Assessing the Impact of China's Steel Consumption Upon the World Price of Steel and its Inputs

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May 2008

The author would like to acknowledge the contributions of several individuals to the completion of this study: Professor Soiliou Namoro, who supervised the project and provided invaluable econometric knowledge and training, as well as general guidance; Professor Thomas Rawski, who helped initate the project and provided insight into China's economy and industry; Professor Frank Giarratani, whose knowledge of the steel industry led to the discovery of several valuable sources of information; and Professor Frederick Tannery, who served as an external examiner in the course of the defense of this thesis. All errors are mine.

Abstract

In this paper, we attempt to estimate the impact of Chinese steel consumption upon the world price of steel mill products and inputs over the past several years. We focus upon the inputs of steel scrap and iron ore as inputs involving competing technologies. We find that an equilibrium relationship exists between China's consumption of steel and prices for steel and its inputs, but we cannot conclude from our analysis that variations in Chinese consumption drive variations in the prices of steel or its inputs.

1. Introduction and Background

China's emergence as an economic powerhouse is paralleled by the growth of its steel industry. During the years between 1998 and 2006, China has become the world's largest producer of steel, producing 423 million tons in 2006, representing a 50% growth from 2004, when the country produced 280 million tons. During the same two-year period, production in the rest of the world (ROW) grew by a more modest 7%. China's share of world steel production grew from 13.5% to almost 35% during the period of our study, as is illustrated by Figure 1, which compares production in China to that of the ROW between April 1998 and December 2007 (all figures and tables are appended to this paper).

Consumption levels in China have closely followed production levels, indicating that Chinese industry consumes the vast majority of the steel produced, and also that Chinese production levels generally supply the needs of domestic consumers[1]. Figure 2, which compares China's production, balance of trade (exports minus imports) and a U.S. steel price index, shows

[1] This is not to say that the industry produces the mix of products required to satisfy all Chinese steel users: only that the raw consumption and production levels are in line with one another. The industry does not, for example, produce enough high quality steels to satisfy domestic demand for "flat" products (Brandt et al. 2008). This aspect of the industry is lost in the use of crude steel trade statistics.

that the absolute value of China's balance of steel trade has rarely exceeded 10% of domestic production.

The sudden growth of China's steel consumption accompanied a drastic break of steel prices from historical levels. A comparison between China's production, balance of steel trade and the price of steel in the U.S. (Figure 2) shows that as China's production and consumption have ramped up, so have steel prices and Chinese exports of steel products. Prices jump considerably from 2004 to 2005, and then remain high even as China's trade balance in steel turns sharply positive after 2005.

As Chinese consumption and steel prices rose, so too did prices for steel inputs: namely iron ore, coke and steel scrap. Iron ore and coke are combined in blast furnaces at larger, integrated plants for raw steel production, while steel scrap is recycled in smaller plants known as mini-mills by being heated with electric current. The value-added of steel produced from integrated mills in the U.S. is generally higher than that of mini-mills. The former produce steel for use in the manufacture of appliances and automobiles, which generally require more specific traits than steel bars used in construction and rails, which are produced almost exclusively by mini-mills in the U.S. However, in the rest of the world (China included), integrated producers still produce steel bars.

Figure 3 below compares the price of iron ore in the U.S. to China's iron ore trade deficit and steel production between 1990 and 2006. Note that the Chinese trade deficit in iron ore, unlike its deficit in steel, does not shrink but nearly doubles between 2003 and 2006. During the same time interval, the price of iron ore in the United States rises by 66%. As in steel, China's share of world iron consumption has increased dramatically since the turn of the century.

Figures 4 and 5 below, which show the same data as Figure 3 for coking coal and scrap steel, show a similar rise in the cost of inputs as Chinese steel production ramps up. Unlike the case of iron ore, however, in the case of scrap metal China's trade deficit does not increase substantially as prices rise, and China actually maintains a surplus in coking coal.

Because of the relatively recent nature of the phenomena elaborated above, little empirical work has been done to determine the impact of Chinese production on steel prices. Most researchers conclude that Chinese conditions are driving prices. Only one study, to our knowledge, has attempted to econometrically gauge the impact of China's demand for steel on U.S. steel prices. Liebman's (2006) analysis on the impact of 2003 safeguards on U.S. steel prices showed that Chinese steel demand played a statistically significant role in U.S. steel price movements, but his analysis suggests that it takes upwards of nine lags for this impact to be realized. This analysis did not incorporate Chinese steel production into its model and focused mainly on Chinese steel imports. It therefore does not show the indirect effect of Chinese consumption on steel prices by omitting this variable's impact on the price of steel inputs.

Unlike Liebman (2006), we do not explicitly incorporate U.S. domestic economic variables into our model because we assume the market for steel products to be global in nature. Regression analysis of steel prices in various markets shows that prices in the various world markets are highly correlated. Furthermore, while the U.S. share of world steel production and consumption is significant (around 10% in each case), changes in capacity and consumption in the U.S. over the period under investigation are relatively small compared to the drastic increase in world, and specifically Chinese, production and consumption. U.S. production and consumption vary by less than 15 million tons during the course of the period, while Chinese production and consumption vary by several hundred million tons. We therefore assume that variables pertaining to U.S. steel production only affect the model via its inclusion in world production outside of China. We focus instead upon consumption in China to explain U.S. prices, which we use as a proxy for world prices. Our expectation is that this variable will be the most useful in explaining price movements for steel and its inputs.

