Endogeneity of Commodity Price in Freight Cost

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Extant research indicated that unit value of cargo goods may affect the freight rate, but there has been no clear economic reason except the idea that higher goods value tends to increase the demand elasticity on freight cost. We provide an economic explanation that commodity price such as iron ore price directly affects freight rates of bulk carriers carrying the ores. The ore price is, however, endogeneous, and a 2SLS panel regression is performed to estimate its impact on freight cost. We also explain how in general when two market regression systems involving commodity values and freight rates of the shipping carrying the commodity interact, latent variables exist to render commodity unit price endogenous.

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Endogeneity of Commodity Price in Freight Cost

Abstract

Extant research indicated that unit value of cargo goods may affect the freight rate, but there has been no clear economic reason except the idea that higher goods value tends to increase the demand elasticity on freight cost. We provide an economic explanation that commodity price such as iron ore price directly affects freight rates of bulk carriers carrying the ores. The ore price is, however, endogeneous, and a 2SLS panel regression is performed to estimate its impact on freight cost. We also explain how in general when two market regression systems involving commodity values and freight rates of the shipping carrying the commodity interact, latent variables exist to render commodity unit price endogenous.

1 Introduction

In this paper, we analyse how value of goods carried can affect the freight cost. The Review of Maritime Transport (2015) indicated unit cost of cargo goods may affect the freight rate, but there has been no clear economic reason except the idea that higher goods value carried in the cargo tends to increase the demand elasticity on freight cost. As demand elasticity on freight cost depends directly on how the freight cost is determined, it is important to first be able to model and estimate freight cost correctly. Moreover, research on this topic has typically employed cost of goods carried as an exogenous variable affecting the associated freight cost. See Zarzoso and Wilmsmeier (2008). This is problematic as commodity price carried by bulk shipping is generally correlated with the residual error in the freight rate regression. We study the iron ore market and the closely associated freight shipping.

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 (see Wilmsmeier et al., 2006), types of cargo and unit value (see Zarzoso and Burguet, 2005; and Wilmsmeier and Zarzoso, 2010), weight, bulk, value and perishability of the product (see Palander, 1935) and competition, and insurance cost when freight cost includes freight insurance. 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. However, there had been no economic theory of how unit value of the carried goods would affect freight cost.

Iron ore is an important and major international commodity that has to be shipped from one port in the exporting country to another in an importing country. As indicated in Serapio (2016), steel making and its requirement of iron ores, as the key component, is predominant in infrastructure and industrialization growths. In 2016 and 2017 as reported in Ng (2017), China imported enormous amounts of iron ores from mines in Australia and Brazil including Vale SA and BHP Billiton Ltd. to meet demands in the steel production industry that had benefitted from rising profit margins. Chinese iron ore imports account for about 70% of world total. Hence Iron ore demand is driven in large part by China's industrial production.

On the other hand, iron ore imports to China are closely related to seaborne trade as these imports are shipped using huge dry bulkers or ore carriers. For a supplier of iron ore to ship the commodity across the oceans to China, the supplier quotes the goods price typically including freight and insurance (cif). The supplier would have arranged with a shipping company to ship the ores and would pay for the freight rate. Most of the Australian, Brazilian, and South African iron ores are shipped to the Qingdao port in China. Since the big production of shipping capacity post 2008, 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 filing for bankruptcy. 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 ores, coking coal for steel production, as well as other commodities such as minerals, grains, and fuel. Thus, understanding the economics of freight cost determination remains a key research issue.

We show by constructing two simultaneous equilibrium models for iron ore price per metric ton and for freight cost per metric ton based on fixed routes, that expected unit value of iron ore carried has a negative effect on freight cost. Each dollar increase in iron ore per dry metric ton would decrease ship freight cost by an average of 3 cents per metric ton, ceteris paribus. This negative effect is also observed in Zarzoso and Burguet (2005) Table 7 via the coefficient of weight-value. This result is also consistent with the idea of increasing demand elasticity on freight cost when the freight demand curve is highly convex and downward sloping. Unlike extant research we show the endogeneity of cargo cost in freight pricing and estimate our results using two-stage least squares panel regression, thus obtaining consistent estimates. We add contribution by also highlighting how endogeneity can easily arise with unobservable latent variables, and 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 the freight cost model in the transportation of one of perhaps the most important metal for China's industrial development.

