Herd behavior in the drybulk market: An empirical analysis of the decision to invest in new and retire existing fleet capacity

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Abstract

We examine whether investors herd in their decision to order or scrap vessels in the drybulk market. We decompose herding into unintentional and intentional, and test for herd behavior under asymmetric effects with respect to freight market states, cycle phases, risk-return and valuation profiles, and ownership of the vessel. We detect unintentional herd behavior during down freight markets and contractions. Furthermore, we find evidence of spill-over unintentional herding effects from the newbuilding to the scrap market. Finally, asymmetric herd effects are evident between traditional and liberal philosophy towards the ownership of the vessel, and during extreme risk-return and valuation periods.

Keywords: herding; ship finance; contracting; scrapping

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1 Introduction

Shipping investment for newbuildings is mainly categorized into replacement, expansionary and new entrance investment. Replacement shipping investment involves the allocation of capital for the purposes of replacing vessels that are no longer capable of fulfilling the company's requirements and are, therefore, available for demolition. Major reasons for replacement realized through the newbuilding market include technical obsolescence, market conditions, international regulations, and company policy. Next, expansionary shipping investment constitutes capital outlay for materializing the growth strategy of shipping companies in response to prevailing or expected market conditions that are usually accompanied by availability of ship finance sources. Lastly, new entrance shipping investment involves the injection of capital into newbuilding acquisitions by newcomers to the industry. The decision to expand fleet capacity is mainly linked to freight market conditions (Engelen et al., 2006; Adland and Strandenes, 2007; Stopford, 2009; Greenwood and Hanson, 2015; among others) as companies expand to maintain or increase their market share. Secondhand prices and their relation to newbuilding prices (Merikas et al., 2008; Stopford, 2009) also constitute a major influence in the decision to order new vessels due to construction lags (Kalouptsidi, 2014), as shipping investors may demand immediate delivery of vessels when freight rates are at high levels. On the other hand, scrapping a vessel is a major decision that irreversibly disposes a capital-intensive asset, while certain vessel features – age, technical obsolescence and condition –, international regulations and the market state will influence the likelihood of a vessel being sent for demolition. Generally, for older and poor condition[1] vessels, employment potential and scope for capital appreciation are limited, thus, leading to higher scrapping levels. In addition to vessel age and deteriorating condition, technical obsolescence is also likely to result in reduced running cost efficiency, greater maintenance and crew costs, and higher insurance premia; therefore, drive vessels to the scrapyard. Furthermore, vessel retirement taking place due to regulatory changes is a compulsory decision. In terms of market state, if freight conditions are such that it is not economically feasible to operate vessels, then shipping investors are faced with the decision to continue operations at a loss, lay-up or scrap the vessel. Operating at a loss and lay-up are reversible options with expectations as to future profitability playing an important role. In contrast, scrapping is an irreversible decision that shipping investors have traditionally preferred to avoid, even during severe oversupply conditions when outstanding debt obligations and equity base depletion are further obstacles. The decision to scrap vessels is linked to the prevailing freight, secondhand and scrap market conditions. Buxton (1991) argues that there is little economic sense in operating a vessel or selling her in the sale-and-purchase market when both markets have deteriorated significantly. Knapp et al. (2008) confirm the hypothesis of an inverse relation between vessel earnings and the probability of a ship being scrapped, establish a positive relation between scrap prices and scrapping probability, and find no significant relation between flag, ownership or safety factors and scrapping. Recently, Alizadeh et al. (2016) examine the capacity retirement in the drybulk market by employing a combination of vessel specific and market variables. The study confirms the previously established negative association between earnings and scrapping, and the fact that higher scrap prices lead to elevated

[1]Younger vessels in poor condition may also be scrapped earlier than older vessels in good condition, if the scrapyard appears as a more feasible option than a costly vessel overhaul.

scrapping activity; while the probability of scrapping increases with age, interest rates, and freight volatility. Finally, market expectations are key in shipping investment/divestment decisions under freight income uncertainty (Stopford, 2009) and the application of real options theory provides shipping companies with valuable flexibility in the decision making process (Dixit and Pindyck, 1994; Dikos, 2008; Gkochari, 2015; Kyriakou et al., 2017).

However, vessel ordering and scrapping activity is a strategic decision that, among other factors, may be the outcome of shipowners revising their own market outlook upon observing the actions of others, i.e., there is a degree of herd behavior involved. Herd behavior is generally used to describe trading decisions that are based on the collective actions in a market rather than personal beliefs and information (Hwang and Salmon, 2004). This trading behavior can lead a group of investors to move in the same direction and, as a consequence, herding can cause asset prices to deviate from their fundamental values (Bikhchandani et al., 1992; Nofsinger and Sias, 1999). Therefore, examining herd behavior may provide an understanding of its influence on asset values (Chang et al., 2000). For example, investors might be interested in the existence of herding, as reliance on common rather than private information may cause assets to deviate from the fundamental values and present profitable opportunities. Herding has also attracted the attention of academics because the associated behavioral effects on asset price movements may affect their risk-return characteristics and, therefore, can have implications for asset pricing models[2]. In addition, according to Scharfstein and Stein (1990), classical economic theory suggests that investment decisions reflect the rationally formed expectations of agents, i.e., decisions made utilizing all the available information in an efficient manner; in contrast, investment may also be driven by group psychology (herd behavior), which weakens the link between information and market outcomes. Our aim is to provide an understanding of some of the forces that may lead to herd behavior in the shipping markets. Existing literature on investigating herd behavior is mainly concentrated on herding between institutional/retail investors (e.g., Lakonishok et al., 1992; Sias, 2004; Kumar and Lee, 2006) or herding towards the market consensus (e.g., Christie and Huang, 1995; Chang et al., 2000). Our paper falls within the latter strand and tests for herding behavior in the newbuilding and scrap markets of drybulk vessels.

Our main contribution to the ship finance literature is the fact that this paper, to the best of our knowledge, is the first to examine herd behavior in the shipping industry. To that end, we first test for overall herd behavior and, then, for unintentional and intentional herding. To achieve the latter, we augment our herding equation to provide evidence on whether investors base their decisions on common elements that they share or just mimic the decisions of few reputable investors due to an informational disadvantage[3]. Further, we test for asymmetric herd behavior effects in terms of extreme market movements, contraction and expansion phases; and whether there are any spill-over herding effects from one market

[2]In the drybulk market, the efficient market hypothesis (EMH) and asset pricing models focus mainly on the term structure of freight rates, vessel price formation, risk premium and trading strategies (Kavussanos and Alizadeh, 2002; Adland and Koekebakker, 2004; Kavussanos et al., 2004; Adland and Strandenes, 2006; Alizadeh and Nomikos, 2006; Alizadeh and Nomikos, 2007). However, herding behavior may not always be regarded as an anomaly which contradicts the efficient market hypothesis; rather, if it is assumed that investors trade in the direction of informed investors, then asset prices may converge faster to their fundamental values (Gavriilidis et al., 2013; Economou et al., 2015).

[3]Only recent studies have concentrated on the issue of intentional and unintentional herding (Holmes et al., 2013; Galariotis et al., 2015).

to another. Finally, we provide additional tests for asymmetric effects based on the notion of an old and a new generation of shipowners, and extreme risk-return profiles and market valuation periods.

Furthermore, while the existing literature focuses on financial markets and assets, our contribution is the examination of herd behavior in a real assets market setting; therefore, we overcome the problem of using proxies to capture direct real assets investment/divestment. For example, several studies (see Philippas et al., 2013; Babalos et al., 2015; among others) examine herd behavior in the real estate market based on Real Estate Investment Trusts (REITs), as these products represent a good proxy for the real estate market (Hsieh and Peterson, 2000; Zhou and Lai, 2008; Lee and Chiang, 2010) because their assets consist of investments in real estate.

Overall, our results indicate that shipping investors unintentionally herd in their decision to contract new and/or scrap older vessels, and we attribute this herd behavior to relative homogeneity. Moreover, we establish asymmetric herd behavior as unintentional herding is likely to be encountered only during down markets in both the newbuilding and scrap markets. This result is complemented by the detection of unintentional herding in the scrap market, which is more profound during contraction phases. Therefore, we also highlight the importance of decomposing total herding into unintentional and intentional herding, as examining only total herding would reveal no asymmetric herd behavior in the two markets. Next, we show that the scrap market is affected by spill-over herding effects in the newbuilding market, and this can be attributed to the social interaction (hence, social mood driving herding) among the participants and the fact that the investment decision to contract a new vessel and/or scrap an old one is taken by the participants who belong in both markets. Additional tests on asymmetric herd behavior reveal that unintentional herding when contracting new vessels stems from relative homogeneity in terms of liberal philosophy towards the ownership of vessels (in addition to possible similar academic backgrounds and analytical skills); whereas intentional herding exists in the case of the traditional philosophy towards vessel ownership and the contracting of newbuildings. In terms of extreme risk-return profiles and market valuation periods, we present evidence that investors herd unintentionally in their decision to scrap vessels during extreme low risk-return profiles and high market valuation periods. Furthermore, we establish intentional herd behavior during high risk-return profiles and market valuation in the decision to scrap old and contract new vessels respectively. Our findings may have theoretical and empirical implications for market participants and academics alike, as the herding and asymmetric behavioral effects found need to be taken into account by market participants or theoretical models that attempt to describe the behavior of agents in the newbuilding and scrap market of the drybulk industry.

The remaining of this paper is structured as follows. Section 2 discusses herding, how it is measured and decomposed into unintentional and intentional. Section 3 provides evidence of asymmetric herd behavior during extreme market movements, and contraction and expansion phases. Herding spill-over effects are investigated in Section 4, whereas additional tests for asymmetric herding effects are conducted in Section 5. Section 6 concludes the paper.

2 Herding measurement and detection

The intuition behind the herding measure that follows is that investors may ignore prior heterogeneous beliefs in order to follow correlated patterns around the aggregate market behavior (Christie and Huang, 1995; Chang et al., 2000). The empirical tools employed to examine herd behavior towards market consensus can be broadly classified into two measures and methods. Christie and Huang (1995) detect herding among investors by the cross-sectional standard deviation ($CSSD$) of stock returns, and their empirical approach is based on rational asset pricing models and herding in periods of market stress. They argue that, during normal periods, rational asset pricing models predict that the dispersion in cross-sectional returns increases with the absolute value of market returns, as investors trade on private and diverse information. On the other hand, during extreme market movements, investors suppress their private information and mimic collective actions in the market, leading to lower return dispersions. Therefore, herding is be more prevalent during extreme market movements, which are defined as the occurrence of extreme returns on the market portfolio. To differentiate between their assumptions, they isolate the level of dispersion into the lower and upper tails of the returns distribution and test whether these differ from the average level of dispersion[4]. In addition, herding may be examined by the cross-sectional absolute deviation ($CSAD$) of stock returns of Chang et al. (2000), where herding is assumed to be a function of the dispersion measure that is either non-linearly decreasing or reaches a maximum at a certain threshold level of the expected absolute market return and declines thereafter. In this paper, we utilize an adjusted[5] $CSAD$ to investigate herding in the drybulk market for vessel contracting and scrapping

$$CSAD_t^{\vartheta} = \frac{1}{N}\sum_{i=1}^{N}\left|I_{i,t}^{\vartheta} - \bar{I}_t^{\vartheta}\right|, \quad \vartheta \in \{C, S\}, \tag{1}$$

where $CSAD_t^{\vartheta}$ is the cross-sectional absolute deviation of contracting ($\vartheta = C$) and scrapping ($\vartheta = S$) of vessels, $I_{i,t}^{\vartheta}$ is the number of vessels in the i^{th} sector (i = capesize, panamax, handymax, handysize) that are contracted (newbuildings) or scrapped at time t, and $\bar{I}_t^{\vartheta} = \sum_{i=1}^{4} I_{i,t}^{\vartheta}/4$ is the cross-sectional average number of vessels contracted or scrapped. For the estimation of $CSAD^{\vartheta}$ we use data provided by Clarksons Shipping Intelligence Network for the period January 1996–May 2015. The evolution of $CSAD^{\vartheta}$ for vessel contracting and scrapping over time is presented in Figure 1. In general terms, the $CSAD^{C}$ measure is relatively stable with three notable exceptions where deviations from the market consensus are significantly increasing: the advance of the drybulk market to all-time highs (2007–2008), and the two periods after the market crash when market participants believed that the worse was over (2010 and 2013–2014). On the other hand, the $CSAD^{S}$ measure moves in a more erratic way and increasing deviations from the aggregate market behavior are more frequently observed: the Russian and Asian crises (1996–1999), the dotcom bubble (2000–

[4]Herding can also take place during normal market periods (Hwang and Salmon, 2004).

