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An analysis of iron ore prices during the latest commodity boom

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Abstract
This paper performs a quantitative analysis of iron ore prices, and is an extension of Wårell (2014), which analyzed the change in iron ore pricing regime on iron ore prices using data from 2003 until September 2012. However, considering that the iron ore market still was characterized by surging prices in 2012, it is of interest to see if the same conclusions hold today when the latest commodity boom has come to an end. The quantitative analysis uses monthly data between January 2003 and June 2017, and performs both statistical tests for structural breaks and a reduced price regression of the most important factors for iron ore prices during the time period. The overall results indicate that the change in pricing regime does not have a significant impact on the iron ore prices when extending the time period; rather, it is the end of the commodity boom in 2014 that is picked up as a structural break in the price series. Furthermore, results regarding whether the variables are cointegrated are more inconclusive when analyzing the entire commodity boom. However, the result that GDP growth in China has had the strongest impact on iron ore prices is though robust when extending the time period. To conclude, even though the commodity boom now has come to an end the developments in China still seems to be the most influential factor determining international iron ore prices.

Keywords Iron ore prices · Commodity boom · Structural breaks · Cointegration

Introduction

The main purpose of this paper is to perform a quantitative analysis of iron ore prices during the latest commodity boom. The main motivation of the study is to investigate which factors that can explain the iron ore price movement during a time period that is characterized by dramatic changes in the price series. Wårell (2014) performed a similar study, based on monthly data between January 2003 and September 2012. The motivation for the study was the breakdown of the producer pricing system in the end of 2008. Before that the iron ore prices were mainly characterized by an annual negotiation system, i.e., a benchmark price were negotiated annually between large producers and consumers in the two dominating regions. However, during the latest commodity boom, this pricing system broke down, and today, the pricing regime for iron ore is based on spot market prices. One of the main explanations for the breakdown of the benchmark system was

the growing importance of the Chinese market, which is also evident considering that the benchmark system resulted in a FOB price, while the spot market indices are mostly based on CFR China prices.[1] The iron ore pricing system today is based on several indices, which are developed by benchmarking companies following certain systematic procedures.[2] The main reason for the difficulty to define one price for iron ore is due to its heterogeneous nature; i.e., the quality between different iron ores varies considerably and premiums for high-grade ores are still based on negotiations. In recent years, the difference in prices between different grades of ores has increased, indicating the need to clearly state which quality the price refers to Löf and Ericsson (2017).

The main conclusion from the quantitative analysis in Wårell (2014) was that the change in pricing regime did not have a significant impact on the iron ore price in the econometric model. Iron ore prices, GDP growth in China and the

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[1] FOB is a price "free on board," which implies that the cost of freight is only included to a certain port. CFR indicates that the cost and freight is included in the price; i.e., the seller must cover the cost of transporting the ore to a destination.

[2] There are five indices regularly quoted in the media as the iron ore price: Metal Bulletin index (62% Fe, CFR Tianjin Port, China), Platts index (62% Fe, CFR China), The Steel Index (62% Fe, CFR China), IRESS (61.5% Fe, CFR Australia), and CME Group Futures (62% Fe, CFR China).

freight rates were found to be cointegrated, and the short-run results indicated that GDP growth in China had the strongest impact on the iron ore price series between 2003 and 2012. However, as this study was performed when the most recent commodity boom was still, ongoing questions regarding the validity of these results could be made. Could it be that the results obtained in Wårell (2014) are significantly affected by the fact that they were estimated during an ongoing commodity boom? This paper will perform a similar analysis to Wårell (2014) in order to see whether the conclusions of the effect on iron ore prices still holds. The quantitative analysis of iron ore prices will thus be performed in order to investigate the most important factors influencing prices during the entire commodity boom.

The most recent commodity boom, which seriously affected prices for many important primary commodities, was more persistent than commodity booms in the past. The prolonged duration of this commodity boom attracted a lot of attention and discussion regarding whether it represented a so called *super cycle* (Heap 2005; Cuddington and Jerrett 2008). According to this literature, a super cycle is defined as a prolonged price cycle for a broad range of primary commodities, with an upward trend for roughly 10 to 35 years, making a complete cycle last for about 20 to 70 years. It is further argued that the super cycle is demand driven, and that it will last for as long as the strong demand growth continues. The proponents of the super cycle thesis see the industrialization and urbanization of China as the main cause for the current super cycle. Other views of the prolonged duration of the most recent commodity boom are rather that an extended investment cycle has been the main driver (Radetzki et al. 2008; Radetzki 2013; Radetzki and Wårell 2017). This view argues, in line with standard microeconomic theory, that the high-commodity prices prevail until sufficient capacity to meet the accelerated growth in demand is installed. When using a simplified example of different investment cycles Radetzki et al. (2008) illustrate that a resource boom can last for 12 to 15 years, due to investment lags and persisting capacity constraints. We can conclude today, in mid-2017, that the boom is over and that the high prices lasted until about 2014, when sizable new iron ore capacity was finally brought to the market. The reduced demand growth caused by a slowdown in China's economic expansion in recent years of course also helped to punctuate the boom.

The paper proceeds as follows: the next section will present the development of the latest commodity boom, with a special focus on iron ore prices. The following section will focus on answering the question regarding if the change in pricing regime has had a significant effect on the iron ore prices when using an extended time period to incorporate the entire boom, both using tests for structural breaks and a reduced regression model. Furthermore, the analysis of iron ore prices is also extended to include breaks for the end of the commodity boom, as well as including more explanatory variables to the regression analysis. In the last section, some concluding remarks are made.

Iron ore prices during the commodity boom

This part draws to some extent from Sect. 6 in Radetzki and Wårell (2017), which discusses important characteristics of commodity booms. Of special interest here is of course the latest commodity boom, which started about 2004 and has just recently run its course. This section will start with a more general discussion of the commodity boom, and will subsequently discuss the situation in the iron ore market. Commodity booms are defined for the purpose of the present analysis as a sharp simultaneous increases in the real price of a broad group of commodities. The most recent commodity boom was importantly triggered by a demand shock. Producers were caught unaware, with little spare production capacity, so prices in many markets exploded. The demand shock was largely due to fast macroeconomic expansion, mainly in China, in the early years of the boom, as is illustrated in Table 1.