In Section 2, we construct simultaneous equilibrium models of the international iron ore market and the dry bulk freight market on imports of the commodity to China. In Section 3, we collect monthly data and provide empirical estimation and tests of the linear models using panel regression method. In Section 4 we explain how some latent variables can cause iron prices to be endogenous in the determination of freight costs. The effect of iron ore price on freight cost is estimated using two-stage least squares method. Section 5 provides the conclusions.

add BDI into eq(1)Demand and eq(3)Equilibrium price.

2 Simultaneous Models

The demand equation for iron ores at each month t is represented as follows:

Demand

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

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. 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 assumed to be independent of ϵ_{Dt}. We postulate that the coefficients $a_2 > 0$.

As with many research studies, Bekaert and Hoerova (2014) showed VIX predicts economic activity and has high predictive power for financial instability. VIX is the ticker symbol for the Chicago Board Options Exchange (CBOE) Volatility Index. The VIX is a popular measure of the stock market's expectation of the S&P 500 index future volatility. It is traded on the CBOE and VIX is known as the "fear gauge" or the "fear index." 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. Thus $a_3 > 0$ in Eq.(1). VUX is also independent of ϵ_{Dt}.

The supply of iron ore at month t via the aggregated supply of ores from various international locations j as well as sources not linked to the exporting ports is represented by Eq.(2) below:

Supply

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

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

In equilibrium, $D_t^R = S_t^R = Q_t^R$ is the iron ore amount demanded D_t^R, supplied S_t^R, and thus also quantity shipped Q_t^R, aggregated across all routes j in month t. Equating Eqs. (1) and (2), the market-clearing iron ore price is:

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

where $\theta_0 = (a_0 - b_0)/(a_1 + b_1)$, $\theta_1 = a_2/(a_1 + b_1) > 0$, $\theta_2 = a_3/(a_1 + b_1) > 0$, and $\epsilon_t = (\epsilon_{Dt} - \epsilon_{St})/(a_1 + b_1)$. We assume this zero mean residual error is independent across time, but can be heteroskedastic.

Ship Freight

Consider the shipping of iron ores. Let $j = 1, 2, .., N$ be routes starting from j to Qingdao where $t = 1, 2, \ldots, T$ are times in months. Let P_{jt}^S be ship freight spot price rate on route j at month t in \$/ton paid by the exporter carrying the goods. This price is fixed on the carrying of iron ores at the different ports associated with j. The demand equation for freight at j at month t to carry iron ores is represented as follows:

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

where demand at time t at port j decreases with increasing freight rate at port j, but increases with China industrial production growth rate X_t. Iron ore price also affects freight demand negatively if its price increases. This is because the importer of iron ores, China, has an inventory stockpile of the ores. When iron ore market price is high, China importers may delay imports and draw down its inventory. When the iron ore price drops, then the China importers will demand more to replenish the stockpile. Thus iron ore prices will affect current shipping demand negatively. $c_1, c_2, c_3 > 0$. ε_{Dt} is the residual demand noise that is independent of industrial production growth, but is not independent of endogenous freight rate and may also be correlated with the iron ore price.

