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How long do we keep up with the Joneses? Herding time horizons in the dry bulk shipping markets

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ABSTRACT

We estimate intentional and unintentional herding in the dry-bulk, ocean-going segment that spans from August 1998 to January 2020 and measure how this can impact vessel orders. As the results suggest, while intentional herding has a large effect on the orders of the newbuilding vessels, the impact is very short-lived. On the contrary, unintentional herding, related to common environmental factors, has a smoother but more time persistent effect on the newbuilding vessels. The findings suggest that the key players in the market do not only affect the dry-bulk market with their decisions but also the logistics trade and ultimately the world economy. Thus, the inclusion of the dry bulk key shipowners by the policymakers in the discussions before reaching an important decision could minimise the volatility of the overall sector.

1. Introduction

It is a universal truth that only a small part of world trade does not take place via sea routes (UNCTAD, 2019). However, it was not until recently that shipping has gained the attention of scholars, primarily because it acts as a leading indicator for the world economy at large (Kilian, 2009; Kilian & Zhou, 2018). Despite its central role in world trade, shipping is usually of a family-oriented nature (Harlaftis & Theotokas, 2004; Mihaylova, 2018) while the secretive approaches used by practitioners (Melas, 2019) have made the dissemination of information for the industry extremely difficult.

In the 21st century, two major disruptions have shed more light into the industry, notably by increasing the number of stakeholders. Initially, the rising cost of capital has led the owners of shipping companies to float in the financial markets rather than seek debt from investors or financial institutions (see, inter alia, Alexandrou et al., 2014; Andriosopoulos et al., 2013; Merikas et al., 2009; Papapostolou et al., 2016). More recently, the use of Automated Identification Systems in the maritime field has not only enabled the tracking of vessels while afloat but also provides better estimations for the supply and demand functions of the industry, when data are provided aggregated (see Adland et al., 2017; Cerdeiro et al., 2020; Michail & Melas, 2020 for a detailed review).

While these disruptions have highly affected the shipping industry since outside investors can expand their portfolios in the shipping industry while being more informed for the performance of the companies, the investment procedures that take place in the maritime sector have long been documented to be highly affected by behavioral aspects of the investors and less by rational decisions (Zannetos, 1959). The reason for this is that, initially, the decision to invest in newbuilding vessels has a two-year time lag from the order until the delivery of the vessel (Kalouptsidi, 2014). Moreover, the expected life of a vessel is approximately 25 years, thus forcing investors to decide the residual value of her, taking into account the current prevailing commodity prices (Kagkarakis et al., 2016; Michail & Melas, 2020).

The combination of these two specificities in the maritime sector makes decision-making in the shipping industry more burdensome and forces investors to rely heavily on factors like market sentiment (see Duru (2018) as well as Moutzouris & Nomikos (2020) for a detailed review on the matter). Moreover, Melas and Michail (2020) have additionally shown that investors follow a herding behavior in the acquiring process of assets rather than in their scrapping decision. The results are exactly opposite when compared with the financial assets since the latter showcase herding behaviors in the sell side rather than the buy side. Nevertheless, while research has provided evidence on the effect that herding has in the shipping industry no results have yet been provided on the time horizon that the effects take place.

Based on the latter, in the current study employs a dataset that spans from August 1998 to January 2020 and uses intentional and unintentional herding to examine, for the first time in the literature, how the two variables affect vessel orderbook. In contrast with previous studies (Papapostolou et al., 2017), our main focus is not on the behavior of herding, but how herding can affect the shipping industry.

Our results suggest that, while significant, intentional herding has a one-off effect on the orders of new building vessels. Thus, it appears that major exogenous developments that happen in the markets can spread fear or greed among the participants and make them follow the example of other, well-established shipping

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investors, in effect mimicking their behavior. This intentional behavior appears to be short-lived but much larger than the unintentional herding behavior, hence leading to higher volatility in the markets. On the other hand, unintentional herding appears to be more persistent over time, thus suggesting that similar academic backgrounds or analytical skills can also have an impact on decisions.

