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THREE ESSAYS ON THE CHINESE STEEL INDUSTRY

A DISSERTATION APPROVED FOR THE
DEPARTMENT OF ECONOMICS

BY

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DEDICATION

to

My parents

Baozhong Su, and

Manqi Tang

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Abstract

The first chapter takes an overview of the Chinese steel industry. The intermediate goods trade has become a significant feature of the international economy. Nevertheless, questions regarding price negotiation and the determinants of importing firms' profitability remain unanswered. Using firm level data, we attempt to address these issues in the context of the Chinese steel industry. Despite being the largest producer of steel in the world, the Chinese steel industry has maintained a very low level of profitability. This paper suggests that the low profitability of Chinese steel producers results from the abnormally high degree of market segmentation in China. A recently developed econometric method in panel data spatial analysis is adopted here, to explain the level of geographic fragmentation in the Chinese steel industry. Our results reveal that local steel production depends only on local demand rather than on cross-region demand. Production is responsive, as a 10% increase in local GDP induces more than 8% increase in local steel production, while the cross-province spill-over demand is insignificant under several reasonable model settings. Less efficient firms survive because of the segmented market, so Chinese steel producers realize lower profit in the face of high input prices.

The second chapter develops a model of global supply chain to study how profits are shared between intermediate input suppliers and final good producers. Differences in market structures are shown to be main driving forces in profitability differences along the global supply chain. Applying Melitz and Ottaviano (2008)'s

framework of heterogeneous firms into the problem, we model the downstream (final good) market as the monopolistic competition, while the upstream (intermediate input) market in oligopolistic (Cournot) competition. We show how increases in the entry cost in the upstream market and segmentations in the final good market increases (decreases) the market power of intermediate input (final good) producers, which increases (decreases) the profitability of intermediate input (final good) producers. We also show how increases in the demand of the final good affect the price of the intermediate input, which determines the profit sharing between intermediate input and final good producers. Using firm level data from the Chinese steel industry, we calibrate the model. Our results show a 20% increase in the final good demand would induce 25% increase in the input price. Our results also suggest the regional trade costs in the Chinese steel market are about three times as firm's average marginal cost, and a 10% decrease in regional trade costs would lower the input prices by 22%.

The third chapter estimates a dynamic structural model of firm investment and importing decisions. Using firm level data from the Chinese steel industry, both activities are found to have positive effects on productivity. Particularly, firms engaging into both activities enjoy a 3.72% productivity premium in the long run. Moreover, the result suggest that in the Chinese steel industry there is a huge entry cost and fixed cost in the import market for raw materials. These costs create a self-selection issue in the import market. After controlling for this issue, I find that more productive firms benefit to a larger degree from importing. Furthermore, simulation of the import market shows that a 10% decrease in entry and fixed costs would net 8.9% productivity gains for a typical firm.

Evidences presented in this dissertation shed lights on many aspects. First, it firstly document the market structure in the Chinese steel industry, using a newly developed panel data spatial analysis approach to reveal a segmented market in this industry; Second, we introduce the market vertical linkage to a classical new trade model to show the relationship between the inter-regional trade barriers and the upstream market price, which is a valuable contribution to the international trade literature under the global value chain context; Last but not the least, firms' importing and investment behavior as well as their effects on productivity dynamics are structurally estimated, so that the gains from import is well measured while addressing the endogeneity issues. In all, my dissertation focuses on the low profitability issue in the Chinese steel industry. Based on detailed firm level data, it provides reasonable explanations from several perspectives, which also shows many potentials for researches in the future.

Chapter 1

Market Structure in The Chinese Steel Industry

1.1 Introduction

The Chinese steel industry alone has been growing an average of 20% every year over the past decade and is an important component of China's economy. In 2008, China's total output of crude steel reached 500 million metric tons (mmt), and accounted for 38% of the entire production in the world, compared to 5.1% in 1980. Meanwhile, in 2008, China consumed 450 mmt of crude steel and exported 50 mmt which was 15% of the world steel trade. Furthermore, the Chinese steel industry absorbs a large part of employment in the Chinese economy. In 2008, there were nearly two million people employed in over 300 firms.

On the other hand, the Chinese steel makers maintain a low level of profitability. The average profitability, measured by the profit-sales ratio, is 3% in recent years, comparing with 10% for the steel industries in other countries and 6% for other Chinese manufacturing sectors. As pointed out by the Chinese steel association in 2012, the Chinese steel industry is "the least profitable" sector among all Chinese industries. In this paper, using firm level data, we attempt to answer the question why the Chinese steel industry maintains a low profitability level, compared to other Chinese manufacturing sectors and to steel industries in other countries.

China has been through a remarkable period of economic development during the past three decades. Underlying this rapid growth, Chinese manufacturing firms have shown improvement in their economic performance. Researchers have suggested several factors as essential to Chinese firms' productivity and profitability. For example, Thompson (2003) and Adams *et al.* (2006) attribute Chinese firms' productivity improvement to China's open-economy policies, from which domestic firms can obtain advanced technologies and management through spill-overs from foreign direct investment.

At the same time, the intermediate goods trade has become an increasingly prominent feature of the international economy. Hummels *et al.* (2001) point out that intermediates comprise about 20% of total exports by value. Yeats (1998) shows that the intermediate goods trade has grown faster than the trade of final goods, suggesting a growing integration in global production. Meanwhile, prices for intermediate goods often come from bilateral negotiations. Thus, firm bargaining power becomes critical since input prices can strongly affect importers' profitability. Intuitively, a high level of demand from importers can reduce negotiated prices due to the quantity discount. However, in some global commodity markets, such as crude oil and iron ore markets, suppliers have the opportunity to collude and push up prices. Therefore, the determinants behind firms' bargaining powers warrant attention.

For China, import dependence has become more severe recently. According to the National Bureau of Statistics in China (CSB), 50% of crude oil, more than 70% of iron ore, and around 50% of machine tools production in China are classified as import-dependent. Research suggests that the relationship between Chinese manufacturing firms and their input suppliers abroad is very important for profitability. Bernard *et al.* (2007), and Manova and Zhang (2009) find that there is a positive relationship between productivity and imports in China: more productive firms are more likely to import their inputs.

Besides their import dependence, Chinese firms are characterized by a low degree of geographic concentration. Many sectors, like steel and petrochemical industries, have firms widely dispersed around the country. Lu and Tao (2009) follow Ellison and Glaeser (1997)'s method to measure the geographic concentration in Chinese manufacturing sectors and find that most Chinese sectors are "not very concentrated." Li and Lu (2009) use Chinese firm level data to show that geographic concentration encourages firms' vertical integration.

The Chinese steel industry deserves attention for many reasons. First, China is now the biggest producer of steel in the world and continues to grow. Second, market concentration in this industry is unusually low. Third, the Chinese steel industry has maintained a very low profitability. Fourth, there is a clear contrast between the state owned enterprizes (SOEs) and non-SOEs in this industry. Finally, the Chinese steel industry is highly importing dependent on the primary input, iron ore. This paper attributes the low profitability and many of these characteristics in the Chinese steel industry to the underlying segmented market.

The rest of the paper is organized as follows. Section 1.2 briefly reviews the literature on inter-regional trade barriers. Section 1.3 introduces the data used in this paper. Section 1.4 takes an overview on the Chinese steel industry. Section 1.5 uses spatial analysis to explain the segmentation in the Chinese steel industry. Section 1.6 concludes.

1.2 Literature Review

Recent studies (See Young (2000), Poncet (2005)) point out that although China is more and more important in the international market, it is less integrated domestically. Their empirical examination of inter-provincial trade data shows a decrease in the level of inter-province exchanging in contrast to an increase in the level of international purchasing. They argue that high trade barriers, which come from local government protectionism, among Chinese provinces reduce inter-province trade. Similarly, Poncet (2005) and Li and Lu (2009) also argue for the existence of sizable inter-province trade barriers by examining price differentials of homogeneous goods across regions in China.

On the other hand, other researchers have looked for evidence of trade barriers within China by examining the convergence of output and growth and found mixed results. For example, Zhang and Tan (2004) find convergence in products and labor markets but not in capital markets. Also, Xu (2002) sees convergence of output growth, while Xu and Voon (2003) and Fan and Wei (2006) confirm the convergence of the price index across provinces in China. Naughton (2003) also finds that inter-region trade barriers do exist in service and intermediate goods trade.

Trade barriers in the international trade literature could result from many aspects such as ice-burg costs (freight costs), tariffs, border effects, culture differences like colonial heritage and so forth. However, trade barriers among different regions within the same country could not take all of these forms. Examining anecdotal evidence, some researchers discuss the effect of local government protectionism as a type of inter-regional trade barriers (See Li *et al.* (2003), and Bai *et al.* (2004)). For example, as in Li *et al.* (2003), local government in Shanghai approved the joint venture of a local automobile firm with Volkswagen to be the **only** supplier for local taxi cabs. Similarly, newspapers from Guangzhou are prohibited from sale in Shenzheng by the local Shenzheng government, despite being two neighboring cities (See

Gilley (2001)).

In China, local government protectionism often takes the form of non-tariff barriers, such as purchasing quotas, license registration control, and fees for selling non-local products. Since the economic reform of the late 1970s, local governments have been assigned more administration and discretion over local economies, in contrast to the central planning era. As a result, local governments have an incentive to protect their economies, especially their state owned enterprizes (SOEs), in order to obtain higher levels of fiscal transfer and associated benefits.

Research has looked at local protectionism in China. Young (2000) argues that local protectionism results from opportunistic rent-seeking by local governments in a transition economy, and on-going reform would continue to create more such opportunities so that the local protectionism is getting worse. Bai *et al.* (2004) examine and compare local protectionism in different Chinese industrial sectors. They find that local protectionism is higher in more profitable sectors, as well as sectors with more SOEs. Meanwhile, Poncet (2005) measures the magnitude of inter-province trade barriers in China, using the province level trade data. He estimates the border effect through a gravity equation, and finds trade barriers among Chinese provinces are high and rising. Also, he argues that local protectionism comes not only from maximizing the local benefits, but also from stabilizing social economies. Specifically, Ma *et al.* (2007) test the market integration in several Chinese energy sectors by investigating price data from different cities. They conclude that gasoline and diesel markets seem to be integrated, yet coal and electricity markets are not.

1.3 Data

The data for our analysis is from a newly released proprietary firm level data of Chinese manufacturing firms over 1998-2007. This data is collected by the Chinese

Statistic Bureau (CSB) through annual enterprize surveys, and covers all firms with annual revenue above 5 million Renminbi (RMB). It reports the main financial summaries of each firm. All numbers are booked in current values, which we deflate into net values with associated price indices.[1]

All firms are coded into four-digit standard industrial classification (SIC) code. The Chinese steel industry is narrowed to firms with code number 3220 (steel refinery) to restrict our analysis.[2] The original ownership is coded into 22 categories. We first follow Manova and Zhang (2009) to group these ownerships into four categories: state owned, private owned, joint venture, and foreign owned. However, there are very few joint venture and foreign owned firms (less than 10%). Then we re-group all firms into state owned enterprizes (SOE) and non-state owned enterprizes (non-SOE).

We also clean the raw data to reduce measurement errors.[3] Finally, this yields an unbalanced panel data of 770 firms over 10 years, and 2601 observations. It covers approximately 95% revenue in the Chinese steel industry each year. Table 2.2 shows statistics of some key variables.[4]

[1]The revenue and the cost are deflated by the production price index; the fixed asset is deflated by the industry fixed asset price index. The workers' wage is deflated by the consumption price index (CPI). The input price, which is nominated by U.S. dollars, is converted by the nominal exchange rate and deflated by the Chinese CPI (a proxy for the GDP deflator).

[2]Such classification is based on the principle business so that there is no overlapping that one firm is coded with two different SICs

[3]Observations with negative revenue, negative long-run investment, negative total fixed asset, or negative number of workers are dropped. Further, we drop firms that only appear one year in the database. There are 428 firms only show up one year over the ten-year period

[4]It is necessary to clarify the definition of some variables. Here we use total output value as a proxy for revenue. The total revenue is the main variable to examine the market structure and market shares are based on total revenue. The profit is measured as the total pre tax profit (i.e. net profit) plus value added tax (VAT). We use the annual average total fixed net asset (TFA) as a proxy for capital, which comes from averaging the monthly values of the fixed asset. The number of workers is also from the monthly average numbers

Year	Number of Firms	Revenue		Capital		Profit		Workers	
		mean	std	mean	std	mean	std	mean	std
1998	177	829.61	2220.70	714.82	2742.48	12.56	61.63	6383	18259
1999	219	777.77	2115.59	678.77	2734.87	5.15	97.92	5189	15645
2000	209	870.65	2410.61	751.53	2854.97	34.63	118.09	4972	15357
2001	199	1078.86	2746.55	869.96	3486.75	47.42	146.05	4678	14661
2002	198	1255.78	3232.93	838.69	3413.97	63.05	198.52	4310	13770
2003	180	1597.01	4057.93	825.28	3437.17	121.15	399.37	3803	12430
2004	321	818.27	2831.22	293.35	1641.92	50.36	378.08	1423	5728
2005	371	905.87	3025.18	298.42	1520.36	44.48	331.32	1375	5892
2006	358	1099.40	3304.17	391.68	2014.72	57.21	316.43	1514	5962
2007	315	1289.54	3506.03	450.44	2311.23	79.87	442.72	1540	5939

Note: revenue, capital and profit are in million RMB

Table 1.1: Descriptive Statistics of Chinese Steel Firms: 1998-2007

1.4 Overview of the Chinese Steel Industry

The steel industry has been an important part of the Chinese economy since the 1950s. In 2007, the total value-added in this sector captured 4% of the entire Chinese GDP.[5] It has strong connections with its upstream industries, such as iron ore mining, coal mining, petroleum and natural gas, and with its downstream industries as well, such as automobile, shipbuilding, construction, home appliances, etc. As the Chinese economy is still driven by state-oriented investment in sectors with high steel demand such as automobile and infrastructures, the Chinese steel industry is perceived to have an optimistic future.

Following Helpman *et al.* (2008) and Chaney (2008), we split the market expansion into two sources: expansions of the intensive margin and of the extensive margin. The intensive margin represents incumbents increasing their capacity and output, and the extensive margin captures new entrants' output. Figure 1.1 decomposes the market expansion by the intensive margin and the extensive margin. We can see that the intensive margin dominates the market expansion in the Chinese steel industry. This is because the new entrants are most small and medium

[5] CSB year book, 2008

enterprizes (SMEs).

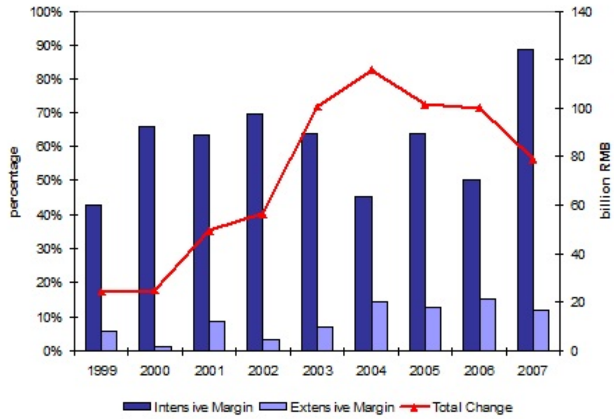


Figure 1.1: Intensive Margin vs. Extensive Margin

With the rapid growth, the Chinese steel industry is highly import dependent on the primary input, iron ore. More than 70% of iron ore demand in China depends on imports, mainly from Australia, Brazil and India. Their shares in the total imports were 41%, 23% and 21%. In 2008, China consumed (1,268 mmt) more than 50% of the world iron ore supply (2,197 mmt) and consumed (434.7 mmt) more than one third of the world steel output (1201.9 mmt).

Although China is the biggest iron ore consumer in the world, the Chinese steel industry does not appear to have enough bargaining power to limit price increases. In 2005, the Chinese steel industry started the iron ore importing price negotiation with foreign iron ore companies. Due to the high concentration in the iron ore market, foreign suppliers control the market price. Table 2.1 shows the results of recent agreements between the steel industry and foreign iron ore suppliers. The huge increase in input prices has limited the profitability of Chinese steel makers.

For example, in 2010, China imported 618 mmt of iron ore, with the price increasing by 30% ($48.51) per ton. As a result, Chinese steel firms had to pay $30.01 billion more. However, in 2010, the total profit by Chinese steel makers was only $13.6 billion under the average exchange rate (1:6.6). In 2010, the average profit

			Price Increasing	
Time of the Agreement	Buyer	Seller	Fine Ore	Lump Ore
2008.1	BaoSteel	Tinto	79.88%	96.50%
2007.3	NSC,Pohang	CVRD	65%	71%
2006.12	Baosteel	CVRD	9.50%	9.50%
2006.6	BaoSteel	BHP	19%	19%
2005.2	NSC	Tinto	71.50%	71.50%

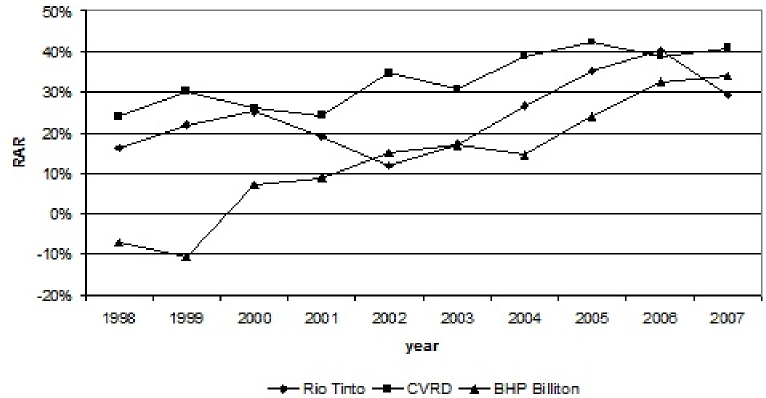
Source: Chinese Steel Statistics

Table 1.2: Negotiation on Iron Ore Prices

rate in the Chinese steel industry was only 3.5%, lower than the 6% average for all Chinese manufacturing industries, and also lower than 10% profitability level in the world steel industry. On the other hand, upstream iron ore suppliers maintain a high profitability. BHP Billiton's net profit increased by 116.5% to \$127.2 billion in 2010, and CVRD's operation profit also increased by 69.2% at the third quarter of 2010.