The supply equation for freight at j at month t is:

$$\boxed{S_{jt}^S = d_0 + d_1 P_{jt}^S - d_2 D_j - d_3 B_t + \varepsilon_{St}} \tag{5}$$

where D_j is the distance of the exporting port to Qingdao in terms of nautical miles, and B_t is the bunker fuel price in \$/ton. $d_1 > 0$. The more remote the cargo load point is from the destination, the higher is the risk in the delivery as weather, ocean conditions, and the longer voyage would escalate the risk. Hence remote exporting ports would see more shipping capacity shift to destinations that are closer. The supply capacity thus decreases with distance D_j from the destination port, and $d_2 > 0$. Higher bunker fuel price (high sulphur) implies it is more costly to operate the ship and will reduce supply of the shipping capacity, hence $d_3 > 0$. Both the distance and the fuel price are transformed by taking natural logarithms. ε_{St} is the residual supply noise that is independent of D_j and B_t.

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

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

where $\gamma_0 = (c_0 - d_0)/(c_1 + d_1)$, $\gamma_1 = c_2/(c_1 + d_1) > 0$, $\gamma_2 = d_2/(c_1 + d_1) > 0$, $\gamma_3 = d_3/(c_1 + d_1) > 0$, $\gamma_4 = c_3/(c_1 + d_1) > 0$, and $\eta_{jt} = (\varepsilon_{Dt} - \varepsilon_{St})/(c_1 + d_1)$. The residual error η_{jt} is assumed to be independent across time and across 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, 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, VIX. Their mean effects would be reflected in constants relating to ports or in coefficients of the distance variables across the ports.

At this juncture we suppose that the residual errors to the two equilibrium price systems, ϵ_t and η_t could be correlated contemporaneously. There could be common unobserved latent factors that can affect the iron ore price P_t^R and the freight rate P_{jt}^S simultaneously.

3 Estimation and Testing

Monthly iron prices and other macrovariables are collected from Thomson Reuters Datastream whereas freight prices indicating cargo as iron ores were obtained from Clarksons database. 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 the same port for that month. The variables data are collected for the sample period December 2013 to May 2019. Descriptive Statistics of the data Variables Used in the study are shown in Table 1.

From Table 1, it can be seen that freight rate is the most volatile in terms of ratio to its mean. Iron ore price, growth rate, VIX index are also relatively volatile. For freight rates, the rates are also different with respect to voyage distances, tending to increase with the distances.

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 regression may lead to spurious results unless the random variables in the linear regression are co-integrated. The unit root test results on

Table 1: Descriptive Statistics of Variables Used in the Study: iron-ore price in USD per metric ton, PRC industrial production growth rate, VIX index, natural log of distance in nautical miles, natural log of high Sulphur 380 bunker fuel, freight rates in USD per metric ton of cargo, and cargo volumes in metric tons. The sample period is from December 2013 to May 2019. Sample size is 264. 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 $	72.26	17.94	59.09	68.41	81.06
Growth Rate $\times 10^{-3}$	5.43	1.44	5.00	5.00	6.00
VIX Index	15.05	3.78	12.37	13.95	16.95
ln (Distance)	8.67	0.49	8.18	8.86	8.98
ln (Fuel Price)	5.95	0.30	5.80	5.96	6.17
Freight Rate $	9.62	4.88	5.90	8.18	12.32
Cargo Volume $\times 10^4$	20.82	5.40	17.00	18.39	22.99

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 0.25 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.

We run a linear regression based on Eq.(3) using White (1980)'s heteroscedastic consistent covariance matrix estimator (HCCME) for obtaining the inferences. The results are reported in Table 3. We also run an ADF unit root test on the estimated residuals of the regression to check for co-integration.

Note that in Eq.(3), the regressor is $-VIX_t$ so that a positive $\hat{\theta}_2$ in Table 3 indicated that when VIX_t increased, market iron ore prices decreased, supporting the fear phenomena that is well-known in financial markets as well as base metals commodity markets. The growth of China's production index is more significant in pushing up iron ore prices as seen in the positive $\hat{\theta}_1$ at p-value of 0.031. ADF statistic on estimated residuals $\hat{\epsilon}_t$ shows unit root is rejected at a

Table 2: Unit Root Test of Iron Ore price, Growth rate, and VIX index time series over monthly data from December 2013 to May 2019. Sample size is 264. 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.