Our research bares serious implications not only for shipping investors but also for the all the stakeholders of the international supply chain industry. Given the intrinsic volatility of the shipping market that leads to herding behavior this will undoubtedly affect vessel orders. The availability of vessels will not only affect shipping investors via its impact on ship prices but it will also have a strong, supply-side effect, on the equilibrium for freight rates, as previous research have already shown (Melas & Michail, 2020b). Furthermore, given the spillover effects that are apparent in freight rates (Tsouknidis, 2016) a change in one vessel category will affect the freight rates of other segments. Thus, it is easily understood that the initial herding behavior ignites a series of events that not only affects the dry bulk category but also bares consequences for both shippers and ship-owners in all segments and international trade at large (Bernhofen et al., 2016; Brancaccio et al., 2020; Kilian & Zhou, 2018; Michail et al., 2020).

Policy wise, the strongest implication lies in the fact that the key players could have a particularly strong impact on the overall market in particular points in time, given the evidence for intentional herding. Bearing also in mind that shipowners ultimately drive the supply curve of the industry (see Stopford, 2013 and Melas & Michail, 2020b), there is a strong potential that the key players can alter the equilibrium point and thus change the freight rates in the market. Such an event is not only worthy of attention in the maritime industry but additionally it can have various economic spillovers. As such, and given the fact that the shipping transportation consists of the 85% of the world trade (UNCTAD, 2019), changes in freight rates CAN ultimately affect the global logistics sector.

Further to this, dry bulk ocean-going transportation in particular has a strong connection with the world economy (see Funashima, 2020; Hamilton, 2019; Kilian, 2009; Kilian, 2019; Kilian & Zhou, 2018 for the fruitful discussion on the matter). Given that, changes in the equilibrium price could eventually affect overall world trade behavior. The concluding remark of the discussed relationship between the dry bulk major shipowners and their influence in the market is that the policy-makers of the maritime industry, like IMO and ILO, are strongly encouraged to follow a more inclusive procedure when policies are considered, since unnecessary power struggles can lead to externalities in the global economy.

Following this introduction, the remainder of this paper is organized as follows: section 2 provides a review of the literature on the issue, section 3 describes the methodology and the data used, section 4 discusses the empirical results obtained, and section 5 concludes on the findings.

2. Literature review

Shipping has served as a frutiful setting for behavioral research given its notorious volatility (see Alexandridis et al., 2018; Scarsi, 2007) that drives investors to rely both on fundamentals (Moutzouris & Nomikos, 2020) and on sentiment (Melas & Michail, 2020b; Papapostolou et al., 2014) when their economic decisions are concerned.

The overall literature of the field lies primarily in three different pillars of the behavioral research agenda, namely, over-extrapolation (Greenwood & Hanson, 2015), herding behavior (Papapostolou et al., 2017) and sentiment (Papapostolou et al., 2016). While over-extrapolation has been thoroughly researched for the last 70 years (Zannetos, 1959) and sentiment has long been documented to affect the equilibrium of the industry (Melas & Michail, 2020b) as well as the stock markets (Papapostolou et al., 2014), little attention has been given up to now in the herding behavior that shipping investors exhibit.

Herding is defined as the imitation of actions between investors/economic agents (Spyrou, 2013). Investors can imitate others either intentionally, due to the fact that they believe to have asymmetry of information when compared to key players in the market, or unintentionally, due to the same shame informational channels used (Krokida et al., 2020)[1].

Overall the concept of intentional and unintentional herding behavior has been theoretically and quantitavely examined for a long period. Scharfstein and Stein (1990) proposed a model in which managers ignore their own private information and herd on the investment decisions of others, while Banerjee (1992) developed a model of herd behavior unaffected by the principal-agent incentive problems. Similarly, Bikhchandani et al. (1992) employ herding by putting forth a model of informational cascades to explain conformity and short-lived phenomena such as fads and fashions, while Froot et al. (1992) show that speculators with short horizons may herd on the same information. Welch (1992) explained how investors might choose to ignore their private information and herd on the decisions of earlier investors. Finally, apart from its obvious on investments ata large, it also believed to be on of the main causes of the boom-bubble-bust cycle according to Duru (2013). An overview, along with more details on the breakdown between intentional and unintentional herding can also be found in Gemayel and Preda (2018).

