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Endogeneity of commodity price in freight cost models

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Abstract

In this paper, we answer a novel question on how the value of goods carried can affect the freight cost. We focus on the issue based on a more specialized freight market involving transport of seaborne iron ore from mining ports to Qingdao in China during the period 2014 to 2019. We construct simultaneous systems of demand–supply equations on both the iron ore market and the freight market. In the models, we explain how endogeneity of iron ore as a regressor can arise due to the nexus between the two markets, and that the freight demand is largely a derived demand from iron ore demand by PRC firms importing the iron ore. Employing instrumental variable two-stage least squares regression, it is shown that iron ore price negatively affects, ceteris paribus, the freight rate of bulk carriers ferrying the iron ore. Industrial growth, bunker fuel oil, Baltic Dry Index, and transport distance have positive effects on the freight rates.

Keywords: Freight rate, Iron ore price, Endogeneity, Panel regression

1 Introduction

The Review of Maritime Transport (2015, p.53) reported, "Despite the fact that there is no obvious reason for the connection between the freight rate and value of a product,[1] a wide range of works describe the relationship between a product's unit value and the freight charged". The wide range of works refer to studies on the shipping transport costs of traded goods in container vessels in the context of international trade (Wilmsmeier et al., 2006, Martínez-Zarzoso and Suarez-Burguet, 2005, Wilmsmeier and Martínez-Zarzoso, 2010, etc.). More specifically, Wilmsmeier and Sánchez (2009) analysedtransport cost determinants for containerized food imports to South America and showed that a 10 per cent rise in the value of the commodity increased transport costs by around 7.6 percent. Wilmsmeier and Martínez-Zarzoso (2010, Tables 3,4) performed linear regression of freight costs on cargo product values, amongst other independent variables, and showed a positive relationship. However, this range of studies mostly used ad valorem freight rates that implicitly reflected cargo values, so the impact of cargo value could be driven by the nature of the data that were used. The extension of this result to specialized commodity cargo transport is not obvious. Other studies on dry bulk shipping freight rates did not consider unit value of cargo as an explanatory variable (Alizadeh and Talley, 2011, Linda, 2014).

The issue about the relationship between dry bulk freight rate and value of the transported product is therefore an interesting problem, and this study contributes to a better understanding of this relationship by studying the dry bulk freight market and the seaborne iron ore market.

Iron ore is a major international commodity that has to be shipped from one port in the exporting country to another in an importing country. Serapio (2016) discussed how steel making and its requirement of iron ore as the key component

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[1] Many shipping firms, logistics firms, and freight brokers indicated on their public web pages that freight rates are determined based on factors such as nature and quantity of the shipped goods, locations of the origin and destination and the distance, seasonal and holiday factors, type and size of the vessel used, market competitiveness, exchange rate, port tariffs and port conditions, fuel prices, and trade regulation policies between the importing and exporting countries, without mention of the unit value of the cargo being carried.

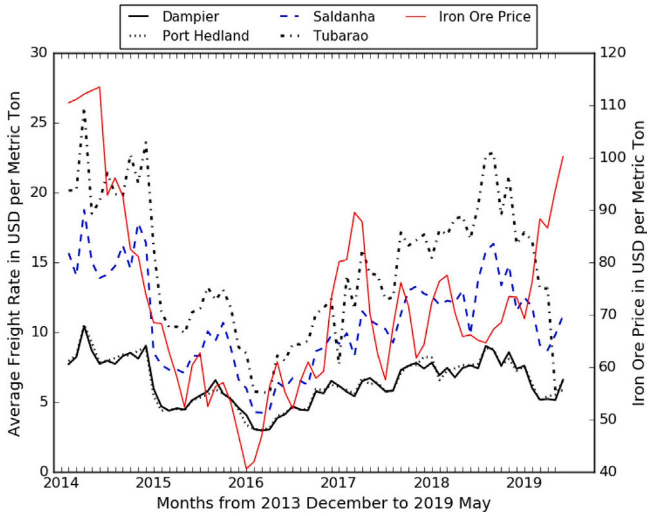

Fig. 1. Graph of average freight rates at loading ports of Dampier, Hedland, Saldanha, and Tubarao. The freight rates are measured in USD per metric ton. The iron ore price is in USD per metric ton. 2014–2019.

predominant in infrastructure and industrialization growths. Ng (2017) reported that in 2016 and 2017, China (PRC) imported enormous amounts of iron ore from mines in Australia and Brazil to meet escalating demands in the PRC steel production industry that had benefitted from rising profit margins. By 2019, Chinese iron ore imports accounted for about 70% of world total imports. Hence seaborne iron ore demand has been driven in large part by China's industrial production.

The seaborne iron ore market and the shipping freight market that transports the ore from the exporting country to PRC are two separate but inter-connected markets. The relationship, if any, between the market price of iron ore and the freight rate, requires demand and supply modelling as well as empirical analyses. Fig. 1 shows monthly time series plots of the iron ore average spot freight rates on 4 shipping routes originating at Dampier, Port Hedland, Saldanha, and Tubarao. Their destination is Qingdao port in PRC. The monthly time series plot of iron ore market price is also included.

In Fig. 1, there appears to be a high positive correlation between the average freight rates and the iron ore price. However, their co-movements could be due to other macro-factors driving both these price variables. This point is best illustrated by an important study by the U.S. Bureau of Labor Statistics (Reed, 2014) on American inflation experience where a high positive correlation is shown between rising U.S. apparel cost index and U.S. medical care cost index as both were driven by inflation-induced demands. However, there are sub-periods in Fig. 1 with reversals in co-movement such as during 2014 to 2015, and 2018 to 2019.

A positive pairwise (zero-order) correlation coefficient between freight rate and iron ore price, however, does not necessarily imply a positive partial correlation coefficient when the effects of other explanatory variables on the prices are removed or controlled. The sign of this partial correlation corresponds to that of the regression coefficient of one price on another. Going from positive correlation between two prices to a linear regression of one on another, however, requires careful modelling of the structural demand and supply in both markets. Least squares regression may face pervasive endogeneity bias when price is included as an explanatory variable.

Unlike extant research that provides an outright specification of unit cargo value as a determinant of transport cost, we model the effect of iron ore price on freight cost using demand–supply structural models and then estimate our results using two-stage least squares panel regression, thus obtaining consistent estimates. We show and explain the endogeneity of commodity cargo cost in freight pricing. We point to careful treatment of price effect when two market systems are working alongside as in these iron ore and bulk carrier markets. The study is important in establishing this unit value impact on freight cost modelling in the transportation of one of the most important metals for China's industrial development.

In the next section, we construct a theoretical relationship between freight rate and iron ore price. We also provide real examples to motivate the structural equations employed in the modelling. In Section 3, we perform estimation and testing on the equilibrium iron ore market model. In Section 4, we discuss the inherent endogeneity characteristics with iron ore price and employ two-stage least squares regression method to obtain unbiased estimates and test the freight price versus iron ore price model. Section 5 concludes with general implications on connected commodity and freight pricing markets.

