The Geography of Market Power: Evidence from the Chinese Steel Industry

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Abstract

This paper examines how the geographic distribution of supply and demand shapes market power in the Chinese steel industry. Drawing on novel data, we develop and estimate an equilibrium model that accommodates spatial demand variations and rich firm heterogeneity—encompassing differences in location, product quality, production coefficients, and cost efficiencies. Using this framework, we simulate the impact of shifts in downstream demand and evaluate the welfare implications of mergers and acquisitions under various market frictions—an issue central to China's industrial policy.

Key Words: Spatial Differentiation, Misallocation, Market Power, Merger Analysis, Sales Aggregation

JEL Classification: G34, L13, L61, R12

1 Introduction

Steel is one of the most essential materials in the modern world, playing a crucial role in everything from food preservation to construction and manufacturing. China is the world's largest producer and consumer of steel, contributing nearly half of global output. Yet, despite its immense scale, the industry faces intense competition and persistent inefficiencies.

A common measure of market power, the concentration ratio of the top firms, highlights China's fragmented industry structure compared to other major producers like the U.S. and Japan. However, steel is costly to transport, making simple concentration ratios an inadequate measure of market power. Another key issue in China is the geographical misallocation of capacity, requiring steel to be hauled over long distances. While China produces half of the world's steel, a quarter of that production is concentrated in Hebei, whereas a significant portion of downstream demand lies in the Yangtze River Delta.

China's steel industry is also undergoing a major restructuring, driven by shifts in economic policy and changing regional demand. Current capacity, shaped by past growth patterns, may no longer align with the evolving needs of downstream industries. Recognizing this, government reports have repeatedly emphasized the urgency of restructuring and has regarded mergers and acquisitions (M&A) as a crucial policy tool for enhancing industry performance.[1] However, several frictions complicate the process. First, existing M&A activities in China's steel industry, mostly government-directed, highlight a trend of large firms acquiring smaller ones, potentially creating a scale bias that favors larger firms over smaller but more efficient ones when selecting acquirers. Second, local protectionism influences whether consolidation efforts prioritize regional mergers or nationwide integration.[2] Third, ownership restrictions may limit the ability of private firms to acquire state-owned firms.

Given these frictions, understanding their trade-offs is crucial for informed policymaking. However, our knowledge of how these factors shape the steel market remains limited. This paper bridges this gap by developing a structural model that incorporates firm heterogeneity—capturing differences in quality and cost efficiency—alongside the geographic

[1]For example, on September 19, 2016, the State Council issued a top-level strategic plan titled "Guiding Opinions on Promoting Mergers, Reorganizations, and Handling Zombie Enterprises in the Steel Industry", aiming to consolidate approximately 60% to 70% of China's steel production into around ten major steel groups. A subsequent policy guideline issued in 2022 by the central government—*the Guiding Opinions on Promoting the High-Quality Development of the Steel Industry*—reinforces the critical role of mergers and reorganizations in promoting the development of the industry. The policy encourages leading firms to pursue mergers and reorganizations while also promoting cross-regional and cross-ownership consolidation to enhance industry efficiency and global competitiveness.

[2]There is extensive literature discussing the presence of local protectionism in China. See for example, Bai et al. (2004), Barwick et al. (2021), Fang et al. (2024).

distribution of supply and demand. This framework enables a comprehensive evaluation of market power, a deeper assessment of friction trade-offs, and better informed industry policies.

We develop and estimate an empirical model that incorporates rich firm heterogeneity and the geographic distribution of steel producers alongside spatial variations in downstream demand. On the demand side, downstream firms purchase steel to manufacture final products such as automobiles, appliances, and buildings. We model their choices using a standard logit framework, where product quality, price, and transportation costs influence purchasing decisions. However, rather than observing firm-level sales in each market, our data is aggregated at the destination-region level by firm. As a result, we adapt the standard contraction mapping approach (Berry, 1994; Berry et al., 1995) for estimation. We then estimate the model using a generalized method of moments (GMM), employing input prices (iron ore and coal) as instrumental variables to correct for price endogeneity. Our results indicate that steel demand is highly elastic, with an average price elasticity of 4.26. The implied markup averages 24%, with significant geographical variation.

On the supply side, each steel firm operates a blast furnace with a fixed labor force and produces steel using a Leontief technology that combines iron ore, coke, and coal. Leveraging detailed input and output data on prices and quantities, our production function estimation captures firm heterogeneity across multiple dimensions, including input costs, output quality, input-specific efficiency, yield rates, and unobserved cost efficiency. We find that much of this heterogeneity stems from unobserved cost efficiency, which strongly correlates with product quality. Additionally, after controlling for product quality and location differences, private firms tend to be more cost-efficient than their state-owned counterparts. This distinction is crucial for merger analysis, as the extent of cost savings depends on the transferability of firm-level heterogeneity.