[5]The $CSAD$ measure is adjusted and estimated based on the number of new vessels contracted or older vessels scrapped rather than the returns on individual assets and the market. In the analysis that follows, we have also used the $CSSD$ measure to test for herding behavior; our results have remained qualitatively and quantitatively similar.

2002), the subprime, financial, and shipping crashes (2008–2009), and the period when the freight market took another dive after a short-lived upturn (2011–2013).

[INSERT FIGURE 1 HERE]

Next, to detect herding activity in the market, we adopt the non-linear OLS specification of Chang et al. (2000) and estimate the relation between the cross-sectional absolute deviation measure and the overall market average of contracting or scrapping vessels[6]

$$CSAD_t^{\vartheta} = \gamma_0 + \gamma_1 \left|\bar{I}_t^{\vartheta}\right| + \gamma_2 \left(\bar{I}_t^{\vartheta}\right)^2 + \upsilon_t^{\vartheta}. \tag{2}$$

Chang et al. (2000) argue that, if investors tend to follow the aggregate market behavior during periods of large average price movements, then the linear and increasing relation between dispersion and market return (under rational asset pricing models) no longer holds and it may become non-linearly increasing or decreasing. The linear part of the above dependence is picked up by the positive γ_1 coefficient, while the non-linear part by γ_2. If $\gamma_2 < 0$, the cross-sectional deviation of contracting or scrapping increases less than linearly,or even decreases, in the market average when the latter is large in absolute terms. This is interpreted as evidence of herd behavior and, as such, the coefficient of the non-linear term should be negative and statistically significant. Therefore, we assume that, if herd behavior is encountered in the market for contracting newbuildings or scrapping older vessels, then γ_2 has to be negative and statistically significant.

2.1 Intentional and unintentional herd behavior

Herd behavior can be classified as intentional or unintentional. In the case of intentional herding, investors mimic each other's actions with intent. This type of behavior is normally observed in less sophisticated investors who attempt to copy reputable or well-established investors, as obtaining the full information of well-established investors would incur high costs. Generally, intentional herding is characterized by some sort of informational or professional asymmetry. From the informational asymmetry perspective, investors may resort to herding when they have an informational disadvantage; which can be an actual or perceived disadvantage (Devenow and Welch, 1996). Intentional herding can also arise due to professional asymmetry as a result of ability or reputation. This is often encountered in financial intermediaries' or hedge funds' managers who are assessed periodically; hence, managers of low ability or reputation may mimic the actions of high ability or reputation peers (Scharfstein and Stein, 1990; Villatoro, 2009). In contrast, unintentional herding occurs when investors make similar investment decisions as a result of a common element in their environment (Hirshleifer et al., 1994; Bikhchandani and Sharma, 2000). Common elements may include relative homogeneity (Teh and de Bondt, 1997) and characteristic trading (Bennett et al., 2003). Relative homogeneity refers to investors who process the information or signals (e.g., financial ratios) received in a similar manner due to the fact that they share

[6]We report the OLS results of the empirical estimation as in Hwang and Salmon (2004), Chiang and Zheng (2010), Economou et al. (2011) and Galariotis et al. (2015), among others. For robustness purposes, the Generalized Method of Moments (GMM) procedure has also been used and the results have remained qualitatively similar.

similar academic backgrounds or analytical skills (Wermers, 1999), whereas characteristic trading refers to investment decisions based on specific characteristics of the assets, which eventually lead to style investing (e.g., growth, income, momentum, industry).

To decompose the $CSAD_t^{\vartheta}$ measure into intentional and unintentional deviations, we employ three metrics that adequately capture important shipping information, are similar to all market participants and may affect the decision to order a new or scrap an old vessel; however, we recognize the fact that there may be other metrics that drive the investment decision. The metrics cover key areas of the shipping market and are classified into two categories: valuation (price-earnings ratio) and market conditions (secondhand-newbuilding price ratio and Baltic Dry Index). All data required for the calculation of the metrics are provided by Clarksons Shipping Intelligence Network for the period January 1996–May 2015.

The first valuation-specific metric is the price-earnings (PE) ratio for vessels: $PE_{i,t} = P_{i,t}^{SH} - E_{i,t}$, where $P_{i,t}^{SH}$ is the log-price of the 5-year old secondhand vessel and $E_{i,t}$ the log-earnings (1-year time-charter rates[7]) in sector i and month t. The PE ratio is used to predict subsequent asset returns (Campbell and Shiller, 1998; Rangvid, 2006; Alizadeh and Nomikos, 2007) and reflects the relative degree of overvaluation/undervaluation in asset prices. The estimate of earnings is forward-looking and reflects the expected earnings from operating the vessel for one year from the point of valuation, i.e., high (low) PE ratios translate to high (low) current vessel prices relative to the one-year earnings. Papapostolou et al. (2014) argue that high PE ratios are associated with low investor sentiment levels, which may lead to higher levels of scrapping and low investment in newbuilding orders. The second metric is the secondhand-newbuilding price (SNB) ratio which belongs to the market conditions category: $SNB_{i,t} = P_{i,t}^{SH} - P_{i,t}^{NB}$, where $P_{i,t}^{NB}$ is the log newbuilding vessel price. Newbuilding vessels have longer useful economic lives than identical secondhand vessels of certain age (e.g., five or ten-year old vessels), which, in general, means that their cost is also higher. However, during prosperous freight rate markets, investors prefer to take advantage of the prevailing conditions immediately and favor the purchase of secondhand vessels to avoid the construction lag of newbuildings[8]. This creates an immediate delivery premium which drives SNB to higher levels. Papapostolou et al. (2014) show that SNB is related to investors' sentiment in the drybulk market and, as such, we expect that a higher ratio can lead to more vessel orders and less scrapping. The final metric is the 1-year change on the Baltic Dry Index (BDI): $BDI_{R,t} = BDI_t - BDI_{t-12}$, where BDI_t is the log BDI level in month t. Similarly to SNB, we expect that higher freight market levels can tempt investors to order new vessels, with the scrapping of older vessels remaining at a minimum.

To provide support that the metrics contain valuable information that may affect the decision to order and scrap vessels, we estimate regressions of the type: $I_t^{\vartheta} = \beta_0 + \beta_1 \mathbf{X}_t + \upsilon_t^{\vartheta}$; where $I_t^{\vartheta} = \sum_{i=1}^{4} I_{i,t}^{\vartheta}$ is the total number of vessels contracted or scrapped and $\mathbf{X}_t$ includes the aggregate metrics PE_t, SNB_t and the $BDI_{R,t}$. To calculate the aggregate metrics PE_t

[7]Fixed daily freight rate (US$/day) received by the shipowner for chartering (leasing or letting-out) a vessel for a 1-year period.

[8]The building of new vessels is characterized by significant construction lags. The actual construction time, which ranges on average between 1–3 years, may often be lengthened considerably by the lack of available berth capacity in shipyards or due to order backlog. For example, Kalouptsidi (2014) quantifies the impact of time-to-build on shipping investments and estimates that the average construction time almost doubled in 2001-2008.

and SNB_t for the drybulk market, we assign weights $\omega_{i,t}$ to each metric of sector i based on the market share (in terms of deadweight tonnage) of the sector in the total drybulk fleet: $PE_t = \sum_{i=1}^{4} \omega_{i,t} PE_{i,t}$ and $SNB_t = \sum_{i=1}^{4} \omega_{i,t} SNB_{i,t}$. The results are provided in Appendix A.1 and show that the proposed metrics explain a significant variance proportion of the number of vessels ordered and scrapped. Finally, to distinguish between intentional and unintentional herding, we run the regression

$$CSAD_t^{\vartheta} = \beta_0 + \beta_1 \mathbf{X}_t + \upsilon_t^{\vartheta}, \tag{3}$$

and define the intentional herding measure $CSAD_t^{\vartheta,I} = \upsilon_t^{\vartheta}$. Then, the unintentional herding measure is given by the difference between total herding and intentional herding

$$CSAD_t^{\vartheta,U} = CSAD_t^{\vartheta} - CSAD_t^{\vartheta,I}. \tag{4}$$

Therefore, we can think of the υ_t^{ϑ} term as a measure of clustering due to market participants responding to uncorrelated information, whereas $CSAD_t^{\vartheta,U}$ as a measure of clustering due to correlated information that is analyzed in a similar manner.

[INSERT TABLE 1 HERE]

Having decomposed the total herding measure into the unintentional and intentional measures, we next estimate the benchmark herding model given by Eq. 2. The results are reported in Table 1 and are grouped into three categories: total herding ($CSAD_t^{\vartheta}$), unintentional herding ($CSAD_t^{\vartheta,U}$) and intentional herding ($CSAD_t^{\vartheta,I}$). In terms of total herding, the cross-sectional contracting and scrapping dispersions increase with the magnitude of the cross-sectional market average number of contracting and scrapping, a feature that is consistent with rational asset pricing models. Furthermore, we find that herd behavior is present in both markets, as reflected by the negative and statistically significant value of $\hat{\gamma}_2$. The results are quantitatively and qualitatively similar in the case of unintentional herding. On the other hand, there is no evidence of reduced cross-sectional dispersion around the market average of contracting and scrapping in the case of intentional herding. Therefore, we conclude that, in the period January 1996–May 2015, shipping investors unintentionally herded in their decision to contract new and/or scrap older vessels; we attribute this herd behavior to relative homogeneity. Specifically, investors reached analogous investment decisions as a result of sharing a similar academic background and/or equivalent analytical/technical skills, elements that eventually led to processing the correlated information received (shipping metrics) in a similar way.

