WAVES IN SHIP PRICES AND INVESTMENT*

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We study the link between investment boom and bust cycles and returns on capital in the dry bulk shipping industry. We show that high current ship earnings are associated with high used ship prices and heightened industry investment in new ships, but forecast low future returns. We propose and estimate a behavioral model of industry cycles that can account for the evidence. In our model, firms overextrapolate exogenous demand shocks and partially neglect the endogenous investment response of their competitors. As a result, firms overpay for ships and overinvest in booms and are disappointed by the subsequent low returns. Formal estimation of the model suggests that modest expectational errors can result in dramatic excess volatility in prices and investment. *JEL* Codes: E32, L16, G02.

I. Introduction

Boom-bust cycles in investment are among the most studied phenomena in macroeconomics. Since Kydland and Prescott (1982), it has been understood that these cycles are more pronounced in settings in which there is a lag between investment plans and their realization. Economists have sought to understand how a variety of frictions, including time-to-build delays and other adjustment costs, could explain the behavior of firm- and aggregate-level investment.

We show that biased expectations play an important role in driving boom-bust investment cycles in competitive industries. Firms overinvest in booms (and underinvest in busts) because they mistakenly believe that current earnings will persist. We show that in part, this is because individual firms fail to recognize the degree to which investments by other firms will affect future earnings. These errors mean that investment cycles are tightly

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linked to predictable variation in the return on capital: investment booms are followed by low returns.

Our setting is dry bulk shipping, a highly volatile and cyclical industry in which earnings, investment, and returns on capital appear in waves. This industry is an ideal setting for our analysis for two reasons. First, the industry is highly competitive, so the returns to investing depend critically on the behavior of other firms. However, because building a new ship takes 18–36 months, firms may naturally neglect their competitors' likely supply response. Second, shipping capital is quite homogeneous: individual ships differ mainly in terms of size and age. This enables us to directly measure returns on capital.

We show that returns to investing in dry bulk ships are predictable and tightly linked to boom-bust cycles in industry investment. Using monthly data from 1976 to 2011, we measure the returns to a representative firm that purchased a ship, operated it for a period of time, earning a cash flow stream in the form of lease rates, and later sold the ship. Returns to owning a ship are enormously volatile, but also predictable. We show that high current ship earnings are associated with higher ship prices and higher industry investment, but predict low future returns on capital. The economic magnitude of return predictability is large: our baseline regressions suggest that expected one-year forward excess returns range from −36% to +24%.

One should not be surprised that ship earnings and returns fluctuate significantly over time. Supply is essentially fixed in the short run due to time-to-build delays. Coupled with inelastic demand for shipping services, this means that temporary imbalances between global demand for shipping cargo and the size of the fleet can lead to large changes in ship lease rates.

At the same time, fluctuations in short-term lease rates do not imply anything about the expected returns on shipping capital. Consider a neoclassical benchmark in which the required return on capital is constant over time. What is the competitive response to an unexpected jump in shipping demand in such a setting? Current earnings would temporarily spike, raising contemporaneous realized returns. But firms would respond to the spike in earnings by building additional ships. Over time, earnings would fall back to their steady-state level as more ships were added to the fleet. The prices of used ships—which are long-lived capital assets—would initially jump modestly in anticipation of heightened near-term cash flows, before gradually returning to their steady state. In equilibrium, enough ships would be ordered to bring the expected return to investing in ships down to the required return. In short, the combination of forward-looking rational behavior on the part of ship owners and competitive industry dynamics would ensure that earnings exhibit a high degree of mean reversion but that expected returns were constant.

Although this benchmark is appealing, it is inconsistent with the fact that boom-bust investment cycles are linked to predictable variation in the returns on shipping capital. What can explain these patterns? A first possible explanation is that the required return on shipping capital varies over time. In this case, investment is high during booms, but prices are fair because investors require lower returns going forward. However, we argue that the variation in expected returns is too large and disconnected from traditional proxies for cyclical risk premia to be understood this way. Moreover, we show that investing in ships is far riskier in booms than it is in busts.

We argue that a more natural explanation is that there is overinvestment in booms because firms mistakenly believe that abnormally high profits will persist into the future. Models in which market participants extrapolate exogenously given profits are common in behavioral finance (e.g., Barberis, Shleifer, and Vishny 1998). In a competitive industry, however, profits are not exogenous but are an equilibrium outcome that reflects the aggregate supply response to demand shocks. It follows that firms may overextrapolate profits either because they overestimate the persistence of the exogenous demand shocks facing the industry or because they do not fully foresee the natural long-run endogenous supply response to those demand shocks.

Both types of errors are plausible. The idea that firms may overextrapolate future demand is related to the well-known representativeness heuristic in which subjects draw strong conclusions from small samples of data (Tversky and Kahneman 1974; Rabin 2002). The idea that firms may neglect the long-run response of supply to demand shocks is more subtle, but is supported by laboratory evidence. Camerer and Lovallo (1999) describe a number of experiments in which subjects overestimate their own skill in responding to common shocks and underestimate the skill and responsiveness of their competitors. This reflects a form of boundedly rational behavior that we refer to as "competition neglect." Informal references to competition neglect appear in narrative accounts of the dry bulk shipping industry.

This is natural, because as Kahneman (2011) notes, competition neglect can be particularly strong when firms receive delayed feedback about their investment decisions.

To interpret the empirical evidence, we adapt the standard q-theory model of industry investment dynamics in which firms compete to produce homogeneous services from a long-lived capital asset. Specifically, we explore how industry dynamics change when firms hold biased beliefs about the persistence of exogenous demand shocks and about the endogenous supply response of their competitors. In the absence of these biases, the return on capital is unpredictable by construction.

We introduce competition neglect to the model by assuming that each firm underestimates the investment response of its rivals by a constant proportion. Because this expectational error affects the current price of capital and current industry investment, these errors have a real impact on the future cash flows generated by capital. Specifically, a positive demand shock leads to overinvestment, which predictably depresses future lease rates and ship prices. Even though the required return on capital is constant, firms' tendency to underestimate the competition generates predictable variation in returns. We also allow firms to overestimate the persistence of the exogenous demand process. Similar to the case in which firms neglect the competition, allowing for demand extrapolation implies that high current levels of industry demand are associated with overinvestment and low future returns.

We estimate the model parameters using a simulated minimum distance estimator (Gourieroux, Monfort, and Renault 1993; Newey and McFadden 1994). This estimator chooses parameters such that the simulated data from our model best matches key aspects of the real-world data. The main parameters of interest are the degree of competition neglect among market participants and the degree of demand overextrapolation. We estimate the degree of competition neglect to be about 45%. This means that firms do not fully anticipate the investment response of their peers when reacting to demand shocks. At the same time, market participants are partially forward-looking and anticipate a portion of the industry supply response. We estimate the true persistence of demand shocks to be 0.60 on an annual basis, with market participants behaving as if they believe persistence were 0.70. In summary, our estimates suggest that modest expectational errors can result in dramatic excess volatility in prices and investment.

How do we separately identify demand overextrapolation and competition neglect in our estimation? The ideal experiment to isolate competition neglect would be to examine the industry response to a large shock to fleet supply that was unrelated to the demand—for example, if a large number of ships sank at the same time. In practice, it is hard to envision an important economic shock that would satisfy this exclusion restriction. Instead, we isolate these effects using two features of the data. A first feature that allows us to identify both effects is the fact that both earnings and investment negatively forecast future returns in a multivariate forecasting regression. This multivariate pattern suggests that two separate biases are at work. The second relevant feature of the data comes from the joint behavior of prices and earnings. Despite the fact that the actual autocorrelation of earnings is quite low, ship prices are highly volatile, suggesting that the autocorrelation of earnings perceived by firms is quite high. Allowing for both competition neglect and demand overextrapolation helps match the high volatility of prices while keeping the autocorrelation of earnings low.

Our article adds a natural behavioral twist to the neoclassical q-theory theory of firm investment in competitive settings (Abel 1981; Hayashi 1982; Abel and Eberly 1994). Particularly relevant is Kalouptsidi (2014), who develops a fully rational model of shipping industry investment that features constant required returns and procyclical time-to-build delays (in Section V, we explain how our findings relate to her results). Our main contribution to the investment literature is to show that moderate behavioral biases can generate dramatic volatility in investment and the price of capital along with the attendant predictability in returns. In this regard, our article is related to the cobweb model of industry cycles, first suggested by Kaldor (1934).[1] According to the cobweb theory, producers set quantities one period in advance under the naive assumption that current prices will persist, which generates predictable oscillations in prices and quantities. Indeed, the cobweb is a limiting case of our model when firms completely neglect the competition and radically overextrapolate demand.

1. See also Ezekiel (1938), Nerlove (1958), Muth (1961), Freeman (1975), and Rosen, Murphy, and Scheinkman (1994).

Our findings are also related to an extensive literature in asset pricing that documents return predictability in stock and bond markets (see Cochrane 2011). Some of this literature invokes behavioral forces to explain predictability, including investors' extrapolation of past returns (Greenwood and Shleifer 2014; Barberis et al. 2015). However, in contrast with much asset pricing literature, here we directly analyze the returns on real capital investments, as opposed to the more common approach of studying the returns on financial claims on corporate cash flows.[2] There is also a small literature on the link between prices and earnings in dry bulk shipping (Alizadeh and Kavussanos 2001; Adland and Koekebakker 2004; Alizadeh and Nomikos 2007), although this literature has not studied the link between investment and returns.

The next section provides a brief overview of the dry bulk shipping industry and describes our data. Section III summarizes the relationships between ship earnings, used ship prices, industry investment, and the future returns on shipping capital. These patterns motivate a behavioral model of industry cycles that we develop in Section IV. Section V estimates the model using a simulated minimum distance estimator. Section VI concludes.

II. Dry Bulk Carriers: Earnings, Prices, and Investment

In this section, we describe key features of the dry bulk shipping industry. We then discuss our data on ship earnings and used ship prices, which we use to measure the returns on a representative investment in shipping capital, as well as our data on industry-wide investment. Our monthly time-series data on the industry come from Clarkson, the leading ship broker and provider of data to shipping market participants. Summary statistics for our sample, which runs from January 1976 to December 2010, are listed in Table I.

II.A. Background on Dry Bulk Shipping

Solid commodities—primarily iron ore, coal, and grains—are transported in large cargo ships known as dry bulk carriers. In 2011, bulk carriers had a combined capacity of 609 million

2. Many papers have studied the returns to real estate investments (see the survey by Ghysels et al. 2012). However, we are not aware of any publications studying investment return predictability in capital-intensive industries in a manner analogous to our article.

TABLE I

SUMMARY STATISTICS

Variable	N	Mean	Median	Std. dev.	Min	Max	ρ_1	ρ_{12}	ρ_{24}
Panel A: annual real ship earnings and real ship prices (January 1976–2010)									
Π	420	4.09	2.77	4.07	−0.58	26.37	0.96	0.21	−0.11
Π (gross)	420	5.40	4.00	4.61	0.64	30.05	0.96	0.24	−0.07
P	420	32.74	30.79	15.08	11.41	98.78	0.98	0.51	0.23
$\frac{\Pi}{P}$	420	0.11	0.11	0.06	−0.02	0.33	0.93	0.21	−0.13
Panel B: fleet dynamics (January 1976–2010)									
$Deliveries_{t+1}$	420	0.065	0.062	0.034	0.018	0.186	0.98	0.53	0.08
$Demolition_t$	420	0.017	0.013	0.014	0.001	0.063	0.99	0.66	0.27
Inv_t	420	0.048	0.047	0.039	−0.031	0.175	0.98	0.56	0.15
Panel C: order book dynamics (January 1996–2010)									
$NetContracting_t$	169	0.114	0.090	0.101	0.029	0.443	0.99	0.39	−0.04
$Orders_t$	180	0.269	0.147	0.230	0.072	0.789	0.99	0.80	0.47
Panel D: ship excess returns (various date ranges)									
rx_{t+1}	420	0.094	0.088	0.307	−0.672	0.875	0.96	0.04	−0.14
rx_{t+2}	408	0.202	0.137	0.443	−1.030	1.195	0.98	0.44	−0.11
rx_{t+3}	396	0.311	0.237	0.523	−0.746	1.499	0.99	0.66	0.22

Notes. This table shows the mean, median, standard deviation, extreme values, and 1-month, 12-month, and 24-month autocorrelation coefficients for the main time-series data used in the article. All variables are based on time-series data on the dry bulk shipping industry provided by Clarkson. The sample is monthly and runs from January 1976 from December 2010, with the exception of order book data, which is only available beginning in January 1996. Panel A provides summary statistics for real ship earnings and real ship prices. Real earnings are revenues minus costs and expressed in December 2011 dollars. All nominal figures are converted to December 2011 dollars using the U.S. Consumer Price Index. Earnings (Π) are net of economic depreciation, assumed to equal 4% of the initial ship price, while gross earnings do not account for economic depreciation. The real price (P) is the price of a five-year old ship in December 2011 dollars. Panel B shows fleet dynamics. $Deliveries_{t+1}$ is deliveries over the following 12 months, $Demolition_t$ is demolitions over the past 12 months, and $Inv_t = Deliveries_{t+1} - Demolition_t$. Each of these variables is scaled by the time t fleet size. Panel C summarizes order book dynamics. Specifically, $NetContracting_t$ is net contracting (new contracting minus cancellations) over the past 12 months, and $Orders_t$ is the current size of the order book, both scaled by the time t fleet size. Panel D summarizes the log excess returns on ships at a one-, two-, and three-year horizon (rx_{t+k}). The one-year holding period return for a used ship is defined as net earnings over the 12-month period plus the capital gain from selling the ship at the price in 12 months, all divided by the initial ship price. Our measures of ship earnings, prices, and returns in Panels A and D are based on 76,000 DWT Panamax ships. However, fleet and order book dynamics data shown in Panels B and C are for the entire dry bulk carrier fleet.

deadweight tonnes (DWT) across 8,868 ships with a combined market value of approximately $180 billion. The market for shipping dry bulk cargo is highly competitive with hundreds of firms operating ships, and no single firm owning more than a few percent of the fleet.[3]

3. There are few, if any, barriers to entry in dry bulk shipping and few scale economies to operating a larger fleet. The average shipping firm in recent years only owns five ships (Stopford 2009) and the top 19 owners (excluding the Chinese

The demand for shipping bulk cargo is volatile and driven by the amount of seaborne bulk trade. There are many determinants of demand: while seaborne bulk trade is tied to global economic growth, it is also heavily affected by evolving geographic trade patterns and geopolitical events (Stopford 2009). The combination of inelastic demand for shipping—there are few cost-effective alternatives for the international transport of bulk goods—and fixed short-term supply implies that market imbalances would lead to large changes in ship lease rates. As a result, industry earnings are only weakly linked with economic growth: we estimate the correlation between the annual growth in ship earnings and annual U.S. GDP growth to be 0.11.