The inflation during the period covered by the table is strikingly lower than that recorded in previous time periods when commodity booms have occurred. The MUV index, reported biannually by the World Bank, seems to be more appropriate than other indices for deriving constant dollar prices of commodities. Simply expressed, it provides the (inverse) size of the basket of manufactured exports that could be obtained for one US dollar at different times. It overcomes the problem of exchange rate changes not immediately reflected in export prices that would arise with the use of a national price index. And since it relates to manufactured exports, it provides an appropriate counterpoint for measuring the price changes of raw materials in international trade. In the 1950s and 1960s, the World Bank among others referred to the MUV index as an "index of international inflation". In more recent times, the index has become less representative of global inflation trends, since it does not cover the increasingly important manufactured exports from non-OECD countries, nor prices of the sharply expanding trade in services.

When measured by the MUV index, international inflation works out at an anemic annual average of 1.5%. This is noteworthy, since the 15-year period displayed has been characterized by relatively high global economic growth, averaging 2.8% for the world as a whole. It is further noted that the MUV index displays negative inflation from 2012 and onwards, indicating that the development of raw materials in international trade has been weak since the commodity boom has come to an end. It is clear that the commodity boom has been forcefully driven by developing countries, and especially China, and not by the more mature economies. The average yearly

Table 1 Growth patterns during the commodity boom (percent)

Year	MUV index	GDP growth world	GDP growth OECD	GDP growth China
2002	−1.	2.1	1.6	9.1
2003	5.2	2.9	2.0	10.0
2004	6.8	4.5	3.2	10.1
2005	3.1	3.8	2.7	11.4
2006	2.5	4.3	3.0	12.7
2007	6.1	4.3	2.5	14.2
2008	7.8	1.8	0.2	9.7
2009	−6.2	−1.7	−3.5	9.4
2010	3.7	4.3	2.9	10.6
2011	11.0	3.2	1.8	9.5
2012	−0.7	2.4	1.2	7.9
2013	−0.4	2.6	1.4	7.8
2014	−1.5	2.8	1.9	7.3
2015	−9.6	2.7	2.3	6.9
2016	−4.0	2.4	1.7	6.7

Source: IMF 2007a, *World Economic Outlook*, 2017; OECD, *Economic Outlook*, 2017; World Bank, *Commodity Price Data*, 2017

growth in the OECD region between 2002 and 2016 has been a moderate 1.7%, compared to the rampant expansion in China, where economic growth attained an annual average of 9.6%. China's share of global GDP in 2016 (PPP terms) was assessed by the IMF (2017) at 18.3%, which implies that the country now has surpassed both US and the European Union's share of global GDP. This implies that China today represents the largest economy in the world. However, when considering GDP per capita, the country is still far behind both the USA and the countries in the European Union. There is thus still potential for continued GDP growth in China, considering its sheer volume. The population in China is almost 1.4 billion people, which is more than four times as many as the population in the USA and about 2.7 times more than the population of the European Union.

Figure 1 presents a selection of monthly commodity price indices between January 2005 and September 2017. The aggregate commodity price index experienced a steady increase from 2003 and onwards, and reached a peak at 220 (2005 = 100) in July 2008, just before the onset of the financial crisis. Also, the energy index reached its peak in that month, at an even higher level, as is illustrated in Fig. 1. However, the metal and mineral price behaves somewhat differently both considering that it takes off in 2006, but also since the index was not severely disturbed by the financial crisis. The index dipped from 175 in August 2008 to a low of 106 in March 2009; it then rose quickly to attain an even higher peak in the beginning of 2011 (at 256 in February that year). Between 2012 and 2015, we can see that all three indices displayed move at similar levels; the metal and mineral index was even below the other two. However, after 2015, the metal and mineral index is clearly higher compared to the energy price index.

A closer scrutiny of the years during the financial crisis throws some light on its price impact. First, on a global scale, the recession, even if it hit hard in the end of 2008, was short and not very deep, as is evident from Fig. 2. Only in 2009 did global output contract, but already in 2010, it bounced back to a growth over 4%. Second, only mature economies were seriously afflicted, with two consecutive years of growth substantially below trend. Third, the recession was much weaker in China (which, as noted, since some time dominates commodity demand growth), and in the other developing countries of the world as well. Thus, the boom persevered despite the occurrence of the 2008–2009 recession, because of continued fast growth mainly in China, and other countries in emerging and developing Asia.

Some clarifications to the developments of the commodity boom are though called for. *First*, not all events of sharply accelerating macroeconomic performance give rise to booming prices in commodity markets. Other preconditions have to prevail, e.g., a tight production capacity situation and relatively small inventories. Such preconditions typically emerge after prolonged periods of weak commodity prices which discourage investments in capacity expansion and in still a sense that supply is secure, and that there is limited need for inventory holding. This has clearly been the case for many primary commodities prior to the beginning of the century. Many commodity prices had been severely depressed for nearly three decades (see e.g., Humphreys 2015).

Historically, it has been assumed that it takes about 5 years on average for new green field capacity to be in place in minerals and metals industries (see, e.g., Radetzki and Wårell 2017). The argument was that 5 years should be enough to rectify market imbalances caused by unexpected

Fig. 1 Monthly commodity price indices in constant US$, 2003–2017. 2005 = 100. *Source*: IMF, commodity prices on the web
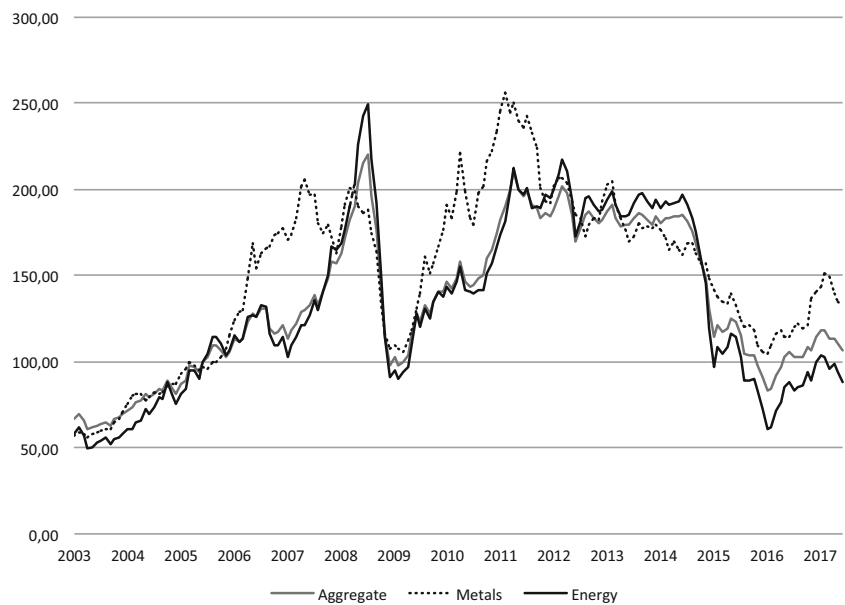
spurts in demand. However, this assumption has proved wrong in the latest commodity boom. Investments are subject to a variety of lags, comprising the time to bring together needed financial packages, to overcome various regulatory impediments, including increasingly restrictive environmental legislation in recent times. Adding to this the time needed to overcome the investors' unpreparedness to act, due to the history of depressed prices and general lack of interest in the mining industry, it is clear that the latest commodity boom has lasted longer not only due to a persevering strong demand, but also due to a slow response in supply. Today, when new supply has entered many commodity markets, the fundamentals between supply and demand seem to be more in balance.

