# Identifying Supply and Demand Elasticities of Iron Ore

**ZHIRUI ZHU**[1]

*Professor Gale A Boyd, Faculty Advisor*

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**Duke University**

**Durham, North Carolina**

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[1] The author is a Duke economics major planning to graduate in May 2012 and can be contacted at zz20@duke.edu, 919-450-7316

## ABSTRACT

This paper utilizes instrumental variables and joint estimation to construct efficiently identified estimates of supply and demand equations for the world iron ore market under the assumption of perfect competition. With annual data spanning 1960-2010, I found an upward sloping supply curve and a downward sloping demand curve. Both of the supply and demand curves are efficiently identified using a 3SLS model. The instruments chosen are strong and credible. Point estimation of the long-run price elasticities of supply and demand are 0.45 and -0.24 respectively, indicating inelastic supply and demand market dynamics. Back-tests and forecasts were done with Monte Carlo simulations. The results indicate that 1) the predicted prices are consistent with the historical prices, 2) world GDP growth rate is the determining factor in the forecasting of iron ore prices.

**Keywords:** Iron Ore; Supply, Demand, Simultaneous Equation, Simulation

**JEL Classification Codes:** C30, Q31

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# 1 INTRODUCTION

Understanding the market structure of commodities has long been a hot topic in microeconomics. Undoubtedly, one of the central roles of modern economics is to explain a market phenomenon through a specific model.

Frankel (Frankel & Rose, 2009) studied eleven different agricultural and mineral commodities such as wheat, corn, oil, silver and copper using OLS. However, iron ore, as a very important metal commodity in global market, is not included in this study.

As the intermediate product to produce pig iron and steel, iron ore is considered the second largest open-traded commodity in the world (Crowson, 2011; Frankel & Rose, 2009; Gonzalez & Kaminski, 2011; Hu et al., 2010). However, until 2010, the world seaborne iron ore market has still used an annual benchmark pricing system. Every March the price is privately settled by a small group of mining companies and steelmakers and the price was then fixed until March of the following year.

Despite that industries and policymakers have spent large amount of resources to study iron ore market (UNCTAD, 2011), the majority of the research the academic papers focus on steel market and few studies have focused on iron ore (Crandall, 1981; Igarashi, Kakiuchi, Daigo, Matsuno, & Adachi, 2008; Malanichev & Vorobyev, 2011; Rogers, 1987). Most of the existing iron ore pricing models are constructed based on game theory principles (Hui & Xi-huai, 2009; Priovolos, 1987). These models suggest that the international iron ore market has been a seller dominated market due to the severe unbalance of iron ore supply and demand as well as high monopolization. Therefore, the negotiation for the range of price can be depicted through the bilateral oligopolistic theory.

Labson (1997) was the first economist who studied changing patterns of world iron ore production, consumption, and trade based on empirical econometric analysis. He predicts that developing Asian region, mainly China, would account for majority of the increase in annual steel consumption in the first decade of the 21st century. The world's major iron ore exporters such as Australia, Brazil, and India would increase production accordingly to meet the growing demand. After Labson, most of the iron ore related papers are mainly qualitative analyses without taking economic approaches (Gonzalez & Kaminski, 2011; He, 2011; Wang & Yan, 2011). The most recent empirical research was done by Li (Li, Wang, Ren, & Wu, 2011) who studied the linear relationship between iron ore price and oil price and between iron ore price and the Baltic dry index[2] respectively based on an autoregressive model, (AR)(1). The paper concluded that iron ore price was positively correlated with oil price but negative correlated with shipping index.

Though iron ore pricing mechanism and China's recent impact have been broadly acknowledged and commented (Fei Lu, 2009; He, 2011; Reuters, 2011; The Financial Times, 2009; Yu & Yang, 2010), clearly, they have not been fully understood. Since few empirical experiments have been performed on iron ore, as a valuable commodity, it is important to understand what determines the supply and demand for iron ore and by what equilibrium process iron ore prices and quantities are determined. Therefore, the first goal of this paper is to develop a structural model that can explain the iron ore market by economic activities.

One central econometric question in empirical studies of markets is how to infer the structure of supply and demand from actual observations of equilibrium prices and

[2] The Baltic Dry Index (BDI) is a number issued daily by the London-based Baltic Exchange. The index provides "an assessment of the price of moving the major raw materials by sea. Taking in 23 shipping routes measured on a time charter basis, the index covers Handysize, Supramax, Panamax, and Capesize dry bulk carriers carrying a range of commodities including coal, iron ore and grain

quantities (Manski, 1995). The key challenge to such study is to differentiate whether each data point characterizes part of the demand or the supply curve. Correct identification requires instruments which shift prices in ways that are uncorrelated to unobservable shifts in each curve. For example, one classic instrumental variable (IV) example introduced by Wright (1928) is weather, which has been considered a natural instrument for agricultural commodity supply shifts and can be used to facilitate unbiased demand estimation. Therefore, the second goal of this paper is to select valid IVs to identify the supply curve and the demand curve.

The third goal is to use Monte Carlo simulations to examine the predictive power of the model. By randomly generating 1000 paths based on designed probability distribution, the Monte Carlo method produces a probabilistic picture of the distribution of predicted iron ore prices and quantities. It can provide a framework for decision making that incorporates the risk tolerance to policymakers and investors.

According to my results, the price elasticity of supply of iron ore is positive and the price elasticity of demand is negative. Both the supply and demand curves are price inelastic. Economic activities including GDP changing and mining technology improvements as well as lag price variables are the major drivers of long-run price movements.

This paper is organized as follows. In section 2, I conduct a short history review of the iron ore market and its pricing system. In section 3, I outline the econometric methods I use to construct the simultaneous equations. Then, I introduce my data set in section 4. Section 5 shows an empirical analysis on iron ore price mechanism based on the conventional econometric framework. Section 6 introduces simulation results and section 7 concludes by summarizing the findings and suggesting areas of further research.

## 2 GLOBAL IRON ORE INDUSTRY

### IRON ORE SUPPLY – THE BIG THREE

Iron ore is currently mined in about 50 countries. The majority originates from Brazil, Australia, China, India, the United States and Russia. Since iron mines are often remote from steel mills, ore needs to be shipped in bulk carriers (Gonzalez & Kaminski, 2011).

Despite the decline in 2009, world production of iron ore has grown by 95% or 893 Mt since 2001. In developed markets, except for that of Australia, iron ore production has increased by 22% during the same period. Australian production grew by 140% to reach 432 Mts. Production in Brazil also has grown rapidly over the past 10 years by 78% to reach 357 Mt in 2010. In 2010, the world total iron ore production was 1,827 Mt, while Australia and Brazil together accounted for 44% of the total supply (Appendix Fig. 1, Fig. 2) (UNCTAD, 2011).

The current iron ore trade market is dominated by the Big Three - Vale, Rio Tinto and BHP Billiton. These three largest mining companies controlled 35% of the total world production in 2010. An alternative way to measure the corporate control of iron ore is to analyze the share of global seaborne trade of the leading companies. Since a large portion of the total iron ore production is produced in captive mines, these iron ore products do not enter the world trade market and, thus, does not affect the general supply and demand equilibrium. Using seaborne method, the shares of the Big Three are considerably higher than the 35% evaluated by examining the entire world ore market. Three companies control about 70% of the seaborne market in total (UNCTAD, 2011).

## IRON ORE DEMAND – CHINA

Iron ore has been the biggest beneficiary of the commodities super cycle over the past decade. As previously discussed, the bilateral negotiation has been between members of the major mining producers in Australia, India and Brazil, and large steelmakers. In 1970's, European steelmakers determined the market demand with the Japanese buyers taking over in the 80's and 90's. In the 2000's, Chinese steelmakers started to play a dominant role in the buyer's market (Appendix Fig. 3).

The recent rise of iron ore demand in China is largely due to the unprecedented steel demand (Hu et al., 2010). With rapid urbanization, industrialization and income growth in recent years, China is expanding its consumption of steel at an accelerated speed. Many infrastructure projects, including airports, bridges, public buildings and residential houses, have been built over the past 20 years (Pretorius J. et al., 2011).

By far China is currently the world's largest iron ore net importer. In 2010, China alone imported 183,068 Mt ($618 million) of iron ore, accounting for 70% of total world imports (Pretorius J. et al., 2011). Compared to 2009, this number slightly decreased by 2%, indicating the first decrease in this figure since late 90's[3] (He, 2011; UNCTAD, 2011).

In addition to the expansion in domestic steel demand, as Cheung (Cheung, Morin, & Bank of Canada, 2007) pointed out, China's export channel constitutes another source for its growing demand of resources. A large volume of manufacturing activities has been outsourced from developed countries to China due to the low labor cost (Fei Lu, 2009; Cheung et al., 2007).

The average grade of Chinese domestic ore is much lower than a standard 64% grade

[3] Plots see figure 2, section 4

and is even lower in small and medium size mines. One notable point is that there was almost a 50% decline of Fe content in iron mines in China from 2008 to 2009. Chinese researchers point out that small and medium size mines in China account for most of the production, low iron content in mines directly causes China's dependence on imports as domestic producers are unable to raise their output (Appendix Fig. 4) (Fei Lu, 2009; Hu et al., 2010; UNCTAD, 2011; The Financial Times, 2009).

## IRON ORE PRICING

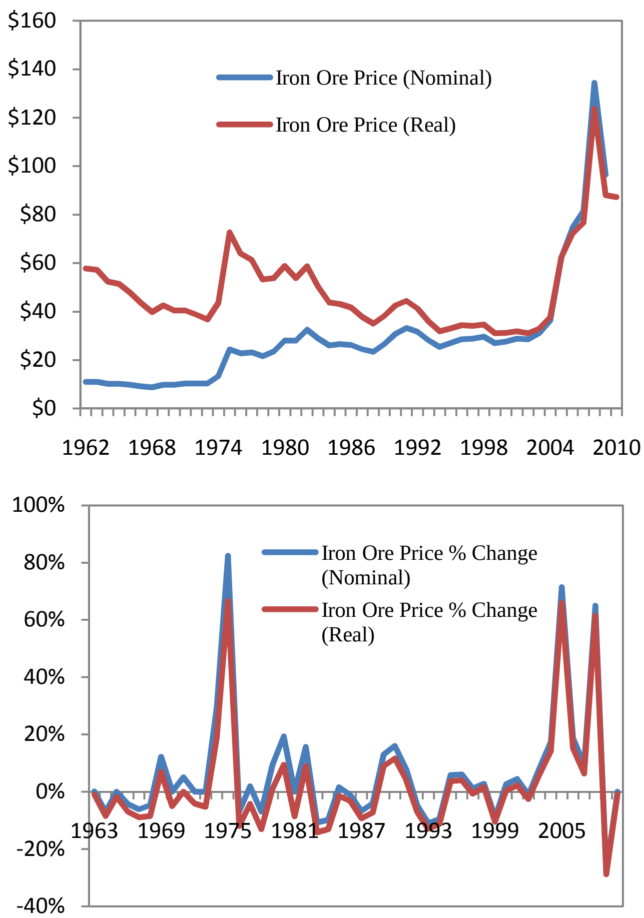
Since post-World War II, iron ore prices had been decided behind closed doors in negotiations between mining companies and steelmakers. Because the price has long been in a benchmark system, the changes in price from year to year were fairly non-speculative (Fig. 1). In fact, mines on average produce about 2 billion tons of iron ore annually, of which more than 95% is traded on bilateral contract bases (Anonymous, 2009; MacDonald, 2009).

In 2004, Chinese steelmakers obtained the right to negotiate the ironstone benchmark price for the first time, together with the Japanese steelmakers, and became the major representatives on the demand side. However, many news reports indicate that China had relatively weak bargaining power despite its status as the world's largest steel producer and biggest iron ore importing country at the time. The benchmark price was mainly settled between the Big Three and the Japanese steelmakers although Chinese steelmakers were also present in the negotiations. Meanwhile, the global ore import price from 2004 to 2008 had increased 18%, 71%, 20%, 9% and 96% respectively (He, 2011; Yu & Yang, 2010) (Fig. 1). In 2009, China arrested four business representatives from Rio Tinto's China branch and accused them of stealing state trading secrets. In the same year, China rejected the iron ore price cut of 33%

negotiated by Rio Tinto and Japan, claiming that the price was unacceptably high and would cause overall losses to domestic steelmakers (Yu & Yang, 2010). At the same time, China has been working hard to engage in the emerging spot market. By importing the majority of the iron ores needed from India, China aims to force the Big Three to accept the spot price mechanism and increase its bargaining power to price making (UNCTAD, 2011).

Due to the pressure from the Chinese market, the iron ore annual pricing system officially ended in 2010 and moved to a spot market system (Pretorius J. et al., 2011; Yu & Yang, 2010)

**Figure 1 64.5% Fe Content Iron Ore Price and Rate of Change (1962-2010)**




*Data Source: UNCTAD database, Nominal price iron ore, 64.5% Fe content (Brazilian to Europe, 1962-2010), real price deflected using GDP deflator from the World Bank database*

## 3 THE SUPPLY-AND-DEMAND MODEL

In this section, I describe the world iron ore supply-and-demand model, and explain each of the instrumental variables included in the equation. Lin (2005) constructed a sophisticated supply-and-demand model of world oil market based on the well-developed econometric theory of simultaneous equation (Goldberger, 1991; Stock & Watson, 2003). I base some of the notations on hers.

