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## Sinking Ships: Illiquidity and the Predictability of Returns on Real Assets in Recessions*

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**Job Market Paper**

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Abstract

*Using the context of the dry-bulk shipping industry, I document that future returns on real assets are strongly predictable and negatively related to current asset prices, earnings, and investment during recessions. However, there is no such relationship outside recessions. This asymmetry points against existing explanations of return predictability, such as predictable boom-bust cycles arising from firms overreacting in good times. Instead, I argue that predictability arises in recessions due to liquidity constraints and limits to arbitrage. When cash flows evaporate, distressed firms are forced to sell assets to their liquidity-constrained peers, resulting in falling prices and rising expected returns for buyers. This theory is corroborated by narratives from industry practitioners and dynamics of forced auction sales. Considering that shipping is virtually a model case of a competitive industry operating large and expensive assets, the results likely generalise to other capital-intensive sectors of the economy.*

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# I. Introduction

Do rational traders arbitrage away pricing inefficiencies in the markets for real assets? If there are limits to such arbitrage,[1] when do they matter? Macroeconomists have long recognized that market illiquidity and collapsing collateral values in downturns can lead to a vicious circle, amplifying the fall in investment and economic activity (Kiyotaki and Moore, 1997). On the other hand, unchecked surges in asset prices can also result in a familiar boom-bust cycle, in which overbuilding of physical capital during good times deepens the subsequent recessions and delays recoveries (Beaudry et al., 2017; Rognlie et al., 2018). This paper provides evidence indicating significant market illiquidity and asset mispricing in capital-intensive industries during recessions, but inconsistent with the boom-bust dynamics.

Specifically, I study the link between movements in asset prices, investment, and future returns on real assets in the context of the dry bulk shipping industry. I find no association between the current level of industry activity and future returns on investments during expansions. In other words, good times do not predictably lead to bad times. However, I find that during recessions, the returns on capital are strongly and negatively related to the industry earnings, asset prices, and investment. That is, the worse is the plunge, the handsomer is the expected reward to those who buy ships. This empirical evidence points to a different mechanism than existing behavioural and risk-based explanations of return predictability. The documented predictability of returns during recessions can be naturally explained by lack of liquidity and limits to arbitrage in the industry during downturns, which cause asset prices to fall below their fundamental value and future expected returns to increase.

Dry bulk shipping provides the perfect setting for my analysis. With a large number of small shipowners and little scope for differentiation, it resembles perfect competition. It is, nevertheless, a highly capital-intensive industry. Because it takes several years to build a ship, the aggregate dry bulk fleet responds slowly to developments in the demand for shipping services, which in turn is closely linked to global macroeconomic conditions. The combination of fairly inelastic demand and supply that is practically fixed in the short run results in enormous variability of freight rates, and hence also industry earnings and prices of second-hand ships on the well-established sales and purchase market.

Shipping industry is also considered to be one of the notable examples of boom-bust cycle dynamics. Recurring plunges in dry bulk earnings are often blamed on overordering

[1] See Gromb and Vayanos (2010) for a comprehensive and structured survey of literature on limits to arbitrage in financial markets.

of ships in good times, which ultimately causes a substantial supply glut and collapse in freight rates (Stopford, 2009). In line with this view, a prominent study by Greenwood and Hanson (2015) reports that second hand ship prices, earnings, and industry investment all negatively forecast future excess returns on owning ships during 1976-2010. The authors suggest a behavioural theory of waves in asset prices and investment, according to which firms tend to overextrapolate current conditions into the future. Firms then overreact during good times, and are predictably disappointed by the subsequent low returns.

I document empirical evidence that sheds new light on the industry cycle. Motivated by the fact that the demand for shipping services is closely linked to the state of the world economy, and tends to weaken substantially in recessions, I investigate whether the predictability of shipping excess returns varies systematically over the global business cycle. To evaluate the presence and magnitude of return predictability separately during macroeconomic expansions and recessions, I estimate regime-dependent predictive regressions. Specifically, I regress subsequent 12-, 24-, and 36- months cumulative excess returns on owning a five year old ship on each of current second hand ship prices, earnings, and industry investment, allowing the coefficients to differ between the two regimes. My monthly sample runs from 1976 through 2020, and I use the OECD based Recession Indicator for OECD and Non-member Economies as the regime dummy indicator of global recessions – one of the most comprehensive indicators of global recessions available.[2]

I find that return predictability in shipping is strongly countercyclical. During global recessions, the estimates of predictive slope coefficients on most variables and forecasting horizons are statistically significant and economically large. For example, a one standard deviation decrease in real ship prices during recessions predicts a 12 percentage point (or 0.4 standard deviation) increase in the subsequent 12-months excess returns, and a 25 percentage point (or 0.6 standard deviation) increase in excess returns over the following 24 months. Meanwhile, I cannot reject the null of no predictability during other times, and the estimates of slope coefficients are small in absolute value. Furthermore, in the majority of cases I can reject the null that slope coefficients in predictive regressions are equal across the two regimes. The results are robust to various checks designed to control for potential biases, outliers, inference issues, and measurement errors.

These findings are difficult to explain with the idea that firms overreact to industry conditions, because the latter implies that returns would be predictable following both good and bad times. Yet, I find only weak evidence of predictability in the whole estimation sample when not allowing for regimes.[3] Importantly, there is also little evidence that

[2]The results are similar when alternative indicators of recessions are used, such as NBER recession dates for the US, the Wold Bank dates for global recessions, as well as industry-specific recession indicators.

[3]As I elaborate later, the difference compared to results reported in Greenwood and Hanson (2015) arises

the documented return predictability reflects systematic variation over time in the rate of return required by investors. Discount rate variation is one of the leading research avenues in modern asset pricing (Cochrane, 2011), and at first glance the finding that return predictability emerges strongly during recessions concurs with the intuition that required risk premia increase during downturns. Yet, I find that low ship prices and earnings in recessions are associated with low future shipping risk. Moreover, the ability of predictive regressors to forecast future returns also does not weaken when controlling for variation over time in measures of the economy-wide risk premium. Lastly, ships appear to have particularly low hedge value (and hence could be required to generate higher returns) when ship prices, earning, and investments are high, rather than low.

Instead, I argue, the countercyclical return predictability is a natural manifestation of binding financial constraints and limited arbitrage in the industry during downturns. When earnings fall and cash flows dry up in recessions, many firms are forced to sell their assets in order to raise cash, either to cover bills or repay outstanding debts under creditors' pressure. At the same time, the potential buyers – mostly other firms in the industry – are also tight on cash, and can find it difficult to borrow funds. Their ability to absorb assets from the distressed firms is therefore limited: prices of used ships have to fall below their fundamental value to equilibrate the distressed supply with the constrained demand. The worse is the recession, the more constrained the buyers are, and so the deeper prices fall, resulting in higher excess returns to the firms that do manage to buy ships. The lack of financing and falling prices for second hand tonnage also lead to a collapse in industry investment, implying a negative association between investment and future returns as well.[4] To sum up, substantial return predictability in recessions then reflects asset prices falling below their fundamental value due to the lack of liquidity and the resulting cash-in-the-market pricing.

The view that financial woes put huge downward pressure on second hand prices and investment during recessions is supported by numerous accounts from shipping industry experts and practitioners. The dearth of financing is an especially recurring narrative during crisis episodes, when ships can sell at a multiple of their scrap value.[5] As further

due to a combination of longer data set, slight differences in data construction, and the use of a novel robust statistical testing procedure, each materially contributing to the difference in conclusions. None of these affect the result that return predictability strongly emerges in recessions, however.

[4]First, a fall in industry investment is driven by, and therefore correlated with the fall in earnings and asset prices. Second, constrained ordering of new ships due to financial frictions also implies higher expected earnings per ship in a few years time. Observe that while sales of second hand ships at depressed prices simply represent a transfer from the sellers to the buyers, plunges in industry investment likely reflect efficiency losses due to financial constraints.

[5]See section IV for a detailed review of narratives from industry experts.

evidence of this mechanism, I find that the incidence of auction sales of ships increases sharply during recessions. Auction sales are distressed sales that follow arrests of ships by creditors and court orders. Because the process incurs large costs, an auction sale is an extreme outcome that is in everyone's interest to avoid.[6] Indeed, Franks et al. (2020) show that in the vast majority of cases owners and banks are able to negotiate workouts that avoid arrests, often through "voluntary" sales of assets. Systematic spikes in auction sales thus indicate that firms experience significant financial troubles in recessions.

It is only natural to expect financial constraints to play a critical role in industries where firms require both large amounts of capital and considerable specialist knowledge to operate. This can result in substantial information asymmetries between firms and capital providers, as well as limit the ability of potential outside arbitrageurs to supply liquidity to the industry. Shipping is the case in point: dominated by many small, often family-owned firms with specialist knowledge and informal corporate structures, the industry traditionally relies on bank financing, and, in addition, is characterised by high volatility of cash flows and asset prices. For these reasons, lenders to shipping companies typically possess considerable industry expertise, while outsiders can find it difficult to make a profitable jump into the sector. There are at least several other important industries that share some of these key characteristics and thus are likely to exhibit similar dynamics, including shale oil and gas, airlines, and specialised real estate.

I formalize the mechanism described above and show how return predictability emerges countercyclically in a model of a competitive capital-intensive industry, in which firms are exposed to both aggregate and idiosyncratic shocks. Because of limited commitment problems on the firms' side, the optimal financial contracts in the model take the form of simple non-recourse debt secured by the resale value of capital.[7] In an expansion, most firms generate enough cash flows to repay debts and also have spare liquidity to purchase assets at their full fundamental value from the distressed firms hit by bad idiosyncratic shocks. In a recession, however, even firms with good idiosyncratic shocks have limited spare liquidity, and are unable to borrow, while the amount of capital that firms with bad shocks must sell increases. The worse is the aggregate shock, the deeper the asset price falls below the fundamental value in order to equilibrate constrained demand and the forced sales. The buyers end up earning high excess returns, which are larger the deeper the recession is.

My paper is closely related to the literatures on liquidity constraints and fire sales.

[6] On top of opportunity costs of foregone cash flows during an arrest, Franks et al. (2020) estimate the direct costs of arrest and auction to be around 8% of the vessel's value.

[7] In fact, Franks et al. (2020) document that this is the commonplace debt contract in the shipping industry.

Shleifer and Vishny (1992) were among the first to argue that when a financially distressed firm liquidates assets, other firms in the same industry, who are the natural buyers, are also likely to be experiencing hard times. This leads to specialized assets selling for prices below their value in best use, and also creates the possibility of misallocation if less efficient users end up buying them.[8] There has been a substantial empirical literature testing this hypothesis, notably Pulvino (1998) in the context of the airline industry, Campbell et al. (2011) in the context of the housing market, and Rajan and Ramcharan (2016) in the context of the US banking industry during the Great Depression. Franks et al. (2022) document that fire sale discounts in the airline industry predominantly reflect the liquidity channel and quality impairments due to under-maintenance of assets, while they find no evidence of misallocation. Because in this paper I focus on relatively new, five year old ships, under-maintenance is unlikely to be a major driver of my results. The sharp increases in expected returns that I document when asset prices fall in recessions, coupled with the ample evidence of financial woes faced by the shipping firms, provides further evidence in support of systemic illiquidity and asset mispricing in capital-intensive industries during macroeconomic downturns.

The question of why external arbitrageurs may not be able to provide liquidity and eliminate mispricing in the market is the subject of the literature on limits to arbitrage, with seminal contributions by Shleifer and Vishny (1997) and Gromb and Vayanos (2002) among others. While the majority of that literature is concerned with financial markets, the present paper provides evidence consistent with significant limits to arbitrage in the markets for real assets. The resulting illiquidity during downturns can affect not only asset prices, but also real investment in affected industries.

Lastly, this paper also contributes to the extensive empirical asset pricing literature on return predictability.[9] Notably, Rapach et al. (2009), Henkel et al. (2011), and Dangl and Halling (2012) document that predictability of stock market returns is significantly stronger during recessions. However, in contrast with most of the asset pricing literature which focuses on returns on financial assets, this paper directly analyses the returns on real capital investments. Greenwood and Hanson (2015) is among few prior papers that study return predictability on real assets in capital-intensive industries.[10] I significantly extend prior findings by documenting that predictability of returns on owning ships is present only during global recessions. To the best of my knowledge, the present paper is

[8]The dynamic version of this idea has been at the centre of the literature on financial accelerator in macroeconomics, notably Kiyotaki and Moore (1997), Bernanke et al. (1999) and Gertler and Karadi (2011), among others. For a review of literature on fire sales in macroeconomics see Shleifer and Vishny (2011).

[9]For a survey of this literature, see Cochrane (2011).

[10]Other studies also looked at return predictability in real estate markets, see Ghysels et al. (2013).

also the first in the predictability literature to suggest that this phenomenon arises due to liquidity constraints faced by firms in the industry.

## II. Dry bulk shipping: background and data

In this section I briefly outline the important features of the dry bulk shipping industry. I then describe the data set used in the empirical investigation.

### *II.A. Basic facts about dry bulk shipping*

Dry bulk shipping is an attractive industry for economic analysis, with a growing number of recent studies in the literature that focus on it.[11] With a large number of small shipowners and little scope for differentiation, dry bulk shipping closely resembles a perfect competition environment. Indeed, the largest firm owns only around 3% of the fleet, and there is a long tail of small shipowners with just one ship each (Kalouptsidi, 2014).

Dry bulk vessels mainly transport raw materials such as iron ore, grain, coal, phosphates and bauxite (five "major bulks"), as well as minor bulks. There are four major dry bulk ship categories: Handysize (below 40,000 DWT[12]), Handymax (40,000 - 60,000 DWT), Panamax (60,000 - 100,000 DWT), and Capesize (above 100,000 DWT). As Kalouptsidi (2014) points out, since vessels in different size categories can carry different products, take different routes, and approach different ports, practitioners sometimes treat them as different markets. However, the separation is not rigid, since in practice ships often move between adjacent segments in response to freight rates.

Demand for seaborne shipping is closely related to developments in the world economy and international trade. At least in the short run, it is fairly price inelastic: changes in transport costs have little impact on the volume of cargo transported. This is due to the fact that shipping bulk goods by sea is one of the cheapest options with few alternatives, and, moreover, freight rates constitute a relatively small fraction of the overall costs that shippers face (Stopford, 2009).

The elasticity of supply of shipping services in the short run depends on the aggregate conditions. Roughly, it can be in one of the two regimes: (i) very inelastic during normal times, when most of the vessels are in active operation, and (ii) very elastic during industry recessions, when freight rates are low and a substantial fraction of ships may be laid

[11] Notably, Kalouptsidi (2014), Greenwood and Hanson (2015), Franks et al. (2020) and Campello et al. (2023).

[12] Deadweight tonnes - a standard measure of ship size according to how much weight it can carry.

up (Evans, 1988). In the long run, on the other hand, the world fleet is determined by deliveries and scrappages. Since it takes one to four years to build a ship, and the average economic life of a ship is around 25 years, the fleet changes only slowly in response to developments in demand (Stopford, 2009).

The combination of often inelastic supply and inelastic demand for shipping services should make it hardly surprising that freight rates and earnings are highly volatile. Given that the industry's fleet is practically fixed in the short run, even relatively modest changes in the demand for shipping cargo can lead to large changes in freight rates.