Figure I shows the composition of the dry bulker fleet over time. The fleet consists of smaller ships (Handymax and Handysize), mid-sized ships (Panamax), and larger ships (Capesize). Ships of different sizes are close substitutes because they provide a homogeneous service. Consequently, earnings and prices are nearly perfectly correlated across different ship sizes. For instance, the time-series correlation between the price of five-year old Capesize ships and five-year old Panamax ships is 0.97. Investment in different ship sizes has also been highly synchronized. Figure I, Panel B shows that if we define investment as the 12-month percentage change in capacity (in DWT), there is a high correlation between investment in Panamax ships and fleet-wide investment.

II.B. Data on Ship Earnings and Prices

Ship owners generate income by leasing out their vessels for a defined period in the "time charter" market. In this market, a charterer pays the owner a daily lease rate for the life of the contract, typically 12 months. The owner furnishes the charterer with the ship and must pay for the crew and maintenance, but the remaining costs, including fuel, are borne by the charterer. We use these lease rates to compute earnings and holding period returns, which conveniently normalizes the holding period to one year.

We compute net earnings, defined as the real (constant 2011 dollars) cash flows, net of costs, earned by leasing a ship out over

government–owned COSCO) held only 20% of industry capacity in 2006 (Bornozis 2006).

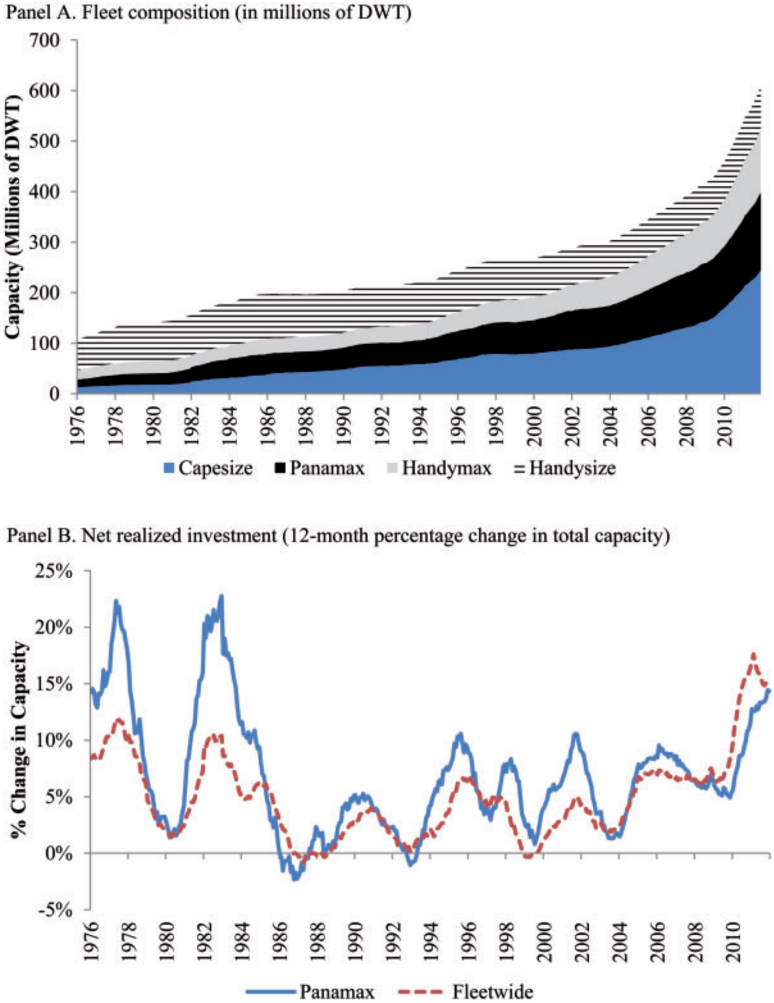

FIGURE I

The Dry Bulk Carrier Fleet

This figure illustrates the evolution of the dry bulk carrier fleet. Panel A shows the composition the dry bulk carrier fleet from 1976 to 2011 in deadweight tonnes (DWT). Handysize ships carry 10,000–35,000 DWT, Handymax ships carry 35,000–59,000 DWT, Panamax ships carry 60,000–80,000 DWT, and Capesize ships carry more than 80,000 DWT. Panel B shows a simple measure of net realized investment—the 12-month percentage change in capacity—for the entire fleet as well as for Panamax ships.

the next year. Clarkson provides us with monthly estimates of the 12-month lease rate for different ships based on recent transactions and its polling of brokers.[4] For simplicity, our measure of ship earnings is based on time charter rates for Panamax ships—a mid-sized bulk carrier that is representative of the broader fleet. However, as shown in the Online Appendix, our results are not sensitive to this choice.[5]

For a five-year old ship, the owner earns the lease rate for an average of 357 days a year; the boat is docked for maintenance for the remaining 8 days a year. Although the lessor pays fuel and insurance costs, the ship owner must provide a crew at a daily cost estimated to be \$6,000 a day in 2011 dollars (based on Table 8.4 in Stopford 2009). Thus, real annual earnings are:

$$\Pi_t = 357 \cdot DailyLeaseRate_t - 365 \cdot DailyCrewCost_t - Depreciation_t, \quad (1)$$

where *DailyLeaseRate*, *DailyCrewCost*, and *Depreciation* are expressed in constant 2011 dollars using the CPI index. *Depreciation* refers to economic depreciation: after 12 months of operation, a five-year-old ship is now a slightly less valuable six-year-old ship because it offers one less year of future services. If we had data on the prices of both five-year-old and six-year-old ships, we could measure economic depreciation directly. Since we only have data on the prices of five-year-old ships, we assume that the annual depreciation cost equals 4% of the ship's initial market price, reflecting a 25-year average economic life ($\frac{1}{25} = 4\%$). Because economic depreciation is assumed to be a constant fraction of the ship's initial market price, this only affects the average return on ships and has no effect on any of the forecasting results that follow.[6]

4. To verify data reliability, we obtained microdata on lease rates and prices for a sample of transactions between December 2009 and November 2012. Monthly averages of lease rates were 98.2% correlated with the lease rate series from Clarkson. The average sale price for five-year-old Panamax ships was 99.8% correlated with our price series.

5. Our earnings series is for 65,000 DWT ships and our price series if for 76,000 DWT ships. To be consistent, we multiply the lease rate for 65,000 DWT ships by $76 \div 65$. However, this adjustment makes little difference.

6. This depreciation cost can be thought of as the sum of two components. First, a ship owner must pay a small out-of-pocket maintenance cost so that he starts the next year with a six-year-old ship that is in good working order. Second, a six-year-old ship in good working order is worth less than a five-year-old ship in good working order.

Although our estimate of ship earnings is an approximation, it is consistent with the approach used by other researchers (Alizadeh and Nomikos 2006; Stopford 2009) and case studies of the shipping industry (Stafford, Chao, and Luchs 2002; Esty and Sheen 2011).

The time-series of net earnings is shown in Figure II. Real ship earnings are highly volatile. Annual earnings had a monthly standard deviation of \$4.1 million, compared to a mean of \$4.1 million. Figure II also shows that earnings are rapidly mean-reverting. Whereas the 1-month autocorrelation of our earning series is 0.96, the autocorrelation at a 12-month horizon is only 0.21 and turns slightly negative (–0.11) at a 24-month horizon. This high degree of estimated mean reversion is not sensitive to the time period in question: the 24-month autocorrelation of earnings is −0.12 is the first half of our 1976–2010 sample and −0.11 in the second half.

New ships can be ordered through shipyards or purchased on a used basis in a liquid secondhand market. In recent years, at least 10% of the bulker fleet has traded on a secondary basis each year (Kalouptsidi 2014). According to Stopford (2009), adverse selection is not a significant concern in this market.[7] Just as with many financial assets, there is a large common time-series component of prices that is shared by ships of all sizes and ages.[8] We focus on this common time-series component and, as with earnings, proxy for this component using the price of a five-year-old Panamax ship. We express the price in constant 2011 dollars. As shown in Figure II, the real price closely tracks real earnings throughout the 1976–2010 period: the correlation between real earnings and prices is 0.87 in levels and 0.91 in 12-month changes.

Although real earnings and real prices are highly correlated, the ratio of earnings to price is far from constant. When real earnings are high, real ship prices are also high, but prices do not rise proportionately, leading to a higher ratio of earnings to

7. Bulk carriers are like cars that always drive 60 mph on an empty highway. Thus, age, mileage, and maintenance history—all of which are publicly observable—are sufficient statistics for value.

8. Kalouptsidi (2014) finds that the cross-sectional coefficient of variation of individual ship prices (cross-sectional standard deviation divided by the cross-sectional mean) is only 13% in the typical quarter over her 1998–2010 sample.

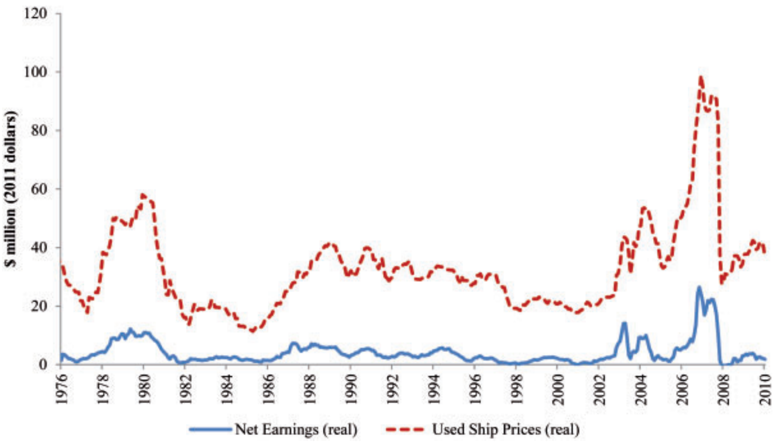

FIGURE II

Real Earnings and Prices for Dry Bulk Carriers

This figure plots the real earnings and used prices for 76,000 DWT Panamax dry bulk carriers from 1976 to 2010. Real earnings are revenues minus operating costs and economic depreciation and are expressed in December 2011 dollars. Economic depreciation is 4% of the initial ship price. The real price (P) is the price of a five-year-old ship in December 2011 dollars.

prices. This is precisely what one would expect if firms understand that real earnings are mean reverting.

II.C. Returns on Shipping Capital

Using earnings and prices, we can compute the holding period return for an investment in ships. The one-year holding period return on a ship is the 12-month change in the used price P, plus the net earnings Π accruing to an owner who signed a 12-month lease immediately after purchasing the ship, scaled by the initial used price

$$R_{t+1} = \frac{P_{t+1} - P_t + \Pi_t}{P_t} \tag{2}$$

We use used prices instead of new prices because a buyer of a used ship has immediate access to the ship and thus its rental income. As is common in asset-pricing studies, we forecast excess returns as opposed to raw returns. Thus, our main dependent variable is the log excess return on ships, defined as

$rx_{t+1} = \log\ (1 + R_{t+1}) - \log\ (1 + R_{f,t+1})$.[9] To compute multiyear excess log returns, we assume a ship owner signs a new 12-month time charter each year. Thus, we can compute multiyear cumulative excess returns by summing one-year log excess returns. Table I shows that holding period returns are incredibly volatile: average one-year excess returns are 9%, with a standard deviation of 31%. In the Online Appendix, we compare our return series with the annual "return on shipping investments" series computed by Stopford (2009): the correlation between the two is 0.92.

II.D. Data on Investment Plans: The Order Book

At the industry level, investment occurs only when a new ship is purchased, not when a used ship changes ownership. Beginning in 1996, Clarkson provides monthly data on the industry order book, which is the ledger of ships that have been ordered at shipyards around the world. The order book evolves according to

$$(3)\quad Orders_{t+1} = Orders_t + Contracting_t - Deliveries_t - Cancel_t.$$

Thus, the change in the order book in year t equals new orders (*Contracting*), minus ships delivered in that year (*Deliveries*), minus previous orders that were cancelled (*Cancel*). All items in equation (3) are in DWT and therefore reflect changes in the total industry-wide fleet capacity.

Based on equation (3), we construct two measures of investment plans, all scaled by current fleet size: net contracting activity (i.e., contracting minus cancellations) over the past 12 months ($NetContracting_t$) and the size of the current order book ($Orders_t$). The average size of the order book is 27% of the fleet during the 1996–2010 period for which we have order data. As shown in Table I, investment is extremely volatile: in the peak year, net contracting amounted to 44% of the existing stock of ships.

9. We measure the 12-month nominal return on riskless government bonds by cumulating the monthly *RF* series from Ken French. Since we subtract off the nominal riskless return, we compute nominal shipping returns in equation (2).

II.E. Data on Investment Realizations: Changes in Fleet Capacity

The fleet size evolves according to

$$Fleet_{t+1} = Fleet_t + Deliveries_t - Demolitions_t + Conversions_t - Losses_t, \quad (4)$$

with all terms expressed in DWT. Changes in the bulker fleet are primarily driven by deliveries (when new ships come online and fall out of the order book) and demolitions (when old ships are scrapped). *Conversions* and *Losses* capture rare events in which ships are repurposed from one use to another (e.g., a tanker is converted to a bulk carrier) or are lost in accidents.

The *Deliveries* term in equation (4) represents the realization of past investment plans. Once ordered, a ship typically takes 18–36 months to be built and delivered (Kalouptsidi 2014).[10] *Demolitions* are driven by the aging of the fleet—as ships become older, they become more costly to maintain and eventually must be scrapped. However, the demolition of an old ship may be postponed when current lease rates are high and accelerated when current lease rates are low. Thus, aggregate *Demolitions* partially reflect active disinvestment decisions made by ship owners.

Figure III, Panel A shows deliveries and demolitions since 1976 (these data are available for a longer period than the order book data). The dashed line shows the net change in fleet-wide capacity, computed according to equation (4), and scaled by current fleet size. The fleet has grown from 100 million DWT in 1976 to over 600 million DWT in 2011. Panel B shows that deliveries commove strongly with lagged earnings: when earnings are high, more ships are ordered with new deliveries hitting the market a few years later.

III. Predictability of Shipping Returns

We now investigate the relationship between current earnings, prices, investment, and the subsequent returns to ship

10. Time-to-build delays increase during booms (Kalouptsidi 2014). Thus, a buyer could be justified in paying a higher price for a used than a new ship when current lease rates are high. Such a dynamic occurred in 2007–2008.