3 Asymmetric herd behavior during up and down markets, expansion and contraction phases

In this section, we examine whether there is an asymmetric relationship between $CSAD_t^{\vartheta}$ and the cross-sectional market average of contracting and scrapping. Christie and Huang (1995), Chang et al. (2000) and Demirer et al. (2010) show that herding effects are expected to be more pronounced during periods of market losses. To test whether shipping investors react differently during months when the freight market is up compared to months when the freight market is down, we follow the approach of Chiang and Zheng (2010) who use a dummy variable approach in a single model expressed by

$$CSAD_t^{\vartheta} = \gamma_0 + \gamma_1(1 - D^d)\left|\bar{I}_t^{\vartheta}\right| + \gamma_2 D^d\left|\bar{I}_t^{\vartheta}\right| + \gamma_3(1 - D^d)\left(\bar{I}_t^{\vartheta}\right)^2 + \gamma_4 D^d\left(\bar{I}_t^{\vartheta}\right)^2 + \upsilon_t^{\vartheta}, \quad (5)$$

where $D^d = 1$ if $BDI_{R,t} < 0$ (down market), and 0 otherwise (up market).

[INSERT TABLE 2 HERE]

Table 2 reports the estimates of the models for total herding ($CSAD_t^{\vartheta}$), unintentional herding ($CSAD_t^{\vartheta,U}$) and intentional herding ($CSAD_t^{\vartheta,I}$) under asymmetric market conditions. Our $\hat{\gamma}_3$ and $\hat{\gamma}_4$ coefficients provide consistent evidence with the results presented in Section 2.1. Particularly, we find a negative sign for the unintentional contracting herding coefficient regardless of whether the market is up or down, while the results show stronger herd behavior in months of declining freight rates. In good markets, contracting a newbuilding vessel may seem attractive as higher freight rates due to charterers' preferences to be associated with top tonnage may result in newbuildings being first in line for competitive charter bidding[9]. The chartering aspect has also been important by enabling newbuilding transactions to be financially viable through the existence of quality time charter contracts from "first" class charterers, thereby, providing a degree of security for providers of credit. In poor markets, newbuildings are also likely to be competitive due to construction lags, which may prove beneficial to shipping investors contracting for low priced tonnage in depressed markets and hoping to benefit from an improved market on delivery.

Furthermore, we detect unintentional herd behavior in the scrap market only in down freight markets, which is consistent with the negative relation between scrapping and market conditions (Buxton, 1991; Knapp et al., 2008; Alizadeh et al., 2016), i.e., freight conditions are such that it is not economically feasible to operate vessels. To test the equality of the herding coefficients between up and down markets, we conduct a Wald test for the null hypothesis H_0: $\hat{\gamma}_3 = \hat{\gamma}_4$. The chi-square statistics reliably point towards rejection of the null hypothesis in the case of unintentional herd behavior in both the newbuilding and scrap markets, confirming the asymmetric herd behavior described above. It is also interesting to observe that the results of the benchmark total herding model (Table 1) are reversed, as we do not detect total herd behavior when asymmetric freight market conditions are considered. Therefore, our results identify: (1) the importance of decomposing total herding into unintentional and intentional herding, as examining only total herding suggests no asymmetric herd behavior in any of the two markets, and (2) that unintentional herd behavior is likely to be encountered in both the newbuilding and scrap markets during down freight markets.

Next, we test asymmetric herd behavior during contraction and expansion phases in the newbuilding[10] and freight markets. To date the newbuilding vessel prices and earnings

[9] In practice, time charter contracts may not always be available and, consequently, lead investors with a speculative bet at or near the top of the market.

[10] We have also tested for asymmetric herd behavior during contraction/expansion phases in the scrap market; the results have remained qualitatively and quantitatively similar.

turning points, we use the non-parametric algorithm of Bry and Boschan (1971) as modified by Harding and Pagan (2002); the turning points and assumptions made are provided in Appendix A.2. This method captures the turning points in an efficient way with a minimum set of assumptions which is sufficient for our purposes. For our analysis, we estimate the turning points on the bulkcarrier newbuilding price index and Clarksea average bulker earnings index, both provided by Clarksons Shipping Intelligence Network. To test whether shipping investors behave differently during contractions and expansions phases, we follow the approach of Chiang and Zheng (2010) and use a dummy variable in the herding equation

$$CSAD_t^{\vartheta} = \gamma_0 + \gamma_1(1-D^{con})\left|\bar{I}_t^{\vartheta}\right| + \gamma_2 D^{con}\left|\bar{I}_t^{\vartheta}\right| + \gamma_3(1-D^{con})\left(\bar{I}_t^{\vartheta}\right)^2 + \gamma_4 D^{con}\left(\bar{I}_t^{\vartheta}\right)^2 + \upsilon_t^{\vartheta}, \quad (6)$$

where D^{con} takes value 1 (0) during contraction (expansion) phases in the newbuilding and earnings markets.

[INSERT TABLE 3 HERE]

Table 3 presents the regression estimates for testing asymmetric herding effects under newbuilding prices (Panel A) and earnings (Panel B) contraction/expansions phases. The results of Panel A indicate that total herding is present in both the newbuilding and scrap markets (consistently with our discussion in Section 2.1) during expansion phases in the newbuilding market. However, the Wald test for the null hypothesis that the herding coefficients are equal during contractions and expansions cannot be rejected, hence, the herding asymmetry found during expansion phases cannot be confirmed. Similar results are observed in the case of unintentional herding in the newbuilding market, where the Wald test fails to reject the null hypothesis of herding symmetry during expansion phases, even though $\hat{\gamma}_3$ is negative and statistical significant. In contrast, we find evidence of unintentional herding in the scrap market during contraction phases, as $\hat{\gamma}_3$ is negative and statistically significant, and the null hypothesis H_0: $\hat{\gamma}_3 = \hat{\gamma}_4$ is rejected at the 5% significance level according to the Wald test. In terms of intentional herding, we detect no asymmetric effects in any of the two markets. Panel B reports the results under the different earnings phases and, in all cases, we find no evidence of herding asymmetric behavior under contraction or expansion phases[11]. Therefore, we conclude that unintentional herding in the scrap market is more profound during contraction phases in the newbuilding market, which also complements our results that unintentional herding is stronger during down markets. A possible explanation of this phenomenon is that contraction periods in the newbuilding market probably indicate deteriorating overall market conditions; thus, market participants – who analyze the information received in a similar manner – may herd in their decision to scrap an older vessel which may be uneconomical viable to operate.

Finally, we test whether investors revealed any asymmetry in herd behavior during the Asian/Russian crises, the dotcom collapse and the recent subprime and financial crises (results are presented in Appendix A.3). The results are in line with the above discussion and suggest that unintentional herding in the scrapping decision is stronger during crises periods (Asian/Russian crises and dotcom collapse), although some unintentional herding when contracting new vessels is also detected during the dotcom collapse. When all crises are taken

[11] We have also identified the turning points based on an aggregate scrap price index; however, the results showed no asymmetric herd behavior during contraction and expansion phases.

into account, we detect no asymmetric herding effects and, therefore, the decision to build a new or scrap an old vessel is generally not affected by the examined crises.

4 Spill-over herding effects

Stopford (2009) categorizes the shipping industry into four separate but interrelated markets: the newbuilding market, the freight market, the sale and purchase market, and the demolition market; whereas Wijnolst and Wergeland (1996) offer an alternative classification: the real market for ships (newbuilding and demolition) and spot freight, and the auxiliary markets for timecharters and secondhand vessels. In either case, the dynamics of these markets are closely related as the same investor is trading in all markets. Furthermore, social interaction and social mood may also be a driving force of herding. Olson (2006) suggests that emotions are prone to contagion among participants in a group, directly impacting the overall behavior of the group. In the case of shipping, social interaction enables word of mouth sharing of information between investors/shipowners within a relatively small and niche market, while companies normally operate a mixture of young and old vessels across sectors of the drybulk market. Therefore, in an integrated drybulk market facilitated by efficient information flow and processing, investment and divestment activities are unlikely to be insulated, especially when a company has to make a decision on both contracting a new vessel and scrapping an old one. To take into account the possibility of spill-over herding effects from the newbuilding to the scrap market, and vice versa, we modify[12] the herding specification of Eq. 2 which assumes a closed system in that no effects from one market to the other are involved, and estimate

$$CSAD_t^C = \gamma_0 + \gamma_1 \left|\bar{I}_t^C\right| + \gamma_2 \left(\bar{I}_t^C\right)^2 + \gamma_3 \left(\bar{I}_t^S\right)^2 + \upsilon_t^C, \quad (7)$$

$$CSAD_t^S = \gamma_0 + \gamma_1 \left|\bar{I}_t^S\right| + \gamma_2 \left(\bar{I}_t^S\right)^2 + \gamma_3 \left(\bar{I}_t^C\right)^2 + \upsilon_t^S. \quad (8)$$

All variables are defined in Section 2 and the benchmark herding equation (Eq. 2) is modified to take into account the fact that participants in the newbuilding (scrap) market may actually exhibit herd behavior as a response to extreme movements in the scrap (newbuilding) market[13].

[INSERT TABLE 4 HERE]

Table 4 presents the regression estimates from testing for possible herding spill-over effects between the newbuilding and scrap markets. Consistently with our earlier findings, total and unintentional herd behavior is present in both markets, as reflected by the negative value and statistical significance of $\hat{\gamma}_2$. In terms of total and intentional herding, we find

[12] Whether herd behavior in one market is affected by events taking place in another market has been previously examined (Klein, 2013). For example, Chiang and Zheng (2010) find that events in the US market help explain herd behavior in other markets. When testing for herding effects in international markets, prior studies (Chiang and Zheng, 2010; Economou et al., 2011; Galariotis et al., 2015) have added the return of the US market as an extra variable in the benchmark model.

[13] The correlation coefficients between $\left(\bar{I}_t^C\right)^2$ and $\left(\bar{I}_t^S\right)^2$, $\bar{I}_t^C$ and $\left(\bar{I}_t^S\right)^2$, and $\left(\bar{I}_t^C\right)^2$ and $\bar{I}_t^S$ are -0.127, -0.126 and -0.188 respectively; suggesting no multicollinearity in our Equations 7–8.

no evidence of spill-over effects. However, in the case of unintentional herding, adding $\left(\bar{I}_t^C\right)^2$ into Eq. 8 enhances the explanatory power as suggested by the higher adjusted-R^2. Furthermore, the negative sign and statistical significance of $\hat{\gamma}_3$ reveal spill-over herding effects running from the newbuilding to the scrap market; this is also supported by the rejection of the null hypothesis H_0: $\hat{\gamma}_2 = \hat{\gamma}_3$ at the 1% significance level. This result can be attributed to the social interaction (hence, social mood driving herding) among participants and the fact that the decision to contract a new vessel and scrap an old one is taken by participants who are active in both markets. Additionally, fleet replacement programmes and scrap-and-build schemes may also be contributing factors for the spill-over effects found; although in theory, the scrap-and-build scheme states that scrapping a vessel should take place first and the order confirmation for a new replacement vessel second. Therefore, when analyzing herding activity in the shipping industry, one cannot disregard the fact that the different markets within the industry are integrated. Finally, as spill-over effects in the shipping industry have been previously established in terms of volatility (Kavussanos, 2003; Chen et al., 2010; Drobetz et al., 2012; Tsouknidis, 2016), we complement the existing literature from a different perspective.