### 3.1 A LINEAR MODEL

Although the iron ore market has characteristics of both oligopoly and monopolistic competition, I believe the underlying price is still be determined by the interaction of fundamental demand and supply. Therefore, for this paper, I try to estimate the world iron ore market based on the perfect competition model in which the market price acts to equilibrate supply and demand[4].

Let $P_t$ represent the price of iron ore at time $t$, let $Q_t$ represent the quantity of world total iron ore production in the same period $t$, and let $X_t$ be a vector of covariates characterizing the market. Based on the perfect competition assumptions, both buyers and sellers are price takers. Let $Q_D$ represent the market demand quantity which price-taking consumers would purchase and let $Q_S$ represent the market supply quantity which price-taking firms would offer. $Q_D$ and $Q_S$ are both functions of price, $P_t$.

4 World iron ore market behaves more like under oligopoly as previously discussed, future research needs to be applied

To estimate the price elasticities of supply and demand, I assume a log-linear model with fixed coefficients and additive residuals. Both of the two functions are estimated by ordinary least squares (OLS). Since I am estimating price elasticity of iron ore, all the variables are in natural logarithms to indicate the relationship between changing quantity, changing price and changing other covariates.

The OLS structural form of the model is given by:

$$\text{Demand: } \ln Q_{Dt}(\cdot) = \beta_t \ln P_t + \sum \gamma_t X_t + \mu_t \qquad (3.1.1)$$

$$\text{Supply: } \ln Q_{St}(\cdot) = \alpha_t \ln P_t + \sum \Delta_t Z_t + v_t \qquad (3.1.2)$$

$$\text{Market Clearing: } Q_D(\cdot) = Q_S(\cdot) \qquad (3.1.3)$$

For valid OLS estimation, the error $\mu$ and $v$ should satisfy the assumptions that

$$\mathrm{E}[\mu|P] = 0 \text{ and } \mathrm{E}[v|P] = 0$$

$$\mathrm{Cov}(\mu_t, v_t) = 0$$

$$\mu \sim \mathrm{N}(0, \sigma_\mu^2 I_T) \text{ and } v \sim \mathrm{N}(0, \sigma_v^2 I_T)$$

$I_T$ is a $T \times T$ identity matrix, and $\sigma^2$ is a parameter which determines the variance of each observation, $\mu = (\mu_1, \mu_2 \ldots\ldots \mu_T)$ and $v = (v_1, v_2 \ldots\ldots v_T)$.

Note that OLS estimations could introduce two problems. First, OLS estimators of the coefficients on price are inconsistent since price is endogenously determined in the supply-and-demand system (Goldberger, 1991). Second, if the error terms in the supply-and-demand equations are correlated, then the OLS estimates is lacking of efficiency (Lin, 2005).

## 3.2 METHODS FOR EFFICIENT IDENTIFICATION

### 3.2.1 TWO-STAGE LEAST SQUARES (2SLS)

As mentioned above, applying equation-by-equation OLS lacks both identification and efficiency. To address the identification problem, I reconstruct the model as a 2SLS model.

In general, a valid instrument should meet three requirements (Goldberger, 1991; Manski, 1995; Stock & Watson, 2003):

- The instrument must be correlated with the endogenous variable ($P_t$), conditional to the other covariates.
- The instrument cannot be correlated with the error terms ($\mu_t$ and $v_t$) in the explanatory equation.
- Exclusion should also be applied when instrumental variables are selected to differentiate the supply and the demand equation[5].

### 3.2.2 INSTRUMENTS SELECTION

To develop the model, I start with selecting instruments in the demand equation. In general, economists believe that income and consumption related variables are demand exclusive variables. Real world GDP is a good approximation of global income growth rate. Therefore, I use real world GDP as an instrument in the demand

[5] An exogenous supply shifter does not affect demand except through its effect on price and can be used as a valid instrument for price in the demand equation. Similarly, an exogenous demand shifter does not affect supply except through its effect on price and can be used as a valid instrument for price in the supply equation.

equation. Since more GDP growth should result in more iron ore demand, I expect the coefficient for GDP and price to be positive. Scrap steel is a close substitute for iron ore. Hence its price is also included in the demand function. I expect that a higher scrap price causes a higher iron ore price as buyers shift out of scrap steel and into iron ore. Therefore, the coefficient of scrap price should be positive.

In section 2, I mentioned that in the mid 2000s, the ore price rally was mainly due to a strong demand from China. Meanwhile there was no indication of any significant technological changes in that period. As a result, I include a demand shock dummy in the demand equation.

$$\text{Demand Shock (t)} = \begin{cases} 0, & t < 200\text{x} \\ 1, & t \geq 200\text{x} \end{cases}$$

One problem associated with the demand shock is that imports of iron ore by China picked up gradually from 2002 to 2006. Thus, it is hard to justify the year in which the shock actually occurred. A breakpoint test from 2002 to 2006 is performed to find the year that fits the data the best. The breakpoint test is a linear regression of lag price and lag quantity on price[6],

$$\ln(P_t) = \xi_0 + \xi_1 \ln(P_{t-1}) + \xi_2 \ln(Q_{t-1}) + \xi_3 \text{YD} + \xi_4 \text{YD} \times \ln(P_{t-1}) + \xi_5 \text{YD} \times \ln(Q_{t-1}) + \varepsilon$$

This demand shock dummy captures the upward shift of the demand curve. Accordingly, I expect the coefficient for demand shock and price to be positive.

In the supply equation, the supply of a non-renewable resource should follow

[6] Chow Test: YD represents a year dummy of the test year. Null hypothesis is that $H_0 : \xi_3 = \xi_4 = \xi_5 = 0$ versus the alternative $\xi_3 \neq \xi_4 \neq \xi_5 \neq 0$. I choose the most significant price and quantity structural change point as the year shock happened.

Hotelling's rule which includes real interest rate in the supply equation. According to Hotelling's rule, a commodity stored underground can be regarded as a capital asset. The commodity owner has two options, either to sell the product or to postpone its sale and keep underground inventories (Cynthia Lin & Wagner, 2007; Hotelling, 1931; Kronenberg, 2008; Slade & Thille, 2009). Accordingly, a higher interest rate should cause a lower ore production and I expect the coefficient relating the price of iron ore and interest rate to be negative.

Ideally, a variable describing ore mining technological improvements should be included in the supply function. However, this type of data is not accessible. Instead, I use a linear time trend (1, 2… t) to capture the technological improvements.

The equation can be written as,

$$Q_{tS} = \alpha_t \, lnP_t + e^{(\gamma Time_t + \varepsilon)} \qquad (3.2.1)$$

$\gamma$ can be interpreted as the growth rate of quantity and I expect the coefficient ($\gamma$) to be positive.

In addition, a supply shock dummy is introduced to capture the ore price jump in 1975.

$$\text{Supply Shock (t)} = \begin{cases} 0, & t < 1975 \\ 1, & t \geq 1975 \end{cases}$$

Crandall (Crandall, 1981) mentioned that 1975 ore price jump might be the result of the declining of extraction in the Mesabi Iron Range, the largest range of four major iron ranges in Minnesota. Since the U.S. was the major iron ore consumer in the

1970s, the shortage of internal supply in the U.S. caused the global ore price rally in 1975. Due to the negative effect of this supply shock, I expect a downward shift of the supply curve and the coefficient relating the price and the shock dummy should be negative.

Finally, I also introduce a price lag variable $P_{t-1}$ in both the supply and the demand functions. Including a lag variable can capture both short run and long run quantity response to price, thus, increases the model's predictive power. Another reason to include a price lag variable in the equation is that if the error terms in the model are auto-correlated, the model is biased due to the serial autocorrelation problem. Adding a lag variable in the regression is one common way to correct serial correlation in time series.

In summary, the log-linear model is given by:

$$\text{Demand: } \ln(Q_{tD}) = \beta_0 + \underset{(-)}{\beta_1 \ln(P_t)} + \underset{(+/-)}{\beta_2 \ln(P_{t-1})} + \underset{(-)}{\beta_3 \ln(\text{Scrap Price}_t)} + \underset{(+)}{\beta_4 \text{ Demand Shock}_t} + \underset{(+)}{\beta_5 \ln(\text{GDP}_t)} + \mu \quad (3.2.2)$$

$$\text{Supply: } \ln(Q_{tS}) = \gamma_0 + \underset{(+)}{\gamma_1 \ln(P_t)} + \underset{(+/-)}{\gamma_2 \ln(P_{t-1})} + \underset{(-)}{\gamma_3 \ln(\text{Interest Rate}_t)} + \underset{(+)}{\gamma_4 \text{ Time}_t} + \underset{(-)}{\gamma_5 \text{ Supply Shock}_t} + v \quad (3.2.3)$$

$$\text{Market clearing: } Q_{tD} = Q_{tS} \quad (3.2.4)$$

In the long-run, I assume price is stable. Therefore,

$$P_t = P_{t-1} = \hat{P}$$

The long run price elasticities for the demand and supply equation are

$$\frac{\partial Q_D}{\partial \hat{P}} = (\beta_1 + \beta_2) \tag{3.2.5}$$

$$\frac{\partial Q_S}{\partial \hat{P}} = (\gamma_1 + \gamma_2) \tag{3.2.6}$$

Thus, the long-run structural model is given by:

Demand: $\ln(Q_t) = \beta_0 + (\beta_1 + \beta_2) \ln(\hat{P}) + \beta_3 \ln(\text{Scrap Price}) + \beta_4 \text{ Demand Shock} + \beta_5 \ln(\text{GDP}) + \mu$

(3.2.7)

Supply: $\ln(Q_t) = \gamma_0 + (\gamma_1 + \gamma_2) \ln(\hat{P}) + \gamma_3 \ln(\text{Interest Rate}) + \gamma_4 \text{ Time} + \gamma_5 \text{ Supply Shock} + v$

(3.2.8)

### 3.2.3 THREE-STAGE LEAST SQUARES (3SLS)

The second problem with equation-by-equation OLS is that the error terms of the supply and demand equations might be correlated, which causes an inefficiency problem.

Therefore, besides using a 2SLS model, I also introduce a three-stage least squares model to estimate the supply and demand equations. A 3SLS model follows the assumption that (Goldberger, 1991; Lin, 2005)

$$\text{Cov}\ (\mu_t\ ,\ v_t) \neq 0$$

It is more efficient than 2SLS since it uses all the available information at one time.

In this paper, I use a variety of methods (OLS, 2SLS, and 3SLS) to estimate the world supply and demand for iron ore under the assumptions of a perfectly competitive market. And I expect the 3SLS estimates to produce the most identified, consistent and efficient results.

The tradeoff between 2SLS estimations for supply and demand equations and 3SLS estimations is that if the model is correctly specified, 3SLS estimations are superior because of increased efficiency. However, if one equation (e.g. supply equation) is miss-specified, this miss-specification negatively impacts the 3SLS estimate of the parameters in the other equation (e.g. demand equation).

All the regressions are calculated by STATA 11.

## 4 DATA

I begin with a preliminary examination of the data set, starting with the variables included in the annual supply-and-demand model.

Figure 2 contains time-series plots for eight variables of interest. For iron ore price series, I use 64.5% Fe content iron ore (Brazil to Europe) price from the UNCTAD database (Fig. a). World iron ore production series is collected from the U.S. Geological Survey database (Fig. c). World GDP (Fig. g) and U.S. scrap price (Fig. b) are collected from the UNCTAD database. The annualized realized American real interest rate is defined as the 10-year Treasury-bill rate at auction less the percentage change in the American chain price index based on Frankel's method (Frankel & Rose, 2009) (Fig. h). Iron ore price and world GDP have deflated by world real GDP deflator from the World Bank.

For recent monthly price series, I use 63.5% Fe content iron ore (IOECI635 INDEX, India to China, 2008-2011) price collected from Bloomberg. World iron ore production data are not recorded on monthly basis. Hence I am not able to construct a supply-and-demand model based on monthly data. Iron ore monthly inventory storage amount and iron ore import/export amount are collected from the Bureau of Statistics of China. U.S. 1-year Treasury swap rate, Baltic Dry Shipping Index, global pig iron and steel monthly production are collected from Bloomberg. Since GDP deflator is recorded on quarterly bases, the monthly iron ore price, swap rate and shipping index are deflated by monthly U.S. Producer Price Index deflator from the World Bank.