	Iron Ore Prices $	Growth Rates	VIX Index
ADF-Statistics	-2.0857	-9.3395***	-5.0541***
p-Value	0.250	0.000	0.000
1%	-3.539	-3.535	-3.535
5%	-2.909	-2.907	-2.907
10%	-2.592	-2.591	-2.591

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

p-value of 0.064, so the regression is co-integrated.

For each month, various global 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 ores to Qingdao in China. The busy ports sometimes have up to over twenty different ships a month. During the sample period we study, from December 2013 till May 2019, there were eleven major routes shipping iron ores to Qingdao. However, for freight data available on a continuous basis for each month in the sample period of December 2013 to May 2019, there were only the ports of Dampier, Hedland, Saldanha Bay, and Tubarao.

Next we perform a multivariate (different j) multiple regression (more than one explanatory variable) on Eq.(6) by stacking observations $\left(P^S_{11}, P^S_{12}, P^S_{13}, \ldots, P^S_{1T}, P^S_{21}, P^S_{22}, P^S_{23}, \ldots, P^S_{2T} \ldots\ldots, P^S_{N1}, P^S_{N2}, P^S_{N3}, \ldots, P^S_{NT}\right)^T$ as the dependent vector. Similarly, the errors are stacked up such that its covariance matrix has clusters of different variances across j. Basically this is panel regression with fixed port treatment effect and 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 ores to Qingdao account for 74% of the total number of 5088 trips in over 50 ports in our sample. We also report the Hausmann test of null of random effects

Table 3: Linear Regression of Iron Ore Prices on Explanatory Variable based on Eq.(3). Sample period December 2013 to May 2019. Sample size of 66. The t-statistics are computed using White's HCCME. See White (1980).

Parameter	Estimated Coefficient	Standard Error	t-stats	p-Value
θ_0	64.994***	11.753	5.530	0.000
θ_1	3624.57**	1646.73	2.201	0.031
θ_2	0.814*	0.421	1.931	0.058
F-statistic	4.641***	p-Value	0.013	
Adj. R^2	0.092			
ADF-statistics Residual Error	-2.761*	p-Value	0.064	

Note: ***, **, *, indicate 1-tail 1%, 5%, and 10% significance levels respectively.

against fixed effects. The iron price variable used in the regressor is $-P_t^R$.

The results in Table 4 show that indeed random effect null is rejected at a significance level of less than 1%. Based on the fixed effect results, as postulated by the Eq.(6), increases in China's industrial production and economic activities during December 2013 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 port has positive correlation with freight rate, but the effect is not significant. Increases in bunker fuel oil increases freight rates significantly, a result that is intuitive and established in existing literature. However, iron ore price has negligible negative impact on freight rate, which is a surprising result. The Durbin-Wu-Hauman test if regressor iron ore price is exogenous rejected this null at a p-value of 0.001. Therefore, the small estimated coefficient of $\hat{\gamma}_4$ due to 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 projected iron ore prices as instrumental variables.

Table 4: Panel Regression of Freight Prices on Explanatory Variables based on Eq.(6). Sample period December 2013 to May 2019. Sample size 264. Port location is fixed effect. There are 4 port locations in the sample. The t-statistics are computed based on clustered effects. Hausman's test of H_0 : random effects against fixed effects is reported. Test if the iron ore regressor variable is endogenous is also reported using the Durbin-Wu-Hausman test statistic.

Parameter	Estimated Coefficient	Standard Error	t-stats	p-Value
γ_0	-44.875	32.921	-1.363	0.174
γ_1	95.911	112.63	0.852	0.395
γ_2	0.590	2.563	0.230	0.818
γ_3	8.220***	2.064	3.981	0.000
γ_4	0.0002	0.009	0.021	0.984
F-statistic	70.678***	p-Value	0.000	
R^2	0.525			
Hausman Test of H_0: Random Effect	16.137***	p-Value	0.006	
Durbin-Wu-Hausman Test of Iron price Endogeneity	20.800 ***	p-Value	0.001	

Note: ***, **, *, indicate 1-tail 1%, 5%, and 10% significance levels respectively.