When studying individual mineral and metal commodities behavior during the boom, we note that the situation in the iron ore market was extreme. Figure 3 presents price indices for aluminum, copper, nickel, and iron ore (January 2003 = 100). Here, we can clearly see the breakdown of the producer pricing system for iron ore prices in the end of 2008, as the price volatility increases considerably after that. We further note that the iron ore prices takes off about the same time and reach highs that the other mineral and metals are not even close to. The main explanation for the extreme increase in iron ore prices in 2009 is that the demand from steel producers, predominantly located in China, could not be met with existing supply. In 2009, the Chinese government made a massive stimulation to the Chinese economy, which boosted the demand from the steel industry and in turn put an upward pressure on iron ore prices (Ou 2012). Thus, the supply shortage forcefully drove iron ore prices, and it was not until 2014

Fig. 2 Annual growth of GDP. Percent. *Source*: IMF, World Economic Outlook, 2017; OECD, Economic Outlook, 2017
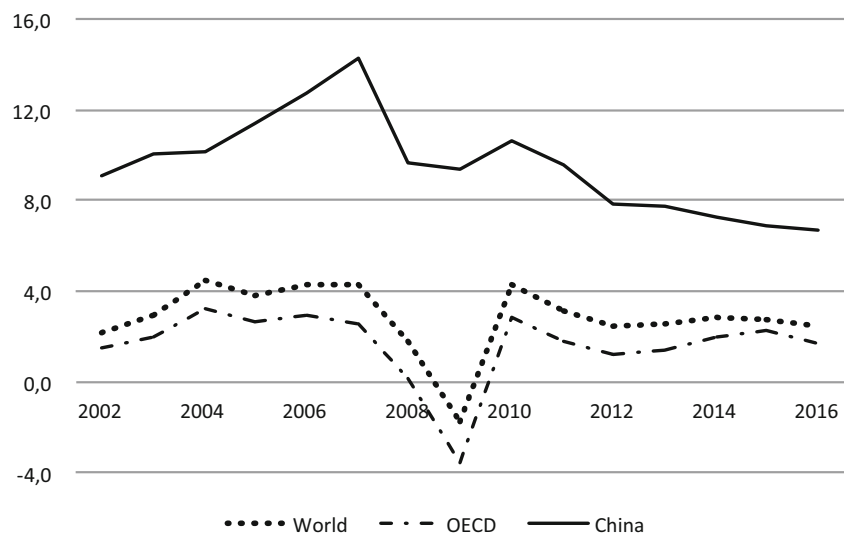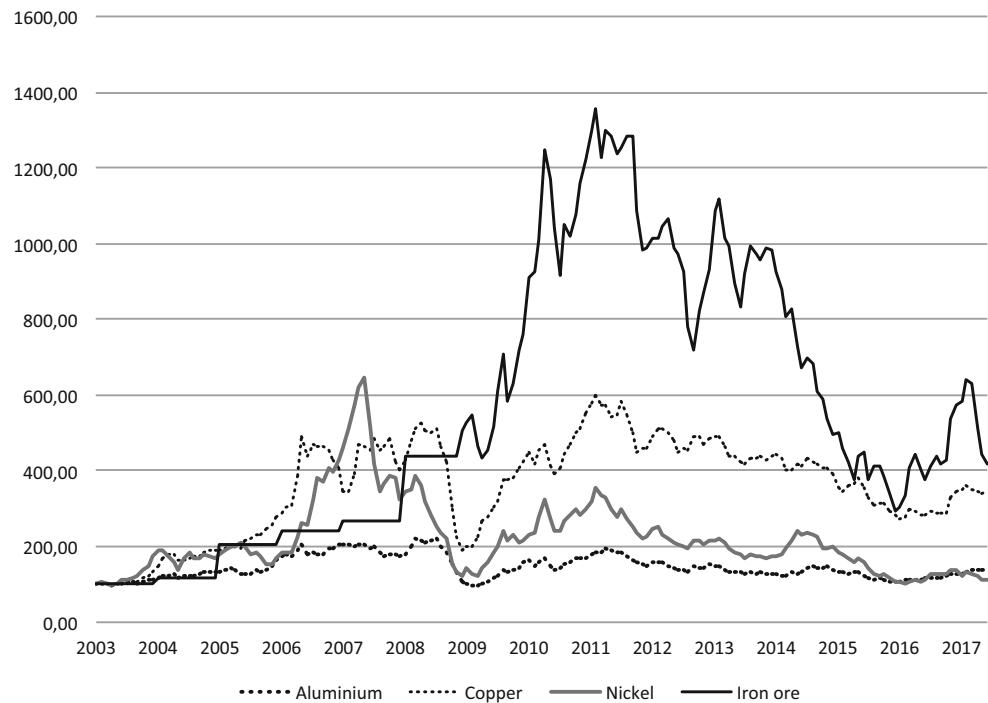
Fig. 3 Monthly commodity prices in constant US$ (Jan 2003 = 100), 2003–2017. *Source*: IMF, commodity prices on the web

when large amounts of new capacity were brought to the market that the iron ore prices started to converge to the same levels as the other mineral and metals.

Considering the extraordinary behavior of iron ore prices during the latest commodity boom an investigation of the most important factors influencing the price during the entire commodity boom is called for. The quantitative analysis in the next section will depart from Wårell (2014), who investigated the iron ore prices until September 2012, in order to see if the conclusions regarding important explanatory factors of the iron ore prices still hold when the commodity boom has come to an end.

Quantitative analysis of iron ore prices

The quantitative analysis of iron ore prices is performed between January 2003 and June 2017. Similar to Wårell (2014), we will start to investigate whether the change in pricing regime has had a significant effect when extending the time period to incorporate the entire commodity boom. The analysis in this part is thus centered on different statistic tests to detect structural breaks in the iron ore price series, were both exogenously determined breaks, as well as endogenously determined breaks, will be tested for. The analysis will then continue by performing a reduced price regression, where it is assumed that iron ore prices is a function of a number of exogenous variables that affects the demand and supply of iron ore. The analysis will include a simple discrete dummy

variable (0/1) that can be used to test if the change in pricing regime has had a significant effect on iron ore prices.