Using the estimated model, we conduct counterfactual experiments to assess the effects of various restructuring strategies. We allow for three potential sources of merger effects: increased market power, lower iron ore prices, and higher unobserved cost efficiency. To illustrate the trade-offs associated with different frictions, we simulate mergers under different scenarios, varying both the selection criteria for leading firms and the scope of consolidation. Specifically, we define four merger scopes—regional vs. nationwide and within-ownership vs. cross-ownership—resulting in four primary scenarios. Within each scope, we select the leading firm based on either its size or cost efficiency, yielding a total of 24 counterfactual experiments (3 levels of merger effects $\times$ 4 scopes $\times$ 2 leader selection criteria).

Our findings suggest that mergers led by firms selected for efficiency, rather than size,

yield greater cost reductions on average. Removing ownership restrictions further enhances cost-efficiency gains. Interestingly, regional and within-ownership mergers generate larger average cost savings than cross-regional mergers, as they allow smaller but more efficient private firms to lead consolidation efforts. Welfare decreases when mergers increase market power without improving cost efficiency but rises when mergers are more restrictive (regional or within ownership), curbing market power. The most significant welfare gains occur when mergers are both regionally and ownership-restricted and led by the most efficient firms. In this scenario, a modest increase in market power, combined with a 12.5% reduction in costs, leads to a 26.7% markup increase, a 4% price reduction, and an 8.6% expansion in sales. These changes drive a 37.9% rise in variable profits and a 14.4% gain in consumer surplus—the highest among our counterfactual scenarios—resulting in an overall welfare improvement of 24.1%. Additionally, the concentration ratio of the top 10 firms (CR10) reaches 61.1%, aligning with the policy objective.

Finally, we use our model to predict market outcomes in response to shifting downstream demand. We focus on the construction sector, which accounted for 45% of total steel consumption in 2017. The recent slowdown in real estate development has significantly reduced steel demand. To quantify this impact, we use the observed change in completed floor space in 2023 and our model estimates to compute new steel demand by province. Our analysis reveals substantial regional variation, with northern regions experiencing a 1% increase, while other areas face declines ranging from 0.16% to 10.50%. In response to this demand shock, firms universally scale back production, yet prices remain stable. While the geographic flow of steel sales remains largely unchanged—given that local purchases constitute the largest share—northern firms reduce shipments to the central-southern region by 1% of their total production. With its relatively smaller demand reduction, the central-southern region becomes slightly more self-sufficient, reducing shipments to eastern and southwestern markets.

Our paper is related to the empirical literature that studies market power using the demand approach (Berry, 1994; Berry et al., 1995). The literature on the steel industry has mainly focused on productivity measurement using the production function approach. For instance, Collard-Wexler and De Loecker (2015) study the effects of the minimill technology on productivity in the US steel industry. Brandt et al. (2022) study productivity differences by ownership in the Chinese steel industry. One exception is Li et al. (2025), who estimate both a representative consumer demand model and a production function but omit spatial differentiation and strategic interactions among firms. Our paper integrates both approaches within an equilibrium framework, incorporating downstream demand that accounts for product quality, distance, and price, as well as firm supply that varies across mul-

tiple dimensions. By explicitly modeling strategic interactions among firms, our approach enables a more comprehensive analysis of mergers.

There has been empirical literature on spatial differentiation and market power. For instance, Pinkse et al. (2002) and Houde (2012) study the gasoline market. McManus (2007) study nonlinear pricing of specially differentiated stores in a specialty coffee market. Miller and Osborne (2014) study spatial differentiation and price discrimination in the U.S. cement industry. Our paper is the first to study the geography of market power in the steel industry. Building on existing studies that incorporate Bertrand competition with spatial differentiation, our analysis explores the interaction between merger effects and frictions.

The remainder of the paper is structured as follows. Section 2 provides an overview of the Chinese steel industry, including key institutional details, data description, and empirical patterns. Section 3 develops a structural model of demand and supply that incorporates the geographic distribution of steel producers and spatial variations in downstream demand. Section 4 outlines the estimation procedure used to recover key economic parameters. Section 5 presents the main estimation results, while Section 6 explores counterfactual analyses to evaluate the effects of weakening demand and potential mergers. Finally, Section 7 concludes.