4 Endogeneity of Iron Ore Price and 2SLS Estimation

In Eqs. (3) and (6), we see how equilibrium iron ore price and freight price of ships transporting the iron ores are determined. We see how in these two equations, China's industrial growth, which is observable, affects both the ore and the freight prices. The growth is also specified to be independent of residuals ϵ_t and η_t.

Suppose there are latent (unobservable) variables affecting market iron ore prices and the iron bulk carrier shipping rates simultaneously. For example, Chinese steel producers may decide on some months to use more iron obtainable from scrap metals. They will thus demand less of iron in the open market and also demand less of ships carrying the ores from other export countries. But we cannot observe such Chinese steel producers' decisions. Another example is where local political situation in the country with port j disrupts both iron ore production and supply as well as the related shipping supply in that country. We cannot observe the exact nature and timings of small disruptions from time to time. Yet another example could be some unobserved political interventions by an influential country to curtail supply of iron ores to China by applying brakes to both iron ore producers and shipping firms in a particular country that exports iron ores to China.

If the above variables were observable, then we can test their effects on both iron ore price and freight rate in Eqs. (3) and (6) by introducing them as additional regressors. They would play the role like the growth variable. However, as they are latent and not observable, their effects are contained in the residual variables ϵ_t and η_{jt} in Eqs. (3) and (6) respectively. Hence, ϵ_t and η_{jt} (for all j's or for some j's) are correlated and thus mutually dependent. This implies that iron ore price as regressor in Eq. (6) is correlated with and thus mutually dependent on the residual error η_{jt} (for all j's or for some j's). Presence of latent variables thus lead to endogeneity in iron ore prices in the regression of freight rate in Eq. (6). This leads to biased and inconsistent panel regression estimates in Table 4.

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.

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

and then re-run the panel regression using instead the following

$$P_{jt}^S = \gamma_0 + \gamma_1 X_t + \gamma_2 D_j + \gamma_3 B_t - \gamma_4 \hat{P}_t^R + \nu_{jt} \tag{7}$$

where the residual error ν_{jt} is now independent of all the regressors. Regressor $\hat{P}_t^R$ now acts like an instrumental variable that is independent of the residual error. The results of the panel regression in Eq. (7) are reported in Table 5. In addition we report the Hausman test of the null of random effect.

Table 5: 2SLS Panel Regression of Freight Prices on Explanatory Variables based on Eq.(7). Sample period December 2013 to May 2019. Sample size 264. Port location is fixed effect. There are 4 port locations in the sample. The t-statistics are computed based on clustered effects.

Parameter	Estimated Coefficient	Standard Error	t-stats	p-Value
γ_0	-43.065	30.187	-1.427	0.155
γ_1	193.18*	106.38	1.816	0.071
γ_2	0.543	2.463	0.221	0.826
γ_3	8.279***	1.764	4.694	0.000
γ_4	0.032***	0.011	-2.912	0.004
F-statistic	71.102***	p-Value	0.000	
R^2	0.526			
Hausman Test of H_0: Random Effect	9.684*	p-Value	0.085	

Note: ***, **, *, indicate 1-tail 1%, 5%, and 10% significance levels respectively.

In Table 5, Hausman's χ^2 test of the null of random effect rejects the null at 10% significance level. Using fixed effect on port locations, the panel regression stronger and more significant estimates of the positive impact of growth, the positive impact of bunker fuel price and the negative impact of expected iron ore price.

Each dollar increase in iron ore per dry metric ton would correspond to a decrease ship freight cost by an average of 3.2 cents per metric ton, ceteris paribus. This result is also consistent with the idea of increasing demand elasticity on freight cost when the freight demand curve is highly convex and downward sloping. The economic reasoning that arises out of the two market clearing systems is as follows. Increasing (decreasing) iron ore price would reduce (increase) the market demand of the ore by steel producers in China. For increasing market ore price, the producers can also substitute local scraps or use its inventory and slow down demand of imported ores. For decreasing market ore price, the producers can accelerate demand to build up inventory. Since most of the iron ores are carried by dry bulkers to Qingdao from overseas ports, demand for these ships are at the same time diminished (increased). The reduced (increased) freight demand would lead to decrease (increase) in the freight rates.

