1.73)*	(4.96)***	(4.15)***	(1.09)
	[4.83]***	[2.72]***	[1.68]*	[3.65]***	[2.98]***	[0.77]
	{4.21}***	{2.69}***	{1.64}	{3.10}***	{2.58}**	{0.61}
Liquidity Measure	Price Premium	Price Premium	Price Premium	Price Dispersion	Price Dispersion	Price Dispersion
Controls						
Firm-Subsector Fleet	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Country × Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99,928	99,928	99,928	99,928	99,928	99,928
Adjusted R^2	0.048	0.077	0.025	0.048	0.077	0.025

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table C.4. Uncertainty, Asset Liquidity, and Investment and Disinvestment for Pure-Play Firms

This table reports output from Eq. (1) estimated on the sample of firms operating in only a single subsector over the sample period ("pure-play" firms). The dependent variables are the investment (Panel A) and disinvestment rates (Panel B). The investment (disinvestment) rate is calculated at the firm-quarter level by dividing the number of ships acquired (disinvested) by the lagged number of ships held. Subsector controls are Δ *Subsectoral BDI* and *Cash Flow*, and are defined in Table 2. *Uncertainty* is the quarterly average of annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector. The *Liquidity* measure is defined as the price premium, which is the quarterly average resale price minus the purchase price divided by the purchase price, across all used ship transactions in a given subsector. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Fixed effects for headquarter country, firm, and year-quarter are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm and year-quarter.

Panel A: Investment (Ships Acquired)

	Investment	New	Used
	(1)	(2)	(3)
Uncertainty	–0.011***	–0.009***	–0.002*
	(–4.99)	(–5.01)	(–1.75)
Liquidity	0.224**	0.162**	0.062
	(2.41)	(2.33)	(0.79)
Uncertainty × *Liquidity*	0.022***	0.018***	0.004
	(4.66)	(3.17)	(0.07)
Liquidity Measure	Price Premium	Price Premium	Price Premium
Controls			
Subsector	Yes	Yes	Yes
Firm Fleet	Yes	Yes	Yes
Fixed Effects			
Country × Year-Quarter	Yes	Yes	Yes
Firm	Yes	Yes	Yes
Observations	14,497	14,497	14,497
Adjusted R^2	0.054	0.055	0.055

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Panel B: Disinvestment (Ships Disinvested)			
	Disinvestment	Demolition	Sale
	(1)	(2)	(3)
Uncertainty	–0.059***	–0.044***	–0.015**
	(–5.18)	(–2.99)	(–2.21)
Liquidity	0.471*	0.290*	0.181
	(1.94)	(1.89)	(1.14)
Uncertainty × *Liquidity*	0.026***	0.018***	0.008
	(4.19)	(3.47)	(0.99)
Liquidity Measure	Price Premium	Price Premium	Price Premium
Controls			
Subsector	Yes	Yes	Yes
Firm Fleet	Yes	Yes	Yes
Fixed Effects			
Country × Year-Quarter	Yes	Yes	Yes
Firm	Yes	Yes	Yes
Observations	14,497	14,497	14,497
Adjusted R^2	0.048	0.046	0.046

Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.5. Investment and Disinvestment Controlling for Financing Constraints

This table reports output from Eq. (1). The dependent variable is the investment (disinvestment) rate. The investment (disinvstment) rate is calculated at the firm-subsector-quarter level by dividing the number of ships acquired (disinvested) by the lagged number of ships held. Subsector controls consist of Δ*Subsectoral BDI* and *Cash Flow*, and are defined in Table 2. *Uncertainty* is the quarterly average of annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector. The *Liquidity* measure is defined as the price premium, which is the average resale price minus the purchase price divided by the purchase price, across all used ship transactions in a given subsector. *FC* is either the size-age index calculated as in Hadlock and Pierce (2010) or an indicator variable for whether a given firm is private. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Fixed effects for headquarter country, firm, subsector, and year-quarter are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm-subsector and year-quarter.

	Investment		Disinvestment	
	(1)	(2)	(3)	(4)
Uncertainty	–0.043***	–0.098***	–0.072***	–0.044***
	(–3.38)	(–4.84)	(–4.62)	(–5.14)
Liquidity	0.175***	0.266***	–0.120*	0.469
	(3.91)	(5.04)	(–1.83)	(0.85)
Uncertainty × *Liquidity*	0.038***	0.008***	0.024***	0.019***
	(4.92)	(5.25)	(2.95)	(4.45)
FC	–0.725*	–0.186*	0.760	0.657
	(–1.92)	(–1.86)	(0.07)	(1.13)
Uncertainty × *FC*	–0.118**	–0.012	0.001	0.000
	(–2.17)	(–1.64)	(1.03)	(1.10)
Liquidity Measure	Price Premium	Price Premium	Price Premium	Price Premium
FC Measure	Size-Age	Private	Size-Age	Private
Controls				
Subsector	Yes	Yes	Yes	Yes
Firm-Subsector Fleet	Yes	Yes	Yes	Yes
Fixed Effects				
Country × Year-Quarter	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	No	Yes	No
Observations	99,928	99,928	99,928	99,928
Adjusted R^2	0.051	0.051	0.048	0.048

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table C.6. Uncertainty, Asset Liquidity, and Investment and Disinvestment Tonnage

This table reports output from Eq. (1). The dependent variables are the investment and disinvestment rates. The investment (disinvestment) rate is calculated at the firm-subsector-quarter level by dividing the DWT of ships acquired (disinvested) by the lagged DWT of ships held. Subsector controls consist of Δ *Subsectoral BDI* and *Cash Flow*, and are defined in Table 2. *Uncertainty* is the quarterly average of annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector. The *Liquidity* measure is defined as the price premium, which is the average resale price minus the purchase price divided by the purchase price, across all used ship transactions in a given subsector. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Fixed effects for headquarter country, firm, subsector, and year-quarter are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm-subsector and year-quarter.