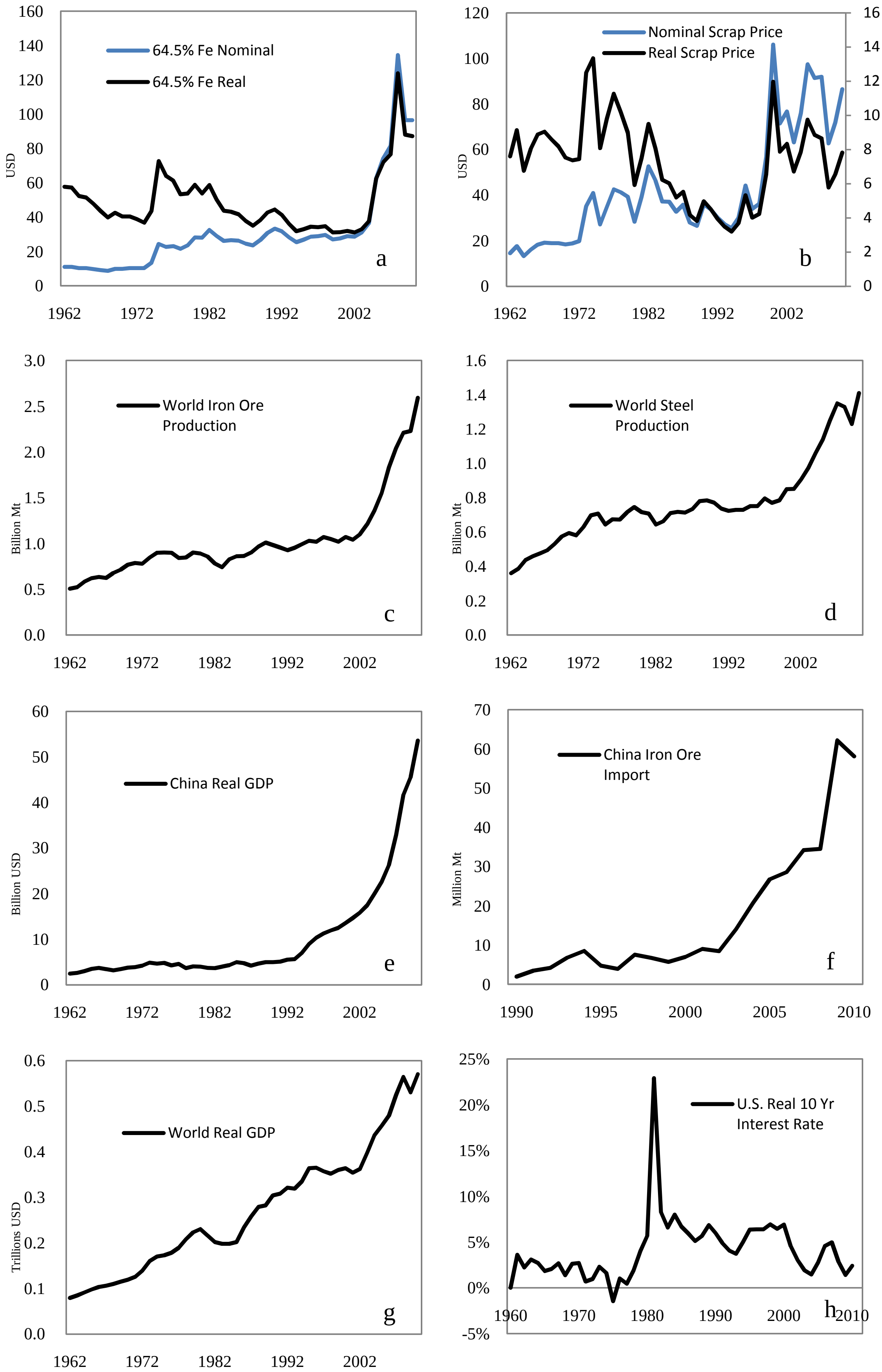
Figure 2 indicates that there are two spikes in the iron ore price graph, corresponding to the 1975 supply shock and the 2005 demand shock. There are clear upward trends in the real world GDP graph and the world steel production graph. Real China GDP and China iron ore import amount rallied in the 2000s, indicating strong growth and iron ore demand in China. There is no clear upward or downward trend in real scrap price from 1960 to 2010, indicating a cyclic price trend.

Data summary table (table 1) and instrumental-variable covariance matrix are presented in the appendix (Appendix table 1).

**Table 1 Summary statistics for annual and monthly data**

| Variable | Time | Mean | Median | S.D. | Min | Max |
|---|---|---|---|---|---|---|
| ***Price and Quantity*** | | | | | | |
| Nominal Iron Ore Price (USD) | 1960-2010 | 30.0 | 26.6 | 25.2 | 8.8 | 134.4 |
| Real Iron Ore Price (USD) | 1962-2010 | 48.9 | 43.1 | 18.1 | 31.1 | 123.7 |
| World Iron Ore production (Million Mt) | 1960-2010 | 1006.2 | 902.0 | 447.1 | 503.0 | 2590.0 |
| ***Annual Model Covariates*** | | | | | | |
| Real World GDP (Billion USD) | 1962-2010 | 269.3 | 234.0 | 135.7 | 79.4 | 570.0 |
| Real U.S. Scrap Price (USD) | 1962-2010 | 7.3 | 7.5 | 2.4 | 3.2 | 13.3 |
| Real U.S. Interest Rate (%) | 1962-2010 | 4.1 | 3.6 | 3.5 | -1.5 | 22.9 |
| ***Monthly Model Covariates*** | | | | | | |
| Real Iron Ore Price (USD) | 6/06 – 12/11 | 83.3 | 62.1 | 47.1 | 32.4 | 168.7 |
| Inventory Level Index | 6/06 – 12/11 | 64.7 | 68.0 | 16.9 | 38.7 | 96.9 |
| China Pig Iron output (Mt) | 6/06 – 12/11 | 43.8 | 43.1 | 6.5 | 33.5 | 55.1 |
| Real U.S. Scrap Price (USD) | 6/06 – 12/11 | 31.0 | 28.5 | 9.9 | 10.5 | 60.2 |
| Real U.S. 1-Yr Swap rate (%) | 6/06 – 12/11 | 10.6 | 9.6 | 4.5 | 4.6 | 17.5 |
| BIDY Shipping Index (USD) | 6/06 – 12/11 | 38.0 | 29.5 | 26.8 | 6.6 | 107.1 |

**Figure 2 World iron ore price and production, U.S. scrap price, world steel production, world GDP, China real GDP, China iron ore imports and U.S. real interest rate plots (1962 – 20010)**



# 5 RESULTS

## 5.1 ANNUAL SUPPLY AND DEMAND MODEL (1962-2010)

Table 1 presents the naive version of the log-log model using OLS based on the model Frankel applied in his paper (Frankel & Rose, 2009). In the regression, quantity is the dependent variable and price and other covariates are independent variables. OLS-1 includes a lag price variable and OLS-2 does not.

**Table 1. Naive estimates for annual iron ore price and quantity**

| | OLS-1 | OLS-2 |
|---|---|---|
| | Wd Ore Pd | Wd Ore Pd |
| Ore Price $_{(t)}$ | 0.0475 | 0.156 |
| | (0.76) | (1.42) |
| Ore Price $_{(t-1)}$ | 0.151 | |
| | (1.75) | |
| Scrap Price | 0.0304 | 0.0285 |
| | (1.17) | (1.09) |
| Time | -0.000282 | -0.00162 |
| | (-0.07) | (-0.43) |
| Interest Rate | $-0.0323^{*}$ | $-0.0377^{*}$ |
| | (-2.29) | (-2.48) |
| Wd GDP | $0.675^{***}$ | $0.680^{***}$ |
| | (5.66) | (6.31) |
| Supply Shock | $-0.219^{**}$ | $-0.185^{*}$ |
| | (-3.13) | (-2.46) |
| Demand Shock05 | $0.212^{*}$ | 0.236 |
| | (2.12) | (1.65) |
| Constant | 2.432 | 2.508 |
| | (0.79) | (0.89) |
| *N* | 47 | 48 |
| adj. $R^2$ | 0.97 | 0.96 |

1) All variables are in logarithms except time and shock du*mmy* 2) Wd Ore Pd stands for world iron ore production, Wd GDP stands for world real GDP, Ore Price (t-1) stands for iron ore price with 1 year lag, Interest Rate stands for U.S. 10-year treasury bond interest rate (real), Time stands for a time trend, Demand Shock05 stands for dummy variable equals to 1 if Yearr≥2005, Supply Shock stands for dummy variable equals to 1 if Year≥1975 3) *t* statistics in parentheses $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

According to the OLS regressions, interest rate and the supply shock are negatively correlated with world ore production. World GDP and the demand shock are positively correlated with ore quantity. However, the coefficients of ore price, lag price, scrap price and time trend are not significant.

Despite some of the coefficient estimators have the expected sign as I discussed in section 3, the coefficient estimator of iron ore price appears to be weak and the naive regression equation represents neither the supply curve nor the demand curve. Hence, the Frankel's model is not helpful in terms of explaining the market fundamentals of iron ore.

Therefore, instead of putting all the covariates into one equation, I distribute these covariates into two equations and treat them as instrumental variables of $P_t$.

To test whether the instruments are correlated with price, I have done regression on the price versus all of the instruments (Column 1, table 3). $P_{t-1}$, the demand shock, time and the supply shock are significantly correlated with $P_t$, while scrap price, world GDP and interest rate are not. In addition, all the demand shifters are jointly significant at 0.1% level (Column 3, table 3) and all the supply shifters are jointly significant at 1% level (Column 2, table 3). The supply curve might be better identified than the demand curve since demand shifters are more significant than supply shifters.

One noticeable fact is that in both table 1 and table 3, I assume the demand shock happened in 2005. This assumption is based on a Chow test in different years ranging from 2002 to 2006 (table 2).

**Table 2 Results of Chow test from 2002 to 2006**

| Year | 2002 | 2003 | 2004 | 2005 | 2006 |
|---|---|---|---|---|---|
| *P-Value* | 0.0025 | 0.0026 | 0.0015 | 0.0001 | 0.0153 |

1) Chow Test is a regression on $\ln(P_t) = \xi_0 + \xi_1 \ln(P_{t-1}) + \xi_2 \ln(Q_{t-1}) + \xi_3 YD + \xi_4 YD \times \ln(P_{t-1}) + \xi_5 YD \times \ln(Q_{t-1}) + \varepsilon$ 2) YD represents a year dummy of the test year 3) Null hypothesis is that $H_0 : \xi_3 = \xi_4 = \xi_5 = 0$ versus the alternative $\xi_3 \neq \xi_4 \neq \xi_5 \neq 0$.

**Table 3 Effect of instruments on annual iron ore price**

| | OLS<br>Ore Price $_{(t)}$ | OLS-Demand<br>Ore Price $_{(t)}$ | OLS-Supply<br>Ore Price $_{(t)}$ |
|---|---|---|---|
| Ore Price $_{(t-1)}$ | $0.479^{***}$ | $0.653^{***}$ | $0.923^{***}$ |
| | (5.06) | (6.85) | (8.13) |
| **Demand Shifters** | | | |
| Scrap Price | 0.0572 | 0.0609 | |
| | (1.15) | (1.21) | |
| Wd GDP | 0.206 | -0.0504 | |
| | (1.24) | (-1.30) | |
| Demand Shock05 | $0.600^{***}$ | $0.366^{***}$ | |
| | (6.24) | (3.80) | |
| P-value for all demand | | | $0.000^{***}$ |
| **Supply Shifters** | | | |
| Time | $-0.0171^{**}$ | | 0.00523 |
| | (-2.90) | | (1.60) |
| Interest Rate | -0.00538 | | -0.00295 |
| | (-0.32) | | (-0.16) |
| Supply Shock | $0.172^{*}$ | | -0.0959 |
| | (2.18) | | (-1.45) |
| P-value for all supply | | $0.0034^{**}$ | |
| Constant | -3.240 | 2.492 | 0.231 |
| | (-0.76) | (1.96) | (0.51) |
| *N* | 47 | 48 | 47 |
| P-value from joint test of all coefficients (Prob > F) | $0.00^{***}$ | $0.00^{***}$ | $0.00^{***}$ |
| adj. $R^2$ | 0.90 | 0.82 | 0.81 |

1) All variables are in logarithms except time and shock dummy 2) P-value stands for jointed test of all coefficients = 0 (Ho) 3) Wd GDP stands for world real GDP, Ore Price $_{(t-1)}$ stands for iron ore price with 1 year lag, Interest Rate stands for U.S. 10-year treasury bond interest rate (real), Time stands for a time trend, The demand shock05 stands for dummy variable equals to 1 if Yearr≥2005, Supply Shock stands for dummy variable equals to 1 if Year≥1975 4) $t$ statistics in parentheses $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

The iron ore import price in 2004, 2005 and 2006 increased by 18%, 71% and 20% respectively. Therefore, assuming the shock happened in 2005 is realistic both from a statistical and a theoretical point of view.

Table 4 presents estimations of the structural equations 3.2.2 and 3.2.3.These constitute my main results. Under the perfect competition, the coefficients of price should be negative in the demand function and positive in the supply function. All three methods (OLS, 2SLS and 3SLS) indicate a negative slope of the demand curve and a positive slope of the supply curve. These results agree with the economic theory and our original hypothesis.

The coefficients of price in demand equations estimated using OLS and 2SLS are not significant at any level. In contrast, price coefficient estimator using 3SLS is significant at the 1% confidence level. Under the 3SLS model, most of the instrumental variables are robust, which also indicates that these instruments are strong and reliable.

Tests of endogeneity of instruments in both the supply and the demand equations indicate that an endogeneity problem exists in the regression[7]. Therefore, instrumental-variable is preferred over the OLS in my model. Test of over-identifying restrictions results[8] indicate that there is no significant evidence of over-identification problem in the 2SLS model.