### *II.B. Data*

The data on ship prices, earnings, and investment comes from Clarksons Research, one of the leading providers of intelligence on global shipping. The sample runs from January 1976 until December 2020. For the main results, I use data on 5-year-old 76,000 DWT Panamax-class vessels – mid-size bulk carriers typically considered representative of the broader fleet.[13] Because Greenwood and Hanson (2015) (henceforth GH) use the same database, I mostly rely on their approach when constructing the time series used in the empirical analysis. These include:

- Real ship price $P_t$ – second hand prices of 5-year-old ships, expressed in constant 2011 dollars using the CPI index,[14] available monthly.

- Real net earnings $\Pi_t$ – earnings per ship net of depreciation, in constant 2011 dollars. This is a monthly series of annual real earnings accruing to an owner of a Panamax class ship who leases their vessel for the next 12 months via a time charter agreement.[15] The owner typically provides crew and maintenance, while the charterer bears all the remaining costs, including fuel. Accounting for the fact that a ship spends an average of 8 days per year on maintenance, the annual earnings are computed as:

$$\Pi_t = 357 \cdot DailyLeaseRate_t - 365 \cdot DailyCrewCost_t - Depreciation_t. \tag{1}$$

[13] As I verify in the Appendix, the results equally apply to smaller Handysize and larger Capesize ships.

[14] Retrieved from FRED and provided by the US Bureau of Labour and Statistics.

[15] Owners may also choose to operate ships themselves and earn spot freight rates instead. Stopford (2009) demonstrates that spot trading and time chartering remain two important competing strategies of employing ships, between which firms actively choose. For this reason, it is unlikely that a measure of earnings based on spot fright rates would yield significantly different results. The choice to use time charter rates has to do mostly with data availability from Clarksons and the fact that it is significantly more straightforward to compute earnings based on time charter rates rather than spot freight rates. For example, I do not need the data on ship utilization and fuel costs, which can be highly variable.

Here $DailyLeaseRate_t$ is the 12-months time charter rate[16] in month $t$, expressed in 2011 dollars using the CPI, $DailyCrewCost_t$ is estimated to be around \$6,000 in 2011 dollars, and depreciation rate is set at 4% of the value of the ship, in line with the linear depreciation method typically employed in shipping.

- Investment $I_t$ measures aggregate investment decisions of the shipping industry participants over the past year, relative to the current size of the fleet.[17] Specifically:

$$I_t = \sum_{\tau=t-11}^{t} \Big( NetContracting_\tau - Demolitions_\tau + Additions_\tau - Removals_\tau \Big) / Fleet_t, \quad (2)$$

where $NetContracting_\tau$ is the new orders placed for newbuilt ships in month $\tau$ net of cancellations of previously made orders, while $Demolitions_\tau$ represents scrapping of the old fleet in month $\tau$. Demolitions are typically timed according to market conditions, e.g. can be postponed during booms or brought forward during downturns, and hence constitute part of active investment decisions. $Additions_\tau$ and $Removals_\tau$ represent rare conversions of ships into and out of the bulkcarrier fleet, while $Fleet_t$ is the total size of the global bulk cargo fleet in month $t$. In line with GH, I focus on the smoothed 12-month investment measure due to high volatility of $NetContracting_\tau$ and $Demolitions_\tau$ on the monthly basis.

All variables in (2) are expressed in deadweight tonnes (DWT) and are directly available from Clarksons, with the exception of $NetContracting_\tau$. The latter is constructed from the available monthly ship orderbook data as:

$$\begin{aligned} NetContracting_\tau &= NewOrders_\tau - Cancellations_\tau \\ &= Orderbook_{\tau+1} - (Orderbook_\tau - Deliveries_\tau), \end{aligned} \quad (3)$$

where $Orderbook_\tau$ is the total outstanding orders for new ships in month $\tau$, and $Deliveries_\tau$ is newbuilt ships delivered in month $\tau$, both measured in DWT. Unfortunately, as the orderbook data is only available going back to January 1996, my

[16]While second-hand ship prices are reported for 76,000 DWT ships, time charter rates are reported for 65,000 DWT vessels. GH propose a simple adjustment and multiply time charter rates by 76/65. From the detailed notes on the data, however, I discovered that there were changes in the underlying vessel sizes also *within* the same series. For example, the price series was reported for 60,000 DWT Panamax vessels until 1993; 68,000 DWT between 1993 and 1997; 70,000 DWT between 1997 and 2001; 73,000 DWT between 2001 and 2010; and finally 76,000 DWT since 2010. Thus, to be consistent, I adjust observations where size of the ship is $S_t < 76,000$ by $76,000/S_t$. Doing these adjustments one way or another does not affect my main result that returns on ships are strongly predictable in recessions, but not in expansions. However, the adjustment matters for the result that returns are predictable over the entire period, as I discuss later.

[17]Note that the investment measure is for the entire bulkcarrier fleet, not just Panamax ships.

investment series is significantly shorter compared to other variables.[18]

- $rx_{t+K}$ – cumulative log excess return on ships over the following $K$ months, $K \in \{12, 24, 36\}$. To be precise, this is the excess return that accrues to an owner who leases their ship for $K$ months by signing sequential 12-months time charter contracts every year.

  I first compute the nominal 12-months holding period return as

$$r_{t+12} = \frac{P^N_{t+12} + \Pi^N_t}{P^N_t} - 1, \tag{4}$$

  using nominal ship prices and earnings.[19] The 12-month log excess return are then computed as:

$$rx_{t+12} = \ln(1 + r_{t+12}) - \ln(1 + r^f_{t+12}), \tag{5}$$

  where $r^f_{t+12}$ is the cumulative Treasury Bill rate from Ken French's database.[20] Given the assumption that a ship owner signs a new 12-months time charter contract each year, 12-months excess returns can be simply summed up to compute 2- and 3-years cumulative excess returns $rx_{t+24}$ and $rx_{t+36}$. Table 1 summarizes the shipping data.

In addition, as an indicator of global recessions in the empirical analysis I use the OECD global recession indicator $\mathbb{1}^R_t$ – a composite recession indicator for OECD and Non-member economies[21] provided by FRED and based on OECD business cycle turning points developed as part of the Composite Leading Indicators (CLI) project. The OECD CLI system is based on the growth cycle approach, where business cycles and turning points are measured and identified in the deviation-from-trend GDP series.[22] The turning

[18]While data on ex-post fleet delivery realisations is available going all the way back to 1976, it is difficult to back out at what time the orders for these ships were made. This is due a substantial and uncertain time to build: it can take 1 to 4 years to build a ship, and there are often delays past contracted dates. Even average time to build is hardly constant, as it increases with the amount of outstanding orders. For these reasons, I choose to stick with a shorter investment series which best captures the firms' investment decisions at time $t$.

[19]Nominal values denoted by the superscript *'N'*, and are computed similarly to their real counterparts.

[20]By subtracting the nominal risk-free interest rate from the nominal returns on ships, I also account for (possibly predictable) effects of inflation.

[21]The full list of countries covered is: Australia, Austria, Belgium, Canada, Chile, Colombia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States, Brazil, China, India, Indonesia, Russia, South Africa.

[22]GDP is used as the reference for identification of turning points in the growth cycle for all countries except China, for which the OECD relies on the value added of industry at 1995 prices.

Table 1: Summary statistics

| Variable | $T$ | Mean | Median | Std. dev. | Min. | Max. | $\phi_1$ | $\phi_{12}$ | $\phi_{24}$ | ADF test |
|---|---|---|---|---|---|---|---|---|---|---|
| Net Earnings $\Pi_t$ | 540 | 3.67 | 2.32 | 4.25 | -1.03 | 26.91 | 0.97 | 0.44 | 0.17 | 0.02 |
| Price $P_t$ | 540 | 33.92 | 31.68 | 16.71 | 12.36 | 103.23 | 0.98 | 0.59 | 0.31 | 0.07 |
| Investment $I_t$ | 289 | 0.069 | 0.040 | 0.098 | -0.040 | 0.423 | 0.99 | 0.52 | 0.20 | 0.02 |
| $rx_{t+12}$ | 528 | 0.057 | 0.051 | 0.302 | -0.686 | 0.862 | 0.96 | 0.08 | -0.15 | $<0.01$ |
| $rx_{t+24}$ | 516 | 0.121 | 0.060 | 0.446 | -1.154 | 1.201 | 0.98 | 0.46 | -0.05 | $<0.01$ |
| $rx_{t+36}$ | 504 | 0.187 | 0.075 | 0.529 | -0.891 | 1.442 | 0.99 | 0.71 | 0.33 | 0.31 |

*Notes.* $T$ is the number of observations. $\phi_k$ is the lag $k$ autocorrelation. ADF test contains p-values from the Augmented Dickey-Fuller Test (alternative hypothesis: stationary time series).

point detection algorithm is based on the Bry and Boschan routine (OECD, 2022). It should be noted that due to the growth cycle approach, the OECD indicator tends to call recessions rather frequently in comparison with other, more conservative definitions of recessions. Nevertheless, this is one of the most comprehensive global recession indicators available. As discussed in section III.C.1, my results are robust when using alternative indicators.

## *II.C. Time series properties of ship earnings, prices, and returns*

Figure 1, Panel A shows that ship earnings and prices are highly volatile and closely track each other. Both series also appear strongly mean-reverting. For example, while the 1-month autocorrelation of the earning series is 0.97, at 12- and 24-months horizons it is only 0.44 and 0.17, respectively. It should not be surprising that ship earnings and prices are highly autocorrelated at the monthly frequency: there is simply not much that firms can do to respond to demand shocks, given the long time to build. However, the high degree of competition ensures that within 2-3 years shipping capacity adjusts sufficiently to revert earnings per ship back to the normal competitive level. This logic remains valid even if the demand process for shipping services is a random walk.

Industry investment is shown in Figure 1, Panel B and closely follows the movements in ship prices and earnings. Indeed, the correlation between asset price and industry investment is 90%. Lastly, Panel C shows the 12- and 24-months cumulative log excess returns on owning ships. These series are also highly volatile, with 12-month returns ranging from -69% to 86%. Because the returns are cumulative, overlapping observations induce high degree of persistence from month to month in the series, which disappears within 1-2 years.

In agreement with the above arguments, the ADF test reported in Table 1 rejects a unit

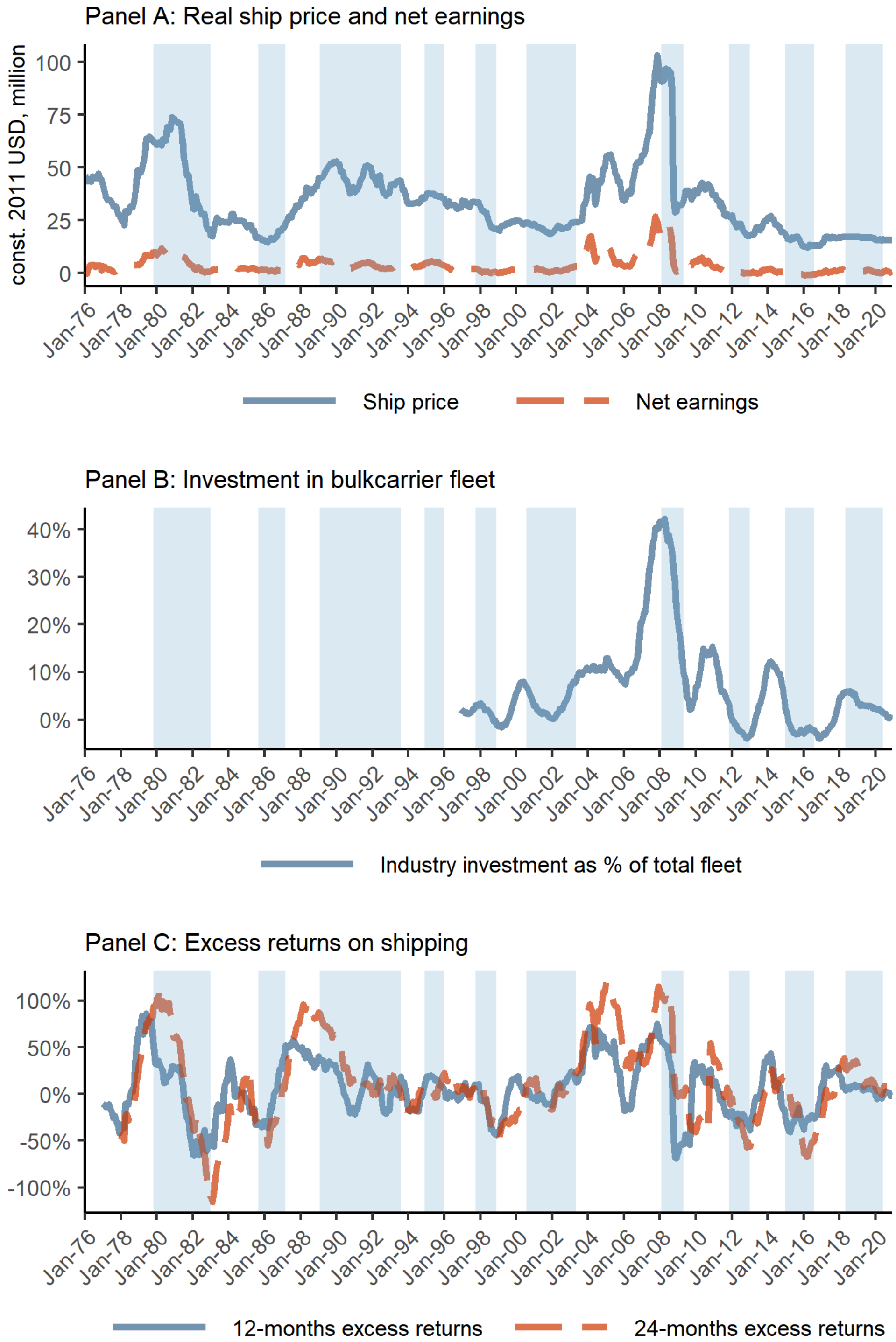


Figure 1: Ship price, earnings, investment, and returns

*Notes.* In this and subsequent figures the light blue bars indicate OECD global recessions.

root in real ship prices at the 10% level, and in net earnings per ship and investment at the 5% level. We can also reject a unit root in 12- and 24-months cumulative excess returns at less than the 1% significance level. Although the ADF test does not reject presence of a unit root in 36-months cumulative returns, this is likely due to the high level of autocorrelation induced by the overlapping nature of the observations.[23]

## III. Countercyclical predictability of shipping returns

We now turn to investigating the relationship between current ship earnings, prices, and investment, and future excess returns. In contrast to previous literature, I find only weak evidence that the returns in shipping are predictable in the whole sample. However, I show that predictability appears strongly during global recessions, and is not present during expansions.

### *III.A. Return predictability in simple univariate regressions*

Greenwood and Hanson (2015) (GH) document that during the period of 1976-2010 variables like earnings, second hand ship prices, and industry investment all negatively forecast returns on owning ships over the following 1 to 3 years in univariate linear predictive regressions of the form

$$rx_{t+K} = a + bX_t + v_{t+K} \tag{6}$$

where $rx_{t+K}$ is $K$-months cumulative log excess return between $t$ and $t+K$, $X_t$ is a predictive regressor, and $v_{t+K}$ is the error term. The previously reported predictability is both statistically significant and economically large.