5 Additional tests for asymmetric herding effects

5.1 Traditional versus liberal philosophy towards the ownership of the vessel

As discussed earlier, unintentional herding can be attributed to relative homogeneity, i.e., investors processing the information or signals received in a similar manner due to the fact, for example, that they share similar academic backgrounds or analytical skills. In this section, we test whether the unintentional herd behavior found in Section 2.1 is indeed an outcome of relative homogeneity. However, we assume that relative homogeneity refers also to shipping investors having a more liberal philosophy towards the ownership of the vessel; this, is manifested by the utilization of less traditional[14] sources of finance, such as the equity and bond capital markets (Grammenos and Papapostolou, 2012). We call shipping investors who do not pose the common element of liberal philosophy towards the ownership of the vessel as the traditional generation, whereas investors of relative homogeneity with respect to the above element as the liberal generation. To distinguish the traditional from the liberal generation, we split our sample into two sub-periods: January 1996–December 2003 (traditional generation) and January 2004–May 2015 (liberal generation). The categorization is based on the fact that after 2003, as can be observed in Figure 2, we have experienced a massive wave of equity and bond offerings in terms of capital raised, which is also an indication of the liberal philosophy towards the ownership of the vessel. One, of course, has to take into account the main reasons behind the emergence of the liberal generation: (1) the drybulk market conditions in 2003–2008 were extremely good due to the Chinese economic boom and increased demand for seaborne trade; as a result, there was a need for increasing the size of shipping companies and funds to finance the overall fleet expansion programme,

[14] Most shipping companies start out by raising capital from the owner's own funds and the banking system (Grammenos and Papapostolou, 2012).

(2) the appetite of investment banks for a fee-generating income by completing equity and bond offering deals, (3) the temporary difficulty of the banking system in providing on time the necessary funds in 2009–2013, and (4) the entrance of private equity funds in 2006–2015.

[INSERT FIGURE 2 HERE]

To test whether any asymmetric herd behavior effects exist in the market due to the difference between the old and new generation of investors, we employ a dummy variable in the herding equation

$$CSAD_t^{\vartheta} = \gamma_0 + \gamma_1(1-D^{trad})\left|\bar{I}_t^{\vartheta}\right| + \gamma_2 D^{trad}\left|\bar{I}_t^{\vartheta}\right| + \gamma_3(1-D^{trad})\left(\bar{I}_t^{\vartheta}\right)^2 + \gamma_4 D^{trad}\left(\bar{I}_t^{\vartheta}\right)^2 + \upsilon_t^{\vartheta}, \quad (9)$$

where $D^{trad} = 1$ if market participants do not share the common element of liberal philosophy towards the ownership of vessels (traditional generation); and 0 otherwise (liberal generation).

[INSERT TABLE 5 HERE]

Table 5 reports the results from testing herding activity between the traditional and liberal generation of shipping investors. We find unintentional herd behavior in the contracting decision of the liberal generation of investors, which is in line with our argument that this is a group of investors who share similar academic backgrounds, analytical skills and philosophy towards the ownership of the vessel (negative sign and statistical significance of $\hat{\gamma}_3$ coefficient, supported by the rejection of the null hypothesis H_0: $\hat{\gamma}_2 = \hat{\gamma}_3$ at the 1% significance level). In terms of the decision to scrap, there is no clear evidence of asymmetric effects for unintentional herd behavior between the traditional and liberal generation as both $\hat{\gamma}_3$ and $\hat{\gamma}_4$ are statistically negative and different according to the Wald test; however, herding is stronger in the case of the traditional generation of investors. Therefore, we conclude that unintentional herding in the contracting of vessels stems from relative homogeneity in terms of, not only similar academic background/skills, but also liberal philosophy towards the ownership of vessels.

Furthermore, our results support asymmetric effects in intentional herd behavior of the traditional generation when deciding to contract new vessels and reiterate the definition of intentional herding that is characterized by informational or professional asymmetry. The traditional philosophy towards the ownership of the vessel normally dictated high degree of commitment by shipowners to the vessel/company due to the high risk and cost involved in newbuilding orders. Consequently, contractors of new tonnage were usually established market players with a view to employing the vessel for its full economic life. For that reason, and the fact that the sophistication of the shipping industry and the tools employed to assist the decision to order a new vessel were in scarcity prior to 2004, investors probably mimicked a few reputable and major investors in the market in an effort to reduce their informational disadvantage without losing their market share.

5.2 Asymmetric effects under extreme risk-return profiles and market valuation periods

Next, we examine whether herd behavior differs during extreme risk-return profiles and market valuation periods. Christie and Huang (1995) suggest that herding dominates during periods of market stress, whereas Gleason et al. (2004) and Tan et al. (2008) argue that herding effects are stronger during periods of high volatility. To detect possible asymmetric herd behavior under extreme market returns and volatility, we calculate the Sharpe ratio (SR) to represent the risk-return profile of the drybulk market: $SR_{i,t} = \sum_{s=t-M+1}^{t} \Delta E_{i,t} / \sqrt{\sum_{s=t-M+1}^{t} \Delta E_{i,t}^2}$, where $\sum_{s=t-M+1}^{t} \Delta E_{i,t}$ is the one-year realized return and $\sqrt{\sum_{s=t-M+1}^{t} \Delta E_{i,t}^2}$ the one-year realized volatility of BDI. To calculate the aggregate SR metric for the drybulk market, we assign weights $\omega_{i,t}$ on the metric of sector i as in Section 2.1. Furthermore, we check for asymmetric herding effects during periods of extreme valuations in the market, i.e., test whether there is any difference in herd behavior at extreme values in terms of the PE metric of Section 2.1. In our analysis, we assume that herd behavior should be more prevalent: (1) during periods of extreme SR values, as the return on investment is either extremely high or low compared to the associated risk; (2) during extreme PE values, as secondhand vessel prices are extremely high or low compared to the corresponding earnings. To detect any asymmetric effects, we use a dummy variable in the following herding equation

$$CSAD_t^{\vartheta} = \gamma_0 + \gamma_1 D^U \left| \bar{I}_t^{\vartheta} \right| + \gamma_2 D^L \left| \bar{I}_t^{\vartheta} \right| + \gamma_3 D^U \left(\bar{I}_t^{\vartheta} \right)^2 + \gamma_4 D^L \left(\bar{I}_t^{\vartheta} \right)^2 + \upsilon_t^{\vartheta}, \tag{10}$$

where D^U (D^L) equals 1 if SR, PE are in the upper (lower) α-quantile[15] of the distribution with $\alpha = 0.10$.

[INSERT TABLE 6 HERE]

Table 6 presents the estimates of the herding specification in Eq. 10. In terms of extreme SR profiles (Panel A), the results indicate that unintentional herding is present in the scrap market during extreme low SR periods and the Wald test for the null hypothesis that the herding coefficients – between extreme high and low periods – are equal can be rejected, confirming the herding asymmetry. Similar results are observed in the case of intentional herding in the scrap market, however during extreme high SR profiles; with $\hat{\gamma}_3$ found negative and statistically significant and the null hypothesis H_0: $\hat{\gamma}_3 = \hat{\gamma}_4$ rejected at the 5% significance level according to the Wald test. The fact that investors herd unintentionally in their decision to scrap vessels during extreme low SR periods comes as no surprise. Indeed, one would expect well-informed investors, who analyze information in a similar manner, to scrap vessels as it is deemed uneconomical to operate them when the return on investment is substantially low compared to the associated risk – especially when at the extreme low profiles a negative return on investment is observed (see Figure 3). Furthermore, the intentional herding during high SR periods may be attributed to investors mimicking a few reputable ones who may wish to scrap vessels before a downturn in the market materializes according to their expectations. Another possibility is the clustering of scrapping activity which, in the long run,

[15] We have also tested for $\alpha = 0.01, 0.05, 0.10$. Here, we present results only for $\alpha = 0.10$ as this is the level at which asymmetric herding effects are found.

can be a reflection of increased vessel deliveries (Zannetos, 1966) and, subsequently, an attempt to relieve an oversupplied market (see Figure 3). However, the clustering of scrapping activity may also be the outcome of practical delays in the scrapping of vessels or simply a case of lagged demolition reporting into the public domain (Adland and Strandenes, 2007).

[INSERT FIGURE 3 HERE]

Panel B reports the results under extreme PE periods, where evidence of asymmetric herd behavior is found only during periods of extreme high PE periods. Specifically, $\hat{\gamma}_3$ is negative and statistically significant in the cases of unintentional and intentional herding in the scrapping and contracting decisions, respectively. In both cases, the herding asymmetry is further confirmed by the rejection of the null hypothesis H_0: $\hat{\gamma}_3 = \hat{\gamma}_4$ at the 1% significance level. Therefore, we conclude that unintentional herding exists in the scrap market when vessels values are at extreme levels compared to their expected earnings. As such, informed investors may scrap old vessels to achieve better prices in anticipation of a drop in asset values to reflect the earnings in the market. This can also be linked to investors' unintentional herd behavior in their decision to scrap during extreme low risk-return profiles as it is not economically feasible to operate vessels (see Figure 3). Finally, investors herd intentionally when contracting new vessels during extremely high PE periods, and as Figure 3 suggests, ordering new vessels during an oversupplied market is driven by unsophisticated investors who incorrectly inflate the orderbook in their attempt to follow reputable investors ordering new vessels. From the reputable investors' viewpoint, contracting of newbuildings during extreme high PE periods can be related to increasing market share and the benefit of construction lags in anticipation of improved market conditions. On the other hand, from the unsophisticated investors' viewpoint, revising own opinions about the future prospects of the market upon observing the actions of others (informational disadvantage) and fear of losing market share, may eventually lead to intentional herding in ordering new vessels.

6 Conclusions

Our paper contributes to the literature by examining and providing original evidence on herd behavior in the shipping industry. We detect unintentional herding in the decision to contract new and/or scrap older drybulk vessels, suggesting that investors herd due to common elements they share and not because they mimic the decisions of established and reputable investors.

In terms of up and down freight markets, we find no clear evidence of asymmetric effects in unintentional herd behavior when contracting new vessels, although herding is stronger during down markets. On the other hand, the results show strong unintentional herding when scrapping vessels during down markets. Hence, we confirm – from a different perspective – the negative relation between scrapping and market conditions already established in the literature. Furthermore, it is evident that the different cycle phases of the market do play a significant role in herd behavior, as herding exists when scrapping vessels during contraction phases. Given the herding spill-over effects found from the newbuilding to the scrap market, we argue that herding in the scrap market is affected by herding in the newbuilding market and add to the current shipping literature on spill-over effects in terms of herding rather than volatility. Therefore, when examining herding, one has to take into account the fact that the two markets are integrated.

Additional tests on asymmetric herding effects reveal that unintentional herding in the decision to contract a new vessel is based on relative homogeneity in terms of liberal philosophy towards the ownership of the vessel. At the same time, the traditional generation seems to mimic the decision of few established and reputable investors when scrapping old vessels, as intentional herding is detected. Furthermore, extreme low risk-return profiles and high market valuation periods affect herd behavior differently.

The decision to expand or retire fleet capacity plays a key role in shipping investment/divestment and has an impact on not only the shipping company, but also on the development of the shipping market. Our results may be of interest to decision-makers – investors, providers of capital, agencies, and regulators – overseeing the development of the shipping industry. For example, knowing that herding exists in the capacity expansion or retirement decision may assist in shaping shipping strategies that are necessary to be successful in a competitive environment. Furthermore, the agencies responsible for controlling the capacity of the market or capital providers who may unintentionally contribute to the oversupply of vessels may take into account the herding effects and stipulate economic and financial policies that promote development in the industry without creating supply and demand imbalances. This paper focuses on the existence of herd behavior among shipping investors rather than on the design of optimal investment/divestment strategies and efficient policies. Modelling and incorporating herding in the aforementioned decisions and policies can be a direction of further research. For example, agents have a (real) option to invest/divest at a time of their choice. However, each agent's optimal option exercise strategy will be contingent on not only own signals, but on the observed actions of other agents as well. Therefore, given imperfect information, if an informational cascade occurs, then agents might start exercising their options sequentially based on positive or negative signals received. Finally, we do not focus on factors that are an indispensable part of the operating capacity level, such as, the size of the company and the chartering policy, or the type of market operating in. Certainly, the different economic and microstructure characteristics of the above areas will have an asymmetric impact on herd behavior, and this can be another possible path for future research.