Figure 1.2 illustrates the upward trends of return to asset ratios (RAR) by three iron ore suppliers. We can see that after 2002, all the three suppliers' RARs are above 30%. This is in sharp contrast to the Chinese steel industry. As the Chinese Steel Association pointed out, in recent years the profitability of the Chinese steel industry (around 3%) is the lowest among the entire manufacturing industry (around 6%), and is well below the world average level in the steel industry (around 10%).

It is necessary to introduce the background of the iron ore importing price negotiation between the Chinese steel industry and foreign suppliers. Baosteel, the biggest Chinese steel maker, represents the entire industry to negotiate with foreign suppliers (BHP Billiton, Tinto, and CVRD). Other small and medium firms (SMEs) cannot bargain with foreign suppliers. Additionally, the Chinese government regulates the iron ore imports. Only 72 firms out of more than 300 firms are "qualified" to import iron ore. Also, all iron ore trading in China is processed through spot markets. Any future market or speculation behavior for steel or iron ore is not



Source: Financial Statements from Rio Tinto, CVRD, BHP Billiton

Figure 1.2: Iron Ore Companies Profitability (RAR): 1998–2007

allowed. All of these are disadvantages for small steel firms.

In spite of these limitations, from 1998 to 2007, the number of firms in the Chinese steel industry increased by 90%. SOEs gradually exited as the whole market expanded. Over 80% of firms in 1998 were SOEs, but this ratio fell below 40% in 2007. On the other hand, there was a rapid expansion within non-SOEs. Non-SOEs took 15% of firms at 1998, but increased to more than 50% in 2007. These facts can be well illustrated in figure 1.3. First, many non-SOEs entered the market so that there were fewer SOEs at the end of the sample period. Second, expansion of the market output was mainly due to the growth of established big SOEs. Third, SOEs did not have significant higher profitability than non-SOEs, but the better performed ones were mainly SOEs. Fourth, the whole market became less concentrated but within SOEs, the market concentration slightly increased[6].

These facts imply that better performing SOEs dominate the market. They have large market share both in revenue and in profit. During the sample period, the Chinese steel industry gradually concentrated to these big SOEs, but private firms' entry has increased market competitiveness.

[6]The calculated Herfindahl Hirschman Index of the entire market drops from 25.3% in 1998 to 5.0% in 2007; and that is from 5.6% to 5.7% for state owned firms, and from 5.2% to 3.1% for non-state owned firms.

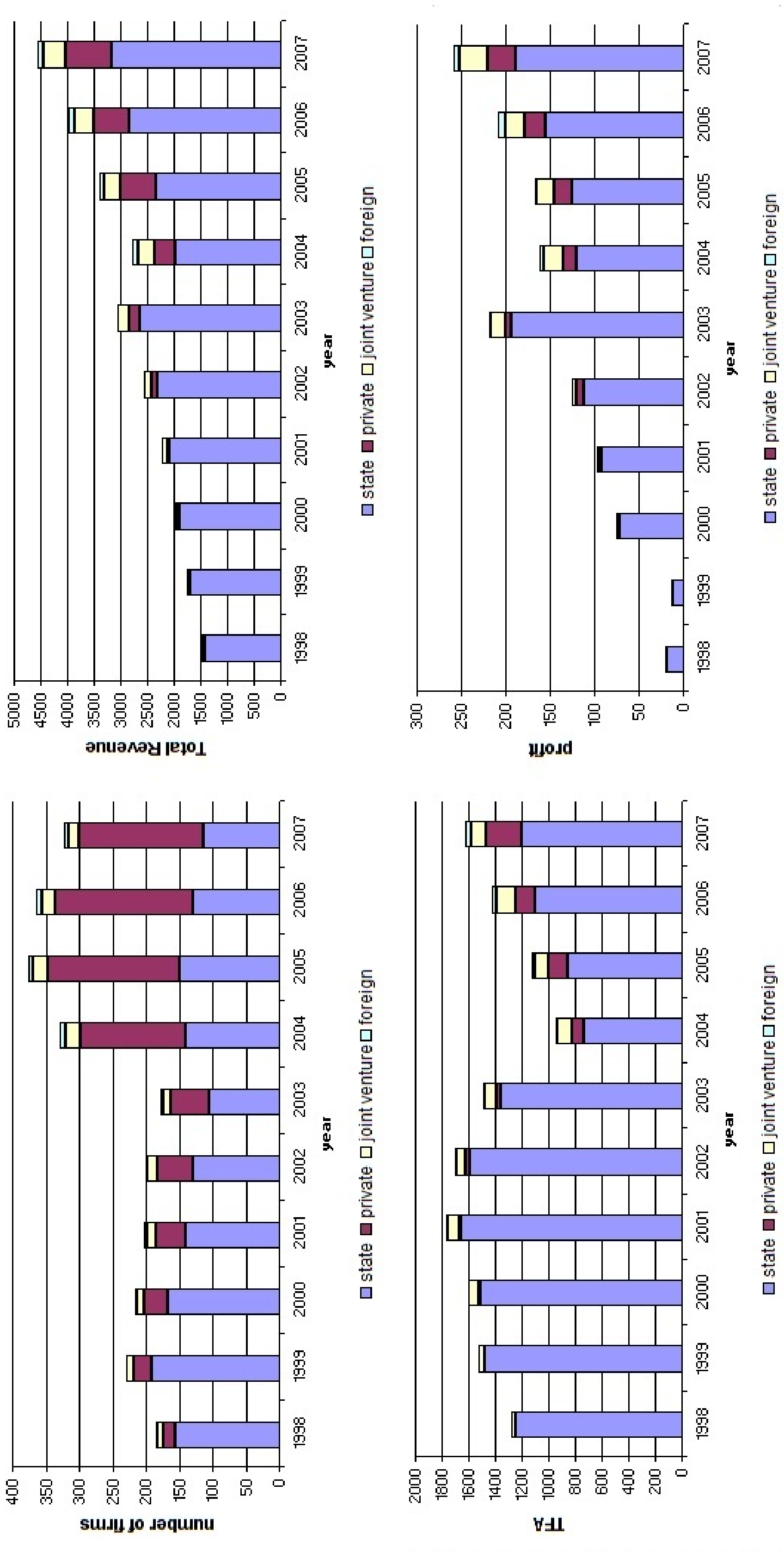
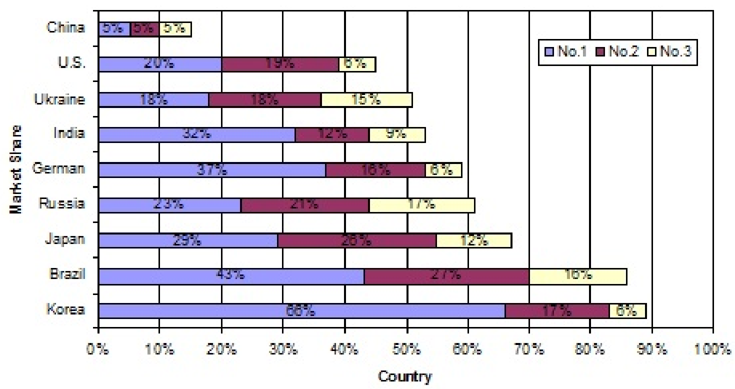


Figure 1.3: Market Structure by Ownership, 1998-2007

1.5 Market Structure: Regional Fragmentation

The Chinese steel industry has a very low market concentration and may be the most fragmented of such markets in the world. The top-3 firms' total market share is around 15%, far below that of other established producers. Figure 1.4 compares the top-3 firms' total market shares in different countries in 2006. The No.1 steel firm in Korea, Pohang, took 66% of the market. In Japan, the largest steel firm, Nippon Steel, accounted for 20% of the market. However, for China, the market shares of top-3 firms were all around 5% in 2006.



Source: Chinese Steel Statistics

Figure 1.4: Chinese Steel Market Concentration

The low market concentration in China results from high level of entry and regional restrictions. From figure 1.5, we can see that there are three entry peaks in the Chinese steel industry since 1949. The first one was in 1958 during the "Great Leap Forward." At that time, many SOEs were established under the government plans. The second entry peak was in 1993. Former president Deng Xiaoping took a trip to southern China in 1992 to push the economic reform forward. The second entry peak was still driven by SOEs, yet many private firms entered the market as well. The last entry peak happened in 2003. China joined the WTO in 2001 and there was an overheating in the Chinese economy in late 2003. Between 2003 and

2004, many non-SOEs were established, and most of them were SMEs.

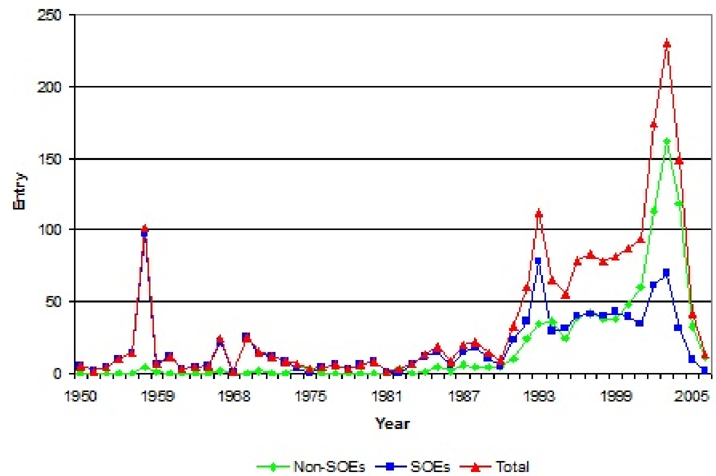


Figure 1.5: Chinese Steel Firms' Entry: 1950–2006

1.5.1 Geographic Distribution

The boom of SMEs' entry is due in part to the huge demand from the end-markets and to the lax environmental standards in China. By 2008, there were over 300 steel firms in China. This number is far larger than most countries, even accounting for China's size. The geographic distribution of Chinese steel firms is very disperse and from figure 1.6, we can see that almost every province has several steel makers. It directly results in a low market concentration and a highly fragmented industry.

One possible explanation for the market fragmentation lies in the government industrial policies. Before the 1980s, the Chinese steel industry was dominated by SOEs. They were established near iron ore mines or large cities according to industrial plans, such as AnSteel, PanSteel, and WuSteel. During the "Great Leap Forward," there were a large number of small steel firms built up. At that time, steel production in China was administrated by governmental plans. In part, this also reflected that fact that Chinese iron ore mines are spread over the country so steel making firms were established around the country.

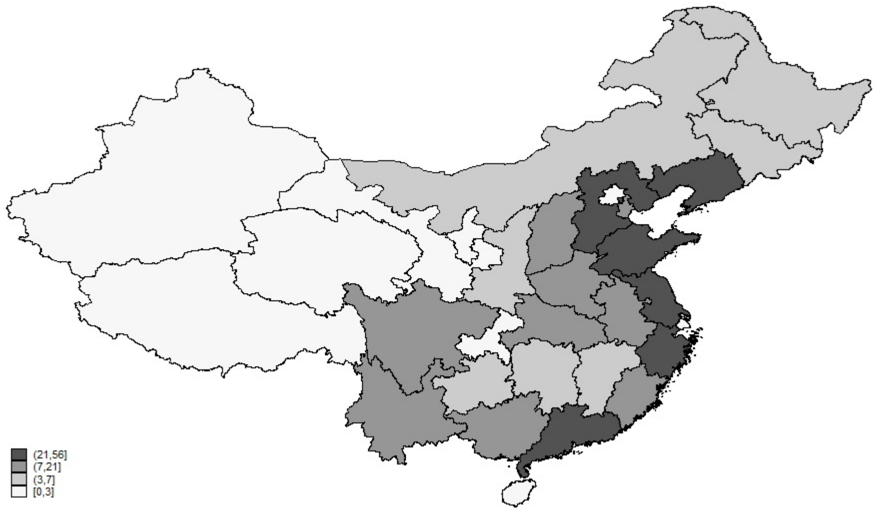


Figure 1.6: Geographic Distribution of Chinese Steel Firms at 2007

Another potential explanation is that large intra-national trade costs drive the dispersion. Besides the discussion in the introduction, Poncet (2005) reveals a increased trade cost between Chinese provinces from 1992 to 1997. Naughton (2003) show the potential impact of increases in inter-provincial trade barriers in the 1990s. The existence of the intra-national trade cost would lead to excessive entry in the overall market, because there is little substitution between provinces. The increased local demand for steel calls for more local suppliers.

1.5.2 Spatial Analysis

According to the analysis above, market concentration in the Chinese steel industry is unusually low. Here, we use spatial analysis to test the role of intra-national trade costs by measuring the spatial demand spill-overs across provinces.

We collect the aggregated steel outputs on the province level (both in crude steel and steel, in million metric tons), province GDP in manufacturing industries, province industry output price indices (PPI), and geographic distances between province capital cities. Comparing figure 1.7 and figure 1.8, we can see a positive relationship between the local steel production and the local GDP, i.e. more developed areas correspond to areas of higher steel output. The correlation coefficient between local GDP and local steel output is averagely 51% over the sample period.

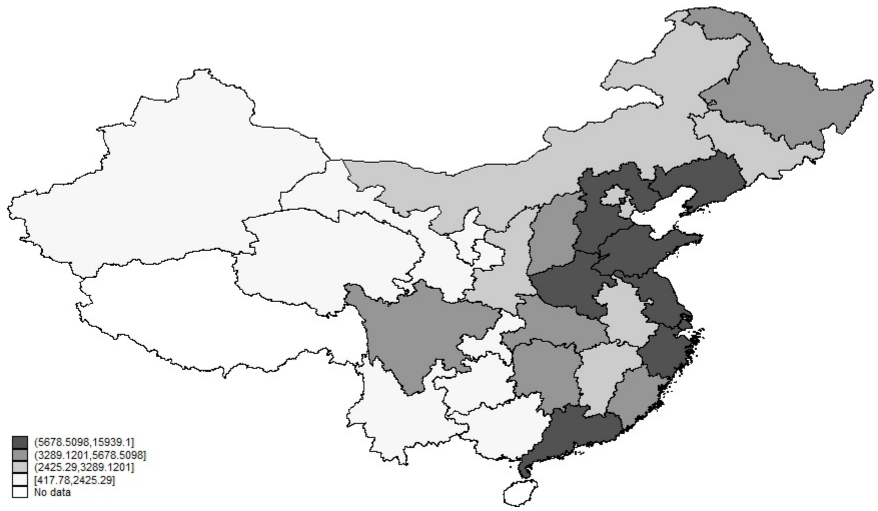


Figure 1.7: Geographic Distribution of Manufacturing GDP at 2007: 100 million RMB

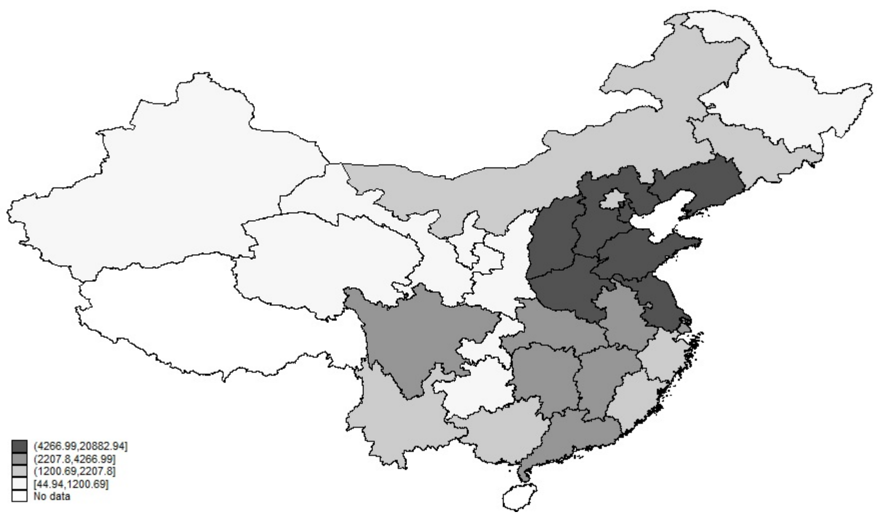


Figure 1.8: Geographic Distribution of Steel Output at 2007: million metric tons

Steel is the basic raw material for many manufacturing sectors, such as automobile, ship building and machinery. Growth and development in these downstream markets call for huge amounts of steel. As the Chinese steel association pointed out, the rapid expansion of the Chinese steel industry is mainly driven by the demand from the economic growth in China. Therefore, we seek to investigate the impact of manufacturing output on steel production in China.