[7] Tests of endogeneity - $H_0$: all the demand/supply variables are exogenous Demand equation: Robust score chi2(1) = 1.09953 (p = 0.2944), therefore do not reject the $H_0$; Supply equation Robust score $chi^2(1)$ = .183699 (p = 0.6682), therefore do not reject the $H_0$

[8] Test of over-identifying restrictions: Demand equation: Score $chi^2(3)$ = 25.324 (p = 0.0000), Supply equation: Score $chi^2(3)$ = 25.2671 (p = 0.0000)

**Table 4 Annual Supply and Demand using Iron Ore Production for Quantity**

| | OLS<br>Wd Ore Pd | 2SLS<br>Wd Ore Pd | 3SLS<br>Wd Ore Pd |
|---|---|---|---|
| **Demand Function** | | | |
| Ore Price $_{(t)}$ | -0.0693 | -0.463 | -0.928$^{***}$ |
| | (-0.61) | (-1.71) | (-4.33) |
| Scrap Price | 0.0612 | 0.0811 | 0.0910$^{**}$ |
| | (1.57) | (1.77) | (2.66) |
| Demand Shock05 | 0.464$^{***}$ | 0.608$^{***}$ | 0.744$^{***}$ |
| | (6.21) | (5.01) | (7.65) |
| Wd GDP | 0.435$^{***}$ | 0.419$^{***}$ | 0.404$^{***}$ |
| | (12.62) | (10.42) | (11.69) |
| Ore Price $_{(t-1)}$ | 0.0917 | 0.353 | 0.688$^{***}$ |
| | (0.99) | (1.86) | (4.45) |
| Constant | 9.039$^{***}$ | 9.894$^{***}$ | 10.76$^{***}$ |
| | (8.54) | (7.56) | (9.77) |
| ***$R^2$*** | 0.95 | 0.93 | 0.88 |
| **Supply Function** | | | |
| Ore Price $_{(t)}$ | 0.322$^{**}$ | 0.601$^{***}$ | 0.900$^{***}$ |
| | (3.22) | (3.88) | (6.84) |
| Interest Rate | -0.0418$^{*}$ | -0.0410 | -0.0122 |
| | (-2.02) | (-1.81) | (-0.82) |
| Time | 0.0261$^{***}$ | 0.0247$^{***}$ | 0.0231$^{***}$ |
| | (16.81) | (13.77) | (15.11) |
| Supply Shock | -0.175$^{***}$ | -0.148$^{*}$ | -0.138$^{**}$ |
| | (-3.36) | (-2.56) | (-2.99) |
| Ore Price $_{(t-1)}$ | 0.0680 | -0.190 | -0.450$^{***}$ |
| | (0.67) | (-1.26) | (-3.48) |
| Constant | 18.76$^{***}$ | 18.69$^{***}$ | 18.48$^{***}$ |
| | (93.55) | (84.84) | (97.84) |
| ***$R^2$*** | 0.94 | 0.93 | 0.89 |
| ***Durbin–Watson*** | 1.04 | 1.54 | 1.94 |
| ***N*** | 47 | 47 | 47 |

1) All Variables are in logarithms except Time and Shock Dummy 2) Wd Ore Pd stands for world iron ore production in natural logrithm3) *t* statistics in parentheses $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ 4) D – Statistic stands for Durbin–Watson statistic, the Durbin-Watson statistic lies in the range 0-4. A value of 2 or nearly 2 indicates that there is no first-order autocorrelation; acceptable range is 1.50 - 2.50 5) OLS stands for ordinary least squares, 2SLS stands for two-stage least squares, 3SLS stands for three-stage least squares

For the demand equation, all of the regression coefficients have the expected signs. A higher ore price will lead to a lower quantity demand. This result agrees with the theoretically downward sloping demand curve. The demand shock dummy, representing the China effect, shifts the demand curve up in parallel by 0.74. World GDP, as a very important demand driver, also has a positive impact on world iron ore production.

The positive relationship between scrap price and world ore production is reasonable given my assumption that scrap steel and iron ore are substitutes. This indicates that a higher scrap price causes a higher iron ore price as buyers shift out of scrap steel and into iron ore. For future studies, the structural model should include an equation for scrap price and estimate a three-equation 3SLS system.

The interpretation of $P_{t-1}$ is unclear at this stage. Assuming at the face value, the 3SLS estimations indicate that a time (t-1) price increase has a positive effect on ore demand at time (t). The in-depth explanation for the price elasticity of demand and the interpretation of $P_{t-1}$ are given later in the long-run model section.

For the supply equation, all of the regression coefficients have the expected signs. Furthermore, all of the coefficients are statistically significant at the 0.1% confidence level, except for the coefficient of interest rates. This result corroborates earlier studies that no statistical evidence has been found in empirical research to support Hotelling’s rule (Kronenberg, 2008). Therefore, a negative but not significant coefficient of interest rate is reasonable in my model.

In the supply equation, ore price has a positive effect on production, which indicates an upward slope of the supply curve. This agrees with my hypothesis as well. The coefficient of the time trend is 0.023. This coefficient indicates that the long-term growth rate of ore production that do not explained by my other covariates, is approximately 2.3% on annul basis. The supply shock dummy, representing the resource shortage, has a negative effect on ore production, which shifts the supply curve down in parallel by 0.14. Again, interpretation of the price elasticity of supply and the coefficient of $P_{t-1}$ will be explained in the discussion of the long-run model below.

With regard to the overall fit, the $R^2$ of my model is in the 0.89-0.94 range, which indicates a relatively high predictive power. However, my sample size is relatively small (47 observations) comparing to a general standard (above 150 observations). Therefore, caution should be taken when making any predictions using my model.

For the 3SLS estimate of the demand equation, the Durbin-Watson test value of 1.94 indicates the presence of autocorrelation. D value of 1.94 falls into the range of $d > d_{upper}$, thus, serial correlation is rejected at the 1% confidence level[9]. On the other hand, Durbin-Watson test values for OLS and 2SLS fall into the Durbin-Watson range ($d_{lower} < d < d_{upper}$), indicating possible serial correlation in the residuals (Appendix Fig. 5).

In summary, the annual $P_t$-$P_{t-1}$ supply-and-demand model is given by:

[9] D statistic from 0.95665 to 1.82 for a regression with 10 independent variables and 47 observations. My source is a Stanford professor's class notes (http://www.stanford.edu/~clint/bench/dwcrit.htm)

***$P_t$ - $P_{t-1}$ Model***

$$\text{Demand: } Q_{tD} = \underset{(9.77)}{10.7558} - \underset{(-4.33)}{0.9283}P_t + \underset{(4.45)}{0.6875}\, P_{t-1} + \underset{(2.66)}{0.0910}\, \text{Scrap Price}_t + \underset{(7.65)}{0.7437}\, \text{Demand Shock}_t + \underset{(11.69)}{0.4039}\, \text{GDP}_t + \mu \qquad (5.1.1)$$

$$\text{Supply: } Q_{tS} = \underset{(97.84)}{18.4794} + \underset{(6.84)}{0.9002}P_t - \underset{(-3.48)}{0.4499}\, P_{t-1} - \underset{(-0.82)}{0.0122}\, \text{Interest Rate}_t + \underset{(15.11)}{0.0231}\, \text{Time}_t - \underset{(-2.99)}{0.1379}\, \text{Supply Shock}_t + v \qquad (5.1.2)$$

## LONG-RUN ANNUAL SUPPLY AND DEMAND MODEL (1962-2010)

As equations 3.2.6 and 3.2.7 indicate, the long run model has the same form as that of short run, replacing $P_t - P_{t-1}$ with $\hat{P}$. The $P_t - P_{t-1}$ model avoids serial correlation problem (see appendix table 3, 3SLS without $P_{t-1}$), but the coefficients of $\hat{P}$ in the supply-and-demand equations values for the long-run elasticity.

**Table 5 Price elasticities of supply and demand**

<table>
<tr><th></th><th></th><th></th><th>Coefficient</th><th>S.D.</th><th>Z</th><th>P>|z|</th><th colspan="2">95% Conf. Interval</th></tr>
<tr><td rowspan="2">Coefficient of $\hat{P}$</td><td>Demand</td><td>$\beta_1+\beta_2$</td><td>-0.241**</td><td>0.090</td><td>-2.68</td><td>0.007</td><td>-0.417</td><td>-0.065</td></tr>
<tr><td>Supply</td><td>$\gamma_1+\gamma_2$</td><td>0.450***</td><td>0.045</td><td>9.93</td><td>0.000</td><td>0.361</td><td>0.539</td></tr>
</table>

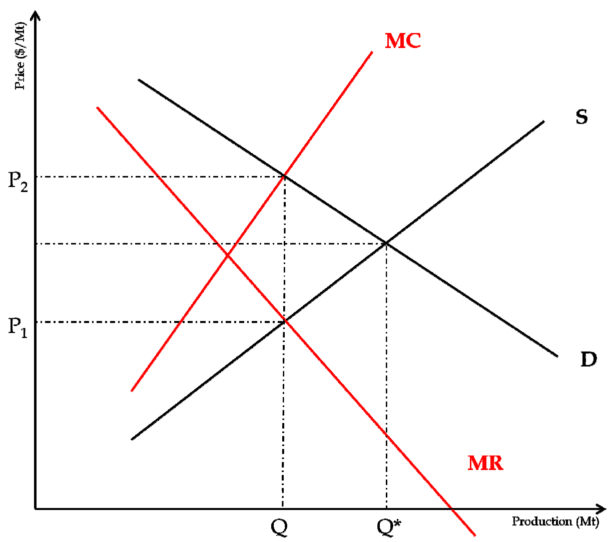
*t* statistics in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5 presents the price elasticity values of supply and demand. The price elasticity of demand is -0.24 indicating that iron ore is price inelastic. Although there is no similar elasticity type of research of iron ore available to compare my results to, it is well-known that steel is price inelastic and the price elasticity of demand of steel is in the range of -0.2 to -0.3(GONZÁLEZ & KAMIÑSKI, 2011; Malanichev & Vorobyev, 2011). My research indicates that iron ore, as a middle product to make steel, has a similar price elasticity of demand comparing to steel. The price elasticity of supply of iron ore is 0.45. Although it is still inelastic but is higher than the elasticity of demand. This indicates that the slope of the supply curve is steeper than that of the demand curve showing that the sellers are more price-sensitive than the consumers.

The combined coefficient of the supply equation is still significant at 0.1% confidence level but the coefficient of the demand equation is significant only at 1% confidence level. The results agree with the table 2's results - all the demand shifters are jointly more significant than the supply shifters, so the supply curve can be better identified than the demand curve.

Instead of the perfect competition model, figure 3 illustrates a standard bilateral monopoly supply-demand model in which there are both a monopoly and a monopsony in the same market. In such case, the market price (P) and output (Q) are determined by forces like bargaining power from both the buyer and the seller.

**Fig.3 Iron Ore Pricing Diagram**



In a standard bilateral monopoly model, the price is settled between $P_1$ and $P_2$ depending on the bargaining power from the buyer and the seller. Estimating the actual MC and MR curve under oligopoly requires advanced game theory knowledge and is, thus, beyond the scope of this paper. However, a relatively steep supply curve and a relatively flat demand curve can be interpreted as a result of sellers' domination in price determination (the Big Three mining companies). The sellers' overwhelming bargaining power constitutes an incentive for China to move the market to a spot system.

Using the coefficient estimator results from table 5, $P_t$-$P_{t-1}$ model (equations 5.1.1 and 5.1.2) can be written as the long-run structural model,

***Long-run Structural Model***

Demand: $Q_{tD} = \underset{(9.77)}{10.7558} - \underset{(-2.68)}{0.2408}\,\hat{P} + \underset{(2.66)}{0.0910}\text{ Scrap Price} + \underset{(7.65)}{0.7437}\text{ Demand Shock} + \underset{(11.69)}{0.4039}\text{ GDP} + \mu$

Supply: $Q_{tS} = \underset{(97.84)}{18.4794} + \underset{(9.93)}{0.4503}\,\hat{P} - \underset{(-0.82)}{0.0122}\text{ Interest Rate} + \underset{(15.11)}{0.0231}\text{ Time} - \underset{(-2.99)}{0.1379}\text{ Supply Shock} + v$

## 5.3 MONTHLY REDUCED FORM MODEL (2006-2011)

Studying short-term price movement becomes meaningful due to the emerging spot market system. Here, I initiate a trial study using recent monthly data. Future research should be conducted once more data become available.

Table 6 presents the monthly regression results for 2006 to 2011. Building a supply-and-demand model using monthly data is not feasible since data of world total production of iron ore is only available on an annual basis. Since the monthly model uses more recent data, new variables can be included in the model.

The monthly model has many Chinese market related variables since China is the major price driver in the 2000s. Therefore, instead of using 64.5% Fe content iron ore price (Brazil to Europe), I use 62%-Fe content Tian Jin-port[10] iron ore price in this regression. The inventory covariate represents the inventory amount stocked at Tianjin port by iron ore sellers. This index was first recorded in 2009. The pig iron output and steel output represent the total amount of pig iron and steel production respectively in China[11].

The coefficients of both inventory and lagged inventory are positive and significant, indicating that inventory and price are moving in the same direction. The correlation coefficient between ore price and scrap price is positive means that a higher scrap price leads to a higher iron ore price. This result is consistent with my yearly model.