	DWT Invested	DWT Disinvested
	(1)	(2)
Uncertainty	–0.096***	–0.226***
	(–5.80)	(–3.67)
Liquidity	0.244*	0.118
	(1.77)	(0.98)
Uncertainty × *Liquidity*	0.036***	0.022***
	(3.34)	(4.64)
Liquidity Measure	Price Premium	Price Premium
Controls		
Subsector	Yes	Yes
Firm-Subsector Fleet	Yes	Yes
Fixed Effects		
Country × Year-Quarter	Yes	Yes
Firm × Subsector	Yes	Yes
Observations	99,928	99,928
Adjusted R^2	0.058	0.050

Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.7. Uncertainty, Asset Liquidity, and Investment and Disinvestment with Firm-Level Uncertainty Measure and Alternative Fixed Effects

This table reports output from Eq. (1). The dependent variables are the investment and disinvestment rates. The investment (disinvestment) rate is calculated at the firm-subsector-quarter level by dividing the number of ships acquired (disinvested) by the lagged number of ships held. *Uncertainty (Firm)* is the quarterly average of annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector, averaged across all subsectors that a firm operates in weighted by the number of ships it operates in the subsector. The *Liquidity* measure is defined as the price premium, which is the average resale price minus the purchase price divided by the purchase price, across all used ship transactions in a given subsector. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Fixed effects for firm, subsector, and year-quarter are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm-subsector and year-quarter.

	Investment	Disinvestment
	(1)	(2)
Uncertainty (Firm)	–0.161***	–0.158***
	(–3.34)	(–4.11)
Uncertainty (Firm) × *Liquidity*	0.005***	0.027***
	(5.54)	(3.34)
Liquidity Measure	Price Premium	Price Premium
Controls		
Firm-Subsector Fleet	Yes	Yes
Fixed Effects		
Firm	Yes	Yes
Subsector × Year-Quarter	Yes	Yes
Observations	99,928	99,928
Adjusted R^2	0.094	0.114

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table C.8. Uncertainty, Asset Liquidity, and Investment and Disinvestment: Weighted Least Squares

This table reports output from Eq. (1) with observations weighted by the fraction of firms with publicly-traded options in the subsector-quarter. The dependent variables are the investment and disinvestment rates. The investment (disinvestment) rate is calculated at the firm-subsector-quarter level by dividing the number of ships acquired (disinvested) by the lagged number of ships held. *Uncertainty* is the quarterly average of the annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector. The *Liquidity* measure is defined as the price premium, which is the average resale price minus the purchase price divided by the purchase price, across all used ship transactions in a given subsector. Subsector controls are Δ*Subsectoral BDI* and *Cash Flow*, and are defined in Table 2. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Fixed effects for headquarter country, firm, subsector, and year-quarter are included as indicated. All regressions are estimated using weighted least squares over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm-subsector and year-quarter.

	Investment	Disinvestment
	(1)	(2)
Uncertainty	–0.137***	–0.149***
	(–8.55)	(–3.26)
Liquidity	0.163***	0.145***
	(5.18)	(2.84)
Uncertainty × *Liquidity*	0.005***	0.015***
	(6.19)	(5.56)
Liquidity Measure	Price Premium	Price Premium
Controls		
Subsector	Yes	Yes
Firm-Subsector Fleet	Yes	Yes
Fixed Effects		
Country × Year-Quarter	Yes	Yes
Firm × Subsector	Yes	Yes
Observations	99,928	99,928
Adjusted R^2	0.059	0.047

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Appendix D Decomposition and Dynamics of Uncertainty

D.1 Decomposed Uncertainty

Our main measure of uncertainty in a shipping subsector is obtained by averaging option-implied equity volatilities of firms operating in that subsector, weighted by the number of ships in that subsector each firm operates. Implicitly, this measure allows for the contribution of each firm's uncertainty to the subsectoral uncertainty to be proportional to its market share in that subsector. We test whether our results are robust to an alternative weighting scheme that decomposes each firm's implied volatility across subsectors based on the share of its fleet belonging to the respective subsectors. Specifically, in each quarter, we select eight (i.e., number of subsectors in our sample) or more firms in ascending order by the size of the total fleet. This gives a system of eight or more equations in which each firm's loading on each subsector's implied volatility (eight unknowns) is the fraction of that firm's fleet in that subsector. From this equation system, we solve for each subsector's implied volatility in that period. Table D.1 reports the results from estimating our baseline specification using this alternative decomposed uncertainty measure. The coefficient estimates are similar in both statistical significance and economic magnitude to those reported in Table 2, suggesting that our results are not an artifact of the scheme used in allocating firms' implied volatilities across subsectors.

Table D.1. Decomposed Uncertainty, Asset Liquidity, and Investment and Disinvestment

This table reports output from Eq. (1). The dependent variable is the investment (disinvestment) rate. The investment rate is calculated at the firm-subsector-quarter level by dividing the number of ships acquired (disinvested) by the lagged number of ships held. *Uncertainty* is an alternative implied volatility measure that decomposes each firm's implied volatility across subsectors based on the share of its fleet belonging to the respective subsectors. Subsector controls consist of Δ *Subsectoral BDI* and *Cash Flow*, and are defined in Table 2. The *Liquidity* measure is defined as the price premium, which is the quarterly average resale price minus the purchase price divided by the purchase price, across all used ship transactions in a given subsector. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Fixed effects for headquarter country, firm, subsector, and year-quarter are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm-subsector and year-quarter.

	Investment (Ships Acquired)			Disinvestment (Ships Disinvested)		
	Total	New	Used	Total	Demolish	Sale
	(1)	(2)	(3)	(4)	(5)	(6)
Uncertainty	–0.089***	–0.077***	–0.012	–0.052***	–0.034**	–0.018
	(–3.30)	(–3.57)	(–0.17)	(–3.25)	(–1.98)	(–0.07)
Liquidity	0.169**	0.144*	0.018	–0.176*	–0.120	–0.055
	(2.22)	(1.76)	(1.41)	(–1.86)	(–0.24)	(–0.62)
Uncertainty × *Liquidity*	0.022***	0.014***	0.008	0.013**	0.008**	0.005
	(3.92)	(3.84)	(1.44)	(2.05)	(2.36)	(1.18)
Liquidity Measure	Price Premium	Price Premium	Price Premium	Price Premium	Price Premium	Price Premium
Controls						
Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Subsector Fleet	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Country × Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99,928	99,928	99,928	99,928	99,928	99,928
Adjusted R^2	0.053	0.053	0.051	0.048	0.047	0.048