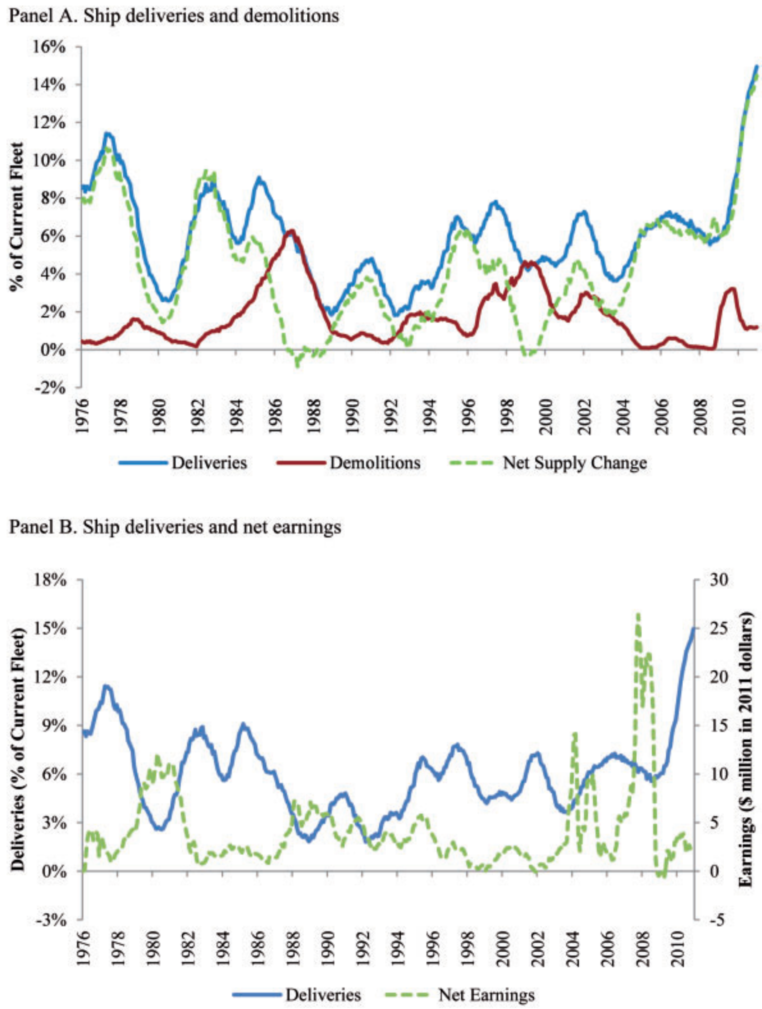

FIGURE III

Co-movement of Investment with Earnings

Panel A shows ship deliveries, demolitions, and the total net change in supply from 1976 to 2010, all expressed as a percentage of the current fleet size. Panel B shows deliveries and current net earnings.

owners. We start with a simple calculation suggesting that ship prices are far too volatile given the rapid mean reversion in earnings. We then demonstrate this result more formally using return forecasting regressions.

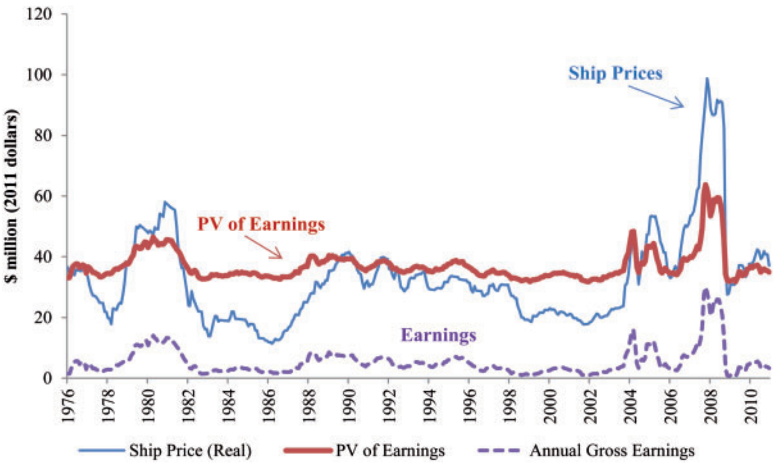

FIGURE IV

Pricing of Dry Bulk Carriers: Model-Implied Present Value versus Market Price of a Used Ship

Our present value calculation is based on the pattern of mean reversion in gross ship earnings. We use a 13% constant real discount rate. The calculation assumes that the ship owner will earn the current time charter rate for the next 12 months (less operating costs), 0.24 times the current gross earnings plus 0.76 times the sample average level of gross earnings ($5.4 million) from months 12 to 24, after which they will earn the sample average of real gross earnings. Ships older than 15 years earn 85% of the long-run average. At year 25, we assume the ship will be scrapped and the estimated scrap value is based on Clarkson data. The mean of model-implied PV series is $37.0 million and the mean of actual ship prices is $32.7 million. The volatility of model-implied PV series is $5.0 million and the volatility of actual ship prices is $15.1 million.

III.A. A Suggestive Present Value Calculation

A simple way to evaluate the apparent volatility in used ship prices is to consider a benchmark in which discount rates are constant. In the spirit of Shiller (1981), Figure IV plots the actual time series of used ship prices versus a simple model-implied present value of ship earnings based on a constant 13% real discount rate, which ensures that the average model-based price is close to the time-series average of prices. To calculate the present value, we assume that the buyer of a five-year-old ship receives the current lease rate for 12 months (less operating costs) following purchase, and then signs a new lease in 12 months. We estimate the rate on this new lease based on the time-series autocorrelation of lease rates for the full sample. After this initial two-year period, we assume the buyer receives the sample average real gross earnings of \$5.4 million each year. This is a reasonable since there is no correlation between current earnings and those after 24 months. Because older ships tend to lease at lower rates (Stopford 2009), we make a proportional adjustment once the ship is 15 years old, reducing earnings by 15%. Finally, we assume that ships have an economic life of 25 years, so a five-year-old ship will be scrapped in 20 years and the owner will receive a scrap value. The details of this calculation are provided in the Online Appendix.

Figure IV shows that the model-implied present value of the cash flows from a ship are considerably less volatile than actual ship prices. Consistent with Shiller (1981) and subsequent work on the excess volatility of asset prices (e.g., Campbell 1991), the standard deviation of model-implied present values is \$5.0 million, compared with a standard deviation of \$15.1 million for used ship prices. This discrepancy is driven by the fact that the present value calculation is not very responsive to changes in current earnings, which are expected to be almost completely reverted away one year later. In contrast, actual market prices are extremely responsive to current ship earnings. Taken together, this suggests that investors value ships as if they anticipate considerably less mean reversion in earnings than there has been in the actual data.

III.B. Earnings, Prices, and Future Returns

Although Figure IV is suggestive of episodes of mispricing, it is clearly sensitive to our model of fair value. To avoid having to construct a model-implied notion of fair value, we adopt the standard asset-pricing approach of using time-series variables to forecast excess returns. This approach originates from a simple idea: if required excess returns are constant and ships are always fairly priced, then expected excess returns should equal required excess returns at each date and hence returns should be unpredictable. If excess returns are instead predictable, this must either be because ship owners have time-varying required excess returns that move with the forecasting variable, or because the forecasting variable is linked to temporary mispricing.[11]

11. Although expected excess returns are constant under this benchmark null, expected raw returns may fluctuate due to movements in riskless interest rates; this is why we forecast excess returns rather than raw returns.

We organize our empirical investigation around forecasting regressions of the form

$$rx_{t+k} = a + b \cdot X_t + u_{t+k}, \tag{5}$$

where rx_{t+k} denotes the k-year log excess return between t and $t+k$ and X_t denotes real earnings, real prices, or investment at time t. The k-year forecasting regressions are estimated with monthly data. To deal with the overlapping nature of returns, we report Newey and West (1987) standard errors allowing for serial correlation at up to $1.5 \times 12 \times k$ monthly lags—for example, we allow for serial correlation at up to 18 months in our one-year (12-month) forecasting regressions.

We begin by studying the relationship between current earnings and future returns. This relationship is illustrated in Figure V, Panel A, where we plot current earnings versus future two-year excess returns. The figure shows that when current real earnings are high, future returns are low. Current earnings negatively predict returns because ship prices react strongly to transient movements in earnings. Table II reveals that this pattern holds over both shorter and longer holding periods. For one-year returns, the regression coefficient is −0.020. This means that a 1 standard deviation increase in real earnings leads to an 8 percentage point decline in expected returns over the following year. The results for two-year returns are approximately twice that magnitude: a 1 standard deviation increase in earnings leads to a 16 percentage point decline in expected returns over the next two years. The magnitudes are impressive given the mean and volatility of shipping returns: one-year returns have a mean of 9% and a standard deviation of 31%.

The middle columns of Table II show that used ship prices also negatively forecast returns. Because ship prices react strongly to transient movements in earnings, the ability of ship prices to predict future earnings is limited, so high prices negatively predict future returns. This is perhaps not surprising given the strong positive correlation between prices and earnings. However, the economic magnitude of these results is stunning. A 1 standard deviation increase in real prices ($15.1 million) is associated with a 10 percentage point decline in future one-year returns. At the peak price of $98.9 million in November 2007, the regression implies that the expected excess return over the following year was −36% (the subsequent realized one-year excess

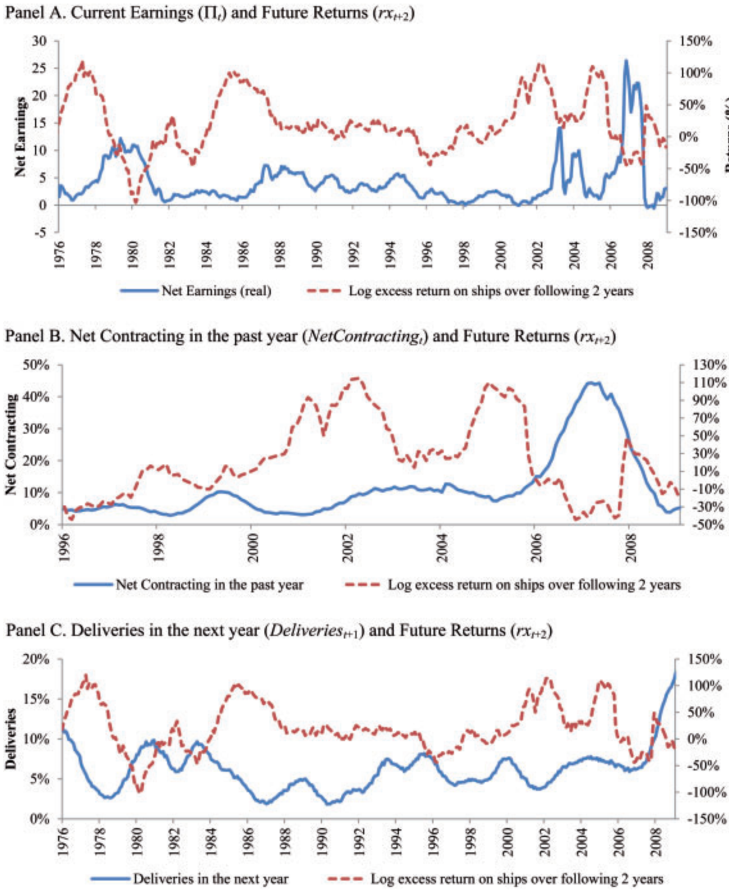

FIGURE V

Forecasting Future Returns

This figure illustrates the relationship between several forecasting variables and the future excess return on ships over the following two years. Panel A shows the relationship between current earnings and future returns; Panel B shows the relationship between net contracting over the past 12 months and future returns; Panel C shows the relationship between deliveries in the following 12 months and future returns.

return was –66%). The volatility of our one-year excess return forecasts based on ship prices is 10.3%. This can be compared with the volatility of expected excess returns on the U.S. stock market of 5.5% a year, which Cochrane (2011, Table I) argues is "a lot."

TABLE II

FORECASTING SHIP RETURNS USING SHIP EARNINGS AND PRICES

	X = real earnings Π			X = used ship price P			X = earnings yield $\frac{\Pi}{P}$		
k	1-year	2-year	3-year	1-year	2-year	3-year	1-year	2-year	3-year
b	−0.020*	−0.039**	−0.049**	−0.007**	−0.012**	−0.016**	−0.253	−1.370	−1.896
	(0.008)	(0.012)	(0.019)	(0.003)	(0.004)	(0.006)	(0.739)	(1.091)	(1.427)
T	420	408	396	420	408	396	420	408	396
R^2	0.07	0.13	0.15	0.11	0.18	0.22	0.00	0.03	0.05

Notes. This table reports univariate time-series forecasting regressions of the form $rx_{t+k} = a + b \cdot X_t + u_{t+k}$, where rx_{t+k} denotes the k-year log excess return on ships. X alternately denotes real earnings Π, the current real price of a five-year-old ship P, or the earnings yield $\frac{\Pi}{P}$. The k-year forecasting regressions are estimated with monthly data, so we are forecasting excess returns over the following $12 \times k$ months. To deal with the overlapping nature of returns, in parentheses we report Newey-West (1987) standard errors allowing for serial correlation at up to $1.5 \times 12 \times k$ monthly lags—that is, we allow for serial correlation at up 18, 36, and 54 month lags, respectively, when forecasting one-, two-, and three-year returns. $^{+}$, *, and ** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

The right columns of Table II show that the ratio of earnings to price, $\frac{\Pi}{P}$, forecasts returns. When ships have high earnings relative to prices, this forecasts low future returns, albeit with modest statistical significance. This result may seem surprising given the widely known result that high earnings yields tend to forecast high future returns in a variety of different assets classes (e.g., Campbell 1991; Koijen et al. 2013). Both results can be understood using present value logic, however. Specifically, a high earnings-price yield must either forecast high future returns, low future earnings growth, or a high future earnings-price yield. In many asset-pricing settings, earnings-prices yields are persistent and have little ability to forecast cash flow growth; thus, high earnings-price yields are associated with higher future returns. In shipping, however, competition ensures that a high earnings yield strongly forecasts low future earnings growth. Since the earnings yield on ships is moderately persistent, this means that earnings yields must negatively forecast shipping returns.[12]

12. There is nothing inconsistent about the finding that earnings, price, and earnings yields all negatively forecast returns. The Campbell-Shiller (1988) return log-linearization implies that $r_{t+1} \approx \kappa + \Delta\pi_{t+1} - \phi(\pi_{t+1} - p_{t+1}) + (\pi_t - p_t)$ where $x = \log(X)$ and ϕ is a constant close to 1. Letting $\beta[y, x] = \frac{Cov[y,x]}{Var[x]}$, it is easy to show that (i) $\beta[r_{t+1}, \pi_t] < 0$ iff $\beta[p_t, \pi_t] > \beta[\pi_{t+1}, \pi_t] - \phi\beta[\pi_{t+1} - p_{t+1}, \pi_t]$—that is, earnings negatively predict returns if prices react strongly to transient movements in earnings; (ii) $\beta[r_{t+1}, p_t] < 0$ iff $1 > \beta[\pi_{t+1}, p_t] - \phi\beta[\pi_{t+1} - p_{t+1}, p_t]$—that is, prices negatively

III.C. Investment

We now show that high investment forecasts low future returns. Figure V, Panel B plots the time series of net orders of new ships ($NetContracting_t$) over the past year, expressed as a percentage of the current fleet, together with the future two-year excess returns on ships. The figure shows a negative correlation ($\rho = -0.33$). The corresponding regressions are shown in Table III. Whether we measure investment as net contracting or the outstanding order book, industry investment negatively forecasts shipping returns in the subsequent years. The coefficients of -1.010 and -1.400 shown in the first and second columns of Table III imply that a 1 standard deviation increase in $NetContracting_t$ is associated with a 10 percentage point decline in returns over the next year, and a 14 percentage point decline over the next two years combined.