In order to measure the neighboring spill-over effect on local steel production, spatial analysis is adopted here. We test whether the local steel production depends on other provinces' demand. First, a linear regression equation can be specified as:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln GDP_{it} + \beta_2 \ln PPI_{it} + \epsilon_{it} \tag{1.1}$$

Here Y_{it} is the total output of steel in province i at year t. GDP_{it} denotes the locally real industrial GDP, PPI_{it} is the manufacturing industry output price indices. Here, we want to test the cross-province dependence of steel production on GDP. If there is a pattern of substitution across provinces, then the local steel production would not only depend on local demand but also on other provinces' demand. That is, other provinces' demand has spatial effects. Therefore, the above regression would yield a biased result.

Variables	units	mean	sd	min	max
Output	10^4 tons	2005.224	2663.763	1.08	20882.94
Market share	%	3.45%	3.68%	0.00%	19.84%
GDP	100 million RMB	2583.652	2816.266	46.15	15939.1
PPI	%	103.4479	4.844971	93.7	129.4
Distance	kilometer	1280.786	677.0099	103.6108	3463.171

Table 1.3: Province Data Statistics: 2000-2007

Spatial econometrics is a growing field, and recent research has extended spatial methods to panel data frameworks. Baltagi and Li (2001) use spatial analysis on a panel data to estimate the demand for liquor in U.S. They get the best 1-year ahead forecasting if the spatial correlation and state heterogeneity are both controlled. Cattaneo *et al.* (2011) adopt a fixed effect spatial lag model to describe the provincial coal demand in China. They find that the fixed effect spatial lag model fits the existing data better. Furthermore, Girardin and Kholodilin (2009) introduce the spatial analysis into a dynamic panel data model to forecast the growth rates of gross regional product of Chinese provinces. Their forecasts become much better after accounting for spatial effects. In macroeconomics area, Steiner (2010) adopts an instrumental variables approach to study the contagion in capital account policies, and finds these policies are correlated contemporaneously across countries. Since the time length here is not as long as in Girardin and Kholodilin (2009) (1979-2007), we employ the fixed effect spatial lag model as in Cattaneo *et al.* (2011).

As suggest by Elhorst (2010), the fixed effect spatial lag model is appropriate to address the spatial correlation. The specification is that other provinces' outputs (LHS variables) also enter the linear equation with a weighting matrix. Then the original model becomes a spatial Durbin model with time and region fixed effect.

$$y_{it} = \beta_0 + \rho \sum_{j \neq i} w_{ij} y_{jt} + \mathbf{X_{it}} \beta + \theta \sum_{j \neq i} w_{ij} \mathbf{X_{jt}} + \alpha_i + \mu_t + \epsilon_{it} \tag{1.2}$$

In equation 1.2, the dependent variable, y_{it}, is the logarithm of the regional steel output (mmt) for province i at year t ($i = 1, ...N, t = 1, ..., T$). The variable $\sum_{j \neq i} w_{ij} y_{jt}$ is the weighted steel output in other provinces (y_{jt} is the logarithm of the regional steel output for other provinces). Here w_{ij} is the i, j-th element in a $N \times N$ spatial weighting matrix which is derived from the geographic distance between each two province capital cities. ρ can be used to measure the spatial lag effects from other provinces. β_0 is a constant term. $\mathbf{X_{it}}$ is a vector of two exogenous variables: industrial GDP and production price index (PPI) in province i at time t, and both are in logarithm form. Similarly, $\sum_{j \neq i} w_{ij} \mathbf{X_{jt}}$ contains the regional industrial GDP and production price index in other provinces, also in natural logarithm, which can be used to measure the"spill-over" effects.

Moreover, we also introduce a spatial fixed effect α_i and a time fixed effect μ_t to control unobserved heterogeneity. The spatial fixed effects capture unobserved province-specific while time invariant variables, and the time fixed effects control for the time-specific effect such as national wide unobservable variable.

If there exist cross-province "spill-over" effects, then the classical panel data estimation would give us an inconsistent result. We estimate the spatial model using maximum likelihood suggested by Elhorst (2010), and the results are shown in table 1.4. We also list estimation results with/without controlling for the unobserved heterogeneity.

Further, we calculate the direct and indirect effects of independent variables as in **?**, where the direct effect measures the effects of local GDP and PPI on local steel production (i.e. $\partial Y_{it}/\partial \mathbf{X}_{it}$), and the indirect effect measures the effects of GDP and PPI from other provinces on local steel production (i.e. $\partial Y_{it}/\partial \mathbf{X}_{jt}$). These results are shown in the lower panel of table 1.4. Comparing the results in different model specifications, we find local industrial GDP always exerts a significant positive effect on local steel output. However, the indirect effect of GDP is not significant after controlling for the spatial fixed effect. It means the local steel production in China is not affected by the demand from other provinces.

On the other hand, both the direct and indirect effects of the PPI is insignificant under any model setting which means the steel output is not sensitive to the price level.

The estimation results suggest that *only* the local GDP matters. A 10% increases in local GDP will increase the local steel output by more than 8%, which is equal to 1.6 mmt on the average. This simple spatial estimation is consistent with my argument that other provinces' economic development would not impose a positive effect on the local steel production.

These results are consistent with the story in which a fragmented market could severely reduce the bargaining power of the whole industry. Although the Chinese steel industry is huge, it is segmented into many sub-markets in each province. Therefore, the Chinese steel industry cannot exert its bargaining power as its to-

Coefficient		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln GDP_i$		0.8488***	0.8515***	0.8463***	0.8481***	0.8014***	0.8195***	0.8112***	0.8157***
		(0.0571)	(0.0573)	(0.0636)	(0.0639)	(0.0584)	(0.0605)	(0.0651)	(0.0617)
$\ln PPI_i$		-0.3261	-0.1932	-0.6168	-0.4594	-0.1950	-0.7278	-0.4576	-0.9843
		(1.3610)	(1.3683)	(1.4752)	(1.4858)	(1.3703)	(1.3865)	(1.4959)	(1.3817)
$w \cdot \ln Y_j$		0.2350**	0.1140	0.2530**	0.1200	-0.5750**	-0.7980***	-0.2922	-0.8120***
		(0.1144)	(0.1786)	(0.1155)	(0.1782)	(0.2333)	(0.2648)	(0.2169)	(0.2655)
$w \cdot \ln GDP_j$		.	0.2771	.	0.2778	.	0.6044	.	0.5962
		.	(0.2733)	.	(0.2810)	.	(0.5228)	.	(0.5334)
$w \cdot \ln PPI_j$		.	-0.1932	.	-0.1288	.	-0.7278	.	-0.9843
		.	(1.3683)	.	(0.0911)	.	(1.3865)	.	(1.3815)
	Direct Effect	0.8548***	0.8545***	0.8490***	0.8547***	0.8117***	0.8227***	0.8177***	0.8218***
		(0.0568)	(0.0574)	(0.0640)	(0.0612)	(0.0588)	(0.0582)	(0.0649)	(0.0648)
$\ln GDP_i$	Indirect Effect	0.2775	0.4161*	0.3132	0.4331	-0.2934*	-0.0285	-0.1752	-0.0427
		(0.1813)	(0.2009)	(0.1901)	(0.2287)	(0.0886)	(0.2817)	(0.1224)	(0.2876)
	Total Effect	1.1323***	1.2705***	1.1622***	1.2878***	0.5183***	0.7941***	0.6424***	0.7791***
		(0.1923)	(0.2046)	(0.2026)	(0.2332)	(0.0950)	(0.2883)	(0.1338)	(0.2948)
	Direct Effect	-0.3819	-0.2434	-0.6313	-0.4328	-0.1432	-0.2935	-0.4839	-0.5732
		(1.3285)	(1.3745)	(1.4873)	(1.4943)	(1.3570)	(1.3990)	(1.4212)	(1.3570)
$\ln PPI_i$	Indirect Effect	-0.1206	-8.3889	-0.2413	-8.1265	0.0487	-7.5723	0.0944	-7.8888
		(0.5215)	(5.7967)	(0.6529)	(5.9678)	(0.5097)	(5.2642)	(0.3675)	(5.0727)
	Total Effect	-0.5025	-8.6324	-0.8726	-8.5593	-0.0945	-7.8658	-0.3895	-8.4620
		(1.7839)	(5.9206)	(2.0685)	(6.0062)	(0.8822)	(5.3335)	(1.1292)	(5.0913)
adj.R^2		0.5111	0.5185	0.4949	0.5018	0.4692	0.4720	0.4451	0.4473
Spatial FE		No	No	Yes	Yes	No	No	Yes	Yes
Year FE		No	No	No	No	Yes	Yes	Yes	Yes
Obs		232	232	232	232	232	232	232	232

Standard errors in parentheses
$* \ p < 0.05, ** \ p < 0.01, *** \ p < 0.001$

Table 1.4: Panel Data Spatial Analysis for Regional Steel Production: 2000-2007

tal output would suggest. The loss of bargaining power means the foreign iron ore suppliers strongly control the import price, which reduces Chinese steel firms' profitability.

1.6 Conclusion

In this paper, we take a close look at the Chinese steel industry. We examine firm heterogeneity in profitability, productivity, and market structure. We attempt to explain the low profitability in Chinese steel firms given the huge amount of output by the entire industry.

We first document a clear trend of structural adjustment in the Chinese steel industry. Small and poorly performing SOEs exited the market, and many non-SOEs entered the market. Large SOEs expanded their outputs and improved their productivity and dominated the market. Second, by comparing with steel industries in other countries, we find the market concentration in the Chinese steel industry is extremely low.

Then, we use a spatial panel data analysis approach to study the spill-over effect of other provinces' demand on local steel production. We calculate the direct effect which captures the effect of local demand, and indirect effect which captures the effect of other provinces' demand, under different model settings. After controlling for the spatial fixed effect and time fixed effect, we cannot find any significant indirect effect from the local industrial GDP, while its direct effect is always significantly positive. Our result suggest that other provinces' GDP cannot affect the local steel production. The market segmentation would come from the local government protection, and make more steel firms survive in each local market, which is a possible explanation for the low market concentration in the Chinese steel industry.

Under the background of consolidation in upstream suppliers, understanding the nature of firm heterogeneity in the Chinese steel industry is important because of its implication for market structure dynamics under the context of the vertical market linkage. The possibility is raised by our findings. In order to obtain the bargaining power against upstream suppliers, the downstream market needs to increase the market concentration by consolidation and crowding out SMEs, especially within SOEs. A promising area for future research is the market linkage and the interaction between upstream and downstream firms.

Chapter 2

Market Structures and Profit Sharing along the Global Supply Chains

2.1 Introduction

This paper is motivated by the iron-ore importing price negotiations between the Chinese steel industry and foreign suppliers. In spite of being the biggest iron ore buyer in the world, the Chinese steel industry does not appear to have much pricing power. Table 2.1 shows the increases in imported iron ore prices from 2005 to 2008. Compared with the high profitability of iron-ore suppliers (averaging above 100% in terms of return to asset ratio), the Chinese steel firms are far less profitable (around 3% in terms of return to asset ratio).

Recently, both Antràs and Chor (2012) and Costinot, Vogel, and Wang (2011) study the specialization patterns along global supply chains, while Koopman, Wang, and Wei (2012) study the measurement issues of exports when global value chain is in presence. The profit sharing along global supply chain, however, is under

Time of the Agreement	Buyer	Seller	Price Increasing Fine Ore	Price Increasing Lump Ore
2008.1	BaoSteel	Tinto	79.88%	96.50%
2007.3	NSC,Pohang	CVRD	65%	71%
2006.12	Baosteel	CVRD	9.50%	9.50%
2006.6	BaoSteel	BHP	19%	19%
2005.2	NSC	Tinto	71.50%	71.50%

Source: Chinese Steel Statistics

Table 2.1: Negotiation on Iron Ore Prices

investigated. As we can see in the above, the profitability along the supply chain may vary from 100% in the upstream industry to 3% in the downstream industry. What may explain these huge differences in profitability?

In this paper we develop a model to study how profits are shared between intermediate input suppliers and final good producers. Differences in market structures are shown to be main driving forces in profitability differences along the global supply chain. Applying Melitz and Ottaviano (2008)'s framework of heterogeneous firms into the problem, we model the downstream (final good) market as the monopolistic competition, while the upstream (intermediate input) market in oligopolistic (Cournot) competition. We show how increases in the entry cost in the upstream market and segmentations in the final good market increases (decreases) the market power of intermediate input (final good) producers, which increase (decrease) the profitability of intermediate input (final good) producers. We also show how increases in the demand of the final good affect the price of the intermediate input, which determines the profit sharing between intermediate input and final good producers. Using firm level data from the Chinese steel industry, we calibrate the model. Our results show a 20% increase in the final good demand would induce 25% increase in the input price. Our results also suggest the regional trade costs in the Chinese steel market are about three times as firm's average marginal cost, and a 10% decrease in regional trade costs would lower the input prices by 22%.

The rest of the paper is organized as follows: Section 2.2 models a market vertical linkage and derives its equilibrium properties; Section 2.3 introduces the data and calibrates our model and simulates the "integrated" scenario. Section 2.4 concludes.

2.2 Market Vertical Linkage

We consider an open economy with a (domestic) downstream market and an (foreign) upstream market. A homogeneous intermediate good is produced by heterogenous upstream firms. Heterogenous downstream firms, using this intermediate good as an input, produce differentiated final products. We allow for free entry in both markets. The downstream market is not perfectly integrated. because of regional trade barriers. Firms can produce in one region and sell in other regions, and we model this as a game with two stages: in the first stage, potential entrants in the upstream market observe an identical entry cost, and they obtain their productivity levels.[1] Then they make entry decisions. After entering the upstream market, upstream firms engage into a Cournot competition. A market price level comes out as a result. In the second stage, firms enter the downstream market in a similar way, while at the same time post-entry firms have to decide whether they sell products in other regions or not, considering regional trade barriers. Finally, the post-entry downstream firms engage into differentiated product competitions within each region and realize profits.

2.2.1 Downstream Market

The two-stage game requires backward induction to solve. We first look at the downstream market taking as given the upstream market outcomes. Then we go back to the upstream market and find the general equilibrium.

[1] All firms have the information of productivity distributions in two markets.

Demand Function

The downstream market is segmented into M regions, with each region characterized by monopolistic competition. Let's focus on a representative region $l, (l = 1, ..., M)$. Suppose there is a continuum of differentiated products in region l plus a homogenous product as numeraire. In each region, consumers have an identical quadratic utility function as in Melitz and Ottaviano (2008):

$$U = q_0 + \alpha \int_i q_i^s \mathrm{d}i - \frac{\gamma}{2} \int_i (q_i^s)^2 \mathrm{d}i - \frac{\eta}{2} \left(\int_i q_i^s \mathrm{d}i \right)^2 \tag{2.1}$$

Varieties are indexed by i. q_i^s stands for the consumers' expenditure share (in all the varieties) on firm i's product. q_0 indicates the expenditure share of the numeraire good with its price equal to one. Parameters in the demand function, α, η and γ, are all positive. α and η measure the substitution between varieties and the numeraire: e.g. higher α means higher marginal utility than the numeraire, and consumers would like to reduce their consumption on the numeraire. γ measures the substitution pattern among different varieties. When $\gamma = 0$, all the varieties become perfect substitutes, while higher γ means these varieties are less substitutable. Supposing consumers have a positive demand for the numeraire, the utility function above yields a linear inverse demand for each variety in region l:

$$p_i = \alpha - \gamma q_i^s - \eta Q_d \tag{2.2}$$

Here, p_i is the price chosen by firm i in region l, and Q_d is the regional market aggregated output level of all the varieties. We use N_l to measure the mass of sellers in region l, and I_l measures the regional economic size, then the individual demand function of a variety i is:

$$q_i = I_l q_i^s = \frac{\alpha I_l}{\eta N_l + \gamma} - \frac{I_l}{\gamma} p_i + \frac{\eta N_l I_l}{(\eta N_l + \gamma)\gamma} \bar{p}_l \tag{2.3}$$

Here, $\bar{p}_l$ is the regional market average price except the numeraire, $\bar{p}_l = \int_i p_i \mathrm{d}i / N_l$. We can see that there is a positive relationship between a single firm's output and market average price. It is straightforward to see that more firms selling in region l would shrink each firm's market capacity ($\frac{\alpha I_l}{\eta N_l + \gamma}$). The maximum individual price level leads to zero output:

$$p_{max}^l = \frac{\gamma\alpha + \eta N_l \bar{p}_l}{\eta N_l + \gamma} \tag{2.4}$$

This equation means that higher market capacity (bigger α) would result in, *ceteris paribus*, a higher maximum price. As a result, the price elasticity of demand is given as a function of p_{max}:

$$e_i = \frac{p_i}{p_{max} - p_i} \tag{2.5}$$

Therefore, the price elasticity of demand is endogenous in this model which is different from Melitz (2003).

2.2.2 Production and Multilateral Trade in the Downstream Market

Firm heterogeneity is reflected in their productivity. Suppose each firm's marginal cost is constant but different from each other. Firms' productivity determines their marginal cost. Melitz and Ottaviano (2008) only focus on firms' marginal cost without specifying a production function. Since we need to connect the upstream market and the downstream market, a production function is necessary. Suppose in each region, each downstream firm uses the upstream output as the only input to produce final goods. As in the firm heterogeneity literature (See Chaney (2008)), the production function is constant-return-to-scale and follows:

$$q_i = \frac{x_i}{\varphi_i} \tag{2.6}$$

Here x_i is the input (intermediate product) used by a downstream firm i, and φ_i is the inverse productivity level of firm i. It means that one unit of output in firm i calls for φ_i units of the intermediate good, thus higher φ_i implies lower productivity. As a result, the marginal production cost in firm i is:

$$c_i = P_u \varphi_i \tag{2.7}$$

Here P_u is the upstream market price level. Since the upstream output is homogeneous and upstream firms engage in a Cournot competition, downstream firms just follow the upstream market price, P_u.