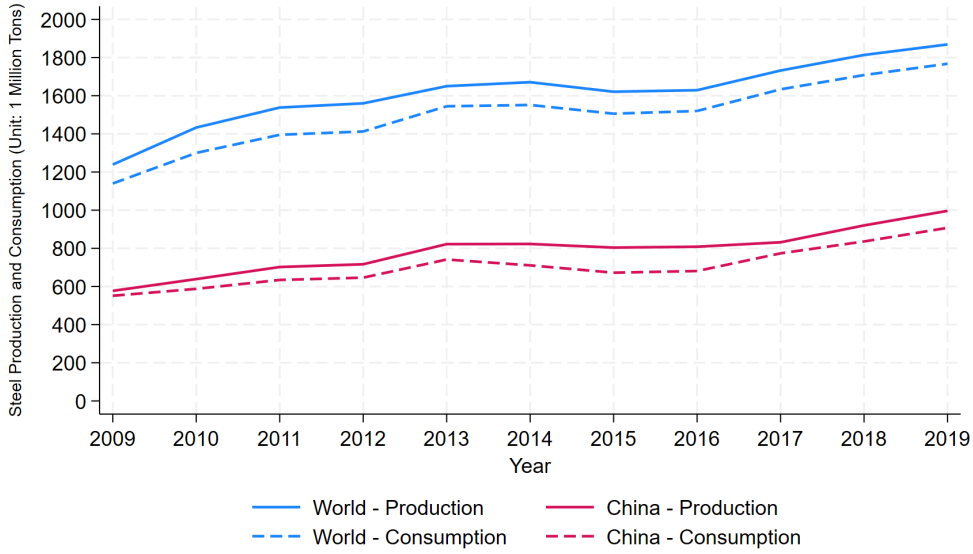
2 Background and Data

2.1 Institutional Details

The Chinese steel industry is the largest in the world, accounting for nearly half of global production (Figure 1). Its rapid expansion has been driven by decades of industrialization, urbanization, and infrastructure investment. The market is vast and fragmented, with both state-owned and private firms playing key roles. Production is concentrated in provinces such as Hebei (21% in 2023) and Jiangsu (12% in 2023), reflecting a combination of upstream and downstream advantages. For instance, both Hebei and Jiangsu benefit from well-developed sea and river ports, facilitating iron ore imports, and are situated in highly industrialized regions with strong steel demand.

In contrast to the dominance of electric arc furnaces (i.e., minimills) in the U.S., the majority of China's steel production is dominated by the blast furnace process. Iron ore, coke, and limestone are melted in a blast furnace to produce molten iron, which is then refined in a basic oxygen furnace to remove impurities and control the carbon content.

Figure 1: Steel Production and Consumption



Notes: Steel production is measured as annual crude steel production; consumption is measured as the annual apparent consumption of finished steel products. Data come from the World Steel Association and various issues of the China Steel Yearbook.

2.2 Data

Our primary data on steel sales is sourced from a steel consulting service company in China, which compiles information from the Chinese Iron and Steel Association and direct firm surveys. The dataset encompasses 87 major steel groups in China that operate 118 firms distributed across six geographic regions in China: North (N), Northeast (NE), East (E), Central South (CS), Southwest (SW), and Northwest (NW).[3] The total steel sales of these firms, measured in tonnage, accounted for 56.3% of total domestic sales in 2017, while their exports constituted 44.2% of the country's total steel exports.[4] The 2017 sales data specifically detail the domestic steel sales from each firm to the six regional markets.

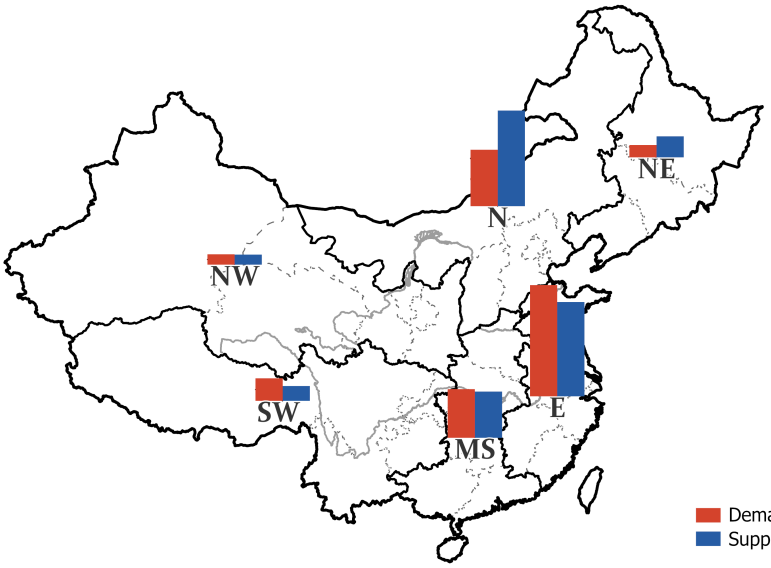
We observe steel flows from J major steel firms in China to the country's six geographic regions - Northeast, North, East, Central and South, Southwest, and Northwest - and the export market, denoted by region 0. Each geographic region encompasses several provinces, illustrated by Figure 2.