In their seminal work, Papapostolou et al. (2017) study looked into the herding behavior of the dry bulk segment both for new contractions and for scrapping of vessels. They show that unintentional herding is apparent especially during the bust of the shipping cycle especially with regards to scrapping. This means that given the same information for the market, shipowners will tend to act similarly, and thus decide to scrap in order to minimise the excess vessel capacity in the market. On the contrary, intentional herding, is not strongly statistically significant, which is translated as a the lack of willingness of shipping investors to follow the big players in the market.

In a similar context, Lee and Yip (2018) also conclude that herding behavior exists in the shipping industry, but on the contrary with Papapostolou et al. (2017), they document that unintentional hearding is apparent in the shipbuilding industry in Korea for the period between April 2003 and September 2009. Additionally, Syriopoulos and Bakos (2019) provide evidence that the herding behavior that is apparent in shipping businesses is also reflected in their floated stocks.

Finally, Melas and Michail (2020a) show that the herding behavior observed in the shipping markets is affected primarily by market sentiment. More interestingly, herding behavior in the shipping context affects the buy side of the market, expressed via the newbuilding orders, and not the sell side. These results are contrarian to what previous studies have shown for the financial markets. Liao et al. (2011) and Hudson et al. (2020), have shown that sentiment is affecting the herding behavior of investors in the financial markets only when the sell-side is considered. The latter differentiation is mainly attributed to the high volatility and the positive skewness of the industry (Theodossiou et al., 2020) that enhances the social transmission bias (Han et al., 2017) of the shipping investors.

In the current research, we focus on the effect that herding behavior has on the overall decision of the market players to acquire new vessels. By employing an impulse response analysis, we look into the time horizon of the shocks that intentional and unintentional herding have on the new building vessels. While our results confirm the findings of previous studies, a more detailed pattern of their behavior is revealed. While unintentional herding causes a mild but with bigger time span response, intentional herding has a one off sharp impact on the newbuilding orders. The latter shows that while unintentional herding is slowly build through the various information channels of the industry, in extreme situations, investors tend to follow the leaders of the market sharply.

[1] The interested reader can refer to Bikhchandani and Sharma (2001) for an overview of the theoretical and empirical research on herd behavior.

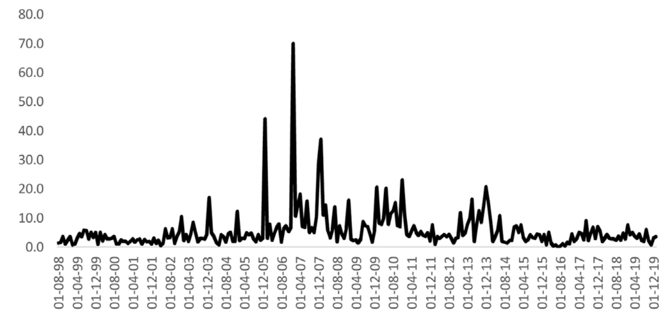

Fig. 1. CSAD contracting.

3. Methodology and data

3.1. Herding behavior in shipping

Herding, in a broad sense, can be viewed as the type of behavior where individuals (investors in this case) appear to ignore their idiosyncratic views and perspectives in order to follow what appears to be a generic market consensus (Chang et al., 2000; Christie & Huang, 1995; Papapostolou et al., 2017). As it has been shown in the literature cited in the previous sentence, it is more likely that herding behavior takes place during extreme market movements. This is understandable in both increases and decreases, as investors exhibit something like a fear of missing out in the first case and a fear of the unknown in the second. As such, in times of great uncertainty, it is highly likely for investors to ignore their individual opinions and instead follow either the market's overall path or even market leaders who can potentially have more experience or even better information. In shipping, the first examine herd behavior towards market consensus were Papapostolou et al. (2017), who used the cross-sectional absolute deviation (CSAD) of Chang et al. (2000). In particular, CSAD is specified such that:

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

where $CSAD_t^c$ is the cross-sectional absolute deviation of contracting of the vessels, $I_{i,t}^c$ is the number of vessels in the i-th sector (i = capsize, panamax, handymax, handysize) which are contracted at time t, and $\bar{I}_t^c = (1/I)\sum_{i=1}^{I} I_{i,t}^c$ is the cross-sectional average number of vessels contracted. For the estimation of the $CSAD_t^c$ we use data from Clarksons Shipping Intelligence Network. The evolution of $CSAD_t^c$ can be found in Fig. 1 below.

