Dynamics in the dry bulk market:
Economic activity, trade flows, and safety in shipping

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Abstract

Recent dynamics in iron ore markets are driven by rapid changes in economic activities that affect commodity markets, trade flows, and shipping activities. Time series models for the relation between these variables in Southeast Asia and the Australasian region are supplemented with models for safety and pollution risk. Steel production in China, Japan, and South Korea is related to iron ore exports and vessel activity in Australia, with an estimated time lag of about two months. The Purchasing Manager Index, which is popular among traders as indicator of economic activity, is found to have predictive power both for steel production and for iron ore exports. The growth in economic activity and vessel movements is associated with significantly higher risks for ship accidents and pollution.

Keywords

dry bulk, maritime safety, pollution risk, Southeast Asia, Australia, steel production, iron ore, time series analysis

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1. Introduction

Seaborne trade has more than tripled since 1970 (UNCTAD, 2011). Most of recent trade growth is caused by the rapid economic expansion in Asia, especially in China, with related increases in the demand for dry bulk commodities like iron ore and coal. The latter two commodity flows have grown on average by 5% per year over the period 1984-2010 (UNCTAD, 2011). At the demand side, the combined share of China, Japan, and South Korea in global imports in 2010 was 80% for iron ore, 49% for coking coal, and 46% for thermal coal (Clarksons, 2012). At the supply side, Australia takes a prominent position with global export shares in 2010 of 40% for iron ore, 67% for coking coal, and 21% for steaming coal (Clarksons, 2012). The main destinations of Australian iron ore and coal are located in Southeast Asia: China, Japan, South Korea, Taiwan, and India. In 2010, the combined share of these five countries in Australian exports was 99% for iron ore and 84% for coal (derived from data provided by Braemer Seascope, one of the major dry bulk brokers in shipping).

The demand for iron ore and coking coal depends on steel production, whereas the demand for thermal coal depends on energy consumption which is influenced by population growth and climate. The demand for these dry bulk commodities is further influenced by prices, supply, and proximity of supply. Transport from supply to demand countries implies demand for ship capacity, whereas the supply of vessels depends on freight rates and on the market balance between ship supply and demand (Stopford, 2009), the so-called ship economic cycles. For some of these mechanisms, it takes some time until changes in the economy filter through to the various market components. One industry hypothesis (based on information from Braemer Seascope) is that changes in the economy take about five months to affect ship economic cycles, whereas empirical results indicate time lags of between three and six months (Xu et al., 2011a). Previous studies have investigated several aspects of dry bulk markets, including trade flow forecasting (Veenstra and Haralambides, 2001), effects of freight rates on various drivers of ship economic cycles (Alizadeh and Nomikos, 2003; Tvedt, 2003; Adland et al., 2006; Syriopoulous and Roumpis, 2006; Xu et al., 2011b), effects of ship economic cycles on maritime safety (Bijwaard and Knapp, 2009), and effects of the recent financial crisis (Ching and Lai, 2011).

In this paper, we take a comprehensive approach to provide further insight into the dynamics of dry bulk markets by investigating how changes in the economy affect the markets for commodities and ship services supply. We evaluate the value of several indicators of economic activity to predict dry bulk ship activity, including related safety and pollution risk. The aim is to provide a better insight in these markets, which is of interest to maritime regulators, ship brokers, and ship owners. We concentrate mainly on iron ore and on the dominant ship sizes for this dry bulk market, namely capesize and panamax vessels. Coking coal was also considered, but recent structural breaks in this market complicate a model-based analysis, so that we will only provide a descriptive analysis. As the market for steaming is known to be quite different (Warell, 2005), it will not be considered here and it is left for future research.

The paper has the following structure. Section 2 presents the data on economic activity, trade flows, ship activity, and safety and pollution. Models for these variables are described in Section 3, together with our model selection strategy. The results are in Section 4, where we present various relations of interest with their interpretation. Section 5 concludes.

2. Data

Table 1 provides an overview of the time series variables considered in our analysis, together with the observation period and the data sources. The variables are grouped in four areas of main interest: economic activity, commodity markets, ship activity, and safety and pollution. Table 1 contains also some auxiliary co-factors of interest, including commodity prices and the Purchasing Manager Index (PMI). The PMI is published monthly by the Institute of Supply Management and reflects economic sentiment. This index is widely used by brokers and managers in the shipping industry as an overall indicator for shipping markets. Until now, it has primarily been used for containers, whereas we will consider its potential predictive value for the dry bulk market. The dry bulk vessels that carry iron ore and coal are mostly of capesize and panamax size as defined by Braemer Seascope: panamax for sizes between 60 and 100 thousand DWT, and capesize for 100 thousand DWT and above.

The accident and pollution data were collected from various sources, as indicated in Table 1. Since these data sources employ different classifications of accidents, the data were manually classified according to definitions of the IMO (2000) for very serious and serious accidents. Our database contains information on ship arrivals in Australia and on accidents in the Australasian and Southeast Asian regions. These data are available at the individual ship level and they are aggregated to monthly time series. Because of the specific region covered by the ship activity and accident data, we restrict the economic activity and commodity flows mainly to the same regions of interest, in particular to China, Japan, and South Korea. Because of the large weight of China, we sometimes consider the activity of China alone, together with its specific import need for iron ore.

<< Table 1 to be inserted about here. >>

Figure 1 shows time series plots of the main variables of interest: steel production, and commodity flows for iron ore and coking coal for the main importing countries (China, Japan, and South Korea) and for the main exporting countries (Australia, Brazil, and the USA and Canada). As alternative indicators of economic activity, we considered also industrial production and blast furnace iron production, but steel production turned out to be more useful as it is more directly linked to the commodity flows of iron ore and coal. We sometimes consider total export series, consisting of the sum total of exports of the countries that are available in our database. For iron ore, the total exports are for Australia, Brazil, India, Peru, Russia, South Africa, and the Ukraine, and for coking coal, the total exports are for Australia, Canada, and the USA. Steel production shows a more or less exponential trend which is nearly exclusively due to China, whereas the combined production of Japan, and South Korea is more stable. The same holds true for iron ore imports, with a temporary drop in steel production and imports in 2008. Iron ore exports rise steadily, with a rapidly increasing share for Australia that is less volatile than the Brazilian share. As compared to iron ore, the export of coking coal is smaller (if measured in megaton) and it has a much less pronounced trend. A major cause of this finding is that China was able to satisfy its need for coking coal nearly completely from its own resources until 2008, after which year imports have risen sharply. Because of this recent break in the coking coal market, our analysis will concentrate mostly on iron ore.