The biggest limitation of these regressions is the short time series on the order book. Starting in 1976, however, we have measures of realized changes in fleet capacity. Current changes in capacity can be understood as being driven by past orders and by current demolitions. Disinvestment, as reflected in demolitions, is realized almost immediately because a ship can be scrapped shortly after the decision has been made. Thus, our measure of current disinvestment decisions is demolitions over the past 12 months, $Demolitions_t$. However, in the presence of time-to-build delays, future deliveries are the best guide to current ordering decisions. Under the assumption that orders in the past 12 months translate into deliveries in the next 12 months, we proxy for current investment using realized deliveries over the next year, $Deliveries_{t+1}$. Thus, although the deliveries data enable us to analyze a longer time series, a drawback is that our measure of current investment potentially suffers from some look-ahead bias.[13]

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predict returns if the ability of ship prices to predict future earnings is limited; and (iii) $\beta[r_{t+1}, \pi_t - p_t] < 0$ if $0 > 1 + \beta[\Delta\pi_{t+1}, \pi_t - p_t] - \phi\beta[\pi_{t+1} - p_{t+1}, \pi_t - p_t]$—that is, earnings-price yields negatively predict returns if earnings yields are persistent and negatively predict future earnings growth.

13. This look-ahead bias would only be a concern if the precise timing of deliveries depends on future demand realizations. Since cancellations drive only a small fraction of the variation in deliveries, this is not a serious concern. Specifically, from 1996 to 2011, we obtain almost identical results using raw *Deliveries* or *Deliveries* + *Cancellations*.

TABLE III

FORECASTING SHIP RETURNS USING INDUSTRY INVESTMENT

	Investment measured based on order book (1996–2010)						Investment measured based on changes in fleet size (1976–2010)								
	$X = NetContracting_t$			$X = Orders_t$			$X = Deliveries_{t+1}$			$X = Demolitions_t$			$X = Inv_t$		
k	1-year	2-year	3-year	1-year	2-year	3-year	1-year	2-year	3-year	1-year	2-year	3-year	1-year	2-year	3-year
b	−1.010*	−1.400+	−2.045*	−0.328	−0.502	−1.023+	−3.025*	−4.988*	−2.008	5.297+	9.108	12.721+	−2.941**	−4.994*	−3.858
	(0.510)	(0.713)	(0.927)	(0.251)	(0.381)	(0.576)	(1.227)	(2.075)	(3.564)	(2.949)	(5.716)	(7.370)	(0.969)	(2.081)	(3.536)
T	169	157	145	180	168	156	420	408	396	420	408	396	420	408	396
R^2	0.10	0.11	0.19	0.06	0.06	0.13	0.11	0.10	0.01	0.06	0.09	0.13	0.14	0.14	0.05

Notes. This table reports univariate time-series forecasting regressions of the form $rx_{t+k} = a + b \cdot X_t + u_{t+k}$, where rx_{t+k} denotes the k-year log excess return on ships. X alternately denotes net contracting activity over the past 12 months, the size of the order book, deliveries over the following 12 months, or demolitions over the past 12 months, each scaled by the current fleet size. In the rightmost set of columns, we forecast returns using net investment, $Inv_t = Deliveries_{t+1} - Demolitions_t$. The k-year forecasting regressions are estimated with monthly data, so we are forecasting excess returns over the following $12 \times k$ months. To deal with the overlapping nature of returns, in parentheses we report Newey-West (1987) standard errors allowing for serial correlation at up to $1.5 \times 12 \times k$ monthly lags. +, *, and ** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

In any case, the forecasting regressions using deliveries and demolitions are shown in the right columns of Table III. Both deliveries and demolitions are scaled by the fleet size at time t. High deliveries are associated with low future returns and, conversely, high current demolitions are associated with high future returns. We can combine these measures into a net investment series: $Inv_t = Deliveries_{t+1} - Demolitions_t$. This net investment variable negatively forecasts future returns and is a slightly stronger predictor than either deliveries or demolitions alone.

III.D. Bivariate Forecasting Regressions

We have shown that high levels of earnings, prices, earnings-price ratios, and industry investment each negatively forecast returns in a univariate regression. What is the joint significance of these results? We can address this question by adopting a seemingly unrelated regression approach. A test that the univariate forecasting coefficients at horizons of one and two years are jointly zero for these four variables yields a p-value less than .001.[14]

A related question is whether these different variables contain separate information about future shipping returns. Specifically, is the return forecasting ability of investment driven entirely by variation in current earnings, or do earnings and investment have separate forecasting power? Table IV shows the results of bivariate forecasting regressions using both earnings and investment

$$rx_{t+k} = a + b \cdot \Pi_t + c \cdot Inv_t + u_{t+k}. \tag{6}$$

For investment, we use deliveries minus demolitions as in the rightmost columns of Table III. The results in Table IV show that current earnings and investment contain independent information about future shipping returns. Specifically, compared to the univariate coefficients in Tables II and III, the coefficients on both earnings and investment are slightly smaller in magnitude in these multivariate regressions, but both coefficients remain statistically and economically significant.

14. We run eight time-series regressions: $rx_{t+k} = a + b \cdot X_t + u_{t+k}$ for $k = 1$ and 2 years and $X = \Pi, P, \frac{\Pi}{P}$, and Inv. We test the hypothesis that $b = 0$ in all regressions. We take a system OLS approach and estimate the joint variance matrix using a Newey-West estimator that allows residuals to be correlated within and across equations at up to 36 months.

TABLE IV
BIVARIATE RETURN FORECASTING REGRESSIONS

k	1-year	2-year	3-year
b	−0.017*	−0.034**	−0.045*
	(0.008)	(0.011)	(0.019)
c	−2.772**	−4.393*	−2.590
	(0.910)	(1.996)	(3.406)
T	420	408	396
R^2	0.19	0.24	0.18

Notes. This table reports bivariate time-series regressions of the form $rx_{t+k} = a + b \cdot \Pi_t + c \cdot Inv_t + u_{t+k}$, where rx_{t+k} denotes the k-year log excess return on ships, and the independent variables include net earnings and investment. As in the rightmost columns of Table III, net investment (Inv_t) is defined as deliveries over the next 12 months minus demolitions over the past 12 months. The k-year forecasting regressions are estimated with monthly data, forecasting excess returns over the next $12 \times k$ months. To deal with the overlapping nature of returns, in parentheses we report Newey-West (1987) standard errors allowing for serial correlation at up to $1.5 \times 12 \times k$ monthly lags. $^+$, *, and ** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

III.E. Robustness

How robust are these return forecasting results? The Online Appendix contains a battery of robustness checks, which we summarize here for the sake of brevity.

First, we show that we obtain similar results if, instead of focusing on Panamax ships, we focus on smaller Handymax ships or larger Capesize ships, or if we use the information on fleet composition from Figure I to combine these Handymax, Panamax, and Capesize series into fleet-wide series. This is not surprising given the homogeneous nature of shipping capital. Specifically, the return predictability we find on Panamax ships appears to be representative of the overall bulk carrier fleet. However, returns on larger Capesize ships are somewhat more predictable than the rest of the fleet, whereas those on smaller Handymax ships are somewhat less predictable.

Next we address a set of time-series econometric concerns. First, Figure I may suggest that our forecasting results are driven by a handful of boom-bust cycles. To some degree, this is a limitation of any time-series forecasting exercise, but we find that similar patterns hold in various subsamples. Specifically, our results are qualitatively similar if we drop the 2006–2010 "supercycle," if we focus only on the first half of the sample, or if we restrict attention to the second half. However, there is some evidence suggesting that the magnitude of return predictability has declined modestly since the first half of our sample. Second, we show that our inferences are not driven by our use of overlapping 12-month month returns. For instance, we obtain similar results if we sample the data annually and simply forecast annual returns. Third, we confirm that our forecasting results are not a consequence of the small-sample bias identified by Stambaugh (1999). Specifically, using Amihud and Hurvich's (2004) bias-adjusted estimator does not affect the magnitude or significance of our findings. This is because our forecasting variables are either not very persistent or, if they are more persistent, innovations to our forecasting variables are not sufficiently correlated with returns. Finally, we include a time trend as a control in the regressions. Although there is no theoretical justification for including a time trend, we do it to check that our results are not driven by some omitted slow-moving variable. Including a trend has little effect on the results except for the two order book variables (*NetContracting* and *Orders*), where the results are stronger when we control for the secular growth of the order book over time.

III.F. Risk-Based Explanations for Return Predictability

Faced with evidence of return predictability, a standard response in the asset-pricing literature is to argue that this must be driven by rational changes in diversified investors' required returns. Interpreting our results in this way, one would say that what appears to be overinvestment during booms reflects ship owners' willingness to invest at lower than usual returns: owners expect earnings and prices to fall as much as they do and expect future returns to be low. Thus, before turning to our behavioral interpretation of these predictability results, we first consider—and argue against—standard risk-based explanations of this sort.

One cannot simply assert that changes in expected returns correspond to shifts in rationally required returns. In standard asset pricing theories, required returns depend on the amount of risk faced by diversified investors as well as investors' willingness to bear risk. More formally, these theories imply that the required excess return on ships at time t can be written as

$$E_t[rx_{t+1}] = Corr_t[rx_{t+1}, -m_{t+1}]\sigma_t[rx_{t+1}]\sigma_t[m_{t+1}], \quad (7)$$

where the stochastic discount factor m_{t+1} depends on the marginal utility of diversified investors. Equation (7) says that time variation in required returns must either be driven by a time-varying correlation between shipping returns and investor well-being ($Corr_t[rx_{t+1}, -m_{t+1}]$), variation in the risk of shipping investments ($\sigma_t[rx_{t+1}]$), or variation in the economy-wide price of risk ($\sigma_t[m_{t+1}]$).

Is it reasonable to think that variation in the right-hand side terms in equation (7) could drive the changes in expected returns that we observe in dry bulk shipping? First, we note that the variation in expected returns documented above is large from an economic point of view—from as low as -36% to as high as +24% over a one-year holding period. Thus, a primary challenge to risk-based explanations of our findings is that they would need to invoke enormous time variation in required excess returns.

Next, we consider each of the terms of equation (7) in turn. To start, there is little reason to suspect that $Corr_t[rx_{t+1}, -m_{t+1}]$ varies significantly over time—that is, that ships have time-varying hedge value for diversified investors. There is even less reason to believe that $Corr_t[rx_{t+1}, -m_{t+1}]$ is low when ship earnings, prices, and investment are high.

Turning to the second term in equation (7), a more natural alternative is that time variation in $\sigma_t[rx_{t+1}]$ explains our results—perhaps future shipping risk is low during booms when earnings, prices, and investment are high. This hypothesis fails resoundingly in the data: current earnings, prices, and investment all strongly forecast high future volatility of ship earnings and returns.[15]

Finally, turning to the third term in equation (7), many modern asset pricing theories suggest that the economy-wide risk premia that diversified investors require to hold risky assets (i.e., $\sigma_t[m_{t+1}]$) may fluctuate over the business cycle due to changes in either the aggregate quantity of risk or in investors' willingness to bear risk (Cochrane 2011). To assess the plausibility of these theories in our setting, we ask whether expected and realized returns on ships are correlated with traditional risk premia measures and risk factors from the equity and bond market. By doing so, we are effectively asking whether the time

15. We have estimated regressions of the form $\sigma_{t+1} = a + b \cdot X_t + u_{t+1}$ where the dependent variable is the standard deviation of monthly earnings or capital gains over the following 12 months. For example, when we use current real earnings to forecast future earnings volatility, we obtain $b = 0.27$ with a t-statistic of 4.68. Similarly, current earnings positively forecasts capital gains volatility with a coefficient of $b = 0.007$ and a t-statistic of 3.16.

variation in expected shipping returns documented here can be naturally explained by an omitted economy-wide factor.

We start in Table V, Panel A by showing our main forecasting regressions, while also including proxies for economy-wide risk premia—that is, the ex ante required return on stocks or bonds—as control variables. We include the smoothed earnings yield on stocks, the term spread on long-term government bonds, and the credit spread. The first four columns show that these variables do not by themselves forecast the returns to owning ships. The remaining columns show that ability of $X = \Pi$, P, and Inv to forecast shipping returns is not impacted by the inclusion of these ex ante controls.

In Table V, Panel B, we perform similar horse races, except that we now include ex post realizations of various risk factors, including the excess return on stocks, the excess return on long-term government bonds over short-term government bonds, and the excess return on Baa-rated corporate bonds over Aaa-rated corporate bonds. These regressions effectively ask whether we can forecast the alpha from investing in ships. The first two columns in Table V, Panel B show that the returns on ships are not strongly tied to the returns on these traditional risk factors. For instance, the correlation between 24-month excess returns on ships and the U.S. stock market is only 0.09. The remaining columns in Panel B suggest that controlling for contemporaneous returns on traditional risk factors again has no effect on our key forecasting results.

Taken together, it is difficult to fully reconcile our evidence with standard risk-based theories in which required returns rationally vary over time.

IV. A Behavioral Model of Industry Cycles

A natural interpretation of our findings is that ship earnings, prices, and investment negatively forecast returns because shipping firms make systematic mistakes: biased expectations about future earnings lead firms to overinvest in booms and underinvest in busts, even if required returns are constant. These same errors explain why ship prices are so high in booms, even though earnings mean revert so rapidly in the data.