In general, the $CSAD_t^c$ is relatively stable, excluding three clusters of higher herding behavior, in which deviations from the market consensus appear to be larger than usual. The first relates to the rise of the dry bulk market to all-time highs (2006–2008), and two periods of higher than average herding, when market participants believed that the worse was over (2010–2011 and 2013–2014).

Despite the inferences we can derive from the figure, overall herding may potentially be too generic to be useful. As such, herding behavior can also be further broken down to intentional and unintentional. Intentional herding refers to the action of investors imitating other participants' behavior knowingly (i.e. with intent). This is usually observed in less sophisticated investors who tend to copy well-established investors, given that the latter tend to have more complete information (Papapostolou et al., 2017). On the other hand, unintentional herding is defined as the case when a majority of investors independently reach similar conclusions and hence make similar investment decisions. The rationale behind reaching common conclusions likely lies in a common element in the investors' environment (Bikhchandani & Sharma, 2001; Hirshleifer et al., 1994), which can also include similar academic backgrounds (given that the majority of the material is common) or perhaps things like analogous analytical skills (Wermers, 1999).

Following Papapostolou et al. (2017), to decompose the CSAD into intentional and unintentional deviations, we employ three metrics which are widely accepted and are similar to all market participants. These metrics are (i) the price-earnings (PE) ratio of a vessel, (ii) second hand-newbuilding (SNB) price ratio, and (iii) the Baltic Dry Index. The benefit of the three metrics is that they exploit both the valuation and the current conditions aspect of the markets, allowing us to clear the series from any macroeconomic factors which affect it.

For the PE ratio, we employ the log-price of the 5-year old second hand vessel and deduct from it the log-earnings (1-year time charter rates) of the particular type of vessel, in sector i and month t. The PE ratio has been used extensively in the literature (Alizadeh & Nomikos, 2007; Campbell & Shiller, 1988; Rangvid, 2006) to examine the extent of asset price over- or under-valuation.

The second metric is constructed by deducting the log-price of the second hand vessel from the log-price of the newbuilding vessel. In general, and similar to other real assets such as housing, while new ships have longer useful economic lives than second hand ones, investors may prefer to take advantage of the prevailing conditions and avoid the construction lag by purchasing second-hand vessels and thus drive their prices higher. The rationale behind the use of the third metric is straightforward: higher freight market levels are usually the reason behind higher orders for newbuild vessels and the lack of scrapping of older ones.

Estimation-wise, for the PE and SNB metrics, weighting across sectors is conducted on the basis of the sector's market share, while for notational purposes, we group all three metrics into matrix $\boldsymbol{X}_t$.[2] To distinguish between intentional and unintentional herding we run the regression

$$CSAD_t^c = \beta_0 + \beta_1 \boldsymbol{X}_t + u_t^c \tag{2}$$

where the unexplained part of the regression, namely u_t^c, is defined as the intentional herding measure (i.e. $CSAD_t^{c,I} = u_t^c$), while unintentional herding is given by the difference between total herding and intentional herding, i.e. $CSAD_t^{c,U} = CSAD_t^c - CSAD_t^{c,I}$. After the decomposition, we proceed with a vector autoregression to elaborate on the determinants of the orderbook.

As we have elaborated upon in the previous paragraphs, the aggregate metrics of the shipping market (i.e. the $\boldsymbol{X}_t$) serve to capture the fundamental drivers of the shipping markets, as well as the relative market valuations each point in time in an effort to control for the latent macro factors that have an impact on herding. Controlling for these factors would also imply that we are controlling for common unobserved factors such as common educational backgrounds. As per the literature, common unobserved factors would suggest a similar reaction to shocks (Bikhchandani & Sharma, 2001; Hirshleifer et al., 1994; Wermers, 1999). This measure of a common element in the environment would lead us to unintentional herding, which can be proxied in this case using the estimate for $\hat{y}$ (i.e. the X's and the betas). As such, it is logical that the part of the herding explained by the common fundamentals would be the one that is common in the market environment, i.e. the unintentional part. In other words, fundamentals can only drive the part of herding which is common to all market participants, which in turn can only be driven by common environmental factors.