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

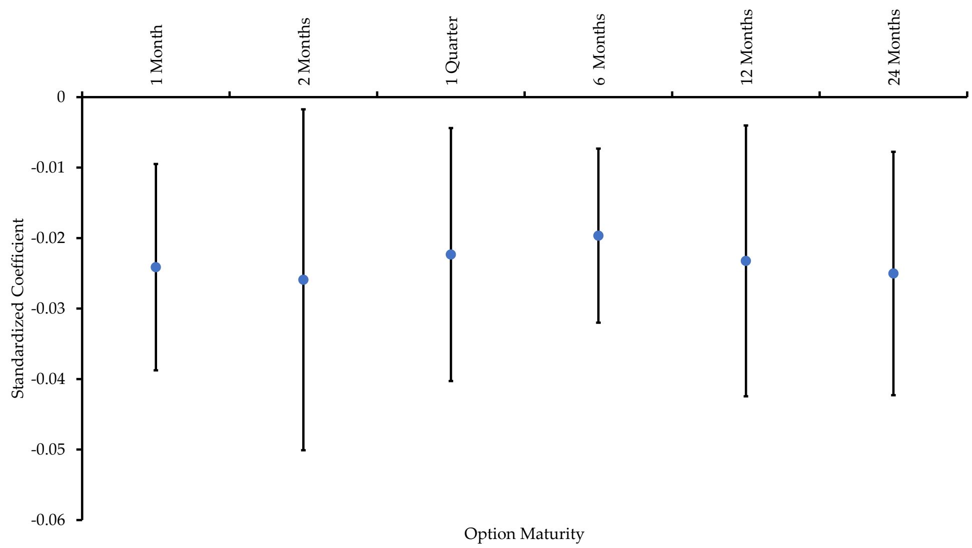
D.2 Dynamics of Uncertainty Effects on Capital Allocation

Recent theoretical work on firm responses to uncertainty shocks shows that the delaying effect of uncertainty on firm investment displays a "drop-and-rebound" pattern (e.g., Bloom (2009)). We empirically examine the dynamic effect of uncertainty on shipping firms' asset allocation decisions by estimating Eq. (1) with leads of the investment and disinvestment rates as the dependent variables. Table D.2 reports the estimation results.

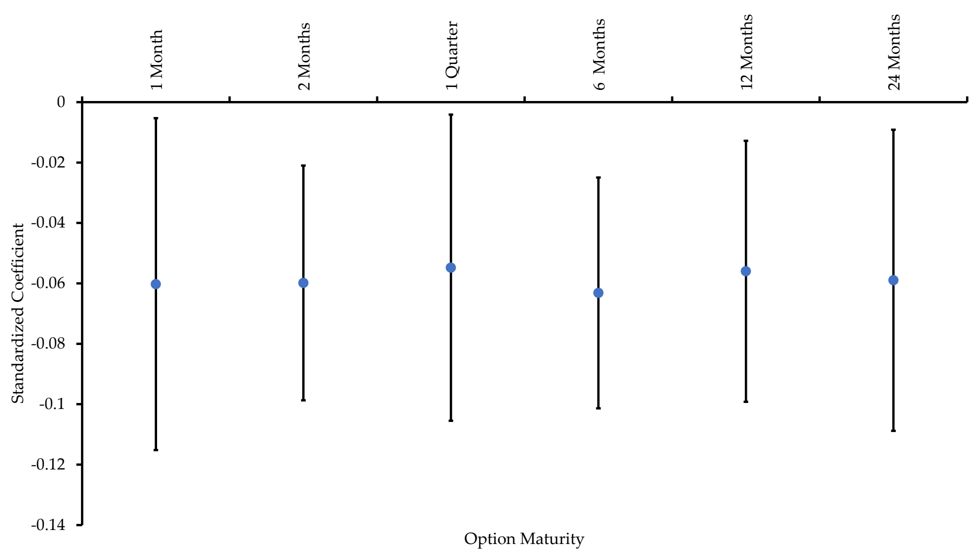
TABLE D.2 ABOUT HERE.

Columns (1) through (6) of Panel A (B) present the relationship between uncertainty and investment (disinvestment) measured one through five quarters ahead. They show that the drop in investment (disinvestment) lasts for up to three quarters ahead, with the magnitude declining over time. By the fourth quarter, there is no significant relation between uncertainty and investment or disinvestment, suggesting capital allocation returns to its baseline level about a year after a change in uncertainty. These results are consistent with delaying effects of uncertainty as dynamic models predict.

Relatedly, we examine the robustness of our results to varying the maturity of the options considered in computing the implied volatilities underlying our *Uncertainty* measure. The results, presented in Figure D.1, suggest that our conclusions are similar regardless of the underlying option maturity. This lack of variation is to be expected for two reasons. First, implied volatility captures market expectations of the volatility of the entire stream of future cash flows, and not only for the maturity period of the option being considered. Second, in our context, implied volatility is highly persistent across maturity horizons. This finding is reassuring for the validity of our results in suggesting that the effects we document are not reactions to short-term uncertainty fluctuations.



(A) Investment



(B) Disinvestment

Figure D.1. Effect of Uncertainty on Investment and Disinvestment by Option Maturity. This figure displays standardized coefficient estimates and 95% confidence bands for *Uncertainty* estimated from the specification in Eq. (1). We report standardized coefficients (the baseline regression coefficient multiplied by the ratio of the standard deviations of the independent and dependent variable) so as to compare the magnitude of the effects across the different option maturities. The dependent variables are investment (Panel A) and disinvestment (Panel B). Each point represents the coefficient corresponding to a particular maturity of options used in computing *Uncertainty*, with "1 Quarter" corresponding to the baseline effects reported in column (1) of Table 2, Panels A and B.

Table D.2. Dynamics of Uncertainty, Asset Liquidity, and Investment and Disinvestment

This table reports output from a variant of Eq. (1) which uses the leads of the investment and disinvestment rates as the dependent variables. The investment (disinvestment) rate is calculated at the firm-subsector-quarter level by dividing the number of ships acquired (disinvested) by the lagged number of ships held. Subsector controls are Δ *Subsectoral BDI* and *Cash Flow*, and are defined in Table 2. *Uncertainty* is the quarterly average of annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector. The *Liquidity* measure is defined as the price premium, which is the quarterly average resale price minus the purchase price divided by the purchase price, across all used ship transactions in a given subsector. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Fixed effects for headquarter country, firm, subsector, and year-quarter are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm-subsector and year-quarter.