Tests for structural breaks

The price series can be divided in two subsections, before and after the introduction of spot prices as is illustrated in Fig. 4. The price data represents monthly prices of Chinese imported iron ore fines (62% Fe spot CFR Tianjin port) presented in US$ per metric ton (retrieved from International Monetary Fund (IMF), 2017-09-18). The price series thus represents import prices where the cost of transportation is included. However, in Wårell (2014), it was discussed that before 2009, the IMF price series most likely does not represent CFR prices, as the spot freight prices increased tremendously in 2007–2008 something, which was not reflected in the iron ore price. A new price series was therefore calculated, using the benchmark prices for iron ore (as reported in UNCTAD 2012) and adding the cost of spot freight rates to the iron ore price series until October 2009 (data from Drewry Shipping Consultants).[3]

Figure 4 shows the iron ore price series, both as presented by IMF and as calculated using benchmark prices of iron ore and then adding relevant spot freight rates. We can thus see that producer prices are more stable than spot prices when

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[3] The new price series represents benchmark prices adding transportation costs until October 2009, since this is about the time when most producers left the benchmark system for spot market price system. The calculation use spot freight rates between Brazil and China, thus not reflecting that the transportation costs differ depending on the source of origin.

Fig. 4 Iron ore prices in US$ per metric tonne 2003–2017. *Source*: IMF, commodity prices on the web
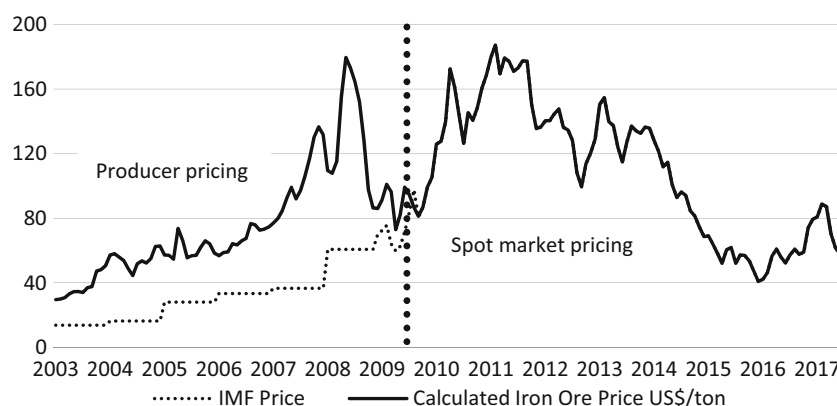
studying the iron ore price series retrieved from IMF, which is not surprising given that the prices before 2009 was negotiated yearly. However, when studying the calculated iron ore price series (when spot transaction costs is added), we cannot conclude that it is the move from producer pricing to spot market pricing that was the cause of the increased price volatility. The volatile situation for shipping freight rates seem to have caused volatility for the iron ore consumer, even before the spot market pricing system was in place. It is though worth noting that the general perception in the industry is that the iron ore price volatility has increased since 2009, also when taking the freight costs into account.

The real iron ore price series is constructed by using the Producer Price Index for OECD total, 2010 = 100. The motivation for using this index when deflating the nominal iron ore price series is to use an index that behaves similar to the MUV index, which unfortunately is only updated biannually. Thus, we want to use an index that measures the price changes of iron ore in international trade. Producer price indices measure the rate of change in prices of products sold as they leave the producer. They exclude any taxes, transport, and trade margins that the purchaser may have to pay. PPIs provide measures of average movements of prices received by the producers of various commodities.

Table 2 shows the test statistics for the calculated iron ore price series, both for nominal and real prices. The first part of the table presents the descriptive statistics of the nominal price

series, and the second part presents the equivalent for the real price series. The variance is often used as a measure of how stable a time series is, as it explains the variation of the series to the calculated mean. When dividing the price series in two sub-periods, the first between January 2003 to November 2008 and the second between December 2008 and June 2017,[4] we note that the variance of the price series are lower when the producer pricing system was dominating the market. When examining the real price series, i.e., when using constant 2010 prices, it is noted that the variance in the price series is reduced somewhat compared to the nominal prices. When dividing the price series in two subsamples, the same conclusion as above holds, i.e., the variance for the time period representing producer pricing is somewhat lower.

A Chow test is performed for both the nominal and real iron ore price series with the purpose to verify that there is an improvement in the fit from dividing the price series in two subsamples (producer and spot market prices). The calculated structural change test performed in Stata, and when using economic growth in China as an explanatory variable for iron ore prices, indicates that there is a structural break in the iron ore price series about the time when spot market was introduced. The F value for the nominal price series is 174.24 and the equivalent for the real price is 157.14, and these are well above the critical value of F which is 4.79 at 1% significance level.

Statistical tests for endogenously determined structural breaks in the iron ore price series are also performed in order to provide a preliminary indication to whether there are reasons to suspect that the change in pricing regime has caused a structural break in the price series. It is further of interest as this was found in Wårell (2014), i.e., when studying iron ore prices until September 2012. Considering that we deal with time series data, we also need to check if the variables are stationary. A variable is stationary if its mean and variance

Table 2 Summary statistics

Variable	Obs	Mean	Standard deviation	Variance	Min	Max
Nom price	174	94.65	41.65	1734.65	29.63	187.18
Producer	71	75.41	35.82	1282.93	29.63	179.41
Spot market	103	107.92	40.33	1626.66	40.88	187.18
Real price	174	94.18	37.55	1409.94	36.42	179.77
Real producer	71	81.77	32.70	1069.53	36.42	176.13
Real spot	103	102.74	38.42	1476.17	39.20	179.77

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[4] The motivation for the chosen break date (November 2008) is that this is about the time when the long-term contract pricing was abolished in favor of spot market pricing. This is further when the price series under inspection started to report the spot market prices instead of the contract prices. The separate time periods are thus named after the dominating pricing mechanism, i.e., producer and market pricing.

do not change over time, and non-stationary if this assumption does not hold. A non-stationary time series is said to contain a so-called unit root, i.e., a process that evolves over time. A structural break in a time series represents a change as a result of some unique economic event, e.g., a change in pricing regime from long-term contracts to spot market pricing. Structural breaks are defined as when there is a permanent effect on the pattern of the time series (Byrne and Perman 2007). Thus, when performing tests for unit root with structural breaks, it is possible to endogenously identify when a break in the time series occurred (Zivot and Andrews 1992).