<< *Figure 1 to be inserted about here.* >>

Figure 2 shows capesize and panamax arrivals, in terms of both the number of vessels and their combined deadweight (DWT), for Western Australia (major iron ore export region) and also combined with Queensland and New South Wales (major coal export regions). Figure 2 shows also the safety of capesize and panamax vessels in terms of the regional accidents (serious, very serious, and pollution) of these vessels operating in the areas of Australasia, China, Indonesia, Japan, and the Philippines. As an alternative indicator of ship activity, we considered global ship employment provided by Braemer Seascope. Here ship employment relates to the total dry bulk capacity needed to carry the required commodities from their origins (exporting countries) to the destinations (importing countries), which incorporates not only the transported volumes but also the transport distances and travel times. For our analysis, it turned out that the monthly ship arrival information was more useful than ship employment data, possibly also because the latter data are available only on a quarterly basis for capesize vessels and on a yearly basis for panamax vessels.

<< *Figure 2 to be inserted about here.* >>

3. Model specification strategy

The main relations of interest are those between economic activity in Southeast Asia and the maritime trade flows resulting from this activity, including potential effects on shipping safety. Figure 3 provides an overview of the five relations of interest: three relations for direct effects of economic activity on commodity markets, ship activity, safety and pollution, and two intermediate relations from commodity markets to ship activity and then to safety and pollution. The information on safety consists of count data, as the monthly number of accidents is too small to consider them as scale variables. The information on the other variables consists of time series of scale variables like volumes of production, import, export, and ship freight. Because of this hybrid nature of the data, we will use two kinds of models: time series models for the relations between economic activity, trade flows, and dry bulk activity, and count data models for safety in terms of economic or ship activity. We discuss the model specification strategy for each of these two types of model. These two strategies employ standard econometric tools (see, for example, Greene, 2008), for which we used the econometric software program EViews (2009).

<< Figure 3 to be inserted about here. >>

For the three types of models where the explained variable is a time series (trade flows or dry bulk activity), we take the following six steps in our specification of a time series model.

I. As the variables display exponential trend patterns, we take their (natural) logarithm. This transformation is also motivated by the fact that the random variation around the trend is roughly proportional to the level of the series, so that the log-transformed series displays a more constant variation around the trend. In some cases we also considered non-transformed series, but in the end we have always chosen for the log-transformed series, also for ease of comparison.

II. We check for the nature of the trend in the log-transformed dependent variable. Visual inspection suggests that the log-transformed series have rather stable linear trends, and we test for the existence of a unit root by means of an Augmented Dickey-Fuller (ADF) test equation with constant and linear trend. The autoregressive lag of the test equation is chosen by minimizing the Schwarz information criterion. The presence of a unit root is rejected in nearly all cases. Otherwise, we take first differences of the log-transformed variables.

III. We test for the predictive power of the proposed factor to explain the dependent variable under consideration by means of the Granger causality test. As the log-transformed variables have linear trends, we perform the standard (vector autoregression) test after detrending the two variables. That is, both log-transformed series are first regressed on a linear trend, and then the standard Granger causality test is performed on the two resulting series of residuals. Various lag specifications of the vector autoregressive testing model are considered: 1-12, 1-6 and 12, 1-6, and sometimes also 1-4 (possibly with 12) and shorter. In some cases, both variables are mutually Granger causal for each other, in which case the forecast model might perhaps become simpler by considering a (lower order) bivariate vector autoregression (VAR) instead of a (higher order) single-equation autoregressive model with explanatory variable and moving average terms (ARMAX). As a VAR implies an ARMAX model for the marginal distribution of the dependent variable conditional on the explanatory factor, we will consider an ARMAX model in all cases.

IV. If the dependent variable of interest is denoted by y and the explanatory factor by x, then the following ARMAX(p, q, r) model with linear trend is specified:

$$\ln(y_t) = \alpha_1 + \alpha_2\, t + \beta_1 \ln(y_{t-1}) + \ldots + \beta_p \ln(y_{t-p}) + \gamma_1 \ln(x_{t-1}) + \ldots + \gamma_q \ln(x_{t-q}) + \varepsilon_t + \delta_1\, \varepsilon_{t-1} + \ldots + \delta_r\, \varepsilon_{t-r}$$

where the ε-terms denote unobserved errors. We start with up to 12 monthly lags to account for possible calendar year effects. This model is estimated by maximum likelihood (or least squares if no MA terms are present). Next we perform stepwise backward elimination to remove insignificant effects. The lags are reduced with special attention for the yearly "sub-frequencies" at lags 1, 2, 3, 4, 6, and 12. We therefore allow for the removal of intermediate lags, so that the resulting model may, for example, have lags 1, 2, and 12. The lag structures of the AR, MA, and X parts will in general be different. The model is simplified until all remaining coefficients are significant (at 5% level), provided that the two diagnostic tests in the next step are reasonably satisfactory.

V. The selected ARMAX model is checked by performing two diagnostic checks, that is, absence of serial correlation and normality. We perform the Breusch-Godfrey test for serial correlation of the model residuals, and we consider different choices for the maximal lag of the residuals in the test equation (ranging from 2 to 12). Sometimes, these test outcomes motivate adjustment of the model by including some additional lags until the residual correlation has become acceptably small. We also consider the skewness and excess kurtosis of the model residuals. Some of the dependent variables contain outliers, and we accept residual leptokurtosis in such cases instead of removing the outliers.

VI. The five foregoing steps (I-V) provide an ARMAX model. This model can be given an interpretation in terms of the lag structure, which indicates reaction delays, and in terms of the sign and magnitude of the coefficients. Another interpretation is given in terms of the dynamic multiplier effects on the dependent variable that are due to changes in the explanatory factor. Hereby we compare two scenarios, where the second one is characterized by the fact that the explanatory factor is one percent larger than in the first scenario at all times from now on. This so-called step-response is computed from the ARMAX model for lags 1 to 4 and also for the long run (in the limit for infinite lag). The MA terms are irrelevant for this response, and we illustrate the involved computations for a simple ARX model with single lags, that is, for an ARMAX model with p = q = 1 and r = 0. The basic relation of interest is then given by $\ln(y_t) = \beta \ln(y_{t-1}) + \gamma \ln(x_{t-1})$, and we consider a step increase for $\ln(x)$ of 0.01 from now onwards. The percentage effect on y is zero at lag zero, and at lag 1 it is γ. At lag 2, we get $\beta\gamma + \gamma = (1 + \beta)\gamma$; at lag 3: $\beta(1 + \beta)\gamma + \gamma = (1 + \beta + \beta^2)\gamma$; at lag 4: $\beta(1 + \beta + \beta^2)\gamma + \gamma = (1 + \beta + \beta^2 + \beta^3)\gamma$; and in the long run: $(1 + \beta + \beta^2 + \beta^3 + \beta^4 + \dots)\gamma = \gamma / (1 - \beta)$. The computations are similar, though somewhat more cumbersome, for higher lag orders.