Panel A: Leads of Investment						
	Investment (Ships Acquired)					
Lead:	t	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
	(1)	(2)	(3)	(4)	(5)	(6)
Uncertainty	–0.081***	–0.077**	–0.062**	–0.034*	–0.010	–0.005
	(–3.23)	(–2.01)	(–2.19)	(–1.88)	(–0.32)	(–1.24)
Liquidity	0.221***	0.308**	0.240**	0.176***	0.229**	0.192**
	(3.77)	(1.99)	(2.54)	(2.86)	(1.98)	(2.04)
Uncertainty × *Liquidity*	0.021***	0.012**	0.014**	0.008	0.011	–0.004
	(3.56)	(2.28)	(2.19)	(0.87)	(1.26)	(–1.41)
Liquidity Measure	Price Premium	Price Premium	Price Premium	Price Premium	Price Premium	Price Premium
Controls						
Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Subsector Fleet	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Country × Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99,928	95,007	90,264	85,794	81,475	77,377
Adjusted R^2	0.049	0.044	0.048	0.042	0.040	0.040

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Panel B: Leads of Disinvestment						
	Disinvestment (Ships Disinvested)					
Lead:	t	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
	(1)	(2)	(3)	(4)	(5)	(6)
Uncertainty	–0.208***	–0.211**	–0.146*	–0.099	–0.102	–0.083
	(–3.99)	(–2.41)	(–1.79)	(–0.04)	(–0.12)	(–0.97)
Liquidity	0.142***	0.205	0.366*	0.041	0.118	0.177
	(2.82)	(1.07)	(0.43)	(1.03)	(0.88)	(0.47)
Uncertainty × *Liquidity*	0.018***	0.015**	0.012*	0.004	0.005	–0.003
	(4.05)	(2.14)	(1.87)	(0.41)	(1.53)	(0.87)
Liquidity Measure	Price Premium	Price Premium	Price Premium	Price Premium	Price Premium	Price Premium
Controls						
Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Subsector Fleet	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Country × Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99,928	95,007	90,264	85,794	81,475	77,377
Adjusted R^2	0.048	0.045	0.045	0.049	0.048	0.048

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix E Alternative Liquidity and Irreversibility Measures

Table E.1. Uncertainty, Asset Liquidity, and Investment: Alternative Liquidity and Irreversibility Measures

This table reports output from Eq. (1). The dependent variable is the investment rate, both the total rate and disaggregated into its components. The investment rate is calculated at the firm-subsector-quarter level by dividing the number of ships acquired (total, new ships acquired, or used ships acquired) by the lagged number of ships held. *Uncertainty* is the quarterly average of annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector. The *Liquidity* measures are defined as the ratio of the number of buyers (unique firms that make a secondary market purchase) to the number of used ships in a given subsector-quarter and the (reverse of the) useful life of a ship in a given subsector. The useful life is defined as the average age (in years) at which ships are demolished in a given subsector. Subsector controls are Δ*Subsectoral BDI* and *Cash Flow*, and are defined in Table 2. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Fixed effects for headquarter country, firm, subsector, and year-quarter are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm-subsector and year-quarter.

	Investment (Ships Acquired)					
	Total	New	Used	Total	New	Used
	(1)	(2)	(3)	(4)	(5)	(6)
Uncertainty	–2.066***	–2.072***	0.006	–0.927***	–0.859***	–0.068
	(–3.47)	(–3.55)	(1.60)	(–5.61)	(–5.41)	(–1.57)
Liquidity	–3.665***	–3.277***	–0.387***	–	–	–
	(–3.38)	(–3.06)	(–3.28)	–	–	–
Uncertainty × *Liquidity*	0.257***	0.257***	0.001	0.026***	0.025***	0.002
	(2.86)	(2.98)	(1.18)	(5.89)	(5.77)	(1.31)
Liquidity Measure	# Buyers/ # Ships	# Buyers/ # Ships	# Buyers/ # Ships	Useful Life	Useful Life	Useful Life
Controls						
Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Subsector Fleet	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Country × Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99,928	99,928	99,928	99,928	99,928	99,928
Adjusted R^2	0.048	0.049	0.037	0.057	0.054	0.038

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table E.2. Uncertainty, Asset Liquidity, and Disinvestment: Alternative Liquidity and Irreversibility Measures

This table reports output from Eq. (1). The dependent variable is the disinvestment rate, both the total rate and disaggregated into its components. The disinvestment rate is calculated at the firm-subsector-quarter level by dividing the number of ships disinvested (total, ships demolished, or ships sold) by the lagged number of ships held. *Uncertainty* is the quarterly average of annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector. The *Liquidity* measures are defined as the ratio of the number of buyers (unique firms that make a secondary market purchase) to the number of used ships in a given subsector-quarter and the (reverse of the) useful life of a ship in a given subsector. The useful life is defined as the average age (in years) at which ships are demolished in a given subsector. Subsector controls are Δ*Subsectoral BDI* and *Cash Flow*, and are defined in Table 2. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Fixed effects for headquarter country, firm, subsector, and year-quarter are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm-subsector and year-quarter.

	Disinvestment (Ships Disinvested)					
	Total	Demolish	Sale	Total	Demolish	Sale
	(1)	(2)	(3)	(4)	(5)	(6)
Uncertainty	–0.511***	–0.340***	–0.171**	–0.500***	–0.284***	–0.217*
	(–4.56)	(–5.88)	(–2.12)	(–3.72)	(–2.79)	(–1.85)
Liquidity	–1.815**	–1.007***	–0.808*	–	–	–
	(–2.02)	(–2.64)	(–1.85)	–	–	–
Uncertainty × *Liquidity*	0.093***	0.074***	0.019	0.020***	0.012***	0.007*
	(3.19)	(2.96)	(1.17)	(5.40)	(4.42)	(1.80)
Liquidity Measure	# Buyers/ # Ships	# Buyers/ # Ships	# Buyers/ # Ships	Useful Life	Useful Life	Useful Life
Controls						
Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Subsector Fleet	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Country × Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99,928	99,928	99,928	99,928	99,928	99,928
Adjusted R^2	0.050	0.055	0.038	0.064	0.083	0.047

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table E.3. Uncertainty, Market Thickness, and Investment and Disinvestment

This table reports output from Eq. (1). The dependent variable is the investment (disinvestment) rate. The investment (disinvestment) rate is calculated at the firm-subsector-quarter level by dividing the number of ships acquired (disinvested) by the lagged number of ships held. Δ *Subsectoral BDI* is the quarterly percentage change in the sectoral indices derived from forward freight agreement prices for routes commonly served by ships in each subsector quoted on the Baltic Exchange. *Cash Flow* is the quarterly income before extraordinary items plus depreciation and amortization divided by lagged total assets, averaged across all firms operating in a given subsector weighted by the number of ships they operate in the subsector. *Uncertainty* is the quarterly average of annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector. The *Market Thickness* measures are defined as the logarithm of the quarterly number of ships, the quarterly number of transactions divided by the lagged number of ships, and the logarithm of the number of firms, in a given subsector. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Fixed effects for headquarter country, firm, subsector, and year-quarter are included as indicated. All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm-subsector and year-quarter.