2. Simultaneous iron ore and freight markets

We construct two simultaneous equilibrium models for iron ore price and for freight rates[2] based on fixed routes. For the period of our empirical study, the inter-quartile range of iron ore prices from 2014 till mid-2019 is about $59 to $80 per metric ton, while

[2] Iron ore price is stated in USD per dry metric ton while freight rate for carrying the seaborne iron ore is typically stated in USD per wet metric ton. Dry metric ton refers to a metric ton where the contents are dry ore. Wet metric ton refers to a metric ton where the contents are ore with about 8% of slurry and

that of freight rates for shipment of iron ore from Tubarao in Brazil to Qingdao in PRC, typically in Capesize dry bulk carriers,[3] is about \$11 to \$18 per metric ton. The average of freight cost at Tubarao to iron ore value per metric ton carried per ship is about 20%. Thus freight cost is a significant portion of overall cost to the iron ore importer in China.

A Capesize dry bulk carrier with a typical 170,000 metric-ton load capacity ferrying iron ore from Tubarao to Qingdao would amount to a freight cost of about \$2.5 million on a freight rate of \$15 per metric ton. There are two main freight quotation methods for iron ore transport. One is by charter rate on a per trip-day basis. The other is for spot rate quote on a per ton basis. PRC iron ore importers are major long-term players in the market and would typically buy the iron ore directly from an overseas mining company on fob basis,[4] and then self-arrange to insure and ship the ore by paying spot rates[5] to dry bulk shipping companies for the freight. During 2014 to 2019, most of the Australian, Brazilian, and South African iron ore are shipped to the Qingdao port in China.

Let the global demand for seaborne iron ore at each month t be represented as follows.

$$D_t^R = a_0 + a_1 P_t^R + a_2 X_t + a_3 VIX_t + \epsilon_{Dt} \tag{1}$$

where ϵ_{Dt} is the demand residual error. P_t^R is the iron ore price in USD per dry metric ton at month t. This is a benchmark price quoted in the market and not the specific purchase price of a specific importer of the iron ore. It is also noted that PRC has the biggest share of this global demand.

Market demand for iron ore should be decreasing in price, hence $a_1 < 0$ in Eq. (1). P_t^R is clearly an endogenous variable and has non-zero correlation with noise ϵ_{Dt}. China's industrial production or overall economic activity growth rate represented by X_t at month t should have a positive impact on iron ore demand, and is assumed to be independent of ϵ_{Dt}. We postulate that the coefficients $a_2 > 0$. This growth rate is measured as the natural logarithm of the relative PRC industrial production index from month to month.

VIX is the ticker symbol for the Chicago Board Options Exchange (CBOE) Volatility Index. It is a popular measure of the stock market's expectation of the S&P 500 index future volatility. VIX is traded on the CBOE and it is known as the "fear gauge" or the "fear index". Warren et al. (2014) showed that VIX has strong linkages with economic and financial fundamentals. Bekaert and Hoerova (2014) showed VIX predicts economic activity and has high predictive power for financial instability. Canorea (2018) found that base metals price movements have a significant negative correlation with VIX movements. Increasing uncertainty with higher VIX depresses demand and thus price, ceteris paribus. Similar negative impacts of VIX were found in gold, silver, and oil commodities. See Daniel and Lipton (2013). Thus it is postulated that $a_3 < 0$ in Eq. (1). Bahloul et al. (2018) also showed that uncertainty measures such as VIX can predict returns on as many as 20 of 21 commodity futures returns. Gozgor et al. (2016) showed that high VIX suppressed agricultural commodity returns. However, since PRC market is not similar to U.S. and European markets in many ways, we assume the effect of VIX on D_t^R occurs only for non-PRC demand. VIX is also assumed to be independent of ϵ_{Dt}.

The market demand residual error ϵ_{Dt} contains an unobserved item equivalent to PRC stockpiling demand, ω_t. When stockpiling ω_t (> 0) increases, this will drive up the equilibrium iron ore price P_t^R if supply curve is unchanged. When the stockpile is reduced, releasing inventory iron ore for use in PRC, then net demand in the seaborne iron ore market will reduce, leading to fall in P_t^R if supply curve is unchanged. The stockpiling activities are real, as reported time and again in the news. For example, UMetal Weekly (2011) reported that China had grown huge stockpiles of iron ore by late 2011. The release of that stockpile in the following several years has been a factor in the falling iron ore price from 2014 to 2016, besides slowing industrial steel manufacturing in that period. Hoyle (2016) in WSJ reported the strong positive effect of China's iron ore stockpiling in later 2016 on the iron ore market price.

The supply of iron ore at month t via the aggregated supply of ore from various international locations j as well as sources not linked to the exporting ports is represented by Eq. (2) below. The demand and supply include quantities utilized by other countries.

$$S_t^R = b_0 + b_1 P_t^R + \epsilon_{St} \tag{2}$$

where ϵ_{St} is assumed to be a supply residual error and independent of X_t and VIX_t. We postulate that the coefficient $b_1 > 0$.

Supply shocks in ϵ_{St} can happen in two ways. Positive shocks or $\epsilon_{St} > 0$ can occur when there is discovery of new iron ore sources or when seaborne transport routes increased. Negative shocks or $\epsilon_{St} < 0$ can happen when there is short-term disruption to supply due to weather or accidents. For example, there was a severe supply cut in iron ore exports from the Australian ports of Hedland and Dampier during the year end of 2014 due to Cyclone Christine (Australian Government Bureau of Meteorology, 2014).

On January 25, 2019, the mining dam at Brumadinho broke and major Brazilian iron ore mining company Vale had to cut production. This contributed to a supply shortage and drove market iron ore price from \$76.16 in January 2019 to \$88.22 in February 2019. Due to the linked simultaneous markets, it also caused a fall in demand of iron ore freight transport at Tubarao in

moisture. We ignore this small difference in the theoretical modelling when we refer to iron ore demand in the iron ore market as being similar to demand for the ship loads carrying the iron ore.

[3] Dry bulk carriers form about 20% of total seaborne transportation, and are a significant supply chain and logistical component for industrial development. They transport iron ore, coking coal for steel production, as well as other commodities such as minerals, grains, and fuel.

[4] The other more expensive method is to buy cif, including insurance and freight cost charged by the ore supplier who also arranges for freight transport.

[5] Since the big production of shipping capacity post 2008, spot freight cost volatility and uncertainty have continued to be critical issues for the shipping industry. The Baltic Exchange Dry Index dropped to a low 796 points in July 2014. Clarksons Research (2015) indicated a number of shipping companies had filed for bankruptcy.

February 2019. At Tubarao, the average freight rate in January 2019 was \$16.52 with transport of 170,000 metric tons. In February 2019, the average freight rate dropped to \$13.1 with transport of 865,000 metric tons.