[2] Auxiliary regressions confirming that the metrics contain valuable information with regards to decision-making, as well as for the relationship between CSAD and herding are available upon request.

Following this, what is left is the part that remains unexplained by the fundamentals, i.e. the error term. In this case, the error term effectively covers the part not explained by the fundamentals. Given that, as we have seen in the previous paragraph, the part explained by the fundamentals (i.e. $\hat{y}$) relates to common environmental factors, what is left are the idiosyncratic factors. In the case of herding, what idiosyncratic means is just an agent-specific type of herding, namely a "conscious" decision to herd, i.e. to follow market leaders, or mimic the market in general (Papapostolou et al., 2017).

Overall, given that in a regression equation the explained and the unexplained part will have to sum up to the dependent variable, the difference between the part driven by the common environment (i.e. $\hat{y}$/unintentional herding) and the overall herding measure can only be intentional herding. This also follows the fact that, by definition, intentional and unintentional herding will add to total herding (Papapostolou et al., 2017).

3.2. The vector autoregressive model

While regression models have often been used to explore the impact of one variable to another, an analysis on the basis of such models can be limiting. In particular, the first limitation lies in the fact that they are likely interrelated, i.e. that an increase commodity prices (e.g. oil) could cause an increase in the BDI, which could in turn also have a second round impact on oil prices, followed by a second round impact on the BDI and so on. To be able to capture such a series of events, the researcher would require a model that is specified in a way that all these potential feedback effects can be accounted for. At the same time, the model would also need to acknowledge that shocks occur unexpected and are thus exogenous to such a setup.

To this end, we also employ a Vector Autoregressive (VAR) specification, as first introduced by Sims (1980). As specified, the VAR is a system of equations which uses the lags of other variables, as well as its own lags, thus creating a circle which allows the researcher to examine the impact from any potential external shock to this system. For example, in a VAR model which only employs the BDI and Oil prices, a BDI shock could be either an increase in demand (positive shock) or an increase in supply (negative shock). As such, the interpretation of external shock becomes easier to identify and thus its effects are clearer to the researcher.

As per usual practice, we estimate the VAR in growth rates (log differences). In particular, the setup employed can be expressed such that:

$$Y_t = c + \sum_{j=1}^{J} \boldsymbol{A} Y_{t-j} + \varepsilon_t \tag{3}$$

where Y_t is a matrix of all the variables employed in the estimation, and c is a vector of constants. As already discussed, the benefit of this specification is that it allows for lagged effects to enter the equation, and provides a better interpretation of the shocks as they are forced to be exogenous to the system of equations.

To estimate the model, data from Clarksons Shipping Intelligence are used for newbuilding orders in the dry bulk sector (Bulk Orders), total dry bulk fleet in deadweight tonnes (Fleet), the Baltic Dry Index (BDI), and for the data employed to calculate the intentional and unintentional herding measures. Data for the Brent oil prices are obtained from the Federal Reserve of St. Louis Database (FRED). The data range from the August 1998 until January 2020, on a monthly basis. For the estimation, a lag length of two was used on the basis of the BIC and Hannan-Quinn information criteria.

3.3. An overview of the data

Before we present the estimation results, we first offer a quick view of the data. Table 1 shows the descriptive statistics of the variables employed in the estimation. Bulk orders, which are measured by the number of vessels ordered, show the largest mean value, with a maximum of 275 vessels ordered in a specific month, across all types of vessels in the dry bulk segment, and a minimum value of zero orders. On average, around 43 vessels are ordered each month, however, with the median value standing 28 and suggesting that the distribution is skewed due to the presence of a few large orders in some months.

Interestingly, the average value of intentional herding is at zero, suggesting that investor behavior averages out to no intentional herding over the course of the sample. On the other hand, and perhaps as expected, unintentional herding has an average value of 5.51 in the sample, suggesting that this is a more prevalent behavior, given precisely the fact that this is not something which is consciously done. Unintentional herding has, nonetheless, much lower maximum values than the intentional one, and hence much lower standard deviation, suggesting that there are no extremes in this type of behavior, due most likely to the fact that there are limits to the similarity of conclusions reached on the basis of information or education. On the other hand, intentional herding has much higher maximum and minimum values suggesting that indeed investors are pursuing this behavior knowingly.