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Table 1: Herding behavior in the drybulk market

The table reports the OLS estimates (denoted by $\hat{\gamma}_0$, $\hat{\gamma}_1$ and $\hat{\gamma}_2$) for the regression model $CSAD_t^{\vartheta} = \gamma_0 + \gamma_1 \left|\bar{I}_t^{\vartheta}\right| + \gamma_2 (\bar{I}_t^{\vartheta})^2 + \upsilon_t^{\vartheta}$ (Eq. 2). $CSAD_t^{\vartheta}$ is the cross-sectional absolute deviation of contracting ($\vartheta = C$) and scrapping ($\vartheta = S$) of vessels; $\bar{I}_t^{\vartheta} = \sum_{i=1}^{4} I_{i,t}^{\vartheta}/4$ is the cross-sectional average number of vessels contracted or scrapped. $CSAD_t^{\vartheta,I} = \upsilon_t^{\vartheta}$, where υ_t^{ϑ} are the residuals of Eq. 3, is the intentional herding measure and $CSAD_t^{\vartheta,U} = CSAD_t^{\vartheta} - CSAD_t^{\vartheta,I}$ the unintentional herding measure. The sample period is January 1996–May 2015. Newey–West t-statistics (with a lag of 12) are reported in $(\cdot)$. Superscripts a, b, c indicate significance at the 1%, 5% and 10% levels.

	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\bar{R}^2$
Total				
$CSAD_t^{C}$	0.8206^{b}	0.3994^{a}	-0.0019^{a}	0.610
	(0.4102)	(0.0684)	(0.0006)	
$CSAD_t^{S}$	0.2615^{c}	0.5496^{a}	-0.0151^{c}	0.735
	(0.1471)	(0.0976)	(0.0089)	
Unintentional				
$CSAD_t^{C,U}$	2.8842^{a}	0.2311^{a}	-0.0018^{a}	0.558
	(0.7238)	(0.0497)	(0.0005)	
$CSAD_t^{S,U}$	0.8364^{a}	0.4260^{a}	-0.0168^{a}	0.598
	(0.2886)	(0.0776)	(0.0043)	
Intentional				
$CSAD_t^{C,I}$	-2.0829^{c}	0.1688	-0.0002	0.218
	(1.0559)	(0.1196)	(0.0011)	
$CSAD_t^{S,I}$	-0.5808	0.1252	0.0016	0.211
	(0.3804)	(0.1502)	(0.0121)	

Table 2: Herding behavior under up and down market states

The table reports the OLS estimates (denoted by $\hat{\gamma}_0$, $\hat{\gamma}_1$, $\hat{\gamma}_2$, $\hat{\gamma}_3$ and $\hat{\gamma}_4$) for the regression model $CSAD_t^{\vartheta} = \gamma_0 + \gamma_1(1-D^d)\left|\bar{I}_t^{\vartheta}\right| + \gamma_2 D^d \left|\bar{I}_t^{\vartheta}\right| + \gamma_3(1-D^d)(\bar{I}_t^{\vartheta})^2 + \gamma_4 D^d(\bar{I}_t^{\vartheta})^2 + \upsilon_t^{\vartheta}$ (Eq. 5). $CSAD_t^{\vartheta}$ is the cross-sectional absolute deviation of contracting ($\vartheta = C$) and scrapping ($\vartheta = S$) of vessels; $\bar{I}_t^{\vartheta} = \sum_{i=1}^{4} I_{i,t}^{\vartheta}/4$ is the cross-sectional average number of vessels contracted or scrapped. $CSAD_t^{\vartheta,I} = \upsilon_t^{\vartheta}$, where υ_t^{ϑ} are the residuals of Eq. 3, is the intentional herding measure and $CSAD_t^{\vartheta,U} = CSAD_t^{\vartheta} - CSAD_t^{\vartheta,I}$. $D^d = 1$ if $BDI_{R,t} < 0$, and 0 otherwise, the unintentional herding measure. The sample period is January 1996–May 2015. Newey–West t-statistics (with a lag of 12) are reported in $(\cdot)$. Chi-square statistics of the Wald test imposing the restriction $\hat{\gamma}_3 = \hat{\gamma}_4$ are reported in $[\cdot]$. Superscripts a, b, c indicate significance at the 1%, 5% and 10% levels.

	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	$\hat{\gamma}_4$	$\bar{R}^2$	Wald test
Panel A: Total							
$CSAD_t^{C}$	1.4842^a	0.3197^a	0.1843^b	-0.0010	0.0082^a	0.649	$[17.711]^a$
	(0.4758)	(0.0803)	(0.0887)	(0.0009)	(0.0028)		
$CSAD_t^{S}$	0.2398^b	0.6008^a	0.5578^a	-0.0254^a	-0.0152	0.734	[0.534]
	(0.1098)	(0.0784)	(0.0845)	(0.0079)	(0.0093)		
Panel B: Unintentional							
$CSAD_t^{C,U}$	2.7471^a	0.2807^a	0.2668^a	-0.0025^a	-0.0055^a	0.625	$[4.390]^b$
	(0.8125)	(0.0489)	(0.0659)	(0.0006)	(0.0014)		
$CSAD_t^{S,U}$	0.9211^a	0.2679^b	0.4814^a	-0.0079	-0.0214^a	0.647	$[2.875]^c$
	(0.3002)	(0.1045)	(0.0818)	(0.0096)	(0.0036)		
Panel C: Intentional							
$CSAD_t^{C,I}$	-1.3659	0.0469	-0.0674	0.0014	0.0133^a	0.368	$[24.615]^a$
	(0.9628)	(0.1143)	(0.1149)	(0.0013)	(0.0031)		
$CSAD_t^{S,I}$	-0.6977^b	0.3403^b	0.0811	-0.0180	0.0059	0.247	[2.342]
	(0.3153)	(0.1349)	(0.1361)	(0.0126)	(0.0112)		

Table 3: Herding behavior during expansion and contraction phases

The table reports the OLS estimates (denoted by $\hat{\gamma}_0$, $\hat{\gamma}_1$, $\hat{\gamma}_2$, $\hat{\gamma}_3$ and $\hat{\gamma}_4$) for the regression model $CSAD_t^{\vartheta} = \gamma_0 + \gamma_1(1 - D^{con})\left|\bar{I}_t^{\vartheta}\right| + \gamma_2 D^{con}\left|\bar{I}_t^{\vartheta}\right| + \gamma_3(1 - D^{con})(\bar{I}_t^{\vartheta})^2 + \gamma_4 D^{con}(\bar{I}_t^{\vartheta})^2 + \upsilon_t^{\vartheta}$ (Eq. 6). $CSAD_t^{\vartheta}$ is the cross-sectional absolute deviation of contracting ($\vartheta = C$) and scrapping ($\vartheta = S$) of vessels; $\bar{I}_t^{\vartheta} = \sum_{i=1}^{4} I_{i,t}^{\vartheta}/4$ is the cross-sectional average number of vessels contracted or scrapped. $CSAD_t^{\vartheta,I} = \upsilon_t^{\vartheta}$, where υ_t^{ϑ} are the residuals of Eq. 3, is the intentional herding measure and $CSAD_t^{\vartheta,U} = CSAD_t^{\vartheta} - CSAD_t^{\vartheta,I}$ the unintentional herding measure. $D^{con} = 1$ (0) during contraction (expansion) phases. The sample period is January 1996–May 2015. Newey–West t-statistics (with a lag of 12) are reported in $(\cdot)$. Chi-square statistics of the Wald test imposing the restriction $\hat{\gamma}_3 = \hat{\gamma}_4$ are reported in $[\cdot]$. Superscripts a, b, c indicate significance at the 1%, 5% and 10% levels.

	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	$\hat{\gamma}_4$	$\bar{R}^2$	Wald test
Panel A: Newbuilding phases							
Total							
$CSAD_t^C$	0.9262^c	0.4009^a	0.3524^a	-0.0021^a	-0.0006	0.607	[1.204]
	(0.5034)	(0.0816)	(0.0978)	(0.0008)	(0.0016)		
$CSAD_t^S$	0.2381	0.5816^a	0.5552^a	-0.0215^b	-0.0141	0.739	[0.550]
	(0.1449)	(0.1221)	(0.1103)	(0.0095)	(0.0112)		
Unintentional							
$CSAD_t^{C,U}$	2.8638^a	0.2313^a	0.2435^b	-0.0017^a	-0.0026	0.557	[0.494]
	(0.8770)	(0.0501)	(0.0938)	(0.0005)	(0.0016)		
$CSAD_t^{S,U}$	0.9084^a	0.3023^a	0.4636^a	-0.0082	-0.0019^a	0.622	$[5.489]^b$
	(0.3092)	(0.0974)	(0.0730)	(0.0066)	(0.0032)		
Intentional							
$CSAD_t^{C,I}$	-1.9642	0.1700	0.1127	-0.0003	0.0019	0.214	[1.077]
	(1.4068)	(0.1417)	(0.1694)	(0.0014)	(0.0032)		
$CSAD_t^{S,I}$	-0.6762^c	0.2807^c	0.0932	-0.0134	0.0056	0.229	$[5.800]^b$
	(0.3589)	(0.1490)	(0.1444)	(0.0110)	(0.0120)		
Panel B: Earnings phases							
Total							
$CSAD_t^C$	0.6434^a	0.4598^a	0.4082^a	-0.0041^c	-0.0014^c	0.619	[0.941]
	(0.2346)	(0.0473)	(0.0657)	(0.0022)	(0.0007)		
$CSAD_t^S$	0.2812^b	0.5271^a	0.5183^a	-0.0066	-0.0137	0.743	[1.266]
	(0.1230)	(0.0731)	(0.1091)	(0.0073)	(0.0102)		
Unintentional							
$CSAD_t^{C,U}$	2.8988^a	0.2074^a	0.2491^a	-0.0012^c	-0.0022^a	0.558	[1.626]
	(0.6579)	(0.0455)	(0.0651)	(0.0007)	(0.0006)		
$CSAD_t^{S,U}$	0.8529^a	0.4029^a	0.4154^a	-0.0118	-0.0165^a	0.599	[0.163]
	(0.2723)	(0.0935)	(0.0808)	(0.0107)	(0.0050)		
Intentional							
$CSAD_t^{C,I}$	-2.2752^a	0.2546^a	0.1583	-0.0029	0.0008	0.231	[1.786]
	(0.8455)	(0.0613)	(0.1284)	(0.0021)	(0.0011)		
$CSAD_t^{S,I}$	-0.5785^c	0.1271	0.1043	0.0049	0.0027	0.211	[0.044]
	(0.3291)	(0.1066)	(0.1409)	(0.0085)	(0.0114)		

Table 4: Herding contagion

The table reports the OLS estimates (denoted by $\hat{\gamma}_0$, $\hat{\gamma}_1$, $\hat{\gamma}_2$ and $\hat{\gamma}_3$) for the regression models $CSAD_t^C = \gamma_0 + \gamma_1 \left|\bar{I}_t^C\right| + \gamma_2(\bar{I}_t^C)^2 + \gamma_3(\bar{I}_t^S)^2 + \upsilon_t^C$ (Eq. 7) and $CSAD_t^S = \gamma_0 + \gamma_1 \left|\bar{I}_t^S\right| + \gamma_2(\bar{I}_t^S)^2 + \gamma_3(\bar{I}_t^C)^2 + \upsilon_t^S$ (Eq. 8). $CSAD_t^\vartheta$ is the cross-sectional absolute deviation of contracting ($\vartheta = C$) and scrapping ($\vartheta = S$) of vessels; $\bar{I}_t^\vartheta = \sum_{i=1}^4 I_{i,t}^\vartheta/4$ is the cross-sectional average number of vessels contracted or scrapped. $CSAD_t^{\vartheta,I} = \upsilon_t^\vartheta$, where υ_t^ϑ are the residuals of Eq. 3, is the intentional herding measure and $CSAD_t^{\vartheta,U} = CSAD_t^\vartheta - CSAD_t^{\vartheta,I}$ the unintentional herding measure. The sample period is January 1996–May 2015. Newey–West t-statistics (with a lag of 12) are reported in $(\cdot)$. Chi-square statistics of the Wald test imposing the restriction $\hat{\gamma}_2 = \hat{\gamma}_3$ are reported in $[\cdot]$. Superscripts a, b, c indicate significance at the 1%, 5% and 10% levels.