The downstream market is not perfectly integrated. Recall that there are M regions, indexed by $l, (l = 1, 2, ...M)$. A representative firm in region l makes decisions on domestic price p_D^l and export price to region h, $p_X^{lh}, (h \neq l))$. Firms maximize their domestic and exporting profits independently. Since the downstream market is similar to a multilateral economy, firms are facing $M-1$ exporting markets. The two profit functions of a representative firm in region l can be written as:

$$\begin{aligned} \pi_D^l(\varphi) &= (p_D^l(\varphi) - P_u\varphi)q_D^l(\varphi) \\ \pi_X^{lh}(\varphi) &= (p_X^{lh}(\varphi) - \tau_{lh}P_u\varphi)q_X^{lh}(\varphi) \end{aligned} \tag{2.8}$$

Each downstream firm i in region l will choose its optimal prices, p_D^l and p_X^{lh}, according to its productivity level $1/\varphi_i$. This means prices are functions of their productivity. Following Melitz and Ottaviano (2008), firms sell products where they can make non-negative profit. This results in the cut-off productivity in region l:

$$\varphi_l^* = \frac{p_{max}^l}{P_u} \qquad \varphi_{lh}^* = \frac{p_{max}^h}{P_u \tau_{lh}} \tag{2.9}$$

Here, p_{max}^l yields zero selling in region l. That is:

$$p_{max}^l = \frac{\alpha\gamma + \eta N_l \bar{p}_l}{\eta N_l + \gamma} \tag{2.10}$$

N_l is the number of sellers in region l. $\bar{p}_l$ is the average price level in region l. Following Melitz and Ottaviano (2008), a representative firm with productivity level φ in region l of the downstream market has its optimal outputs q_d^l, q_x^{lh} and profits π_d^l, π_x^{lh}.

$$\begin{aligned}
q_d^l(\varphi) &= \frac{P_u I_l}{2\gamma}(\varphi_l^* - \varphi) \qquad & q_x^{lh}(\varphi) &= \frac{P_u I_h}{2\gamma}(\varphi_h^* - \tau_{lh}\varphi) \\
p_d^l(\varphi) &= \frac{P_u}{2}(\varphi_l^* + \varphi) \qquad & p_x^{lh}(\varphi) &= \frac{P_u}{2}(\varphi_h^* + \tau_{lh}\varphi) \\
\pi_d^l(\varphi) &= \frac{P_u^2 I_l}{4\gamma}(\varphi_l^* - \varphi)^2 \qquad & \pi_x^{lh}(\varphi) &= \frac{P_u^2 I_h}{4\gamma}(\varphi_h^* - \tau_{lh}\varphi)^2
\end{aligned}$$

Here, φ_l^* is the local cut-off productivity level of the fringe firms at region l. All the firms with $\varphi_i < \varphi_l^*$ will sell their products in the local market. On the other hand, firms with $\varphi_i < \varphi_h^*/\tau_{lh}$ will export from region l to region h. Here, τ_{lh} measures the intra-national transportation cost (freeness of trade) between region l and region h and $\tau_{lh} \geq 1$ for all $l, h \in M$ and $\tau_{ll} = 1$.

We can see that more productive firms tend to export to other regions, and they produce more output, making more profit.

The mark-up ϵ_i in a market (domestic or exporting) is endogenous here which is a key difference from a monopolistic competition model with CES demand function.

The firm i's mark-up ϵ_i is determined by its productivity:

$$\epsilon_i = \frac{(\varphi^* - \varphi)^2}{(\varphi^{*2} - \varphi^2)} \tag{2.11}$$

2.2.3 Entry and Distribution in the Downstream Market

In the downstream market, each firm faces a domestic market and $M-1$ exporting markets. Suppose there is a fixed cost for a firm to establish in the downstream market, f_d. This fixed cost is identical in each region. The free entry condition for a domestic firm in region l is that the expected post-entry total profit over the domestic market and all the exporting market is equal to the fixed entry cost[2].

$$\int_0^{\varphi_l^*} \pi_d^l(\varphi)\mathrm{d}G(\varphi) + \sum_{h \neq l}^{M} \int_0^{\varphi_h^*/\tau_{lh}} \pi_x^{lh}(\varphi)\mathrm{d}G(\varphi) = f_d \tag{2.12}$$

Each firm draws its inverse productivity from the distribution $G(\varphi)$.[3] Follow Yeaple, Helpman, and Melitz (2004) and Chaney (2008), we specify the distribution of productivity $1/\varphi$ following a Pareto distribution with a shape parameter k and the lowest level $1/\varphi_m$. The Pareto distribution is an appropriate approximation for firms' productivity. Del Gatto, Mion, and Ottaviano (2006) empirically show that this Pareto distribution fits well for firms' productivity in many countries.

The Pareto distribution of $1/\varphi$ means φ has distribution:

$$G(\varphi) = \left(\frac{\varphi}{\varphi_m}\right)^k \quad \varphi \in [0, \varphi_m]$$

Recall that φ measures firms' marginal costs. $G(\varphi)$ reveals the draw of firms' cost. Thus, the shape parameter k captures the dispersion of firms' productivity. When $k = 1$, the distribution of φ degenerates to a uniform distribution. Higher k indicates

[2]We misuse the "entry" as establishing.
[3]Recall that higher φ means lower productivity.

a thinner right tail and more firms concentrated in the low productivity part; when k goes to infinite, the productivity distribution shrinks to $1/\varphi_m$.

A good property of the inverse Pareto distribution above is that a truncated conditional distribution has the same shape parameters. Similar to Melitz and Ottaviano (2008), equation 2.15 can be reduced to:

$$\sum_{h=1}^{M} \rho_{lh} I_h (\varphi_h^*)^{k+2} = \frac{2\gamma(k+1)(k+2)(\varphi_m)^k f_e}{P_u^2} \quad l = 1, ..., M \tag{2.13}$$

There are M linear equations, and we can solve for the cut-off productivity levels $\varphi_l^*, l = 1, ..., M$ by Cramer's rule.

$$\varphi_l^* = \left(\frac{2(k+1)(k+2) f_e \gamma}{|P|\lambda} \frac{\sum_{h=1}^{M} |C_{hl}|}{I_l} \right)^{\frac{1}{k+2}} / P_u \tag{2.14}$$

Here, $P_{M\times M}$ is the matrix with its element $P_{lh} = \rho_{lh} = (\tau_{lh})^{-k}$, and $|C_{hl}|$ is ρ_{hl}'s cofactor. $\lambda = (P_u \varphi_m)^{-k}$ results from the lower bound of marginal cost which is assumed to be exogenous.

In order to check the segmented market's effect, let's assume the intra national-trade cost τ_{lh} is proportional to the geographic distance: $\tau_{lh} = \theta d_{lh}$. Then the expression of the cut-off productivity φ_l^* becomes:

$$\varphi_l^* = \theta^{\frac{k}{k+2}} \left(\frac{2(k+1)(k+2) f_e \gamma}{|\tilde{P}|\lambda} \frac{\sum_{h=1}^{M} |\tilde{C}_{hl}|}{I_l} \right)^{\frac{1}{k+2}} / P_u \tag{2.15}$$

So, we can see that a less integrated market would lower down the cut-off productivity level (higher φ^*), which means more less productive firms enter the market.

$$\frac{\partial \varphi_l^*}{\partial \theta} > 0 \tag{2.16}$$

Thus, from the discussion above, the average price level and the mass of sellers in region l are given by:

$$\bar{p}_l = \frac{2k+1}{2k+2} P_u \varphi_l^* \qquad N_l = \frac{2(k+1)\gamma}{\eta} \frac{\alpha - P_u \varphi_l^*}{P_u \varphi_l^*} \tag{2.17}$$

Note sellers in region l come from M regions (include region l itself). Therefore,

$$N_l = G(\varphi_l^*) N_e^l + \sum_{h \neq l} G(\varphi_{lh}^*) N_x^{lh} \tag{2.18}$$

Here, N_e^l is the mass of entrants in region l. Among N_e^l firms, $G(\varphi_l^*)N_e^l$ firms can survive and sell products in region l, and among these $G(\varphi_l^*)N_e^l$ firms, there are $G(\varphi_{lh}^*)N_e^l$ firms exporting from region l to region h. Since we can let the domestic transportation cost $\tau_{ll} = 1$, the equation above gives M equations:

$$\sum_{h=1}^{M} \rho_{hl} \lambda N_e^h = \frac{N_l}{P_u^k (\varphi_l^*)^k} \qquad l = 1, ..., M \tag{2.19}$$

Solving these M equations, we can get the number of entrant in region l, N_e^l.

$$N_e^l = \frac{2(k+1)\gamma}{\eta |P| \lambda} \sum_{h=1}^{M} \frac{(\alpha - P_u \varphi_h^*)|C_{lh}|}{(P_u \varphi_h^*)^{k+1}} \tag{2.20}$$

As in Melitz and Ottaviano (2008), there are N_d^l firms selling in region l and N_x^{lh} exporting from region l to region h.

$$N_d^l = N_e^l G(\varphi_l^*) = N_e^l \left(\frac{\varphi_l^*}{\varphi_m} \right)^k \tag{2.21}$$

$$N_x^{lh} = N_e^l G(\varphi_{lh}^*) = N_e^l \left(\frac{\varphi_h^*}{\tau_{lh} \varphi_m} \right)^k \tag{2.22}$$

Then the effect of θ here is:

$$\frac{\partial N_d^l}{\partial \theta} > 0 \qquad \frac{\partial N_x^{lh}}{\partial \theta} < 0 \tag{2.23}$$

These implies that in a less integrated economy, there will be more firms survive in local markets. So far, we solve for the number of producers and exporters, as well as their geographic distribution in the segmented downstream market. Then, the regional output in the downstream market can be derived by integrating all the survivors in region l.

$$Q_d^l = N_e^l \int_0^{\varphi_l^*} \frac{P_u I_l}{2\gamma}(\varphi_l^* - \varphi)\mathrm{d}G(\varphi) \tag{2.24}$$

$$Q_x^{lh} = N_e^l \int_0^{\varphi_{lh}^*} \frac{P_u I_h}{2\gamma}(\varphi_{lh}^* - \tau_{lh}\varphi)\mathrm{d}G(\varphi) \tag{2.25}$$

These two equations then become:

$$Q_d^l = \frac{1}{2\gamma(k+1)\varphi_m^k} P_u I_l \varphi_l^{*k+1} N_e^l \tag{2.26}$$

$$Q_x^{lh} = \frac{1}{2\gamma(k+1)\varphi_m^k \tau_{lh}^k} P_u I_h \varphi_h^{*k+1} N_e^l \tag{2.27}$$

Furthermore, we can aggregate the regional revenue through the similar way.

$$R_d^l = \frac{1}{2\gamma(k+2)\varphi_m^k} P_u^2 I_l \varphi_l^{*k+2} N_e^l \tag{2.28}$$

$$R_x^{lh} = \frac{1}{2\gamma(k+2)\varphi_m^k \tau_{lh}^k} P_u^2 I_h \varphi_h^{*k+2} N_e^l \tag{2.29}$$

Therefore, we get the market supply in domestic markets and (inter-regional) exporting markets. Next, we can solve the demand for the intermediate good in the upstream.

2.2.4 Demand in Upstream

The vertical linkage is that the upstream total output is the total input in the downstream. It gives the identification condition to connect two markets. Given the production function by downstream firms, one single firm's demand for the intermediate good in one market is:

$$x_i = \varphi_i q_i = \frac{P_u I}{2\gamma}\varphi_i(\varphi^* - \varphi_i) \tag{2.30}$$

Here, φ^* is the inverse cut-off productivity level in either a domestic market or an exporting market. We can see that given the same output q_i, larger φ_i indicates higher demand for the intermediate product.

The total demand for the intermediate good from region l has two parts: those for the domestic selling and those for the exporting selling (given the upstream market price P_u):

$$X_d^l = N_e^l \int_0^{\varphi_l^*} \frac{P_u I_l}{2\gamma}\varphi(\varphi_l^* - \varphi)\mathrm{d}G(\varphi) \tag{2.31}$$

$$X_x^{lh} = N_e^l \int_0^{\varphi_{lh}^*} \frac{P_u I_h}{2\gamma}\varphi(\varphi_{lh}^* - \tau_{lh}\varphi)\mathrm{d}G(\varphi) \tag{2.32}$$

We can get the expressions for the intermediate input demand:

$$X_d^l = \frac{k}{2\gamma(k+1)(k+2)\varphi_m^k} I_l N_e^l P_u \varphi_l^{*k+2} \tag{2.33}$$

$$X_x^{lh} = \frac{k}{2\gamma(k+1)(k+2)\varphi_m^k \tau_{lh}^{k+1}} I_h N_e^l P_u \varphi_h^{*k+2} \tag{2.34}$$

Since downstream firms face a flat price P_u, we can get the expenditure for the intermediate good.

$$E_d^l = \frac{k}{2\gamma(k+1)(k+2)\varphi_m^k} I_l N_e^l P_u^2 \varphi_l^{*k+2} \tag{2.35}$$

$$E_x^{lh} = \frac{k}{2\gamma(k+1)(k+2)\varphi_m^k \tau_{lh}^{k+1}} I_h N_e^l P_u^2 \varphi_h^{*k+2} \tag{2.36}$$

The total upstream output can be derived by summing up market demand over all the downstream regions.

$$Q_u = \sum_{l=1}^{M}(X_d^l + \sum_{h \neq l}^{M} X_x^{lh}) \tag{2.37}$$

Here, Q_u is the total demand for the upstream output. Similarly, we can get the total expenditure by all downstream firms on intermediate goods.

$$E_u = \sum_{l=1}^{M}(E_d^l + \sum_{h \neq l}^{M} E_x^{lh}) \tag{2.38}$$

By plugging in all the expressions derived above, we can get the inverse demand function in the upstream market.

$$Q_u = \Lambda / P_u$$

where

$$\Lambda = \sum_l \sum_h \left(\frac{1}{\tau_{lh}^{k+1}} \frac{k}{k+2} \frac{\sum_{j=1}^{M} |C_{lj}|}{\eta |P|} A_0 \left(\sum_{i=1}^{M} (\alpha - A_0 A_i) \frac{|C_{hi}|}{A_i^{k+1}} \right) \right)$$

and

$$\begin{aligned} A_0 &= \left(\frac{2(k+1)(k+2) f_e \gamma}{|P| \lambda} \right)^{\frac{1}{k+2}} \\ A_i &= \left(\sum_{h=1}^{M} |C_{hi}| / I_i \right)^{\frac{1}{k+2}} \end{aligned}$$

The final expression for Q_u shows us a downward slopping demand curve in the upstream market, and Λ captures the expenditure by downstream firms, i.e. $\Lambda = E_u$.

Therefore, the demand curve is reduced to $P_u = \Lambda / Q_u$. We can see Λ is determined by the downstream market, and the demand curve has a unit price elasticity.

Furthermore, we can also check the effect of the intra-national trade barrier θ. Note θ enters matrices P and C_{ij}, we get

$$\frac{\partial P_u}{\partial \theta} > 0 \tag{2.39}$$

Here, Λ is the demand curve shifter, and larger Λ results in a higher price in the upstream market (larger P_u). This means in a less integrated market, there will be more demand for the intermediate good by downstream firms. So far, we solve the equilibrium in the downstream market. We can see that the price of the intermediate good is important here. We move the upstream market and solve for P_u.

2.2.5 Profitability in the Downstream Market

In the previous sections, we derive the mark-ups for downstream firms.

$$\epsilon_i = \frac{(\varphi^* - \varphi)^2}{(\varphi^{*2} - \varphi^2)}$$

This means that profitability is endogenous in the downstream market, which is different from Melitz (2003). Then we can see that:

$$\frac{\partial \epsilon}{\partial \varphi} < 0$$

This means a low level cut-off productivity (high φ^*) results in a low productivity (low $\bar{\epsilon}$), given the market cut-off productivity level ϕ^*

2.2.6 Cournot Competition in Upstream

The upstream market competition is featured by a Cournot game, i.e. perfect substitutes and quantity competition[4]. Here, we consider an oligopolistic upstream market which is fully integrated. Suppose there are N firms in the upstream market, and firm heterogeneity is also reflected in their productivity ϕ. For simplicity we assume upstream firms only use labor as producing factor and their production functions are constant-return-to-scale which implies a unit wage rate.

Let firms' productivity directly measures firms' marginal cost, i.e. $\phi_j = c_j$. An individual upstream firm's profit function is:

$$\pi_u^j = (P_u - \phi_j)q_j = \left(\frac{\Lambda}{\sum_j q_j} - \phi_j \right) q_j \tag{2.40}$$

Here, similar to the downstream analysis, the inverse of ϕ_j measures firms' productivity. Higher ϕ requires more labor. Due to the perfect substitute among outputs, the market output level Q_u is the sum of all firms' outputs. The first order condition gives the optimal output level: $q_j = \frac{\Lambda Q_u - Q_u^2 \phi_j}{\Lambda}$. Then the upstream market output and price can be derived accordingly.

$$Q_u = \frac{(N-1)\Lambda}{N\bar{\phi}_u} \tag{2.41}$$

$$P_u = \frac{N}{N-1}\bar{\phi}_u \tag{2.42}$$

Here, the inverse of $\bar{\phi}_u$ is the average marginal cost level in the upstream market. We can see that the market price P_u is determined by the average cost and numbers of firms. Less firms and higher marginal costs lead to higher market price.