I, however, find relatively weak evidence of shipping return predictability over the entire sample period, which in my case is 1976-2020. Table 2 presents the estimates of slope coefficients in (6) when using, in turn, ship earnings, prices and industry investments as predictive regressor to forecast cumulative excess returns at 12-, 24-, and 36-months horizons. The first observation is that the strength of statistical evidence for predictability in the whole sample appears substantially weaker than previously reported. We reject

[23] For the ADF test I use the default number of lags in the R *tseries* package: $\lfloor (T-1)^{\frac{1}{3}} \rfloor$. It is known, however, that lag selection can affect the outcome of the test, and that it may suffer from potentially large size distortions. To check the robustness of the result, I also employ state-of-the-art bootstrap model averaging unit root inference by Hansen and Racine (2018). They demonstrate that an automatic model averaging procedure has the lowest size distortions among its peers, while maintaining superior power. This HR test rejects the unit root hypothesis for all series except investment at least at the 10% level.

Table 2: Return predictability in shipping: simple univariate regressions

| | $X$ = net real earnings $\Pi$ | | | $X$ = used ship price $P$ | | | $X$ = investment $I$ | | |
|---|---|---|---|---|---|---|---|---|---|
| $K$ | 12m | 24m | 36m | 12m | 24m | 36m | 12m | 24m | 36m |
| $b$ | -0.007 | -0.019 | -0.018 | -0.004* | -0.009+ | -0.011 | -0.406 | -0.762* | -0.557 |
| | (0.007) | (0.012) | (0.021) | (0.001) | (0.004) | (0.007) | (0.313) | (0.266) | (0.479) |
| | [0.390] | [0.206] | [0.429] | [0.011] | [0.088] | [0.165] | [0.264] | [0.046] | [0.309] |
| $T$ obs. | 528 | 516 | 504 | 528 | 516 | 504 | 277 | 265 | 253 |
| $R^2$ | 0.009 | 0.032 | 0.023 | 0.061 | 0.113 | 0.124 | 0.018 | 0.032 | 0.013 |

*Notes.* This table reports the estimates of slope coefficients in univariate time series regressions of the form $rx_{t+K} = a + bX_t + v_{t+K}$ where $X_t$ is one of the forecasting variables, K is the forecasting horizon in months, and $rx_{t+K}$ is cumulative log excess return between months $t$ and $t+K$. Standard errors are reported in parentheses, and p-values are reported in brackets, all obtained using OS HAR inference. $^{+}$,$^{*}$,$^{**}$, and $^{***}$ indicate significance at the 0.1, 0.05, 0.01, and 0.001 levels, respectively.

the null of no predictability only in three out of nine cases: prices appear to negatively forecast future returns at 1 and 2 year horizons, at the 5% and 10% significance levels respectively, and investment is negatively associated with 2-year ahead returns at the 5% significance level. We do not reject the null of no predictability of returns by net earnings at any horizon at any conventional significance level. Secondly, it is worth noting smaller point estimates of coefficients compared to the previous literature, which partly explain the difference in statistical conclusions. For example, the estimated effects for net earnings are less than half in absolute value than those found by GH.

What explains the difference in findings? There are three contributing factors. Firstly, to address the issue of overlapping observations and autocorrelated residuals, I estimate linear regressions (6) using OLS with the state-of-the-art Heteroscedasticity and Autocorrelation Robust (HAR) inference (Ye and Sun, 2018), which is substantially more robust compared to the Newey-West estimator.[24] Secondly, I have 10 additional years of observations in my dataset. Thirdly, there is a slight difference in the time series construction compared to GH as outlined in footnote 16. All three of these factors end up acting

[24]The overlapping nature of the monthly observations on returns means that in univariate predictive regressions of the form (6) one would expect residuals to be highly autocorrelated. Even with non-overlapping data, one would expect residuals to be autocorrelated if returns are indeed predictable. This creates problems when testing $H_0 : b = 0$, since the recent research shows that even tests based on Newey-West and similar HAC covariance matrix estimators are usually severely oversized and tend to over-reject the null (Harri and Brorsen, 2009). There has been great theoretical progress in heteroscedasticity- and autocorrelation-robust inference starting with seminal papers by Kiefer et al. (2000) and Kiefer and Vogelsang (2002). Accounting for these concerns, I report tests using the Orthonormal Series (OS) Heteroscedasticity and Autocorrelation Robust (HAR) variance estimator that has been shown to have competitive power compared to the alternatives, while maintaining the advantage of asymptotically having a standard F distribution (Lazarus et al., 2018). It is implemented in Stata by Ye and Sun (2018).

against finding predictability in the whole sample.[25] Nevertheless, it is important to note that my main result described in the next section, namely that the predictability strongly emerges in recessionary periods and not otherwise, is not affected by changing the statistical procedure, data transformation, or restricting the sample period to 1976-2010.

To sum up, while there is some evidence of shipping return predictability in my sample, in particular by ship prices, it is considerably weaker than reported in previous literature. We now turn to investigate whether predictability varies systematically over the global business cycle.

## *III.B. Regime-dependent predictability*

The demand for shipping services is driven by the volume of international trade, which in turn is closely related to the state of the global economy. Looking back at Figure 1, we indeed see that ship prices, earnings and industry investment tend to fall during recessions. This raises the possibility that return predictability varies systematically as conditions faced by the shipping firms change over the business cycle.

I test this hypothesis by allowing the predictive relationship to change across recessions and expansions as follows:

$$rx_{t+K} = \mathbb{1}_t^R(a_1 + b_1 X_t) + (1 - \mathbb{1}_t^R)(a_2 + b_2 X_t) + v_{t+K}, \tag{7}$$

where $\mathbb{1}_t^R$ is the OECD based indicator of global recessions. This way, I let coefficients take different values depending on whether month $t$ – the month in which we attempt to forecast returns over the following $K$ months, using data on the predictor variable for month $t$ – is classed as being in a recession or not; but not depending on whether the period spanned by the dependent variable is wholly or partly classed as a recession period. We are interested in whether coefficients $b_1$ and $b_2$ are systematically different across the two regimes. As before, I estimate (7) using OLS with OS HAR inference.

Table 3 presents the results. Firstly, all but two of the estimates of predictive slope coefficients in recessions ($b_1$) are statistically significant at least at the 10% level, while

[25] It is difficult to say how much precisely each of them contributes to the difference, but the following exercise is suggestive. I begin by replicating GH's results for ship earnings and prices exactly, using the same data and the Newey-West estimator. First, I find that the statistical procedure matters. When I change the inference procedure to OS HAR, I can usually reject the null of no predictability at about 5% significance level, compared to 1% significance when using the Newey-West estimator. Second, when I still restrict the estimation period to 1976-2010, but alter the data construction as outlined in footnote 16, coefficient estimates on earnings fall by about 40% in absolute value and lose statistical significance, although the results are largely unchanged for prices. Lastly, once the data is extended to include 10 additional years, coefficient estimates further fall by about 30% in absolute value, and statistical significance also weakens for ship prices.

Table 3: Regime-dependent return predictability in shipping

| | $X$ = net real earnings $\Pi$ | | | $X$ = used ship price $P$ | | | $X$ = investment $I$ | | |
|---|---|---|---|---|---|---|---|---|---|
| $K$ | 12m | 24m | 36m | 12m | 24m | 36m | 12m | 24m | 36m |
| $b_1$ | -0.027$^{***}$ | -0.050 | -0.062$^{+}$ | -0.007$^{**}$ | -0.015$^{+}$ | -0.020$^{+}$ | -0.801$^{*}$ | -0.810$^{+}$ | -1.268 |
| | (0.006) | (0.026) | (0.032) | (0.002) | (0.006) | (0.008) | (0.311) | (0.408) | (0.907) |
| | [0.001] | [0.130] | [0.096] | [0.004] | [0.063] | [0.072] | [0.033] | [0.075] | [0.212] |
| $b_2$ | 0.008 | 0.007 | 0.016 | -0.000 | -0.001 | 0.000 | -0.180 | -0.548 | 0.373 |
| | (0.010) | (0.016) | (0.019) | (0.002) | (0.004) | (0.006) | (0.393) | (0.462) | (0.656) |
| | [0.420] | [0.700] | [0.427] | [0.883] | [0.847] | [0.991] | [0.659] | [0.301] | [0.600] |
| F-test $b_1 = b_2$ | 0.004 | 0.141 | 0.108 | 0.014 | 0.086 | 0.043 | 0.232 | 0.601 | 0.083 |
| $T_1$ obs. | 237 | 225 | 217 | 237 | 225 | 217 | 115 | 103 | 95 |
| $T_2$ obs. | 291 | 291 | 287 | 291 | 291 | 287 | 162 | 162 | 158 |
| $R^2$ | 0.108 | 0.109 | 0.135 | 0.135 | 0.186 | 0.225 | 0.067 | 0.053 | 0.060 |

*Notes.* This table reports the estimates of slope coefficients and F-test statistics for regime switching time series regressions of the form $rx_{t+K} = \mathbb{1}_t^R(a_1 + b_1 X_t) + (1 - \mathbb{1}_t^R)(a_2 + b_2 X_t) + v_{t+K}$, where $\mathbb{1}_t^R$ is the OECD global recession indicator, $X_t$ is one of the forecasting variables, $K$ is the forecasting horizon in months, and $rx_{t+K}$ is cumulative log excess return between months $t$ and $t+K$. Standard errors are reported in parentheses, and p-values are reported in brackets, while the F-test row reports p-value for testing $H_0 : b_1 = b_2$, all obtained using OS HAR inference. $^{+}$,$^{*}$,$^{**}$, and $^{***}$ indicate significance at the 0.1, 0.05, 0.01, and 0.001 levels, respectively.

none is remotely close to being significant in other times ($b_2$). There is particularly strong statistical evidence that in recession months future returns are predictable at the 12-months horizon, as coefficient estimates on net earnings and prices are significant at the 0.1% and 1% levels, respectively. The estimate of the coefficient on investment, for which I have only about half the number of observations, is significant at the 5% level. Most coefficient estimates for predictability at 24 and 36 month horizons are significant at the 10% level.

Secondly, for the majority of these predictive regressions, we can reject the null hypothesis that slope coefficients are equal across regimes $H_0 : b_1 = b_2$, notably at the 1% level for earnings at the 12 months horizon, and at the 5% level for prices at the 12 and 36 months horizons. Even when we cannot reject the null at the standard levels for earnings, the p-values are just above the 10% threshold. Although we fail to reject $H_0 : b_1 = b_2$ for investment at the 12 and 24 months horizons, it is likely because of limited power due to a smaller number of observations.

Lastly, the point estimates of slope coefficients during recessions are substantially larger in absolute value than the estimates in the non-recession regime (or, for that matter, than the estimates in the full sample univariate regressions reported in Table 2). The predictability during recessions is economically large: for example, a one standard deviation fall in net real earnings is associated with 11.5 and 21.3 percentage point increases in the expected cumulative excess returns over the following 1 and 2 years, respectively. Similarly, a one standard deviation decline in real ship prices during recessions predicts an 11.7 percentage point increase in the subsequent 12 months excess returns, and a 25.1 percentage point increase in excess returns over the following 24 months.

The presented empirical evidence thus indicates that return predictability in the shipping industry is both statistically significant and economically large during global recessions, but not at other times.

## *III.C. Robustness*

### *III.C.1 Alternative recession indicators*

As already noted, the OECD global recession indicator is based on the growth cycle approach and thus may tend to call recessions "too often" relative to other established definitions of recessions. In addition, we can see in Figure 1 that while shipping asset prices, earnings, and investments tend to fall during OECD global recessions, as we would expect, there were also some very high ship prices and earnings observed during these periods. Therefore, to check the robustness of my findings, I run regressions of the form (7) using several alternative recession indicators, both macroeconomic and industry-specific. In particular, these include (i) recession dates set by the NBER for the US economy, (ii) the World Bank global recession indicator,[26] (iii) periods with below-median ship prices during OECD global recessions,[27] and (iv) shipping-specific recessions generated by the Bry-Boschan algorithm applied to the ship price series. I find no material difference to the result that returns are strongly predictable in downturns, but not otherwise (see Table A.1 in Appendix A).

### *III.C.2 Further robustness checks*

The Appendix provides a detailed description of several further important robustness checks and extensions. Here I provide a brief summary. First, I verify that the results are

[26]Both NBER and WB recessions indicators are significantly more conservative compared to the OECD one.

[27]The idea is to select the months when the shipping industry is depressed during macroeconomic recessions. The results actually become stronger for ship prices and earnings, indicating that the predictability strengthens at the bottom of the cycle. Similar results are obtained when instead I look at second halves of OECD recessions, which are by construction closer to macroeconomic troughs.

similar for smaller Handysize and larger Capesize vessels, and so are indeed representative of the broader shipping industry (see Table B.1 in Appendix B).

Second, we can see from Figure 1 that the shipping industry has experienced a super boom-bust cycle during 2006-2009. This raises a concern that my main results could be driven by the Great Recession. I show that the results are similar when I only use the data available up until 2006 in the estimation sample (see Table C.1 in Appendix C).

Third, I address the potential concern that my results could be driven by an upward bias in the measure of earnings, and therefore returns, during recessions. The bias could arise because some ships are likely to end up idle during downturns, as their owners may be unable to employ them. In that case, my measure of returns, which assumes ships to always be chartered away, will overstate the true returns to owning ships in recessions.[28] To avoid the bias, I estimate the predictive regressions using excess capital gains (net of depreciation) as the dependent variable, i.e. effectively setting gross ship earnings to zero (see Table D.1 in Appendix D).[29] The results are very similar to those reported in Table 3, hence it is unlikely that they are driven by a potential bias in the measure of returns.

Fourth, to overcome the concern that my findings could be driven by the overlapping observations of returns and the resulting high degree of autocorrelation, I estimate (7) using only annually sampled data, and again get results fully consistent with those in Table 3 (see Table E.1 in Appendix E).

Lastly, because the regressors I use are both persistent and endogenous, the results could potentially be driven by the Stambaugh bias (Stambaugh, 1999). In the local-to-unity case, this bias neither disappears asymptotically nor is consistently estimable. To deal with this problem, I employ the IVX procedure developed by Magdalinos and Phillips (2009) for econometric inference in the vicinity of unity, and adapted by Kostakis et al. (2015) to the context of return predictability. I use this procedure to test for predictability of shipping excess returns in recessions and expansions, and again find strong evidence of countercyclical return predictability (see Table F.1 in Appendix F).

## *III.D. Existing theories of return predictability*

### *III.D.1 Firms over-reaction to market conditions*

GH suggest a behavioural explanation for the return predictability in competitive, capital-intensive industries like shipping. According to their theory, firms tend to over-extrapolate

[28]Moreover, the number of idle ships, and therefore the size of this bias, is likely to increase when the market conditions deteriorate, potentially generating an impression of regime-dependent predictability.

[29]In other words, I set $DailyLeaseRate_t$ and $DailyCrewCost_t$ to zero in (the nominal version of) (1), and then use this amended measure of earnings to compute returns.

current demand conditions, as well as underestimate investment responses of their competitors. Biased expectations of firms about future conditions lead to excess volatility in ship prices, as well as industry overinvestment in new ships during booms and underinvestment in downturns. Ship earnings, prices, and industry investment should then negatively forecast future returns. While this explanation has an intuitive appeal and is echoed in some narrative accounts of shipping cycles, it is not consistent with my finding that the return predictability emerges only during recessions.