The Zivot and Andrews test for one structural break chooses a break date where the t-statistics for a break point is at a minimum. This is where there is the strongest evidence against the null hypothesis of unit root. For the real iron ore price series, the null hypothesis of unit root cannot be rejected given a minimum t-statistics of -3.51, January 2014 (critical value -4.80 at 5% significance level). The result for the nominal price level provides the same result, i.e., that the break in the intercept occurs in January 2014. Interestingly, we note that if we only allow for one structural break, the price series detects the break about the time that the iron ore prices started to decline rapidly (see Fig. 4). This is also confirmed with the Clemente et al. (1998) test for one endogenously determined structural break, both the io and ao model confirm unit root and structural breaks at March 2014 and May 2015, respectively.[5] This is in contrast to the findings in Wårell (2014), when the structural break chosen by the statistical test was about the same time as the movement from producer to spot market pricing, i.e., in the end of 2008.

Considering that a visual investigation of the iron ore price series in Fig. 4 indicate that there might be more than one structural break during this time period, the Clemente et al. (1998) tests that allow for two endogenously determined structural breaks have also been performed. The results from the io model shows that the null hypothesis of unit root cannot be rejected given t-statistics of 3.51 in January 2007, and -4.03 in March 2014 (critical value -5.49 at 5% significance level). The results from the ao model also overwhelmingly indicate that we cannot reject the null hypothesis of a unit root in the price series, and it selects optimal breakpoints in June 2007 and July 2014. Thus, the results when extending the iron ore price series to June 2017 indicates that the change in pricing regime is not picked up as a structural break for the price series; rather, it seems as it is the dates around large changes in the market, especially the time when the commodity boom punctuated in 2014, that is picked up as a structural change in the price series.

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[5] The innovative outlier (io) model assumes that the change in the series affect the level of the series gradually. The additive outlier (ao) model assumes that the change in the series is instantaneously, i.e., that there is a sudden change in the mean that does not affect the dynamics of the series.

Reduced price regression

The previous analysis for structural breaks in the iron ore price series did not indicate that the change in pricing regime was picked up as a structural change. However, we are still interested in analyzing if the change in pricing regime has had a significant effect on the iron ore prices. An analysis of the effects from a change in pricing regime has to control for other effects that has influenced the iron ore price during this period. Economic theory on the supply and demand of iron ore is used to set up reduced price model for iron ore prices (see, e.g., Tilton 1992; Torries 1988; Wårell et al. 2013). Thus, the price equation in reduced form is derived from a simple equilibrium model, where the supply is assumed to be equal to the demand in the market.

First, it is important to consider that iron ore does not constitute an end product in itself; rather, it can be seen as an input used to produce steel. The *demand* for iron ore is therefore highly dependent on the demand for steel, given that almost all iron ore is used in steel production (even though steel can also be produced by scrap, which can thus be seen as a substitute to iron ore). The demand for iron ore can thus be derived from the demand for steel. Income, measured by the world GDP growth, is the variable with the largest impact on the demand for steel. Generally, in situations of high GDP, growth (booms) demand for steel increases, and thus the demand for iron ore. Conversely, when there is a recession, or slowdown in GDP growth, the demand for steel falls, and the effect is thus a decreasing demand for iron ore. The relation between GDP growth and steel demand is also dependent on the structure of the countries industry its maturity in terms of level of development. The current increase in demand for iron ore in developing countries such as China and India is strongly related to the increase in GDP per capita in these countries. The increasing demand for steel (and iron ore) stems both from an increase in infrastructure and industries in the countries, but also from a growing middle class which thus demand more steel intensive products such as cars and kitchen inventories. Given this, the first explanatory variable used to set up the reduced price regression is GDP growth in China.

Another important factor when analyzing iron ore prices is the cost of freight. As iron ore is a bulk product, which is traded internationally, the cost of freight will affect the end consumer price. Furthermore, considering that the iron ore prices are relatively low compared to the final end product (steel), the transportation cost constitutes a rather large share of the final cost for the consumer. The freight rate for the dry bulk market is therefore important to consider when analyzing the final imported iron ore price. The second explanatory variable used to set up the reduced price regression is therefore freight cost.

Turning to factors that affect the *supply* of iron ore, we would like to find data that matches the supply of iron ore in the world market. It is assumed that the short-run supply curve

reflects the sum of all the production of iron ore in the world. Of special interest here is of course traded iron ore as the used price series represents the price for internationally traded iron ore. Export data from major producing countries is therefore used to reflect the supply of iron ore in the world market. Another factor that analysts often discuss as important for iron ore prices is China's import of iron ore. Thus, in order to reflect the supply side, data of export and import have been collected.

However, considering that we are interested in comparing our results to Wårell (2014), the initial regressions will not include a variable reflecting iron ore supply, as this was not specified in the equation presented. The reduced price model specified in Wårell (2014) is

$$\ln Price = \alpha_1 + \alpha_2 \ln GDP\ growth\ China + \alpha_2 \ln Freight$$
$$+ \alpha_3 MD + \varepsilon \tag{1}$$

The iron ore price series that represent the dependent variable in Eq. (1) are monthly real prices of Chinese imported iron ore fines (62% FE spot CFR Tianjin port) collected from the IMF (IMF 2017b, retrieved 2017-09-18). Furthermore, the price series that is used in the regression represents the new calculated price series used when testing for structural breaks, as we see this price series as a better representation for the iron ore price and this price series is also used in the analysis in Wårell (2014). The main impact on the iron ore prices is here assumed to be GDP growth in China as explained above. Monthly GDP growth data is however difficult to get hold of so presented here is quarterly real GDP growth rate in China (retrieved 2017-09-18 from OECD.stat 2017). A prior assumption is that there is a positive relationship between GDP growth in China and the iron ore price, which thus implies that when GDP growth in China increases so does the iron ore price and vice versa. As explained above, another important factor influencing the iron ore price is the freight rate. Since the cost of freight is included in the price (CFR), we expect that an increase of the freight rate cause an increase in the iron ore price. The data on freight rates are the Baltic Dry Index (BDI) from the Baltic Exchange (retrieved 2017-09-18), which presents an assessment of the price of moving major raw materials by sea. A dummy variable (MD) is also included in Eq. (1), which identifies the introduction of spot market prices in December 2008 (with the value 0 before December 2008 and 1 after). The log-linear function form implies that the estimated coefficients can be interpreted as elasticities.

Given that the real iron ore price series is non-stationary (as is indicated in the previous section), a normal OLS regression will produce biased estimates and the standard errors will be invalid. As non-stationary series are common when analyzing time series data, all variables that will be included in the econometric analysis have therefore been tested for stationarity using the Zivot and Andrews test for one structural break allowing for a break in the intercept. The results from the tests are presented in Table 3. The tests are performed on the natural log of the time series. The results show that all variables tested are non-stationary, and thus contain a unit root. This implies that tests for cointegration can be performed.