As in Liebman (2006), we include iron ore and steel scrap prices in our analysis in order to determine the impact of Chinese production on these variables, which in turn impact steel prices. We also estimate our model for two different classes of steel, including an index for "long" steel products and another for "flat" steel products. As Liebman notes, long products are produced almost exclusively by scrap producers in United States, while flat products, especially those higher in value added, are the major product of integrated steel producers. Our expectation is that if Chinese consumption affects one input more than another, its impact on the price of the steels produced using that input will be greater.

Our analysis also diverges from that of Liebman (2006) in that we do not control for the real exchange rate of the U.S. vis-à-vis the world. During the course of our analysis, we noted that adding this variable tended to adversely impact the fit of our model, and we therefore excluded it.

2. Methodology and Data

To test the hypothesis that Chinese consumption is a driving force behind steel, iron and scrap prices, we estimate reduced form vector autoregressive (VAR) models using each of the data series listed above, and then perform Granger causality tests on the data. To capture short-term and long-term interactions among the variables, we perform Granger causality tests at two and six lags.

We estimate the reduced form VAR model:

$$\Delta Y_t = \sum_i^p A_i \Delta Y_{t-i} + \varepsilon_t$$

for p = 2 and 6, where Y_t is a vector including all of our data series, Δ is the difference operator, and A_1-A_p are matrices of parameters. It is upon this model that we perform Granger causality tests.

After performing our Granger causality analysis, we test our data series for cointegration. The results suggest the existence of a long-term equilibrium relationship between our data series. The existence of a cointegrating relationship allows us to estimate a two-lag vector autoregressive error correction model (VECM) for both of our steel product categories.

We estimate the reduced form vector error correction model:

$$\Delta Y_t = \sum A_i \Delta Y_{t-i} + \Pi Y_t + \varepsilon_t$$

where A_1, A_2 and Π are matrices of parameters to estimate. The terms ΠY_t account for the long-term equilibrium relationship among the variables, and it represents the error correction factor of the model.

Next, we calculate cumulative impulse-response functions to estimate the impact of unexpected changes in China's consumption upon price variables[2], and vice versa, in our models. Finally, we perform forecast error variance decomposition analysis to show the contribution of China's consumption of steel to the variance of the error made in predicting our price variables.

Our VECM and VARs include five variables each: the price of a steel commodity, China's consumption of steel (China's production plus imports minus exports), rest of world

[2] For the remainder of this paper, "price variables" should be understood to mean iron ore, scrap and steel prices.

consumption of steel (ROW production minus China's imports plus China's exports), the price of steel scrap and the price of iron ore. All data are monthly for the time period April 1998 to December 2007, the longest time period for which Chinese import-export data are available. All price data are indices tracked by the Bureau of Labor Statistics (BLS). World and Chinese production statistics were obtained from the International Iron and Steel Institute, and rest of world production was obtained by subtracting Chinese production from world production. Steel import and export data for China were obtained from China Data Online, a service of the China Data Center at the University of Michigan[3].

3. Results

3.1 Granger Testing

Granger-causality tests do little to clarify the causal relationship between Chinese consumption and the prices of steel and its inputs in our models. In many instances, bi-directional causality is present. Therefore, the causality tests do not lead to a clear answer to the question as to whether Chinese consumption drives prices or if Chinese consumption, in fact, reacts to those prices. In general, Granger tests fail to reject the hypothesis that steel price fluctuations are not Granger-caused by fluctuations in Chinese steel consumption. The causal relationships between fluctuations in Chinese steel consumption and input price movements are unclear. Our analysis does show that steel price movements appear to be Granger-caused by input price movements. Including six lags shows that fluctuations in Chinese consumption are Granger-caused by fluctuations in iron prices and Granger-cause fluctuations in scrap prices. As

[3] The accuracy of the Chinese statistics is subject to some doubt. Comparing annual values of the data series that we downloaded with those recorded by the UNCOM trade database revealed that while our Chinese import statistics are only slightly lower than those in the UNCOM data set, Chinese export statistics are much lower.

we will show in the next section, some of these relationships appear spurious, producing nonsensical results.

3.2 Cointegration

The existence of a long-term relationship between two or more data series is revealed by testing for cointegration. Data series may be individually non-stationary, like those in our data, but a linear combination of them may be stationary if the variables are cointegrated. We test our data series for cointegration using the Johansen method for each of our two models. The null hypothesis using this method is that there exists at most the tested number of possible cointegrating relationships between the series in a data set. Since we reject the null hypothesis in the case of zero cointegrating relationships, but accept it in the case of one cointegrating relationship, we conclude that a cointegrating relationship exists among our variables. This result suggests that Chinese and world consumption levels appear to have a long-term relationship to price levels for steel, iron ore and scrap. To account for this equilibrium relationship, we build a vector autoregressive error correction model (VECM). This allows us to gauge the influence that unexpected shocks to certain variables have upon other variables after controlling for the equilibrium relationship that links these variables to one another.