#### *III.D.2 Risk-based explanations of return predictability*

One of the leading explanations of return predictability is that the required rate of return changes over time (Cochrane, 2011). At first sight, my central finding that return predictability emerges strongly during recessions squares well with the intuition that risk premia required by investors increase during downturns due to increased uncertainty. However, as we will now see, this risk-based explanation does not appear to be supported by the data.

Following GH, one can decompose the excess rate of return on shipping required by diversified investors as a product of (1) the hedging value of shipping investments, i.e. the correlation between shipping returns and the welfare of a representative investor, (2) future shipping risk, and (3) the economy-wide risk premium.[30]

First, it is difficult to imagine that time variation in the hedge value of ships could account for the magnitude of documented return predictability in recessions. For that to be the case, performance of shipping investments made at the bottom of the cycle, i.e. when ship prices, earnings, and investment are low, must be particularly strongly linked to future developments in the rest of the economy. To investigate whether this is the case, I divide observations in recession months into two groups: when ship prices are high and low, or, more precisely, are above and below the median real ship price we observe in recessions. The notion that during recessions ships have particularly low hedge value at the bottom of the cycle is in sharp contrast with what we see in the data: the correlation between the future 12-months excess returns on ships and the 12-months excess stock market returns[31] is only 0.2 when prices are low in recessions, but 0.7 when ship prices are high in recession periods.[32] We see a similar picture when splitting the recession

[30]Formally, $\mathbb{E}_t[rx_{t+1}] = \text{Corr}[rx_{t+1}, -m_{t+1}]\ \sigma_t[rx_{t+1}]\ \sigma_t[m_{t+1}]\ R^f$, where $m_{t+1}$ is the stochastic discount factor.

[31]Specifically, I use cumulative Mkt-Rf from Ken French's database.

[32]Noting that ship prices, earnings, and investment tend to be high at the start of the recessions, and fall during their course, I also repeat this analysis by dividing each recession into equal first and second halves. Correlations between the future shipping and market returns are substantially lower in the second halves of

months observations by high/low ship earnings, or by high/low industry investment, and also when looking at the longer future horizons. Moreover, the pattern remains the same when instead of excess stock returns I use future world industrial production growth.[33] Therefore, shipping investments appear to have particularly low hedge value when ship prices, earnings, and investment are high when entering recessions, not at the bottom of the cycle. This is the exact opposite of what we would expect to observe if the predictability of shipping returns in recessions was related to time variation in the hedge value of ships.

To test the hypothesis that future shipping risk (and thus the required rate of return) is negatively associated with current ship prices, earnings, and investment particularly during recessions, I regress a measure of future shipping volatility on the current values of predictive regressors, allowing coefficients to differ between recessions and expansions. I estimate the following regime-dependent regression:

$$\sigma_{t+K} = \mathbb{1}_t^R(\alpha_1 + \gamma_1 X_t) + (1 - \mathbb{1}_t^R)(\alpha_2 + \gamma_2 X_t) + \varepsilon_{t+K}, \tag{8}$$

where on the left hand side I use the standard deviation of monthly ship net excess capital gains[34] over the following $K$-months window. Table 4 presents the results. Firstly, the volatility of capital gains appears to be more predictable in expansions, rather than recessions. Secondly, all the slope coefficients are positive across both the regimes, indicating that low ship prices, net earnings, and investment forecast low future volatility, in stark contrast to what we would expect if the return predictability during recessions was linked to the shipping risk. I obtain similar results when using future $K$-months volatilities of ship earnings, prices, or approximated 1-month excess returns[35] on the left hand side.

Finally, I investigate whether controlling for variation over time in the economy-wide risk premium impacts the ability of earnings and asset prices to forecast future returns in dry bulk shipping during recessions. Specifically, I estimate predictive regressions of the

the recessions.

[33] Hamilton (2021) shows that world industrial production (specifically, OECD + 6 non-member economies) is a good indicator of global economic activity. The data is from James Hamilton's website.

[34] One month net excess capital gain is defined as $\Delta px_{t+1} = \ln\left(\frac{P_{t+1}^N - Depreciation_t^N}{P_t^N}\right) - \ln(1 + r_t^f)$, i.e. net of depreciation and in excess of the risk-free rate.

[35] Because the excess returns data is based on the 12-months earnings derived from the 12-months time charter rates, I can only approximate 1-month ahead excess returns as $rx_{t+1} = \ln\left(\frac{P_{t+1}^N + \Pi_t^N/12}{P_t^N}\right) - \ln(1 + r_t^f)$. The correlation between this measure of monthly excess returns and the net excess capital gains used in the main specification is 0.997, highlighting that ship returns are to a large extent driven by capital gains.

Table 4: Forecasting capital gains volatility

| | $X$ = net real earnings $\Pi$ | | | $X$ = used ship price $P$ | | | $X$ = investment $I$ | | |
|---|---|---|---|---|---|---|---|---|---|
| $K$ | 12m | 24m | 36m | 12m | 24m | 36m | 12m | 24m | 36m |
| $\gamma_1$ | 0.007* | 0.002 | 0.002 | 0.001 | 0.000 | 0.000 | 0.442*** | 0.013 | 0.010 |
| | (0.003) | (0.002) | (0.002) | (0.001) | (0.000) | (0.000) | (0.063) | (0.020) | (0.063) |
| | [0.033] | [0.309] | [0.497] | [0.128] | [0.384] | [0.560] | [0.000] | [0.537] | [0.878] |
| $\gamma_2$ | 0.004** | 0.005* | 0.001 | 0.001+ | 0.002** | 0.001* | 0.263*** | 0.434*** | 0.095 |
| | (0.001) | (0.002) | (0.001) | (0.000) | (0.000) | (0.000) | (0.062) | (0.084) | (0.103) |
| | [0.002] | [0.037] | [0.136] | [0.085] | [0.004] | [0.034] | [0.001] | [0.001] | [0.407] |
| F-test $\gamma_1 = \gamma_2$ | 0.095 | 0.277 | 0.927 | 0.216 | 0.056 | 0.267 | 0.004 | 0.001 | 0.397 |
| $T_1$ obs. | 237 | 225 | 217 | 237 | 225 | 217 | 115 | 103 | 95 |
| $T_2$ obs. | 291 | 291 | 287 | 291 | 291 | 287 | 162 | 162 | 158 |
| $R^2$ | 0.397 | 0.195 | 0.032 | 0.290 | 0.257 | 0.065 | 0.570 | 0.407 | 0.028 |

*Notes.* This table reports the estimates of slope coefficients and F-test statistics for regime switching time series regressions of the form $\sigma_{t+K} = \mathbb{1}_t^R(\alpha_1 + \gamma_1 X_t) + (1 - \mathbb{1}_t^R)(\alpha_2 + \gamma_2 X_t) + \varepsilon_{t+K}$, where $\mathbb{1}_t^R$ is the OECD global recession indicator, $X_t$ is one of the forecasting variables, $K$ is the forecasting horizon in months, and $\sigma_{t+K}$ is the volatility of monthly ship net excess capital gains over the period from $t$ to $t+K$. Standard errors are reported in parentheses, and p-values are reported in brackets, while the F-test row reports p-value for testing $H_0 : \gamma_1 = \gamma_2$, all obtained using OS HAR inference. $^{+}$,$^{*}$,$^{**}$, and $^{***}$ indicate significance at the 0.1, 0.05, 0.01, and 0.001 levels, respectively.

following form:

$$rx_{t+K} = \mathbb{1}_t^R(a_1 + b_1 X_t) + (1 - \mathbb{1}_t^R)(a_2 + b_2 X_t) + \beta \mathbf{C_t} + v_{t+K}, \tag{9}$$

where $\mathbf{C_t}$ is a vector of controls intended to proxy for the economy-wide risk premium at time $t$. I follow GH and include the following controls: the smoothed earnings yield on S&P500 stocks from Bob Shiller's database, the credit spread between Moody's BAA and AAA bond yields, and the term spread on US government bonds.[36]

The results in Table 5 show that, if anything, net earnings, ship prices and investment appear to be *stronger* predictors of future excess returns during recessions when macro risk premium controls are included in the regressions. In addition, most of the controls have individually insignificant estimated coefficients, with the exception of the credit spread when investment is used as the predictor. When testing their joint significance, we cannot reject the null that coefficients on all controls are equal to zero in eight out of nine regressions. This evidence is inconsistent with the hypothesis that ship earnings and

[36] Specifically, the difference between the yields on 10-year and 1-year zero coupon Treasury bonds from Gürkaynak et al. (2007).

Table 5: Controlling for economy-wide risk premia

| | $X$ = net real earnings $\Pi$ | | | $X$ = used ship price $P$ | | | $X$ = investment $I$ | | |
|---|---|---|---|---|---|---|---|---|---|
| $K$ | 12m | 24m | 36m | 12m | 24m | 36m | 12m | 24m | 36m |
| $b_1$ | -0.027$^{***}$ | -0.048$^{*}$ | -0.056$^{*}$ | -0.008$^{***}$ | -0.015$^{*}$ | -0.019$^{*}$ | -1.352$^{***}$ | -1.473$^{**}$ | -1.348$^{*}$ |
| | (0.005) | (0.018) | (0.022) | (0.001) | (0.005) | (0.005) | (0.311) | (0.310) | (0.550) |
| | [0.000] | [0.034] | [0.042] | [0.000] | [0.031] | [0.014] | [0.001] | [0.003] | [0.050] |
| $b_2$ | 0.008 | 0.008 | 0.019 | -0.000 | -0.000 | 0.002 | -0.312 | -0.613 | 0.871 |
| | (0.011) | (0.018) | (0.016) | (0.002) | (0.004) | (0.006) | (0.439) | (0.733) | (1.049) |
| | [0.466] | [0.677] | [0.280] | [0.829] | [0.918] | [0.777] | [0.497] | [0.435] | [0.438] |
| Stocks | 0.000 | 0.870 | 1.815 | 0.262 | 1.449 | 2.269 | -1.701 | -9.183 | -37.059 |
| $\frac{E_{10}}{P}$ | (1.557) | (4.149) | (3.510) | (2.141) | (4.501) | (3.829) | (10.379) | (14.092) | (18.560) |
| | [1.000] | [0.844] | [0.632] | [0.909] | [0.764] | [0.585] | [0.875] | [0.550] | [0.117] |
| Credit | -0.378 | -6.985 | -17.191 | -0.786 | -7.979 | -17.841 | 30.085$^{**}$ | 45.732$^{+}$ | 50.384$^{+}$ |
| spread | (10.923) | (23.835) | (20.087) | (11.866) | (24.491) | (17.797) | (8.304) | (21.075) | (21.480) |
| | [0.973] | [0.777] | [0.417] | [0.948] | [0.756] | [0.355] | [0.003] | [0.062] | [0.057] |
| Term | -0.531 | 2.956 | 9.436 | -0.826 | 2.179 | 8.176 | -2.183 | -0.295 | 14.395 |
| spread | (3.997) | (7.744) | (9.745) | (4.097) | (7.372) | (8.876) | (8.992) | (13.831) | (14.776) |
| | [0.899] | [0.722] | [0.388] | [0.847] | [0.782] | [0.409] | [0.820] | [0.984] | [0.385] |
| F-test $b_1 = b_2$ | 0.002 | 0.126 | 0.036 | 0.009 | 0.075 | 0.017 | 0.043 | 0.348 | 0.059 |
| F-test controls | 1.000 | 0.984 | 0.771 | 0.996 | 0.985 | 0.765 | 0.073 | 0.254 | 0.328 |
| $T_1$ obs. | 237 | 225 | 217 | 237 | 225 | 217 | 115 | 103 | 95 |
| $T_2$ obs. | 291 | 291 | 287 | 291 | 291 | 287 | 162 | 162 | 158 |
| $R^2$ | 0.108 | 0.115 | 0.180 | 0.137 | 0.192 | 0.259 | 0.159 | 0.129 | 0.190 |

*Notes.* This table reports the estimates of slope coefficients and F-test statistics for regime switching time series regressions of the form $rx_{t+K} = \mathbb{1}_t^R(a_1 + b_1 X_t) + (1 - \mathbb{1}_t^R)(a_2 + b_2 X_t) + \beta \mathbf{C_t} + v_{t+K}$, where $\mathbb{1}_t^R$ is the OECD global recession indicator, $X_t$ is one of the forecasting variables, $K$ is the forecasting horizon in months, $rx_{t+K}$ is cumulative log excess return between months $t$ and $t+K$, and $\mathbf{C_t}$ is a vector of macro risk premium controls. Standard errors are reported in parentheses, and p-values are reported in brackets, all obtained using OS HAR inference. The first F-test row reports p-values for testing $H_0 : b_1 = b_2$, while the second reports p-values for testing the joint significance of controls. $^{+}$,$^{*}$,$^{**}$, and $^{***}$ indicate significance at the 0.1, 0.05, 0.01, and 0.001 levels, respectively.

prices proxy for the economy-wide risk premium in the results reported in Table 3.[37]

To sum up, the empirical evidence does not favour the risk-based explanation that excess returns are predictable in recessions due to variation over time in the required rate of return.

[37] I obtain similar results when allowing the controls to have different effects during recessions and expansions, i.e. adding interaction terms between $\mathbb{1}_t^R$ and the variables in $\mathbf{C_t}$.

## IV. Liquidity constraints and industry slumps during recessions

What can account for the countercyclical return predictability documented in the previous section, if not industry overreaction and time variation in the required rate of return? In this section, I argue that liquidity constraints faced by the industry participants during recessions result in cash-in-the-market pricing for assets sold by distressed firms, as well as slumps in the industry investment. Those who manage to buy assets in this climate end up earning high excess returns, which are larger the deeper the recession is.

### *IV.A. Financial frictions and return predictability in dry bulk shipping*

The countercyclical return predictability can be naturally explained by binding financial constraints and limited arbitrage in the industry during downturns. When earnings fall and cash flows dry up in recessions, many firms are forced to sell their assets in order to repay outstanding debts. At the same time, the potential buyers, – mostly other firms in the industry, – are also likely to be tight on cash, and may find it difficult to borrow funds. Their ability to absorb second-hand ships from the distressed firms is therefore limited: prices of second-hand ships have to fall below their fundamental value to equilibrate the distressed supply with the constrained demand. The worse is the recession, the more constrained the buyers are, and so the deeper prices fall, resulting in higher excess returns to the firms that manage to buy ships.

Consistent with this mechanism, Figure 2 shows that the incidence of auction sales of ships increases sharply during recessions.[38] Auction sales are distressed sales that follow arrests of ships by creditors and court orders. The process incurs large opportunity costs of forgone income during a vessel's immobilization, which typically lasts about two months.[39] Moreover, there are also significant direct costs of arrests: port fees, crew wages, legal and brokerage fees etc., which add up to around 8% of the ship sale price on average, and can even exceed the ship's value in the most severe cases (Franks et al., 2020). For these reasons, auction sales are extreme and rare outcomes that are in every party's interest to avoid. Indeed, Franks et al. (2020) show that in the vast majority of cases owners and banks are able to negotiate workouts that avoid arrests, often through "voluntary" sales of assets. Therefore, the reported auction sales are only the tip of the iceberg when it comes

[38]The data on auction sales was kindly provided by CW Kellock & Co – an international ship broker and valuer based in London, a part of the Eggar Forrester Group. They maintain one of the most extensive worldwide ship sales databases. While they made it clear that even their records may not capture every single auction sale around the world, there is no reason to suspect any selection bias in their data.