[4]Intermediate products are generally homogeneous, such as cotton, iron ore, crude oil etc. Many intermediate products are global commodities which follow global price levels and can be traded quickly around the world through spot and/or future markets. Although speculation does exist in many intermediate products market, their market prices are determined by fundamental supply and demand.

After deriving the market price and output, an individual upstream firm's optimal output and profit can also be derived.

$$\begin{aligned} q_j &= \frac{\Lambda}{P_u^2}(P_u - \phi) && (2.43) \\ \pi_j &= \frac{\Lambda}{P_u^2}(P_u - \phi)^2 && (2.44) \end{aligned}$$

These results confirm that: less firms result in less output in each firm; more productive firms (lower marginal cost) produce more and make more profit. Particularly, an upstream firm's mark-up can be written as:

$$\epsilon_{=}\frac{P_u - \phi_j}{P_u} = \frac{q_j}{Q_u}$$

That is, firms' profitability is determined by their market shares. Thus, in a highly concentrated market, firms may obtain a high level of profitability.

2.2.7 Equilibrium in Upstream

Now it is necessary to identify the cut-off cost level in the upstream ϕ_u^*. A similar free entry condition of the upstream entrants is to break even the post entry net profit:

$$\int_0^{\phi_u^*} \pi(\phi)\mathrm{d}G(\phi) = f_u \tag{2.45}$$

Furthermore, we also specify a zero profit condition as in Melitz (2003):

$$\pi(\phi^*) = \frac{\Lambda}{P_u^2}(P_u - \phi^*)^2 = 0 \tag{2.46}$$

Here, we also assume upstream firms' productivity comes from similar distribution as downstream firms, i.e. Pareto distribution with shape parameter k_u. The zero profit condition shows that: $N = k_u + 1$. In a less heterogenous market, we would expect a smaller k associated with smaller N.

Then, the free entry condition can identify the cut-off productivity level which determine the price of the intermediate good, P_u.

$$\frac{k\Lambda}{\phi_m^k P_u^2}\left(\frac{1}{k}P_u^2\phi^{*k} - \frac{2}{k+1}P_u\phi^{*k+1} + \frac{1}{k+2}\phi^{*k+2}\right) = f_u \tag{2.47}$$

Since $1/\phi_j$ also follow a Pareto distribution, we have $\bar{\phi} = \dfrac{k}{k+1}\phi^*$. Recall that $P_u = \bar{\phi}_u$, we have a equation to determine P_u

$$P_u = \left(\frac{(k_u+1)(k_u+2)f_u}{2\Lambda}\right)^{\frac{1}{k_u}} \phi_m \tag{2.48}$$

2.3 Calibration

How large is the inter-regional trade cost? What is its effect on downstream firms' profitability and upstream firms' pricing? These questions can be addressed through the model calibration. We process two stages in following parts. First, we estimate structural parameters to calibrate the model. Then we investigate this calibrated model to test the effect of market integration in the downstream market.

In the calibration stage, we first construct firm level productivity in the downstream market, using the firm level data from the Chinese steel industry over 2000-2007. Then we can recover the distribution shape parameter k of the downstream firms' productivity. Next, we estimate the inter-regional trade cost, $\tau_{lh} = \theta d_{lh}$ via an aggregated gravity equation 2.52 using the regional output and geographic data. As a result, we can recover the trade cost matrix P and its associated cofactor matrix C_{lh}.

In the simulation stage, we perform a counterfactual experiment on the calibrated model. Particularly, we simulate the change of the upstream market price P_u as changing the downstream market trade cost. By examining the vertical linkage in terms of the input price, it provides a measurement of the "gains from free (inter-regional) trade", that is "gains from industrial integration".

2.3.1 Data

In our empirical study, we use several data sets. First, we analyze a newly released proprietary firm level data of Chinese manufacturing firms over 2000-2007. This data is collected and provided by the Chinese Statistics Bureau (CSB) through annual firm surveys.

The data covers all firms with annual revenue above 5 million Renminbi (RMB). It also reports the main financial summaries of each firm. All the numbers are booked in current values. We deflate them into net values with various price indices.[5]

All firms are coded into four-digit standard industrial classification (SIC). We narrow the Chinese steel industry to firms with code number 3220 (steel refinery) to restrict our analysis[6]. We also clean the raw data to reduce measurement errors.[7] Finally, this yields an unbalanced panel data of 770 firms over 10 years, and 2601 observations. It covers approximately 95% revenue in the Chinese steel industry each year. Table 2.2 shows statistics of some key variables.[8]

With regards to the regional level information (distance and local GDP), we use the province data from the CSB. It includes the local GDP (in 100 million RMB

[5]The revenue and the cost (so that profits) are deflated by the production price index; the fixed asset is deflated by the industry fixed asset price index. The workers' wage is deflated by the consumption price index (CPI). The input price, which is nominated by U.S. dollar, is converted by the nominal exchange rate and deflated by the Chinese CPI (a proxy for the GDP deflator).

[6]Such classification is based on firms' principle business so that there is no overlapping that one firm is coded with two different SICs

[7]Observations with negative revenue, negative long-run investment, negative total fixed asset, or negative number of workers are dropped. Further, I drop firms that only appear one year in the database. There are 428 firms only show up one year over the ten-year period

[8]It is necessary to clarify the definition of some variables. We use total output value as a proxy for revenue. The total revenue is the main variable to examine the market structure and firms' market shares are based on their total revenue. The profit is measured as the total pre tax profit (i.e. net profit) plus value added tax (VAT). We use the annual average total fixed net asset (TFA) as a proxy for capital, which comes from averaging the monthly values of the fixed asset. The number of workers is also from the monthly average numbers

Year	Number of	Revenue		Capital		Profit		Workers	
	Firms	mean	std	mean	std	mean	std	mean	std
1998	177	829.61	2220.70	714.82	2742.48	12.56	61.63	6383	18259
1999	219	777.77	2115.59	678.77	2734.87	5.15	97.92	5189	15645
2000	209	870.65	2410.61	751.53	2854.97	34.63	118.09	4972	15357
2001	199	1078.86	2746.55	869.96	3486.75	47.42	146.05	4678	14661
2002	198	1255.78	3232.93	838.69	3413.97	63.05	198.52	4310	13770
2003	180	1597.01	4057.93	825.28	3437.17	121.15	399.37	3803	12430
2004	321	818.27	2831.22	293.35	1641.92	50.36	378.08	1423	5728
2005	371	905.87	3025.18	298.42	1520.36	44.48	331.32	1375	5892
2006	358	1099.40	3304.17	391.68	2014.72	57.21	316.43	1514	5962
2007	315	1289.54	3506.03	450.44	2311.23	79.87	442.72	1540	5939

Note: revenue, capital and profit are in million RMB

Table 2.2: Descriptive Statistics of Chinese Steel Firms: 1998-2007

real value), local steel production (in 10 million metric tons), and province distances. Here, geographic distance between two provinces is measured by geographic distance between two provincial capital cities (in kilometers).

Variables	units	mean	sd	min	max
Output	10^4 tons	2005.224	2663.763	1.08	20882.94
Market share	%	3.45%	3.68%	0.00%	19.84%
GDP	100 million RMB	2583.652	2816.266	46.15	15939.1
PPI	%	103.4479	4.844971	93.7	129.4
Distance	kilometer	1280.786	677.0099	103.6108	3463.171

Table 2.3: Province Data Statistics: 2000-2007

To measure the effect of inter-regional trade cost on downstream firms' profitability, we focus on the downstream market first and recover some key structural parameters, particularly those in the equation 2.15. However, since the inter-regional trade volume data is not available, we estimate an aggregate gravity equation (equation 2.53) instead.

We use firm level data to construct firm level productivity and estimate its distribution, then we aggregate firm level data into regional level and match with the regional data. Therefore, we estimate the inter-regional trade cost through an aggregated gravity equation from our model. Finally, we simulated our model with these structural parameters.

2.3.2 Downstream Firms Productivity

First, we need to estimate the shape parameter (k) of firms' productivity with an underlying Pareto distribution. This requires firm level productivity.

There are various ways of productivity estimation. As we discuss in the theoretical part, firms' productivity reflects their ability to transform the intermediate good into final products. Here we measure productivity using firms added value divided by total inputs. Using the notation above, downstream firms' productivity is determined by:

$$1/\varphi_i = \frac{VA_i}{INPUT_i} \tag{2.49}$$

This ratio is calculated directly from the production function for downstream firms. As pointed out by the UBS Investment Bank Research, the cost structure in the Chinese steel industry is dominated by the raw material (iron ore), therefore this ratio is appropriate to reflect firms productivity.

2.3.3 Shape Parameter k

Downstream firms' productivity is assumed to follow a Pareto distribution. The shape parameter k is very important, since k enters many formulas in our modeling part.

Del Gatto, Mion, and Ottaviano (2006) suggest an approach to capture the shape parameter in a Pareto distribution. Since $1/\varphi$ follows a Pareto distribution, with its cumulative distribution $F(1/\varphi)$ observable, a regression below can show the estimator of the shape parameter k.

$$\ln(1 - F(1/\varphi)) = \alpha - k \ln \varphi + \epsilon \tag{2.50}$$

As Del Gatto, Mion, and Ottaviano (2006) point out, the estimator k in the regression 2.50 is a consistent estimator for the shape parameter of $1/\varphi$, with a relatively high goodness of fit. The estimation on the Chinese steel firm level data gives a shape parameter equal to 3.1928. Compare to the results in Del Gatto, Mion, and Ottaviano (2006), the Chinese steel industry has a larger shape parameter which implies more firms are less productive.

2.3.4 Regional Trade Barriers

After recovery the shape parameter k, we can then estimate the inter-regional trade cost. Traditional estimation on trade cost is build up on the gravity equation with bilateral trade volume data. Since the intra national trade volume data is not available, we estimate an aggregate gravity model as an alternative.

$$Q_d^l = \frac{1}{2\gamma(k+1)\varphi_m^k} P_u I_l \varphi_l^{*k+1} N_e^l \tag{2.51}$$

$$Q_x^{lh} = \frac{1}{2\gamma(k+1)\varphi_m^k \tau_{lh}^k} P_u I_h \varphi_h^{*k+1} N_e^l \tag{2.52}$$

Then the total regional output is:

$$Q_l = Q_d^l + \sum_{h \neq l} Q_x^{lh} = \frac{1}{2\gamma(k+1)\varphi_m^k} P_u I_l \varphi_l^{*k+1} N_e^l \sum_{h=1}^{M} \left(\frac{I_h}{I_l} \left(\frac{\varphi_h^*}{\varphi_l^*} \right)^{k+1} / \tau_{lh}^k \right) \tag{2.53}$$

Recall that φ_l $(l = 1, ..., M)$ is determined by equation 2.15, the ratio φ_h/φ_l is then determined by I_h/I_l. Further, we assume that the trade cost is proportional to the geographic distance, $\tau_{lh} = \theta d_{lh}$

Then the last part in the aggregate gravity equation becomes:

$$\sum_{h=1}^{M} \left(\frac{I_h}{I_l} \left(\frac{\varphi_h^*}{\varphi_l^*} \right)^{k+1} / \tau_{lh}^k \right) = 1 + \theta^{-k} \sum_{h \neq l} \left(\frac{\sum_{k=1}^{M} |\tilde{C}_{kh}|}{\sum_{k=1}^{M} |\tilde{C}_{kl}|} \frac{I_h}{I_l} \right)^{\frac{1}{k+2}} = 1 + \theta^{-k} \Sigma \tag{2.54}$$

where

$$\Sigma = \sum_{h \neq l} \left(\frac{\sum_{k=1}^{M} |\tilde{C}_{kh}|}{\sum_{k=1}^{M} |\tilde{C}_{kl}|} \frac{I_h}{I_l} \right)^{\frac{1}{k+2}} / d_{lh}^{k}$$

On the right hand side of equation 2.53, we are interested in the parameter for regional trade barriers, θ. Since P_u and N_e^l are endogenous, we use province and year dummy to control for these endogeneity, as suggested in Del Gatto, Mion, and Ottaviano (2006). We take logarithm of both side of equation 2.53, and linearize the equation. Note that Σ is a multiplier of the neighborhood spill-over effect which shares the same marginal effect of I_l. Finally, we estimate a linear model;

$$\ln Q_{it} = \beta_0 + \beta_1 \ln I_{it} + \beta_1 \theta^{-k} \Sigma_{it} + \alpha_{1i} + \mu_{1t} + \epsilon_{1it} \tag{2.55}$$

The estimation shows a significant result that $\theta = 0.0032$, with $t-$statistics equal to 4.7636. In China, the average geographic distance between two provinces is 1326.5km, which implies an average regional trade barrier is: $E[\tau] = 4.2507$

Recall that τ measures the iceberg trade cost by increasing firms' marginal production cost. Therefore, this value of τ implies that exporting steel to another province increases firms marginal cost by three time more on average in China. This is a huge amount of trade cost which results in a segmented downstream market. Next, we move to the upstream market and simulate market outcome there.

2.3.5 Downstream Market Demand vs. Upstream Market Price

In our model, the demand for the final good in the downstream market, $I_l (l = 1, ..., M)$, is exogenous. We can also calibrate its effects on the upstream market price. Since I_l will determine the total output by downstream firms, which determines the total expenditure on the intermediate good. We adopt a similar method as in the last section to measure the effect of demand for downstream output on the upstream prices.

Recall that

$$\Lambda = E_u = \sum_{l=1}^{M}(E_d^l + \sum_{h\neq l}^{M} E_x^{lh})$$

and

$$X_d^l = \frac{k}{2\gamma(k+1)(k+2)\varphi_m^k} I_l N_e^l P_u \varphi_l^{*k+2} \tag{2.56}$$

$$X_x^{lh} = \frac{k}{2\gamma(k+1)(k+2)\varphi_m^k \tau_{lh}^{k+1}} I_h N_e^l P_u \varphi_h^{*k+2} \tag{2.57}$$

Then we can derive a similar aggregated gravity equation for the total expenditure on the intermediate good.

$$\ln E_{it} = \gamma_0 + \gamma_1 \ln I_{it} + \gamma_1 \theta^{-k} \Sigma_{it} + \alpha_{2i} + \mu_{2t} + \epsilon_{2it} \tag{2.58}$$

Since we already recover the inter-regional trade cost in the last section, we need to force θ to keep the same, while controlling for the province and year specific heterogeneities. The coefficient γ_1 captures the effect of I_{it} on the total expenditure in region i, E_{it}. Our results show that $\gamma_1 = 1.2713$ with p-value 0.083. It implies a responsive effect transfer the demand for the downstream market product to the demand for the upstream market product. Furthermore, we can derive change of upstream prices as a response to the downstream market demand change, since Λ can be interpreted as a demand shifter in the upstream market.

$$\frac{\partial \ln P_u}{\partial \ln I_{it}} = \frac{\partial \ln P_u}{\partial \ln \Lambda} \frac{\partial \ln \Lambda}{\partial \ln I_{it}}$$

Thus, our result shows a responsive change in P_u as I_{it} changing. A 20% increase in the demand for the final product in the downstream market would result in 25.4%

increase in the upstream market price.

2.3.6 Regional Trade Cost vs. Upstream Market Price

We are interested in the effect of the inter-regional trade cost, τ or θ, on the upstream market price, P_u. From the analysis above, the market demand in the upstream market is given by:

$$P_u = \frac{\Lambda}{Q_u} \tag{2.59}$$

Here, Λ is determined by the downstream market conditions, and can be interpreted as a demand shifter in the upstream. Therefore,

$$\frac{\partial \ln P_u}{\ln \Lambda} > 0$$

Recall that Λ is determined by

$$\Lambda = \sum_l \sum_h \left(\frac{1}{\tau_{lh}^{k+1}} \frac{k}{k+2} \frac{\sum_{j=1}^{M} |C_{lj}|}{\eta |P|} A_0 \left(\sum_{i=1}^{M} (\alpha - A_0 A_i) \frac{|C_{hi}|}{A_i^{k+1}} \right) \right) \tag{2.60}$$

Note that θ enters τ, P, $|C|$, A_0 and A_i. We can find that:

$$\frac{\partial \Lambda}{\partial \theta} = (k-1)\theta^{k-2} \tag{2.61}$$

Then, we can calculate the effect of inter-regional trade costs on upstream market prices.

$$\frac{\partial \ln P_u}{\ln \theta} = \frac{\partial \ln P_u}{\ln \Lambda} \frac{\partial \ln \Lambda}{\ln \theta} = 2.1928$$

This result implies an elastic response of upstream market price on downstream market trade costs. A 10% decrease in the inter-regional trade cost would result in 22% decrease in the upstream market price.

2.4 Conclusion

The iron ore importing price negotiation calls for a lot of attention in recent years. As the largest steel maker in the world, the Chinese steel industry yet loss its bargain power and keeps a very low profitability. We explain this issue by modeling a vertical market linkage under the open economy context.

Since the downstream market is characterized by segmentation, we adopt a multi-region model with heterogeneous firms featured by monopolistic competition with variable mark-ups, in order to capture the segmentation in the downstream market. Meanwhile, we use a Cournot competition to model the upstream market. The model shows that regional trade barriers could result in excessive demand for intermediate goods and push up the input price.

Then we calibrate our model with firm level data from the Chinese steel industry. Some structural parameters are recovered. The distribution of firms productivity is highly skewed compare to other manufacturing sectors in other countries, which implies a lot of inefficient firms in the Chinese steel industry. Further, we estimate an aggregated gravity equation of regional steel production. Our results suggest that inter-regional trade barriers in the Chinese steel industry are as triple as firms' marginal cost on average.