This can also be confirmed from Fig. 2, which shows a graphical representation of intentional and unintentional herding. In general, the three clusters observed in the overall herding behavior of Fig. 1, but more particularly in the 2006–2008 period, appear to be driven by investors' intentional herding behavior. Given that in this period freight rates were rising, investors were likely driven by what is known as Fear of Missing Out (FOMO, Przybylski et al., 2013), i.e. blindly following well-established investors.

On the other hand, unintentional behavior dropped significantly over the high freight rates period when intentional herding soared, while it was on the rise before the peak of the freight rates, suggesting that perhaps educated investors were more likely to have reached the conclusion that the market was rising since late 2002. Following the market crash in mid-2008, unintentional herding also collapsed as investors followed an intentional strategy, perhaps out of fear. Overall, it appears that unintentional herding rises when a clear path exists in the market but collapses when crashes occur (e.g. in early 2016).

Finally, Table 2 offers a correlation matrix of the variables. In particular, the diagonal of the matrix is always 1 as it is the correlation of each variable with itself, while the rest of the matrix takes values from −1 to 1. It should be noted of course that these values refer to the contemporaneous impact of the variables and do not reflect any effect their lags could have. In general, it appears that the largest correlation coefficients are found between unintentional herding and the BDI, unintentional and fleet, as well as bulk orders and both intentional and unintentional herding. The latter, which have the largest coefficient of all, offers the first insight that newbuilding orders are heavily dependent on herding. For the total impact of the variables on bulk orders, the VAR model was estimated. Results can be found in the following section.

4. Determinants of newbuilding orders

Fig. 3 offers the impulse responses from the VAR model, as specified above. In particular, it appears that bulk orders respond positively to a shock that increases Brent oil, albeit with a lag as the response does not get positive and significant until about four months later. The chain of causality appears to run through the BDI,

Table 1
Descriptive statistics.

	Brent	BDI	Fleet	Intentional herding	Unintentional herding	Bulk orders
Mean	0.01	0.01	0.00	0.00	5.51	43.19
Median	0.02	0.03	0.00	−0.99	5.13	28.00
Max	0.20	1.57	0.02	60.65	12.42	275.00
Min	−0.31	−2.58	0.00	−10.29	−0.54	0.00
Std. Dev.	0.09	0.63	0.00	6.09	2.70	44.93
Skewness	−0.79	−0.66	1.06	5.33	0.38	2.24
Kurtosis	4.08	4.56	4.35	46.44	2.91	8.82
Jarque-Bera	39.18 (0.00)	45.11 (0.00)	67.80 (0.00)	21.66 (0.00)	6.33 (0.04)	57.55 (0.00)
Observations	257	257	257	257	257	257