[39]These and other delays during legal proceedings explain why the peaks in auction sales sometimes occur slightly after OECD global recessions. In some cases judicial sales of ships can even take 6 months or longer.

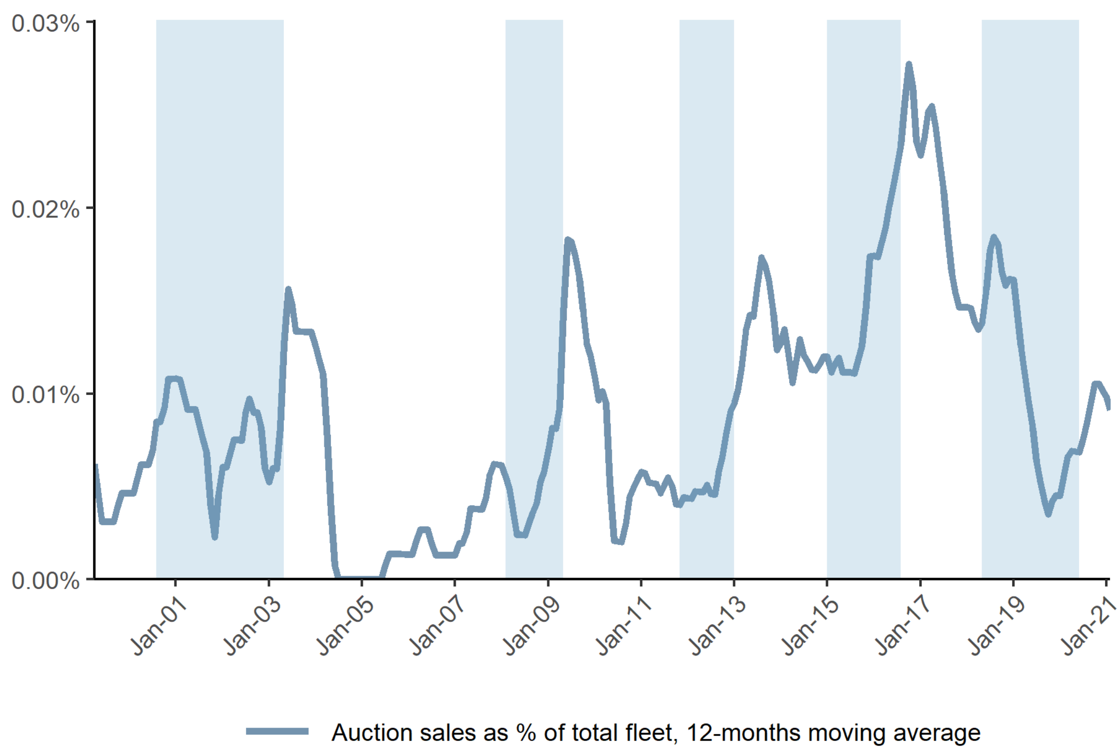


Figure 2: Auction Sales of Ships

to asset sales under financial pressure. Systematic spikes in auction sales nevertheless indicate that shipping firms experience significant financial troubles during recessions.

It is only natural to expect financial constraints to play an important role in an industry like dry bulk shipping. According to Stopford (2009), shipping is dominated by many small players with specialist knowledge, often informal corporate structures, and traditional reliance on bank financing – all the symptoms of acute agency problems. Combined with the high volatility of revenue flows and asset prices, it is not surprising that the sector is classified as "exotic" finance by Moody's, and traditional lenders to the shipping companies typically possess considerable industry expertise. For example, shipping bank loans are usually managed by a separate department, staffed with marketing and credit officers who know and understand the business.

For these very reasons, industry outsiders can find it difficult to jump into shipping and buy assets profitably at the bottom of the cycle, leading to limited arbitrage in the industry and a lack of competition among ship buyers. There is indeed anecdotal evidence that while new investors are attracted to ships during distressed times, it is often difficult for them to make money. According to Randee Day, an eminent shipping expert and executive, shipping is hard: inexperienced newcomers can lose money by buying ships of inferior quality; spending a lot of time and resources on negotiations and transaction fees, thus also risking to miss the cycle; and partnering up with a second-tier ship operator who would make money at their expense through "leakage" on the cost side, and has every incentive to drag on an unprofitable joint venture in order to continue earning their management fees (Day, 2019).

Further empirical evidence that liquidity constraints play an important role in the shipping industry comes from Drobetz et al. (2016). They show that cash flow shocks strongly affect firms' investment and financing decisions. During liquidity crisis episodes, declines in cash flows lead firms to significantly cut investment and shift towards short-term debt. This is especially true for financially weak firms, which appear to underinvest even during benign liquidity conditions, and build up large excess cash reserves in normal times for precautionary reasons. However, the authors show that even financially healthy shipping firms felt strong negative effects during the Global Financial Crisis.

The view that financial woes put huge downward pressure on second hand prices and investment during recessions is corroborated by numerous narratives from shipping industry experts and practitioners. In his book, a prominent shipping pundit Martin Stopford writes:

> Obviously selling a ship at the bottom of a market cycle is disastrous for its owner and a great bargain for the buyer. No shipping company follows this suicidal course of action by choice. "Distress" sales during market troughs are generally forced on companies by cashflow pressures such as bunker bills or a banker who has foreclosed and taken possession of the fleet. (Stopford, 2009, p. 203)

Turning to particular examples, during the 2015-2016 industry slump, one shipping executive commented to the *Financial Times:* "Everybody who's selling, especially good-quality assets, these days they really sell them because they need to [bring in cash]" (Wright, 2016). Similarly, writing about the events of the 2008 Financial Crisis in his blog, a prominent ship broker and finance advisor Basil Karatzas notes:

> There were so many ships to be bought cheaply from distressed shipowners, from distressed shipping banks, from bankrupt KG funds in Germany, from shipbuilders that got stuck with contracts in default and ships at their slipways. (Karatzas, 2017)

Moreover, the lack of financing and competition on the constrained demand side is often cited as the primary reason for why assets sell at such depressed prices during recessions. Discussing financial distress in the shipping sector in 2012, a panel of maritime experts noted that "banks have been unwilling to finance the purchase of second-hand vessels, which is creating a stalled sale and purchase market", and that "this has and will continue to put tremendous pressure on second hand values" (Financier Worldwide, 2012). Despite a wave of private equity money flowing into shipping in the aftermath of the Financial Crisis, mainly attracted by the rock-bottom asset prices, one shipping banker interviewed by the *Financial Times* had estimated that the industry was still facing a $100 billion credit gap at the time (Odell and Makan, 2013). Similarly, practitioners also blamed the "complete dearth of debt financing" for the free fall of vessel prices in 2016, when good quality dry bulk ships "were selling at a multiple of their scrap value" (Karatzas, 2016, 2017).

It is not hard to infer the effect of financial constraints and depressed asset values on the industry investment in recessions. First, the lack of financing makes it difficult for the firms to order new ships: even though the full price of a newbuilt ship may not be payable until the delivery in a couple of years, shipbuilders still rely on substantial stage payments throughout the project as their working capital (Stopford, 2009). Second, as prices of second hand tonnage fall, firms with spare liquidity may prefer used ships to new. "It does make more financial sense to buy second-hand at the moment than order new-builds, given the very attractive prices," commented one ship broker to *Reuters* in 2016 (Wallis, 2016). The orders for new ships are therefore also likely to plunge during recessions, negatively forecasting future excess returns, in line with my empirical results.

Let us now turn to formalizing these insights in a model of a competitive capital-intensive industry with liquidity constraints.

## *IV.B. The model*

In this section I present a model of a financially constrained industry to demonstrate formally how return predictability arises during recessions. The intuition here is related to the idea in Shleifer and Vishny (1992), namely that: "When a firm in financial distress needs to sell assets, its industry peers are likely to be experiencing problems themselves, leading to asset sales at prices below value in best use" (p. 1343).[40] In the model, I allow for the aggregate shock to be continuous. I am then able to demonstrate explicitly that the deeper the recession is, the further below its fundamental value the equilibrium asset price falls, so the future return on assets increases.

Because of commitment problems in the model, the maximum repayment that firms

[40] Unlike Shleifer and Vishny (1992), I do not consider the possibility of misallocation, i.e. assets being sold to less efficient users. This is consistent with both the anecdotal evidence in the previous section, and also with Franks et al. (2022), who do not find evidence of misallocation during fire sales in the context of airline industry.

can promise to creditors is limited by the market value of collateral. In a boom, many firms generate cash flows in excess of promised repayments, so they have spare liquidity they can use to purchase more assets. Even though some firms are hit by bad idiosyncratic shocks and need to sell capital, unconstrained firms have enough spare cash to be able to buy assets at the full fundamental value (and the competition between them ensures that is indeed the equilibrium price). Assets simply earn the required rate of return to their buyers, and there is no predictability.

In a recession, however, even firms with good idiosyncratic shocks have limited spare liquidity, and are unable to borrow at this point. At the same time, the amount of capital that firms with bad shocks have to sell to repay their debts increases. The worse is the aggregate shock, the more constrained the buyers are, and so the deeper asset price falls below the fundamental value in order for constrained buyers to absorb all assets from forced sales. Those who do manage to buy assets in this climate end up earning high excess returns, which are larger the deeper the recession is.

### *IV.B.1 The framework*

The model economy lasts for three periods $t \in \{0, 1, 2\}$. There is a unit mass of identical firms in the industry, and also a large number of potential creditors with deep pockets. All agents are risk-neutral, and do not discount time, so the required rate of return is zero.

Each firm starts with an endowment of $\$n$ in period 0, and also has access to a competitive financial market where it can borrow $\$b$ (lend if $b < 0$). Firms operate a constant return to scale technology, and can invest in capital in period 0, which we assume to be homogenous and perfectly divisible. One unit of capital costs \$1, and generates non-negative cash flows in periods 1 and 2. Firms can also store cash between periods. We assume that owners of each firm maximize period 2 funds available for their consumption.

Period 1 cash generated by each firm is subject to independent aggregate and idiosyncratic firm shocks, both uniformly distributed on $[0, 1]$. Specifically, a firm's cash flow in period 1 is $k_1 \cdot [Z + \varepsilon]$, where $k_1$ is the firm's capital stock held from period 0 to period 1, $Z \sim \mathcal{U}(0, 1)$ is the aggregate shock common to all firms, and $\varepsilon \sim \mathcal{U}(0, 1)$ is the firm-specific shock.[41] Period 2 cash flow is, for simplicity, non-stochastic and fixed at \$1 per unit of capital held from period 1 to period 2. This implies that the fundamental value of assets is always \$1 in period 1.

Capital is irreversible and industry specific: only firms in the industry know how to operate it productively. There is a competitive secondary market for assets in period 1, in

[41] Note that the resulting distribution of $Z + \varepsilon$ is symmetric triangular, with mean 1 and support $[0, 2]$.

which, therefore, only firms in the industry can act as buyers. This is an extreme assumption on the limit of arbitrage in this industry, which reflects the difficulties purchasing niche real assets. Capital becomes worthless in period 2.

### *IV.B.2 Limited commitment and financial contracts*

Financial contracts are subject to limited commitment on behalf of the firms, who can default on existing liabilities specified in the contracts. In case of a default, creditors cannot enforce repayments out of firm's cash holdings, or restrict the firm from using that cash to acquire new assets. They can, however, be contractually given control rights over all or some of the firm's existing assets. In addition, the financial contract can specify the bargaining protocol following a default, in the spirit of Harris and Raviv (1995), and assign bargaining powers to the parties. There is no problem with commitment on the creditors' side, and contracts can, in principle, be conditioned on both aggregate and idiosyncratic states. Because of the latter, we can restrict our attention to default-free contracts without loss of generality.

Since capital becomes worthless in period 2, creditors cannot expect to get any positive repayment from the firms in the last period. In period 1, on the other hand, positive repayment can be supported by the threat of creditors seizing the firm's assets and selling them on the secondary capital market. However, even if the creditors are given full control over existing firm's assets and maximum bargaining power, they cannot negotiate repayment higher than the market value of the underlying collateral. This is because the firm always has an outside option to walk away from the negotiations and keep the cash,

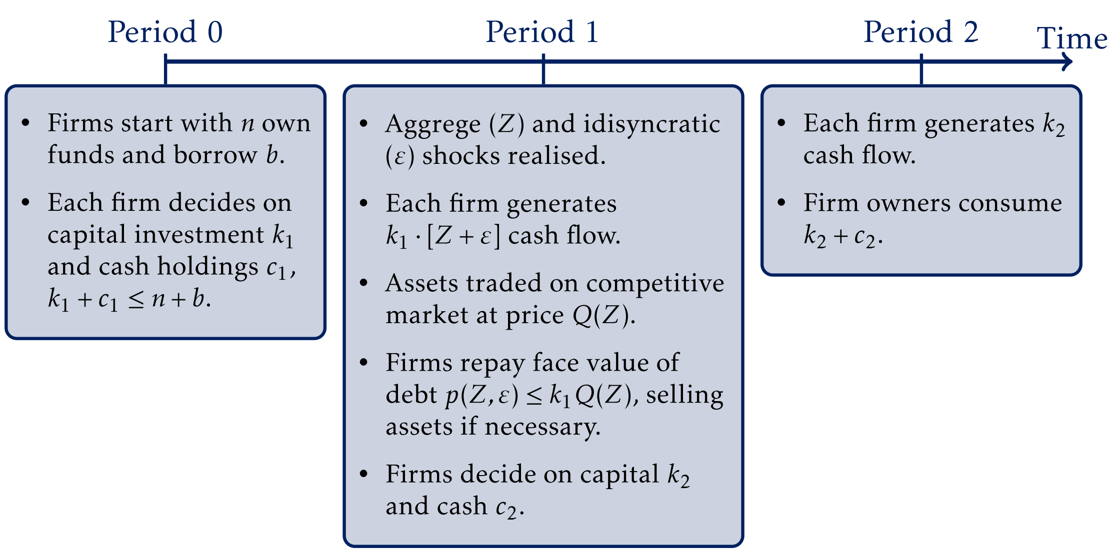


Figure 3: Timeline

which it then can use to buy new assets on the secondary capital market.

To sum up, therefore, financial contracts in period 0 can specify any state-contingent repayment $p(Z,\varepsilon) \leq k_1 Q(Z)$ in period 1, where $k_1 Q(Z)$ is the market value of firm's capital in the aggregate state $Z$. Note that $p(Z,\varepsilon)$ can in principle be negative if a firm decides to get insurance against particular states, as there is no commitment problem on behalf of the creditors.[42] We will see, however, that no firm will use insurance in equilibrium. Figure 3 summarizes the timing of events.