Finally, we use these structural parameters to calibrate our model. Our result first reveals a positive relationship between the demand for the downstream market output and the upstream market price. The effect is responsive that a 20% increase in the final product demand would induce a 25% increase in the upstream market price. Furthermore, our calibration shows a negative relationship between the upstream market price and the regional trade barriers in the downstream market. A 10% decrease of the inter-regional trade cost would lower down the input price by 22%.

Compared with Table 1, our results provide an possibility for the increase of iron ore price in the Chinese steel industry. Considering a 60% increasing of iron ore prices in recent years, our model offers an decent yet underestimated explanation. Some further research could focus on how different market structures affects the bargaining power in supply chains.

Chapter 3

Investment, Importing and Productivity Dynamics

3.1 Introduction

In recent decades, the global economy has been characterized by the increasing importance of the intermediate inputs trade, a reflection of increased international specialization.[1] Empirical studies have found a positive relationship between firm export and import behaviors (See Bernard, Redding, and Schott (2007) and Altomonte and Békés (2008)). This suggests a similar self-selection issue to that of the export market: more productive firms may be more likely to enter import markets. Further, importing could also lead to a productivity effect, since importers can access higher quality and more diverse inputs on the international market. This study aims to further explore the relationship between firm productivity and access to import markets.

Researchers have used micro-level data to study firms' importing behaviors (See Kugler and Verhoogen (2009) and Vogel and Wagner (2010)). They find that im-

[1]According to Hummels *et al.* (2001), around 20% of total exports can be attributed to intermediate goods trading in 1995 which represents 40% growth since 1970.

porters exhibit many similarities to exporters; for example, larger and more productive firms tend to import their inputs. Additionally, empirical research, covering a range of countries and industries, has documented a positive correlation between import activities and productivity levels.[2] One possibility is that less productive firms rely less on the import market due to the associated fixed and sunk costs from involvement (See Kasahara and Rodrigue (2008), Andersson, Lööf, and Johansson (2008), and Castellani, Serti, and Tomasi (2010)). These costs could come from searching for suitable foreign suppliers, product inspection, the negotiation and contract process, as well as obtaining permits from governments which can be severe in developing countries (See Bas and Berthou (2012)).

On the other hand, there is a feedback effect from importing on firms' productivity; that is, importing firms enjoy faster productivity growth. People causally explain the impact of importing on firms' productivity in several ways. Andersson, Lööf, and Johansson (2008) and Castellani, Serti, and Tomasi (2010) argue that importing inputs from foreign countries brings in better knowledge and technology. As a result, the "learning by importing" effect comes from importing firms obtaining and extracting the advanced technologies embodied in the imported intermediate goods. Also, imported goods may be of higher qualities, as well as available in more varieties and specializations, which can improve production efficiency for the final goods (See Halpern, Koren, and Szeidl (2006), Altomonte and Békés (2008), and Muûls and Pisu (2009)).

Under this context, trade liberalization (trade cost elimination) in import markets has a similar interpretation as that in export markets. Besides the traditional trade costs (e.g. tariffs, ice-burg costs) as in the export markets, trade costs in the import markets are also reflected in import qualification, especially for developing

[2]These include Amiti and Konings (2007) on Indonesia, by Kasahara and Lapham (2008) on Chile, by Castellani, Serti, and Tomasi (2010) on Italian firms, by Jabbour (2010) on France, and by Raff and Wagner (2010) on German.

countries and for some raw materials, such as petroleum and iron ore (See Manova and Zhang (2009), and Bas and Berthou (2012)). Governments often restrict certain firms to import intermediate inputs, as is the case for the Chinese steel producers. Therefore, a reduction of trade costs in these context implies more firms will have access to foreign suppliers, allowing them to upgrade their inputs and improve productivity. Amiti and Konings (2007) use manufacturing data from Indonesia to show that the trade liberalization in 1990s with inputs tariff reduction is associated with an increase of firms productivity.

Moreover, the interaction with investment in terms of productivity effects is different from that in the exporting case. Importing directly affect production process by changing inputs. On the other hand, investment would upgrade machinery and appliances to accommodate imported (better and more various) inputs, which may improve productivity as a result. Moreover, investment can also upgrade technology which can directly raise firms' productivity. In this regards, importing and investing activities could be compliments and/or substitutes.[3].

In this paper, I develop and estimate a structural model of importing and investment activities using firm level data from the Chinese steel industry during the period 2000-2006. The model is used to explore the relationship between importing and investment decisions, and their effects on productivity dynamics. First, I show that there are both positive effects from investment and from importing on productivity growth. Firms engaging into both activities can enjoy 3.72% productivity premium in the long run; second, there are significantly higher entry and fixed cost in the import market, comparing with these costs associated with investment; third, these costs create a self-selection issue in import and investment activities, and after controlling for this issue, more productive firms benefit more from these two activities; finally, simulation in the import market implies that a 10% reduction

[3]In firms's exporting case, firms' investing and exporting are more like substitutes, see Aw, Roberts, and Xu (2011)

in both entry and fixed costs would lead to 8.9% productivity gains for a typical firms.

My empirical results suggest several key determinants of underlying productivity growth in the Chinese steel industry. Productivity growth is an endogenous process, affected by investment and importing activities. Only a small number of firms can receive benefits from importing because of restrictions, and these firms are less likely to undertake investment. My result reveals a high entry barrier in the importing market, i.e. the government authorization, which can have deleterious effects on firm decision making. This also enhances the self-selection issue since productivity level is the main factor that drives the participation in the import market, and these importers become even more productive.

My results provide some possible explanation of low productivity issue in the Chinese steel industry. Chinese steel producers are highly import dependent on the main inputs, iron ore, but only a few number of firms have access to the import market. Many small and medium firms are lack of premium input, and thus lower down the average productivity level of the entire industry. As a result, import market participation could be a significant determinant driving firm productivity.

The rest of the paper is organized as follows. Section 3.2 develops a structural model of demand and cost functions and derives production function. Section 3.3 introduces the method of estimation to recover firm-level productivity, which follows Aw, Roberts, and Xu (2011), and discusses the selection of investment and importing behavior. Section 3.4 briefly introduces the data of Chinese steel industry. Section 3.5 and 3.6 present the estimation results and section 3.7 concludes the paper.

3.2 A Structural Model of Importing and Investment

In this section, I derive a theoretical model building on previous work which focus on exporting, investment,and productivity, including Melitz (2003), Das, Roberts, and Tybout (2007) and Aw, Roberts, and Xu (2011). My model studies importing and investment as discrete choices, and examines the evolution of productivity. Firm heterogeneity is characterized by their productivity, capital stocks, and previous decisions to import and invest, which in turn determine the current decisions concerning importing and investment. As a feedback, current decisions can affect the future path of productivity growth, where productivity determines both profitability in the short run and future decisions in the dynamic context.

3.2.1 Static Competition

A non-importing firm i's marginal cost at year t is specified in equation 3.1

$$\ln c_{it}^{N} = \ln c(k_{it}, w_t) - \omega_{it} = \beta_0 + \beta_k \ln k_{it} + \beta_w \ln w_t - \omega_{it} \tag{3.1}$$

In equation 3.1, k_{it} is the firms' capital stock, w_t is market conditions faced by all firms, and ω_{it} is firm productivity. Here, I assume each firm produces a single output and marginal cost is invariant with output level. Firms are differentiated by their capital stock, which is observed in the data, and their productivity, which is unobservable in the data.

Meanwhile, I specify a similar cost function for importing firms, except that each importing firm also has an exogenous cost shifter z_{it} coming from the import market, which follows the model of the export market as in Das, Roberts, and Tybout (2007). Since importers can access better intermediate inputs to reduce their marginal cost, the cost function of importing firms can be written as in equation 3.2.

$$\ln c_{it}^M = \ln c(k_{it}, w_t) - \omega_{it} = \beta_0 + \beta_k \ln k_{it} + \beta_w \ln w_t + z_{it} - \omega_{it} \tag{3.2}$$

The final product market is assumed to be monopolistically competitive as in Melitz (2003), where firms set their prices but have no interaction with each other. Thus, a single firm faces a Dixit-Stiglitz form of demand curve, given by:

$$q_{it} = Q_t \left(\frac{p_{it}}{P_t}\right)^\eta = \frac{I_t}{P_t}\left(\frac{p_{it}}{P_t}\right)^\eta = \phi_t (p_{it})^\eta, \quad \text{where } \phi_t = I_t P_t^{-\eta-1} \tag{3.3}$$

In equation 3.3, P_t and Q_t are the aggregate output and price of the industry respectively, while I_t is the total expenditure of consumers. Thus, the demand for a single product depends on aggregate output and price, its own price, and the elasticity of demand.

With these cost and demand functions, firm i chooses price p_{it} equal to its marginal cost, to maximize its profit. Following Aw, Roberts, and Xu (2011), this condition implies the revenue of non-importing firms is:

$$\ln r_{it}^N = (\eta+1)\ln\left(\frac{\eta}{\eta+1}\right) + \ln \phi_t + (\eta+1)(\beta_0 + \beta_k \ln k_{it} + \beta_w \ln w_t - \omega_{it}) \tag{3.4}$$

Equation 3.4 implies that revenue is determined by aggregate market conditions such as the output and price levels as well as the elasticity of demand, and firm specific conditions such as capital stocks and productivity. Similarly, the importing firms' total revenue (in logarithmic form) can be written as:

$$\ln r_{it}^M = (\eta+1)\ln\left(\frac{\eta}{\eta+1}\right) + \ln \phi_t + (\eta+1)(\beta_0 + \beta_k \ln k_{it} + \beta_w \ln w_t + z_{it} - \omega_{it}) \tag{3.5}$$

A difference in equation 3.5 is that importers' revenue not only depends on the domestic market conditions and on firms' specifics, but also on the international market. Thus, importers' revenue also contains information from importing markets. Estimation of these revenue functions can recover two variables reflecting unobserved firms heterogeneity, z_{it} and ω_{it}. Here, ω_{it} captures unobserved firm heterogeneity that affect revenue for both importers and non-importers. z_{it} captures all sources of revenue heterogeneity arising from importing markets, which are unique for importers. Thus, z_{it} can be referred to as the import shock from the intermediate suppliers.

Under the assumptions of demand and marginal cost functions, firms' profit can be derived from their revenue. As discussed in Melitz (2003), non-importers' profit is proportional to their revenue, determined by the market elasticity of demand η.

$$\pi_{it}^{N} = -\frac{1}{\eta} r_{it}(\phi_t, k_{it}, \omega_{it}) \tag{3.6}$$

Here, the revenue is given as in equation 3.4. Similarly, if a firm chooses to become an importer, then its profit function will include the import shock z_{it}.

$$\pi_{it}^{M} = -\frac{1}{\eta} r_{it}(\phi_t, k_{it}, z_{it}, \omega_{it}) \tag{3.7}$$

The equations above can be used to measure firms' profits from their revenue data, which determine the decisions of adopting investment and entering the import market. I develop a dynamic model to show firms' decisions in the following sections.

3.2.2 Transition of State Variables

For each firm, their state variables include firm productivity ω_{it}, capital stock k_{it}, supply shock z_{it}, and market condition ϕ_t. Following the setting as in Olley and Pakes (1996) and Levinsohn and Petrin (2003), the evolution of firm productivity is assumed to be a Markov process which also depends on firms' status of investment and import participation, as well as on an idiosyncratically random shock ξ_{it}.

$$\begin{aligned}\omega_{it} &= \alpha_0 + \alpha_1\omega_{i,t-1} + \alpha_2(\omega_{i,t-1})^2 + \alpha_3(\omega_{i,t-1})^3 \\ &\quad + \alpha_4 d_{it-1} + \alpha_5 m_{i,t-1} + \xi_{it}\end{aligned} \tag{3.8}$$

In equation 3.8, productivity ω_{it} follows a non-linear Markov process. Here, a dummy variable $d_{i,t-1}$ is the status of investment in year $t-1$, while $m_{i,t-1}$ is another dummy variable of participation in the import market in year $t-1$. $d_{i,t-1}$ is included by assuming that investment has a positive effect on firms' productivity growth. The importing term $m_{i,t-1}$ is also included to allow for a positive effect of better access to the intermediate goods. The stochastic term ξ_{it} is an *i.i.d.* random variable following a normal distribution with zero mean and variance σ_ξ^2, which is uncorrelated with $\omega_{i,t-1}, d_{i,t-1}, m_{i,t-1}$. In all, equation 3.8 provides information about productivity dynamics and incorporates a cubic function of one-period lagged productivity and the interaction between investment and importing.

Investment and importing choices are modeled as dummy variables, which implies that investing or importing would have the expected impacts on productivity regardless of the amount of investment or importing. Some empirical studies find evidence that firms' productivity is the key determinant of discrete choices, such as exporting and investment, but not strongly correlated with the levels of such activities (See Aw, Roberts, and Winston (2007)).

Finally, the import shocks from the suppliers are modeled as a first-order Markov process (one period lag auto-regression), which is similar to the exporting market shock as discussed in Das, Roberts, and Tybout (2007) and Aw, Roberts, and Xu (2011).

$$z_{it} = \rho z_{i,t-1} + \mu_{it} \tag{3.9}$$

Here, μ_{it} is an *i.i.d.* random variable with normal distribution with mean zero and variance σ_μ^2. Equation 3.9 differentiates the importers and non-importers, which is important here since it can capture importers' attributes in their revenue/profit function, arising from inputs. The autoregressive process also implies that the import shock has a persistent yet diminishing effect on firms' revenue and profit in the future.

3.2.3 Investment and Importing Decisions

In this section, the dynamic decisions on import and invest are modeled. Similar to dynamic models in the export market (See Das, Roberts, and Tybout (2007) and Aw, Roberts, and Xu (2011)), the first participation in the import market incurs sunk costs, which implies that the past participation status in the import market is also a state variable for entry decisions. This sunk cost of import can be interpreted as the freeness of trade in the international market, and also as a barrier to obtain the import quotas authorized by the government. A similar sunk cost is also introduced for firms' investment decision. Furthermore, there are fixed costs associated with importing and investment activities. These sunk and fixed costs are associated with productivity dynamics as in equation 3.8.

Since there are two activities need to identified, assumptions about the activity sequence are required to address the identification issue here. Thus, firms are assumed to first observe the sunk cost (γ_{it}^S) and fixed cost (γ_{it}^F) in the importing market, then makes their import decisions in year t. Following the import decision, firms then observe the sunk cost (γ_{it}^I) and fixed cost (γ_{it}^D) associated with investment, and make their investment decisions. These costs are both time and firm variant which reflect the difference of technological adoption and expertise (i.e. entrepreneurship), as well as government preference. Following the assumption in Aw, Roberts, and Xu (2011), I assume these four underlying costs come from a joint distribution G^γ, which is going to be estimated.

In sum, the state variables in year t include market state ϕ_t and firm i's state:

$$s_{it} = (\omega_{it}, k_{it}, z_{it}, m_{i,t-1}, d_{i,t-1})$$

After observing sunk and fixed costs, the firm's value function in year t is:

$$V_{it}(s_{it}, \phi_t) = \int \max_{m_{it}} \left\{ \left(\pi_{it} - m_{i,t-1}\gamma_{it}^F - (1 - m_{i,t-1})\gamma_{it}^S\right) + V_{it}^M(s_{it}), V_{it}^D(s_{it}) \right\} dG^\gamma \tag{3.10}$$

Here $m_{i,t-1}$ is a binary variable denoting firm i's import status in year $t-1$. If firm i imports in year $t-1$, then it has to pay the fixed cost (γ_{it}^F) to keep importing in year t; on the other hand, if it does not import in year $t-1$, it has to pay the sunk cost (γ_{it}^S) to enter the import market. V_{it}^M is the value of an importing firm after making its optimal investment decision, and V_{it}^D is the value of a non-importing firm after making its optimal investment decision. Equation 3.10 shows that a non-importing firm chooses to enter the import market in year t when the present and expected future profit exceeds the associated sunk and fixed costs. Similarly, the value function of an importing firm with its optimal investment decision is:

$$\begin{aligned} V_{it}^M(s_{it}, \phi_t) \quad = \quad & \int \max_{d_{it}} \{ \delta E_t V_{i,t+1}(s_{i,t+1} | m_{it} = 1, d_{it} = 1) - d_{i,t-1}\gamma_{it}^I - (1 - d_{i,t-1})\gamma_{it}^D, \\ & \delta E_t V_{i,t+1}(s_{i,t+1} | m_{it} = 1, d_{it} = 0) \} \, dG^\gamma \end{aligned} \tag{3.11}$$

Equation 3.11 also shows a similar trade-off between the costs associated with investment and the post-investment pay-offs for those firms that decide to import. The associated costs with investment depends on previous investment decisions. If a firm does not make an investment in year $t-1$, then it has to pay the sunk cost (γ_{it}^I), but not the fixed cost (γ_{it}^D); otherwise, it only needs to pay the fixed cost (γ_{it}^D). The sunk cost of investment could be interpreted as the start-up cost, while the fixed cost of investment could come from the adoption of new technologies. If a firm chooses to make an investment, then it has a different productivity growth path in the future. The stronger the impact on firms' productivity growth, the more likely a firm will make an investment. Similarly, the value of a non-importing firms with its optimal investment decision is:

$$
\begin{aligned}
V_{it}^{D}(s_{it},\phi_t) \quad = \quad & \int \max_{d_{it}} \left\{ \delta E_t V_{i,t+1}(s_{i,t+1}|m_{it}=0, d_{it}=1) - d_{i,t-1}\gamma_{it}^{I} - (1-d_{i,t-1})\gamma_{it}^{D}, \right. \\
& \left. \delta E_t V_{i,t+1}(s_{i,t+1}|m_{it}=0, d_{it}=0) \right\} dG^{\gamma} \qquad (3.12)
\end{aligned}
$$

The trade-off still exists in equation 3.12, but the change of productivity path is for non-importing firms. Finally, the expected value function conditional on investment and importing decisions can be written as:

$$
E_t V_{i,t+1}(s_{i,t+1},\phi_t|m_{it},d_{it}) = \int_{\phi'}\int_{z'}\int_{\omega'} V_{i,t+1}(s')dF(\omega'|\omega_{it},m_{it},d_{it})dF(z'|z_{it})dG(\phi'|\phi_t) \tag{3.13}
$$

Equation 3.13 is a three-fold integration over the sate space (ω_{it}, z_{it} and ϕ_t). As shown in equation 3.8, productivity dynamics depend on their importing and investment status. From equation 3.13, we can see that the expected value function is larger for higher productivity levels, thus, in this dynamic model, $V_{it}^{M}(.)$ and $V_{it}^{D}(.)$ are larger, *ceteris paribus*, for more productive firms. This leads to a self-selection issue when more productive firms tend to conduct both investment and import. Since the model allows productivity to evolve endogenously, firms that both import and invest, would tend to keep their status in the future.