	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	$\bar{R}^2$	Wald test
Panel A: Total						
$CSAD_t^C$	0.6674^c	0.4003^a	-0.0019^a	0.0043	0.610	$[4.576]^b$
	(0.3923)	(0.0642)	(0.0006)	(0.0029)		
$CSAD_t^S$	0.3111	0.5407^a	-0.0146^b	-0.0001	0.735	$[3.065]^c$
	(0.1958)	(0.1076)	(0.0071)	(0.0001)		
Panel B: Unintentional						
$CSAD_t^{C,U}$	3.0035^a	0.2305^a	-0.0018^a	-0.0033	0.560	$[4.101]^b$
	(0.7405)	(0.0461)	(0.0005)	(0.0072)		
$CSAD_t^{S,U}$	1.1222^a	0.3741^a	-0.0139^a	-0.0005^a	0.675	$[10.888]^a$
	(0.2477)	(0.0627)	(0.0040)	(0.0001)		
Panel C: Intentional						
$CSAD_t^{C,I}$	-2.3636^b	0.1704	-0.0001	0.0078	0.222	[0.743]
	(1.1271)	(0.1118)	(0.0010)	(0.0094)		
$CSAD_t^{S,I}$	-0.8180^b	0.1683	-0.0008	0.0004^a	0.257	[0.013]
	(0.3579)	(0.1278)	(0.0104)	(0.0001)		

Table 5: Herding behavior: traditional versus liberal philosophy

The table reports the OLS estimates (denoted by $\hat{\gamma}_0$, $\hat{\gamma}_1$, $\hat{\gamma}_2$, $\hat{\gamma}_3$ and $\hat{\gamma}_4$) for the regression model $CSAD_t^{\vartheta} = \gamma_0 + \gamma_1(1 - D^{trad}) \left|\bar{I}_t^{\vartheta}\right| + \gamma_2 D^{trad} \left|\bar{I}_t^{\vartheta}\right| + \gamma_3(1 - D^{trad})(\bar{I}_t^{\vartheta})^2 + \gamma_4 D^{trad}(\bar{I}_t^{\vartheta})^2 + \upsilon_t^{\vartheta}$ (Eq. 9). $CSAD_t^{\vartheta}$ is the cross-sectional absolute deviation of contracting ($\vartheta = C$) and scrapping ($\vartheta = S$) of vessels; $\bar{I}_t^{\vartheta} = \sum_{i=1}^{4} I_{i,t}^{\vartheta}/4$ is the cross-sectional average number of vessels contracted or scrapped. $CSAD_t^{\vartheta,I} = \upsilon_t^{\vartheta}$, where υ_t^{ϑ} are the residuals of Eq. 3, is the intentional herding measure and $CSAD_t^{\vartheta,U} = CSAD_t^{\vartheta} - CSAD_t^{\vartheta,I}$ the unintentional herding measure. $D^{old} = 1$ (0) if market participants belong to the traditional (liberal) philosophy. The sample period is January 1996–May 2015. Newey–West t-statistics (with a lag of 12) are reported in $(\cdot)$. Chi-square statistics of the Wald test imposing the restriction $\hat{\gamma}_3 = \hat{\gamma}_4$ are reported in $[\cdot]$. Superscripts a, b, c indicate significance at the 1%, 5% and 10% levels.

	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	$\hat{\gamma}_4$	$\bar{R}^2$	Wald test
Panel A: Total							
$CSAD_t^C$	0.6340	0.4147^a	0.5309^a	-0.0022^a	-0.0135	0.607	[1.573]
	(0.4938)	(0.0784)	(0.1562)	(0.0008)	(0.0095)		
$CSAD_t^S$	0.2298^c	0.5248^a	0.6106^a	-0.0129	-0.0221	0.734	[0.201]
	(0.1193)	(0.1270)	(0.1501)	(0.0107)	(0.0213)		
Panel B: Unintentional							
$CSAD_t^{C,U}$	3.6913^a	0.2017^a	-0.1514	-0.0016^a	0.0144	0.618	$[3.366]^c$
	(0.5379)	(0.0527)	(0.1533)	(0.0006)	(0.0090)		
$CSAD_t^{S,U}$	0.7279^b	0.3886^a	0.6433^a	-0.0128^a	-0.0489^a	0.622	$[4.664]^b$
	(0.2981)	(0.0761)	(0.1523)	(0.0043)	(0.0175)		
Panel C: Intentional							
$CSAD_t^{C,I}$	-3.0413^a	0.2117^c	0.6639^a	-0.0006	-0.0267^c	0.235	$[3.891]^b$
	(0.8896)	(0.1150)	(0.2399)	(0.0011)	(0.0139)		
$CSAD_t^{S,I}$	-0.5038	0.1378	-0.0317	-0.0001	0.0268	0.215	[1.213]
	(0.3735)	(0.1632)	(0.2391)	(0.0132)	(0.0289)		

Table 6: Herding behavior under extreme risk-return profiles and market valuation states

The table reports the OLS estimates (denoted by $\hat{\gamma}_0$, $\hat{\gamma}_1$, $\hat{\gamma}_2$, $\hat{\gamma}_3$ and $\hat{\gamma}_4$) for the regression model $CSAD_t^\vartheta = \gamma_0 + \gamma_1 D^U \left|\bar{I}_t^\vartheta\right| + \gamma_2 D^L \left|\bar{I}_t^\vartheta\right| + \gamma_3 D^U (\bar{I}_t^\vartheta)^2 + \gamma_4 D^L (\bar{I}_t^\vartheta)^2 + \upsilon_t^\vartheta$ (Eq. 10). $CSAD_t^\vartheta$ is the cross-sectional absolute deviation of contracting ($\vartheta = C$) and scrapping ($\vartheta = S$) of vessels; $\bar{I}_t^\vartheta = \sum_{i=1}^4 I_{i,t}^\vartheta/4$ is the cross-sectional average number of vessels contracted or scrapped. $CSAD_t^{\vartheta,I} = \upsilon_t^\vartheta$, where υ_t^ϑ are the residuals of Eq. 3, is the intentional herding measure and $CSAD_t^{\vartheta,U} = CSAD_t^\vartheta - CSAD_t^{\vartheta,I}$ the unintentional herding measure. D^U (D^L) equals 1 if SR, PE are in the upper (lower) α-quantile of the distribution with $\alpha = 0.10$. The sample period is January 1996–May 2015. Newey–West t-statistics (with a lag of 12) are reported in $(\cdot)$. Chi-square statistics of the Wald test imposing the restriction $\hat{\gamma}_3 = \hat{\gamma}_4$ are reported in $[\cdot]$. Superscripts a, b, c indicate significance at the 1%, 5% and 10% levels.

	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	$\hat{\gamma}_4$	$\bar{R}^2$	Wald test
Panel A: SR extreme state							
Total							
$CSAD_t^C$	4.1285^a	0.1079^b	-0.2329^c	0.0021^c	0.0158^a	0.336	[18.500]^a
	(0.9272)	(0.0535)	(0.1199)	(0.0012)	(0.0034)		
$CSAD_t^S$	1.5609^a	0.0076	0.1984^c	0.0182	0.0053	0.340	[0.186]
	(0.5553)	(0.2615)	(0.1101)	(0.0239)	(0.0113)		
Unintentional							
$CSAD_t^{C,U}$	4.3718^a	0.1568^a	-0.0062	-0.0007	0.0006	0.426	[0.093]
	(1.0099)	(0.0472)	(0.1524)	(0.0009)	(0.0036)		
$CSAD_t^{S,U}$	1.8479^a	-0.3533^a	0.2567^b	0.0539^a	-0.0088^b	0.384	[30.788]^a
	(0.4600)	(0.1348)	(0.1106)	(0.0120)	(0.0044)		
Intentional							
$CSAD_t^{C,I}$	-0.2626	-0.0475	-0.2232^b	0.0028^b	0.0151^a	0.119	[20.907]^a
	(0.5640)	(0.0523)	(0.0988)	(0.0012)	(0.0033)		
$CSAD_t^{S,I}$	-0.2834	0.3588^a	-0.0592	-0.0355^b	0.0142	0.146	[6.487]^b
	(0.1942)	(0.1247)	(0.0897)	(0.0147)	(0.0095)		
Panel B: PE extreme state							
Total							
$CSAD_t^C$	4.9113^a	-0.1825	-0.0675	0.0161^a	0.0047^a	0.127	[16.764]^a
	(0.9295)	(0.1303)	(0.0821)	(0.0036)	(0.0009)		
$CSAD_t^S$	1.9414^a	0.1221	-4.7020^a	0.0081	2.1669^a	0.307	[19.356]^a
	(0.3288)	(0.2614)	(1.0739)	(0.0253)	(0.4814)		
Unintentional							
$CSAD_t^{C,U}$	4.9600^a	0.0329	0.1696^b	-0.0012	-0.0010	0.125	[0.000]
	(0.9571)	(0.2827)	(0.0764)	(0.0083)	(0.0012)		
$CSAD_t^{S,U}$	2.0567^a	0.2616^a	-5.4579^a	-0.0101^a	2.4252^a	0.364	[33.588]^a
	(0.2651)	(0.0658)	(0.8188)	(0.0023)	(0.4200)		
Intentional							
$CSAD_t^{C,I}$	-0.0559	-0.2141^b	-0.2365^b	-0.0172^a	0.0058^a	0.102	[11.286]^a
	(0.4434)	(0.0985)	(0.1042)	(0.0030)	(0.0013)		
$CSAD_t^{S,I}$	-0.1110	-0.1403	0.7432	0.0182	-0.2527	0.085	[1.013]
	(0.1931)	(0.3812)	(0.5367)	(0.0328)	(0.2538)		