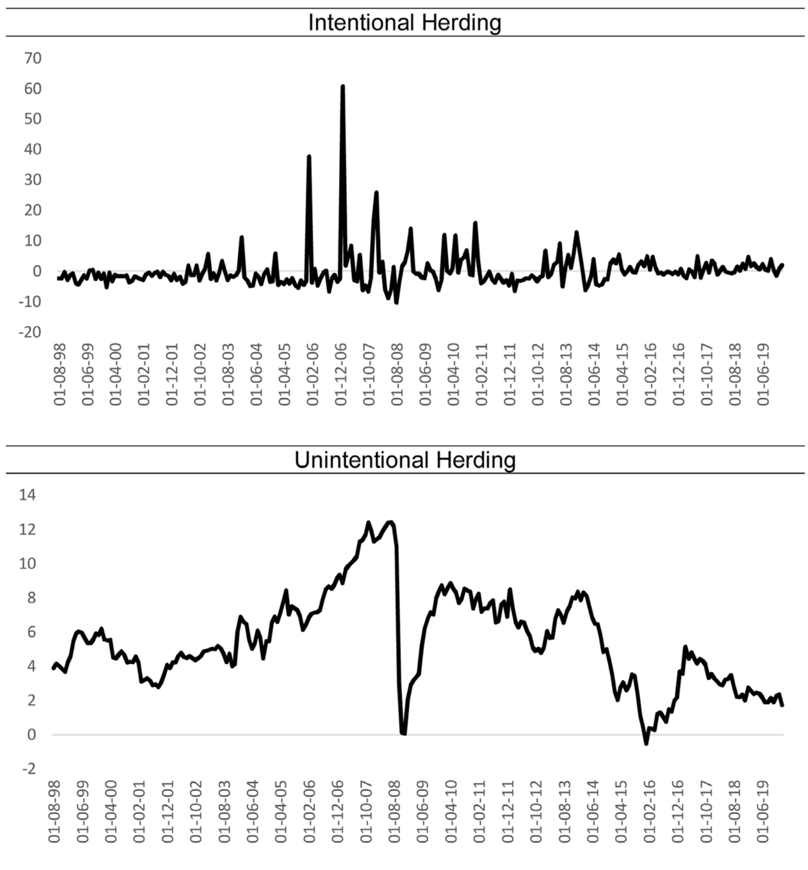

Fig. 2. Herding breakdown.

Table 2
Correlation matrix.

	Brent	BDI	Fleet	Intentional herding	Unintentional herding	Bulk orders
Brent	1	0.18	−0.01	−0.06	0.14	0.05
BDI		1	−0.13	0.00	0.34	0.25
Fleet			1	−0.05	0.47	0.24
Intentional herding				1	0.00	0.62
Unintentional herding					1	0.63
Bulk orders						1

however, given that the BDI has a positive response to a shock in Brent oil. Such a behavior is expected given that higher costs will be passed on to the charterer, via an increase in the spot market freight rates (Michail & Melas, 2021).

The impact from the BDI on bulk orders is higher than the one from Brent, given that, again despite the two-period lag observed, the response is positive and significant across all periods. This suggests the large persistence a price change could have on newbuilding orders, driven by the fact investments in the industry are affected more by the potential gains that one can have rather than the cumulative operating expenses that one would face (Theodossiou et al., 2020). The change in the vessel fleet, on the other hand, causes the expected negative response from bulk orders, given that as the supply of vessels increases, it is more likely that new orders would decline. This serves as sanity check for our model and suggests that it is well-specified with

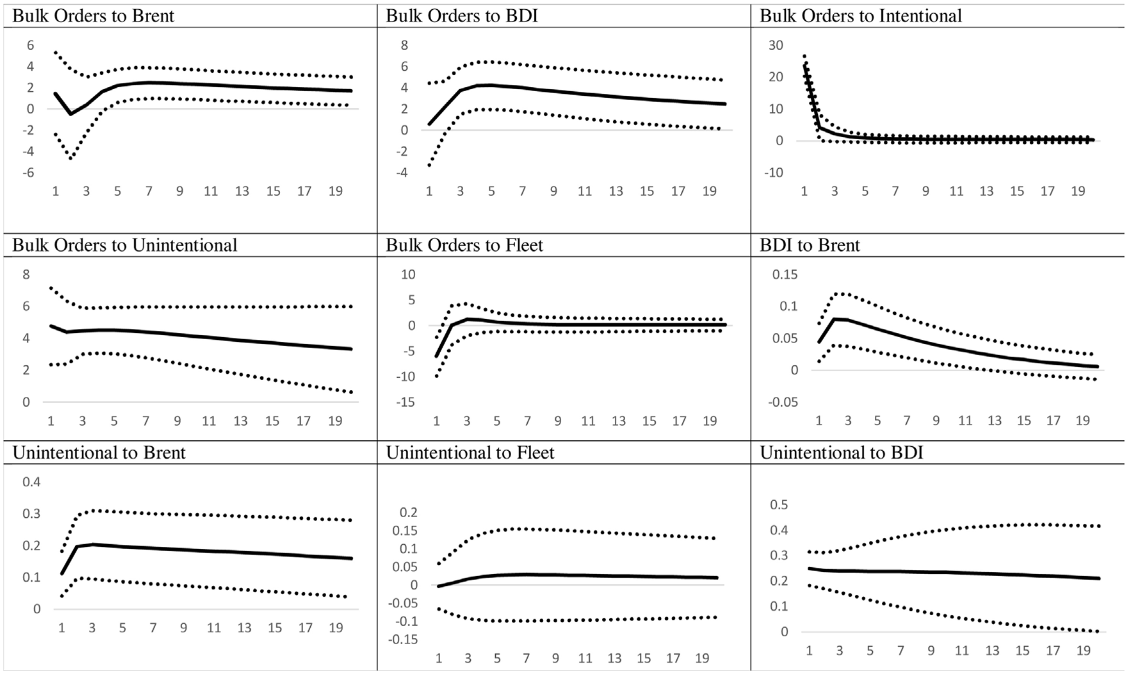

Fig. 3. Impulse responses.

the supply and demand proxies having the expected signs and responses.