[10] Tian jing is a city of China

[11] Iron ore is the middle material to make pig iron and steel

**Table 6 Monthly reduced form estimates for iron ore price**

| | OLS-1<br>Price (t) | OLS-2<br>Price (t) | OLS-3<br>Price (t) | OLS-4<br>Price (t) | OLS-5<br>Price (t) |
|---|---|---|---|---|---|
| Inventory $_{(t)}$ | 0.452** | 0.447** | | | |
| | (2.77) | (2.88) | | | |
| Scrap Price | 0.430*** | 0.410*** | 0.449*** | 0.473*** | 0.487*** |
| | (3.86) | (3.50) | (4.41) | (4.91) | (5.24) |
| 1 Yr Swap Rate | -0.734*** | -0.713*** | -0.740*** | -0.728*** | -0.697*** |
| | (-7.23) | (-6.29) | (-7.53) | (-7.18) | (-6.32) |
| BIDY | -0.155*** | -0.154*** | -0.146*** | -0.146*** | -0.147*** |
| | (-5.96) | (-5.74) | (-5.52) | (-5.31) | (-5.35) |
| Pig Iron Output | 0.229 | | 0.178 | 0.191 | 0.258 |
| | (0.98) | | (0.77) | (0.86) | (1.10) |
| Steel Output | | 0.296 | | | |
| | | (1.18) | | | |
| Inventory $_{(t-1)}$ | | | 0.478** | | |
| | | | (3.29) | | |
| Inventory $_{(t-2)}$ | | | | 0.475*** | |
| | | | | (3.51) | |
| Inventory $_{(t-3)}$ | | | | | 0.487*** |
| | | | | | (3.60) |
| Constant | 2.981** | 2.740* | 2.950** | 2.815** | 2.408* |
| | (3.21) | (2.62) | (3.15) | (2.84) | (2.22) |
| *N* | 66 | 66 | 65 | 64 | 63 |
| *Durbin–Watson* | 1.11 | 1.09 | 1.09 | 1.15 | 1.05 |
| adj. $R^2$ | 0.95 | 0.95 | 0.95 | 0.95 | 0.95 |

1) Price using 62%-Fe content TianJin-port iron ore price, interest rate stands for U.S. 1-year swap rate (real), BDIY stands for Baltic Dry Shipping index, pig iron output stands for China's monthly pig iron output amount, steel output stands for China monthly steel output amount, inventory (t) stands for China iron ore inventory at month t, inventory (t-x) stands for x month lag of inventory (x=1,2,3) 2) t statistics in parentheses $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

The interest rate has a significantly negative effect on monthly ore price. According to my yearly model, in the long run, a higher interest rate should lead to a lower ore production, and, hence a higher ore price due to a supply shortage. However, in this case, the short-run negative relationship between price and interest rate could be the result of speculation. It is reasonable to consider that investors would rather hold U.S. Treasury bonds when interest rate is high and bulk commodities when interest rate is low.

A positive coefficient of shipping index indicates that a higher shipping cost leads to a lower iron ore export price. Since the delivery price is the export price plus the shipping cost, and usually buyers are responsible for the shipping cost, sellers are likely to be willing to take a price cut if the shipping is too expensive.

In general, the Durbin-Watson statistics for my monthly regressions are low ($d<d_l = 1.2$), indicating omitted-variable bias problems in my regression. Therefore, the estimators may be biased and inconsistent.

# 6 SIMULATIONS

One important use of a model is to make reasonable economic forecasts. In this section, I perform both back-tests and forecasts based on Monte Carlo method.

## 6.1 REDUCED FORM MODEL CONSTRUCTION

The alternative of equations 3.2.2 and 3.2.3 is the reduced form version of the equations[12], which can be written as,

$$\mathrm{P_t} = \frac{\beta_0 - \gamma_0}{\gamma_1 - \beta_1} + \frac{\beta_2 - \gamma_2}{\gamma_1 - \beta_1}\,\mathrm{P_{t-1}} + \frac{\beta_3}{\gamma_1 - \beta_1}\,\text{Scrap Price} + \frac{\beta_4}{\gamma_1 - \beta_1}\,\text{Demand Shock} + \frac{\beta_5}{\gamma_1 - \beta_1}\,\text{GDP} + \frac{-\gamma_3}{\gamma_1 - \beta_1}\,\text{Interest Rate} + \frac{-\gamma_4}{\gamma_1 - \beta_1}\,\text{Time} + \frac{-\gamma_5}{\gamma_1 - \beta_1}\,\text{Supply Shock} + \frac{1}{\gamma_1 - \beta_1}\,\mu + \frac{-1}{\gamma_1 - \beta_1}\,\nu \qquad (6.1.1)$$

$$\mathrm{Q_t} = \frac{\beta_0\,\gamma_1 - \beta_1\,\gamma_0}{\gamma_1 - \beta_1} + \frac{\beta_2\,\gamma_1 - \beta_1\,\gamma_2}{\gamma_1 - \beta_1}\,\mathrm{P_{t-1}} + \frac{\beta_3\,\gamma_1}{\gamma_1 - \beta_1}\,\text{Scrap Price} + \frac{\beta_4\,\gamma_1}{\gamma_1 - \beta_1}\,\text{Demand Shock} + \frac{\beta_5\,\gamma_1}{\gamma_1 - \beta_1}\,\text{GDP} + \frac{-\beta_1\,\gamma_3}{\gamma_1 - \beta_1}\,\text{Interest Rate} + \frac{-\beta_1\,\gamma_4}{\gamma_1 - \beta_1}\,\text{Time} + \frac{-\beta_1\,\gamma_5}{\gamma_1 - \beta_1}\,\text{Supply Shock} + \frac{\gamma_1}{\gamma_1 - \beta_1}\,\mu + \frac{-\beta_1}{\gamma_1 - \beta_1}\,\nu \qquad (6.1.2)$$

A simplified version of equation 6.1.1 and 6.1.2 can be written as,

$$\mathrm{P_t} = \tau_0 + \tau_1\,\mathrm{P_{(t-1)}} + \tau_2\,\text{Scrap Price} + \tau_3\,\text{Demand Shock} + \tau_4\,\text{GDP} + \tau_5\,\text{Interest Rate} + \tau_6\,\text{Time} + \tau_7\,\text{Supply Shock} + \varepsilon \qquad (6.1.3)$$

$$\mathrm{Qt} = \Delta_0 + \Delta_1\,\mathrm{P_{(t-1)}} + \Delta_2\,\text{Scrap Price} + \Delta_3\,\text{Demand Shock} + \Delta_4\,\text{GDP} + \Delta_5\,\text{Interest Rate} + \Delta_6\,\text{Time} + \Delta_7\,\text{Supply Shock} + \xi \qquad (6.1.4)$$

[12] The Pt-Pt-1 model is more accurate than the long-run P^ model in terms of predictive power. Therefore, I choose the reduce form model based on the Pt-Pt-1 mode

All the coefficient estimators (α and β) are calculated in table 4. I then calculate new coefficients (Δ and τ) of each input parameter of equations 6.1.3 and 6.1.4 based on the equations 6.1.1 and 6.1.2. The new standard deviations of each coefficient are also calculated using STATA's non-linear estimator combination module (table 7).

**Table 7 Coefficients of reduced form equations (6.1.3 and 6.1.4)**

**Price Formula - $P_t$**

| | | Coefficient | S.D. | Z | 95% Conf. Interval | |
|---|---|---|---|---|---|---|
| $\tau_1$ | $P_{(t-1)}$ | 0.622*** | 0.037 | 17.02 | 0.550 | 0.694 |
| $\tau_2$ | Scrap Price | 0.050** | 0.018 | 2.76 | 0.014 | 0.085 |
| $\tau_3$ | Demand Shock | 0.407*** | 0.036 | 11.21 | 0.336 | 0.478 |
| $\tau_4$ | GDP | 0.221*** | 0.033 | 6.64 | 0.156 | 0.286 |
| $\tau_5$ | Interest Rate | 0.007 | 0.008 | 0.82 | 0.009 | 0.023 |
| $\tau_6$ | Time | -0.013*** | 0.001 | -9.56 | -0.015 | -0.010 |
| $\tau_7$ | Supply Shock | 0.075*** | 0.024 | 3.19 | 0.029 | 0.122 |
| $\tau_0$ | Constant | -4.224*** | 0.888 | -4.75 | -5.965 | -2.482 |

**Quantity Formula - $Q_t$**

| | | Coefficient | S.D. | Z | 95% Conf. Interval | |
|---|---|---|---|---|---|---|
| $\Delta_1$ | $P_{(t-1)}$ | 0.110* | 0.048 | 2.31 | 0.017 | 0.203 |
| $\Delta_2$ | Scrap Price | 0.045** | 0.017 | 2.66 | 0.012 | 0.078 |
| $\Delta_3$ | Demand Shock | 0.366*** | 0.047 | 7.76 | 0.274 | 0.459 |
| $\Delta_4$ | GDP | 0.199*** | 0.040 | 5.03 | 0.121 | 0.276 |
| $\Delta_5$ | Interest Rate | -0.006 | 0.008 | -0.82 | -0.021 | 0.009 |
| $\Delta_6$ | Time | 0.012*** | 0.002 | 4.86 | 0.007 | 0.016 |
| $\Delta_7$ | Supply Shock | -0.070* | 0.030 | -2.33 | -0.129 | -0.011 |
| $\Delta_0$ | Constant | 14.677*** | 0.965 | 15.21 | 12.786 | 16.568 |

### 6.2 BACK-TEST RESULTS

Based on the results of table 7, I substitute each of the coefficient estimators into the equations 6.1.3 and 6.1.4 to get the final price and quantity reduced form equations. Then, I apply the historical values of each covariate spanning 1962 through 2010 to calculate the predicted values of price and quantity. The results are presented in figure 4.a and figure 4.b.

**Figure 4.a Iron ore price and predicted prices (1962-2010)**

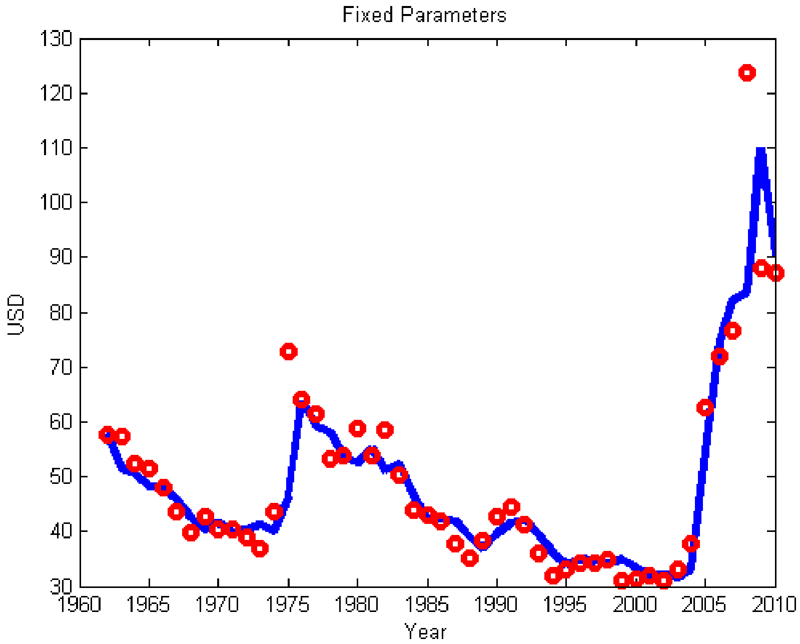
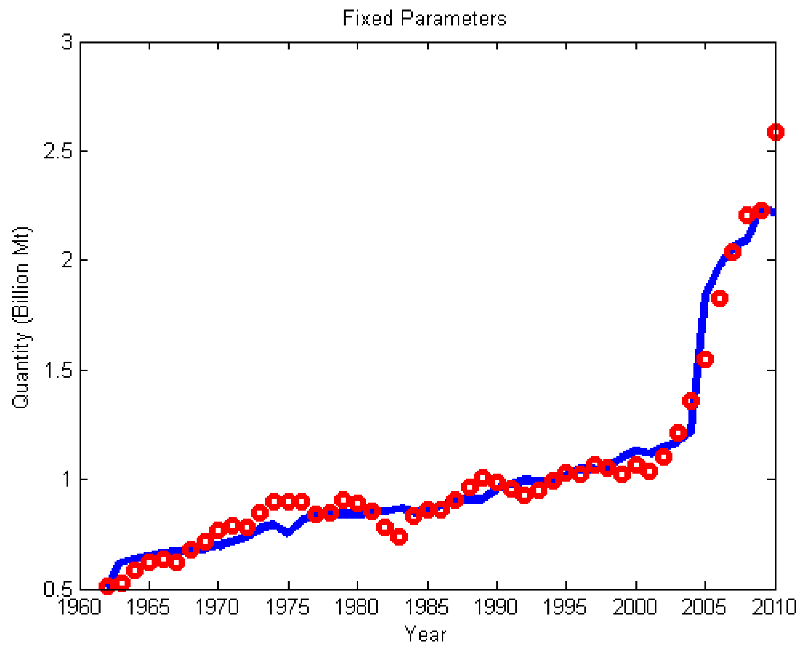



**Figure 4.b Iron ore quantity and predicted quantities (1962-2010)**




1) The red dots represent historical prices and quantities, and the blue lines represent predicted values.