The specification strategy for models explaining shipping safety and pollution risks differs from the above procedure, as the dependent variable consists of count data whereas the explanatory factors consist of time series with trends. The relation between economic or ship activity and safety should be modelled as a long-term relation, as the effect of increased activity in terms of accidents will be spread out over time. Some types of accidents are quite rare, as the average accident rate per month over the period 2001-2010 of very serious accidents is 0.78 and that of pollution accidents is 0.22. We therefore do not aim at unravelling a detailed lag structure of the effect of activity on risk, and instead we consider long-term effects on the mean. We specify the mean risk in terms of the explanatory factor, and for these count data we employ a Poisson count model. As the pollution accident data display some over-dispersion (mean 0.22, standard deviation 0.69), we considered also alternative specifications like the negative binomial. As these alternative models gave largely similar results as the Poisson model, we report only the Poisson results. If the dependent count data variable is denoted by y and the explanatory factor by x, then the Poisson model is given by

$$\text{Prob}(y = k) = \exp(-\lambda)\, \lambda^k / k! \ , \text{ with } \lambda = \exp(\alpha + \beta x).$$

Here λ is equal to the expected value of y, so the result has a natural interpretation as $\exp(\alpha + \beta x)$ is the expected number of accidents per month for a given level (x) of the explanatory factor. The only specification issue remaining is the choice of explanatory factor, and we consider various choices for this factor without incorporating any lags, for reasons explained before. The models are estimated by maximum likelihood, and the significance of factors is evaluated by conventional Z and Wald tests.

4. Results and discussion

This section is structured as follows. For each of the five relations in Figure 3, we present a detailed model for one instance, that is, for a specific choice of dependent variable and explanatory factor. We present models for our final choice of variables from the options listed in Table 1. Economic activity is measured either by steel production in China, Japan, and South Korea or by means of the Purchasing Manager Index. For commodity markets, we consider iron ore exports (from Australia, Brazil, and also an aggregate series) as well as iron ore imports (in China, Japan, and South Korea). The considered indicator of ship activity consists of the number and (deadweight) volume of arrivals in Australia of (capesize and panamax) dry bulk vessels. Finally, ship safety is measured in terms of classes of very serious, serious, and pollution accidents, for capesize and panamax dry bulk vessels in the areas of Australasia, China, Indonesia, Japan, and the Philippines. The data period is January 1995 till December 2011, or a sub-period depending on data availability of the considered variables. Alternative models with other or additional variables are briefly summarized, with the main results (lag structure and step-response) shown in Table 2. We also provide an interpretation and discussion of our findings.

4.1 Effect of economic activity on commodity markets

We start our analysis of this relation by considering the effect of the volume of steel production in China, Japan, and South Korea on the volume of iron ore exports of Australia. Steel production is considered a good indicator of economic activity in Southeast Asia, and Australia is a major provider of the iron ore needed in this region for producing steel. The time series plots of the two variables of interest in Figure 1 indicate roughly exponential trends, and we take the logarithm of monthly iron ore exports from Australia (denoted by LEXIO_A) as the dependent variable and the logarithm of monthly steel production in China, Japan, and South Korea (denoted by LSP_CJK) as explanatory factor. The estimation sample runs from January 1995 to December 2011.

The variable LEXIO_A does not contain a unit root (ADF p-value 0.01). On the other hand, the presence of a unit root is not rejected for LSP_CJK (ADF p-value 0.54). The latter time series shows a break in slope around 2000 and a level break around 2008, but even on the sub-sample 2000-2007 the unit root hypothesis is not rejected (ADF p-value 0.09). Further, LSP_CJK is a significant causal factor (Granger causality p-value 0.02 for 2 lags). The converse relation is also significant, that is, LEXIO_A is significantly Granger causal for LSP_CJK (p-value 0.03 for 2 lags). We considered both a VAR and an ARMAX model for the two log-transformed variables, but the resulting models are not very satisfactory due to the high collinearity between the various lags of the variable LSP_CJK. For this reason, we prefer to take the monthly differences of both variables, so that the unit root of LSP_CJK is removed, accepting some over-differentiation of LEXIO_A. We remark that the two variables are not cointegrated, as one variable has a unit root whereas the other one is trend stationary. The resulting series of monthly growth rates are denoted by DLEXIO_A and DLSP_CJK. These series do not contain a unit root anymore (ADF p-value 0.00 for DLEXIO_A and 0.01 for DLSP_CJK). The Granger causality test for these two variables indicates explanatory power of DLSP_CJK for DLEXIO_A (p-value 0.00), but not the other way round (p-value 0.14). The specification procedure described in Section 3 provides the following ARX model, with y = DLEXIO_A and x = DLSP_CJK and where all coefficients are significant (at the 5% level), except for the constant term (which is included in the model, indicated by 0.00):

$$y_t = 0.00 - 0.61y_{t-1} - 0.31y_{t-2} - 0.21y_{t-3} - 0.18y_{t-5} - 0.18y_{t-6} + 0.43x_{t-2} + 0.36x_{t-3} + 0.45x_{t-12} + \varepsilon_t$$

This equation has an R-squared of 0.39 and does not contain significant serial correlation (Breusch-Godfrey p-value 0.14 for 2 lags and 0.09 for 12 lags). The residuals are somewhat skewed to the left and have some excess kurtosis (skewness -0.83, excess kurtosis 1.35), which is caused by some negative outlying residuals. These outliers occur for isolated months with temporary drops in iron ore exports, most notably in January 2006, March 2007, November 2008, and February 2011. Such temporary disruptions of exports may arise because of adverse weather conditions, since tropical cyclones are frequent between November and April, which affects ports in Western Australia such as Port Headland and Dampier.