In equilibrium, $D_t^R = S_t^R$. Equating Eqs. (1) and (2), the market-clearing iron ore price is:

$$P_t^R = \theta_0 + \theta_1 X_t + \theta_2 VIX_t + \epsilon_t \tag{3}$$

where $\theta_0 = (b_0 - a_0)/(a_1 - b_1)$, $\theta_1 = -a_2/(a_1 - b_1) > 0$, $\theta_2 = -a_3/(a_1 - b_1) < 0$, and $\epsilon_t = (\epsilon_{St} - \epsilon_{Dt})/(a_1 - b_1)$.

Our freight demand and supply model follows generally from classic studies such as Stopford (2009), Alen et al. (2015), Wilmsmeier and Martínez-Zarzoso (2010), and so on. Other past research showed that freight cost is affected by ship operating costs such as crew cost, bunker fuel price, registration charges, port tariffs and connectivity (Márquez-Ramos et al., 2005; Wilmsmeier et al., 2006), types of cargo and unit value (Martínez-Zarzoso and Suarez-Burguet, 2005; Wilmsmeier and Martínez-Zarzoso, 2010), weight, bulk, value and perishability of the product (Palander, 1935) and competition, and insurance cost when freight cost includes freight insurance. Martínez-Zarzoso and Wilmsmeier (2008) showed the relative importance of geographical distance on maritime transport costs, indicating that the more central trade routes fetched lower average transport costs. We employ the key factors in the determination of demand and supply of freight cost.

We consider locations with iron ore mining and port facilities where the produced iron ore are shipped to Qingdao in PRC. The exports of iron ore from these ports form the major portion of seaborne iron ore import by PRC. The freight rates for transporting the iron ore to Qingdao in PRC are determined mainly by PRC demand of Capesize carriers to transport the purchased ore as well as the supply of the bulk carriers from shipping companies.

Let $j = 1, 2, 3, \ldots, N$ be sea routes starting from port j to Qingdao. Let P_{jt}^S be the freight spot rate on route j at month t in \$/metric ton. The spot rate, which includes fuel charges to be borne by the shipping firm, is for the agreed shipment from loading port to the disembarkation port of Qingdao. The demand equation for freight at j at month t to carry iron ore is represented as follows.

$$D_{jt}^S = c_0 + c_1 P_{jt}^S + c_2 X_t + c_3 P_t^R + \varepsilon_{Djt} \tag{4}$$

where demand at time t at port j decreases with increasing freight rate at port j, P_{jt}^S, but increases with China industrial production growth rate X_t. Thus $c_1 < 0$ and $c_2 > 0$. X_t is a macro driver of demand for iron ore as well as demand for shipping.

One critical point to note is that demand for the freight transport of iron ore to PRC is largely derived demand by the PRC iron ore importers as most of the imported iron ore are seaborne. Hence factors that affect the demand of iron ore by PRC firms are mostly also factors that affect the demand of freight transport. Since iron ore price and PRC industrial production growth affects demand of iron ore by PRC firms as part of global demand in Eq. (1), they are also factors that affect freight demand in Eq. (4). The inclusion of iron ore price in the specification of Eq. (4) is a theoretical proposition that the PRC iron ore importers' demand for ore and demand for the shipping to carry the ore are in tandem with effect from the iron ore price. Hence iron ore price affects freight demand negatively, and it is postulated that $c_3 < 0$. ε_{Djt} is the residual demand noise that is independent of X_t.

When there is stockpile decrease (increase), $\omega_t < (>)\, 0$, the derived demand of freight by PRC firms will decrease (increase) at every j. More specifically, ϵ_{Dt} has positive correlation with ε_{Djt}, $\forall j$. Thus, apart from the ore price effect, there is an important nexus between the iron ore market and the shipping freight market at the 4 exporting ports.

The supply equation for freight at j at month t is as follows.

$$S_{jt}^S = d_0 + d_1 P_{jt}^S + d_2 D_j + d_3 B_t + d_4 BDI_t + \varepsilon_{Sjt} \tag{5}$$

where D_j is the distance of the exporting port to Qingdao in terms of nautical miles, B_t is the bunker fuel price in \$/ton, and BDI_t is the Baltic Dry Index. BDI is reported daily by the Baltic Exchange in London. It provides a benchmark for freight rates of vessels ferrying dry bulk commodities such as coal, iron ore, grains, and others. The index tracks rates on about 20 different shipping routes across the globe.

As the iron ore shipment freight rate increases, the supply of shipping capacity would increase, so $d_1 > 0$. In Eq. (5), for each j, d_0 and D_j are constants, but the effect of distance D_j would appear differentially across ports when we use pooling regression. The more remote the cargo load point is from the destination, the higher is the risk borne by the shipping firm in the delivery as weather, ocean conditions, and the longer voyage would escalate the costs and risks. Ceteris paribus we would see more supply of shipping from ports nearer to Qingdao. Thus $d_2 < 0$.

Higher bunker fuel price (high sulphur) implies it is more costly to operate the ship and will reduce supply of the shipping capacity, hence $d_3 < 0$. Dušan and Janić (2017) produced results for general cargo ships showing that distance and fuel cost increase the average shipping rates. Both the distance and the fuel price are transformed by taking natural logarithms. Higher BDI_t in month t implies higher opportunity cost for use of the finite dry bulk shipping capacity, so ceteris paribus, the supply of shipping for transport of iron ore would be reduced. Thus $d_4 < 0$. ε_{Sjt} is the residual supply noise that is independent of D_j, B_t, and BDI_t.

Since the specialized shipping freight market and the iron ore importers are well connected, residual ore demand increase (decrease) would possibly increase (decrease) freight supply capacity as shippers reallocate shipping schedules to meet potential demand changes. Hence ϵ_{Dt} possibly has positive correlation with ε_{Sjt}, $\forall j$.

Equating Eqs. (4) and (5) under economic market clearing equilibrium, we have

$$P_{jt}^S = \gamma_0 + \gamma_1 X_t + \gamma_2 D_j + \gamma_3 B_t + \gamma_4 P_t^R + \gamma_5 BDI_t + \eta_{jt} \tag{6}$$

where $\gamma_0 = (d_0 - c_0)/(c_1 - d_1)$, $\gamma_1 = -c_2/(c_1 - d_1) > 0$, $\gamma_2 = d_2/(c_1 - d_1) > 0$, $\gamma_3 = d_3/(c_1 - d_1) > 0$, $\gamma_4 = -c_3/(c_1 - d_1) < 0$, $\gamma_5 = d_4/(c_1 - d_1) > 0$, and $\eta_{jt} = (\varepsilon_{Sjt} - \varepsilon_{Djt})/(c_1 - d_1)$.