The idea that investors in the shipping market may have biased expectations is apparent in many narrative accounts of

TABLE V

Macro Risk Premium Controls: Panel A

	Ex ante risk premium controls only				Horse race regressions											
Π (ship)					−0.039**	−0.036**	−0.039**	−0.035**								
					(0.011)	(0.010)	(0.011)	(0.010)								
P (ship)									−0.013**	−0.012**	−0.013**	−0.011**				
									(0.004)	(0.004)	(0.004)	(0.003)				
Inv (ship)													−4.942**	−4.985**	−4.855*	−4.830*
													(1.894)	(1.879)	(2.129)	(1.909)
$\frac{E_{10}}{P}$ (stocks)	−1.373			1.604	−1.126			1.462	−1.884			0.168	−0.260			1.907
	(2.970)			(3.479)	(3.046)			(3.687)	(3.176)			(4.105)	(2.844)			(3.873)
TERMSPREAD		8.047		9.724+		5.715		7.301		5.188		5.779		8.009		9.625
		(5.929)		(5.677)		(5.794)		(5.727)		(5.456)		(5.803)		(5.189)		(6.124)
CREDITSPREAD			−12.937	−21.138			−12.810	−19.968			−13.216	−15.054			−3.322	−12.714
			(16.258)	(20.992)			(15.509)	(19.198)			(16.320)	(20.039)			(16.596)	(22.428)
T	408	408	408	408	408	408	408	408	408	408	408	408	408	408	408	408
R^2	0.01	0.05	0.02	0.09	0.14	0.16	0.15	0.19	0.20	0.21	0.21	0.23	0.14	0.20	0.15	0.21

TABLE V

MACRO RISK PREMIUM CONTROLS: PANEL B

	Ex post risk factors only		Horse race regressions					
Π (ship)			−0.040**	−0.042**				
			(0.012)	(0.015)				
P (ship)					−0.013**	−0.013*		
					(0.004)	(0.005)		
Inv (ship)							−4.974*	−4.398*
							(2.098)	(2.101)
rx_{STOCKS}	0.175	0.248	−0.029	0.057	−0.090	0.004	0.161	0.190
	(0.232)	(0.337)	(0.229)	(0.284)	(0.267)	(0.285)	(0.223)	(0.289)
$rx_{LONG-SHORT}$		−0.886**		−0.938**		−0.926**		−0.716*
		(0.272)		(0.204)		(0.219)		(0.335)
$rx_{BAA-AAA}$		−0.066		−0.270		−0.325		0.270
		(1.447)		(1.353)		(1.334)		(1.310)
T	408	408	408	408	408	408	408	408
R^2	0.01	0.11	0.13	0.25	0.19	0.3	0.15	0.22

Notes. This table repeats the time-series return forecasting regressions from Table II and Table III adding ex ante and ex post measures of macro risk premia from U.S. equity and bond markets. The time-series regressions take the form $rx_{t+2} = a + b \cdot X_t + c \cdot Z_t + u_{t+2}$ and $rx_{t+2} = a + b \cdot X_t + d \cdot f_{t+2} + u_{t+2}$, where rx_{t+2} denotes the 24-month log excess return on dry bulk ships, and X_t is alternately real ship earnings, real ship prices, or net industry investment, defined as deliveries minus demolitions as in the rightmost columns of Table III. In Panel A, the control variables are ex ante risk premium measures Z_t, including the smoothed earnings-price ratio on stocks ($\frac{E_{10}}{P}$), the term spread on government bonds (*TERMSPREAD*), and the Moody's Baa-Aaa corporate credit spread (*CREDITSPREAD*). In Panel B, the control variables are ex post risk factor realizations f_{t+2}, including the 24-month realized excess return on stocks (rx_{STOCKS}), the 24-month realized excess return on 10-year government bonds over 1-year government bonds ($rx_{LONG-SHORT}$), and the realized excess return on Baa-rated corporate bonds over Aaa-rated corporate bonds ($rx_{BAA-AAA}$). The smoothed earnings-price ratio on stocks is from Robert Shiller's website; the term spread is the difference between the yield on a 10-year zero-coupon Treasury and a 1-year Treasury from Gürknayak, Sack, and Wright (2007); and the credit spread is the difference between the Moody's Baa yield and the Moody's Aaa yield. rx_{STOCKS} is obtained by compounding *MKTRF* from Ken French's website; $rx_{LONG-SHORT}$ is derived from Gurknayak, Sack, and Wright (2007) data; and $rx_{BAA-AAA}$ is obtained by applying the Shiller, Campbell, and Schoenholtz (1983) return approximation to the Moody's Baa and Aaa yields. In parentheses we report Newey-West (1987) standard errors allowing for serial correlation at up to 36 monthly lags. $^+$, *, and ** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

shipping cycles. For instance, summarizing the work of maritime historians, Stopford writes:

> Fayle [1933] . . . thought the tendency of the cycles to overshoot the mark could be attributed to a lack of barriers to entry . . . . Forty years later, Cufley [1972] drew attention to the sequence of three key events common to shipping cycles: first, a shortage of ships develops, then high rates stimulate over-ordering . . . which finally leads to market collapse. (2009, p. 100)

Indeed, Stopford argues that “many bad decisions have been made because of a misunderstanding of the market mechanism” (p. 133) which may give shipping cycles a cobweb flavor (p. 335–37). Similarly, in his analysis of shipping market fluctuations, Metaxas argues that:

> The duration of the prosperity stage or the “boom” is largely determined by the endemic tendency to over-invest and by the rapidity with which new tonnage can be created in relation to the magnitude of the original increase of demand (1971, p. 227).

What drives biased expectations about future earnings? In a competitive industry, there are two forces that may drive such misperceptions. First, firms may overestimate the persistence of exogenous demand shocks. We refer to this as “demand over-extrapolation.” Second, firms may underestimate the endogenous supply-side response to demand shocks, failing to fully anticipate the effect competition will have in returning earnings to their steady-state levels. Camerer and Lovallo (1999) call this “competition neglect.”

Below we develop a model in which firms may both over-extrapolate demand and neglect the competition. Our model—which adapts an otherwise standard q-theory model of equilibrium dynamics—is related to existing behavioral finance models emphasizing extrapolative expectations. Our key innovation is that cash flows are endogenous and reflect the investment behavior of industry firms. The model captures the two key features of bulk shipping emphasized by prior studies: volatile and mean-reverting demand combined with a sluggish supply response due to time-to-build delays (Stopford 2009; Kalouptsidi 2014). Furthermore, the model is simple enough that we can solve it in closed form and estimate it allowing for both biases.

IV.A. Setup

The aggregate supply of ships is fixed in the short term at Q_t. The inverse demand curve for shipping services at time t is $H_t = A_t - BQ_t$, where H_t denotes the rate for a one-period shipping lease. Thus, higher values of A_t signify stronger demand for shipping services and a higher value of B is associated with a more inelastic demand curve for shipping services. We assume that the exogenous aggregate demand parameter A_t follows an $AR(1)$ process

$$A_{t+1} = \overline{A} + \rho_0(A_t - \overline{A}) + \varepsilon_{t+1}, \tag{8}$$

with $\rho_0 \in [0, 1)$ and $Var[\varepsilon_{t+1}] = \sigma_\varepsilon^2$.

There is a unit measure of identical risk-neutral firms that make investment decisions each period. These firms are price takers in the spot rental market for shipping services. We consider the capital budgeting problem of a representative firm in the industry. The fleet size maintained by the representative firm, denoted q_t, evolves according to

$$q_{t+1} = (1-\delta)q_t + i_t^G = q_t + i_t, \tag{9}$$

where $\delta \in (0, 1)$ is the depreciation rate, i_t^G is gross firm investment at time t, and $i_t = i_t^G - \delta q_t$ is firm net investment. Analogously, the aggregate fleet size, denoted Q_t, evolves according to

$$Q_{t+1} = (1-\delta)Q_t + I_t^G = Q_t + I_t, \tag{10}$$

where I_t^G is aggregate gross investment, and $I_t = I_t^G - \delta Q_t$ is aggregate net investment.

Since the aggregate supply of ships at time t (Q_t) is determined before the aggregate demand shock (A_t) is realized, the model captures the time-to-build delays that are a critical aspect of shipping and many other capital-intensive industries. As a result, ship lease rates can fluctuate significantly in response to temporary supply and demand imbalances in the charter market.

The representative firm earns a net profit of

$$\Pi_t = A_t - BQ_t - C - \delta P_r \tag{11}$$

on each unit of installed capital. As shown in equation (11), net earnings equal the one-period lease rate $H_t = A_t - BQ_t$, less operating costs of C, and less economic depreciation costs of δP_r. We assume that the total profits of the representative shipping firm in period t are given by

$$V_t = q_t \Pi_t - P_r i_t - k \cdot \frac{i_t^2}{2}. \tag{12}$$

The firm's fleet size is q_t and the firm earns a net profit of Π_t on each ship. In addition, a firm making a net investment of i_t pays the replacement cost P_r, which reflects the price of raw ship materials, on each unit of net investment and also incurs convex adjustment costs of $k \cdot \frac{i_t{}^2}{2}$. The adjustment cost parameter k is inversely related to the elasticity of supply. One can roughly interpret a larger k as reflecting more severe time-to-build delays: investment responds more gradually to shifts in demand when k is higher.

IV.B. Competition Neglect and Demand Overextrapolation

The idea of competition neglect is that, when confronted with some change in market conditions, firms in a competitive industry ought to ask themselves, "How should I respond given how I expect all of my competitors to respond?" This is a complex question about the optimal equilibrium response in a competitive market. Instead of answering it, firms may answer the simpler question of how they should respond, assuming that no one else reacts. This mental substitution leads firms to neglect the extent to which their competitors' supply responses will return cash flows to their steady-state levels.

Experimental evidence supports the existence of competition neglect. According to Camerer and Lovallo (1999), individuals appear to overestimate their own skill and speed in responding to common observable shocks and underestimate the skill and speed of their competitors. Kahneman (2011) argues that competition neglect can be particularly dramatic when entry involves significant time-to-build delays because participants only receive delayed feedback about the consequences of their entry and investment decisions. Hoberg and Phillips (2010) suggest that a form of competition neglect affects the US stock market, and that the bias is stronger in more competitive settings.

Although the idea of competition neglect is relatively new, it can be seen as a specific instance of more general biases that have been emphasized in prior research. Specifically, competition neglect is related to the idea that managers may be overly optimistic about their skills relative to the skills of their competitors (Roll 1986) and are prone to forming "inside view" forecasts (Kahneman and Lovallo 1993; Kahneman 2011). When feedback from investment decisions is slow, the role of competition may not be salient (Bordalo, Gennaioli, Shleifer 2012). Competition neglect can also be seen as a consequence of bounded rationality in which managers with limited cognitive resources make forecasts using a simplified model as opposed to a sophisticated dynamic model of supply and demand (Glaeser 2013; Gabaix 2014).[16]

We model competition neglect by assuming that at time t each firm believes that $I_t = \theta i_t$ where the parameter $\theta \in [0, 1]$ measures competition awareness and, conversely, $1 - \theta \in [0, 1]$ measures the degree of competition neglect. If $\theta = 1$, firms have fully rational expectations about how competitors will respond to common profitability shocks. If $\theta < 1$, firms directionally anticipate how competitors will respond but underestimate the magnitude of the response. As a result, competition neglect leads investment to overreact to common shocks. More formally, we use $E_f[\cdot]$ to denote the subjective expectations of individual firms who believe that $E_f[I_{t+j} \mid A_t, Q_t] = \theta E_f[i_{t+j} \mid A_t, Q_t]$. By contrast, we use $E_0[\cdot]$ to denote the unbiased expectations of an econometrician who knows that $E_0[I_{t+j} \mid A_t, Q_t] = E_0[i_{t+j} \mid A_t, Q_t]$.[17]

We also allow firms to overextrapolate the exogenous demand process. While extrapolative expectations deviate from

16. How could firms neglect the competition if data on ship orders are available? Even if firms are fully aware of current orders, they may underestimate the response of future orders to demand shocks. Going further, firms may not make full use of the data. Camerer and Lovallo (1999) relate competition neglect to a phenomenon called "inside view" forecasting, writing: "An 'inside view' forecast is generated by focusing on the abilities . . . of a particular group . . . . In contrast, an 'outside view' ignores special details of the case at hand, constructs a class of similar cases to the current one, and guesses where the current case lies in that class . . . . The inside view tells a colorful story; the outside view recites statistics. In the inside view, there is no special role for anticipation of the number of competitors or their abilities."

17. Since adjustment costs apply to net investment and competition neglect affects expectations of industry net investment, competition neglect has no impact on the steady state and only affects dynamics around the steady state.

the rational ideal, they may not be unrealistic. Psychologists have shown that subjects are prone to overextrapolation in a wide variety of settings. Specifically, subjects often use a "representativeness" heuristic, drawing strong conclusions from small samples of data (Tversky and Kahneman 1974; Rabin 2002). Barberis, Shleifer, and Vishny (1998) and Barberis and Shleifer (2003) develop models in which this heuristic leads agents to overextrapolate recent values of an exogenous cash flow process, resulting in the mispricing of claims on those cash flows. We model demand overextrapolation in a simple way. Specifically, we allow the true persistence ρ_0 of the demand shocks to be less than the persistence perceived by firms, ρ_f. In other words, we assume that the true law of motion is given by equation (10)—that is, $A_{t+1} = \overline{A} + \rho_0(A_t - \overline{A}) + \varepsilon_{t+1}$, but that firms believe the law of motion to be $A_{t+1} = \overline{A} + \rho_f(A_t - \overline{A}) + \varepsilon_{t+1}$ where $\rho_f \geq \rho_0$.

IV.C. Equilibrium Investment and Ship Prices

Each firm chooses its current investment to maximize the expected net present value of its total profits. Standard dynamic programing arguments (see the Online Appendix) show that firm investment is given by the familiar q-theory investment equation

$$i_t^* = \frac{P(A_t, Q_t) - P_r}{k}, \tag{13}$$

where P_r is the replacement cost of a ship, and the market price of a ship is simply the present value of future net earnings expected by firms

$$P(A_t, Q_t) = \sum_{j=1}^{\infty} \frac{E_f[\Pi_{t+j} \,|\, A_t, Q_t]}{(1+r)^j} = \sum_{j=1}^{\infty} \frac{E_f[A_{t+j} - BQ_{t+j} - C - \delta P_r \,|\, A_t, Q_t]}{(1+r)^j}. \tag{14}$$

As in any q-theory setting, firms will invest when the market price of ships exceeds their replacement cost. Conversely, firms will disinvest, demolishing some portion of their existing fleet, when the replacement cost exceeds the market price. A firm's expectations of future earnings (Π_{t+j}) in equation (14) depends on its expectations of both future demand (A_{t+j}) and future industry-wide investment (since $Q_{t+j} = Q_t + \sum_{s=0}^{j-1} I_{t+s}$). Thus, biased expectations about either future demand or future supply will affect current prices and investment, generating return predictability.