3.3 Impulse-Response Functions

Impulse-response functions show the reaction of one variable to an *unexpected* increase in the value of another variable. The emphasis on the word *unexpected* is to distinguish between expected increases, captured in the main body of the model, and unexpected increases that are not accounted for in the main body of the model. A one-unit increase in the impulse variable influences the response variable both directly and indirectly through its impact on all other variables.

Figures 6 and 7 below show cumulative impulse-response functions for our data. The graphs in Figure 6 show the response of price variables to unexpected increases in China's consumption of steel, while the graphs in Figure 7 show the response of China's consumption of steel to unexpected increases in price variables over thirty periods. They show some results that are in line with economic theory, and some that diverge from it, and likely from reality. For instance, one would expect the results that our models generated for the impact of an unexpected rise in Chinese steel consumption upon steel input prices (positive in both models for both inputs). Given that most of China's consumption is supplied by China's production, an increase in China's consumption translates to an increase in China's production, and therefore an increase in the country's consumption of steel inputs, which would be expected to drive up prices. Given the premium paid in the Chinese spot market for iron ore in the short term, it is sensible that prices elsewhere would react to increased buying on that market (*Economist* March 2008).

However, our model generates several results that are not suggested by economic theory. First, it shows steel prices declining in response to an unexpected increase in Chinese consumption. One would expect instead that an increase in consumption, especially consumption that has been shown to increase input prices, would increase steel prices as well. Secondly, it shows Chinese consumption rising in response to an increase in steel prices in the flat products model. Thirdly, all models show China's consumption of inputs increasing in response to an unexpected increase in the price of those inputs. These results are not what one would normally expect: it is unlikely that Chinese economic planners would choose to increase steel or steel input usage in response to prices increasing, unless, of course, they anticipate that the increase represents a new trend in pricing, and hurry to purchase these commodities.

3.4 Forecast Error Variance Decomposition

Forecast error variance decomposition (FEVD) analysis shows “the percentage of the variance of the error made in forecasting a variable… due to a specific shock… at a given horizon” (Stock and Watson 2001). This indicator shows the contribution of each of a set of variables to the variance of the error made in predicting a given variable. This allows us to assess the relative influence that each variable has on the variables of interest. For example, this type of analysis would show how much of the variance of the error for steel prices (the variance of the actual value from the forecasted value) can be attributed to changes in China’s consumption, and how much can be attributed to other variables. This analysis gives us some indication of how powerful the influence of China’s consumption is upon the price of steel and its inputs.

In the long product model, China’s consumption only accounts for a significant portion of the variance observed in scrap prices, rising from less than one percent through the first eight periods, to over six percent by the thirtieth period following a shock in China’s consumption. In the flat product model, China’s consumption accounts for less than one percent of the variance observed in all prices in all thirty time periods. This result suggests that prices are not reacting to unexpected movements in China’s consumption.

4. Conclusions

Although our analysis suggests that there is an equilibrium relationship between our consumption and price variables, the nature of the relationship between price variations for steel and its inputs and variations in China’s consumption of steel remains uncertain. Granger causality testing fails to show that variations in China's consumption drive variations in steel prices, or vice versa. Impulse responses do not resolve this uncertainty. In fact, some responses to shocks make little economic sense, such as suggesting that a sudden increase in China's consumption of steel causes steel prices to decrease. Variance decomposition analysis illustrates that little of the variation of price variables from models predicted by the model can be accounted for by China's consumption. These results suggest that the recent volatility of steel input and output prices is not driven by changes in China's consumption, at least when two lags are employed in the model.

It may be the case that China's consumption of steel is driving the long-term trends that we observe in the prices of steel and its inputs, but that prices simply do not respond in two months to variations in China's steel consumption. Perhaps production and consumption information do not travel rapidly through the market to affect prices, leaving those who negotiate contracts to speculate when determining price levels. Rapid expansion of Chinese production levels may coincide with uncertainty about actual production levels, causing prices to react to expectations made with imperfect information. Additionally, a disconnect between price levels and Chinese consumption decisions could lead to unexpected market outcomes that may explain the unexpected observations in our impulse response function analysis.

Future research to unravel the relationship between China's use of steel and prices for steel and its inputs could take a few directions. A model that could incorporate a longer lag time for changes in China's consumption to affect prices might alter the impact that that variable has upon the price of various kinds of steel, especially if this information takes time to work its way through the market. Alternatively, a model that incorporates investment levels in China and elsewhere may better explain price movements by measuring demand for steel independently of production. Finally, since our price data are U.S. data, it may be appropriate to include some domestic factors to explain short-term price fluctuations, especially in the case of scrap, where export levels have not increased dramatically as prices have risen. However, it may not be until China's consumption growth slows down that we are able to make sense of its impact upon the price for steel and its inputs.

5. Technical Notes

VAR modeling involves regressing stationary versions of each variable on lags of itself and the current and lagged values of the other variables in the model. Because this model assumes variables are stationary to produce accurate results, we first tested the individual data series for stationarity using augmented Dickey-Fuller (ADF) tests. These tests revealed that the data were non-stationary, and therefore we differentiated each series in order to obtain stationary series. Each series required one differentiation to achieve the stationarity required for inclusion in a VAR model.

In addition to the requirement that each variable be stationary, the entire vector itself must also be stationary in order to ensure that the results are not spurious. We therefore performed a test for joint-stationarity of our differentiated series. This test revealed that our differentiated data series were jointly stationary, and so we were able to proceed with the execution of our VAR model.