In addition, we compile information at the firm level from 2009 and 2017 on prices and

[3] See Table A2 in the Appendix for the geographic distribution of the sample firms.

[4] We calculate total domestic sales using output of finished steel products minus export. The inventory size is small compared to the output and the export. Regional sales from firms outside the sample are estimated by subtracting the total regional sales of the sampled firms from the overall sales in each respective region. Similarly, exports from firms not included in the sample are calculated by subtracting the total exports of the firms in our dataset from the national-level export figures.

Figure 2: Steel Supply and Demand by Region in China



Note: The two solid gray lines represent the Yellow River (north) and the Yangtze River (south). Dashed lines outline provincial boundaries, while solid lines define the six regions. Red bars indicate total sales in each region, and blue bars represent total production, based on the authors' calculations using the yearbook.

the physical quantity of inputs and output based on the data collected by the Chinese Iron and Steel Association.[5] The input data include key material and energy inputs, number of workers, size of furnaces (capacity), and utilization rates. Additionally, the dataset includes information on firm ownership type, year of establishment, and location.

Steel trade flow Table 1 provides the percentage of steel from the sample firms in each region sold to their respective destination regional markets and additionally, the overall regional shares of demand and supply. We find an imbalance in demand and supply across regional markets. While the North contributes to 33.9% of total steel output, the region only consumes 20.1%. In contrast, being the most important steel consumer (39.4%), the East merely contributes 33.4% of the output. In addition, we find that steel firms ship the largest fraction of their overall sales in their home markets but sell less to more distant markets. The percentage of the own-market sales varies significant, however. For instance, firms in the Southwest supply almost exclusively in the home market (93.2%), whereas those in the Northeast distribute approximately only one-third of their sales in their home region. Overall, cross-region flows comprise a significant portion of steel sales, notably from the Northeast and the North to the other regions. At last, China's steel output is consumed primarily in the domestic market, as export accounts for only 7.2% of the total sales.

Market structure Table 2 presents the number of firms competing in each regional market, along with a breakdown based on firm location. The data highlight strong competition across regional markets in general. However, the number of competitors in each regional market varies significantly. For example, 99 firms operate in the East, whereas only 61 - roughly half of the 118 firms - compete in the Northwest. These figures align with the main findings from the trade flow data (Table 1), reinforcing the pattern that firms primarily sell in their home regions and are less likely to ship steel to distant markets. While the average market share remains relatively low across regional markets, firms tend to hold a higher market share in their home regions (see Table A3).

Table 3 summarizes regional and national market share of the four largest (CR4) and ten largest firms (CR10) based on firm-level and group-level sales, respectively. The relatively low concentration ratios, as measured by CR4 and CR10, confirm the competitive nature of the steel industry. Specifically, CR4 is only 15.5%, and CR10 is 26.3%, based on the group-level sales. The concentration ratio in China is substantially lower than that of the

[5]These data are collected by the Chinese Iron and Steel Association as part of regular data collection efforts from all firms with annual steel production over 1 million tons. The integration of the sales and the input-output datasets provides complete information for 62 firms. We develop a method in Section 4.3 to address the data discrepancy issue.

world's other major steel producers - the United States, EU, and Japan - whose four largest firms hold a market share of 65%, 78%, and 83%, respectively.[6] However, there is notable regional disparities. The Northeast and Northwest exhibit the highest market concentration whereas the East has the lowest. This regional variation is also evident in Table A4, where the most dominant firm in the Northeast and Northwest holds 16.92% and 13.42% of the market share, respectively.

Ownership Following Brandt et al. (2022), we categorize firms by three basic types of ownership: central state-owned, provincial state-owned, and private firms. Central SOEs operate under the direct supervision of the State-Owned Assets Supervision and Administration Commission (SASAC). Firms that have been merged into central SOEs are also classified as central state-owned. Provincial SOEs fall under the direction of provincial or regional SASACs. Table 4 indicates that SOEs account for 60% of the overall steel sales in the sample, of which the 13 central SOEs contribute to approximately one-third and the remaining from the 39 provincial SOEs. Private firms dominate in number, however, on average provide less than half of the steel from an average central SOE and roughly 60% that of the provincial SOE.