2) Data span 1962 through 2010.

Figure 4a and 4b compare the historical values of price and quantity with predicted values based on the reduced form estimates in table 7. For the price equation (Fig 4.a), the predicted trend line fit the data points remarkably well with the exceptions in 1975 and 2009, corresponding to the 1975 supply shock and 2009 economic recession, respectively. It is not surprising that neither a single supply-shock dummy nor a demand-shock dummy is sophisticated enough to capture the changing price and quantity of the extreme time periods. Hence, other omitted variables including recessions should be considered in the future research.

For the quantity equation, the trend line fits the dots well except for 2010 (Fig 4.b). There are two reasons for the Big Three mining companies increasing ore production sharply in 2010 1) the iron ore price spiked in 2009 2) mining companies were speculating that future price of ore would drop due to China's economic slowdown. Thus, the mining companies had economic incentives to produce and sell more iron ore in 2010 at a high price (MacDonald, 2009). Covariates represent future price expectations should also be incorporated into the supply and demand model[13].

[13] Since the world first iron ore swap was originated in 2008, I am not able to include any future price series into my annually supply-and-demand model due to limited data series (Ice, 2010)

## 6.3 COEFFICIENT ESTIMATOR SENSITIVITY TEST

The purpose of coefficient sensitivity tests is to understand how each coefficient estimator would affect the predicted prices and quantities. Here, I use the coefficient estimator of GDP as an example and the rest of the tests follow the same method.

Instead of assuming the coefficient estimator of GDP being $\overline{\tau_4}$[14], I assume the coefficient estimator of GDP is a probability distribution with mean $\tau_4$ and standard deviation of δ. δ is given in table 7 (section 6.1). Since I am testing the sensitivity of the coefficient of GDP, I am holding other covariates coefficients fixed.

The GDP coefficient estimator can be written as a normal distribution,

$$\chi \sim N\,(\overline{\tau_4}\ ,\ \delta^2) \tag{6.3.1}$$

Assuming Z = $N$ (0,1)[15], the coefficient estimator of GDP can be written as

$$\widehat{\tau_4} = \overline{\tau_4} + \delta Z \tag{6.3.2}$$

I then draw 1000 random numbers of the distribution Z to generate the “possible set” of coefficient estimators of $\widehat{\tau_4}$. Equation 6.1.3 can be written as

$$P_t = \overline{\tau_0} + \overline{\tau_1}\ P_{(t-1)} + \overline{\tau_2}\ \text{Scrap Price} + \overline{\tau_3}\ \text{Demand Shock} + \widehat{\tau_4}\ \text{GDP} + \overline{\tau_5}\ \text{Interest Rate} + \overline{\tau_6}\ \text{Time} + \overline{\tau_7}\ \text{Supply Shock} + \varepsilon \tag{6.3.3}$$

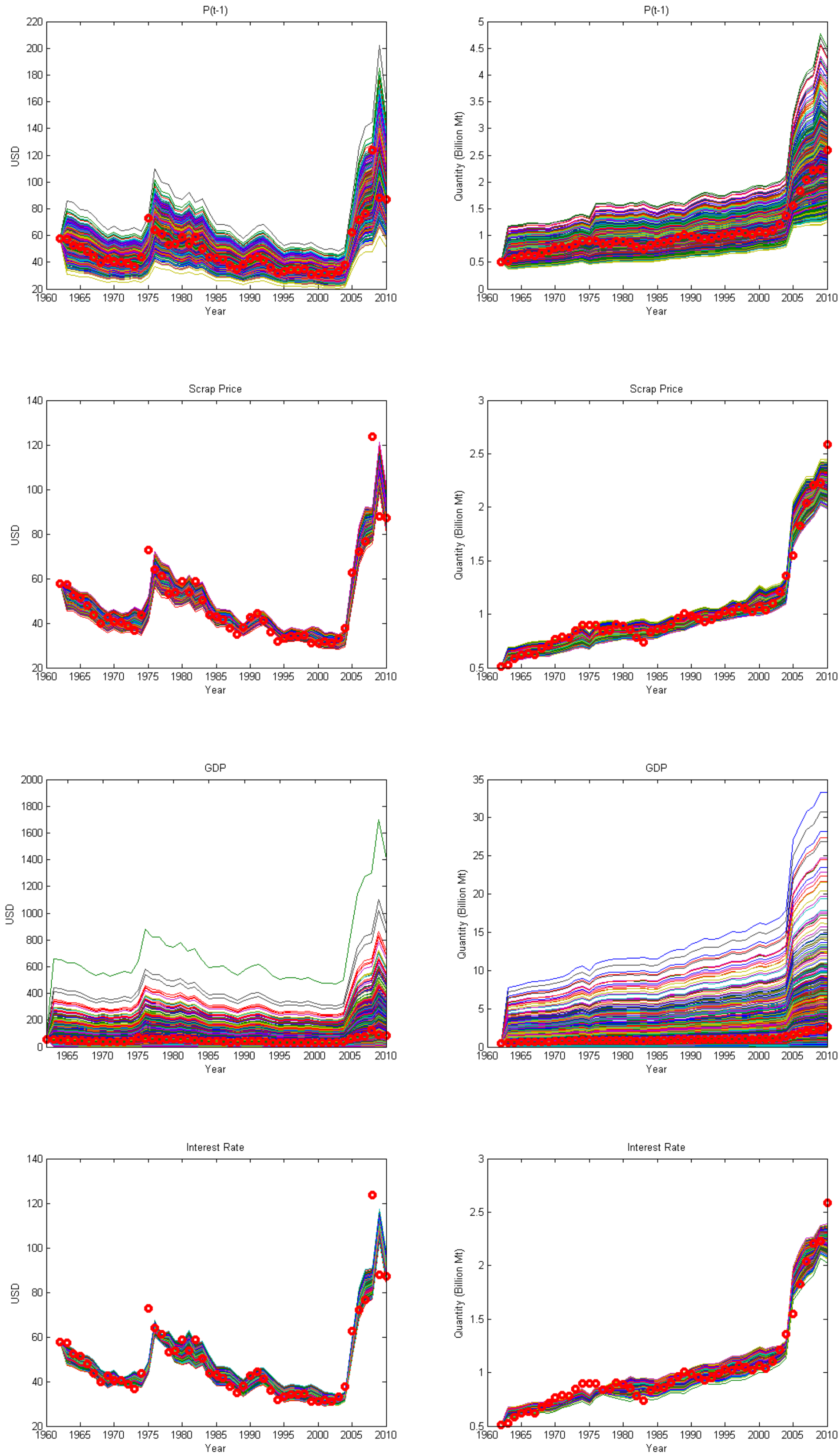
The Monte Carlo technique is applied involving 1000 iterations of equation 6.3.3 using different $\widehat{\tau_4}$ generated previously. Hence, 1000 paths are generate and plotted into figure 5.

---

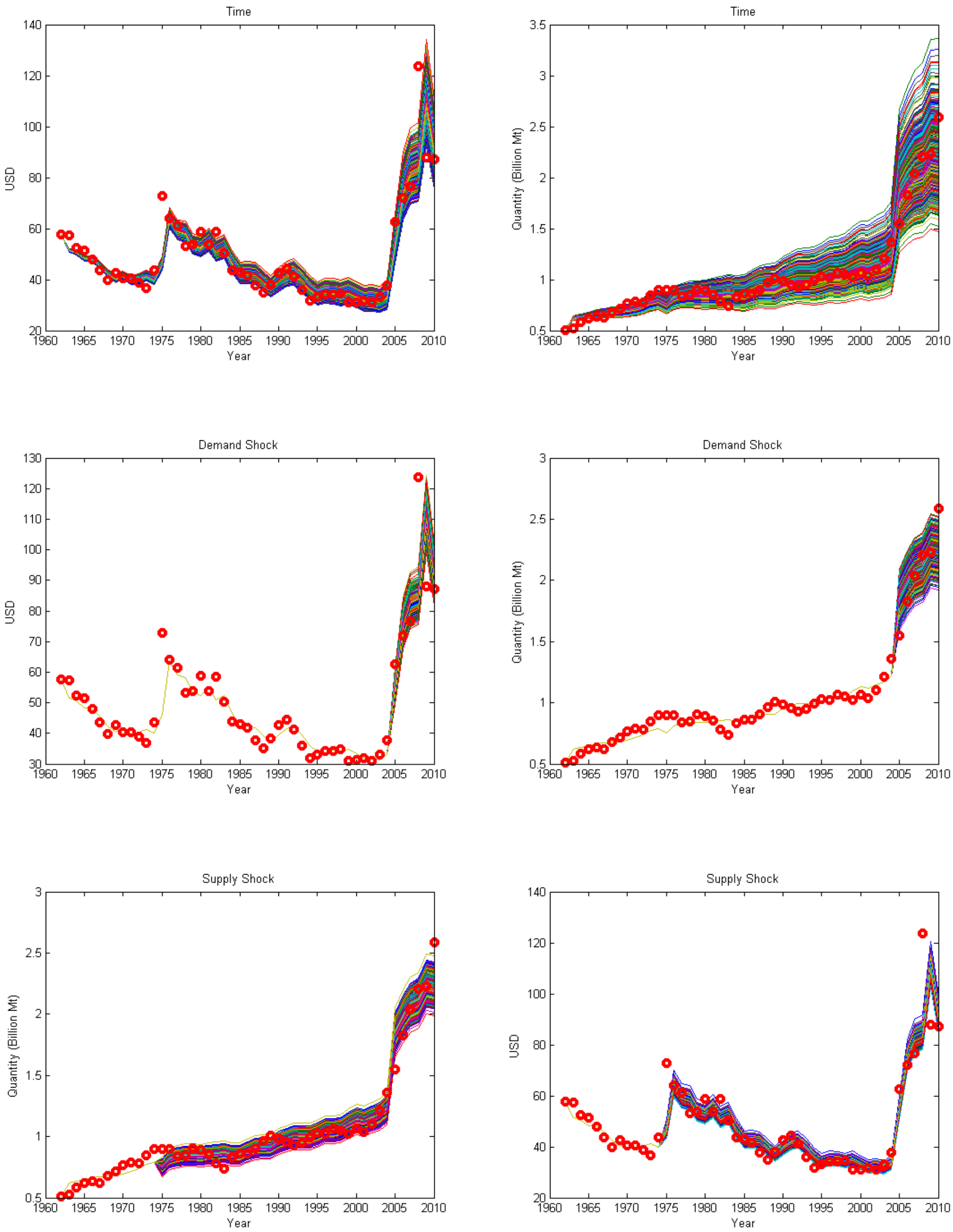
14 The mean of τ

15 Standard normal distribution

## Figure 5.a Covariates sensitivity tests (1962-2010)



## Figure 5.b Covariates sensitivity tests (1962-2010)




1) The red dots represent historical prices and quantities, and each of the color line represents one predicted path. 2) All the left side graphs are price plots and all the right side graphs are quantity plots. 3) Data span 1962 through 2010.

The sensitivity tests results indicate that, on the one hand, the predicted prices and quantities are not sensitive to a small change in the coefficient estimators of scrap price, time and shock dummies, despite these covariates are significant in 3SLS regression. On the other hand, predicted prices and quantities are very sensitive to a small change in the coefficient estimators of GDP and $P_{t-1}$ (Fig 5). Although the mean predicted prices and quantities using the probabilistic coefficients of GDP and $P_{t-1}$ are within a reasonable range, the standard deviations of the predicted prices and quantities are large, reflecting a great degree of uncertainty in the model predictions. In other words, my model projections will not be valid if the coefficient estimators of GDP and $P_{t-1}$ change during the predicting period.

### 6.4 FORECASTS (2011-2020)

Forecast applies similar Monte Carlo method as the sensitivity test. In this case, I assume 1) all the coefficient estimators are fixed to the mean value 2) the coefficient estimators will not change over the period of prediction.

Future prices and quantities are estimated under different GDP growth rate and interest rate scenario assumptions.

In terms of the projection of covariates, I assume the U.S. real scrap price for the next 10 years equals to the average price from 1960 to 2010 ($6.88) under the assumption of cyclical scrap price (Fig. 2, section 4). Future real interest rate is fixed as the average interest rate from 1960 to 2010 when I perform different GDP growth rate scenario analysis. Likewise, GDP growth rate is fixed as the average GDP growth rate from 1960 to 2010 when different interest rate scenario analysis is performed.

In order to calculated different GDP growth rates and corresponding standard deviations, I utilize world real GDP regression on time from 1960 to 2010, 1991 to 2000 and 2001 to 2010 respectively to receive different historical GDP growth rates. The results indicate that the average GDP growth rate over the past 50 years is 3.77% (P= 0.000$^{***}$, S.D. = 0.0009), the growth rate in the 1990s is 2.12% (P= 0.000$^{***}$, S.D. =0.0029) and the growth rate in the 2000s is 5.53% (P= 0.000$^{***}$, S.D. = 0.0064).

Then, for mean GDP growth rate of $\bar{G}$ (3.77%, 2.12% and 5.53%) and standard deviation of $\sigma$ (0.0009, 0.0029 and 0.0064), for each year in the next 10 years, I randomly draw 1000 GDP growth rates, G, and plug them into the equation 5.1.1 and 5.1.2.