While differentiating data in order to achieve stationarity is useful because it allows us to perform Granger-causality tests within a VAR model, doing so also involves the loss of some relevant economic information. Specifically, differenced variables no longer contain valuable information on long-run equilibrium that is contained in the actual levels of the data. For instance, prices and wages are two non-stationary economic variables that tend to move together over time.

The existence of a long-term relationship between two or more data series is revealed by testing for cointegration. Data series may be individually non-stationary, like those in our data, but a linear combination of them may be stationary if the variables are cointegrated. We therefore tested our data series for cointegration. The results suggest that a long-term equilibrium between our variables does exist. Chinese and world consumption levels appear to have a long-term relationship to price levels for steel, iron and scrap.

Cointegration of data suggests the use of an economic model that accounts for the long-term relationship between data series. A vector autoregressive error correction model, or VECM, estimates variables using both differenced and actual data, and accounts for long-term equilibrium suggested by economic theory. It does so by introducing a term that corrects for disequilibrium. We therefore re-estimate our model using this technique.

In order to determine how many lags of each value to include in our VECM model, we utilized three forms of selection criteria: the Akaike information criterion (AIC), Hannan-Quinn information criterion (HQIC) and Schwarz's Bayesian information criterion (SBIC). According to the AIC, adding additional lags to the regressions always yields a better fit to the model. The HQIC yields weaker fits with increasing lags from 1-7 lags. The SBIC yields weaker fits with increasing lags from 1-11 lags. Because there is a trade-off between a better fit and less accurate coefficients with increasing lags, we have chosen to use a two-lag model. However, this choice may not capture all relevant information, as it may take more lags for China's consumption to affect prices.