Engle and Granger (1987) have developed a simple test which detects cointegration between non-stationary variables. This test was performed in Wårell (2014) to detect the existence of cointegration between the tested variables. Cointegration exists if independent non-stationary variables together will follow a long-run equilibrium relationship. In order to test for cointegration, perform a linear regression, and test the resulting residuals for unit root. If the residuals from the linear regression contain a unit root, the presence of cointegration cannot be confirmed. However, if the null hypothesis of a unit root in the residuals can be rejected the variables tested are believed to be cointegrated, and thus follow a long-run equilibrium relationship. The regression performed is as specified in Eq. 1. The regression is performed with and without the inclusion of a time trend. The results from the regression are summarized in Table 4.

The results from the regression, without a time trend, shows that all variables are statistically significant, and have the expected sign. A 1 % increase of GDP growth in China leads to a 1.46% increase in the real price of iron ore. The freight rates also have a significant impact on the iron ore prices, as a 1 % increase of the freight index lead to a 0.23% increase in iron ore prices. We can further see that the market dummy is statistically significant, indicating that there is a significant effect on the iron ore price due to the change in pricing regime. Thus, all of the variables are statistically significant and we can confirm the existence of an effect on the iron ore price due to a change in the pricing regime. When focusing on the results from including a time trend, we get similar results. It is though noted that the time trend is not statistically significant, and also that the fit of the model (as measured by the R-squared) is only moderately increased. Considering the R-squared values, it is noted that the regressions specified have relatively high explanatory power, considering that over 60% of the variation in the price are explained by the variables. However, when comparing these results to Wårell (2014), the R-squared values are considerably lower (as they presented regressions with R-squared values of about 90%), which makes us believe that we need to include more explanatory variables to the regression when we have extended the iron ore price series.

To test for cointegration, the residuals from both regressions are saved and tested for unit root. Considering that structural breaks are confirmed in the time series, Zivot-Andrews test for unit root allowing for a break has been conducted on the saved residuals from both models. The minimum t-statistics of −

Table 3 Zivot-Andrews test for unit root

Variable	Opt lag	T-Stat	Critical value, 5%	Date	Conclusion
Real price	2	− 3.627	− 4.80	January 2014	Unit root
GDP China	0	− 3.589	− 4.80	October 2011	Unit root
Freight	1	− 4.701	− 4.80	November 2010	Unit root

4.382 at December 2008, and − 4.129 at the same month and year, for respective model does not indicate that the variables are cointegrated as the critical value at 5% significance level is − 4.80. Thus, the test statistic does not indicate a rejection of unit root in the residual from the price model, and it can therefore not be confirmed that iron ore prices, GDP growth in China, and freight rates are cointegrated when regressed with a market price dummy variable.

A specific test for cointegration that allows for structural shifts is also performed. The residual-based test of Gregory and Hansen (1996a, 1996b) is used, as it allows for series with regime shifts. The results from the Gregory-Hansen cointegration test is somewhat inconclusive, since when allowing for a break in the constant, the slope and the trend the null of no cointegration can only be rejected at 5% level (at break point May 2012), given a ADF test statistic of − 5.84. If only allowing for shifts in the intercept, or intercept and trend, the test statistics does not indicate that the three variables are cointegrated.

Even though the results for cointegration are not conclusive, we decided to perform an error-correction model (ECM) in order to analyze the short-run adjustments to the long-run equilibrium relationship. The error-correction model as presented by Engle and Granger (1987) and explained in Enders (2010) is specified as follows:

$$\Delta lnPrice = \alpha_1 \Delta lnPrice_{t-1} + \alpha_2 \Delta lnGDP + \alpha_3 \Delta lnFreight$$
$$+ \alpha_4 MD + \alpha_5 EC_{t-1} \qquad (2)$$

Thus, the first differenced iron ore price series is regressed on the lagged level of the on the own first difference, the first differenced GDP growth in China, the first differenced freight rate, and the market price dummy variable. The error-correction term is represented by EC in Eq. 2, and is specified as the lagged residuals from the regression of Eq. 1. The EC term captures the deviation from the long-run equilibrium and the coefficient α_5 is often denoted as the speed of adjustment term, which indicates how long it takes for the time series to move back to the equilibrium level in case of a short-run deviation. The coefficients α_1, α_2, α_3, and α_4 represent the short-run counterparts to the long-run solutions in Eq. 1 (presented in Table 4). The result from the above specified equation both when including a lagged level of the first differenced iron ore price is presented in Table 5.

Interesting to note is that many of the short-run response parameters are statistically significant (at least at a 5% significance level), and display the expected sign. The result of a price change in iron ore prices the preceding time period is adjusted for by 16% in the following time period. The result for the GDP growth shows that a change in GDP growth is reflected by 30% in the change in iron ore price change. A change in freight rates is reflected in the change in iron ore price change by about 13%. The market dummy variable is not statistically significant, in the model when a lagged price change variable is included. A regression when excluding this variable, presented on the right side in Table 5, does not improve the findings. The speed of adjustment parameter is not statistically significant, which thus confirms the conclusion that the three variables are not cointegrated.

To summarize, when analyzing the iron ore price series in order to see if the conclusions from Wårell (2014) hold when extending the price series to June 2017, i.e., to include developments after the commodity boom has ended, some of the

Table 4 Regression results

Variable	Model without time trend		Model with time trend	
	Coefficient	t-stat	Coefficient	t-stat
Constant	− 0.98*	− 2.88	− 1.82*	− 2.75
GDP growth China	1.46*	8.99	1.50*	9.14
Freight	0.23*	5.62	0.25*	5.82
Market dummy	0.88*	15.02	0.80*	10.38
Time trend			0.001	1.48
R-squared	0.62		0.63	
DW	0.27		0.27	

Statistical significance at *1% level, **5% level, and ***10% level

Table 5 Error-correction regression results

Variable	Model with lagged price		Model without lagged price	
	Coefficient	t-stat	Coefficient	t-stat
Δ Price $_{t-1}$	0.16**	2.31		
Δ GDP	0.30*	2.59	0.33*	2.82
Δ Freight	0.13*	4.88	0.14*	5.26
Market dummy	− 0.02	− 1.22	− 0.02	− 1.47
EC $_{t-1}$	0.002	1.22	0.003	1.47
R-squared	0.22		0.20	
DW	1.98		1.75	

Statistical significance at *1% level, **5% level, and ***10% level

conclusions made before are overthrown. For example, the statistical tests for endogenously determined structural breaks do not pick up a structural break about the time for the change in pricing regime. Thus, we cannot conclude that the iron ore price has been affected by the change in pricing regime. Furthermore, we cannot confirm that the iron ore price, GDP growth in China, and freight rates are cointegrated when extending the time period to include the entire boom. This result is in contrast to the findings in Wårell (2014).