Table 1
Descriptive statistics of variables used in the study: iron-ore price in USD per metric ton, PRC industrial production growth rate in %, VIX index, BDI index, natural log of distance in nautical miles, natural log of high Sulphur 380 bunker fuel $ price, freight rate in USD per metric ton. The sample period is from January 2014 to May 2019. Sample size is 65. The mean, standard deviation, 25th percentile (25%), median, and 75th percentile (75%) of the various time series are reported.

Variables	Mean	Std Dev	25%	Median	75%
Iron ore price $	71.70	17.49	59.09	68.39	80.41
Growth rate %	0.538	0.144	0.495	0.501	0.599
VIX index	15.10	3.81	12.37	14.00	16.95
BDI index	977.5	332.7	703.0	943.0	1204.0
ln (Distance)	8.83	0.53	8.33	8.75	9.26
ln (Fuel Price)	5.94	0.30	5.80	5.95	6.16
Average freight rate $	9.47	4.70	5.89	8.09	12.14

Eq. (6) provides the theoretical relationship between freight rate P_{jt}^S at port j and iron ore price P_t^R. The residual error η_{jt} is assumed to be independent of X_t, D_j, B_t, BDI_t for each j, but heteroskedasticity could occur for different j. As our study is on the specific iron ore commodity, and the export port to import port routes were fixed, we exclude variables such as registration charges, port tariffs, product perishability characteristics, measures of competition amongst products, and insurance cost used in some other studies on general commodities. The smaller costs of operations data are difficult to obtain but are contained in the residual variables of η_{jt} within our model. These costs are reasonably assumed not to be correlated with China's industrial growth, world bunker fuel cost, BDI, and VIX. Their mean effects would be reflected in constants relating to ports or proxied by the distance effects across the ports.

3. Estimation and testing

In this section we evaluate the time series properties of the various variables we employ in our study. Then we estimate and test the iron ore pricing relationship in Eq. (3).

Monthly iron ore prices and other macrovariables such as PRC industrial production index, VIX, and BDI are collected from Thomson Reuters Datastream. Freight prices indicating cargo as iron ore were obtained from Clarksons database. Due to limitations in data availability, our sample period is from January 2014 to May 2019. For each month, various global iron ore export ports such as Dampier and Port Hedland from Australia, Port Saldanha Bay from Africa, Tubarao from Brazil, Ponta da Madeira, Subic Bay, and several others provide bulk carriers to transport iron ore to Qingdao in China. The busy ports sometimes have up to over twenty different ships a month. During the sample period there were eleven major routes shipping iron ore to Qingdao. However, for freight data available on a continuous basis for each month in the sample period, there were only the ports of Dampier and Hedland in northern Australia, Saldanha Bay in South Africa, and Tubarao in Brazil. Hence our empirical study uses data from these 4 ports. For each month, the average freight rate at each port is computed for carriers transporting iron ore to Qingdao.

Monthly bunker fuel prices are collected from S&P Global Platts. Monthly price data for freight rate at any port j is obtained by averaging such rates for different ships departing from the same port in that month. Sea distance from port j to Qingdao is computed as natural logarithm of nautical miles obtained from ports.com. Descriptive statistics of the data variables used in the study are shown in Table 1. Fig. 2 shows the time series plots of the various variables.

From Table 1, it can be seen that freight rate, followed by BDI, is the most volatile in terms of the ratio of standard deviation to mean. Iron ore price, PRC industrial production growth rate, and the VIX index are also relatively volatile. For freight rates, the rates are different with respect to voyage distances, increasing with the distance from loading port to disembarkation port at Qingdao. See Fig. 1 shown earlier. The loading port Tubarao in Brazil is the farthest from Qingdao and the average freight rate there was much higher. This is followed by Saldanha Bay in South Africa, Dampier and Port Hedland in Australia. It is also observed that the average freight rate at Tubarao showed a sharp fall in January through May 2019.

To perform multiple linear regression on Eq. (3), we first check the time series properties of the random variables to see if they are stationary. If they are unit root processes, then the regression may lead to spurious results unless the random variables in the linear regression are co-integrated. The unit root test results on the null of unit root or I(1) process are reported in Table 2. The Augmented Dickey–Fuller test statistics are utilized for the test inferences.

From Table 2, it is seen that growth rates and VIX index are stationary or I(0) processes. Iron ore prices are borderline with a p-value of 0.189 in rejecting unit root. We tried differencing but found that it removed too much information such that the regression results suffered from too much noise. Moreover, according to our model, it is more meaningful to model iron ore price level. We analyse further the iron ore time series by computing its sample autocorrelation and partial autocorrelation functions. These are shown in Fig. 3.

Fig. 3 shows that the iron ore price series is possibly an autoregressive process. The PACF sample function indicates it could be AR(1). Hence there is reasonable statistical evidence to treat the dependent iron ore price in Eq. (3) as a stationary variable for regression. We run a linear regression based on Eq. (3) using Newey and West (1987) Heteroskedasticity and Autocorrelation Consistent covariance estimator (HAC) for obtaining the inferences. This regression provides for a test of the iron ore pricing model.

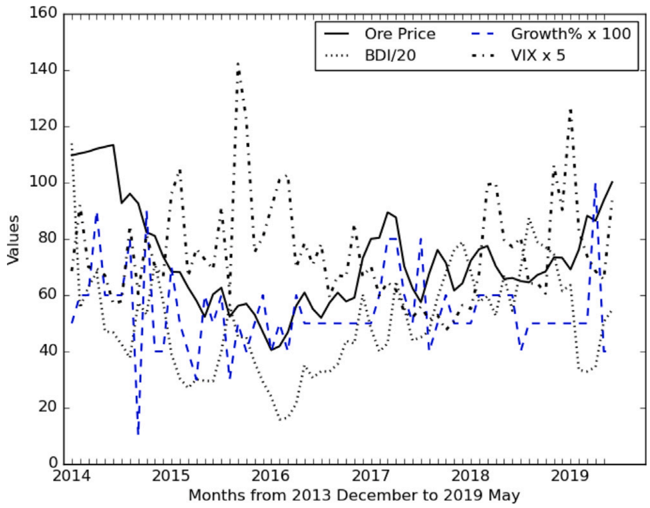

Fig. 2. Time series graph of iron ore price, Growth Rate% (×100), VIX index level (displayed as level ×5), and BDI index level (displayed as level divided by 20). Monthly values are shown in sample period Jan 2014 to May 2019.