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Appendix

Figure 1:
China's Share of World Steel Production

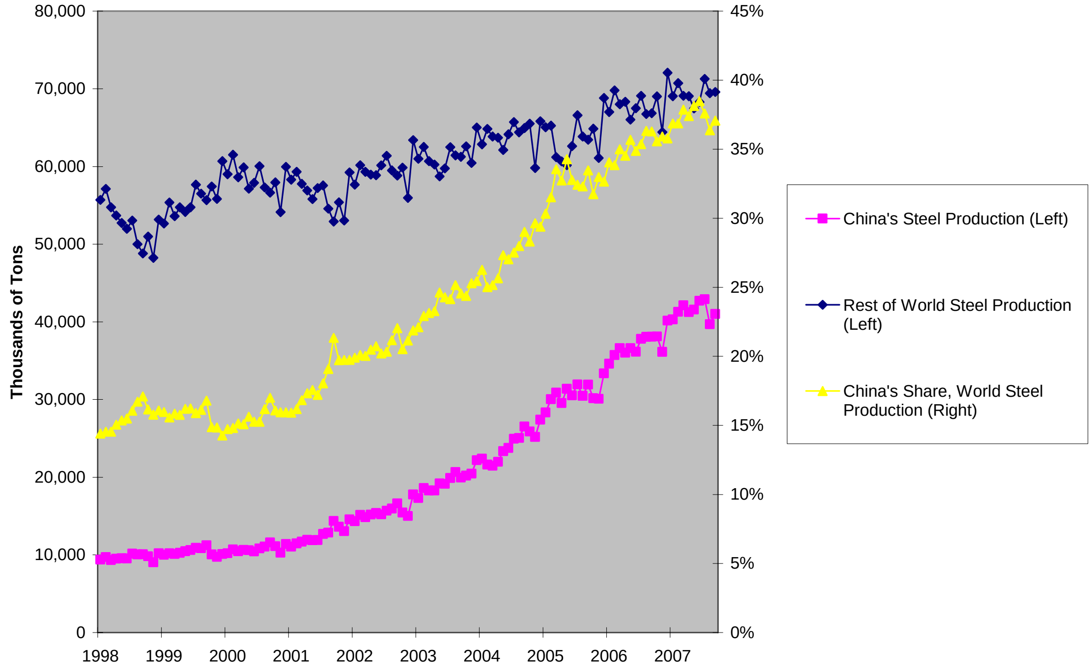


Figure 2:
Chinese Production, Steel Balance and the Price of Steel, 1998-2008

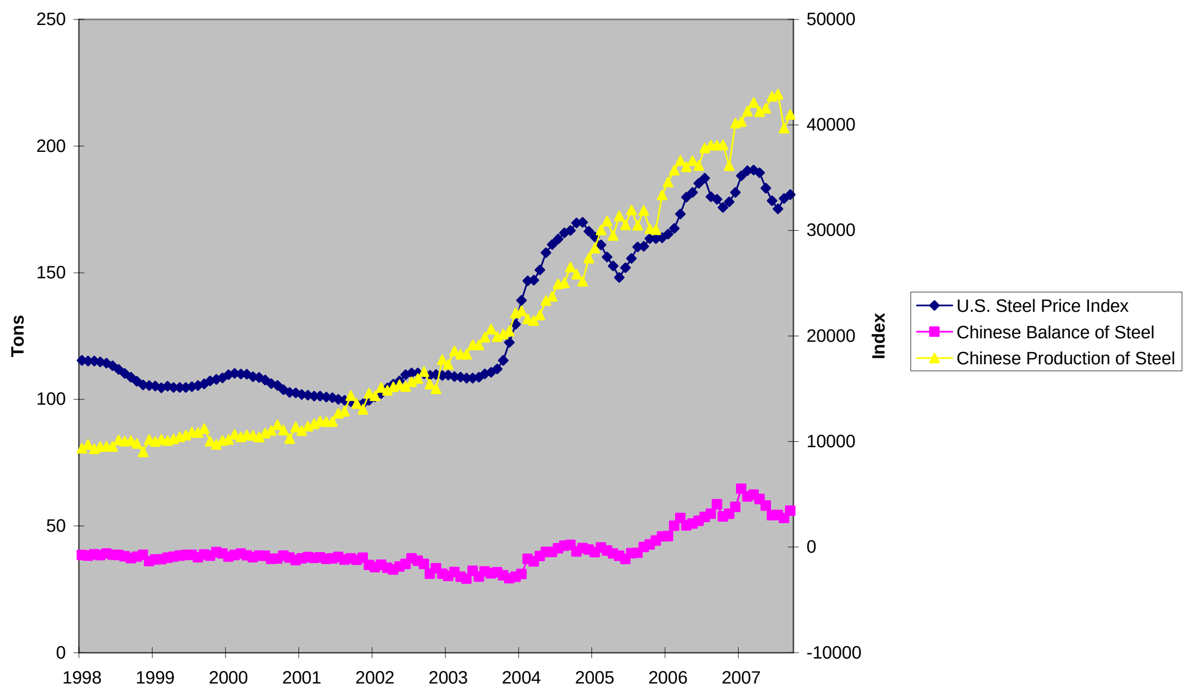
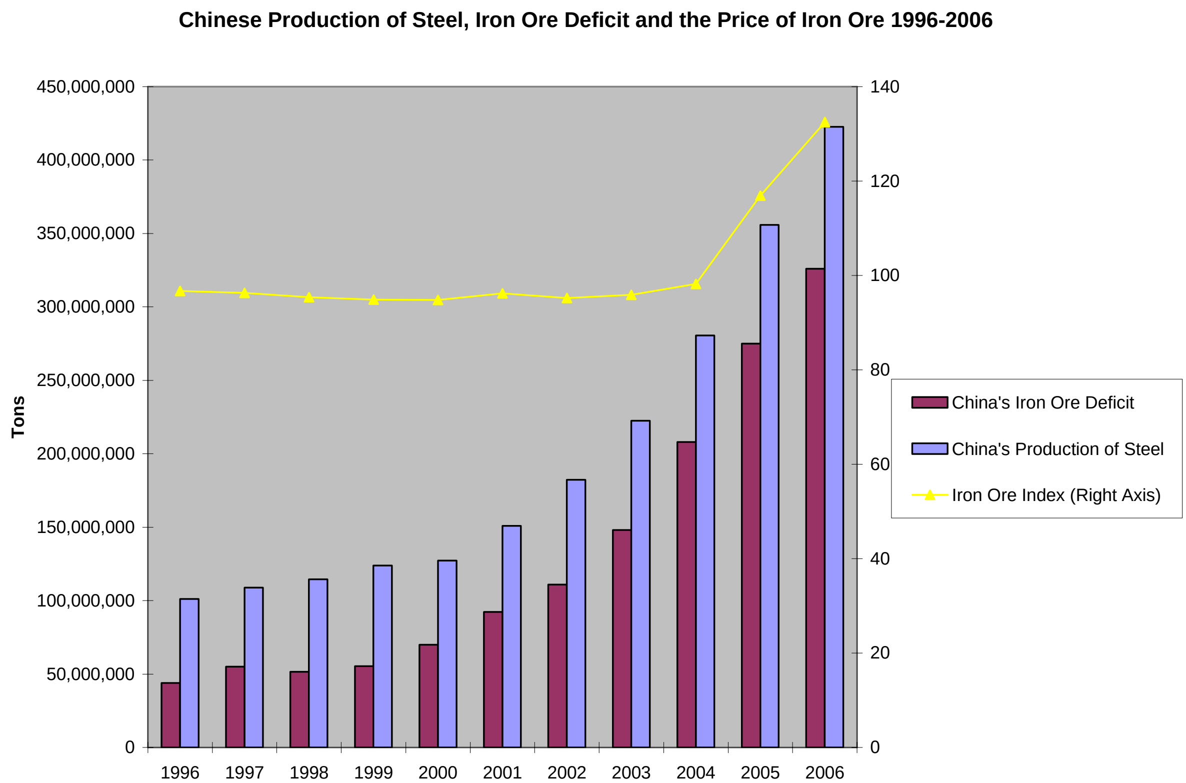