The end of the commodity boom

The previous econometric analysis was performed in order to analyze if the iron ore prices were significantly affected by the change in pricing regime in the end of 2008. The results from the structural break analysis of the extended iron ore price series indicated that it rather was the end of the commodity boom that was detected as a structural break for the iron ore price series. This section will therefore perform a similar analysis as in the "Reduced price regression" section, but using a dummy variable indicating the end of the commodity boom, rather than the change in pricing regime. The other variables are held constant. Table 6 presents the results from regressions of Eq. 1, with the difference that the dummy variable reflects the end of the commodity boom in January 2014 (picked up by the Zivot-Andrews test as a structural break for the iron ore price series). As previously, models with and without a time trend are regressed.

If we first look at the results from the model without including a time trend, we note that GDP growth in China affects prices, with the expected sign. However, the sign of the coefficient for the effect of freight rates is not as expected, and it is only significant at a 10% significance level. We do however note that the dummy variable that reflects the end of the commodity boom in January 2014 is statistically significant, and have as expected a negative effect on iron ore prices. However, the R-squared value for the model specification do indicates that something important is missing from the analysis. This is also obvious when turning the attention to the

model that includes a time trend. We now note that all variables included are statistically significant at a 1% level, and that they also have the expected sign. The explanatory power for the model increases from 0.20 to 0.77, indicating that the specification when including a time trend explains 77% of the variation of iron ore prices between January 2003 and June 2017.

To test this model for cointegration, the residuals from the regressions are saved and tested for unit root. Considering that structural breaks are confirmed in the time series, Zivot-Andrews test for unit root allowing for a break has been conducted on the saved residuals from the model including a time trend. The minimum t-statistics of − 7.224 at January 2014 clearly indicates that the variables are cointegrated. The results from the Gregory-Hansen cointegration test is however more inconclusive, since when allowing for a break in the constant, and the trend the null of no cointegration can only be rejected at 5% level given an ADF test statistic of − 5.56 (at break point November 2014). Even though the results for cointegration are not conclusive, an ECM is regressed in order to analyze the short-run adjustments to the long-run equilibrium relationship. The error-correction model is specified as in Eq. (2), however the dummy variable reflects the end of the commodity boom rather than change in pricing regime. The results from the regressions, both when including a lagged change in the iron ore price series, are presented in Table 7.

The results in Table 7 are very similar to the ones presented in Table 5, i.e., with a dummy variable for the change in pricing regime. Thus, the short-run response parameters are statistically significant, and display the expected sign. The result of a price change in iron ore prices the preceding time period is adjusted for by 16% in the following time period. The results for the GDP growth show that a change in GDP growth is reflected by 30% in the change in iron ore price change. A change in freight rates is reflected in the change in iron ore price change by about 12%. The dummy variable reflecting the end of the commodity boom is not statistically significant, in the model when a lagged price change variable is included. Compared to the results in Table 5, the dummy

Table 6 Regression results end of commodity boom

Variable	Model without time trend		Model with time trend	
	Coefficient	t-stat	Coefficient	t-stat
Constant	4.26*	9.45	− 4.75*	− 9.45
GDP growth China	0.46**	1.85	0.70*	5.23
Freight	− 0.09***	− 1.68	0.18*	5.58
Dummy	− 0.38*	− 4.19	− 0.93*	− 16.77
Time trend			0.01*	20.45
R-squared	0.20		0.77	
DW	0.08		0.36	

Statistical significance at *1% level, **5% level, and ***10% level

variable is significant in the model when the lagged price change has been removed. The speed of adjustment parameter is however not statistically significant.

To conclude, the results indicate that there is a structural break about the time when the commodity boom ended rather when the change in pricing regime occurred. However, the reduced price regression when including a dummy variable for the end of the commodity boom is not conclusive, as it is only significant in the error-correction model when a lagged change in the own price is not included in the model. However, when comparing these results to the error-correction results when using a dummy variable for the change in pricing regime, we conclude that the dummy variable for the end of the commodity boom display significance at least in one of the models presented.

The effect of including variables reflecting the supply

Considering that GDP growth in China was the main driver of the commodity boom, but not the main cause to the end of the boom, we would like to extend the analysis by including a variable that explains the effect of changes in prices stemming from changes in the supply of iron ore. The boom was punctuated mainly due to new capacity brought to the market in 2014. Optimal would be to include a variable that represents iron ore production in the world. However, since this data is difficult to get hold of at a monthly basis, we decided to use iron ore export data. Unfortunately we could not get hold of iron ore export data from all major producing countries (as detailed export data from Australia was not made available), so the data collected is iron ore export data from Brazil. A prior belief is that there is a negative relation between the export data and the prices, as when the supply of iron ore increases this will lead to a reduction in price.

Another factor that to some extent could be seen as the inverse to export data, is import data to the main consumer in the market. Furthermore, it is often discussed that iron ore import to China is an important determinant for iron ore prices (see, e.g., Wårell et al. 2013). We have therefore also collected

data on iron ore imports, in order to see whether it has had a significant impact on the iron ore price. The prior assumption is that there is a positive relation between iron ore import to China and iron ore prices, as when import to the main consumer increases this should lead to an increase in prices. The results when adding monthly iron ore export data, as well as monthly iron ore import to China data, to Eq. 1 is presented in Table 8.

If we first look at the results from the model that includes export from Brazil, we note that all the variables included in the model are statistically significant and displays the expected sign. The dummy variable represents the end of the commodity boom, and we note that it is statistically significant. Furthermore, the variable that reflects iron ore exports from Brazil is statistically significant at 5% significance level, and is negative as we expected as an increase in iron ore exports from Brazil leads to a decrease in the iron ore price since it implies that the iron ore supply has increased. The model that instead uses iron ore imports to China does not show that this variable is significant. However, the other results are very similar to the other models considering that GDP growth in China, freight rates and the dummy variable is still statistically significant.