	Investment			Disinvestment		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ *Subsectoral BDI*	0.005***	0.006***	0.006***	–0.008	–0.002*	–0.002
	(2.79)	(3.82)	(4.14)	(–1.36)	(–1.94)	(–0.74)
Cash Flow	0.362	0.218	0.223	–0.293	–0.087	–0.204
	(1.16)	(1.11)	(0.95)	(–0.56)	(–0.79)	(–0.52)
Uncertainty	–2.642***	–0.028***	–1.433***	–1.387***	–0.137***	–0.618**
	(–3.12)	(–3.32)	(–3.84)	(–3.02)	(–2.86)	(–2.72)
Market Thickness	–4.473***	–0.318***	–3.476***	–1.173**	–0.212*	–0.618*
	(–4.29)	(–2.88)	(–3.91)	(–2.38)	(–1.69)	(–1.78)
Uncertainty × *Market Thickness*	0.328***	0.028***	0.265***	0.171***	0.005**	0.118***
	(3.34)	(3.46)	(4.01)	(3.18)	(2.43)	(3.18)
Market Thickness Measure	# Ships	# Trans.	# Firms	# Ships	# Trans.	# Firms
Controls						
Firm-Subsector Fleet	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Country × Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99,928	99,928	99,928	99,928	99,928	99,928
Adjusted R^2	0.043	0.048	0.048	0.052	0.048	0.048

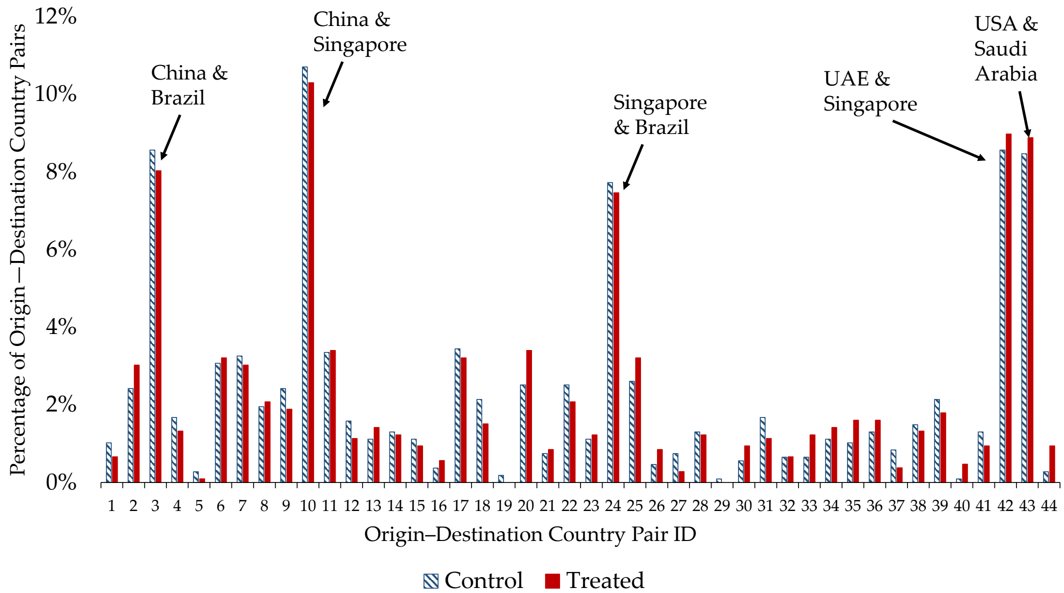
Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Appendix F Quasi-Natural Experiment

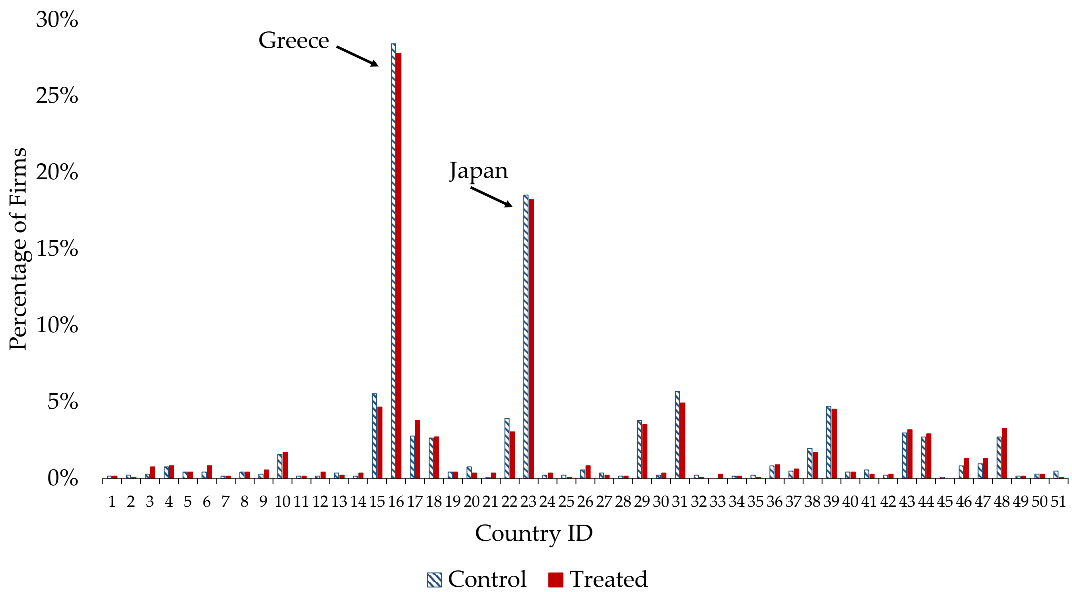
Table F.1. Comparison of Pre-Period Characteristics between Treated and Control Groups

This table reports the mean values, differences, and t-statistics for a set of characteristics corresponding to the 2006–2008 period for the matched sample of treated and control firm-subsectors. The characteristics include the average of the logarithm of *Age*, *DWT*, *RPM*, and *Speed* of ships held by each firm-subsector, averaged across all firm-subsectors in the treated and control groups. We also report the average of the fraction of ships held by each firm-subsector built in *China*, *Japan*, and *Korea*. Finally, the variable *State-Owned* is an indicator variable for whether the parent firm of each firm-subsector is majority owned by a government entity. t-statistics are computed using robust standard errors clustered by match.