Figure 3

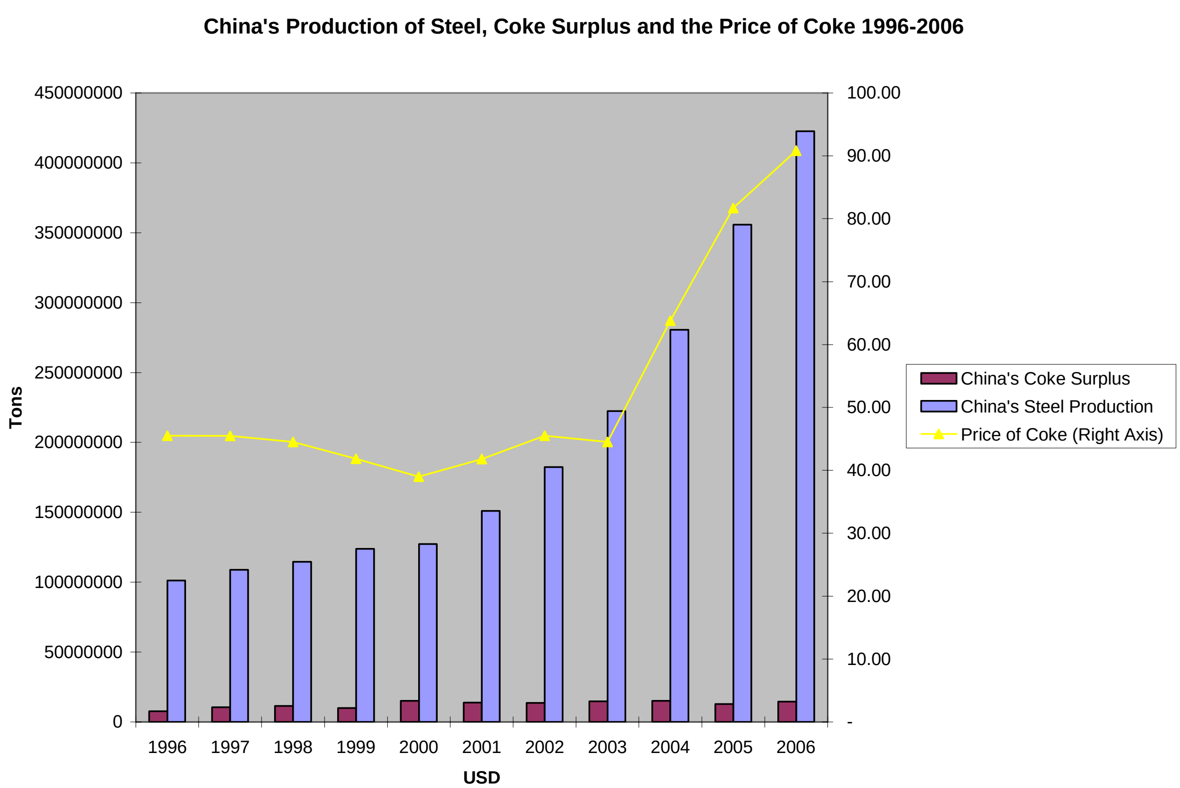


Source of Current Account Statistics: United Nations Commodity Trade Statistics

Source of Iron Ore Prices: Bureau of Labor Statistics

Source of China's Production Statistics: International Iron and Steel Institute

Figure 4

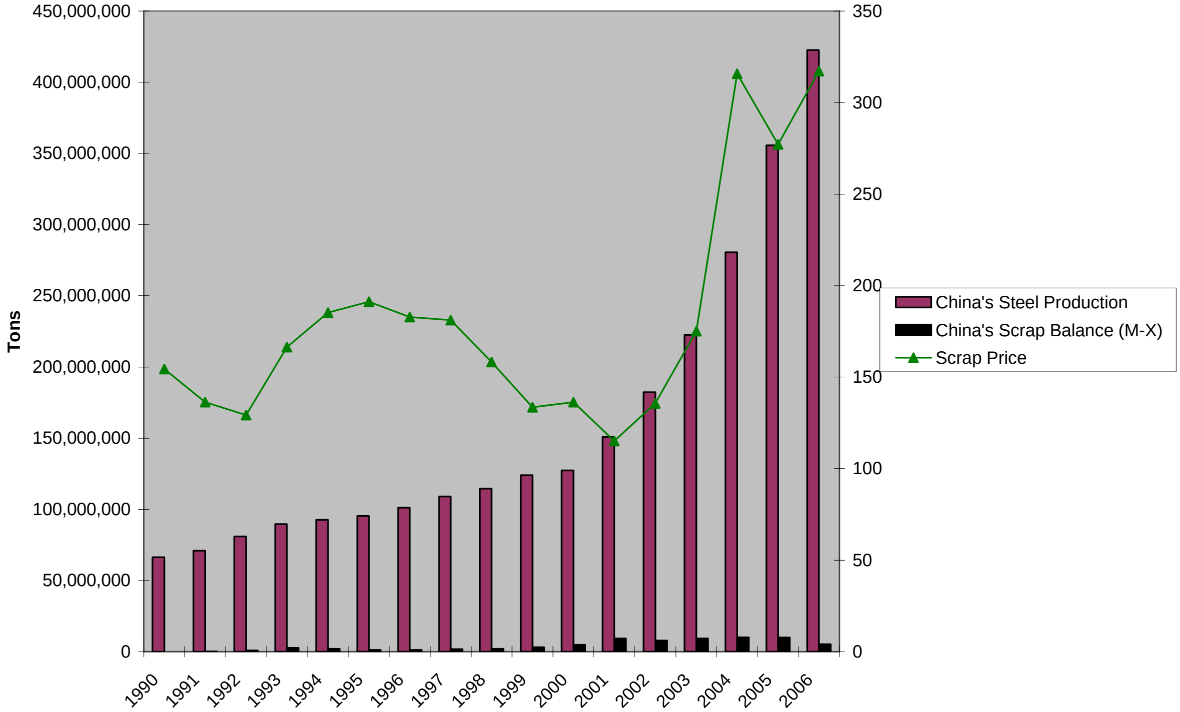


Source of Trade Statistics: United Nations Commodity Trade Statistics

Source of Coke Prices: Energy Information Administration

Source of Steel Production Statistics: International Iron and Steel Institute

Figure 5:
China's Steel Production, Balance of Scrap Trade and Scrap Prices, 1990-2006