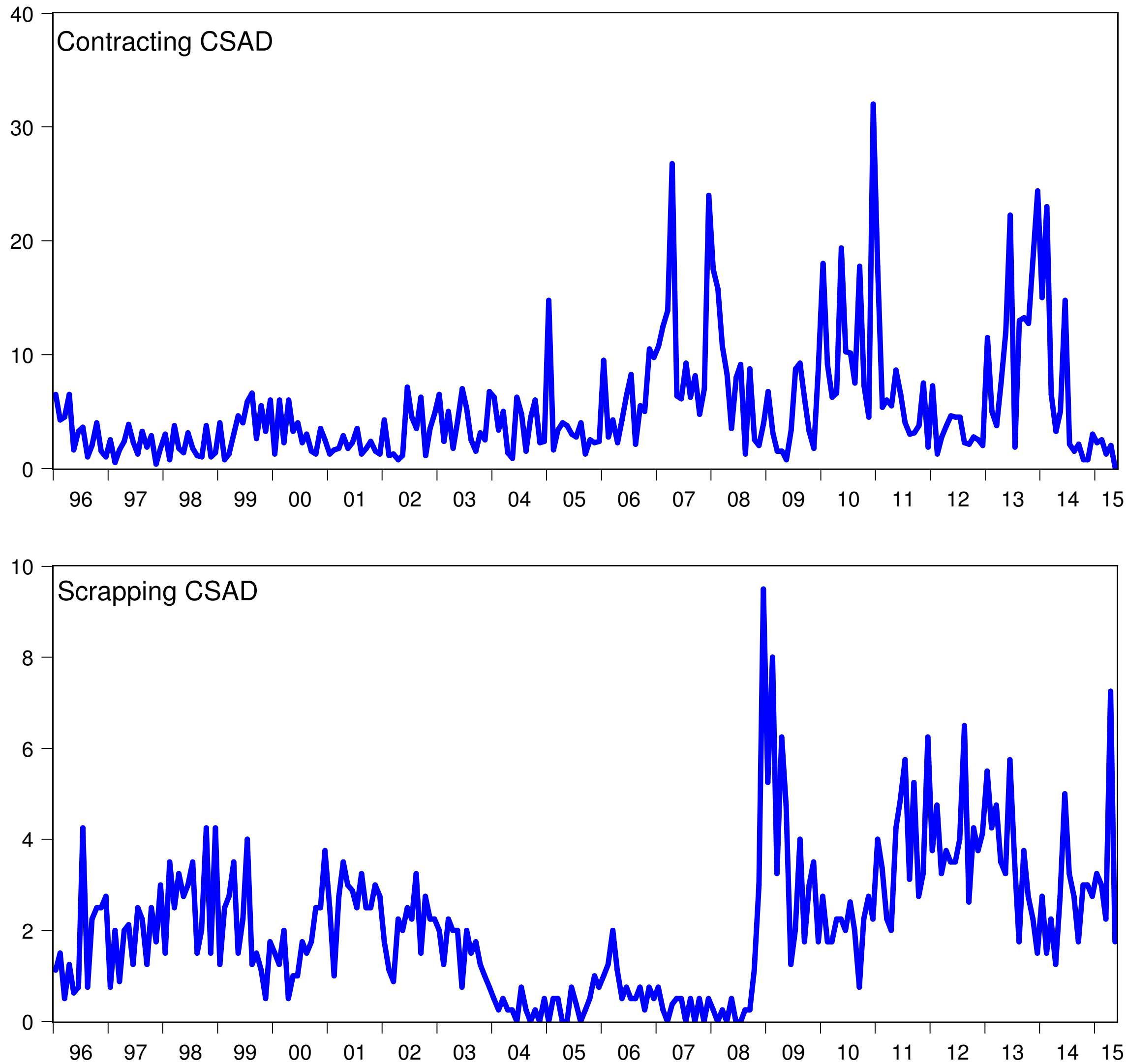

Figure 1: Cross Sectional Absolute Deviation ($CSAD$) for contracting and scrapping vessels in the drybulk market (1996–2015).

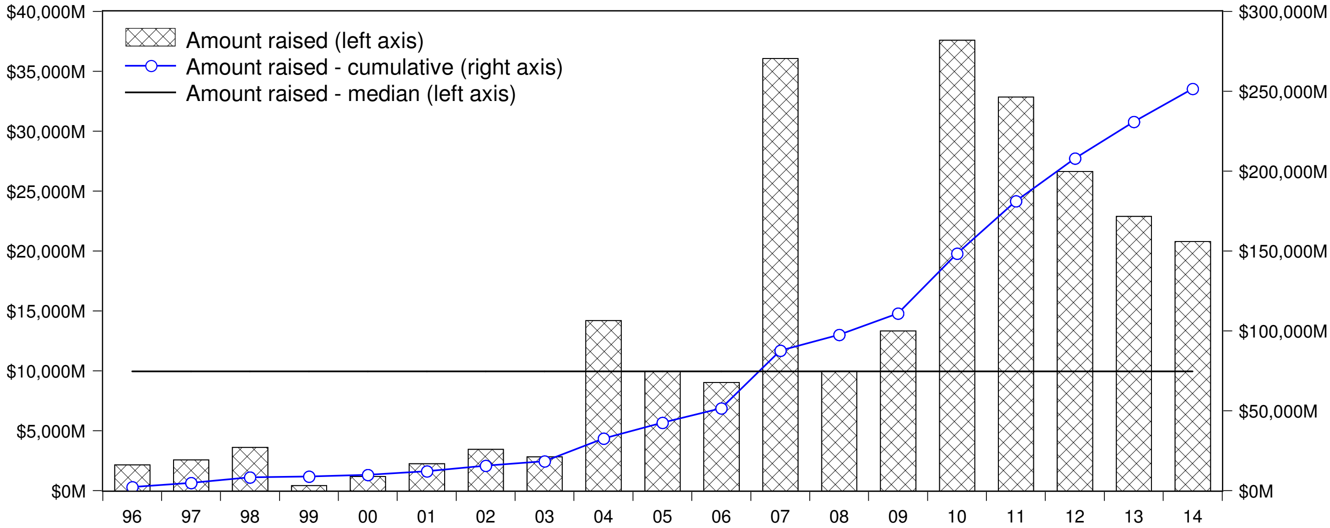

Figure 2: Amount raised (in US$M) by shipping companies (1996–2014): equity and bond offerings. Source: Dealogic, Thomson Reuters and Offering Prospecti.

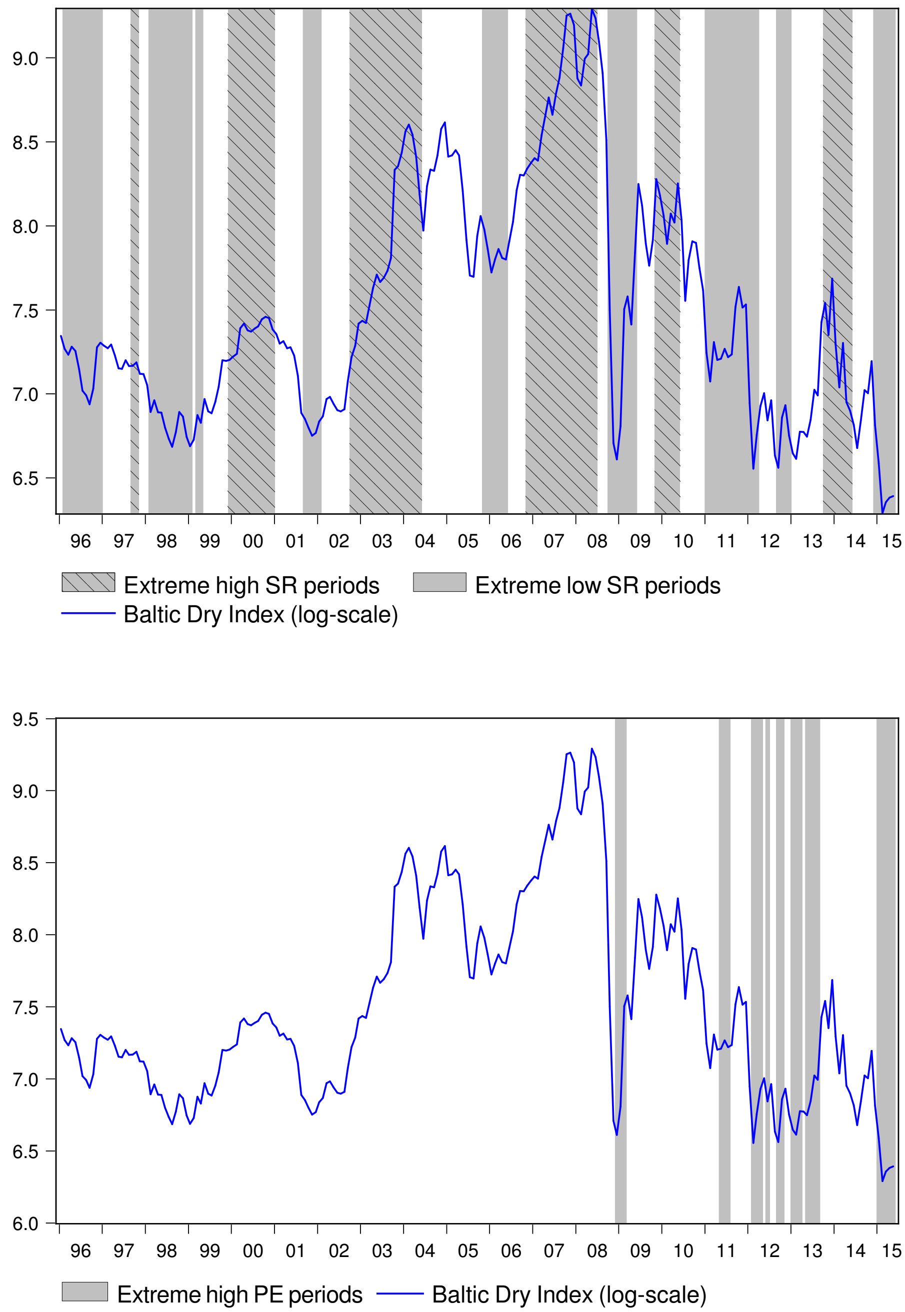

Figure 3: Baltic Dry Index (BDI), extreme periods of SR and PE.

Supplementary Appendices

A.1 Shipping metrics, contracting and scrapping

Table A.1: Shipping metrics, contracting and scrapping

The table reports the OLS etimates (denoted by $\hat{\beta}_0$, $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$) for the regression model $I_t^{\vartheta} = \beta_0 + \beta_1 \mathbf{X}_t + \upsilon_t^{\vartheta}$, where I_t^{ϑ} is the total number of vessels contracted ($\vartheta = C$) or scrapped ($\vartheta = S$) and $\mathbf{X}_t$ includes the aggregate price-earnings ratio PE, secondhand-newbuilding ratio SNB and the 1-year BDI change BDI_R. The sample period is January 1996–May 2015. All variables are stationary according to the Augmented Dickey–Fuller (ADF) test at the 10% significance level or better. The Variance Inflation Factor (VIF) indicates no multicollinearity (multicol.) issues. Newey–West t-statistics (with a lag of 12) are reported in $(\cdot)$. Superscripts a, b, c indicate significance at the 1%, 5% and 10% levels.