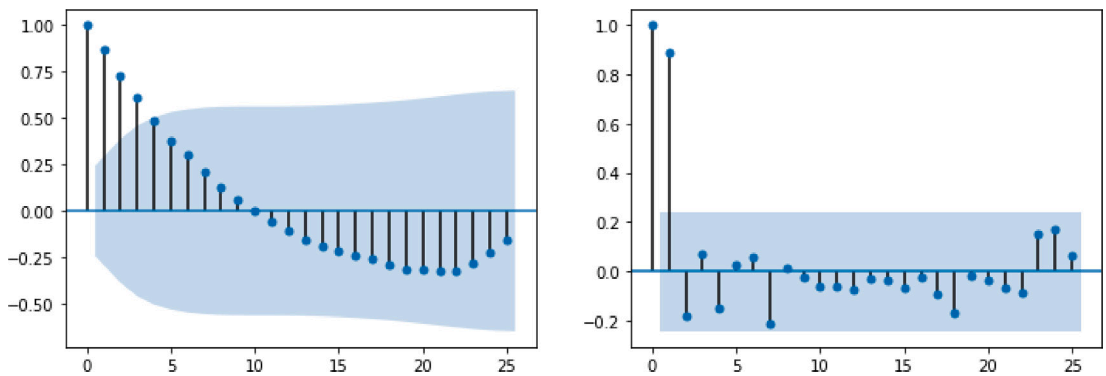

Fig. 3. Autocorrelation Sample Function (left) and Partial Autocorrelation Sample Function (right) of Iron Ore price over monthly sample period January 2014 to May 2019. The plots show ACF and PACF over 25 lags. Standard deviations at 95% significance level are also shown in the grey zones. The standard deviation for ACF is computed using Bartlett's formula. See Bartlett, M. S. (1955, p.289). An introduction to stochastic processes. Cambridge: Cambridge University Press.

Table 2
Unit root tests of iron ore price, Growth rate, and VIX index time series over monthly data from January 2014 to May 2019. Sample size is 65. Augmented Dickey–Fuller (ADF) test statistics, the p-values, and distribution percentile values are reported based on the null of unit root or I(1) process. The number of lags is chosen to minimize the corresponding information criterion. Computation uses the 'adfuller' module in statsmodels.tsa.stattools written for Python.

	Iron ore prices $	Growth rates	VIX index
ADF-statistics	−2.249	−9.288***	−5.011***
p-value	0.189	0.000	0.000
1%	−3.541	−3.537	−3.537
5%	−2.909	−2.908	−2.908
10%	−2.592	−2.591	−2.591

Note:
***Indicates 1-tail 1% significance level.

The results are reported in Table 3. To provide a confirmation on the stationary system of Eq. (3), we also run an ADF unit root test on the estimated residuals of the regression. The estimated residuals should asymptotically display I(0) process.

Table 3 shows that $\hat{\theta}_1 > 0$ and $\hat{\theta}_2 < 0$ are significantly different from zero and have the correct signs according to the model in Eq. (3). If the growth rate is 1%, then ceteris paribus the iron ore will increase by about 37.8%. When VIX_t increased, the global seaborne iron ore market price decreased, supporting the evidence of the fear phenomena that is well-known in financial markets

Table 3
Linear regression of iron ore price P_t^R on PRC industrial growth X_t and VIX_t based on Eq. (3): $P_t^R = \theta_0 + \theta_1 X_t + \theta_2 VIX_t + \epsilon_t$. P_t^R, X_t, and VIX_t are respectively the iron ore price in USD per dry metric ton, the PRC natural log of industrial production growth, and the traded CBOE VIX index. Sample period January 2014 to May 2019. Sample size of 65. The t-statistics are computed using (Newey and West, 1987) HAC covariance estimator.

Parameter	Estimated coefficient	Standard error	t-stats	p-value
θ_0	62.804***	11.110	5.653	0.000
θ_1	37.849**	16.889	2.241	0.029
θ_2	−0.760*	0.449	−1.694	0.095
$F_{2,62}$-statistic	3.540**	p-value	0.035	
Adj. R^2	0.103			
ADF-statistics of residual error	−2.960**	p-value	0.039	

Note:
*Indicate 10% significance levels respectively.
**Indicate 5% level respectively.
***Indicate 1% significance level respectively.

Table 4
Unit root tests of average freight rates of Dampier, Hedland, Saldanha, Tubarao, natural log of fuel price, and the BDI index time series over monthly data from January 2014 to May 2019. Sample size is 65. Augmented Dickey–Fuller (ADF) test statistics, the p-values, and distribution percentile values are reported based on the null of unit root or I(1) process. The number of lags is chosen to minimize the corresponding information criterion. Computation uses the 'adfuller' module in statsmodels.tsa.stattools written for Python.

	Dampier	Hedland	Saldanha	Tubarao	Fuel price	BDI index
ADF-statistics	−2.197	−2.343	−2.541	−2.147	−1.873	−2.617*
p-value	0.207	0.158	0.106	0.226	0.345	0.089
1%	−3.537	−3.539	−3.537	−3.541	−3.539	−3.537
5%	−2.908	−2.909	−2.908	−2.909	−2.909	−2.908
10%	−2.591	−2.592	−2.591	−2.592	−2.592	−2.591

Note:
*Indicates 1-tail 10% significance level.

as well as base metals commodity markets. ADF statistic on estimated residuals $\hat{\epsilon}_t$ shows unit root is rejected at a 5% significance level, so the regression is properly specified and the regression results are not spurious.

To perform multiple linear regression on Eq. (6), we check the time series properties of the random variables, apart from those in Eq. (3), if they are stationary. The unit root test results of monthly average freight rates at Dampier, Hedland, Saldanha, and Tubarao, as well as of natural logarithm of fuel price and BDI index on the null of unit root are reported in Table 4. The Augmented Dickey–Fuller test statistics are utilized for the test inferences.

From the statistical results in Table 4, we cannot reject unit roots for all the average monthly freight rates at the various loading ports. We also cannot reject unit root for the natural log of fuel price. However, unit root can be rejected at 10% significance level for BDI_t. Thus for each port in Eq. (6) there is the dependent variable and at least one independent variable that appear to follow unit root processes. To ensure that a linear regression would be meaningful and not produce spurious results, we test if the variables P_{jt}^S, X_t, B_t, P_t^R, and BDI_t in Eq. (6) are co-integrated. Cointegration means that a linear combination of the regressant and regressors is stationary. We employ the Johansen (1988, 1991) trace statistic and maximum eigenvalue statistic to test the null of no cointegration. The results are reported in Table 5.

Table 5 shows that the null hypothesis of zero or no cointegration is rejected at 1% significance level for all ports based on the maximum eigenvalue statistic. The null hypothesis of at most one cointegrating relationship is not rejected. A single cointegrating relationship is reasonable for the ports as the average freight rate may be cointegrated with the natural log of fuel price. The results from the trace statistic test are basically consistent. The non-spurious linear regression of Eq. (6) for each port implies that a panel regression involving all 4 port equations should also be cointegrated. Without adding unnecessary space, we report that in 4 regressions, one for each port, the estimated coefficients for natural log fuel price and BDI are significantly positive, and the estimated coefficients for natural log growth and ore price are not significantly different from zero. All magnitudes are consistently similar across the regressions. Statistically, there appears to be reasonable homogeneity across the different port regressions. This averts a panel regression concern by Pedroni (2004).