In the above model, we find that changes in the growth rate of steel production affect iron ore exports with a delay of two months. If steel production experiences an everlasting increase of 1% point in its growth rate as compared to a base scenario, this corresponds to monthly differences in all future values for x_t of 0.01. The effects on the growth rate of iron ore exports after 1 to 4 months (in percentages) are respectively 0, 0.43, 0.43 + 0.36 – 0.61×0.43 = 0.56, and 0.43 + 0.36 – 0.61×0.56 – 0.31×0.43 = 0.35. The long-run effect is (0.43 + 0.36+0.45) / (1 + 0.61 + 0.31 + 0.21 + 0.18) = 0.55. The interpretation is that a lasting increase of 1% in the growth rate of steel production in Southeast Asia is estimated to lead to an increase in the growth rate of iron ore exports from Australia of about 0.5%, assuming no port capacity restrictions.

We considered various alternative models for the relation between economic activity and commodity flows, and we summarize the main results. For the above variables in non-differenced form, that is, using y = LEXIO_A and x = LSP_CJK, we find the following model: $y_t = 0.00 + 0.21\, y_{t-1} + 0.27\, y_{t-2} + 0.26\, y_{t-12} + 0.24\, x_{t-2} + \varepsilon_t$. The effect of a step increase of 1% in steel production leads to the following percentage increases in iron ore exports after 1 to 4 months: 0, 0.24, 0.29, and 0.37. The long run effect on the level of exports is 0.92, and a t-test finds that this does not differ significantly from one (p-value 0.48). The interpretation is that a lasting increase in the level of steel production of 1% starts affecting the level of iron ore exports after a two-month delay and with a long-run effect of about 1%, which means that the share of Australia in providing the required iron ore for Southeast Asia is rather stable. This finding is in line with the rather constant share over the observation period.

Results similar as the above are obtained for other choices of the variables: steel production for China alone, iron ore exports from Brazil (adjusting for a large outlier in June and July of 2002, see Figure 1) or from the group of all exporting countries available in the database (see Table 1). Table 2 provides a summary of the results. We tried also to model the export flows of coking coal instead of iron ore, but this did not give results of sufficient interest to report here as this commodity is hard to model (see Section 2).

Another variable of particular interest is the Purchasing Manager Index (PMI) as indicator of economic sentiment. In the practice of short term forecasting of export flows, it may be hard to obtain reliable data on recent steel production that are required for the above models which employ steel production as explanatory factor. The PMI is more readily available, and current month changes in the PMI are positively correlated with the current month growth rate of steel production in China, Japan, and South Korea (correlation 0.17). The PMI has also predictive power in ARMAX models for the growth rate of iron ore exports containing first-differenced PMI as external factor with lag 2. The coefficient of the two-month lagged changes in PMI is 0.01, both for Australian exports and for the total available exports. This means that, if the PMI rises with 1 unit, we expect iron ore exports to rise by 1% after two months (the monthly changes of the PMI ranged between -5.9 and 4.8 over the observation period).

We considered also models with more than one explanatory factor, including combinations of the PMI, commodity prices, and interest rates. The Chinese short term interest rate can be seen as an indicator of economic activity, but it did not provide additional information in modelling iron ore export flows. The price of iron ore (in dollar per ton) has gone up very sharply since 2008, with yearly means below 20 until 2004, below 40 until 2007, and climbing from 62 in 2008 to 80 in 2009, 147 in 2010, and 168 in 2011. These sharp price increases reflect the market stress of recent years, and we were not well able to exploit price as a reliable indicator of iron ore trade flows.

<< Table 2 to be inserted about here. >>

4.2 Effect of commodity markets on ship activity

In line with the preceding analysis, we now consider the relation between iron ore commodity flows in Southeast Asia and ship activity in Australia. More in particular, we consider the effect of iron ore imports in China, Japan, and South Korea (in logarithms, denoted by LIMIO_CJK) on the number of arrivals of capesize and panamax ships in Western Australia (also in logarithms and denoted by LCPX_WA), as this is the main export region for iron ore from Australia. The arrival data are available only from 2001 onwards, and the observation sample is therefore restricted to the period from January 2001 to December 2011. As Figure 2 shows, the arrival data for Western Australia show some isolated downward outliers that are related to adverse weather conditions. We will not remove these outliers and we will accept negative skewness and excess kurtosis of model residuals. Closer inspection of these arrival data reveals a change in trend, which is reasonably linear until 2007 and becomes more irregular and somewhat exponential afterwards. We will therefore estimate models both for the period 2001-2011 and for the period 2007-2011.

For the full data period, both variables do not contain a unit root (ADF p-values of 0.00 for both LIMIO_CJK and LCPX_WA). Further, LIMIO_CJK is Granger causal for LCPX_WA (p-value 0.01 for 4 lags), but the reverse causality is not significant (p-value 0.34 for 4 lags). The ARMAX model resulting from the specification procedure described in Section 3 provides the following ARX model, with y = LCPX_WA and x = LIMIO_CJK:

$$y_t = 1.16 + 0.0043\ t + 0.24 y_{t-1} + 0.16 y_{t-2} + 0.19(x_{t-1} - x_{t-2}) + \varepsilon_t$$

This equation has an R-squared of 0.93 and does not contain significant serial correlation (Breusch-Godfrey p-value 0.31 for 2 lags and 0.74 for 12 lags). The residuals are skewed to the left and have excess kurtosis (skewness -1.14, excess kurtosis 3.07), for reasons explained before. These (negative) residuals are not due to shocks in iron ore imports, but to disruptions in arrivals. The main outlier (five standard deviations below the mean) occurs for November 2008, with smaller outliers (about three standard deviations below the mean) for March 2007 and February 2011. The multiplier effects of a step increase of 1% in iron ore imports on capesize and panamax arrivals in Western Australia are shown in Table 2, with a long-run multiplier of 0. If we consider the sub-period from 2007 onwards, we get a very simple model: $y_t = 0.94 + 0.0083\ t + 0.32x_{t-1} - 0.21x_{t-2} + \varepsilon_t$, with long-run multiplier 0.11.

We considered also an alternative model to explain the ship carrying (deadweight) capacity of capesize and panamax arrivals in Western Australia, instead of the number of these arrivals. Recently built ships of these categories are much larger than older ones, and the yearly average size per arrival has increased from about 147 million DWT in 2001 to 165 million DWT in 2011. The results are very similar to those obtained before for the number of arrivals, and Table 2 shows the results for the period 2007-2011. We also tried to model the effect of coking coal imports in China, Japan, and South Korea on ship arrivals in Queensland and New South Wales, the two main Australian coal exporting regions. We were not able to find a significant relation between these variables, due to the irregular behaviour of the coking coal import series (see Figure 1).