	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\bar{R}^2$
Panel A: Contracting					
I_t^C	-173.155^a	10.168^c	191.269^a	19.193^b	0.497
	(41.769)	(5.312)	(21.843)	(8.459)	
Panel B: Scrapping					
I_t^S	-30.638^b	7.243^a	-7.943^c	-4.607^a	0.582
	(11.923)	(1.767)	(4.629)	(1.442)	
Panel C: Unit Root & Multicol. Tests	I_t^C	I_t^S	PE	SNB	BDI_R
ADF t-statistic	-3.719^a	-2.833^c	-3.017^b	-3.224^b	-3.845^a
VIF			1.740	1.611	1.359

A.2 Turnings points for vessels prices and earnings

The key assumptions made, when using the non-parametric algorithm of Bry and Boschan (1971) as modified by Harding and Pagan (2002), to determine the turning points are: a) an initial peak (trough) located at the highest (lowest) point in the vessel price/earnings series using a window of 5 months on either side of that point; b) a peak (trough) followed by a trough (peak); c) a cycle (defined as peak-to-peak or trough-to-trough) with a minimum duration of 18 months; d) a phase (defined as peak-to-trough or trough-to-peak) with a minimum duration of 5 months; and e) turning points not determined within the first or last 5 months of the vessel price/earnings series. To identify the turning points, we use data on the bulkcarrier newbuilding price index from January 1980–May 2015 and the Clarksea average bulker earning index from January 1990–May 2015 (both indices are provided by Clarksons Shipping Intelligence Network). Here, we report only the turning points that correspond to our sample period January 1996–May 2015.

Table A.2: Turning points timeline

Newbuilding prices turning points									
Capesize		Panamax		Handymax		Handysize		Drybulk	
Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough
1995:08	1997:03	1995:08	1997:01	1995:08	1999:04	1995:08	1999:04	1996:10	1999:05
1997:10	1999:04	1997:10	1999:04	2000:07	2002:02	2000:03	2002:02	2001:02	2002:04
2001:03	2002:08	2000:10	2002:03	2005:05	2006:04	2005:07	2006:04	2005:05	2006:02
2005:05	2006:02	2005:05	2006:04	2008:08	2010:01	2008:09	2013:04	2008:09	2010:01
2008:08	2013:02	2008:08	2009:10	2010:07	2013:03	2014:07		2011:01	2012:08
2014:05		2011:02	2013:06	2014:07				2014:05	
		2014:07							
Earnings turning points									
Capesize		Panamax		Handymax		Handysize		Drybulk	
Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough
1995:01	1996:11	1995:05	1996:09	1995:08	1996:10	1995:05	1996:10	1995:05	1996:09
1997:09	1999:04	1997:03	1999:01	1997:10	1999:03	1997:04	1999:02	1997:03	1999:02
2000:09	2002:01	2000:09	2001:11	2000:10	2001:12	2000:10	2001:11	2000:10	2001:12
2004:12	2006:05	2004:03	2006:02	2004:02	2006:02	2005:03	2006:02	2004:12	2006:01
2007:11	2008:11	2008:06	2008:12	2007:11	2008:12	2008:06	2008:12	2007:11	2008:12
2009:06	2012:08	2010:05	2012:09	2010:05	2012:11	2010:05	2013:02	2010:05	2013:02
2014:03		2014:02		2014:03		2014:03		2013:12	

A.3 Herd behavior and market crises

Table A.3: Herding behavior under the Asian, Russian, subprime/financial crises and dotcom bubble

The table reports the OLS estimates (denoted by $\hat{\gamma}_0$, $\hat{\gamma}_1$, $\hat{\gamma}_2$, $\hat{\gamma}_3$ and $\hat{\gamma}_4$) for the regression model $CSAD_t^{\vartheta} = \gamma_0 + \gamma_1(1 - D^{crisis})\left|\bar{I}_t^{\vartheta}\right| + \gamma_2 D^{crisis}\left|\bar{I}_t^{\vartheta}\right| + \gamma_3(1 - D^{crisis})(\bar{I}_t^{\vartheta})^2 + \gamma_4 D^{crisis}(\bar{I}_t^{\vartheta})^2 + \upsilon_t^{\vartheta}$. $CSAD_t^{\vartheta}$ is the cross-sectional absolute deviation of contracting ($\vartheta = C$) and scrapping ($\vartheta = S$) of vessels; $\bar{I}_t^{\vartheta} = \sum_{i=1}^{4} I_{i,t}^{\vartheta}/4$ is the cross-sectional average number of vessels contracted or scrapped. $CSAD_t^{\vartheta,I} = \upsilon_t^{\vartheta}$, where υ_t^{ϑ} are the residuals of Eq. 3, is the intentional herding measure and $CSAD_t^{\vartheta,U} = CSAD_t^{\vartheta} - CSAD_t^{\vartheta,I}$ the unintentional herding measure. D^{crisis} equals 1 if the period corresponds to one of the following crises: Asian and Russian crises from July 1997 to March 1998 and August 1998 to March 1999, respectively; dotcom collapse from March 2000 to October 2002; subprime and financial crises from August 2007 to March 2009. The sample period is January 1996–May 2015. Newey–West t-statistics (with a lag of 12) are reported in $(\cdot)$. Chi-square statistics of the Wald test imposing the restriction $\hat{\gamma}_3 = \hat{\gamma}_4$ are reported in $[\cdot]$. Superscripts a, b, c indicate significance at the 1%, 5% and 10% levels.

	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	$\hat{\gamma}_4$	$\bar{R}^2$	Wald test
	Asian/Russian crises						
Total							
$CSAD_t^C$	0.8237^c	0.4006^a	0.5523^a	-0.0020^a	-0.0379^c	0.607	[3.195]^c
	(0.4267)	(0.0701)	(0.2101)	(0.0007)	(0.0206)		
$CSAD_t^S$	0.2669	0.5560^a	0.3712^a	-0.0157	0.0109	0.734	[3.060]^a
	(0.1618)	(0.1120)	(0.1236)	(0.0096)	(0.0158)		
Unintentional							
$CSAD_t^{C,U}$	2.9290^a	0.2269^a	-0.0702	-0.0017^a	0.0448	0.556	[0.444]
	(0.8655)	(0.0597)	(0.6279)	(0.0006)	(0.0703)		
$CSAD_t^{S,U}$	0.8270^a	0.4159^a	0.7229^a	-0.0158^a	-0.0603^a	0.606	[29.365]^a
	(0.2862)	(0.0790)	(0.1163)	(0.0043)	(0.0103)		
Intentional							
$CSAD_t^{C,I}$	-2.1272^c	0.1743	0.6328	-0.0003	-0.0837	0.213	[1.704]
	(1.2414)	(0.1239)	(0.6340)	(0.0012)	(0.0647)		
$CSAD_t^{S,I}$	-0.5659	0.1416	-0.3494^c	0.0001	0.0710^a	0.230	[16.896]^a
	(0.3820)	(0.1572)	(0.1907)	(0.0125)	(0.0203)		

Table A.3 continued

	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	$\hat{\gamma}_4$	$\bar{R}^2$	Wald test
	Dotcom collapse						
Total							
$CSAD_t^C$	0.7530	0.4065^a	0.5986^a	-0.0021^a	-0.0296^c	0.607	$[3.472]^c$
	(0.4625)	(0.0730)	(0.1816)	(0.0007)	(0.0152)		
$CSAD_t^S$	0.2252^c	0.5346^a	0.7854^a	-0.0136	-0.0486^a	0.740	$[16.413]^a$
	(0.1223)	(0.0939)	(0.0698)	(0.0087)	(0.0098)		
Unintentional							
$CSAD_t^{C,U}$	3.4192^a	0.1995^a	-0.5576^a	-0.0014^a	0.0537^a	0.624	$[14.539]^a$
	(0.4694)	(0.0455)	(0.2063)	(0.0005)	(0.0148)		
$CSAD_t^{S,U}$	0.8114^a	0.4311^a	0.5942^a	-0.0169^a	-0.0533^b	0.601	$[2.703]^c$
	(0.3087)	(0.0775)	(0.1982)	(0.0044)	(0.0229)		
Intentional							
$CSAD_t^{C,I}$	-2.6914^a	0.2078^c	1.1658^a	-0.0007	-0.0840^a	0.238	$[9.961]^a$
	(0.8671)	(0.1089)	(0.3721)	(0.0010)	(0.0272)		
$CSAD_t^{S,I}$	-0.5930	0.1052	0.1946	0.0032	0.0044	0.215	[0.005]
	(0.3951)	(0.1476)	(0.2209)	(0.0119)	(0.0227)		
	Subprime/financial crises						
Total							
$CSAD_t^C$	0.4915	0.4683^a	0.1558^a	-0.0027	0.0018^c	0.653	$[2.790]^c$
	(0.2978)	(0.0779)	(0.0237)	(0.0026)	(0.0004)		
$CSAD_t^S$	0.1815	0.6234^a	0.4285^a	-0.0237^b	0.0089^a	0.790	$[16.482]^a$
	(0.1455)	(0.1332)	(0.0448)	(0.0101)	(0.0023)		
Unintentional							
$CSAD_t^{C,U}$	2.8053^a	0.2498^a	0.3048^a	-0.0028^a	-0.0025^a	0.592	[0.093]
	(0.6558)	(0.0423)	(0.0410)	(0.0006)	(0.0005)		
$CSAD_t^{S,U}$	0.8059^a	0.4537^a	0.3902^a	-0.0200^a	-0.0083	0.612	$[3.133]^c$
	(0.3008)	(0.0984)	(0.1013)	(0.0064)	(0.0058)		
Intentional							
$CSAD_t^{C,I}$	-2.3306^a	0.2186^a	-0.1481^a	0.0001	0.0044^a	0.334	[1.997]
(0.7694)	(0.0765)	(0.0559)	(0.0027)	(0.0008)			
$CSAD_t^{S,I}$	-0.6308^c	0.1714	0.0402	-0.0038	0.0172	0.247	$[6.236]^b$
	(0.3212)	(0.1093)	(0.0988)	(0.0077)	(0.0056)		

Table A.3 continued

	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	$\hat{\gamma}_4$	$\bar{R}^2$	Wald test
				All crises			
Total							
$CSAD_t^C$	0.9833^a	0.4186^a	0.1869^a	-0.0018	0.0011	0.647	[0.873]
	(0.2994)	(0.0657)	(0.0441)	(0.0023)	(0.0009)		
$CSAD_t^S$	0.2204	0.5979^a	0.4955^a	-0.0218^b	0.0028	0.784	[4.135]^b
	(0.1428)	(0.1470)	(0.0745)	(0.0114)	(0.0059)		
Unintentional							
$CSAD_t^{C,U}$	2.6652^a	0.2921^a	0.2328^a	-0.0037^a	-0.0011	0.591	[3.565]^c
	(0.6174)	(0.0534)	(0.0689)	(0.0008)	(0.0012)		
$CSAD_t^{S,U}$	0.8217^a	0.4308^a	0.4310^a	-0.0180^a	-0.0127^b	0.607	[1.254]
	(0.3041)	(0.0936)	(0.0961)	(0.0058)	(0.0051)		
Intentional							
$CSAD_t^{C,I}$	-1.6982	0.1264	-0.0445	0.0020	0.0022	0.296	[0.002]
	(1.1527)	(0.1030)	(0.1340)	(0.0024)	(0.0025)		
$CSAD_t^{S,I}$	-0.6074^b	0.1686	0.0664	-0.0039	0.0154^c	0.251	[3.920]^b
	(0.2815)	(0.1248)	(0.1293)	(0.0094)	(0.0086)		