	Control	Treated	Difference	t-statistic
Age (Log # Years)	2.422	2.444	–0.022	–0.98
DWT (Log)	12.574	11.989	0.585	1.74
RPM (Log)	4.748	4.752	–0.004	–1.17
Speed (Log)	2.667	2.673	–0.006	–0.86
China	0.099	0.100	–0.001	–0.40
Japan	0.608	0.600	0.008	0.90
Korea	0.160	0.173	–0.013	–0.71
State-Owned	0.088	0.084	0.004	1.19



(A) Distribution of Origin–Destination Country Pairs



(B) Distribution of Headquarter Countries

Figure F.1. Distribution of Shipping Origin–Destination Country Pairs and Headquarter Countries. This figure shows histograms corresponding to the distribution of origin–destination country pairs operated by a random sample of 50 ships each (100 total) in the treated and control firm-subsectors in the year 2008 (Panel A). Historical shipping origin and destination data are obtained from ShipIntel by Maritime Optima and Bloomberg. Panel B shows histograms corresponding to the distribution of headquarter countries of firms (operating the firm-subsectors) in the treated and control groups. The mapping between shipping origin–destination country pairs and the respective IDs is given in Table F.2 and the mapping between headquarter countries and country IDs is given in Table F.3.

Table F.2. Shipping Origin–Destination Country Pair Identifiers

This table provides the mapping between shipping origin–destination country pairs and the respective IDs displayed in Panel A of Figure F.1.

Origin–Destination Country Pair ID	Origin–Destination Country Pair
1	Angola and Malaysia
2	China and Angola
3	China and Brazil
4	China and Ghana
5	China and Hong Kong SAR
6	China and Iraq
7	China and Malaysia
8	China and Philippines
9	China and Saudi Arabia
10	China and Singapore
11	China and United Arab Emirates
12	Ecuador and Panama
13	Ecuador and United States
14	Ghana and Angola
15	Ghana and Singapore
16	Hong Kong SAR and Singapore
17	Iraq and United States
18	Qatar and Brazil
19	Qatar and Saudi Arabia
20	Saudi Arabia and Brazil
21	Saudi Arabia and United Kingdom
22	Saudi Arabia and United States
23	Singapore and Angola
24	Singapore and Brazil
25	Singapore and Iraq
26	Singapore and Japan
27	Singapore and Malaysia
28	Singapore and Panama
29	Singapore and Philippines
30	Singapore and Saudi Arabia
31	Singapore and Sri Lanka
32	South Korea and Japan
33	South Korea and Malaysia
34	South Korea and Singapore
35	South Korea and Spain
36	South Korea and United Arab Emirates
37	Spain and United Kingdom
38	United Arab Emirates and Brazil
39	United Arab Emirates and Iraq
40	United Arab Emirates and Philippines
41	United Arab Emirates and Qatar
42	United Arab Emirates and Singapore
43	United States and Saudi Arabia
44	United States and Brazil

Table F.3. Headquarter Country Identifiers

This table provides the mapping between headquarter countries and country IDs displayed in Panel B of Figure F.1.

Country ID	Country
1	Angola
2	Argentina
3	Australia
4	Belgium
5	Brazil
6	Canada
7	Chile
8	Croatia
9	Cyprus
10	Denmark
11	Ecuador
12	Egypt
13	Finland
14	France
15	Germany
16	Greece
17	Hong Kong SAR
18	India
19	Indonesia
20	Iran
21	Israel
22	Italy
23	Japan
24	Kuwait
25	Libya
26	Malaysia
27	Monaco
28	Netherlands
29	Norway
30	Pakistan
31	Peoples' Republic Of China
32	Philippines
33	Poland
34	Portugal
35	Qatar
36	Russia
37	Saudi Arabia
38	Singapore
39	South Korea
40	Spain
41	Sweden
42	Switzerland
43	Taiwan
44	Turkey
45	Ukraine
46	United Arab Emirates
47	United Kingdom
48	United States
49	Vanuatu
50	Venezuela
51	Vietnam

Table F.4. Uncertainty, Investment, and Disinvestment: A Quasi-Natural Experiment with Parallel Trends

This table reports output from a modified version of Eq. (2) estimated on a matched sample. The modified specification replaces the single treatment period indicator ($Piracy_t$) with annual indicator variables and the country × year-quarter fixed effects with country × year fixed effects. The dependent variable is the investment (disinvestment) rate. The investment rate is calculated at the firm-subsector-quarter level by dividing the number of ships acquired (disinvested) by the lagged number of ships held. *Treat* is an indicator that takes the value of one for the Panamax and LR1 subsectors and zero for the Capesize and VLCC subsectors. $\mathbb{1}_Y$ are annual indicators taking the value of one for the year Y and zero otherwise. Subsector controls are Δ*Subsectoral BDI* and *Cash Flow*, and are defined in Table 2. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Each treated firm-subsector is matched to one control firm-subsector (with replacement) which is its nearest neighbor in terms of treatment propensity. The propensity score is a function of the firm-subsector fleet controls. Fixed effects for headquarter country, firm, subsector, and year are included as indicated. All regressions are estimated over the 2006–2013 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by match.