Source of Trade Statistics: United Nations Commodity Trade Statistics

Source of Scrap Prices: Bureau of Labor Statistics

Source of Steel Production Statistics: International Iron and Steel Institute

Figure 6

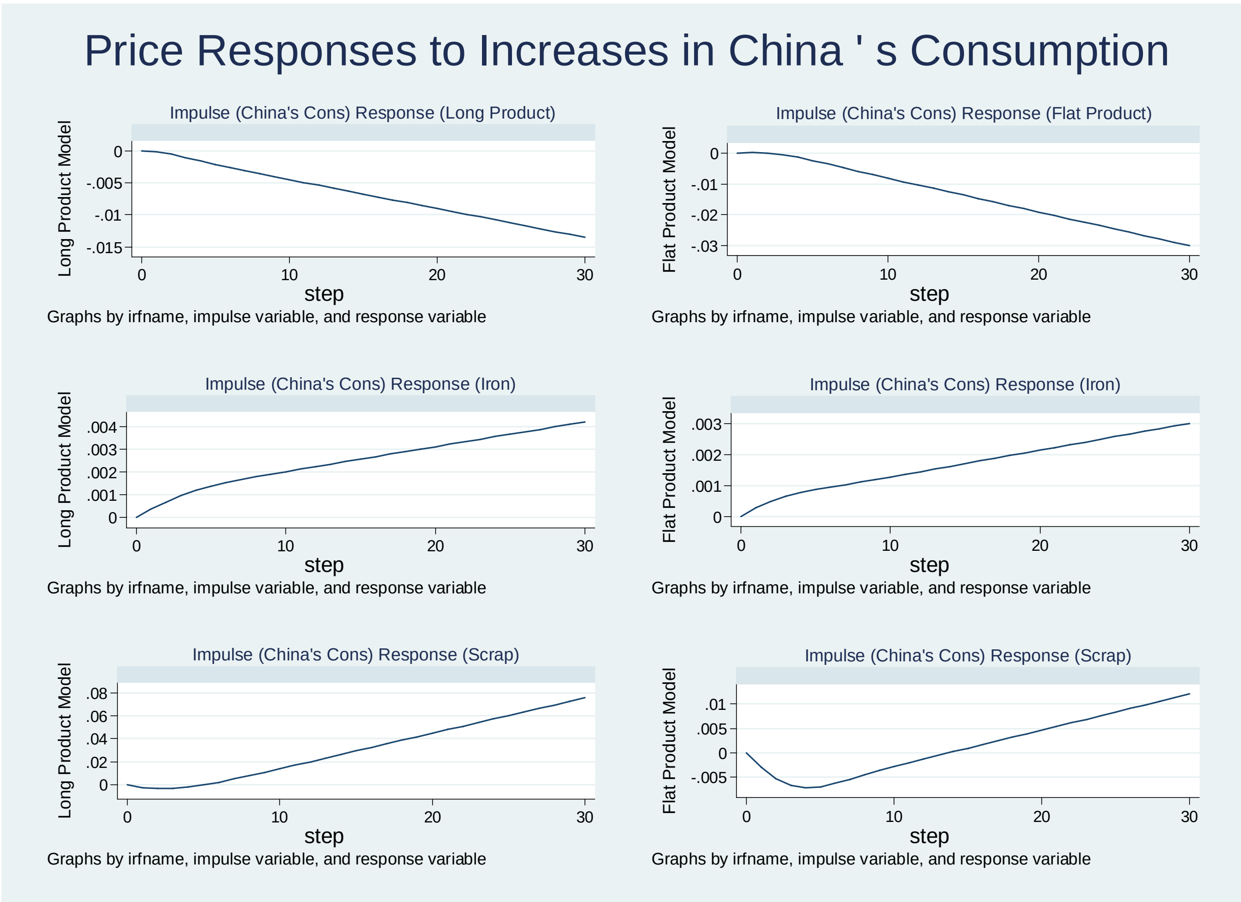
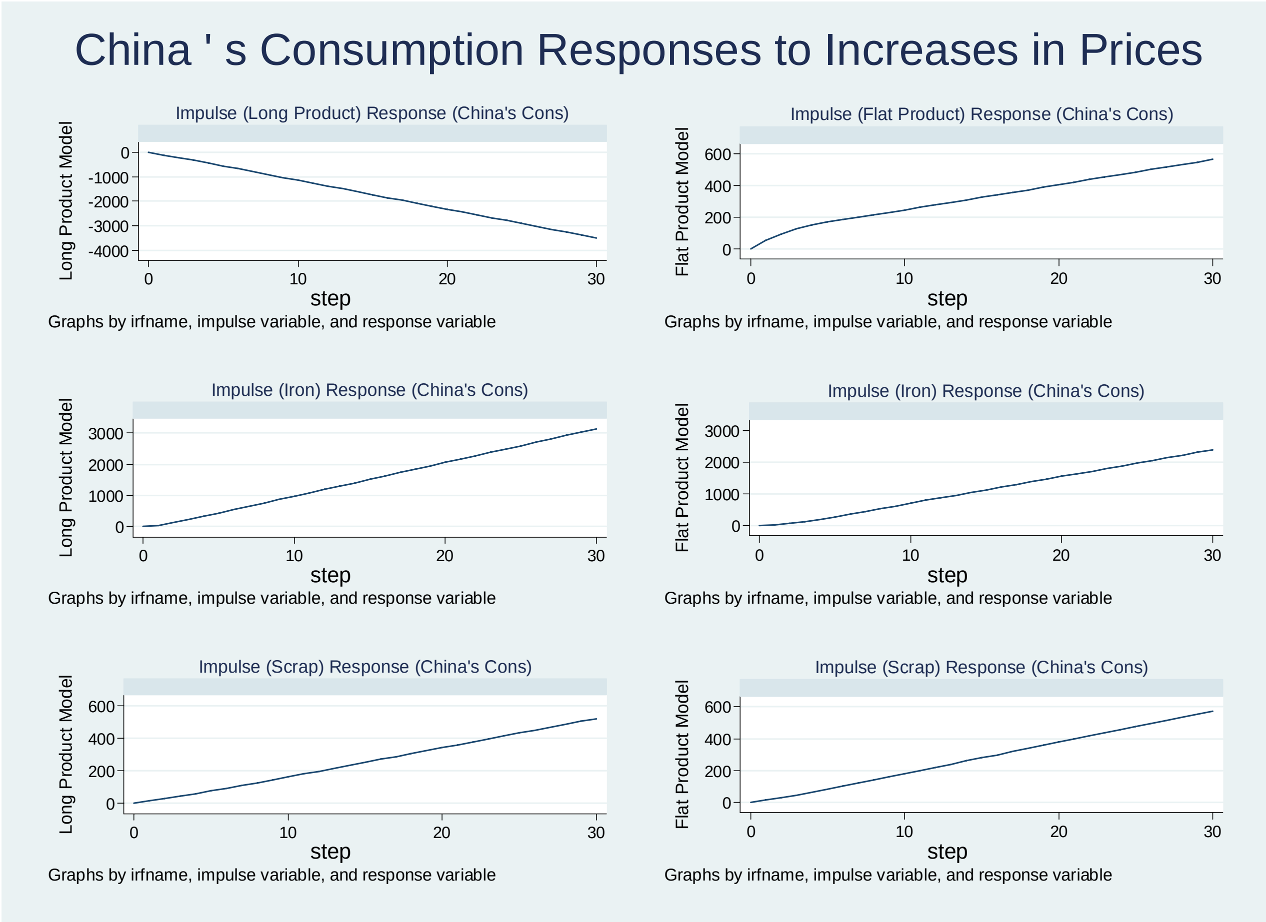