4.3 Effect of economic activity on ship activity

In the two foregoing sections, we considered links from economic activity to commodity trade flows and then onwards to ship activity. We now consider the direct relation between economic activity and ship activity without the intermediate link that runs via the commodity markets. To keep in line with the analysis in preceding sections, we take as dependent variable of interest the number of arrivals of capesize and panamax ships in Western Australia (in logarithms, y = LCPX_WA) and as driving factor we consider steel production in China, Japan, and South Korea (in logarithms, x = LSP_CJK).

If we consider the sub-period from 2007 onwards, containing 60 observations, both variables do not contain a unit root (ADF p-values of 0.00 for LCPX_WA and 0.01 for LSP_CJK). The two variables are only weakly related, as Granger causality tests (with 4 lags) have p-values of 0.11 for forecasting ship activity from economic activity and of 0.69 for the reverse relation. Still, we can specify a very simple ARMAX model that contains only a single lag of the driving factor:

$y_t = 0.97 + 0.0068\, t + 0.28x_{t-1} + \varepsilon_t$.

This equation has an R-squared of 0.80, and it does not contain significant serial correlation (Breusch-Godfrey p-value 0.45 for 2 lags and 0.78 for 12 lags). The residuals are skewed to the left and have excess kurtosis (skewness -1.75, excess kurtosis 4.53), which is caused by three negative outliers in arrivals for March 2007, November 2008, and February 2011 (the same outliers were found in the previous section). The step-response has a lag of one month and a size of 0.28. Therefore, a 1% change in steel production translates to about 0.28% change in arrivals of capesize and panamax vessels in Western Australia one month later.

As steel production causes also exports of coking coal from Australia, we consider also the effect on capesize and panamax arrivals in all ports of Australia (denoted by CPX_A) for the period from January 2001 to December 2011. In this way, arrivals in the regions of Queensland and New South Wales that carry iron ore and coking coal are also included. We consider the growth rates of both variables (first difference of log-transformed series). This gives stationary variables with unidirectional causality from economic activity to ship activity, and the resulting model (with y = DLCPX_A and x = DLSP_CJK) is given by $y_t = 0.00 + 0.33y_{t-12} + 0.33x_{t-2} + \varepsilon_t - 0.76\varepsilon_{t-1}$. As an alternative, arrivals are also measured in terms of the volume (in million DWT) instead of the number of monthly ship arrivals. The results are very similar, as the number and the volume of arrivals are tightly related (their correlation is 0.99 in levels and 0.96 for growth rates). The corresponding multipliers are shown in Table 2. The long-run multiplier is about 0.5, which means that a lasting increase of one percent point in the growth rate of steel production leads to an increase in the growth rate of dry bulk arrivals of about 0.5%. The PMI as indicator of economic activity was not found to have predictive power for ship activity.

4.4 Effects of economic activity and ship activity on safety

The rapid increase in trade flows and ship activities over recent years may have consequences for maritime safety and pollution. As motivated in Section 3, we will consider Poisson count models for the number of ship accidents in terms of explanatory factors measuring activity. We distinguish three types of accidents: pollution, very serious accidents (including total loss), and serious accidents. The available data cover accidents over the period from January 2001 to December 2010 in the regions of Australasia, China, Indonesia, Japan, and the Philippines. The driving activity factors are also related to this area, as we consider arrival data from Australia and steel production data from China, Japan, and South Korea. The arrival and accident data are restricted to dry bulk vessels in the capesize and panamax class.

The lower part of Table 2 summarizes the outcomes of various Poisson count models. If the accident count variable is denoted by y and the explanatory factor by x, then the predicted number of accidents per month is equal to $\exp(\alpha + \beta x)$, where the constant α and the multiplier β are shown in the bottom right part of Table 2. We find a significant positive association between ship activity and accident risk for all three types of accidents. The multiplier for arrival volume (in million DWT) is about 7-8 times as large as that for arrivals, which is explained by the fact that arrivals over the considered period have an average size of 127 thousand DWT (so that one million DWT corresponds to about 8 arrivals). We will discuss only the results for the number of arrivals, as the results for arrival volume are very similar. We will in particular consider the number of accidents predicted by the models for the last two years of the observation sample, that is, 2009-2010. The average number of arrivals per month over this period was 490, and the average number of accidents per month was 0.92 for pollution, 1.17 for very serious accidents, and 4.29 for serious accidents.

The model predictions are as follows: for pollution $\exp(-8.02 + 0.01526\times490) = 0.58$, for very serious accidents $\exp(-1.89 + 0.00418\times490) = 1.17$, and for serious accidents $\exp(-0.63 + 0.00446\times490) = 4.74$. Therefore, the prediction is quite accurate for very serious accidents, whereas the risk is under-estimated for pollution and somewhat over-estimated for serious accidents. The limited predictive power for pollution accidents is explained by the fact that these accidents were very rare in the period 2001-2008 (5 accidents in total) but much more numerous in 2009-2010 (22 accidents). The average ship activity was 358 arrivals per month in 2001-2008 and 490 per month in 2009-2010, so that the increase of the number of pollution accidents is far more dramatic than that of ship activity (37%). The number of pollution accidents in the period 2009-2010 may well be an exception from the general trend. The other types of accident have increased more or less proportional to ship activity, for very serious accidents from 96 in 2001-2008 to 28 in 2009-2010 (yearly mean rose from 12 to 14, an increase of 17%) and for serious accidents from 271 in 2001-2008 to 103 in 2009-2010 (yearly mean rose from 33.9 to 51.5, an increase of 52%).

The above results relate to arrivals and accidents of dry bulk vessels in the capesize and panamax classes. We compare the results for pollution accidents with those that are obtained by incorporating arrival and pollution accident data for the same region of all ship types, including smaller dry bulk ships as well as container ships, tankers, general cargo ships, and others. If we take the volume of arrivals (in million DWT) as driving factor (x), then the Poisson count model provides the following expression for the expected number of pollution accidents: $\exp(-9.16 + 0.14431\, x)$, as compared to $\exp(-7.58 + 0.11104\, x)$ in Table 2. The two slope coefficients are similar (in the sense that the 95% confidence intervals overlap), so that an increase in arrival ship DWT has roughly similar effects on pollution risk for all ship types. The constant terms differ to correct for scale effects, as the average monthly volume of all arrivals is about twice as large as that of dry bulk arrivals in the capesize and panamax classes (48.4 million DWT for capesize and panamax, and 46.6 million DWT for all other ship types).