	Matched Sample Difference-in-Differences					
	Investment (Ships Acquired)			Disinvestment (Ships Disinvested)		
	Total	New	Used	Total	Demolish	Sale
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × $\mathbb{1}_{2006}$	0.012	0.011	0.002	0.011	0.006	0.004
	(0.02)	(0.05)	(0.02)	(0.07)	(0.08)	(0.07)
Treat × $\mathbb{1}_{2007}$	0.027	0.022	0.005	0.016	0.010	0.007
	(0.05)	(0.10)	(0.02)	(0.09)	(0.12)	(0.06)
Treat × $\mathbb{1}_{2008}$	–	–	–	–	–	–
	–	–	–	–	–	–
Treat × $\mathbb{1}_{2009}$	–1.677***	–1.514***	–0.163	–0.184**	–0.122***	–0.062
	(–3.80)	(–4.01)	(–1.24)	(–2.52)	(–2.79)	(–1.24)
Treat × $\mathbb{1}_{2010}$	–1.318***	–1.112***	–0.206	–0.404***	–0.281***	–0.123
	(–2.99)	(–3.27)	(–1.41)	(–3.81)	(–4.19)	(–1.21)
Treat × $\mathbb{1}_{2011}$	–0.991**	–0.893***	–0.098	–0.241**	–0.136**	–0.105
	(–2.51)	(–2.69)	(–1.46)	(–2.43)	(–2.52)	(–1.17)
Treat × $\mathbb{1}_{2012}$	–0.104	–0.089	–0.015	0.002	0.001	0.001
	(–0.35)	(–0.68)	(–0.22)	(0.02)	(0.02)	(0.03)
Treat × $\mathbb{1}_{2013}$	0.081	0.074	0.006	0.014	0.008	0.007
	(0.33)	(0.46)	(0.33)	(0.16)	(0.18)	(0.11)
Controls						
Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Subsector Fleet	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Country × Year	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,651	14,651	14,651	14,651	14,651	14,651
Adjusted R^2	0.066	0.067	0.066	0.075	0.075	0.075

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

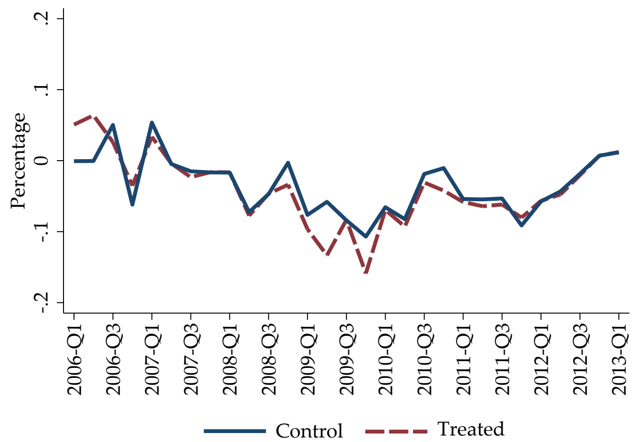
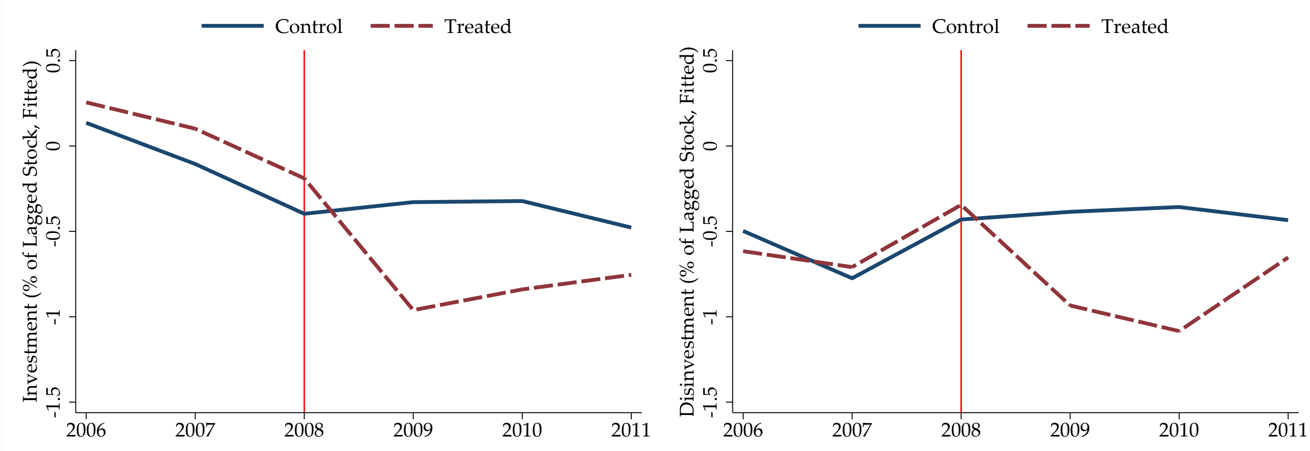


Figure F.2. **△ *Subsectoral BDI* Trends around the Escalation in Somali Piracy.** This figure shows trends in △ *Subsectoral BDI* for treated and control subsectors. Treated subsectors consist of Panamax bulkers and LR2 tankers. Control subsectors consist of Capesize bulkers and VLCC tankers.



(A) Investment Dynamics

(B) Disinvestment Dynamics

Figure F.3. **Investment and Disinvestment Dynamics around the Escalation in Somali Piracy using Synthetic Controls.** This figure shows dynamics of investment (Panel A) and disinvestment (Panel B) for treated firm-subsectors and a synthetic control firm-subsector. The synthetic control unit is constructed according to the method described in Arkhangelsky et al. (2021) in which control group observations are reweighted in order to generate parallel pre-treatment trends in the respective outcome variables.

Table F.5. A Quasi-Natural Experiment: First-Stage Results

This table reports output from the first-stage regression corresponding to the second-stage instrumental variables regression reported in Panel B of Table 3. The dependent variable is *Uncertainty*, defined as the quarterly average of annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector. *Treat* is an indicator that takes the value of one for the Panamax and LR1 subsectors and zero for the Capesize and VLCC subsectors. *Piracy* is an indicator that takes the value of one for the years 2009–2011, and 0 for all other years from 2006–2013. Subsector controls are Δ*Subsectoral BDI* and *Cash Flow*, and are defined in Table 2. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Each treated firm-subsector is matched to one control firm-subsector (with replacement) which is its nearest neighbor in terms of treatment propensity. The propensity score is a function of the firm-subsector fleet controls. Fixed effects for headquarter country, firm, subsector, and year-quarter are included as indicated. All regressions are estimated over the 2006–2013 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm-subsector and year-quarter.