To solve for equilibrium investment and ship prices, we conjecture that net investment is linear in the two state variables

$$i_t = y_i(A_t - \overline{A}) + z_i(Q_t - Q^*), \tag{15}$$

where $\overline{A}$ is the steady-state level of demand and Q^* is the steady-state industry fleet size. We need to solve for the unknown coefficients, namely, y_i and z_i. To do so, we make use of our assumption regarding competition neglect, yielding

$$\begin{aligned} E_f[I_{t+j} \mid A_t, Q_t] &= \theta E_f[i_{t+j} \mid A_t, Q_t] \\ &= \frac{\theta}{k}\big(E_f[P(A_{t+j}, Q_{t+j}) \mid A_t, Q_t] - P_r\big). \end{aligned} \tag{16}$$

If $\theta < 1$, individual firms underestimate the extent to which industry-wide investment reacts to aggregate demand and fleet size. Equation (16) shows that our approach to modeling competition neglect is equivalent to assuming that all firms have adjustment costs k, but each firm believes that its competitors have costs $\frac{k}{\theta}$. In other words, firm overoptimism takes the form of assuming that one is able to adjust to common shocks more nimbly than one's competitors.

In equilibrium, the representative firm optimally chooses its investment given a conjecture about industry-wide investment. When $\theta = 1$, the solution corresponds to a recursive rational expectations equilibrium in which the firm's conjecture about industry-wide investment is precisely the same as the actual level of industry investment (see, e.g., Ljungqvist and Sargent 2004). When $\theta < 1$, the solution is a biased expectations equilibrium in which the representative firm's conjecture about industry-wide investment equals θ times the actual level of industry investment.

Given the linear-quadratic nature of our model, standard techniques yield closed-form solutions for equilibrium investment and prices. In the model's steady state—that is, the long-run competitive equilibrium, the fleet size is $Q^* = \frac{\overline{A} - C - (r+\delta)P_r}{B}$, the lease rate is $H^* = (r + \delta)P_r + C$, operating profits are $\Pi^* = rP_r$, and the ship price equals replacement cost, $P^* = P_r$. Thus, lease rates enable capital to earn its required return and economic profits are zero in the steady state. The more interesting results describe the evolution of ship prices and investment in response to deviations from the steady state.

PROPOSITION 1. (Equilibrium investment and prices) There exists a unique equilibrium and it is linear. Equilibrium net investment of the representative firm is $I_t^* = y_i^*(A_t - \overline{A}) + z_i^*(Q_t - Q^*)$ and equilibrium ship prices are $P_t^* = P_r + ky_i^*(A_t - \overline{A}) + kz_i^*(Q_t - Q^*)$. Firm investment and ship prices are increasing in current shipping demand (i.e., $y_i^* > 0$) and decreasing in current aggregate fleet size (i.e., $z_i^* < 0$). Specifically, we have

$$z_i^* = \frac{kr + B\theta}{2k\theta} - \sqrt{\left(\frac{kr + B\theta}{2k\theta}\right)^2 + \frac{B}{k\theta}} < 0, \tag{17}$$

and $y_i^* = \frac{\rho_f}{k(1-\rho_f) - \frac{B}{z_i^*}} > 0$. Furthermore:

(i) Prices and investment react more aggressively to demand shocks when competition neglect is more severe or when firms believe that demand shocks are more persistent (i.e., $\frac{\partial y_i^*}{\partial(1-\theta)} > 0$ and $\frac{\partial y_i^*}{\partial \rho_f} > 0$).

(ii) Prices and investment react more aggressively to a shortage of industry supply when competition neglect is more severe. However, this reaction does not depend on the perceived persistence of demand shocks (i.e., $\frac{\partial z_i^*}{\partial(1-\theta)} < 0$ and $\frac{\partial z_i^*}{\partial \rho_f} = 0$).

We prove this formally in the Online Appendix and further characterize the equilibrium. For instance, when demand is more inelastic, investment and prices react more aggressively to the current fleet size, but less aggressively to the level of demand. Furthermore, when investment adjustment costs are higher, investment reacts less aggressively to the fleet size and current demand, but prices react more aggressively. This finding parallels Kalouptsidi (2014), who finds that greater time-to-build reduces the volatility of investment while amplifying the volatility of ship prices.

The dynamics of prices and investment described in Proposition 1 are reminiscent of those in Kaldor's (1934) cobweb theory. According to the cobweb theory, producers set quantities one period in advance based on the naive assumption that current prices will persist indefinitely, generating oscillations in price and quantity that converge to a steady state. The cobweb turns out to be a limiting case of our model when firms completely neglect the competition ($\theta = 0$) and radically overextrapolate demand ($\rho_f = 1$). Naturally, in this case, ship prices are just the perpetuity value of current earnings ($P_t^* = \frac{\Pi_t}{r}$). The Online Appendix explores the parallels between our model, where firms are optimizing but make systematic expectational errors, and the cobweb model.

IV.D. Industry Dynamics When Firms Make Investment Mistakes

1. Expected Returns on Capital. How do investment mistakes affect the return on capital? The realized return from owning and operating a ship between time t and $t+1$ is

$$1 + R_{t+1} = \frac{\Pi_{t+1} + P(A_{t+1}, Q_{t+1})}{P(A_t, Q_t)}. \tag{18}$$

By construction, individual firms *expect* that the return on ships will equal the required return—that is, $E_f[R_{t+1} \,|\, A_t, Q_t] = r$. However, the expected returns perceived by the econometrician, $E_0[R_{t+1} \,|\, A_t, Q_t]$, may differ from firms' required returns when either $\theta < 1$ or $\rho_f \neq \rho_0$. Specifically, we can show that

$$E_0[R_{t+1} \,|\, A_t, Q_t] = r - (1-\theta)\left[\frac{(B - kz_i^*)(y_i^*(A_t - \overline{A}) + z_i^*(Q_t - Q^*))}{P_r + ky_i^*(A_t - \overline{A}) + kz_i^*(Q_t - Q^*)}\right] - (\rho_f - \rho_0)\left[\frac{(1 + ky_i^*)(A_t - \overline{A})}{P_r + ky_i^*(A_t - \overline{A}) + kz_i^*(Q_t - Q^*)}\right]. \tag{19}$$

Equation (19) shows that the difference between expected and required returns can be decomposed into a term that vanishes when there is no competition neglect ($\theta = 1$) and a term that vanishes when there is no demand overextrapolation ($\rho_f = \rho_0$). Consider a multivariate regression of returns on demand (A_t) and fleet size (Q_t). In a neighborhood of the steady state ($\overline{A}, Q^*$), we have:

$$\frac{\partial E_0[R_{t+1} \,|\, A_t, Q_t]}{\partial A_t} \approx -(1-\theta)P_r^{-1}y_i^*(B - kz_i^*) - (\rho_f - \rho_0)P_r^{-1}(1 + ky_i^*), \tag{20}$$

and

$$\text{(21)} \qquad \frac{\partial E_0[R_{t+1}\,|A_t, Q_t]}{\partial Q_t} \approx -(1-\theta)P_r^{-1}z_i^*(B-kz_i^*).$$

Thus, $\frac{\partial E_0[R_{t+1}\,|A_t,Q_t]}{\partial A_t} < 0$ if either $\theta < 1$ or $\rho_0 < \rho_f$. And $\frac{\partial E_0[R_{t+1}\,|A_t,Q_t]}{\partial Q_t} > 0$ if $\theta < 1$.

When demand is high or ships are scarce, ship lease rates and prices will be high and firms want to invest. However, when firms neglect the competition ($\theta < 1$), each firm overinvests because it underestimates the response of its competitors. Firms are then surprised by the subsequent level of industry investment, which pushes lease rates below their expectations, resulting in low future returns.

In the absence of competition neglect ($\theta = 1$), firms do not overreact to supply shortages since they accurately forecast the endogenous supply response. However, if firms still overextrapolate demand ($\rho_0 < \rho_f$), then equation (20) shows that high levels of demand continue to forecast low returns because demand shocks revert more quickly than firms expect.

Roughly speaking, equations (20) and (21) show that firms that exhibit competition neglect appear to overextrapolate high current earnings, whether they are due to high demand or low supply. By contrast, firms that overextrapolate the exogenous demand process but correctly anticipate the supply response only overextrapolate high current earnings due to high demand.

Naturally, the amount of return predictability implied by equations (20) and (21) increases in the degree of each of the biases. Interestingly, however, greater competition neglect amplifies the predictability stemming from demand overextrapolation and vice versa. The idea is that perceived persistence of future earnings depends on the interaction between the expected speed of the endogenous competitive response (which is controlled by $1-\theta$) and the perceived persistence of the exogenous demand shocks (which is controlled by ρ_f).

Return predictability due to competition neglect becomes stronger when demand is more inelastic (B is larger) and when supply is more elastic (k is lower). The intuition follows from the logic of Kaldor's (1934) cobweb theorem: investment overreacts more when supply is more elastic; and a given amount of "overinvestment" has a larger effect on future earnings and returns when demand is more inelastic. In contrast, return predictability due to demand overextrapolation becomes weaker when demand is more inelastic and when supply is more elastic. Firms that only overestimate the persistence of demand understand that the competitive supply response will return profits to their steady state more quickly when demand is more inelastic or supply is more elastic, attenuating the resulting mispricing of ships and attendant return predictability.[18]

Since we do not observe the demand process, A_t, we rewrite equation (19) in terms of observables, namely, industry net investment (I_t) and operating earnings (Π_t), which together contain the same information as A_t and Q_t. Doing so we obtain

$$E_0[R_{t+1} \mid \Pi_t, I_t] = r - (1-\theta)\left[\frac{(B - kz_i^*)I_t}{P_r + kI_t}\right] - \frac{(\rho_f - \rho_0)}{1-\rho_f}\left[\frac{(\Pi_t - \Pi^*) + (\frac{B}{z_i^*})I_t}{P_r + kI_t}\right]. \tag{22}$$

Differentiating equation (22), the model delivers the relationships between current earnings, used prices, investment, and future returns that we saw empirically in Section III.

$$\frac{\partial E_0[R_{t+1} \mid I_t, \Pi_t]}{\partial I_t} \approx -(1-\theta)P_r^{-1}(B - kz_i^*) - \frac{\rho_f - \rho_0}{1-\rho_f}P_r^{-1}\left(\frac{B}{z_i^*}\right), \tag{23}$$

and

$$\frac{\partial E_0[R_{t+1} \mid I_t, \Pi_t]}{\partial \Pi_t} \approx -\frac{\rho_f - \rho_0}{1-\rho_f}P_r^{-1}. \tag{24}$$

PROPOSITION 2. (Forecasting regressions) In a neighborhood of the steady-state:

(i) If firms neglect the completion ($\theta < 1$) or overextrapolate demand ($\rho_0 < \rho_f$), then investment, prices, and profits will each negatively forecast returns in univariate regressions.

(ii) Consider a multivariate regression of returns on investment and profits. The coefficient on earnings is negative if and only if there is demand overextrapolation ($\rho_0 < \rho_f$). The coefficient on investment is negative if

18. Formally, when $\theta < 1$ and $\rho_f = \rho_0$, $\frac{\partial^2 E_0[R_{t+1}]}{\partial A_t \partial B} < 0$, $\frac{\partial^2 E_0[R_{t+1}]}{\partial Q_t \partial B} > 0$, $\frac{\partial^2 E_0[R_{t+1}]}{\partial A_t \partial k} > 0$, $\frac{\partial^2 E_0[R_{t+1}]}{\partial Q_t \partial k} < 0$. By contrast, when $\theta = 1$ and $\rho_f > \rho_0$, $\frac{\partial^2 E_0[R_{t+1}]}{\partial A_t \partial B} > 0$ and $\frac{\partial^2 E_0[R_{t+1}]}{\partial A_t \partial k} < 0$.

and only if $\left(\frac{\rho_f-\rho_0}{1-\rho_f}\right)\left(\frac{B}{-z_i^*(B-kz_i^*)}\right) < (1-\theta)$—that is, if and only if competition neglect is relatively important.

Since ship earnings, prices, and investment are all increasing in current demand and decreasing in industry fleet size, each of these variables is associated with low future expected returns. Thus, part i of Proposition 2 states that each of these variables negatively forecasts returns in a univariate sense if there is either competition neglect or demand overextrapolation.

Part ii of Proposition 2 explores the model's implications for a multivariate regression of returns on lagged investment and earnings. With only competition neglect ($\theta < 1$ and $\rho_f = \rho_0$), the coefficient on investment is negative and the coefficient on earnings is 0. In this case, return predictability stems from firms' tendency to overreact to changes in investment opportunities, so the level of investment is sufficient statistic for expected returns. Alternatively, when there is only demand overextrapolation ($\theta = 1$ and $\rho_f > \rho_0$), the coefficient on earnings is negative and the coefficient on investment is positive. In this case, the level of demand (A_t) is a sufficient statistic for expected returns. However, in a multivariate regression of demand on earnings (Π_t) and investment (I_t) the coefficient on the former is positive while the coefficient on the latter is negative.[19] Finally, if both biases exist and competition neglect is relatively important, then both investment and earnings will negatively forecast returns in a multivariate regression. In summary, the model suggests that we need both demand overextrapolation and competition neglect to match the multivariate forecasting results from Section III. Indeed, as we will see in Section V, this result helps us separately identify demand overextrapolation and competition neglect in the data.

2. The Persistence of Earnings, Earnings Volatility, and Price Volatility. How do competition neglect and demand overextrapolation affect second moments such as the volatility of ship prices and earnings? In the Online Appendix, we characterize the second moments of the steady-state distribution perceived

19. Holding fixed earnings, a higher level of investment means that current supply is low. Holding current earnings fixed, a low level of current supply means that current demand must also be low.

by firms with biased expectations as well as the true steady-state distribution observed by the econometrician.

We first consider the autocorrelation of earnings anticipated by firms. Naturally, competition neglect and demand extrapolation both lead firms to overestimate the persistence of earnings, causing prices and investment to overreact to demand shocks.

We can also solve for the true volatilities of prices and earnings in the steady state, as well as the true autocorrelation of earnings. The variances of ship prices and investment are increasing in both the degree of competition neglect and the degree of demand overextrapolation. However, the variance and autocorrelation of earnings are both U-shaped functions of the degree of competition neglect $(1-\theta)$ and the degree of demand overextrapolation $\rho_f - \rho_0$. Both biases lead investment to overreact to deviations of earnings from the steady state, making shipping supply more elastic. Modest amounts of overreaction counteract adjustment costs and reduce the average absolute mismatch between supply and demand, thereby lowering earnings volatility. However, as overreaction increases further, it increases the average mismatch between supply and demand, raising earnings volatility.