### *IV.B.3 Firm's problem*

In period 0, each firm solves:

$$\max \ \mathbb{E}_0\Big[k_2(Z,\varepsilon)+c_2(Z,\varepsilon)\Big] \tag{10}$$

$$\text{s.t.} \quad k_1 + c_1 \leq n + b \tag{11}$$

$$b = \mathbb{E}_0\Big[p(Z,\varepsilon)\Big] \tag{12}$$

$$k_2(Z,\varepsilon)\,Q(Z)+c_2(Z,\varepsilon) \leq k_1\cdot[Z+\varepsilon]+c_1+k_1 Q(Z)-p(Z,\varepsilon) \quad \forall \varepsilon,\ Z \tag{13}$$

$$p(Z,\varepsilon) \leq k_1 Q(Z) \quad \forall \varepsilon,\ Z \tag{14}$$

$$k_1 \geq 0,\ c_1 \geq 0,\ k_2(Z,\varepsilon) \geq 0,\ c_2(Z,\varepsilon) \geq 0 \quad \forall \varepsilon,\ Z \tag{15}$$

The objective function (10) is the expectation of total funds available for consumption to the firm owners in period 2, which consist of cash flow generated by capital $k_2$ held into period 2, as well as cash $c_2$ carried over from period 1 into period 2. We explicitly indicate which variables may potentially depend on the aggregate and idiosyncratic firm shocks. (11) is the budget constraint in period 0, (12) is the break-even condition for the creditors, (13) is the budget constraint in period 1, while (14) constraints the maximum repayment in each state due to the financial frictions discussed above.

We can make several immediate observations:

- Firms do not carry any cash from period 0 into period 1, so $c_1 = 0$. Holding cash over capital can be beneficial only in states where cash flows and asset prices are low, i.e. $Z+\varepsilon+Q(Z) < 1$. But since state-contingent contracts are available, the firm would be better off buying insurance against those states instead.

- In any equilibrium, $Q \leq 1$, otherwise no-one would choose to hold capital in period 1, a contradiction. Similarly, $Q(Z) > 0\ \forall Z$, otherwise the demand for capital would

[42] Note that firms could also in principle contract insurance to be paid out to them in period 2, but because firms can freely store cash, this option is irrelevant.

be infinite in period 1 in some aggregate states.

- Trivially, the period-1 budget constraint (13) must bind at the optimum. This allows us to substitute it directly into the objective function.[43]

With these observations, and explicitly computing the expectations, the problem becomes:

$$\max \; k_1 + \int_0^1 \frac{k_1 \cdot [Z + \frac{1}{2}] - \int_0^1 p(Z,\varepsilon)\,\mathrm{d}\varepsilon}{Q(Z)}\,\mathrm{d}Z \tag{16}$$

$$\text{s.t.} \quad k_1 \leq n + \int_0^1 \int_0^1 p(Z,\varepsilon)\,\mathrm{d}\varepsilon\,\mathrm{d}Z \tag{17}$$

$$p(Z,\varepsilon) \leq k_1 Q(Z) \quad \forall \varepsilon, Z \tag{18}$$

$$k_1 \geq 0 \tag{19}$$

The Kuhn-Tucker first-order conditions with respect to $k_1$ and $p(Z,\varepsilon)$ are, respectively:

$$1 + \int_0^1 \frac{Z + \frac{1}{2}}{Q(Z)}\,\mathrm{d}Z - \lambda + \int_0^1 \int_0^1 \mu(Z,\varepsilon) Q(Z)\,\mathrm{d}\varepsilon\,\mathrm{d}Z + \nu = 0 \tag{20}$$

and

$$\mu(Z,\varepsilon) = \lambda - \frac{1}{Q(Z)}, \tag{21}$$

where the Lagrangian multipliers $\lambda$, $\mu(Z,\varepsilon)$ and $\nu$ must be non-negative. Combining (20) and (21), we get:

$$\lambda = \frac{\int_0^1 \frac{Z+\frac{1}{2}}{Q(Z)}\,\mathrm{d}Z + \nu}{1 - \int_0^1 Q(Z)\,\mathrm{d}Z} > 0, \tag{22}$$

so, unsurprisingly, the period-0 budget constraint (11) binds.

### *IV.B.4 Equilibrium*

**Proposition 1.** *There is a unique, symmetric equilibrium in which all firms exhaust their borrowing capacity, and invest all own and borrowed funds into capital in period 0. Therefore,*

[43] Note that in states where $Q(Z) = 1$, $k_2 + c_2$ simply equals to the right-hand side of the constraint. When $Q(Z) < 1$, the firm will optimally only buy capital, so $c_2 = 0$ and $k_2$ is equal to the right-hand side of the constraint (13) divided by $Q(Z)$. Either way, we can substitute the right-hand side of the constraint (13) divided by $Q(Z)$ instead of $k_2 + c_2$.

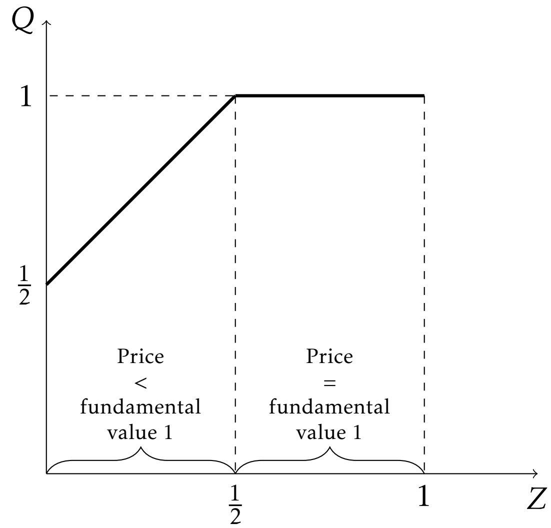


Figure 4: Asset price in period 1 as a function of aggregate shock

*$p(Z,\varepsilon) = k_1 Q(Z)\ \forall \varepsilon, Z$, and optimal financial contracts effectively take the form of simple non-recourse debt secured by resale value of capital. Firms borrow \$$7n$ and thus invest in $8n$ assets in equilibrium. The equilibrium price of capital in period 1 is*

$$Q^*(Z) = \begin{cases} 1 & \text{if } Z \geq \frac{1}{2} \\ Z + \frac{1}{2} & \text{if } Z < \frac{1}{2}. \end{cases} \tag{23}$$

Figure 4 shows the equilibrium asset price as a function of the aggregate shock $Z$. The price is equal to the fundamental value of 1 when the aggregate shock is sufficiently favourable ($Z \geq \frac{1}{2}$), but falls linearly with the shock when it is low ($Z < \frac{1}{2}$). The intuition for this result is that when the aggregate shock is low, there are more firms that are forced to sell their assets and less firms with spare liquidity to purchase them. Figure 5 illustrates forced supply of assets, $\underline{K}^S$, and the capacity of the rest of the industry to absorb them, $\overline{K}^D$, as functions of the aggregate shock $Z$, assuming that the price of capital is 1. When $Z < \frac{1}{2}$, the forced supply of assets exceeds the demand capacity, so the price has to fall in order to equilibrate the market. The formal proof of the proposition follows.

*Proof.* First, we verify that individual firm's optimality conditions are satisfied. As $k_1 > 0$, $\nu = 0$. Plugging (23) into (22), we obtain $\lambda = 9$. Using (21), this implies that $\mu > 0\ \forall Z$, since $\mu$ increases in $Z$, and $\mu = 7$ even when $Z = 0$. Therefore, it is indeed optimal for each firm to borrow until constraint (14) binds in all states, and invest all funds into capital.

Second, since all firms face the same constraints, this proposed equilibrium is symmetric, and each firm invests the same amount of capital. Substituting (23) into binding

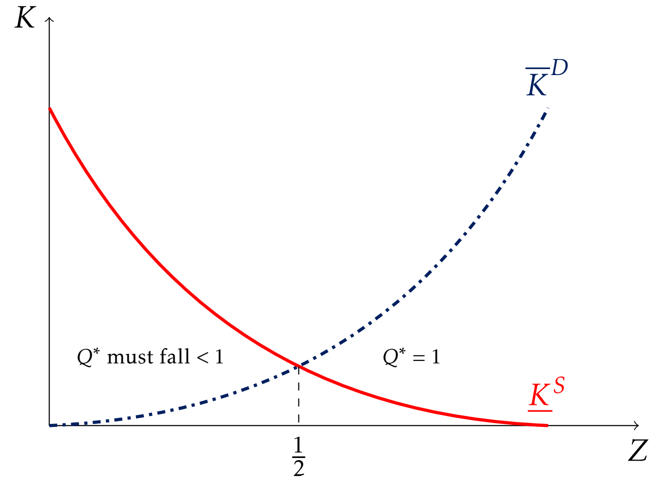


FIGURE 5: FORCED SUPPLY VS. DEMAND CAPACITY AT $Q = 1$

constraints (14), (12), and (11), it is easy to verify that $k_1 = 8n$, and hence $b = 7n$.

Third, we need to verify that $Q^*$ in (23) is indeed the equilibrating price on the market for assets in period 1 in every state $Z$. When $Q = 1$, unconstrained firms are indifferent between selling and buying capital, since each unit earns \$1 in period 2 with certainty. However, there are firms that must sell some assets, since their period-1 cash flow is not enough to cover debt repayments, in this case $p = k_1$. A marginal firm that has just enough cash to repay debt in state $Z$ is one with $Z + \varepsilon = 1$, so every firm with $\varepsilon < 1 - Z$ has to sell at least $k_1 \cdot [1 - Z - \varepsilon]$ assets. This means that the market must have enough liquidity to absorb at least

$$\underline{K}^S = \int_0^{1-Z} k_1 \cdot [1 - Z - \varepsilon] \, \mathrm{d}\varepsilon = \frac{1}{2} k_1 [1 - Z]^2 \tag{24}$$

assets. On the other hand, firms with $\varepsilon \geq 1 - Z$ can spend at most $k_1 \cdot [Z + \varepsilon - 1]$ on buying assets, so the total market demand when $Q = 1$ is at most:

$$\overline{K}^D = \int_{1-Z}^{1} k_1 \cdot [Z + \varepsilon - 1] \, \mathrm{d}\varepsilon = \frac{1}{2} k_1 Z^2. \tag{25}$$

It is easy to verify that $\overline{K}^D \geq \underline{K}^S$ as long as $Z \geq \frac{1}{2}$, as required.

When $Q < 1$, on the other hand, all firms with spare liquidity want to buy assets. However, the firms whose cash flow falls below the market value of their capital, i.e. those with $\varepsilon < Q - Z$, have no choice but to sell $k_1 \cdot [Q - Z - \varepsilon]$ worth of assets in order to make debt repayments. The total supply of capital on the market is therefore:[44]

$$K^S(Q) = \int_0^{Q-Z} k_1 \frac{Q-Z-\varepsilon}{Q}\,\mathrm{d}\varepsilon = k_1 \frac{(Q-Z)^2}{2Q}. \tag{26}$$

All other firms spend their spare cash, $k_1 \cdot [Z+\varepsilon-Q]$, on purchasing assets, so the aggregate demand for assets is:[45]

$$K^D(Q) = \int_{Q-Z}^{1} k_1 \frac{Z+\varepsilon-Q}{Q}\,\mathrm{d}\varepsilon = k_1 \frac{(1-Q+Z)^2}{2Q}. \tag{27}$$

Market clearing condition $K^S(Q) = K^D(Q)$ yields the equilibrium price $Q^* = Z + \frac{1}{2}$, which is indeed smaller than 1 when $Z < \frac{1}{2}$, as required.

Lastly, to prove uniqueness, we note that $Q^*(Z)$ given in (23) is, in fact, the lower bound on values that the equilibrium asset price could possibly take in each state $Z$. To see this, suppose the total amount of physical capital in the industry is $K$. In state $Z$, it generates the aggregate cash flow of $K \cdot [Z + \frac{1}{2}]$. Even if the entire capital stock is traded on the market in order to repay outstanding debts (which would always be enough, since each firm's debt cannot exceed the market value of its capital), there is enough liquidity for firms to be able to pay at least $Z + \frac{1}{2}$ per unit of capital. Competition for assets will ensure that $Z + \frac{1}{2} \le Q \le 1$ when $Z < \frac{1}{2}$, and $Q = 1$ otherwise. Using (22) we then can show that possible values of $\lambda$ are bounded below by 8.[46] In turn, using (21), the lower bounds on $Q$ and $\lambda$ imply that $\mu$ is at least 7, i.e. the constraint (14) on firms' repayments always binds in equilibrium. But there is only one equilibrium in which all firms fully exhaust their borrowing constraints: the symmetric equilibrium we have found above. The equilibrium is necessarily symmetric because all firms face the same binding constraints and asset prices in period 1, and we only needed symmetry to derive the equilibrium prices. *Q.E.D.*

**Corollary 1** (Countercyclical return predictability)**.** *When the aggregate shock is $Z < \frac{1}{2}$, the period-2 return $\frac{1}{Q^*(Z)} - 1$ is negatively related to industry earnings and the price of assets in period 1. However, the period-2 return is constant, and hence there is no predictability when $Z \ge \frac{1}{2}$.*

This is the central result, in accordance with the empirical finding. Note that pre-

[44] This is the "net" supply, since, in principle, firms could sell more capital than they have to sell, but then buy some of it back. This would make no difference to the market price.

[45] Likewise, this is the "net" demand.

[46] Examining equation (22), we see that the nominator is at least $\int_0^1 [Z + \frac{1}{2}]]\,\mathrm{d}Z = 1$ (when setting $\nu = 0$ and $Q(Z) = 1\ \forall Z$), while the denominator is at most $1 - \int_0^1 Q^*(Z)\,\mathrm{d}Z = \frac{1}{8}$ (when setting $Q(Z) = Q^*(Z)$ in (23)). Together, these imply that $\lambda$ is at least 8.

dictability kicks in once aggregate earnings fall below average. Thus, perhaps contrary to common intuition, there does not need to be a particularly deep recession for asset prices to drop below the fundamental value.

#### *IV.B.5 Industry investment*

It is feasible to extend the model to also incorporate industry investment, which would only require a sacrifice of simplicity and tractability. One way to do it is adding a competitive capital producing sector that faces convex production costs. This would imply an upward sloping supply of new assets, in addition to sales of existing capital in period 1.[47] It is then not difficult to deduce what happens to industry investment. In an expansion, there is enough liquidity to absorb the combined supply of existing and new assets at the price equal to their fundamental value, and the industry achieves the efficient level of investment in period 1. In a recession, however, asset price must fall below the fundamental value due to liquidity constraints faced by the buyers, as before. The lower is the price, the lower industry investment falls below its efficient level, as the gap between the marginal cost of producing capital and return on assets widens. In this case, while sales of second hand assets at depressed prices represents a transfer from the sellers to the buyers, a plunge in industry investment is a manifestation of industry inefficiencies due to financial constraints. This mechanism generates a negative association between industry investment and future returns, in line with my empirical findings.

## V. Conclusion

In this paper I study the link between earnings, asset prices, industry investment, and the subsequent returns on capital in the context of the dry bulk shipping industry. I document that future excess returns on owning ships are strongly and negatively related to the current level of industry activity during global economic recessions, but there is no evidence of such predictability during expansions. The empirical evidence is at odds with the explanations of predictability previously suggested in the literature. I propose an explanation that links the countercyclical predictability of returns on ships to the liquidity constraints faced by the firms and limits to arbitrage in the industry. Specifically, due to the resulting market illiquidity, ship prices and industry investment plunge excessively during recessions. These results likely generalise to similar capital-intensive industries with many small players, such as shale oil and gas, airlines, and specialised real estate.

[47] In fact, assuming that costs of producing capital are quadratic, it is still possible to obtain closed-form solutions – the details can be made available upon request.