Whereas the relation between ship activity and ship safety is a direct one, the relation between economic activity and ship safety is more indirect as it involves the intermediate effects on commodity trade flows and shipping. The results in Table 2 show that steel production in China, Japan, and South Korea has explanatory power for the number of pollution accidents and the number of serious accidents, but not for very serious accidents. For practitioners, the PMI is more readily available than production figures, but we find that the PMI has predictive power only for pollution accidents and not for the other two types of accident. These findings confirm that safety is best explained by factors related to immediate causes, that is, intensity of maritime traffic, and less well by underlying deeper factors like economic activity and sentiment.

As a final step in our analysis, we will provide a projection of the number of accidents for the period 2011-2015. Such an extrapolation should be interpreted with due reservation, as the models are estimated over the period 2001-2010 where activity increased considerably, see Figure 2. For future scenarios, the driving factor will move ever more outside of the sample range, and it is well-known that extrapolation beyond the sample range may be very unreliable, especially for nonlinear models like our count data models. We take the models with the volume of arrivals as our forecast models, and we use a simple linear trend extrapolation of this volume (in million DWT per month) obtained by regressing yearly totals over the period 2001-2010 on a linear trend. The predicted monthly volumes (in million DWT) are 66.6 for 2011, 69.9 for 2012, 73.2 for 2013, 76.5 for 2014, and 79.8 for 2015, from which projected numbers of accidents per month are obtained by the models in Table 2. When aggregated to yearly totals, we obtain the following projected numbers of accidents per year: for pollution respectively 10, 14, 21, 30, and 43, for very serious accidents 16, 17, 19, 21, and 23, and for serious accidents 62, 68, 75, 83, and 92. As compared to 2010, with 16 pollution accidents, 13 very serious accidents, and 47 serious accidents, the accident risks for 2015 are roughly twice as large. These results should merely be seen as an indication that future ship accident risks may increase considerably if ship activities continue to expand as rapidly as in the first decade of this century.

5. Conclusions

We analysed how changes in economic activity affect commodity markets and ship activity with related impacts on safety and pollution. Insight in these relations may be helpful for planning by ship brokers and ship owners and for the evaluation by policy makers of ship economic cycles and risks of accidents and pollution. Our analysis focused mostly on Southeast Asia and Australia, where the most important players on the demand and supply side for iron ore and coking coal are located.

We obtained the following main results. The combined steel production of China, Japan, and South Korea has predictive power for iron ore exports and for capesize and panamax arrivals in Australia. It takes about two months before an increase in steel production starts affecting iron ore exports and ship arrivals. The Purchaser Manager Index (PMI) has predictive power for steel production, and this indicator of economic sentiment could provide useful information for industry stakeholders such as brokers, ship owners, and regulators if steel production figures are not readily available. Commodity prices are positively related to exports, reflecting considerable market stress of recent years.

Accident risks are positively related to economic activity and to ship activity, both for very serious accidents and for serious accidents, and also for pollution. This positive association was analysed for capesize and panamax vessels trading between Southeast Asia and Australia, and the results indicate potential sharp risk increases if ship activities continue to expand as rapidly as in the first decade of this century. The PMI has also predictive power for pollution accidents, but not for the considered classes of serious and very serious accidents. The results for pollution risk of all ship types are comparable to those obtained for capesize and panamax vessels.

We restricted the attention almost exclusively to iron ore, and we suggest using similar methodologies for steaming coal, and later also for coking coal (long enough after the break in this market around 2008). Accident and pollution risks were evaluated for dry bulk vessels of capesize and panamax class in Australasia and Southeast Asia. An analysis of the pollution risk of other ship types is also relevant, especially for oil tankers, but such an analysis is complicated by the limited availability of sufficiently detailed ship arrival data for the major import countries of crude oil.

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Figure 1: Economic activity and commodities (in megaton)