The random draw of GDP growth rate is following the probability distribution that

$$\Pr(\bar{G} - 1\sigma \leq G \leq \bar{G} + 1\sigma) \approx 0.68$$

$$\Pr(\bar{G} - 2\sigma \leq G \leq \bar{G} + 2\sigma) \approx 0.95$$

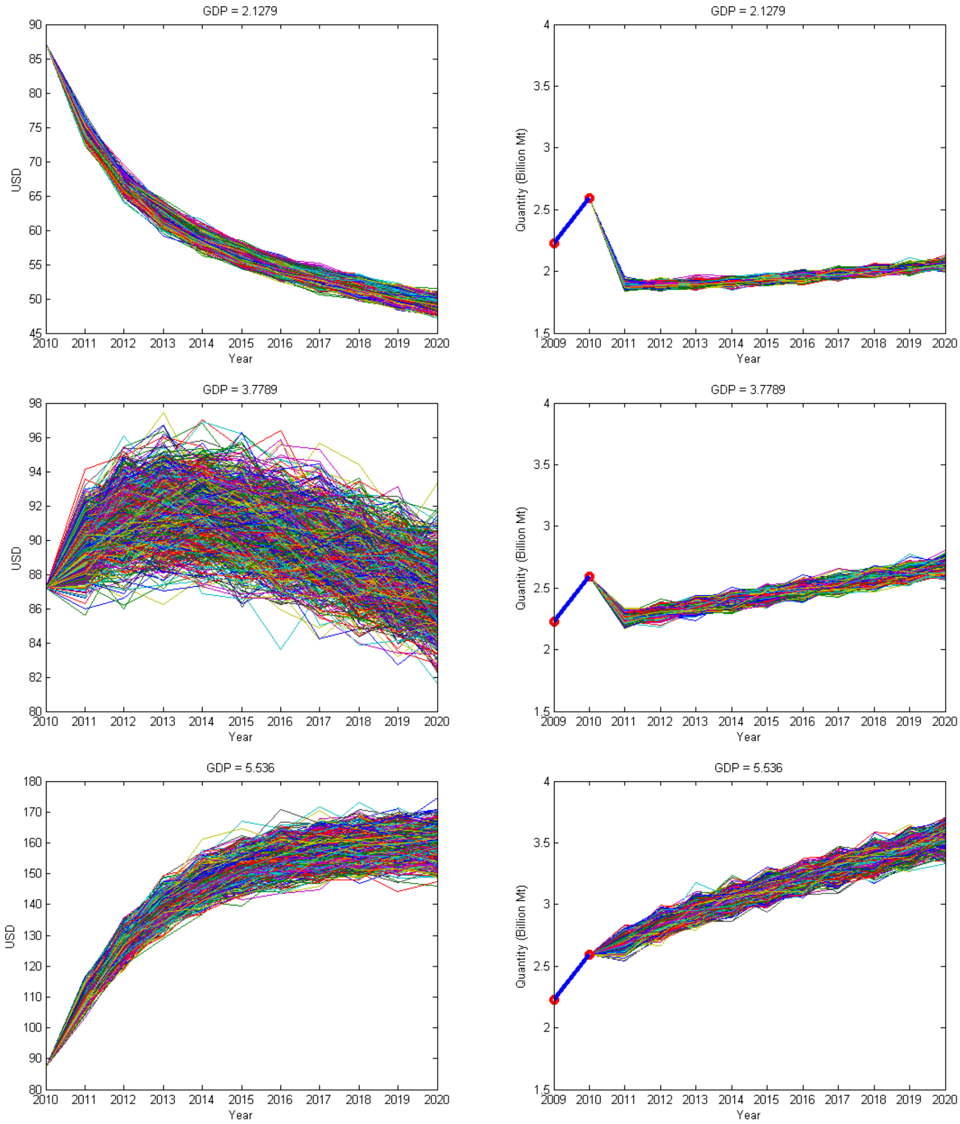
$$\Pr(\bar{G} - 3\sigma \leq G \leq \bar{G} + 3\sigma) \approx 0.99$$

For GDP scenario analysis, I forecast future iron ore price and quantity based on the real GDP growth rates in the 1990s, 2000s and from 1960s to 2010s. I consider the 50-year average growth rate simulation as the "benchmark situation" and consider the GDP growth rates in the 90s and 00s as two extreme cases.

Simulation results indicate that, at a low growth rate of 2.1%, (the 10-yr average growth rate of the 90s), the mean of predicted iron ore prices is $49 (S.D. = 0.7), and imply a 10-year compound annual growth rate (CAGR) of -5.6%. At a benchmark GDP growth rate of 3.7% (the average growth rate from 1960 to 2010), the mean of predicted iron ore prices is $87 (S.D. = 1.7) and the 10-year CAGR is almost 0%. At a high GDP growth rate of 5.5% (the 10-yr average growth rate of the 00s), the mean of predicted iron ore prices is $159 (S.D. = 4.4) and the 10-year CAGR is almost 6.2%.

In terms of the future production quantities, 2.1% GDP growth rate leads to a production amount of 2,057 million Mt (10 Yr CAGR = -2.3%), 3.7% GDP growth rate leads to a production amount of 2,673 million Mt (10 Yr CAGR = 0.3%) and 5.5% GDP growth rate leads to a production amount of 3,533 million Mt (10 Yr CAGR = 3.2%).

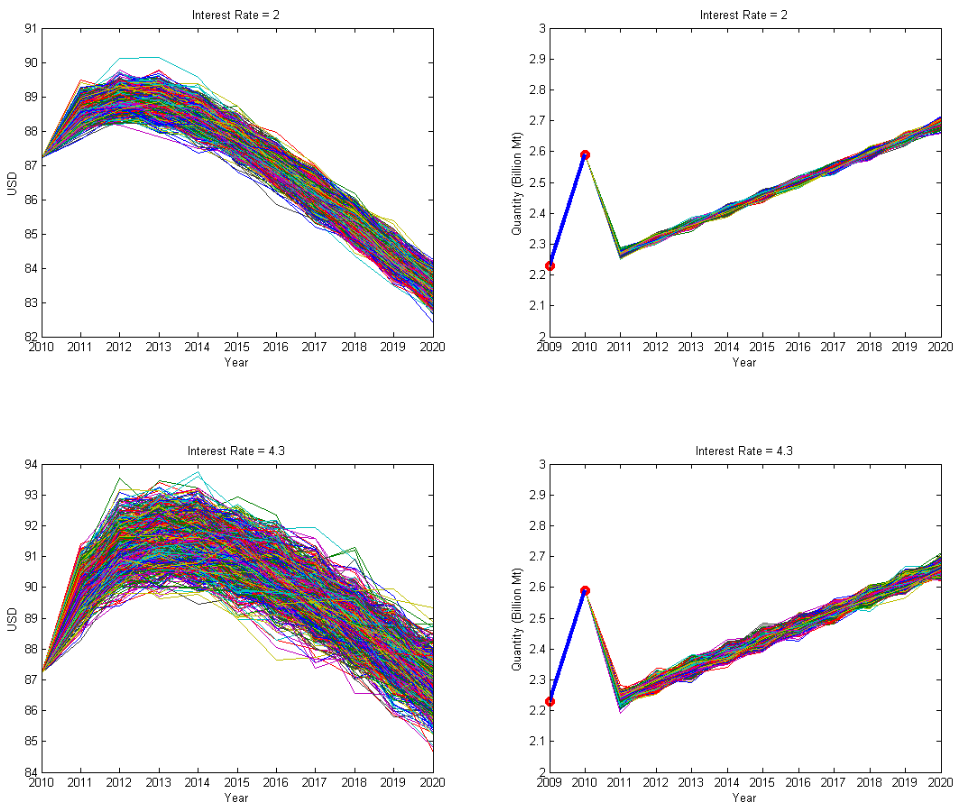
**Figure 6 Prices and quantities forecasts – GDP (2011-2020)**



The simulation results indicate that a high world real GDP growth rate leads to a high iron ore price and production quantity. For the past ten years, the world GDP growth is mainly due to the resource intensive growth of emerging markets, (Cheung et al., 2007; Essl, 2009). It is reasonable that a high GDP growth rate leads to high iron ore consumption, consequently, a high price.

The benchmark situation also suggests that the production quantities of iron ore will keep increasing in the next ten years and reaches a peak at 2014 before starting to drop. This projection aligns with the expectation from the mining industry that the iron ore price could drop in the next two to three years (Pretorius J. et al., 2011).

**Figure 7 Prices and quantities forecasts – Interest rates (2011-2020)**



The interest rate scenario analysis holds other covariates fixed. If the U.S. real interest rate is at 2%, the mean of 2020 predicted prices is $83 (S.D. = 0.3) and the quantity is 2,690 million Mt. If the U.S. real interest rate is at 4.3% (average interest rate in the 1980s), the mean of 2020 predicted prices is $87 (S.D. = 0.6) and the mean of predicted quantities is 2,690 million Mt. The predictions agree with the Hotelling's rule that mine owners are willing to extract more resources when the interest rate is low and to extract less when the interest rate is high.

The non-continuous break points appearing in quantity prediction graphs indicate that the model is not able to capture the production spike in 2010. In other words, the model treats the 2010 production quantity as a statistical outlier. The model suggests that quantity will drop to the 2009 level in 2011, unless world can keep growing at 5.5%.

# 7 CONCLUSTION

I used instrumental variables and joint estimation to construct efficiently identified estimates of supply and demand equations for the world iron ore market under the assumption of perfect competition.

With annual data spanning 1960 through 2010, the supply curve was identified using OLS, 2SLS and 3SLS, while the demand curve was identified using 3SLS only. The instruments I picked were both strong and credible under the 3SLS estimation. Seven out of ten coefficient estimators were statistically significant at 0.1% confidence level. Two of the remaining estimators were significant at 1% level and only the estimator of interest rate was not significant based on my estimations. In conclusion, 3SLS yields efficient and consistent coefficient estimators.

The annual model indicates that the long-run iron ore supply curve appears to be upward sloping while the long-run demand curve for iron ore appears to be downward sloping. This agrees with the theory of a perfect competition market. The price elasticity of supply is 0.45 and the price elasticity of demand is -0.24, which indicates that both the supply curve and the demand curve are price inelastic and the demand curve is more inelastic than the supply curve. Under the 3SLS estimation, all of the coefficient estimators show predicted signs, indicating that the hypothesis is reasonable.

I found some evidence that, in addition to the instrumental variables included in the annual model, other variables such as iron ore inventory level and shipping cost also affected the short-run price of iron ore. However, it is difficult to conclude anything based on the monthly model due to the potential of omitted-variable bias and serial correlation problems.

The simulation results indicate that the annual model captures most of the historical price fluctuations. In addition, choosing different world GDP growth rates and the coefficient estimator of GDP could yield a wide range of price predictions based on the simulation results. In other words, the coefficient estimator of GDP is the limiting factor of the model and determines the validity of the model predictions.

There are two shortcomings associated with my research.

First, I assumed both demand and supply functions are linear with fixed coefficients and additive errors. This assumption could be revised in future work based on the methods developed by Angrist (2000) and by Newey, Powell and Vella (1999).

Second, I discussed the world iron ore market based on a simple perfect competition assumption. However, as I described in section 2 and 5, the actual market is a bilateral negotiation oligopoly and this market is moving to a spot price system. When Labson (1997) first studied changing patterns of iron ore market, he constructed a dynamic model including the interaction of iron ore and steel. My annual model indicates that scrap steel also has a complicated interaction with iron ore. Therefore, for future research, a dynamic model considering the interactions among iron ore, steel and scrap steel based on an oligopoly market assumption is recommended.