We perform a multivariate (different j) multiple regression (more than one explanatory variable) on Eq. (6) by stacking observations $\left(P_{11}^S, P_{12}^S, P_{13}^S, \dots, P_{1T}^S, P_{21}^S, P_{22}^S, P_{23}^S, \dots, P_{2T}^S \dots \dots, P_{N1}^S, P_{N2}^S, P_{N3}^S, \dots, P_{NT}^S \right)^T$ as the dependent vector, where N is the number of panels. Similarly, the errors are stacked up such that its covariance matrix has clusters of different variances across j. Basically this is panel regression with clustered standard errors.

To employ a balanced panel we use the data based on exporting ports Dampier and Hedland in Australia, Saldanha Bay in Africa, and Tubarao in Brazil. These 4 major ports in shipping iron ore to Qingdao account for 74% of the total number of 5088 trips in

Table 5

Cointegration trace and maximum eigenvalue tests involving average freight rate, Industrial growth, Fuel price, Iron ore price, and BDI. Monthly variables are from sample period January 2014 to May 2019. The results are obtained with no deterministic trend and 1 lag. Computation uses the 'coint_johansen' module in statsmodels.tsa.vector_ar.vecm written for Python.

Null Hypothesis	Trace statistic	1% critical value	Maximum eigenvalue	1% critical value
Dampier				
Zero cointegration	67.58**	67.64	42.09***	35.74
At most 1 Cointegration	25.50	46.57	12.38	29.06
At most 2 Cointegrations	13.11	29.51	7.10	22.25
At most 3 Cointegrations	6.01	16.36	6.01	15.09
At most 4 Cointegrations	0.005	6.94	0.005	6.94
Port Hedland				
Zero cointegration	76.21***	67.64	43.36***	35.74
At most 1 Cointegration	32.86	46.57	18.29	29.06
At most 2 Cointegrations	14.57	29.51	8.30	22.25
At most 3 Cointegrations	6.27	16.36	6.20	15.09
At most 4 Cointegrations	0.068	6.94	0.068	6.94
Saldanha Bay				
Zero cointegration	82.66***	67.64	49.30***	35.74
At most 1 Cointegration	33.36	46.57	18.89	29.06
At most 2 Cointegrations	14.48	29.51	7.97	22.25
At most 3 Cointegrations	6.51	16.36	6.49	15.09
At most 4 Cointegrations	0.020	6.94	0.020	6.94
Tubarao				
Zero cointegration	61.36**	67.64	38.22***	35.74
At most 1 Cointegration	23.14	46.57	13.16	29.06
At most 2 Cointegrations	9.98	29.51	7.33	22.25
At most 3 Cointegrations	2.65	16.36	2.46	15.09
At most 4 Cointegrations	0.190	6.94	0.190	6.94

Note:

**Indicate 1-tail 5% significance level.

***Indicate 1-tail 1% significance level.

over 50 ports on more than 10 major routes in our sample. In the panel regression, we also introduce the natural logarithm of the distance in nautical miles from loading port to Qingdao. This deterministic variable across the ports is important as it contains useful information as reflected in Fig. 1. This variable also proxies largely for the fixed effect in the panel. As we observed earlier in Fig. 1, there is also a structural break in the average freight rate at Tubarao. As reported by BBC, the collapse of a mining dam at Brumadinho on 25 Jan 2019 drastically curtailed the production of iron ore by Vale in Brazil and led to lower demand for freight transport at Tubarao during January to May 2019. Therefore we add a structural break dummy variable S_t in the panel for Tubarao. This structural break dummy variable takes the value 1 for Tubarao panel in the months of Jan to May 2019, and zero otherwise for all other equations. We employ Eq. (7) in place of Eq. (6) for the panel regression:

$$P^S_{jt} = \gamma_0 + \gamma_1 X_t + \gamma_2 D_j + \gamma_3 B_t + \gamma_4 P^R_t + \gamma_5 BDI_t + \gamma_6 S_t + \eta_{jt}. \tag{7}$$

We also report the Durbin–Wu–Hausmann test of null of iron ore price exogeneity. The iron ore price variable used in the regressor is P^R_t. As we introduce covariance clusters, it is not appropriate to use the Hausman test statistic for fixed versus random effects. This is because the random effect model uses a specific covariance matrix (see Davidson and MacKinnon (1993, p.324)) that is inconsistent with our heteroskedastic covariance matrix. The linear panel regression results are shown in Table 6.

The results in Table 6 show that increases in China's industrial production and economic activities during January 2014 to May 2019 are related to increases in freight prices. However, this impact on freight rates is not significant, unlike that on iron ore prices. Distance of loading port from disembarkation or destination port Qingdao has positive correlation with freight rate. The effect is significant. Increases in bunker fuel oil increases freight rates significantly, a result that is intuitive and established in the existing literature. Increase in BDI also increases freight rate significantly as expected.

The January–May 2019 negative structural effect on Tubarao freight rates is highly significant. However, iron ore price has negligible impact on freight rate, which is a surprising result. The Durbin–Wu–Hauman test of the exogeneity of regressor iron ore price is rejected at 10% significance level. Therefore, the small estimated coefficient of $\hat{\gamma}_5$ of iron ore price is biased and inconsistent as a result of its regressor endogeneity.

In the next section, we show how endogeneity in iron ore prices can occur, and perform a two-stage least squares estimation using the projected iron ore price as an instrumental variable.

4. Endogeneity of iron ore price

In Eqs. (3) and (6), we see how equilibrium iron ore price and freight price of ships transporting the iron ore are determined. In Section 2, we elaborated on the critical observation that demand for iron ore freight transport to PRC is largely derived demand

Table 6

Panel regression of freight prices on explanatory variables based on Eq. (7): $P_{jt}^S = \gamma_0 + \gamma_1 X_t + \gamma_2 D_j + \gamma_3 B_t + \gamma_4 P_t^R + \gamma_5 BDI_t + \gamma_6 S_t + \eta_{jt}$. P_{jt}^S, X_t, D_j, B_t, P_t^R, BDI_t, and S_t are respectively the freight spot rate on route j in USD per metric ton, the PRC natural log of industrial production growth, distance of exporting port j to Qingdao in natural log of the number of nautical miles, log of bunker fuel price in $/ton, iron ore price in USD per dry metric ton, the Baltic dry index, and structural break dummy variable that takes value 1 for Tubarao for months Jan to May 2019 and otherwise zero. Sample period January 2014 to May 2019. Sample size 260. There are 4 port locations in the sample. The t-statistics are computed based on clustered panel effects. The test if the iron ore regressor variable is exogenous is also reported using the Durbin–Wu–Hausman test statistic.