Price Responses to Increases in China ' s Consumption
Impulse (China's Cons) Response (Long Product)
Long Product Model
0
-.005
-.01
-.015
0
10
20
30
step
Graphs by irfname, impulse variable, and response variable
Impulse (China's Cons) Response (Flat Product)
Flat Product Model
0
-.01
-.02
-.03
0
10
20
30
step
Graphs by irfname, impulse variable, and response variable
Impulse (China's Cons) Response (Iron)
Long Product Model
.004
.003
.002
.001
0
0
10
20
30
step
Graphs by irfname, impulse variable, and response variable
Impulse (China's Cons) Response (Iron)
Flat Product Model
.003
.002
.001
0
0
10
20
30
step
Graphs by irfname, impulse variable, and response variable
Impulse (China's Cons) Response (Scrap)
Long Product Model
.08
.06
.04
.02
0
0
10
20
30
step
Graphs by irfname, impulse variable, and response variable
Impulse (China's Cons) Response (Scrap)
Flat Product Model
.01
.005
0
-.005
0
10
20
30
step
Graphs by irfname, impulse variable, and response variable

Figure 7


China ' s Consumption Responses to Increases in Prices
Impulse (Long Product) Response (China's Cons)
Long Product Model
0
-1000
-2000
-3000
-4000
0
10
20
30
step
Graphs by irfname, impulse variable, and response variable
Impulse (Flat Product) Response (China's Cons)
Flat Product Model
600
400
200
0
0
10
20
30
step
Graphs by irfname, impulse variable, and response variable
Impulse (Iron) Response (China's Cons)
Long Product Model
3000
2000
1000
0
0
10
20
30
step
Graphs by irfname, impulse variable, and response variable
Impulse (Iron) Response (China's Cons)
Flat Product Model
3000
2000
1000
0
0
10
20
30
step
Graphs by irfname, impulse variable, and response variable
Impulse (Scrap) Response (China's Cons)
Long Product Model
600
400
200
0
0
10
20
30
step
Graphs by irfname, impulse variable, and response variable
Impulse (Scrap) Response (China's Cons)
Flat Product Model
600
400
200
0
0
10
20
30
step
Graphs by irfname, impulse variable, and response variable