	Uncertainty
	(1)
Treat × *Piracy*	1.638***
	(17.06)
Δ *Subsectoral BDI*	–0.103*
	(–1.67)
Cash Flow	0.274
	(0.16)
Controls	
Firm-Subsector Fleet	Yes
Fixed Effects	
Country × Year-Quarter	Yes
Firm × Subsector	Yes
Lee et al. (2022) Diagnostics	
First Stage F-ratio	153.23
5% Adjustment Factor	1.00
1% Adjustment Factor	1.00
Observations	14,651

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Appendix G Lumpiness of Investment and Disinvestment

This Appendix presents results from estimating alternative specifications and on alternative samples to the baseline model. Panel A provides results estimated using the investment and disinvestment measures calculated at the semi-annual and annual horizons as the dependent variables. Panel B presents results from estimating a zero-one inflated beta regression model. This method is appropriate for dependent variables that are proportions, and therefore tend to be bounded and have a mass of probability at zero, one, or both. In such cases, linear models may be inappropriate as the effect of explanatory variables might be non-linear and the variance tends to decrease when the mean gets closer to either the zero or one boundary. The zero-one inflated beta regression consists of three components. First, it fits the range of the dependent variable lying between zero and one (non-inclusive) to a beta distribution where the mean is a function of explanatory variables. It further allows zeros and one values of the dependent variable to be explained by two distinct (but potentially correlated) processes. Specifically, it fits separate logit regressions for the zero and one values of the dependent variable. The model is jointly estimated via maximum likelihood. See Ospina and Ferrari (2012) for more details. In our implementation, we use the same set of explanatory variables across all three processes, and values of the dependent variable lying above one are capped at one. For brevity, we report coefficient estimates solely from the first process; i.e., the beta distribution for values of the dependent variable between zero and one.

Table G.1. Robustness Tests to Address Lumpiness of Investment and Disinvestment

This table reports output from variants of Eq. (1). Panel A reports output from semi-annual and annualized versions of Eq. (1). The dependent variable is the investment (disinvestment) rate. The investment (disinvestment) rate is calculated at the firm-subsector-semi-year or firm-subsector-year level by dividing the number of ships acquired (disinvested) by the lagged number of ships held. The independent variables are similarly computed at the semi-annual or annual level. Panel B reports results from estimation procedures accounting for zero investment and disinvestment rates. Columns (1) and (4) report results from a linear probability model (LPM) which takes the form of Eq. (1), where the dependent variable is an indicator which takes the value of one if the investment (disinvestment) rate in a firm-subsector-quarter is positive, and zero otherwise. Columns (2) and (5) report estimates from a conditional logit model, using the same dependent variables as in columns (1) and (4). Columns (3) and (6) report estimates from a zero-one inflated beta (ZOIB) model where the dependent variable is investment (disinvestment) rate, bounded below at zero and bounded above at one. Subsector controls are Δ*Subsectoral BDI* and *Cash Flow*, and are defined in Table 2. *Uncertainty* is the quarterly average of annualized daily implied volatility of nearest-to-money American call options expiring at the end of the next quarter, averaged across all firms operating in a given subsector, weighted by the number of ships they operate in the subsector. The *Liquidity* measure is defined as the price premium, which is the quarterly average resale price minus the purchase price divided by the purchase price, across all used ship transactions in a given subsector. Firm fleet controls are the average *Age*, *DWT*, and *RPM* of ships held by the firm-subsector in the lagged quarter. Fixed effects for headquarter country, firm, subsector, and year-quarter are included as indicated. We opt for a reduced set of fixed effects when estimating the conditional logit model and ZOIB model as the estimation routines for these models do not converge under the full set of baseline fixed effects (due to the incidental parameters problem). All regressions are estimated over the 2006–2019 period. t-statistics are reported in parentheses, computed using robust standard errors clustered by firm-subsector and year-quarter.

Panel A: Investment and Disinvestment Measured at Longer Horizons

	Investment		Disinvestment	
	Semi-Annual	Annual	Semi-Annual	Annual
	(1)	(2)	(3)	(4)
Uncertainty	–0.210***	–0.432***	–0.122***	–0.314***
	(–3.88)	(–4.12)	(–3.94)	(–2.87)
Liquidity	0.439***	0.726***	0.564***	0.918***
	(4.84)	(3.87)	(5.39)	(4.40)
Uncertainty × *Liquidity*	0.031***	0.040***	0.038***	0.072***
	(3.68)	(4.54)	(4.19)	(5.71)
Liquidity Measure	Price Premium	Price Premium	Price Premium	Price Premium
Controls				
Subsector	Yes	Yes	Yes	Yes
Firm-Subsector Fleet	Yes	Yes	Yes	Yes
Fixed Effects				
Country × Time	Yes	Yes	Yes	Yes
Firm × Subsector	Yes	Yes	Yes	Yes
Observations	52,684	27,780	52,684	27,780
Adjusted R^2	0.049	0.049	0.055	0.055

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Panel B: Accounting for Zero Investment and Disinvestment						
	Investment			Disinvestment		
	LPM	Logit	ZOIB	LPM	Logit	ZOIB
	(1)	(2)	(3)	(4)	(5)	(6)
Uncertainty	–0.027***	–0.036***	–0.070***	–0.015***	–0.022***	–0.009***
	(–4.32)	(–3.53)	(–3.67)	(–4.97)	(–3.58)	(–5.14)
Liquidity	0.066	0.142	0.216**	0.181	0.212	0.074
	(0.90)	(0.70)	(2.05)	(0.02)	(0.45)	(0.67)
Uncertainty × *Liquidity*	0.011***	0.024***	0.032***	0.022***	0.017***	0.031**
	(3.09)	(3.05)	(5.08)	(4.53)	(4.41)	(2.01)
Liquidity Measure	Price Premium	Price Premium	Price Premium	Price Premium	Price Premium	Price Premium
Controls						
Subsector	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Subsector Fleet	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Country × Year-Quarter	Yes	No	No	Yes	No	No
Firm × Subsector	Yes	No	No	Yes	No	No
Subsector	No	Yes	Yes	No	Yes	Yes
Year-Quarter	No	Yes	Yes	No	Yes	Yes
Observations	99,928	48,693	82,606	99,928	55,998	82,606
Adjusted R^2	0.088	NA	NA	0.076	NA	NA
Pseudo R^2	NA	0.079	0.247	NA	0.124	0.118

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.