Parameter	Estimated coefficient	Standard error	t-stats	p-value
γ_0	−83.47***	16.002	−5.216	0.000
γ_1	1.290	0.992	1.300	0.195
γ_2	6.509***	0.631	10.31	0.000
γ_3	5.148***	1.907	2.699	0.007
γ_4	0.006	0.009	0.599	0.550
γ_5	0.004***	0.001	7.401	0.000
γ_6	−3.617***	0.878	−4.119	0.000
$F_{6,253}$-statistic	196.11***	p-value	0.000	
R^2	0.823			
Durbin–Wu–Hausman test $F_{1,253}$ H_0 : Iron ore price exogenous	3.315 *	p-value	0.070	

Note:

*Indicate 1-tail 10% significance level.

***Indicate 1-tail 1% significance level.

based on iron ore demand by PRC importers. Thus the factors of iron ore price and PRC industrial production growth affects both the demand for iron ore in Eq. (1) and also the demand for freight in Eq. (4). The iron ore demand residual error ϵ_{Dt} comprising stockpiling is also positively correlated with the freight demand residual error ε_{Djt} and possibly also with ε_{Sjt} due to the nexus between the seaborne iron ore market and the dry bulk iron ore freight markets.

From Eq. (3), it is obvious that iron ore market price P_t^R is correlated with both ϵ_{Dt} and ϵ_{St}. This arises out of the simultaneous equations model of iron ore demand–supply pricing in Eqs. (1) and (2). Given the said nexus, though we do not observe the residual errors in the iron ore and the freight markets, we are able to infer that iron ore market price P_t^R is also correlated with η_{jt}.

This implies that iron ore price as regressor in Eq. (6) is correlated with and is thus mutually dependent on the residual error η_{jt} since η_{jt} is a function of both ε_{Djt} and ε_{Sjt}. Hence the derived demand leads to endogeneity in iron ore prices in the regression of freight rate in Eqs. (6) and (7). The endogeneity led to biased and inconsistent panel regression estimates in Table 6.

To resolve this endogeneity problem in the regression, we employ two-stage least squares (2SLS) method by first projecting iron ore prices using Eq. (3) regression to obtain the time series of the estimated iron ore prices.

$$\hat{P}_t^R = \hat{\theta}_0 + \hat{\theta}_1 X_t + \hat{\theta}_2 VIX_t$$

where the notation ^ denotes OLS estimate. Then we re-run the panel regression using the following instead.

$$P_{jt}^S = \gamma_0 + \gamma_1 X_t + \gamma_2 D_j + \gamma_3 B_t + \gamma_4 \hat{P}_t^R + \gamma_5 BDI_t + \gamma_6 S_t + v_{jt} \tag{8}$$

where the residual error v_{jt} is now independent of all the regressors. Regressor $\hat{P}_t^R$ now acts like an instrumental variable that is both independent of the residual error and highly correlated with the original P_t^R. The results of the panel regression in Eq. (8) are reported in Table 7.

The results in Table 7 show that all estimated coefficients are significantly different from zero at the 1% level, except for that of industrial production growth at 5% significance level. All estimated coefficients have the correct signs as postulated by the economic models discussed in Section 2. China's industrial growth during January 2014 to May 2019 increases demand for steel. Higher demand for steel leads to higher demand for iron ore, including seaborne ore, and hence higher demand for dry bulk shipping of such ore from the overseas ports. This leads to higher freight rates; $\hat{\gamma}_1 > 0$.

Higher bunker fuel price and higher BDI reduce the supply of freight at any particular port, and hence lead to higher freight rates at these ports; $\hat{\gamma}_3, \hat{\gamma}_5 > 0$. Longer distance of transport from export port to destination port Qingdao implies higher transport risks and thus decreases freight supply ceteris paribus. This leads to higher freight rate for a longer distance of transport; $\hat{\gamma}_2 > 0$. The January-May 2019 negative structural effect on Tubarao freight rates is highly significant; $\hat{\gamma}_6 < 0$.

Unlike the results in Table 6 that contains endogeneity bias, the estimated coefficient of the fitted iron ore price in Table 7 is significantly negative at 1% significance level. This negative impact is postulated in the economic models in Section 2. See Eq. (6) where the coefficient γ_4 is negative according to the modelling. The economic reasoning that arises out of the two market clearing systems is as follows. An iron ore price increase negatively affects demand of freight in Eq. (4) as freight demand is derived from iron ore demand in PRC. The negative demand shift given unchanged freight supply curve implies that equilibrium freight price

Table 7
Panel regression of freight prices on explanatory variables based on Eq. (8): $P_{jt}^S = \gamma_0 + \gamma_1 X_t + \gamma_2 D_j + \gamma_3 B_t + \gamma_4 \hat{P}_t^R + \gamma_5 BDI_t + \gamma_6 S_t + v_{jt}$. P_{jt}^S, X_t, D_j, B_t, $\hat{P}_t^R$, BDI_t, and S_t are respectively the freight spot rate on route j in USD per metric ton, the PRC natural log of industrial production growth, distance of exporting port j to Qingdao in natural log of the number of nautical miles, log of bunker fuel price in \$/ton, fitted iron ore price in USD per dry metric ton, the Baltic Dry Index, and structural break dummy variable that takes value 1 for Tubarao for months Jan to May 2019 and otherwise zero. Sample period January 2014 to May 2019. Sample size 260. There are 4 port locations in the sample. The t-statistics are computed based on clustered panel effects.

Parameter	Estimated coefficient	Standard error	t-stats	p-value
γ_0	−82.07***	13.393	−6.128	0.000
γ_1	3.629**	1.571	2.310	0.022
γ_2	6.508***	0.634	10.27	0.000
γ_3	5.462***	1.610	3.393	0.001
γ_4	−0.058***	0.022	−2.689	0.008
γ_5	0.004***	0.001	7.074	0.000
γ_6	−3.586***	0.948	−3.783	0.000
$F_{6,253}$-statistic	197.52***	p-value	0.000	
R^2	0.824			

Note:
**Indicate 1-tail 5% significance level.
***Indicate 1-tail 1% significance level

Table 8
Tests on estimated residuals based on Eq. (8). Sample period January 2014 to May 2019. Sample size for estimated residuals of each port's average freight rate regression is 65. The 4 ports are Dampier, Hedland, Saldanha Bay, and Tubarao. The ADF-statistic reports the test of the null of unit root of the estimated residual. The sample correlation of the estimated residuals with the iron ore price regression residual in Eq. (3) are also tested on the null of zero correlation using $\frac{1}{\sqrt{T}}$ as standard deviation where T is the sample size.

Test	Estimate	p-value
ADF-statistics of $\hat{v}_{1t}$	−2.803*	0.058
ADF-statistics of $\hat{v}_{2t}$	−2.867*	0.049
ADF-statistics of $\hat{v}_{3t}$	−3.819***	0.003
ADF-statistics of $\hat{v}_{4t}$	−3.692***	0.004
Sample correlation $(\hat{\epsilon}_t, \hat{v}_{1t})$	−0.534***	0.000
Sample correlation $(\hat{\epsilon}_t, \hat{v}_{2t})$	−0.491***	0.000
Sample correlation $(\hat{\epsilon}_t, \hat{v}_{3t})$	0.355***	0.001
Sample correlation $(\hat{\epsilon}_t, \hat{v}_{4t})$	0.329***	0.002

Note:
*Indicate 1-tail 10% significance level.
***Indicate 1-tail 1% significance level.

will be reduced as in Eq. (6). The estimated coefficient of iron ore price $\hat{\gamma}_4$, −0.058, indicates that each expected \$ increase in iron ore price per metric ton is associated with a decrease in average freight rate of 5.8 cents per metric ton.