An interesting response can be viewed with regards to intentional and unintentional herding. In particular, intentional herding appears to cause a large impact on bulk orders, with newbuildings rising by around 22 vessels. Still, this shock appears to be of a very short-term nature, as the response moves to zero in the third period after it. On the other hand, unintentional herding has a smaller but more persistent impact on newbuilding orders, with the response being statistically significant across all periods. As such, the important distinction between the two is that, firstly, the standard deviation shock on intentional is higher than the unintentional one, and secondly, that shipping investors tend to order much more vessels when they follow an intentional herding behavior but for a shorter period. On the other hand, unintentional herding is much more persistent given that it refers to a state which likely lasts for longer as the graphical representation in Fig. 2 has shown.

In the second part of Fig. 3, the responses of unintentional herding to other variables can be observed. In particular, unintentional herding has a statistically significant and positive response to a positive shock in Brent oil, suggesting perhaps a similar way of thinking regarding the impact an oil price increase could have on freight rates, i.e. due to a common academic background or general understanding of the markets.

Unintentional herding is also affected by the BDI, with the impact being positive, significant, and persistent over the response horizon. Similarly, the opposite behavior is observed with regards to bulk orders. Bulk orders have a zero impact on unintentional herding. This again suggests that unintentional herding is based on the fundamentals and does not let the behavior of other investors have an effect on it.

Overall, the results point out to a few significant conclusions: firstly, freight rates, proxied by the BDI, have an important impact on newbuilding orders. Similarly, operating costs, using Brent oil as a proxy, also have a similar impact. Secondly, intentional and unintentional herding behavior have an impact on newbuilding orders, even though the extent and persistence of the shock is much more different. Intentional herding has a large, almost one-off, impact that dissipates fast, while unintentional herding has a smaller but more persistent impact.

5. Conclusions

In this paper, we have aimed to examine the main factors which affect the orderbook of maritime vessels, with emphasis on the herding behavior of investors. Our results, using a Vector Autoregression (VAR) approach, show that intentional and unintentional herding behavior have an impact on newbuilding orders, even though the extent and persistence of the shock is much more different. Intentional herding has a large, almost one-off, impact that dissipates fast, while unintentional herding has a smaller but more persistent impact.

In addition, the findings also point out some other significant conclusions. To begin with, freight rates have an important impact on newbuilding orders. Similarly, operating costs, using Brent oil as a proxy, also have an impact in newbuilding choices. Finally, shipping market fundamentals have a strong impact on unintentional herding, suggesting that this type of behavior relates mostly to the way investors reach conclusions on the basis of their training and information availability.

Our results have important policy implications, mostly pertaining to the market power that leading shipowners could have. While previous studies have documented that the shipping industry is demand-driven, our results provide evidence that the leaders of the market affect the supply side not just via their own decisions, but also by affecting the behavior of smaller players. Thus, especially in turbulent periods, managerial decisions by the key players in the market can potentially spill over to the whole industry and thus further enlarge the long-documented volatility of the shipping market (Theodossiou et al., 2020).

Given the above, it would perhaps be advocated that when changes are to be implemented by maritime organizations, they could perhaps be first discussed thoroughly with all the involved parties before formally turning them into legislation. The reason, as suggested earlier, is that abnormal obstructions of the market, in the forms of reactions by larger players to unexpected legislations, such as carbon emissions of vessels (Adamopoulos, 2020; Zis & Cullinane, 2020) could enhance the market's inherent volatility. Higher volatility could ultimately affect smaller shipowners via having a strong effect on their cashflows, their overall costs, and ultimately the overall viability of their firms.

Conflicts of interest statement

The authors whose names are listed immediately below certify that they have NO affiliation with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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