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## Appendix A. Alternative recession indicators

In this appendix, I estimate regressions of the form (7) using several alternative recession indicators, both macroeconomic and industry-specific. First, Panel A of Table A.1 presents the results when the NBER indicator for recessions in the US is used. Due to the sheer size of the US economy, one would expect it to correlate with periods of global downturns. However, the NBER indicator is significantly more conservative than the OECD one, calling recessions with a frequency that is four times lower. Overall, the results are similar

Table A.1: Regime-dependent predictability: alternative recession indicators

Panel A: NBER US recessions

| | $X$ = net real earnings $\Pi$ | | | $X$ = used ship price $P$ | | | $X$ = investment $I$ | | |
|---|---|---|---|---|---|---|---|---|---|
| $K$ | 12m | 24m | 36m | 12m | 24m | 36m | 12m | 24m | 36m |
| $b_1$ | -0.025* | -0.027*** | -0.031 | -0.007* | -0.009*** | -0.011 | -1.662** | -1.595*** | -2.847*** |
| | (0.009) | (0.006) | (0.018) | (0.003) | (0.002) | (0.006) | (0.466) | (0.269) | (0.507) |
| | [0.014] | [0.001] | [0.116] | [0.033] | [0.001] | [0.107] | [0.004] | [0.000] | [0.000] |
| $b_2$ | 0.004 | -0.013 | -0.008 | -0.003 | -0.009 | -0.010 | 0.324 | -0.611 | 0.288 |
| | (0.009) | (0.016) | (0.029) | (0.002) | (0.005) | (0.008) | (0.474) | (0.635) | (0.578) |
| | [0.684] | [0.484] | [0.786] | [0.156] | [0.133] | [0.260] | [0.510] | [0.390] | [0.644] |
| F-test $b_1 = b_2$ | 0.041 | 0.443 | 0.516 | 0.416 | 0.959 | 0.908 | 0.005 | 0.140 | 0.019 |
| $T_1$ obs. | 56 | 56 | 56 | 56 | 56 | 56 | 26 | 26 | 26 |
| $T_2$ obs. | 472 | 460 | 448 | 472 | 460 | 448 | 251 | 239 | 227 |
| $R^2$ | 0.057 | 0.044 | 0.052 | 0.077 | 0.116 | 0.135 | 0.101 | 0.047 | 0.086 |

Panel B: World Bank global recessions

| | $X$ = net real earnings $\Pi$ | | | $X$ = used ship price $P$ | | |
|---|---|---|---|---|---|---|
| $K$ | 12m | 24m | 36m | 12m | 24m | 36m |
| $b_1$ | -0.021+ | -0.037** | -0.039* | -0.007** | -0.011** | -0.012* |
| | (0.011) | (0.013) | (0.016) | (0.002) | (0.003) | (0.005) |
| | [0.072] | [0.006] | [0.021] | [0.003] | [0.002] | [0.023] |
| $b_2$ | -0.004 | -0.016 | -0.015 | -0.004* | -0.008 | -0.010 |
| | (0.008) | (0.012) | (0.022) | (0.001) | (0.004) | (0.007) |
| | [0.580] | [0.231] | [0.532] | [0.026] | [0.101] | [0.212] |
| F-test $b_1 = b_2$ | 0.129 | 0.019 | 0.279 | 0.216 | 0.461 | 0.765 |
| $T_1$ obs. | 42 | 42 | 42 | 42 | 42 | 42 |
| $T_2$ obs. | 486 | 474 | 462 | 486 | 474 | 462 |
| $R^2$ | 0.040 | 0.054 | 0.067 | 0.082 | 0.125 | 0.154 |

Table A.1: continued

| Panel C: Below-median ship prices in OECD recessions | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $X$ = net real earnings $\Pi$ | | | $X$ = used ship price $P$ | | | $X$ = investment $I$ | | |
| $K$ | 12m | 24m | 36m | 12m | 24m | 36m | 12m | 24m | 36m |
| $b_1$ | -0.044$^{*}$ | -0.081$^{**}$ | -0.109$^{**}$ | -0.010$^{**}$ | -0.020$^{***}$ | -0.027$^{***}$ | -0.260 | -0.258 | -1.247 |
| | (0.017) | (0.026) | (0.037) | (0.004) | (0.005) | (0.008) | (0.518) | (0.528) | (0.813) |
| | [0.012] | [0.003] | [0.005] | [0.009] | [0.000] | [0.001] | [0.617] | [0.627] | [0.132] |
| $b_2$ | -0.004 | -0.013 | -0.012 | -0.004$^{+}$ | -0.007 | -0.009 | -0.380 | -0.663 | -0.220 |
| | (0.009) | (0.012) | (0.020) | (0.002) | (0.004) | (0.007) | (0.407) | (0.380) | (0.558) |
| | [0.638] | [0.350] | [0.571] | [0.060] | [0.138] | [0.244] | [0.403] | [0.156] | [0.714] |
| F-test $b_1 = b_2$ | 0.045 | 0.021 | 0.013 | 0.156 | 0.026 | 0.038 | 0.866 | 0.462 | 0.192 |
| $T_1$ obs. | 116 | 109 | 109 | 116 | 109 | 109 | 54 | 47 | 47 |
| $T_2$ obs. | 412 | 407 | 395 | 412 | 407 | 395 | 223 | 218 | 206 |
| $R^2$ | 0.027 | 0.060 | 0.058 | 0.073 | 0.140 | 0.160 | 0.026 | 0.089 | 0.060 |

| Panel D: Shipping industry recessions identified by Bry-Boschan algorithm | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $X$ = net real earnings $\Pi$ | | | $X$ = used ship price $P$ | | | $X$ = investment $I$ | | |
| $K$ | 12m | 24m | 36m | 12m | 24m | 36m | 12m | 24m | 36m |
| $b_1$ | -0.028$^{***}$ | -0.029$^{+}$ | -0.032$^{*}$ | -0.007$^{***}$ | -0.009$^{+}$ | -0.011$^{*}$ | -1.059$^{***}$ | -0.885$^{*}$ | -0.870$^{+}$ |
| | (0.006) | (0.015) | (0.015) | (0.002) | (0.004) | (0.005) | (0.228) | (0.338) | (0.447) |
| | [0.000] | [0.089] | [0.047] | [0.000] | [0.068] | [0.043] | [0.000] | [0.017] | [0.076] |
| $b_2$ | -0.000 | -0.019 | -0.014 | -0.004 | -0.011$^{*}$ | -0.013$^{+}$ | 0.265 | -0.775 | -0.277 |
| | (0.009) | (0.011) | (0.025) | (0.002) | (0.004) | (0.006) | (0.574) | (0.584) | (0.666) |
| | [0.978] | [0.130] | [0.611] | [0.132] | [0.029] | [0.090] | [0.649] | [0.233] | [0.699] |
| F-test $b_1 = b_2$ | 0.020 | 0.597 | 0.306 | 0.133 | 0.745 | 0.778 | 0.012 | 0.902 | 0.265 |
| $T_1$ obs. | 268 | 256 | 247 | 268 | 256 | 247 | 148 | 136 | 127 |
| $T_2$ obs. | 260 | 260 | 257 | 260 | 260 | 257 | 129 | 129 | 126 |
| $R^2$ | 0.300 | 0.112 | 0.063 | 0.335 | 0.193 | 0.162 | 0.401 | 0.167 | 0.108 |

*Notes.* This table reports the estimates of slope coefficients and F-test statistics for regime switching time series regressions of the form $rx_{t+K} = \mathbb{1}_t^R(a_1 + b_1 X_t) + (1 - \mathbb{1}_t^R)(a_2 + b_2 X_t) + v_{t+K}$, where $\mathbb{1}_t^R$ is either the NBER US recession indicator (Panel A), the World Bank global recession indicator (Panel B), indicator of periods with below-median ship prices during OECD recessions (Panel C), or the Shipping industry recession indicator identified by Bry-Boschan algorithm applied to the ship price series (Panel D); $X_t$ is one of the forecasting variables, $K$ is the forecasting horizon in months, and $rx_{t+K}$ is cumulative log excess return between months $t$ and $t+K$. Standard errors are reported in parentheses, and p-values are reported in brackets, while the F-test row reports p-values for testing $H_0 : b_1 = b_2$, all obtained using OS HAR inference. $^{+}$,$^{*}$,$^{**}$, and $^{***}$ indicate significance at the 0.1, 0.05, 0.01, and 0.001 levels, respectively.

to the ones presented in Table 3 in the main text. While there are a lot less recessionary observations when using the NBER indicator, the predictive slope coefficients on net earnings and prices during recessions are statistically significant at the 12- and 24-months horizons, at the 5% and 0.1% levels respectively. At the 36-months horizon, the p-values are just short of clearing the 10% bar. The evidence of industry investments being able to predict future returns during NBER recessions is surprisingly strong despite the limited number of observations: all coefficient estimates are significant at least at the 1% level. As before, there is no indication of return predictability during expansions. However, some point estimates in expansions are now closer to those in recessions, likely because a few global recessions are now classified as expansions. This makes it more difficult to reject the null of $b_1 = b_2$.

I also obtain similar results when using the World Bank indicator of global recessions and downturns created by Kose et al. (2020). This is a very conservative indicator requiring the global output per capita to contract in order for a period to be classed as a recession, which happened only 3 times during my sample.[48] As shown in Panel B of Table A.1 coefficients on ship earnings and prices are statistically significant at all horizons in recessions, but only in a single case otherwise.[49] Point estimates are also considerably larger in recessions in absolute value, although (as with NBER recessions) we mostly cannot reject the null of $b_1 = b_2$.

I conduct two further exercises to check that my main results are robust when using recession indicators that might better capture the shipping industry downturns. First, I cut OECD global recessions in half, keeping as recessionary observations only those months when the real ship prices were below median in each OECD recession. Thus, I focus on periods during macroeconomic recessions when ship prices were low, and leave out peak observations. As we see in Panel C of Table A.1 this refinement only strengthens the results for industry earnings and real prices. The coefficient estimates are strongly statistically significant in recessions, and around 50% larger compared to those in Table 3 in the main text. We do not obtain any meaningful results for industry investment, likely due to small number of observations.

Lastly, I also generate a purely shipping-industry specific recession indicator by applying the Bry-Boschan algorithm[50] to the real ship price series. The algorithm identifies 13 peaks and troughs in the data, with periods between peaks and troughs classed as recessions. Of course, when constructing a regime indicator based on the predictor variable, one

[48]Note that I also include periods identified as "downturns" when global growth was near-zero. Still, the World Bank's indicator calls recessions and downturns more than 5 times less frequently compared to the OECD's growth cycle approach.

[49]I do not report results for industry investment because there are too few (15) observations in recessions.

[50]See Bracke (2011) for the details. I select fairly standard parameter values: window = 6 months, phase = 6 months, and cycle = 18 months.

should be mindful of the potential look-ahead bias. These reservations notwithstanding, the results in Panel D of Table A.1 again largely confirm my main results: coefficient estimates are both economically large and statistically significant in the periods classed as industry recessions at all forecasting horizons, with very little evidence for predictability outside recessions.

## Appendix B. Alternative ship types

Here I verify that the results are not limited to the Panamax class ships, and are indeed representative of the broader industry. I estimate predictive regressions (7) for smaller 32k DWT Handysize ships, and larger 150k DWT Capesize vessels. The steps to construct the datasets for these types are identical to the construction of the main dataset.

Table B.1 presents the results. Overall, they are fully in line with the results I obtained for Panamax class vessels: for both ship types, coefficients on ship prices, earnings, and investment are all negative and statistically significant for most regressors and forecasting horizons during recessions. Among the only three exceptions, two of the p-values are only marginally above the 10% threshold. Similarly, in the majority of cases we can reject $H_0 : b_1 = b_2$.

Table B.1: Regime-dependent predictability: alternative ship sizes

| Panel A: Handysize ships | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $X$ = net real earnings $\Pi$ | | | $X$ = used ship price $P$ | | | $X$ = investment $I$ | | |
| $K$ | 12m | 24m | 36m | 12m | 24m | 36m | 12m | 24m | 36m |
| $b_1$ | -0.045* | -0.083* | -0.108+ | -0.014** | -0.025+ | -0.034+ | -1.043*** | -0.933*** | -1.118 |
| | (0.018) | (0.025) | (0.046) | (0.004) | (0.011) | (0.016) | (0.185) | (0.213) | (0.774) |
| | [0.033] | [0.011] | [0.057] | [0.010] | [0.085] | [0.093] | [0.000] | [0.001] | [0.199] |
| $b_2$ | 0.031 | 0.039 | 0.057 | 0.001 | -0.005 | -0.005 | 0.134 | -0.536 | 0.515 |
| | (0.022) | (0.042) | (0.045) | (0.006) | (0.004) | (0.009) | (0.381) | (0.393) | (0.614) |
| | [0.186] | [0.392] | [0.246] | [0.910] | [0.349] | [0.612] | [0.732] | [0.244] | [0.449] |
| F-test $b_1 = b_2$ | 0.002 | 0.098 | 0.053 | 0.055 | 0.130 | 0.062 | 0.011 | 0.391 | 0.033 |
| $T_1$ obs. | 241 | 229 | 217 | 241 | 229 | 217 | 119 | 107 | 95 |
| $T_2$ obs. | 291 | 291 | 291 | 291 | 291 | 291 | 162 | 162 | 162 |
| $R^2$ | 0.097 | 0.105 | 0.125 | 0.134 | 0.154 | 0.196 | 0.117 | 0.066 | 0.083 |

Table B.1: continued

| Panel B: Capesize ships | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $X$ = net real earnings $\Pi$ | | | $X$ = used ship price $P$ | | | $X$ = investment $I$ | | |
| $K$ | 12m | 24m | 36m | 12m | 24m | 36m | 12m | 24m | 36m |
| $b_1$ | -0.015*** | -0.028 | -0.036 | -0.005** | -0.010+ | -0.014* | -0.747* | -0.971* | -1.674+ |
| | (0.003) | (0.015) | (0.019) | (0.001) | (0.005) | (0.006) | (0.242) | (0.343) | (0.841) |
| | [0.000] | [0.119] | [0.109] | [0.006] | [0.096] | [0.042] | [0.021] | [0.018] | [0.094] |
| $b_2$ | 0.006 | 0.008 | 0.016 | 0.001 | 0.001 | 0.001 | -0.124 | -0.420 | 0.571 |
| | (0.005) | (0.010) | (0.012) | (0.002) | (0.003) | (0.004) | (0.420) | (0.477) | (0.990) |
| | [0.301] | [0.477] | [0.248] | [0.731] | [0.836] | [0.729] | [0.774] | [0.404] | [0.585] |
| F-test $b_1 = b_2$ | 0.012 | 0.164 | 0.110 | 0.009 | 0.096 | 0.049 | 0.271 | 0.295 | 0.044 |
| $T_1$ obs. | 241 | 229 | 217 | 241 | 229 | 229 | 119 | 107 | 95 |
| $T_2$ obs. | 252 | 252 | 252 | 252 | 252 | 252 | 162 | 162 | 162 |
| $R^2$ | 0.152 | 0.105 | 0.148 | 0.159 | 0.170 | 0.228 | 0.099 | 0.038 | 0.073 |

*Notes.* This table reports the estimates of slope coefficients and F-test statistics for regime switching time series regressions of the form $rx_{t+K} = \mathbb{1}_t^R(a_1 + b_1 X_t) + (1 - \mathbb{1}_t^R)(a_2 + b_2 X_t) + v_{t+K}$, where $\mathbb{1}_t^R$ is the OECD global recession indicator, $X_t$ is one of the forecasting variables, $K$ is the forecasting horizon in months, and $rx_{t+K}$ is cumulative log excess return between months $t$ and $t+K$. Standard errors are reported in parentheses, and p-values are reported in brackets, while the F-test row reports p-values for testing $H_0 : b_1 = b_2$, all obtained using OS HAR inference. $^{+}$,$^{*}$,$^{**}$, and $^{***}$ indicate significance at the 0.1, 0.05, 0.01, and 0.001 levels, respectively.