IV.E. Model Extensions

We have explored a number of extensions to this baseline model. First, the Online Appendix shows that our model continues to generate return predictability if we allow for asymmetric investment adjustment costs or introduce a wedge between new-build prices and scrap prices.[20] Second, it is straightforward to allow ship replacement costs to fluctuate over time. Specifically, if the replacement cost follows an $AR(1)$, investment and ship prices would be functions of three state variables: the time-varying replacement cost, A_t, and Q_t. (Investment would be decreasing in replacement cost and ship prices would be increasing in replacement cost.) Third, we could add a set of sophisticated firms who hold unbiased expectations. Unbiased

20. Total profits are $V_t = q_t \Pi_t - (P_r^+ 1^+[i_t] + P_r^- 1^-[i_t]) \cdot i_t - (k^+ 1^+[i_t] + k^- 1^-[i_t]) \cdot \frac{i_t^2}{2}$. If the new-build price exceeds the scrap price ($P_r^+ > P_r^-$), there is a region of inaction where net investment is zero. If the adjustment costs associated with disinvestment to exceed those associated with investment ($k^+ < k^-$), investment responds more aggressively to above average earnings than to below average earnings and equilibrium prices are concave in the state variables, leading to negatively skewed returns on capital. These patterns are reversed if $k^+ > k^-$.

firms would lean against the wind, investing less (more) when biased firms are overinvesting (underinvesting). Because it would affect tomorrow's fleet size and earnings, this contrarian investment response would dampen the magnitude of boom-bust cycles and return predictability. The degree of dampening depends on the fraction of unbiased agents and their investment adjustment costs (which play an analogous role to arbitrageur risk aversion in behavioral finance models).

V. Estimating the Model in the Dry Bulk Shipping Industry

We now estimate the parameters of our structural model using a simulated minimum distance estimator or what is sometime called "indirect inference" (Gourieroux, Monfort, and Renault 1993; Newey and McFadden 1994). Estimating the model enables us to assess whether one needs to posit severe competition neglect to rationalize return predictability. The estimation also allows us to effectively run a horse race between competition neglect and demand overextrapolation, to determine which bias is more important in the data.

V.A. *Indirect Inference Estimation Procedure*

The basic intuition behind our estimation procedure relies on the analogy principle. We are interested in estimating an L-dimensional vector of unknown parameters of the model. We choose $M \geq L$ time-series sample statistics that are jointly informative about these parameters. These statistics include time-series means and variances of various quantities (e.g., ship returns, earnings, and prices) and the coefficients from a variety of predictive regressions described in Section III. For a given set of model parameters, we simulate 100,000 years of data in the model and then compute the analogous time-series statistics in the simulated data.[21] To estimate the model parameters, we search for the parameter values such that the time-series statistics estimated using the simulated data are as close as possible to those that we observe in the actual data.

21. Simulating an extremely long time series enables us to treat the simulated statistics as a deterministic function of the model parameters, so we can ignore "simulation noise" when computing standard errors.

Asymptotic standard errors for our parameter estimates are obtained in the usual fashion. Intuitively, standard errors for the structural model parameters are smaller when the time-series statistics are estimated more precisely in the data and when the simulated statistics are more sensitive to changes in the structural model parameters. Because we are trying to match $M \geq L$ sample statistics, we must minimize a weighted distance between the sample statistics and the simulated statistics. We weight each statistic inversely by its estimated variance—that is, we use a diagonal weighting matrix that weights each statistic inversely to its estimated variance. The Online Appendix explains the estimation procedure in greater detail.

We match the following 22 time-series statistics which can be estimated for the full January 1977 to December 2009 sample:

- Average and variance of returns, earnings, and prices (six statistics)
- Autocorrelation of earnings at one month, one year, and two years (three statistics)[22]
- Slope coefficients from univariate regressions that use earnings, prices, earnings/price, and investment to forecast one- and two-year returns (eight statistics)
- Slope coefficient from a regression of current investment on current prices (one statistic)[23]
- Slope coefficients from multivariate regressions that use earnings and investment to forecast one- and two-year returns (four statistics).

We calibrate the risk-free rate as well as B, δ, C, and $\overline{A}$ in our estimation procedure. That is, we do not estimate these parameters but simply assume values for them. However, our estimates of $(1-\theta)$ and $(\rho_f - \rho_0)$ are not sensitive to the values we choose for these parameters.

- The risk-free rate: we assume a constant real risk-free rate of 2%, which we subtract from the shipping return to compute excess returns in our simulated data.

22. We match the one-month autocorrelation in the data with ${\rho_0}^{1/12}$ in our simulation under the assumption that there is no supply response at a monthly horizon.

23. Since our model has a one-year time-to-build whereas the actual time to build is closer to two years, we match this simulated statistic to the coefficient from a regression of Inv_t on $P_{t\text{-}1}$ in the data.

- The rate of depreciation: as in Section II, we assume that $\delta = 4\%$.
- Slope of the demand curve: as shown in the Online Appendix, only the product of the demand and supply slopes, $\frac{B}{k}$, is determined by our time-series statistics. Since we are not interested in estimating the demand slope, B, or the supply slope, $\frac{1}{k}$, we are free to choose one of these parameters. We arbitrarily set $B = 0.10$.
- Operating costs and average demand: we assume annual operating costs of $C = 365 \times (\frac{6}{1000}) = \$2.19$ million as above. We assume average demand of $\overline{A} = 50$.[24]

This leaves us with seven parameters to estimate: the degree of competition neglect $(1 - \theta)$, the extent of demand overextrapolation $(\rho_f - \rho_0)$, the true persistence of demand (ρ_0), the volatility of demand shocks (σ_ε), the investment adjustment cost parameter (k), the required return on ships (r), and the replacement cost of ships (P_r).

V.B. Estimation Results

Table VI lists the time-series statistics from the actual data and the associated standard errors. To account for serial correlation, we report Newey-West (1987) standard errors allowing for serial correlation at up to 36 months.[25] The table then shows the value of these statistics in the simulated data using the estimated parameters. Our parameter estimates along with their associated standard errors are shown below. To build intuition for the model identification, we successively estimate the model (i) imposing the rational expectations null, (ii) allowing for competition neglect but not demand overextrapolation, (iii) allowing for demand extrapolation but not competition neglect, and (iv) allowing for both competition neglect and demand extrapolation.

24. These parameters affect the equilibrium fleet size, but not investment, prices, earnings, and returns. As a result, they have a small effect on scaled investment $(\frac{I_t}{Q_t})$. However, as shown in the Online Appendix, our assumptions have little effect on our estimates of $(1 - \theta)$ and $(\rho_f - \rho_0)$.

25. We take a seemingly unrelated regression approach to our vector of sample statistics and estimate the covariance matrix using a Newey-West estimator that allows residuals to be correlated within and across statistics at up to 36 months. The empirical statistics listed in Table VI differ slightly from those in Tables I, II, III, and IV because here we restrict attention to the January 1977 to December 2009 sample where we have the requisite data for all 22 statistics.

TABLE VI

INDIRECT INFERENCE ESTIMATION OF THE STRUCTURAL MODEL

		Empirical values		Simulation values (1) Rational expectations	(2) Imposing $\rho_f = \rho_0$ only	(3) Imposing $\theta = 1$ only	(4) Unrestricted expectations
Statistic		m	(Std. err.)	m	m	m	M
1	$E[rx_{t+1}]$	0.109*	(0.052)	0.106	0.124	0.097	0.099
2	$Var[rx_{t+1}]$	0.095**	(0.020)	0.062	0.072	0.072	0.083
3	$E[P_t]$	32.448**	(3.645)	31.312	28.464	33.005	35.226
4	$Var[P_t]$	238.683*	(111.58)	9.722	8.012	16.467	34.810
5	$E[\Pi_t]$	4.166**	(0.757)	3.948	4.048	3.752	3.871
6	$Var[\Pi_t]$	17.339*	(8.804)	30.307	28.910	29.672	25.182
7	$Corr[\Pi_t, \Pi_{t+1/12}]$	0.961**	(0.020)	0.943	0.933	0.941	0.958
8	$Corr[\Pi_t, \Pi_{t+1}]$	0.204	(0.150)	0.453	0.401	0.421	0.505
9	$Corr[\Pi_t, \Pi_{t+2}]$	−0.090	(0.092)	0.187	0.144	0.150	0.228
10	$\beta(rx_{t+1} \mid \Pi_t)$	−0.021**	(0.007)	0.000	−0.003	−0.006	−0.012
11	$\beta(rx_{t+2} \mid \Pi_t)$	−0.041**	(0.013)	0.000	−0.004	−0.009	−0.018
12	$\beta(rx_{t+1} \mid P_t)$	−0.007**	(0.002)	0.000	−0.006	−0.007	−0.009
13	$\beta(rx_{t+2} \mid P_t)$	−0.012**	(0.004)	0.001	−0.008	−0.011	−0.015
14	$\beta(rx_{t+1} \mid \frac{\Pi_t}{P_t})$	−0.433	(0.786)	0.004	−0.081	−0.199	−0.424
15	$\beta(rx_{t+2} \mid \frac{\Pi_t}{P_t})$	−1.533	(1.145)	0.001	−0.106	−0.325	−0.672
16	$\beta(rx_{t+1} \mid \frac{I_t}{Q_t})$	−3.233*	(1.541)	0.292	−3.842	−3.974	−5.537
17	$\beta(rx_{t+2} \mid \frac{I_t}{Q_t})$	−4.959*	(2.477)	0.391	−5.444	−6.422	−8.960
18	$\beta(\frac{I_t}{Q_t} \mid P_t)$	0.001**	(0.000)	0.002	0.001	0.002	0.002
19	$\beta_1(rx_{t+1} \mid \frac{I_t}{Q_t}, \Pi_t)$	−2.830+	(1.617)	1.120	−3.053	2.463	−0.730
20	$\beta_2(rx_{t+1} \mid \frac{I_t}{Q_t}, \Pi_t)$	−0.017*	(0.009)	−0.001	−0.001	−0.009	−0.010
21	$\beta_1(rx_{t+2} \mid \frac{I_t}{Q_t}, \Pi_t)$	−4.147+	(2.424)	2.333	−6.285	4.524	−1.895
22	$\beta_2(rx_{t+2} \mid \frac{I_t}{Q_t}, \Pi_t)$	−0.035**	(0.011)	−0.002	0.001	−0.015	−0.015

TABLE VI
(CONTINUED)

Minimum distance criterion function	(1) Rational expectations $J = 99.07$		(2) Imposing $\rho_f = \rho_0$ only $J = 51.34$		(3) Imposing $\theta = 1$ only $J = 60.06$		(4) Unrestricted expectations $J = 41.41$	
Parameter estimates:	b	(Std. err.)	b	(Std. err.)	b	(Std. err.)	b	(Std. err.)
$1-\theta$	—	—	0.579**	(0.128)	—	—	0.454**	(0.144)
$\rho_f - \rho_0$	—	—	—	—	0.106**	(0.037)	0.098**	(0.036)
ρ_0	0.496**	(0.079)	0.437**	(0.069)	0.481**	(0.053)	0.600**	(0.047)
σ_ε	4.916**	(1.001)	4.939**	(1.003)	4.947**	(0.827)	4.335**	(0.785)
k	1.546**	(0.280)	1.617**	(0.260)	1.379**	(0.190)	1.427**	(0.175)
r	0.126**	(0.017)	0.142**	(0.020)	0.114**	(0.014)	0.110**	(0.012)
P_r	31.312**	(3.047)	28.464**	(3.266)	33.005**	(4.120)	35.226**	(4.822)
Hypothesis tests on estimated parameters:								
H_0: $\theta = 0$	N/A		$t = 3.30$		N/A		$t = 3.79$	

Notes. We match $M = 22$ simulated statistics to empirical statistics from our data to estimate $L = 7$ parameters in the model. We generate a simulated 100,000-year time series using the model and find the model parameters that minimize the sum of the squared differences between simulated and empirical statistics, weighting each statistic inversely to its estimated variance. We estimate the covariance matrix of the sample statistics using a Newey-West (1987) style estimator for seemingly unrelated regression. +, *, and ** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

In column (1) we first estimate the model imposing the rational expectations null (i.e., imposing $\theta = 1$ and $\rho_f = \rho_0$). The five model parameters in Table VI are precisely estimated. Under rational expectations, the model can match the average level of returns, earnings, and prices as well as the autocorrelation of earnings. However, this constrained model is completely unable to match our forecasting regression results. Although it matches the volatility of earnings, the rational expectations model generates prices and returns that are far less volatile than those seen in the data.

In column (2) we next estimate the model allowing for competition neglect but not demand overextrapolation (i.e., we allow $1 - \theta > 0$, but impose $\rho_f = \rho_0$). We estimate that $1 - \theta = 0.58$ with a standard error of 0.13. Thus, we have considerable power against both the cobweb model (the t-statistic for the hypothesis that $\theta = 0$ is $t = 3.30$) and the rational expectations model (the t-statistic for the hypothesis that $\theta = 1$ is $t = 4.54$). When we only allow for competition neglect, the model can largely match the average level of returns, earnings, and prices; the autocorrelation of earnings; and the univariate return forecasting results. By matching the univariate regression results, the model fit improves substantially relative to the rational expectations null. Formally, the minimized criterion function falls to 51.34 when we allow $1 - \theta > 0$, compared to 99.07 in the case in which we impose fully rational expectations. However, with only competition neglect, the model still has difficulty matching the volatility of returns, earnings, and prices. Consistent with Proposition 2, the model also cannot match the multivariate regression results when we impose $\rho_f = \rho_0$.

How can we reconcile the finding that the rational expectations null is rejected with Kalouptsidi (2014), who argues that a rational model with constant required returns can fit ship earnings and prices over a shorter 1998–2010 sample? In Kalouptsidi's model, used ship prices are highly volatile because procyclical time-to-build delays mean that high levels of earnings are expected to persist in booms. Her estimation suggests that the 1998–2010 period was an ex ante unlikely path in which high prices were not followed by high future earnings, but instead were followed by low future returns. Looking over the longer 1976–2010 period, however, we find that the negative forecasting relationship between prices and future returns is pervasive and reflects the tendency of prices to overreact to transient earnings shocks.

In column (3) we estimate the model allowing for demand extrapolation but not competition neglect (i.e., we allow $\rho_f > \rho_0$, but impose $\theta = 1$). We obtain $\rho_f = 0.59 > 0.48 = \rho_0$ and easily reject the hypothesis that $\rho_f = \rho_0$ with a t-statistic of 2.83. Again, the model can largely match first moments, the autocorrelation of earnings, and the univariate return forecasting results. However, as before, the model has more difficulty matching the second moments and struggles to match our multivariate forecasting results. Overall, the model fit when we rule out competition neglect is slightly worse than when we rule out demand overextrapolation: the criterion function is 51.34 when we impose $\rho_f = \rho_0$, but rises to 60.06 when we impose $\theta = 1$.