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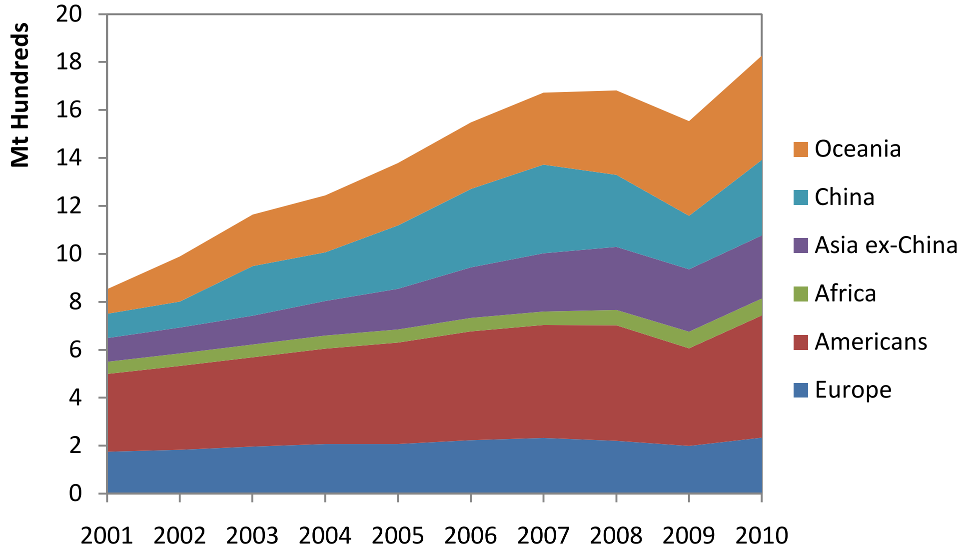
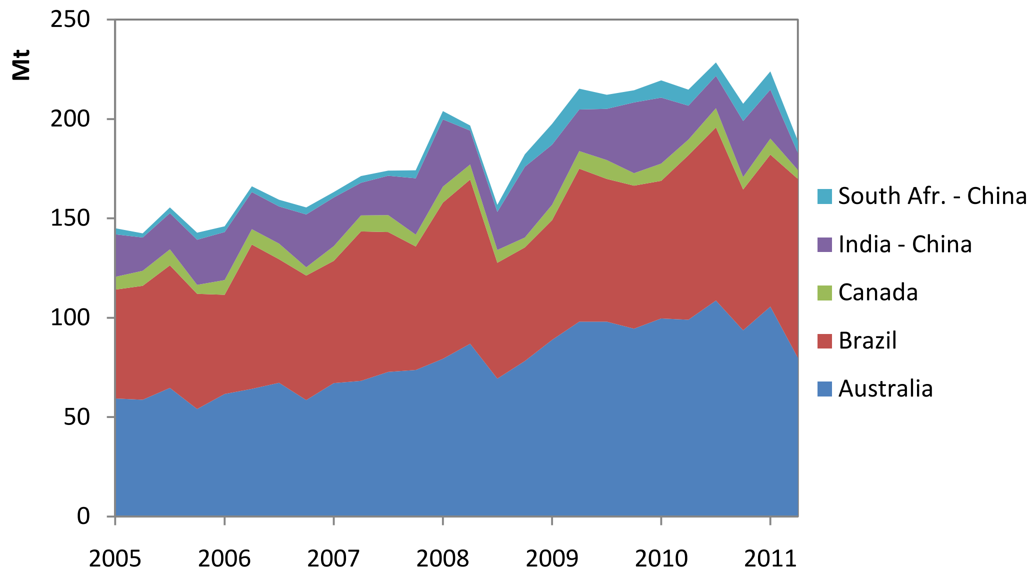
# APPENDIX

## Appendix Figure 1 Iron Ore World Production (2001-2010)



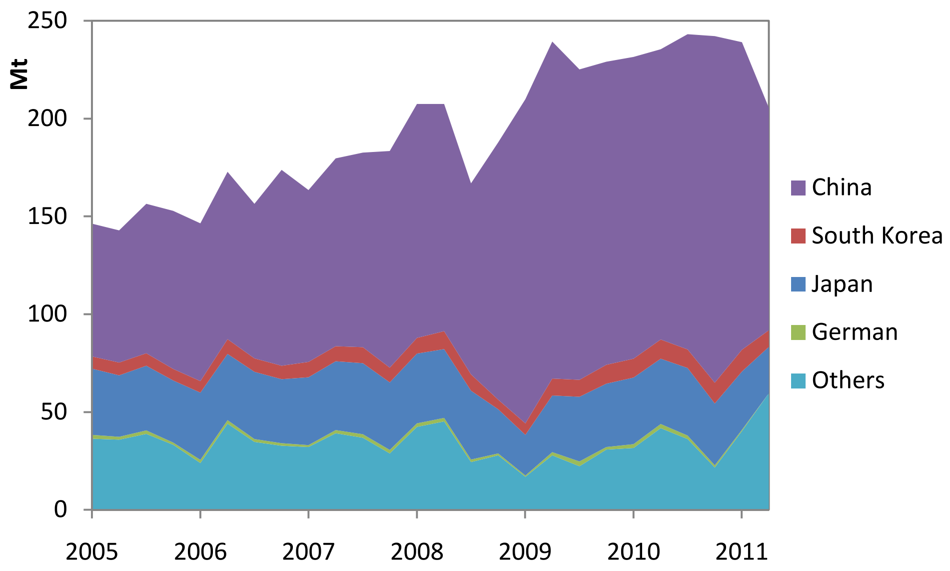

*Data Source: UN Database, World Steel Association*

## Appendix Figure 2 Iron Ore Exports by Country (2005-2011)



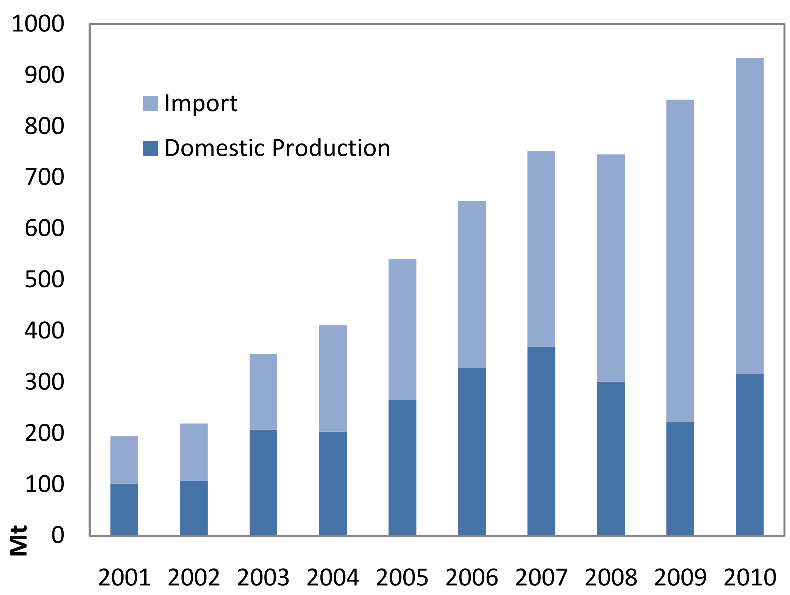

*Data Source: Bloomberg*

## Appendix Figure 3 Iron Ore Imports by Country (2005-2011)




*Data Source: Bloomberg*

## Appendix Figure 4 China Iron Ore Domestic Production and Imports (2001-2010)




*Data Source: UN, World Steel Association*

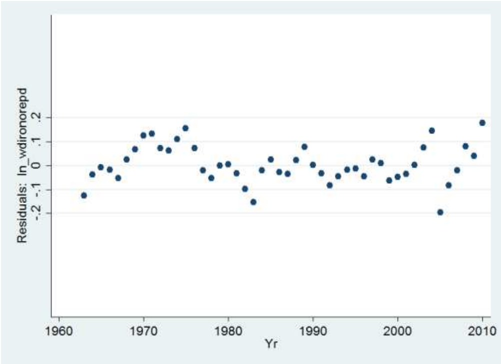
**Appendix Table 1 Variable Correlation Matrix**

| | Wd Ore Pd | $P_t$ | $P_{t-1}$ | Scrap Price | Demand Shock | Wd GDP | Interest Rate | Time | Supply Shock |
|---|---|---|---|---|---|---|---|---|---|
| Wd Ore Pd | 1 | | | | | | | | |
| $P_t$ | 0.3830*** | 1 | | | | | | | |
| | (0.007) | | | | | | | | |
| $P_{t-1}$ | 0.2903* | 0.8700*** | 1 | | | | | | |
| | (0.045) | (0.000) | | | | | | | |
| Scrap Price | -0.1067 | 0.3159* | 0.2646 | 1 | | | | | |
| | (0.466) | (0.027) | (0.069) | | | | | | |
| Demand Shock | 0.7909*** | 0.5231*** | 0.3754** | 0.1272 | 1 | | | | |
| | (0.000) | (0.000) | (0.009) | (0.384) | | | | | |
| Real Wd GDP | 0.8928*** | 0.0654 | -0.0124 | -0.3352* | 0.6005*** | 1 | | | |
| | (0.000) | (0.655) | (0.934) | (0.019) | (0.000) | | | | |
| Real Interest Rate | 0.0565 | -0.2116 | -0.2228 | -0.4373** | -0.1797 | 0.3122* | 1 | | |
| | (0.700) | (0.149) | (0.132) | (0.002) | (0.217) | (0.031) | | | |
| Time Trend | 0.8986*** | 0.0385 | -0.0360 | -0.3139* | 0.6300* | 0.9830* | 0.2898* | 1 | |
| | (0.000) | (0.793) | (0.808) | (0.028) | (0.000) | (0.000) | (0.043) | | |
| Supply Shock | 0.6319*** | 0.0554 | 0.0244 | -0.3818* | 0.2784* | 0.8132*** | 0.4615*** | 0.7894*** | 1 |
| | (0.000) | (0.706) | (0.869) | (0.007) | (0.048) | (0.000) | (0.001) | (0.000) | |

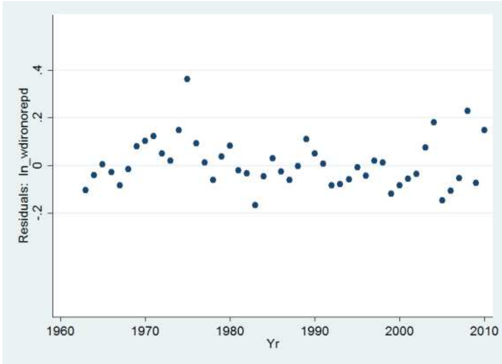
t statistics in parentheses $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

## Appendix Figure 5 OLS, 2SLS, 3SLS Residuals Plots 1960-2010

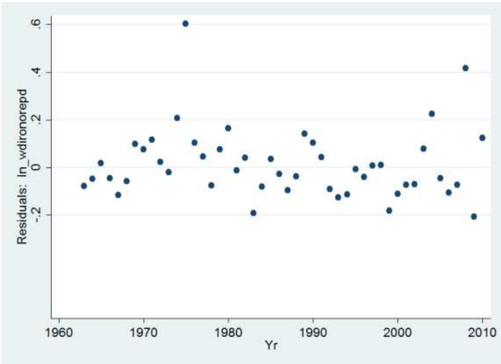
Residual Plot - OLS



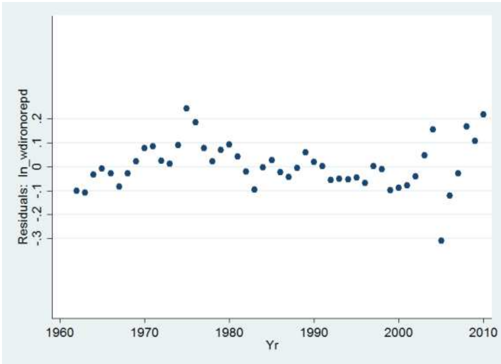

Residual Plot – 2SLS




Residual Plot – 3SLS




Residual Plot – 3SLS without $P_{t-1}$



**Appendix Table 2 Annual Supply and Demand using Iron Ore Production for Quantity (Different Demand Shock and with/without $P_{t-1}$ )**

| | 3SLS-2003<br>Wd Ore Pd | 3SLS-2004<br>Wd Ore Pd | 3SLS-2005<br>Wd Ore Pd | 3SLS-2005<br>Wd Ore Pd |
|---|---|---|---|---|
| **Demand Function** | | | | |
| Ore Price $_{(t)}$ | -0.383 | -1.060*** | -0.928*** | -0.247** |
| | (-1.57) | (-4.21) | (-4.33) | (-2.92) |
| Scrap Price | 0.0719* | 0.0832* | 0.0910** | 0.0572 |
| | (2.04) | (2.20) | (2.66) | (1.86) |
| Wd GDP | 0.448*** | 0.428*** | 0.404*** | 0.363 *** |
| | (13.51) | (11.49) | (11.69) | (10.88) |
| Ore Price $_{(t-1)}$ | 0.483* | 0.936*** | 0.688*** | |
| | (2.39) | (4.76) | (4.45) | |
| Demand Shock03 | 0.397*** | | | |
| | (5.97) | | | |
| Demand Shock04 | | 0.621*** | | |
| | | (7.02) | | |
| Demand Shock05 | | | 0.744*** | 0.691*** |
| | | | (7.65) | (8.02) |
| Constant | 8.371*** | 9.696*** | 10.76*** | 11.90 *** |
| | (8.80) | (8.59) | (9.77) | (10.82) |
| ***$R^2$*** | 0.91 | 0.83 | 0.88 | 0.93 |
| **Supply Function** | | | | |
| Ore Price $_{(t)}$ | 1.151*** | 1.005*** | 0.900*** | 0.476*** |
| | (7.39) | (6.90) | (6.84) | (10.32) |
| Interest Rate | -0.0418** | -0.0351* | -0.0122 | -0.00262 |
| | (-2.81) | (-2.36) | (-0.82) | (-0.16) |
| Time | 0.0203*** | 0.0219*** | 0.0231*** | 0.0254*** |
| | (13.88) | (14.61) | (15.11) | (17.56) |
| Supply Shock | -0.0324 | -0.0830* | -0.138** | -0.166** |
| | (-0.84) | (-1.99) | (-2.99) | (-3.39) |
| Ore Price $_{(t-1)}$ | -0.703*** | -0.562*** | -0.450*** | |
| | (-4.68) | (-3.98) | (-3.48) | |
| Constant | 18.59*** | 18.58*** | 18.48*** | 18.29*** |
| | (94.05) | (96.41) | (97.84) | (94.49) |
| ***$R^2$*** | 0.84 | 0.87 | 0.89 | 0.92 |
| ***D - Statistic*** | 1.22 | 2.26 | 1.94 | 1.09 |