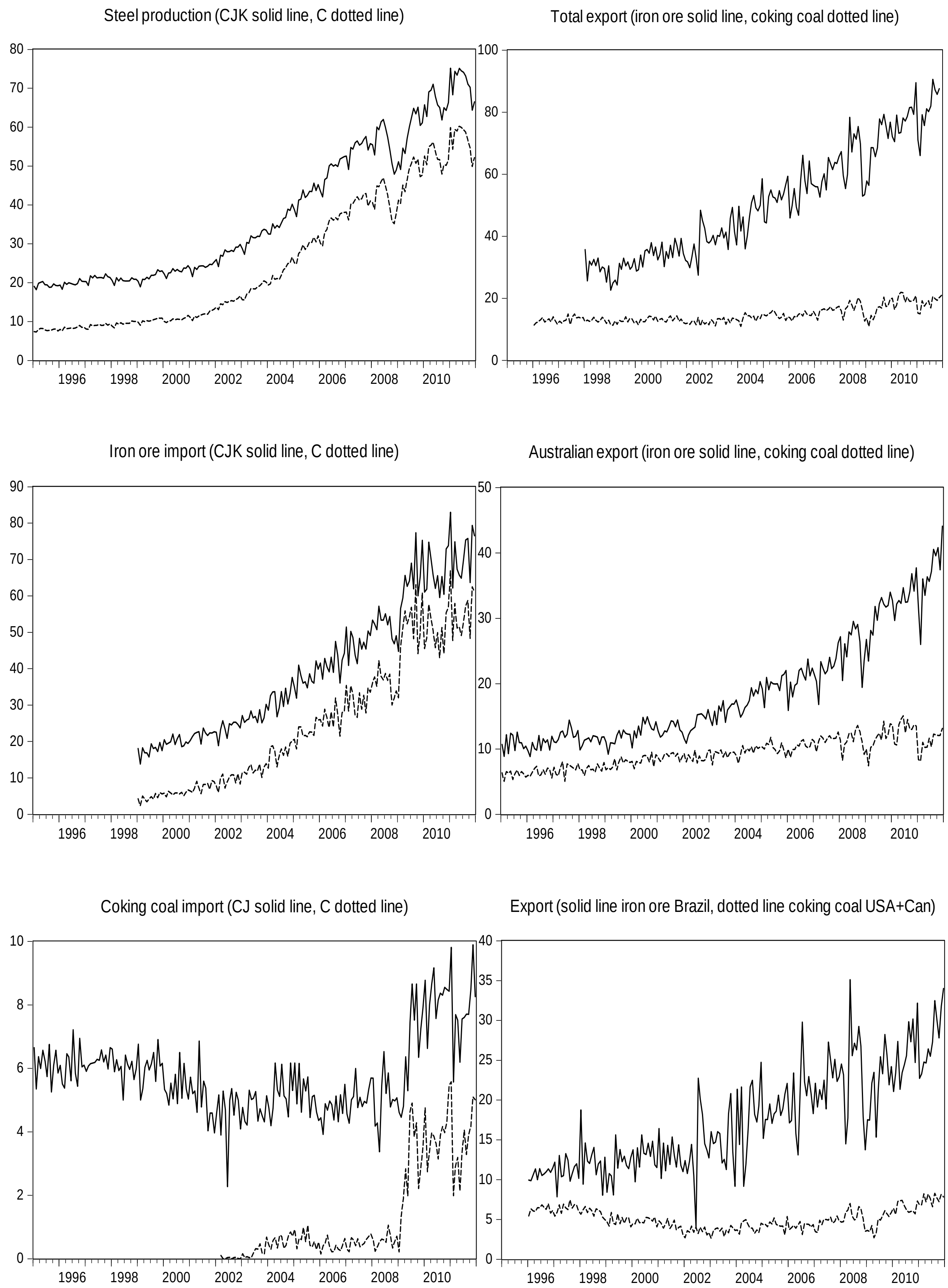

Figure 2: Arrivals and accidents of capesize and panamax vessels

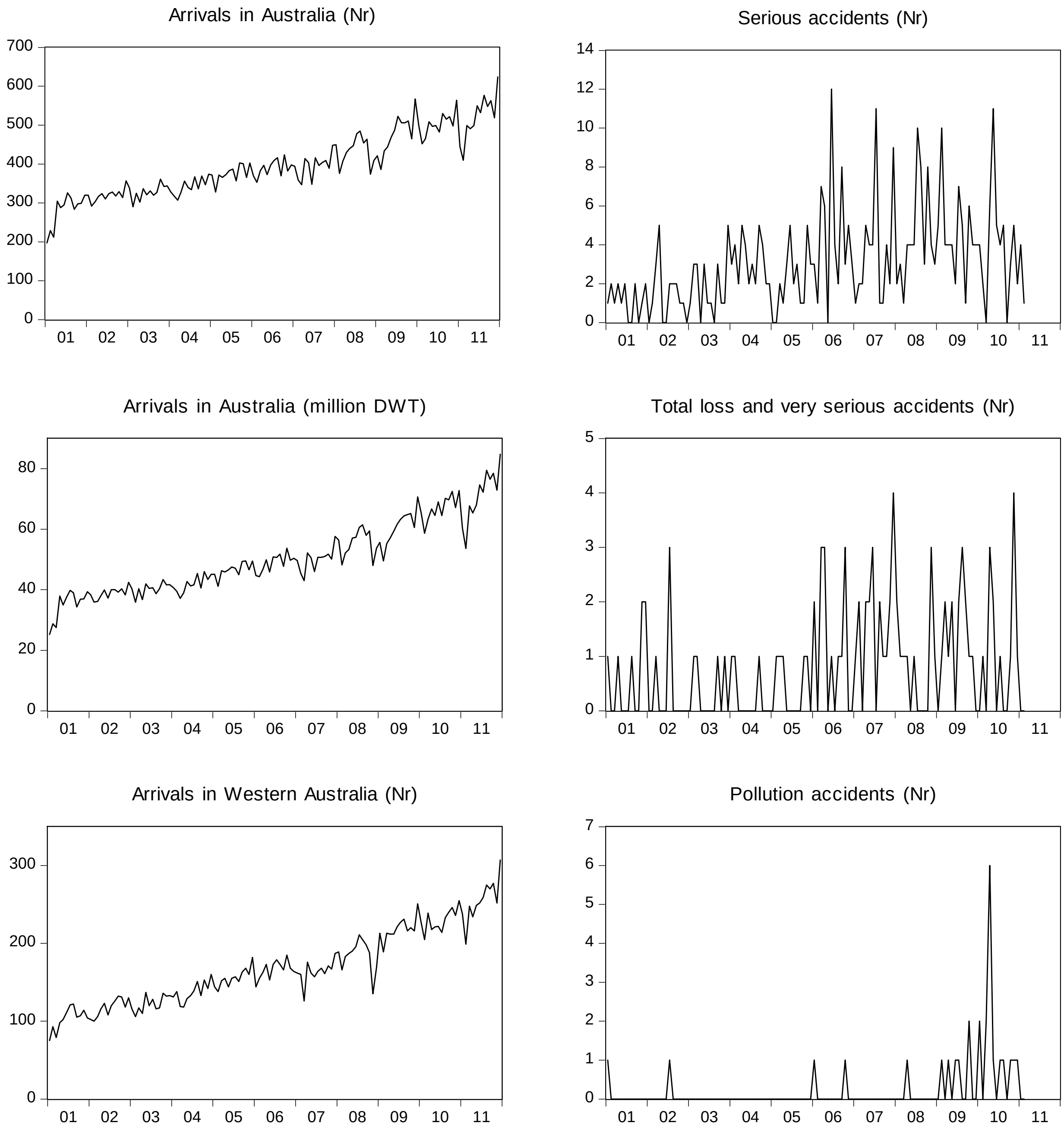

Figure 3: Relations in the dry bulk market

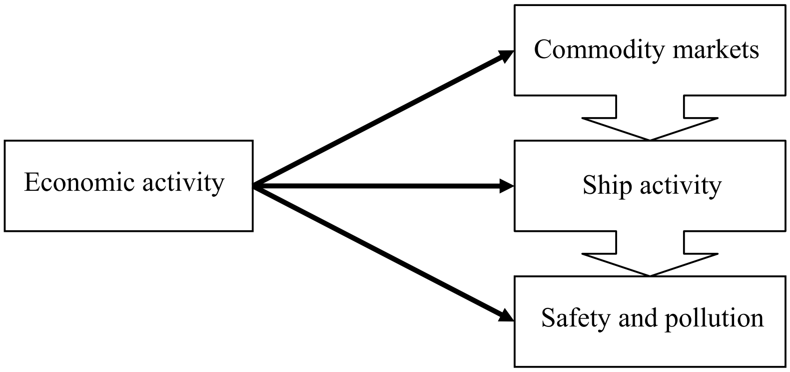

Table 1: Overview of data

Variable	Units	Region	Period	Source
Economic activity				
Steel production	Mt	China, Japan, South Korea	1995-2011	SIN
Industrial production	Mt	China, Japan, South Korea	1995-2011	SIN
Blast furnace iron production	Mt	China, Japan, South Korea	1998-2011	SIN
Purchasing manager index	Index	Global	1995-2011	ISM
China short term interest rate	Rate	China	1997-2011	OECD
Commodity markets				
Iron ore import	Mt	China, Japan, South Korea	1999-2011	SIN
Iron ore export	Mt	Total [b]	1998-2011	SIN
Coking coal import	Mt	China, Japan	2002-2011	SIN
Coking coal export	Mt	Total [c]	1996-2011	SIN
Iron ore / coking coal production	Mt	China	1995-2011	BS
Iron ore / coking coal price	$/t	--	1995-2011	IMF / SIN
Ship activity				
Dry bulk arrivals (cpx)	Nr [a] / MDwt [a]	Australia [d]	2001-2011	AMSA
Ship employment dry bulk	MDwt	Global	2001-2011	BS
Safety and pollution				
Accidents and pollution (cpx)	Nr [a]	Australasia and SE Asia [e]	1995-2010	IMO, IHSF, LMIU, AMSA