Each 1% increase in China's industrial production growth rate would correspond to an increase of \$1.93 freight rate per ton, ceteris paribus. Each \$1 increase in bunker fuel per ton would correspond to an increase in average freight rate of 38 cents per ton, ceteris paribus. Distance has a positive but not significant effect on average freight rate. This could partly be explained by the fixed treatment effect on the port locations. Compared with Table 4, the estimated coefficients for growth and expected iron price are now significant at 10% and 1% levels respectively. These results accord with the dual market systems in our econometric model.

Table 6: Tests on Estimated Residuals based on Eq.(7). Sample period December 2013 to May 2019. Sample size for estimated residuals of each port's average freight rate regression is 66. 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 $\sqrt{T}$ as standard deviation where T is the sample size.

Test	Estimate	p-Value
ADF-statistics of $\hat{\nu}_{1t}$	-3.933***	0.002
ADF-statistics of $\hat{\nu}_{2t}$	-3.522***	0.007
ADF-statistics of $\hat{\nu}_{3t}$	-5.292***	0.000
ADF-statistics of $\hat{\nu}_{4t}$	-5.291***	0.000
Sample correlation $(\hat{\epsilon}_t, \hat{\nu}_{1t})$	-0.452***	0.000
Sample correlation $(\hat{\epsilon}_t, \hat{\nu}_{2t})$	-0.442***	0.000
Sample correlation $(\hat{\epsilon}_t, \hat{\nu}_{3t})$	0.259**	0.018
Sample correlation $(\hat{\epsilon}_t, \hat{\nu}_{4t})$	0.224**	0.034

Note: ***, **, *, indicate 1-tail 1%, 5%, and 10% significance levels respectively.

To ensure that the panel regression system in Eq.(7) and Table 5 is not spuriously estimated, the estimated residuals $\hat{\nu}_{jt}$ are tested for unit root for each j. The sample correlations of the estimated residuals $\hat{\epsilon}_t$ from Eq.(3) and the $\hat{\nu}_{jt}$'s are also computed and tested on the null of zero correlations. The results are reported in Table 6.

The results in Table 6 show that ADF-test statistics reject the presence of unit roots in the estimated $\hat{\nu}_{jt}$'s, and hence establish the co-integration of the panel regression. The sample correlations show that zero correlation is rejected. This result provides robustness to our interpretation that the endogeneity of unit iron ore prices enters the two systems of simultaneous iron ore and freight prices via common latent factor(s) in their residual errors.

5 Conclusions

In this paper, we analyse how value of goods carried can affect the freight cost. Existing research indicated there has been no clear economic reason except the idea that higher goods value carried in the cargo tends to increase the demand elasticity on freight cost. Using simultaneous equilibrium in both the freight rate and iron ore markets, we can explain how iron ore unit prices negatively affect the freight rates of the dry bulkers carrying them. This is consistent with the popular notion that increased cargo value increases the demand elasticity of freight cost as the freight demand curve is downward sloping and possibly strongly convex. We show the endogeneity of the iron ore price and how an instrument variable can be constructed to estimate its impact.

We show how unobservable latent variables can easily arise to simultaneously affect both the market iron ore price as well as the freight rate of ships carrying those ores as exports to China. The presence of iron ore price as a regressor in the freight cost immediately makes it an endogenous variable. We thus point to the importance of careful treatment of commodity price effect when two market systems are working alongside. This provides an important understanding of the freight market serving perhaps the most important metal in the industrial development of China, the second largest economy in the world. It is however, also important to note that the price modelling may differ with another mineral commodity that is not so closely tied with fixed shipping routes.

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