## Appendix C. Excluding the Global Financial Crisis

Figure 1 shows that the shipping industry has experienced a super boom-bust cycle during 2006-2009. This raises a concern that the results could potentially be driven by this unprecedented boom followed by the Global Financial Crisis. To address it, I estimate the regime-switching predictive regressions using the data through 2006. Specifically, I compute forward returns only with earnings and prices available up to 2006. This way I only use predictive regressors up to 2005, 2004, and 2003 to forecast forward returns at the 12-, 24-, and 36-months horizons, respectively. Since there is less than 10 years worth of observations on industry investment up to 2005, I exclude investment from this robustness check.

Table C.1 present the results. We can safely conclude that the main finding of return predictability being concentrated during recessions is not driven by the Great Recession. Estimates of predictive slope coefficients are in fact slightly larger than those obtained in the whole sample, and all but one are statistically significant. In the majority of cases we can also comfortably reject $H_0 : b_1 = b_2$.

Table C.1: Regime-dependent predictability in shipping: 1976-2006

| | $X$ = net real earnings $\Pi$ | | | $X$ = used ship price $P$ | | |
|---|---|---|---|---|---|---|
| $K$ | 12m | 24m | 36m | 12m | 24m | 36m |
| $b_1$ | -0.035 | -0.115** | -0.154* | -0.010* | -0.025*** | -0.033** |
| | (0.018) | (0.024) | (0.038) | (0.003) | (0.003) | (0.006) |
| | [0.127] | [0.008] | [0.015] | [0.017] | [0.001] | [0.004] |
| $b_2$ | 0.022+ | 0.032 | 0.005 | -0.001 | -0.001 | -0.010 |
| | (0.010) | (0.018) | (0.059) | (0.007) | (0.007) | (0.009) |
| | [0.100] | [0.122] | [0.940] | [0.896] | [0.937] | [0.312] |
| F-test $b_1 = b_2$ | 0.076 | 0.003 | 0.107 | 0.256 | 0.014 | 0.051 |
| $T_1$ obs. | 169 | 169 | 169 | 169 | 169 | 169 |
| $T_2$ obs. | 191 | 179 | 167 | 191 | 179 | 167 |
| $R^2$ | 0.115 | 0.273 | 0.310 | 0.159 | 0.364 | 0.450 |

*Notes.* This table reports the estimates of slope coefficients and F-test statistics for regime switching time series regressions of the form $rx_{t+K} = \mathbb{1}_t^R(a_1 + b_1 X_t) + (1 - \mathbb{1}_t^R)(a_2 + b_2 X_t) + v_{t+K}$, where $\mathbb{1}_t^R$ is the OECD global recession indicator, $X_t$ is one of the forecasting variables, $K$ is the forecasting horizon in months, and $rx_{t+K}$ is cumulative log excess return between months $t$ and $t+K$. Standard errors are reported in parentheses, and p-values are reported in brackets, while the F-test row reports p-values for testing $H_0 : b_1 = b_2$, all obtained using OS HAR inference. $^{+}$,$^{*}$,$^{**}$, and $^{***}$ indicate significance at the 0.1, 0.05, 0.01, and 0.001 levels, respectively.

## Appendix D. Potential upward bias in returns during recessions

One potential concern with my measure of shipping returns is that it assumes that an owner is always able to lease their ship out at the prevailing time charter rates. However, some ships may end up idle during recessions due to the lack of demand and the difficulty in finding business for them. Because of this, the measures of earnings and returns based on time charter rates may tend to overstate the true earnings and returns to owning ships especially during recessions. Furthermore, it is likely that the number of idle ships increases as the demand for shipping services falls, and ship earnings, prices, and investment decrease. The predictive variables therefore would be negatively correlated with this bias in the measure of returns, generating an impression of regime-dependent predictability.

To address this concern, I test whether the net excess capital gains on ships are also predictable during recessions. Specifically, I estimate regressions of the form:

$$\Delta px_{t+K} = \mathbb{1}_t^R(a_1 + b_1 X_t) + (1 - \mathbb{1}_t^R)(a_2 + b_2 X_t) + v_{t+K}, \tag{D.1}$$

Table D.1: Forecasting net excess capital gains

| | $X$ = net real earnings $\Pi$ | | | $X$ = used ship price $P$ | | | $X$ = investment $I$ | | |
|---|---|---|---|---|---|---|---|---|---|
| $K$ | 12m | 24m | 36m | 12m | 24m | 36m | 12m | 24m | 36m |
| $b_1$ | -0.050*** | -0.080* | -0.094* | -0.012*** | -0.022* | -0.027* | -1.865*** | -2.079*** | -2.769** |
| | (0.007) | (0.029) | (0.032) | (0.003) | (0.006) | (0.007) | (0.312) | (0.419) | (0.748) |
| | [0.000] | [0.050] | [0.026] | [0.001] | [0.018] | [0.018] | [0.001] | [0.001] | [0.006] |
| $b_2$ | -0.008 | -0.022 | -0.016 | -0.004 | -0.008+ | -0.009 | -1.040+ | -2.108* | -1.288 |
| | (0.010) | (0.017) | (0.015) | (0.002) | (0.004) | (0.005) | (0.454) | (0.473) | (0.638) |
| | [0.458] | [0.249] | [0.358] | [0.096] | [0.099] | [0.134] | [0.051] | [0.011] | [0.114] |
| F-test $b_1 = b_2$ | 0.001 | 0.171 | 0.110 | 0.006 | 0.136 | 0.065 | 0.253 | 0.948 | 0.092 |
| $T_1$ obs. | 237 | 225 | 217 | 237 | 225 | 217 | 115 | 103 | 95 |
| $T_2$ obs. | 291 | 291 | 287 | 291 | 291 | 287 | 162 | 162 | 158 |
| $R^2$ | 0.189 | 0.230 | 0.248 | 0.229 | 0.327 | 0.382 | 0.176 | 0.260 | 0.249 |

*Notes.* This table reports the estimates of slope coefficients and F-test statistics for regime switching time series regressions of the form $\Delta px_{t+K} = \mathbb{1}_t^R(a_1 + b_1 X_t) + (1 - \mathbb{1}_t^R)(a_2 + b_2 X_t) + v_{t+K}$, where $\mathbb{1}_t^R$ is the OECD global recession indicator, $X_t$ is one of the forecasting variables, $K$ is the forecasting horizon in months, and $\Delta px_{t+K}$ is cumulative log net excess capital gain between months $t$ and $t+K$. Standard errors are reported in parentheses, and p-values are reported in brackets, while the F-test row reports p-value for testing $H_0 : b_1 = b_2$, all obtained using OS HAR inference. $^{+}$,$^{*}$,$^{**}$, and $^{***}$ indicate significance at the 0.1, 0.05, 0.01, and 0.001 levels, respectively.

where $\Delta px_{t+K}$ is the capital gain over the following $K$ months, net of depreciation and in excess of risk free rate, computed as detailed in the footnote 34. We are effectively setting the ship earnings to zero, which should eliminate the above-mentioned bias.

Table D.1 presents the results, which are very similar to the ones reported in Table 3. All coefficient estimates are statistically significant in recessions at least at the 5% level, and in the majority of cases we either reject $H_0 : b_1 = b_2$, or are close to rejecting it. We can therefore rule out that my main results are driven by a bias in the measure of returns.

## Appendix E. Annual sampling

As already discussed, the monthly observations of 12-, 24-, and 36-months excess returns overlap to a large degree. While I take the utmost care to account for this by relying on the OS HAR inference, a concern remains that the apparent statistical significance of predictive coefficients may be driven by the high degree of autocorrelation in the error term.

It is not immediately clear why this problem would manifest itself only during recessions, and not at other times. But to gain further confidence that my results are not driven

Table E.1: Regime-dependent predictability: annual sampling

| | $X$ = net real earnings $\Pi$ | | | $X$ = used ship price $P$ | | | $X$ = investment $I$ | | |
|---|---|---|---|---|---|---|---|---|---|
| $K$ | 1y | 2y | 3y | 1y | 2y | 3y | 1y | 2y | 3y |
| $b_1$ | -0.020$^{***}$ | -0.029$^{+}$ | -0.039$^{+}$ | -0.006$^{***}$ | -0.010$^{*}$ | -0.014$^{*}$ | -1.095$^{***}$ | -0.974$^{***}$ | -1.234$^{+}$ |
| | (0.004) | (0.014) | (0.020) | (0.002) | (0.004) | (0.006) | (0.181) | (0.191) | (0.592) |
| | [0.000] | [0.056] | [0.069] | [0.001] | [0.019] | [0.024] | [0.000] | [0.000] | [0.071] |
| $b_2$ | 0.039$^{***}$ | 0.027 | 0.029 | 0.004 | 0.001 | -0.001 | 1.456$^{***}$ | 0.590 | 1.256 |
| | (0.008) | (0.024) | (0.042) | (0.004) | (0.005) | (0.008) | (0.386) | (0.597) | (0.878) |
| | [0.000] | [0.255] | [0.501] | [0.403] | [0.775] | [0.947] | [0.001] | [0.347] | [0.183] |
| F-test $b_1 = b_2$ | 0.000 | 0.149 | 0.155 | 0.042 | 0.059 | 0.160 | 0.000 | 0.020 | 0.008 |
| $T_1$ obs. | 19 | 18 | 17 | 19 | 18 | 17 | 9 | 8 | 7 |
| $T_2$ obs. | 25 | 25 | 25 | 25 | 25 | 25 | 14 | 14 | 14 |
| $R^2$ | 0.212 | 0.113 | 0.121 | 0.163 | 0.144 | 0.166 | 0.283 | 0.046 | 0.067 |

*Notes.* This table reports the estimates of slope coefficients and F-test statistics for regime switching time series regressions of the form $rx_{t+K} = \mathbb{1}_t^R(a_1 + b_1 X_t) + (1 - \mathbb{1}_t^R)(a_2 + b_2 X_t) + v_{t+K}$, where $\mathbb{1}_t^R$ is the OECD global recession indicator, $X_t$ is one of the forecasting variables, $K$ is the forecasting horizon, and $rx_{t+K}$ is cumulative log excess return between $t$ and $t+K$. The data used in estimation is annually sampled in June. Standard errors are reported in parentheses, and p-values are reported in brackets, while the F-test row reports p-values for testing $H_0 : b_1 = b_2$, all obtained using OS HAR inference. $^{+}$,$^{*}$,$^{**}$, and $^{***}$ indicate significance at the 0.1, 0.05, 0.01, and 0.001 levels, respectively.

by overlapping observations, I estimate (7) using only annually sampled data. Specifically, I pick only the observation in June from each year, such there is a 12 months gap between the observations. This, of course, significantly reduces the number of observations, but completely eliminates the overlapping data problem at the 12-months horizon, and significantly reduces it at the 24- and 36-months horizons. Table E.1 reports the results. Despite the limited number of observations, all my results survive both qualitatively and quantitatively.

## Appendix F. Stambaugh bias and near-unit-root inference

Shipping earnings and prices are both highly persistent at monthly frequency and endogenous. In finite samples this gives rise to an amplifying bias in the estimates of slope coefficients, and may lead to incorrect inference in favour of predictability, as was first demonstrated by Stambaugh (1999). Moreover, in the local-to-unity case, the bias is still present in the limit, and correcting this asymptotic bias is generally not possible, since it depends on the localizing coefficient that is not consistently estimable (Phillips and Lee, 2013).

Table F.1: Regime-dependent predictability: the IVX approach

| | $X$ = net real earnings $\Pi$ | $X$ = used ship price $P$ | $X$ = investment $I$ |
|---|---|---|---|
| $K$ | 1y | 1y | 1y |
| $A_1$ | -0.020$^{+}$ | -0.006$^{*}$ | -1.032 |
| | [0.054] | [0.029] | [0.105] |
| $A_2$ | 0.043$^{*}$ | 0.005 | 1.798$^{*}$ |
| | [0.017] | [0.344] | [0.033] |
| $\chi^2$-test $_{A_1=A_2}$ | 0.002 | 0.057 | 0.008 |

*Notes.* This table reports the IVX estimates of slope coefficients in time series regressions of the form $rx_{t+1} = \mathbb{1}_t^R(c_1 + A_1 X_t) + (1 - \mathbb{1}_t^R)(c_2 + A_2 X_t) + u_{t+1}$, where $\mathbb{1}_t^R$ is the OECD global recession indicator, $X_t$ is one of the three forecasting variables, and $rx_{t+1}$ is the 1-year log excess return between $t$ and $t+1$. Data is annually sampled in June. p-values are reported in brackets, and the $\chi^2$-test row of each panel reports the p-values for testing $H_0 : A_1 = A_2$. $^{+}$,$^{*}$,$^{**}$, and $^{***}$ indicate significance at the 0.1, 0.05, 0.01, and 0.001 levels, respectively.

Similarly to the overlapping data issue discussed in Appendix E, however, it is not clear why the bias would show up only during recessions, and not otherwise. To further check that my results are not driven by the Stambaugh bias, I employ the IVX estimation method developed by Magdalinos and Phillips (2009) for econometric inference in the vicinity of unity. It was adapted to the context of return predictability testing by Phillips and Lee (2013) and Kostakis et al. (2015), and is considered state of the art in the predictability literature. The basic idea behind the IVX approach is to remove the endogeneity by means of data-filtered instruments, the persistence of which can be explicitly controlled, so they remain in the class of near-stationary processes.

The IVX methodology assumes that the true data generating process has only one lag, i.e.:

$$y_{t+1} = c + AX_t + u_{t+1}, \tag{F.1}$$

where $y_t$ is a dependent variable and $X_t = \mu + \rho X_{t-1} + \nu_t$ is a persistent predictor variable. Because my excess returns series is cumulative over at least 12 months,[51] it is not possible to estimate (F.1) using the monthly data. Therefore, I sample the data annually in June of each year as is Appendix E, and use the IVX procedure to estimate regime-switching

[51] Recall that 12 months is the duration of the time charter contracts used in the computation of earnings and returns, see Section II.

regressions of the form:

$$rx_{t+1} = \mathbb{1}_t^R(c_1 + A_1 X_t) + (1 - \mathbb{1}_t^R)(c_2 + A_2 X_t) + u_{t+1}, \tag{F.2}$$

where $rx_{t+1}$ is the 1-year log excess return between years $t$ and $t+1$.

Table F.1 presents the results. We see that point estimates in recessions are very close to the estimates at the 12-months horizon reported in Table 3. They are statistically significant, except for investment, which just misses the 10% threshold. Moreover, $H_0 : A_1 = A_2$ is rejected at least at the 10% level. This evidence indicates that the Stambaugh bias is unlikely to constitute a large fraction of the OLS estimates and drive my main findings.