To test for cointegration, the residuals from the regression are saved and tested for unit root. Considering that structural

Table 7 Error-correction regression results end of commodity boom

Variable	Model with lagged price		Model without lagged price	
	Coefficient	t-stat	Coefficient	t-stat
Δ Price $_{t-1}$	0.16**	2.28		
Δ GDP	0.30*	2.62	0.33*	2.85
Δ Freight	0.12*	4.80	0.13*	5.15
Dummy	− 0.02	− 1.39	− 0.02***	− 1.67
EC $_{t-1}$	0.002	1.03	0.002	1.22
R-squared	0.23		0.20	
DW	1.98		1.76	

Statistical significance at *1% level, **5% level, and ***10% level

Table 8 Regression results including iron ore exports and imports

Variable	Model with exports Brazil		Model with imports China	
	Coefficient	t-stat	Coefficient	t-stat
Constant	− 4.98*	− 9.81	− 4.38*	− 7.66
GDP growth China	0.77*	5.66	0.70*	5.23
Freight	0.20*	6.00	0.17*	5.19
Export Brazil	− 0.24**	− 2.23		
Import China			0.06	1.34
Dummy	− 0.93*	− 16.89	− 0.92*	− 16.47
Time trend	0.01*	16.36	0.01*	11.67
R-squared	0.78		0.77	
DW	0.42		0.38	

Statistical significance at *1% level, **5% level, and ***10% level

breaks are confirmed in the time series, Zivot-Andrews test for unit root allowing for a break has been conducted on the saved residuals from the model including export data from Brazil. The minimum t-statistics of − 6.936 at January 2014 indicates that the variables are cointegrated, and that the structural break picked up for the residuals corresponds to the end of the commodity boom. The results from the Gregory-Hansen cointegration test is however once again inconclusive, since when allowing for a break in regime and trend, the null of no cointegration can only be rejected at 5% level given an ADF test statistic of − 6.36 (at break point August 2012). Even though the results for cointegration are not conclusive, we perform an ECM in order to analyze the short-run adjustments to the long-run equilibrium relationship. The error-correction model is specified is as follows:

$$\Delta \ln Price = \alpha_1 \Delta \ln Price_{t-1} + \alpha_2 \Delta \ln GDP + \alpha_3 \Delta \ln Freight$$
$$+ \alpha_4 \Delta \ln Export + \alpha_5 D + \alpha_6 EC_{t-1} \quad (4)$$

Thus, the first differenced iron ore price series is regressed on the lagged level of the own first difference, the first differenced GDP growth in China, the first differenced freight rate, the first differenced export from Brazil, and the dummy variable that reflects the end of the commodity boom. The error-correction term is represented by EC in Eq. 2, and is specified as the lagged residuals from the regression of eq. 1, when including monthly export data, as well as a time trend. The results from Eq. (4) are presented in Table 9, both with and without the inclusion of a lagged level of the first differenced iron ore price.

The results in Table 9 indicate that the differenced export from Brazil is not statistically significant in the error-correction model, indicating that even though it is picked up as significantly affecting iron ore prices in the linear regression model, it cannot be confirmed in the error-correction model that corrects for the problem with non-stationarity.

This conclusion holds both for the model with and without the inclusion of a lagged price series.

Overall, the results indicate that the most important factors during the time period January 2003 and June 2017 for explaining iron ore prices have been GDP growth in China, as well as freight rates. All the presented models are robust regarding this result; i.e., these variables display significance in all the models. This result is also robust to the findings in Wårell (2014), as it was found that these two variables significantly affected the iron ore prices in all the tested models. However, when extending the data to incorporate the entire commodity boom, we cannot confirm that the variables are cointegrated. A structural break about the time for the end of the commodity boom is picked up at by the endogenously determined structural break tests; however, its effect on iron ore prices cannot be confirmed in all the error-correction regressions. Thus, we cannot statistically confirm that the change in pricing regime, or the end of the commodity boom, has had a statistically significant effect on iron ore prices. The results for including iron ore exports from Brazil is not conclusive, as the error-correction model cannot statistically confirm that this variable had a significant effect on iron ore prices.

Concluding remarks

The main purpose of the paper was to perform a quantitative analysis of iron ore prices during the latest commodity boom, in order to study which factors that can explain the iron ore price movement during a time period characterized by dramatic changes in the price series. Wårell (2014) performed a similar study, based on monthly data between January 2003 and September 2012, i.e., using a time series that still reflected surging iron ore prices. The main result from that study was that the change in pricing regime in the end of 2008 was picked up as a structural break for the price series, and that

Table 9 Error-correction regression results export data

Variable	Model with lagged price		Model without lagged price	
	Coefficient	t-stat	Coefficient	t-stat
Δ Price $_{t-1}$	0.17**	2.35		
Δ GDP	0.30*	2.59	0.33*	2.83
Δ Freight	0.13*	4.85	0.14*	5.15
Δ Export Brazil	− 0.03	− 0.76	− 0.02	− 0.51
Dummy	− 0.02	− 1.38	− 0.02	− 1.66
EC $_{t-1}$	0.002	1.04	0.002	1.23
R-squared	0.23		0.20	
DW	2.00		1.76	

Statistical significance at *1% level, **5% level, and ***10% level

iron ore prices, GDP growth in China and freight rates were cointegrated in the long run. It was also concluded that the most important factor for iron ore prices up to 2012 was GDP growth in China. One additional purpose of this study was therefore to see if the results obtained in Wårell (2014) were significantly affected by the fact that they were estimated when the commodity boom was still ongoing.

The results from the endogenously determined structural break tests indicate that it is not the change in pricing regime that is picked up as a structural break; rather, it is the end of the commodity boom that is indicated as a structural break in the extended price series. Regarding the results from the reduced price regressions, we find similar to Wårell (2014) that the iron ore price during the entire commodity boom is significantly affected by GDP growth in China and freight rates. As well, the dummy variable reflecting the change in pricing regime was not significant in the short-run response model. However, the result regarding cointegration is not conclusive when extending the time period to include the entire boom, which is in contrast to the finding in Wårell (2014). This is perhaps due to the fact that it is more difficult to find convergence to a long-run trend between variables that are characterized by dramatic volatility in both directions, i.e., including both boom and bust periods.

We also extended the reduced price regression to include the end of the commodity boom as a dummy variable, instead of using the change in pricing regime, and the results indicate that this variable increases the fit of the model. Thus, the end of the commodity boom seems to have had a stronger impact on the iron ore prices during the entire commodity boom, which is not very surprising considering that this marks an end of the definition of a boom period. In addition, we tested to include variables reflecting iron ore supply given that the commodity boom was ended when sizable new capacity was brought to the market. In the long-run regression, iron ore exports from Brazil had a significant effect on iron ore prices, but this could not be confirmed in the error-correction model results. One explanation for this might be that iron ore export

data from Brazil might not be representative enough to reflect iron ore supply. Future research, using more comprehensive data on the effect of iron ore supply, is needed to determine the long-run effects on prices.

To conclude, similar to the findings in Wårell (2014), the single most important impact on the iron ore price during the entire commodity boom, both in the long run and in the short run, stems from GDP growth in China. The developments of freight rates have also had a significant effect on iron ore prices during the commodity boom, however to a lesser extent.

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