In this dynamic discrete choice model, firm heterogeneity is reflected in their previous status in importing and investing activities, capital stock, productivity and import shocks. These state variables together determine firms' revenue, thus profit. These productivity effects, taking required sunk and fixed costs into account, result in the optimal choices on investing and importing. I will show how to estimate structural parameters in the model, including those in static cost and demand functions, productivity evolution and costs parameters in the next section.

3.2.4 Equilibrium

In this section, I summarize my model and show the equilibrium which follows the frame work by Weintraub, Benkard, and Van Roy (2008). As discussed above, in each period t, firm i's state variables $s_{it} \in \mathbb{S}$ includes market condition $\phi_t \in \phi$, import shocks z_{it}, capital stock k_{it}, productivity ω_{it} and previous status m_{it-1}, d_{it-1}. A symmetric Markov Perfect Strategies can be defined as an action $a_{it} \in \mathbb{A}$, where $a_{it} = \{m_{it}, d_{it}\}$ in my case. particularly,

$$m_{it} : \mathbb{S} \times \phi \to \{0, 1\}$$

is each firm's importing strategy, and

$$d_{it} : \mathbb{S} \times \phi \to \{0, 1\}$$

is each firm's investment strategy. As in the last section, $E_t V_{i,t+1}(s_{i,t+1}, \phi_t | a_{it})$ is the value function as the expected discounted payoffs at firm i's state and market state ϕ_t. We can interpret a part of market state ϕ_t includes information that firm i chooses strategy $a' \in \mathbb{A}$ and others choose strategy $a \in \mathbb{A}$. Then a Markov Perfect Equilibrium strategies a satisfies that

$$E_t V_{i,t+1}(s_{i,t+1}, \phi_t | a_{it}, a_{-it}) \geq E_t V_{i,t+1}(s_{i,t+1}, \phi_t | a'_{it}, a_{-it}), \forall a'_{it} \in \mathbb{A}$$

The equilibrium presented above follows Weintraub, Benkard, and Van Roy (2008). They show that when the number of firms is large, firms' strategies, which ignore rivals' state s_{-it} but condition on the average market (industrial) state, can well approximate a Markov Perfect Equilibrium. They argue that when there are many firms and the market is not concentrated, each firm cannot benefit by deviating to another strategy by keeping track on the aggregate market state. As discussed in the following sections, their argument is applicable in my studies here. Therefore, the strategy defined above can approximate the Markov Perfect Strategy. Thus, in each period, each firm keeps track on the market condition ϕ_t, and solve their optimization problem individually. Then, the industry equilibrium can be calculated as a result.

3.2.5 Gains from Import

From the model, we can see that the benefits from importing can be measured by comparing value functions which endogenize the importing choice. Also, these value functions are increasing by productivity level, which result in a self-selection issue, i.e. more productive firms are more likely to import. Furthermore, since there are two choices, import and investment, the net return to import also depends on the choice of investment. In this section, I discuss the gains from importing.

We can define the marginal gains from importing as the difference between value function $V_{it}^M(.)$, which is the value function of importers, and $V_{it}^D(.)$, which is the value function of non-importers. The gains from importing also depends on the previous choice of investment due to the sunk cost and fixed cost associated with investment. The gains from importing can be calculated from value functions as in equation 3.14

$$G_{it}^{Import}(s_{it}, \phi_t | d_{it-1}) = V_{it}^M(s_{it,\phi_t|d_{it-1}}) - V_{it}^D(s_{it,\phi_t|d_{it-1}}) \tag{3.14}$$

Costs associated with investment and importing endogenize these choices, therefore the self-selection issue is under control in equation 3.14. In the following sections, I show the estimation of parameters in my model step by step and quantify the gains from import.

3.3 Empirical Estimation

In this section, I develop an empirical model which corresponds to the structural model in previous sections to recover the parameters in demand and cost functions, as well as in the dynamic discrete choice model. The estimation is processed in two stages. In the first stage, the parameters in the demand and cost functions are estimated, and then the firm level productivity and the import shock (ω_{it}, z_{it}) are constructed accordingly. In the second stage, a dynamic discrete choice model on investment and importing choices is estimated. The dynamic estimation will recover the sunk and fixed costs associated with these two activities. Therefore, my model allows for the estimation of the market elasticity of demand η, the aggregate industrial condition ϕ_t, parameters in the cost function (equation 3.1 and 3.2), parameters in the productivity function (equation 3.8), parameter of importing market shocks (equation 3.9).

3.3.1 Demand and Cost Estimation

First, I jointly estimate the demand, cost, and productivity functions. According to equations 3.4 and 3.5, the unobserved error term $-(1+\eta)\omega_{it} + u_{it}$ represents productivity level. I follow Olley and Pakes (1996) and proxy for the unobserved productivity term using observed variables to control the endogeneity of capital stock. As discussed by Levinsohn and Petrin (2003), the intermediate expenditure e_{it} is a better proxy than the lagged capital stock, because it changes more smoothly than capital stock. Here I use total wage payment as a proxy for the intermediate expenditure. Since the marginal cost is assumed to be constant, the marginal intermediate expenditure does not depend on total output or the import shocks z_{it}. Recall that productivity is correlated with capital stocks; both capital stock and wage payment enter the productivity function (equation 3.8), $\omega_{it}(\ln k_{it}, \ln e_{it})$. Since the aggregate demand shock and market conditions are only time variant, I construct time dummies D_t to control for these factors. Combining the revenue function for importers and non-importers, the revenue function can be re-written as follows:

$$\begin{aligned} \ln r_{it} &= \gamma_0 + \sum_{t=1}^{T} \gamma_t D_t + (1+\eta)(\beta_k \ln k_{it} + z_{it}\mathbf{1}_{Import} - \omega_{it}) + u_{it} \qquad (3.15) \\ &= \gamma_0 + \sum_{t=1}^{T} \gamma_t D_t + g(k_{it}, e_{it}) + v_{it} \end{aligned}$$

In equation 3.15, the error term v_{it} is equal to $z_{it}\mathbf{1}_{import} + u_{it}$ where $\mathbf{1}_{import}$ is a dummy variable denoting importing firms. The function $g(k_{it}, e_{it})$ captures the combined effect of capital and productivity, which is specified as a cubic function of $\ln k_{it}$ and $\ln e_{it}$. The import shock z_{it} is directly estimated from equation 3.15. The composite error term v_{it} is serially correlated for importers, but *i.i.d.* for non-importers, which makes it possible to separate z_{it} and u_{it} for importers. The fitted value of function $g(.)$ is an estimation of $(1+\eta)(\beta_k \ln k_{it} - \omega_{it})$. Therefore, the productivity term is:

$$\omega_{it} = -\frac{1}{1+\eta}\hat{g}(.) + \beta_k \ln k_{it} \qquad (3.16)$$

Substituting equation 3.16 into equation 3.8, we can get:

$$\begin{aligned} \hat{g}_{it}(.) \;=\;& \beta_k(1+\eta)\ln k_{it} - \alpha_0(1+\eta) + \alpha_1(\hat{g}_{i,t-1} - \beta_k(1+\eta)\ln k_{i,t-1}) \qquad (3.17) \\ & -\frac{\alpha_2}{1+\eta}(\hat{g}_{i,t-1} - \beta_k(1+\eta)\ln k_{i,t-1})^2 + \frac{\alpha_3}{(1+\eta)^2}(\hat{g}_{i,t-1} - \beta_k(1+\eta)\ln k_{i,t-1})^3 \\ & -\alpha_4(1+\eta)d_{i,t-1} - \alpha_5(1+\eta)m_{i,t-1} - \alpha_6(1+\eta)d_{i,t-1}m_{i,t-1} - \xi_{it}(1+\eta) \end{aligned}$$

Equation 3.17 is estimated to recover the parameters in the demand and cost functions. Here, the elasticity of demand η is measured by the average profit margin over all firms, as in equations 3.6 and 3.7. Finally, the productivity term can be constructed by:

$$\hat{\omega}_{it} = -\frac{1}{1+\hat{\eta}}\hat{g}_{it} + \hat{\beta}_k \ln k_{it} \tag{3.18}$$

So far, I estimate a static empirical model derived from the theoretical model. Particularly, I recover parameters in demand and cost functions, and construct firm level productivity and import shocks (ω_{it} and z_{it}), controlling for the simultaneity problem. The estimation results of the static empirical model will be used to estimate dynamic decisions. Firms choose whether to undertake investment and/or importing, based on these individual and aggregate conditions.

3.3.2 Estimate Firms Decisions

In this section, I analyze investment and importing decisions. As the basis of dynamic models of firms' entry in export markets (See Roberts and Tybout (1997) and Das, Roberts, and Tybout (2007)), previous status is the key determinants in firms' behavior. Decisions on investment and import are binary variables. I use the current productivity and capital stock, as well as previous importing/investing status, to predict current decisions. So each firm's decision is based on the likelihood function for the observed firms' status ($m_{i,t-1}$, $d_{i,t-1}$ and k_{it}) and unobserved status (ω_{it}). Firm i's contribution to its probabilities of importing and investment can be written as:

$$P(m_{it}, d_{it} | \omega_{it}, k_{it}, m_{i,t-1}, d_{i,t-1}) \tag{3.19}$$

This reduced form equation (equation 3.19) demonstrates the joint decision on investment and importing (m_{it} and d_{it}). The probabilities in year t are conditional on firm i's current and previous state variables. The previous status of importing and investment are included to capture the transition patterns. I use the probit model to estimate the reduced form probability which measures the basic relationship between importing and investing decisions and productivity levels.

The fixed and sunk costs for importing and investment activities can be estimated via discrete choices by firms to participate in the import market and to conduct investment. Firms' participation in the import market can reveal information about sunk cost γ_{it}^{S} and fixed cost γ_{it}^{F} associated with importing. Similarly, decisions regarding investment can reflect information on sunk cost γ_{it}^{I} and on fixed cost γ_{it}^{D} associated with investment. Here, these costs are *i.i.d.* exponential distribution across all firms in every year.

The dynamic estimation is based on the likelihood function for the observed patterns of importing and investment status. Using the parameters recovered from the static model, firm i in year t's likelihood function follows equation 3.19. Assuming the sunk and fixed costs are *i.i.d.* for each firm, the joint distributions of (m_{it}, d_{it}) are the product of marginal distributions of m_{it} and d_{it}. The dynamic model developed above leads us to the conditional probabilities of import market participation and investment decisions, considering the associated costs. Firms participate in the import markets after comparing the pre-entry costs and the expected post-entry pay-off (the expected increase of value function in the future). Thus, the probability to enter the import market can be written as in equation 3.20.

$$P(m_{it} = 1 \mid s_{it}) = P(m_{i,t-1}\gamma_{it}^{F} + (1 - m_{i,t-1})\gamma_{it}^{S} \leq V_{it}^{M} - V_{it}^{D}) \tag{3.20}$$

Investment decisions comes from comparing associated costs and the expected pay-off. Conditional probability of investing is shown in equation 3.21:[4]

$$
\begin{aligned}
P(d_{it} = 1 \mid s_{it}) \quad = \quad & P(d_{i,t-1}\gamma_{it}^{I} + (1 - d_{i,t-1})\gamma_{it}^{D} \leq \\
& \delta E_t V_{i,t+1}(s_{it+1} \mid m_{it}, d_{it} = 1) - \delta E_t V_{i,t+1}(s_{it+1} \mid m_{it}, d_{it} = 0))
\end{aligned} \tag{3.21}
$$

The probabilities of import and investment decision depend on the value functions $E_t V_{i,t+1}$, V_{it}^{M} and V_{it}^{D}. The estimation of these value functions as well as the cost parameters follows a Bayesian Monte Carlo Markov Chain approach proposed by Aw, Roberts, and Xu (2011). The difference is that the import shock z_{it} is directly estimated in the static model.

3.4 Data

The model derived above is used to analyze productivity growth in the Chinese steel industry. I employ firm-level data which is collected by the Chinese Statistic Bureau (CSB) for the years 2000-2006 from its annual enterprize survey. It is supplemented with firm-level import information from Chinese Custom data. Finally, these micro data is combined with some macro-level statistics from the Chinese Statistics Year Books to capture aggregate market conditions. The annual survey of Chinese manufacturing is concentrated on large and medium size firms in China which have total annual sales more than 5 million RMB (approximately 0.7 million in US dollars). It covers 95% of total market value and thus provides a representative data source for the firm level study.

Steel is a fast-growing sector in China, expanding by an average of 20% every year in the sample period. China is now the largest steel maker in the world. In 2008, Chinese total output of crude steel accounted for 38% of world production.

[4]Note here, m_{it} enters the state variable vector since the theoretical model assume that firms investment decision is made after import decision.

In spite of this, the Chinese steel producers have generally maintained a very low profitability level (3%), compared with other Chinese manufacturing sectors (6%) or with steel producers in other countries (10%). Furthermore, the Chinese steel industry is highly import dependent on its inputs, iron ore. More than 70% of iron ore demand in China is repliant on imports, mainly from Australia, Brazil, and India. In 2008, China consumed more than 50% of the world iron ore supply.[5] Overall, the Chinese steel industry provides an excellent example to study the relationship among investment, importing and productivity growth.

The data I use is a balanced panel of 569 firms over 7 years.[6] A rich set of financial and accounting variables are reported in the dataset, such as total sales, capital stocks, and investment. Table 3.1 shows some summary statistics (number of firms and their size (measured by their revenue)) over the sample period, differentiated into importing firms and non-importing firms. We can see only about 4% of firms import in the sample period, and there is a clear difference between importers and non-importers. Both importers and non-importers have experienced rapid growth in their sales (which is used here to proxy for revenue). However, sales of importers are almost seven times as that of non-importers on average. This is similar for profitability, i.e. importers are on average larger and more profitable.

For investment, we can see that levels of investment by non-importers is far below that of importers during the sample period. The average investments of importers are more than ten times those of non-importers in 2006. Since the steel industry is a highly capital intensive and material dependent, importers expand their market shares by more investment and access to better raw materials, which lead to a high level of profitability.

[5] According to the Chinese Steel Association.

[6] First, I follow the Brandt, Van Biesebroeck, and Zhang (2011) method to merge the firm level data over years, and add the import information from the Chinese custom data. My analysis focus on firms who survive through all the sample period with SIC number 3200, which indicates the ferrous metal refinery. In order to exclude the effect from entrants on market structure, my analysis only focus on the incumbents.

Table 3.1: Importers vs. Non-Importers: 2000-2006

year	Non-Importers				Importers			
	# of Firms	**Sales**	**Invest**	**Profit**	**# of Firms**	**Sales**	**Invest**	**Profit**
2000	547	455	35	2.1%	22	2752	249	6.4%
2001	544	520	43	1.6%	25	2630	152	9.3%
2002	539	520	35	2.0%	30	3660	278	8.2%
2003	546	790	52	2.5%	23	6031	204	9.5%
2004	533	959	52	3.5%	36	9340	488	10%
2005	540	1276	64	4.2%	29	13671	934	5.3%
2006	544	1364	87	3.3%	25	19186	1328	6.8%

Note: millions of RMB, in mean level

3.4.1 Empirical Pattern for Import and Investment

The empirical model of the last section explains decision process in investment and import market participation. Here, I summarize some empirical patterns of transition probabilities. It is useful to understand the underlying factors driving inter-temporal decisions. Table 3.2 shows transition probabilities for investing and importing participation conditional on the last period status of a firm. The first row reports the unconditional distribution of firms' activities over all the sample period. It shows that in each year, 61% of firms do neither investment nor importing. Meanwhile, 33% of firms make investment but do not import, and 0.6% of importing firms do not make investment. There are 0.1% of firms involve both activities. In all, 217 firms (represent 38% of observations) involve into at least one of these two activities for at least one year.