Notes

- *All data are observed monthly, except for ship employment that is observed quarterly.*
- *Units: Mt = megaton; MDwt = deadweight in millions; $/t = US dollar per ton; [a] = restricted to cpx, that is, capesize and panamax.*
- *Regions: [b] = Australia, Brazil, India, Peru, Russia, South Africa, Ukraine, and USA; [c] = Australia, Canada, USA; [d] = New South Wales, Queensland, Western Australia; [e] = Australasia, China, Indonesia, Japan, and the Philippines.*
- *Sources: SIN = Ship Intelligence Network of Clarksons; ISM = Institute of Supply Management; OECD = Organisation for Economic Development and Co-operation; BS = Braemer Seascope; IMF = International Monetary Fund; AMSA = Australian Maritime Safety Authority; IMO = International Maritime Organization; IHSF = Information Handling Services Fairplay; LMIU = Lloyd's Maritime Intelligence Unit.*

Table 2: Model outcomes

				ARMAX			Multipliers				
Dependent (*y*)	Region	Factor (*x*)	Region	p	q	Tot	1	2	3	4	Long
Economic activity to Commodity markets											
Iron ore export (Mt) [b]	Aus	Steel production (Mt) [b]	CJK	6	12	8	0	0.43	0.56	0.35	0.55
Iron ore export (Mt) [a]	Aus	Steel production (Mt) [a]	CJK	12	2	4	0	0.24	0.29	0.37	0.92
Iron ore export (Mt) [a]	Aus	Steel production (Mt) [a]	C	12	12	6	0	0.30	0.39	0.12	0.67
Iron ore export (Mt) [a]	Bra	Steel production (Mt) [a]	C	1	2	3	0	0.21	0.32	0.38	0.45
Iron ore export (Mt) [a]	Tot	Steel production (Mt) [a]	CJK	12	2	6	0	0.48	0.48	0.48	0.21
Commodity markets to Ship activity											
Dry bulk (Ncpx) [c]	WAus	Iron ore import (Mt) [a]	CJK	2	2	3	0.19	0.05	0.05	0.02	0.00
Dry bulk (Ncpx) [d]	WAus	Iron ore import (Mt) [a]	CJK	0	2	2	0.32	0.11	0.11	0.11	0.11
Dry bulk (Dcpx) [d]	WAus	Iron ore import (Mt) [a]	CJK	0	2	2	0.32	0.17	0.17	0.17	0.17
Economic activity to Ship activity											
Dry bulk (Ncpx) [d]	WAus	Steel production (Mt) [a]	CJK	0	1	1	0	0.28	0.28	0.28	0.28
Dry bulk (Ncpx) [b c]	Aus	Steel production (Mt) [b]	CJK	12	2	2	0	0.33	0.33	0.33	0.50
Dry bulk (Dcpx) [b c]	Aus	Steel production (Mt) [b]	CJK	12	2	2	0	0.33	0.33	0.33	0.51

Dependent (*y*)	Region	Factor (*x*)	Region	Const	Multiplier	p-value
Ship activity to Safety and pollution						
Pollution (Ncpx)	ACJ	Dry bulk (Ncpx)	Aus	-8.02	0.01526	0.000
Pollution (Ncpx)	ACJ	Dry bulk (Dcpx)	Aus	-7.58	0.11104	0.000
Very serious (Ncpx)	ACJ	Dry bulk (Ncpx)	Aus	-1.89	0.00418	0.001
Very serious (Ncpx)	ACJ	Dry bulk (Dcpx)	Aus	-1.76	0.03045	0.001
Serious (Ncpx)	ACJ	Dry bulk (Ncpx)	Aus	-0.63	0.00446	0.000
Serious (Ncpx)	ACJ	Dry bulk (Dcpx)	Aus	-0.40	0.03056	0.000
Economic activity to Safety and pollution						
Pollution (Ncpx)	ACJ	Steel production (Mt)	CJK	-5.55	0.08030	0.000
Pollution (Ncpx)	ACJ	PMI	Global	-6.30	0.08520	0.035
Very serious (Ncpx)	ACJ	Steel production (Mt)	CJK	-0.06	0.00075	0.869
Very serious (Ncpx)	ACJ	PMI	Global	0.43	-0.00909	0.507
Serious (Ncpx)	ACJ	Steel production (Mt)	CJK	-0.84	0.03935	0.000
Serious (Ncpx)	ACJ	PMI	Global	0.88	-0.00198	0.830

Notes

- *Regions: CJK = China, Japan, and South Korea; C = China; Aus = Australia; WAus = Western Australia; Bra = Brazil; ACJ = Australasia, China, Indonesia, Japan, and the Philippines. For iron ore export, "Tot" is total from Australia, Brazil, India, Peru, Russia, South Africa, Ukraine, and the USA.*
- *Units: Mt = megaton; Ncpx = number of capesize and panamax arrivals or accidents; Dcpx = million deadweight (DWT) of capesize and panamax arrivals. The class of very serious accidents includes total loss.*
- *For ARMAX, "Tot" is the total number of AR, MA and X lagged terms included in the model; for example, the first model in the table contains AR terms at lags 1, 2and 12, and a single X term at lag 2, so 4 lagged terms in total.*
- *All variables for the relations between economic activity, commodity markets, and ship activity are taken in logarithms (denoted by [a]), and sometimes in first differences of logarithms, that is, in growth rates (denoted by [b]). Multipliers are step-responses to a 1% growth in the factor level (case [a]) or to a 1% point increase in the factor growth rate (case [b]). The estimation period for these relations is 1995-2011 if not indicated otherwise (by [c] for 2001-2011 and by [d] for 2007-2011).*
- *In the models for safety and pollution, all variables (accidents, dry bulk arrivals, and economic activity) are in levels, and the estimation period is 2001-2010.*