To ensure that the panel regression system in Eq. (8) is co-integrated and the regression results in Table 7 are not spurious, the estimated residuals $\hat{v}_{jt}$ are tested for unit root for each j. This is termed the residual-based test discussed in Hayashi (2000, p.644). Appropriately cointegrated panel regression would yield fitted residuals that asymptotically exhibit stationarity. To check the correlation of ϵ_t and η_{jt} which led to the endogeneity problem, we test the null of zero correlation on the sample correlations of the estimated residuals $\hat{\epsilon}_t$ from Eq. (3) and the $\hat{v}_{jt}$'s from Eq. (8). The results are reported in Table 8.

The results in Table 8 show that ADF-test statistics reject the presence of unit roots in the estimated $\hat{v}_{jt}$'s, and hence establish the appropriateness of the panel regression as each panel is cointegrated. The sample correlations of $\hat{\epsilon}_t$ and $\hat{v}_{jt}$ show that zero correlation is rejected. This result provides evidence of the endogeneity of unit iron ore prices in the linear regression that arises out of the two systems of simultaneous iron ore and freight prices.

To check for the robustness of the empirical results, we consider adding lagged independent variables in Eq. (8). But the sample autocorrelations of B_t and BDI_t in Eq. (8) are very high at 0.9737 and 0.8017 respectively. Adding them leads to multi-collinearity issue with the relatively limited sample size. Therefore we perform regression on Eq. (8) with an added explanatory variable of lagged X_{t-1}. The results are reported in Table 9.

Comparing with the results in Table 7, it is shown that the coefficient estimates remain stable and are robust to the introduction of the lagged key explanatory variable of industrial growth that largely drives the iron ore and shipping demands. The estimated coefficient of the industrial growth X_t is 3.259, positively significant at 1% level. However, the estimated coefficient of the lagged

Table 9
Panel regression of freight prices on explanatory variables based on Eq. (8) plus explanatory variable of lagged X_{t-1}: $P^S_{jt} = \gamma_0 + \gamma_1 X_t + \gamma_2 D_j + \gamma_3 B_t + \gamma_4 \hat{P}^R_t + \gamma_5 BDI_t + \gamma_6 S_t + \gamma_7 X_{t-1} + v_{jt}$. P^S_{jt}, X_t, D_j, B_t, $\hat{P}^R_t$, BDI_t, S_t, and X_{t-1} are respectively the freight spot rate on route j in USD per metric ton, the PRC natural log of industrial production growth, distance of exporting port j to Qingdao in natural log of the number of nautical miles, log of bunker fuel price in $/ton, fitted iron ore price in USD per dry metric ton, the Baltic Dry Index, structural break dummy variable that takes value 1 for Tubarao for months Jan to May 2019 and otherwise zero, and lagged PRC natural log of industrial production growth. Sample period January 2014 to May 2019. Sample size 260. There are 4 port locations in the sample. The t-statistics are computed based on clustered panel effects.

Parameter	Estimated coefficient	Standard error	t-stats	p-value
γ_0	−81.82***	13.769	−5.942	0.000
γ_1	3.259***	1.232	2.646	0.009
γ_2	6.451***	0.638	10.10	0.000
γ_3	5.501***	1.659	3.315	0.001
γ_4	−0.051***	0.016	−3.115	0.002
γ_5	0.004***	0.001	7.003	0.000
γ_6	−3.529***	0.957	−3.689	0.000
γ_7	−0.501	0.620	−0.808	0.420
$F_{7,248}$-statistic	163.53***	p-value	0.000	
R^2	0.822			

Note:
***Indicates 1-tail 1% significance.

industrial growth X_{t-1} is −0.501 and is not significantly different from zero. The estimated coefficient of the fitted iron ore price in Table 9 is −0.051 and is significantly negative at 1% significance level. R^2 decreased by a bit when compared with that in Table 7.

5. Conclusions

In this paper, we analyse how the value of goods carried can affect the freight cost. This is an unanswered question as indicated by the Review of Maritime Transport (2015, p.53). Regression results in the context of general and container cargoes typically show a positive relationship, though that could be due to the use of ad valorem transport cost data. We focus on the issue based on a more specialized freight market involving transport of seaborne iron ore from mining ports to Qingdao in China during the period 2014 to 2019. To enable the investigation, we construct simultaneous systems of demand–supply equations on both the iron ore market and the freight market.

Using these simultaneous equilibrium models of iron ore market pricing and the dry bulk freight rate pricing, we show how iron ore price can negatively affect the freight rate of bulk carriers ferrying the iron ore. We then collected data and tested the iron ore pricing model and also the freight price versus iron ore price model. In the models, we explain how endogeneity of iron ore as a regressor can arise due to the nexus between the two markets, and that the freight demand is largely a derived demand from iron ore demand by PRC firms importing the iron ore. We explain that when using linear regression, this endogeneity could produce a biased and inconsistent estimate of the coefficient of iron ore price.

We show how an instrumental variable can be constructed to provide an unbiased and consistent estimate of the impact of the iron ore price on freight rate. We thus point to the importance of careful treatment of the commodity price effect in simultaneous market systems. This two-stage least squares method yields the result that as iron ore price or unit cargo price increases, ceteris paribus, freight rate decreases. Our empirical estimation and testing produce coefficient estimates that are significant and have the right signs as depicted by the models. In particular, industrial growth, bunker fuel oil, BDI, and transport distance have positive effects on the freight rates while iron ore price has a negative effect on the freight rate.

Our economic model and econometric analyses provide an important understanding of the freight market serving perhaps the most important metal in the industrial development of China. There are implications on other similar commodities that have global demand and require international shipping transport. As can be seen, when there is a nexus between the two markets, such as having a derived demand on the freight transport, then the freight price and the commodity price will not be independent. Derived demand will generally lead to negative correlation between the two prices. How large is this negative effect will depend on the context and the nature of the two markets.

There are, however, some limitations in our analyses. Firstly, there is a trade-off between model parsimony and a non-intricate linear model of supply and demand. Secondly, we have limited monthly data on the variables. Data on a more frequent basis would give a larger sample size that can help in reducing any sampling errors. Interesting variables such as stockpiling statistics and time-stamped shipment orders, that are not available, could certainly throw more light on the research question.

CRediT authorship contribution statement

Kian Guan Lim: Conceptualization, Methodology, Data, Programming, Analyses, Writing, Editing, Revision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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