Finally, we estimate the unrestricted model. Our estimates, shown in column (4) of Table VI, suggest that both competition neglect and demand overextrapolation are useful for explaining our empirical results. Specifically, we now obtain $1 - \theta = 0.45$ and $\rho_f = 0.70 > 0.60 = \rho_0$, and we can reject (i) the hypothesis that $\theta = 0$ ($t = 3.79$), (ii) the hypothesis that $\theta = 1$ ($t = 3.16$), as well as (iii) the hypothesis that $\rho_f = \rho_0$ ($t = 2.72$). Furthermore, comparing the simulated and sample statistics, we can see that the unrestricted estimation allows us to better match the high volatility of earnings, prices, and returns as well as the multivariate forecasting results. Allowing for both biases enables us to better match the univariate forecasting results. Overall, the minimized criterion function falls to 41.41, less than half the value in the rational expectations case.

Why does allowing for both competition neglect and overextrapolation improve the model fit? How are the parameters governing competition neglect and overextrapolation separately identified in the model? The model is trying to simultaneously match (i) the high volatility of prices and returns; (ii) the low autocorrelation of earnings; (iii) the univariate forecasting ability of earnings, prices, and investment; and (iv) the multivariate forecasting results using earnings and investment. Therefore, either competition neglect or demand overextrapolation in isolation can do a reasonable job of matching (ii) and (iii), but individually struggles to match (i) and (iv). With only demand overextrapolation or only competition neglect, we need low values of ρ_f and ρ_0 to match the low autocorrelation of earnings, but this makes it difficult to match the high volatility of prices and returns. Furthermore, as described in Proposition 2, we cannot match our multivariate forecasting results using either demand overextrapolation or competition neglect in isolation.

When we allow for both biases, we can use higher values of ρ_f and ρ_0 in combination with a higher value of $(1-\theta)$. As discussed in Section IV, higher values of $(1-\theta)$ and $(\rho_f-\rho_0)$ raise the perceived autocorrelation of earnings, which makes ship prices and returns more volatile.[26] At the same time, higher values of $(1–\theta)$ and $(\rho_f-\rho_0)$ reduce the actual autocorrelation of earnings because both lead investment to overreact to demand shocks. When we allow both $(1-\theta)>0$ and $(\rho_f-\rho_0)>0$, we are able to match the multivariate forecasting results.

To provide a more formal analysis of the sources of parameter identification in our model, Table VII reports the scaled sensitivity matrix suggested by Gentzkow and Shapiro (2014). The elements of the scaled sensitivity matrix are a natural unit-free measure of identification sensitivity: $[\mathbf{\Lambda}'_{SCALE}]_{ml}$ is the standard deviation response of model parameter l to a 1 standard deviation increase in data statistic m. Examining this matrix for our unrestricted estimator suggests that:

- $(1-\theta)$: The estimated degree of competition neglect is sensitive to the magnitude of univariate return forecasting coefficients (statistics 10–17): more negative coefficients raise our estimate of $(1-\theta)$. Furthermore, the negative coefficients on investment in multivariate regressions that control for earnings (19 and 21) raise the estimated degree of competition neglect.
- $(\rho_f-\rho_0)$: The estimated degree of demand overextrapolation is sensitive to the magnitude of univariate return forecasting coefficients (statistics 10–17): more negative coefficients raise our estimate of $(\rho_f-\rho_0)$. The low autocorrelation of earnings (7, 8, 9) also raises the estimated degree of demand overextrapolation. Finally, the negative coefficients on investment in multivariate regressions controlling for earnings (19 and 21) lower the estimated degree of demand overextrapolation.

26. The standard deviation of prices in the data is five times that implied by the rational expectations version of our model. Even if we allow for both biases, the observed volatility is over twice the model-implied volatility. The poor fit on this dimension is because price volatility is estimated imprecisely and thus receives a low weight in the estimation.

TABLE VII
SENSITIVITY OF PARAMETER ESTIMATES TO SAMPLE STATISTICS

	Statistic	$1-\theta$	$\rho_f-\rho_0$	ρ_0	σ_ε	k	R	P_r
1	$E[rx_{t+1}]$	0.02	−0.07	0.04	−0.02	0.03	0.71	−0.11
2	$Var[rx_{t+1}]$	−0.04	−0.07	0.29	0.29	−0.02	0.02	−0.09
3	$E[P_t]$	0.19	0.29	0.09	0.18	0.06	−0.68	0.65
4	$Var[P_t]$	0.02	0.01	0.11	0.00	0.01	−0.06	0.05
5	$E[\Pi_t]$	0.11	−0.03	0.01	0.05	0.11	1.40	0.04
6	$Var[\Pi_t]$	−0.04	0.06	−0.44	0.51	0.02	−0.07	0.14
7	$Corr[\Pi_t, \Pi_{t+1/12}]$	0.06	−0.11	0.63	−0.21	−0.02	−0.02	0.02
8	$Corr[\Pi_t, \Pi_{t+1}]$	0.04	−0.12	0.47	−0.16	0.05	0.04	−0.01
9	$Corr[\Pi_t, \Pi_{t+2}]$	0.07	−0.21	0.77	−0.26	0.10	0.07	−0.01
10	$\beta(rx_{t+1}\|\Pi_t)$	−0.09	−0.10	−0.30	0.12	0.07	0.15	−0.07
11	$\beta(rx_{t+2}\|\Pi_t)$	−0.07	−0.08	−0.32	0.14	0.05	0.07	−0.06
12	$\beta(rx_{t+1}\|P_t)$	−0.13	−0.21	0.28	−0.05	0.23	0.02	0.02
13	$\beta(rx_{t+2}\|P_t)$	−0.10	−0.15	0.09	0.03	0.17	−0.13	0.03
14	$\beta(rx_{t+1} \mid \frac{\Pi_t}{P_t})$	−0.04	−0.05	−0.11	0.04	0.02	0.07	−0.06
15	$\beta(rx_{t+2} \mid \frac{\Pi_t}{P_t})$	−0.04	−0.05	−0.14	0.05	0.02	0.05	−0.06
16	$\beta(rx_{t+1} \mid \frac{I_t}{Q_t})$	−0.10	−0.16	0.27	−0.03	−0.28	0.03	0.01
17	$\beta(rx_{t+2} \mid \frac{I_t}{Q_t})$	−0.09	−0.13	0.13	0.04	−0.31	−0.11	0.03
18	$\beta(\frac{I_t}{Q_t} \mid P_t)$	0.02	0.03	0.06	0.01	−0.89	0.04	−0.02
19	$\beta_1(rx_{t+1} \mid \frac{I_t}{Q_t}, \Pi_t)$	−0.31	0.22	−0.14	0.02	0.03	0.06	−0.02
20	$\beta_2(rx_{t+1} \mid \frac{I_t}{Q_t}, \Pi_t)$	0.03	−0.15	−0.17	0.08	0.03	0.09	−0.05
21	$\beta_1(rx_{t+2} \mid \frac{I_t}{Q_t}, \Pi_t)$	−0.40	0.26	−0.15	0.04	0.02	0.02	−0.02
22	$\beta_2(rx_{t+2} \mid \frac{I_t}{Q_t}, \Pi_t)$	0.08	−0.18	−0.23	0.11	0.02	0.05	−0.04

Notes. This table reports the (transposed) scaled sensitivity matrix, Λ'_{SCALE}, as suggested by Gentzkow and Shapiro (2014). The elements of the sensitivity matrix $\mathbf{\Lambda} = (\mathbf{\Gamma}'\mathbf{W}\mathbf{\Gamma})^{-1}\mathbf{\Gamma}'\mathbf{W}$ are the partial derivatives of the parameter estimates with respect to the sample statistics, evaluated at the true parameter vector. The elements of the scaled sensitivity matrix $\mathbf{\Lambda}_{SCALE} = [diag(\mathbf{V})]^{-\frac{1}{2}}\mathbf{\Lambda}[diag(\mathbf{S})]^{\frac{1}{2}}$ (where $\mathbf{V} = \mathbf{\Lambda}\mathbf{S}\mathbf{\Lambda}'$ is the asymptotic variance of the parameter estimates and $\mathbf{S}$ is the asymptotic variance of the sample statistics) are a unit-free measure of sensitivity: $[\Lambda'_{SCALE}]_{ml}$ is the standard deviation response of model parameter l to a 1 standard deviation increase in data statistic m. We report the (transposed) scaled-sensitivity matrix Λ'_{SCALE} corresponding to our unrestricted estimation in column (4) of Table VI.

- ρ_0: The estimated true persistence of demand is sensitive to the autocorrelation of earnings at various horizons (statistics 7, 8, 9) and the variance of earnings since $Var[\Pi_t]$ is proportional to $Var[A_t] = \frac{\sigma_\varepsilon^2}{1-\rho_0^2}$. Our estimate of ρ_0 is also somewhat sensitive to the return forecasting coefficients (10–17).

- σ_ε: The estimated volatility of demand shocks is primarily sensitive to the variance of excess returns $Var[rx_{t+1}]$ (statistic 2) and the variance of earnings $Var[\Pi_t]$ (6).
- k: The estimated adjustment cost parameter is primarily sensitive to the coefficient from a regression of $\frac{I_t}{Q_t}$ on P_t (statistic 18) since $\beta\left(\frac{I_t}{Q_t} \mid P_t\right) = \frac{1}{(kQ^*)}$.
- r: The estimated level of required returns is sensitive to the average level of excess returns (statistic 1) since $E[rx_{t+1}] = r - r_f$, the average level of prices (3), and the average level of earnings (5) since $E[\Pi_t] = rP_r$.
- P_r: The estimated replacement cost is sensitive to the average level of prices (statistic 3).

V.C. *Expectations of Market Participants*

Figure VI uses our model estimates to back out the expectations of market participants. The figure displays the evolution of demand, fleet size, earnings, and prices following an unexpected eight-unit (roughly 2 standard deviations) shock to demand. We start the model in the steady state at $t = 0$ and show the impulse responses following a demand shock at $t = 1$. We contrast the path that firms initially expect following this shock with the path expected by the econometrician.

The top left panel shows the path of demand. Approximately two years after the initial shock, demand has fallen by half. Firms, however, expect this decline to occur in closer to four years. Because they neglect the competition and form biased beliefs about the path of demand, firms invest aggressively, quickly increasing the fleet size as shown in the top right panel of Figure VI. In contrast, firms expect the fleet size to rise more gradually to meet the new demand.

The bottom panels of Figure VI show firms' beliefs about the evolution of earnings and prices. As can be seen, earnings revert quickly, returning to steady state in four years. In contrast, firms believe this reversion is likely to take place over seven years. Based on their beliefs about earnings, firms overpay for ships immediately following the shock. However, ship prices eventually fall below their steady-state level as firms are disappointed by the level of subsequent earnings.

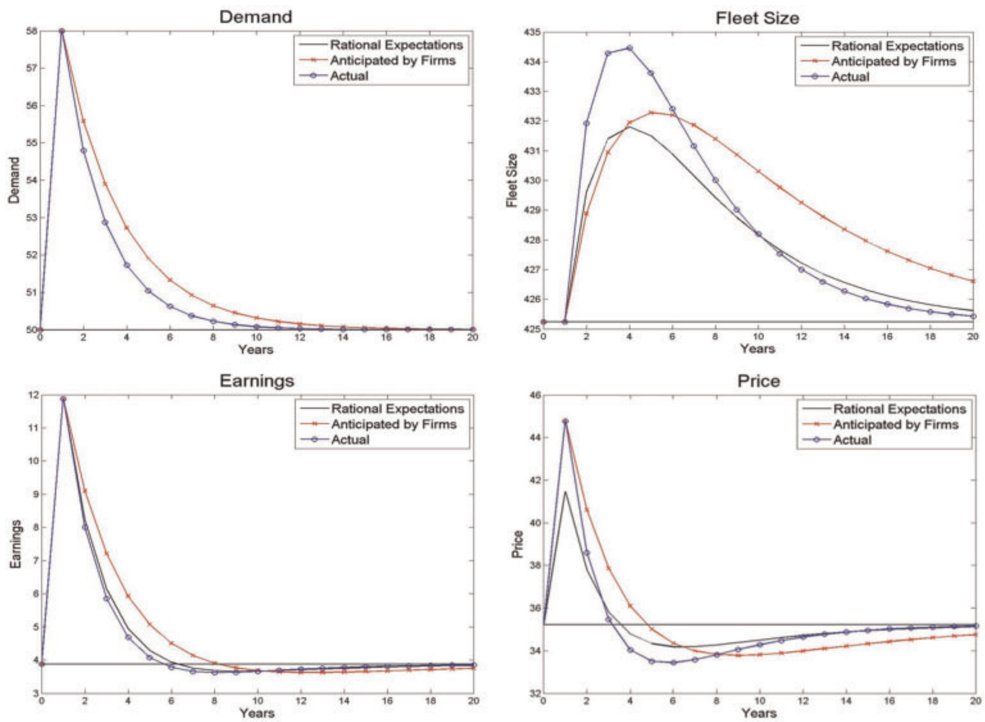

FIGURE VI

Model-Implied Impulse Response Functions

This figure shows the model-implied impulse response functions following a one-time shock to demand. The figures correspond to the estimates in the final column of Table VI which allow for both competition neglect ($\theta < 1$) and demand overextrapolation ($\rho_f > \rho_0$). Following an eight-unit demand shock at $t = 1$, the figures contrast the impulse response under rational expectations ($\rho_f = \rho_0$ and $\theta = 1$) with the impulse response anticipated by firms who suffer from both biases and the actual impulse response when firms suffer from both biases.

The panels in Figure VI show not only the expected path and realized path, but also the path that would have occurred had agents in the model held fully rational expectations. This is the path that would obtain if we imposed $\theta = 1$ and $\rho_f = \rho_0$, but held all other parameters fixed. The panels show that market participants' expectational errors create significant excess volatility in prices and investment. However, because firms overinvest following a positive demand shock, earnings mean revert more quickly and are therefore less volatile than in the rational expectations case.

VI. Conclusion

We developed a model of industry equilibrium dynamics in which firms make two natural forecasting errors. First, they fail to accurately forecast demand, believing it to be more persistent than it actually is. Second, they fail to fully anticipate the endogenous supply responses of their competitors and the effect these responses will have on earnings. As a result, firms overinvest during booms and are predictably disappointed by future earnings, resulting in predictable variation in the returns on real capital. Estimating the model using data from the dry bulk shipping industry, we show that modest expectations errors generate excess volatility in investment and prices as well as dramatic predictability in the returns on capital.

A number of capital intensive industries, including chemicals, oil exploration, and real estate, have experienced boom-bust cycles that resemble those we have documented in dry bulk shipping. Competition neglect may well have played a role in driving these cycles. For instance, looking back at U.S. real estate over the past two centuries, Glaeser (2013) argues that "The recurring error appears to be a failure to anticipate the impact that elastic supply will eventually have on prices." It is hard to overstate the role competition plays in normalizing profits and returns on capital over the long run. However, in industries where feedback from investment decisions occurs with a lag, the impact of competition may not be as salient as other routine managerial challenges.

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