Table 3.2: Firms' Annual Transition Rates

Status at Year T	**Status at Year $T+1$**			
	Neither	**Invest only**	**Import Only**	**Both**
All	0.615	0.337	0.007	0.001
Neither	0.924	0.074	0.002	0.000
Invest only	0.125	0.839	0.002	0.035
Import only	0.273	0.046	0.546	0.136
Both	0.007	0.259	0.021	0.713

Note: Numbers in the matrix measure the proportion of firms in two status at two neighboring period

The second to fifth row in Table 3.2 shows several clear patterns of each activity from year t to year $t+1$. First, status is significantly persistent over year. If a firm does not invest nor import in year t, then it has 92% possibility of doing neither in year $t+1$. Similarly, firms that only invest or import have 84% and 55% stay in the same status, and 71% of firms that involve both activities in year t keep undertaking both activities in year $t+1$.

Second, firms that invest or import in year t tend to start the other activity in year $t+1$, especially for importers without investment in year t. We can see 18% of importers that make no investment in year t involve both activities in year $t+1$. However, if a firm makes neither of the two decisions in year t, it has very low probability to involve in any of these two activities in year $t+1$.

Third, non-importers without investment in year t tend to do neither activity again in year $t+1$, although they show a small probability of starting investment. In the third row, we can see that within firms that only invest in year t, 87% of them would probably invest again in year $t+1$, and with a small probability to enter importing markets. Furthermore, we can find in the third row of Table 3.2 that if a firm enters importing market in year t, it would stay in importing markets and start to invest, and a similar distribution can be found in the fifth row.

Fourth, firms that undertake both activities are less likely to give up either. We can see in the last row of Table 3.2 that only 2% of firms that conduct both activities in year t stop investing in year $t+1$. On the other hand, firms in import markets without investing in year t have small chance to give up their import status in year $t+1$, but 13% of non-importing firms with investment in year t stop investing in year $t+1$. In all, importing status has a dominant effect on firms' decisions on both of these two activities.

Table 3.2 shows the need to model investment and importing decisions jointly. Firms undertaking one or both of investment and importing would have higher capital stock and productivity levels which results in a self-selection issue in firms' decisions. Meanwhile, status in investment and importing would affect productivity evolution as a feedback. Finally, the return of investment on productivity is probably conditional on import status, thus importing firms enjoy more benefits in their productivity growth from their own investment .

3.5 Estimation Result

3.5.1 Static Model Estimation Result

The first stage estimation on equation 3.6, equation 3.7 and equation 3.17 is reported in Table 3.3.[7]

Table 3.3: Demand, Cost and Productivity Dynamic Parameter Estimation

Parameters	Discrete Invest	Continuous Invest
η	-9.3204***	-9.3204***
	(1.1761)	(1.1761)
$\ln k_{it}$	-0.0454***	-0.0457***
	(0.0007)	(0.0007)
ω_{it-1}	0.9116***	0.9046***
	(0.0126)	(0.0126)
ω^2_{it-1}	0.7875***	0.7437***
	(0.0841)	(0.0838)
ω^3_{it-1}	-1.9093***	-1.9230***
	(0.2908)	(0.2928)
d_{it-1}	0.0051***	0.0010***
	(0.0016)	(0.0002)
m_{it-1}	0.0052**	0.0052*
	(0.0032)	(0.0031)
N	2790	2790
R^2	97.6%	97.6%

Standard errors in parentheses
$*p < 0.15, **p < 0.10, ***p < 0.05$

From Table 3.3, we can see that the estimated price elasticity of demand is high ($\eta = -9.32$), which implies the profitability level is 10% (profit over sales value). The coefficient on $\ln k_{it}$ estimates the effect of capital stock on firms' marginal cost

[7] I use the bootstrap method to estimate η from the coefficient

in firms' cost function β_k. It is negative and significant as expected, which implies that marginal cost is lower for firms with higher capital stock.

The coefficients in the productivity dynamics (equation 3.8) reveals several interesting facts. The coefficients ω_{it-1}, ω_{it-1}^2 and ω_{it-1}^3 reflect a non-linear relationship between lagged and current productivity. They shows the marginal effect from the lagged productivity displays a concave shape. The coefficients of d_{it-1} and m_{it-1} tell the short-run effect of investment and import status on firms productivity. The coefficient of d_{it-1} captures the direct effect of investment in year $t-1$ on productivity level in year t, and it is positive and significant, which implies a 0.51% productivity premium. The direct effect of last year import status on current productivity is measured by coefficient of m_{it-1} which is significantly positive, which implies that importing firms have on average 0.52% higher productivity. Such productivity impacts could come from better raw material and "learning by importing," and it is much higher than that for investment. Considering coefficients of d_{it-1} and m_{it-1}, we can see that firms that engage into both activities have productivity 1% higher than who do neither (0.6% in continuous investment case).

The coefficients of d_{it-1} and m_{it-1} can also measure the long-run effect of investment and importing on productivity. Compared with a firm who never undertakes investment or importing, a firm which has both activities will have a mean productivity that is 3.72% higher. A firm which only does investment will be 1.84% more productive, while a firm which only engages in importing will be 1.88% more productive in the long run. These facts for the long-run effects provide a linkage among investment, import and productivity growth.

Finally, I construct the estimation of firm level productivity from equation 3.17. The average productivity estimates is 0.038, with 5% and 95% percentile equal to (-0.106, 0.288). The distribution of productivity is important to display firm heterogeneity and explain firms' self-selection in the investment and import decisions.

3.5.2 Investment and Importing Decisions

The estimation result of the static model recovers firm level productivity and market conditions. These results can be used to measure the correlation of decisions on investment and importing. Table 3.5 reports the result of the probit estimations of investing and importing decisions on several variables including productivity level, capital stocks (in logarithmic form), previous decisions. These probit model can tell the correlation of different firm heterogeneity with importing and investment status. The estimation results are shown in table 3.5.

Table 3.4: Investment and Importing Decisions, probit model with controlling year effects

Variables	Investment	Importing
$m_{i,t-1}$	0.0859	2.1774***
	(0.1723)	(0.1422)
$d_{i,t-1}$	2.3848***	0.3170***
	(0.0653)	(0.1463)
ω_{it}	0.3804	2.7673***
	(0.3059)	(0.7163)
$\ln k_{it}$	0.1635***	0.0555
	(0.0253)	(0.0504)
N	3414	3414

Standard errors in parentheses
$*p < 0.15, **p < 0.10, ***p < 0.05$

In table 3.5, positive effects of productivity on import participation indicates that more productive firms tend to import their raw materials. Similarly, the positively significant coefficient of capital in the investment equation reveals a positive relationship between capital stock and investing. Since the capital stock can measure firms size, table 3.5 also tells that larger firms tend to make investment.

On the other hand, the productivity term does not show a positive relationship with the investment activity. This result reflects that more productive firm tend not to make investment although investment has a limited productivity effect. Combining with the result in the last section, we can see that there is a strong correlation between productivity and importing.

The lagged variables ($m_{i,t-1}$ and $d_{i,t-1}$) both have positive effects on each other at the current year. This implies that firms' investment and importing activities are correlated. Particularly, the previous investment has a significantly positive effect on the importing decision, which means firms need to make a investment to increase their productivity and size in order to access the import market. It would imply an entry barrier in the import market. And there is no significant correlation between lagged importing and current investment.

In all, the estimation results of the probit model reveal that investment and importing activities have positive effects on each other. Productivity and capital stocks positively affect these decisions. Combined these results with productivity dynamics, we can see that, importing status plays a dominant role in productivity evolution as well as in investment and importing decisions. Particularly, we can see that importers enjoy a productivity premium and more productive firms tend to import. Investment has limited effect on firms productivity growth, yet it can improve productivity by increasing the capital stock, which results in larger firms tending to undertake investment.

Overall, it should be recognized that productivity, constructed by the structural estimation, captures firm heterogeneity which is correlated with decisions to invest and import. Since productivity can be directly connected to profitability, the correlation between productivity and importing can explain the low and skewed distribution of firms' profitability in the Chinese steel industry.

A large number of small and medium firms are blocked from the import market, and they cannot access to premium inputs. On the other hand, their investment is not effective enough to improve their productivity level. Meanwhile, a few of large importing firms with high productivity level enjoy a lot of benefits from the import market, and they become even more productive and profitable. As a result, the profitability in the Chinese steel industry has a low average level and a highly skewed distribution.

3.5.3 Dynamic Model Estimation Result

The remaining parameters are the costs associated with importing and investment activities, which are estimated in the second stage estimation of the dynamic model. These parameters are estimated by the likelihood function which is the product over the joint-probability of these two activities of each firm, as given in equation 3.19. γ^I, γ^D, γ^F, and γ^S measure, respectively, exponential distributions of fixed cost of investment, sunk cost of investment, fixed cost of import and sunk cost of import. The coefficients in table 3.5 are the means and standard deviation of the posterior distribution of the parameters from the MCMC simulation (See the algorithm in the appendix)

Table 3.5: Dynamic Parameter Estimation

Parameters	Coefficients	Std. Err.
γ^S (Import SC)	1341.8200***	(230.9707)
γ^F (Import FC)	713.7533***	(251.8825)
γ^D (Investment SC)	14.1378	(41.0510)
γ^I (Investment FC)	37.9048***	(4.9697)

Standard errors in parentheses
$*p < 0.15, **p < 0.10, ***p < 0.05$
Note: Means and Standard Error of the Posterior Distribution, in million RMB

These costs associated with importing and investment reveal the underlying determinants that drive importing and investment decisions. First, we can see that the costs associated with importing are much higher than that with investment. Particularly, there is no significant sunk cost for investment. It is much easier for firms to start new investment than to enter the import market. Second, the sunk cost of importing (γ^S) is higher than the import fixed cost (γ^F), which means that entering the importing market is more difficult than keeping the importing status. In other words, import market entrants face a higher barrier than incumbents. However, the costs associated with investment are different. The fixed cost of investment is higher than its sunk cost. This implies that it is easier to start a new investment but there would be a lot of expense with it in the later years.

Compared with profit, we can find the magnitude of these costs. First, the entry cost of import is more than 15 times as the average profit by Chinese steel firms. The fixed cost of import, which is faced by the importers, is also about 8 times as the average profit. These costs associated with importing block many firms away from the import market. In my sample data, there are only 4% observations have import record. Second, the sunk cost of investment is insignificant while the fixed cost of investment is about 40% of the average profit. These relatively low costs associated with investment result in more firms involved into invest than importing.

Since the import market access is controlled by the government with import permits, the sunk cost of importing can be interpreted as obtaining permission to access the foreign suppliers. Many small and medium firms cannot get such permission. On the other hand, since the steel industry is highly capital intensive, it requires large amount of investment to maintain, replace and upgrade refinery equipment. It is relatively easier to start a new investment, compared with importing, since there is no similar government hurdles. However, there would be a lot of other expenditures associated with new investment, such as managerial cost and accounting cost from bank loans and adoption of new technologies.

The estimation of productivity dynamic shows a stronger effect of importing on productivity growth, but many firms are blocked from the import market thus cannot enjoy the benefits from imported raw materials. While many firms can easily undertake investment, but due to the limited effect of investment on productivity growth, many firms maintain a low level of productivity.

3.5.4 In Sample Performance

In order to assess my model, I use the estimated parameters to simulate the import and investment decisions, and then compare the simulated pattern with the real data pattern. Here, productivity, importing and investment are all endogenous from firm inter-temporal optimization. Each firm, based on its conditions (capital stock, productivity, etc.) at the initial year (2000), chooses its optimal strategies on importing and investment. Then, productivity evolves accordingly. Thus, I only use firm information in the initial year, and simulate all the years information after then.

First, I compare the mean level of participation rate of importing and investment for each year. Table 3.6 shows that my model generate a decent result. The overall correlation between real data and simulated data is around 40%, with particularly better results in late years.

Table 3.6: Import and Investment Participation Rates

	Importing		Investment	
Year	Actual	Predicted	Actual	Predicted
2000	0.039	0.011	0.350	0.132
2001	0.044	0.014	0.369	0.142
2002	0.053	0.019	0.392	0.153
2003	0.040	0.030	0.401	0.204
2004	0.063	0.046	0.390	0.234
2005	0.051	0.056	0.381	0.257
2006	0.044	0.063	0.366	0.271

Second, I generate the transition matrix for the predicted data. Compare table 3.2 with table 3.7, we can see that my predictions are closed to the actual data, particularly in the second and third rows. These two groups are firms that have no activity and that only have investment only. These two groups account for 96.5% of the sample observations. However, the transition of importing is hard to fit very well, although this group only takes less than 5% of the sample observations. In all, the predicted transition matrix is close to the real data pattern we observed.

Table 3.7: Firms' Annual Transition Rates: Predicted

Predicted Data				
Status at Year T	Status at Year $T+1$			
	Neither	Invest only	Import Only	Both
All	0.8012	0.1647	0.0000	0.0018
Neither	0.9465	0.0517	0.0000	0.0000
Invest only	0.0465	0.8978	0.0000	0.0558
Import only	0.0427	0.0000	0.9275	0.0298
Both	0.0000	0.0000	0.0200	0.9800

3.6 Free Trade in Import Market

Trade liberalization for imports means lower entry cost and thus more firms could access to foreign suppliers. As a result, there would be an improvement in productivity. Moreover, due to the correlation between investment and importing activities, firms would be more likely to be involved in the investment which would further increase their productivity.

In this section, I first calculate the gains from importing via equation 3.14 using the estimated value functions. Table 3.8 shows the results. We can see first that the gains from importing is all positive for firms with different productivity level. Second, gains from importing is increasing by productivity level. This means that more productive firms get more benefits from importing, even after controlling for the self-selection issue. Third, gains from importing for investing firms is slightly higher than the non-investing firm while such difference is smaller for more productive firms.

Then, a counterfactual exercise is conducted here to show the change of firm productivity by reducing the costs in the import market. Each firm optimize its choice of importing after observing the new sunk cost and fixed cost in the importing market. In my model, the decrease of the sunk cost and fixed cost can increase the post-entry value function for non-importers, and the decrease of the fixed cost can increase the value function of importers so that they are more likely to keep

Table 3.8: Gains from Importing (million RMB)

	V_t^M		V_t^D		$G^{Import} = V_t^M - V_t^D$	
ω_{it}	$d_{t-1} = 1$	$d_{t-1} = 0$	$d_{t-1} = 1$	$d_{t-1} = 0$	$d_{t-1} = 1$	$d_{t-1} = 0$
-0.2220	781.04	780.99	777.98	777.94	3.06	3.05
-0.1151	796.66	796.57	792.37	792.29	4.29	4.28
-0.0082	826.02	825.82	819.57	819.39	6.45	6.43
0.0987	877.52	877.10	867.76	867.38	9.76	9.72
0.2056	959.21	958.45	945.34	944.64	13.87	13.81
0.3124	1072.06	1070.91	1054.25	1053.16	17.81	17.75
0.4193	1206.51	1205.02	1185.88	1184.43	20.63	20.59
0.5262	1344.91	1343.25	1323.16	1321.52	21.75	21.73
0.6331	1468.98	1467.27	1447.50	1445.79	21.48	21.48

importing and enjoy the productivity increase from importing. I process my experiments with two reductions in γ^S and γ^F, by 10% and by 90%. My simulation is processed similarly as in the last section to simulate the industrial evolution after the initial year.

Table 3.9 shows the change of mean level of productivity under different cost reductions in each year. We can see an increase in firm productivity across years. With 10% decrease in sunk cost and fixed cost associates with importing, the mean productivity could increase by 8.9% on average, such increase is even more for 90% decrease in these costs. Since the productivity term directly enter the cost function, increase in productivity results in decrease in marginal cost.

Table 3.9: Average Productivity Level from Cost Reduction

		Reduce γ^S, γ^F	
Year	Original	10%	90%
2000	0.0709	0.0709	0.0709
2001	0.0901	0.0954	0.0913
2002	0.1217	0.1287	0.1360
2003	0.1497	0.1647	0.1827
2004	0.1783	0.1978	0.2237
2005	0.2017	0.2232	0.2594
2006	0.2250	0.2478	0.2893

3.7 Conclusion

This paper estimates a structural model to construct firms' productivity and measures its linkage with both investment and importing activities. It characterizes joint decisions on investing and importing depending on productivity level, import market conditions, capital stock and prior decisions on investing and importing. Moreover, it also explains how these decisions can affect the productivity evolution endogenously. The model is estimated using firm-level data from the Chinese steel industry between 2000-2006.

Several conclusions can be drawn here. First, productivity dynamic is an endogenous process, responding to investment and importing decisions. Compared with firms which undertake neither activities, in the long run, importing behavior alone can increase their productivity by 1.9%, while investment alone has limited effect; and conducting both can increase productivity by 3.2%. Second, the marginal returns to investment and importing are increasing with productivity levels, suggesting more productive firms enjoy more benefits from both activities. Since these two activities have positive feedbacks on productivity growth, this reinforces the self-selection that more productive firms are more involved in both activities. Third, there is a huge entry cost in the importing market, which is more that ten times of the average profit level, and also a high level of fixed cost associated with importing. These costs keep many small and medium firms away from the importing market, thus these firms cannot enjoy the productivity effect from importing. Fourth, the sunk cost and fixed cost associated with investment is small which allow more firms undertake investment, but the productivity effect from investment is limited. Finally, my counter factual experiment shows a significant effect on productivity from the import costs reduction, i.e. only 10% decrease in sunk cost and fixed cost from the import market can increase firm productivity by 8.9% on average.

In all, these empirical findings reveal the role of firm heterogeneity in their productivity which drives the Chinese steel makers to make investment as well as their import markets participation. The relationship between productivity and decisions to invest and import lead to a self-selection issue which distinguishes the performance of importing and non-importing firms. On the other hand, my results also reveal the importance of import market participation. Free access to better raw material could contribute to a large amount of productivity gains.

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