Firm Size Firms vary significantly in size. Table 4 shows that firms at the 90th percentile sell nine times more steel than those at the 10th percentile. This disparity is evident within each ownership category. Firm capacity, measured by the total cubic meters of the blast furnaces the firm operates, displays a consistent pattern. From Table 5, we find that the average firm size in the fourth quartile is significantly larger than in the first quartile: the difference is more than ninefold.

3 Model

This section presents a framework for demand and supply that accounts for producer locations and spatial variations in demand. Each province constitutes a distinct market, indexed by $n \in \{0, 1, 2, \ldots, N\}$. Each plant j produces a specific variety of steel, indexed by $j \in \{0, 1, 2, \ldots, J\}$. The industry consists of both single-plant firms and multi-plant firm groups, which compete against a competitive fringe in each market where they operate. We take the set of existing plants, their ownership structures, and their market presence as given, focusing on the short-run pricing and production decisions of firms.

[6] These figures are extracted from Brandt et al. (2022), who report CR4 of EU and Japan in 2015 and the United States in 2017.

Table 1: Region-to-Region Steel Flow (in Percentage)

		Destination Region								
		N	NE	E	CS	SW	NW	Export	All-Sample	All-Total
Supply	N	55.1%	1.7%	24.4%	8.8%	2.3%	2.9%	4.8%	18.3%	33.9%
	NE	8.0%	35.4%	29.2%	11.5%	0.3%	0.4%	15.1%	5.6%	7.5%
	E	2.0%	0.8%	78.6%	9.9%	1.9%	0.3%	6.5%	18.6%	33.4%
	CS	4.7%	0.5%	17.7%	66.5%	5.8%	2.0%	2.8%	7.8%	16.4%
	SW	0.6%	0.0%	2.2%	3.1%	93.2%	0.6%	0.4%	3.0%	5.3%
	NW	3.3%	0.2%	3.9%	5.2%	24.4%	62.1%	0.9%	2.1%	3.6%
	Other	19.5%	4.2%	38.4%	17.4%	7.9%	3.6%	9.0%	44.6%	
	All	20.1%	4.4%	39.4%	17.2%	8.0%	3.7%	7.2%	100.0%	

[1] The figure in each cell of the region-to-region matrix represents the percentage of steel from the sample firms in each region or from outside firms sold to each destination region (column).
[2] The last row presents the shares of total steel demand contributed by each region.
[3] The last column presents the shares of steel provided by each region.

Table 2: Number of competing firms in each regional market by firm location

		Destination Region							
		N	NE	E	CS	SW	NW	Export	All domestic
Supply Region	N	49	24	40	36	25	24	18	49
	NE	8	8	8	8	4	4	7	8
	E	18	17	30	23	18	16	19	30
	CS	13	9	15	18	14	10	12	18
	SW	1	2	3	2	8	2	2	8
	NW	4	3	3	4	5	5	2	5
	All	93	63	99	91	74	61	60	118

[1] The figure in each cell represents the number of sample firms located in the row region sold to the destination column region.

3.1 Demand

Steel demand originates from various downstream industries across all provinces. To model consumer behavior in each market, we adopt a logit discrete choice framework. The indirect utility of consumer i in province n purchasing from firm j is given by:

$$u_{i,jn} = \xi_{jn} + \alpha p_j + \beta \tau_{jn} + \epsilon_{i,jn}, \tag{1}$$

where ξ_{jn} represents the unobserved desirability (quality) of firm j's product in market n, p_j is firm j's steel price, and τ_{jn} denotes the distance between firm j and the center of province n. The term $\epsilon_{i,jn}$ is an idiosyncratic preference shock, which we assume to be i.i.d. across consumers, following a Type I extreme value distribution.

Table 3: CR4 and CR10 in Regional Markets

	Firm		Group	
Regional Market	CR4	CR10	CR4	CR10
N	11.84%	25.94%	21.81%	33.69%
NE	33.80%	49.43%	34.59%	50.36%
E	15.27%	25.94%	19.51%	31.92%
CS	17.85%	32.09%	27.47%	40.29%
SW	24.63%	40.65%	27.74%	44.22%
NW	37.84%	47.25%	39.44%	49.08%
Export	18.64%	30.20%	24.00%	36.00%
All domestic regions	8.53%	16.96%	16.51%	27.36%

Table 4: Firm Sales by Ownership

Ownership	Firm Number	Mean	Std Dev	10th	90th
Total	118	4.64	4.52	0.84	10.00
Central SOE	13	7.96	6.90	2.53	21.2
Provincial SOE	39	5.7	4.57	0.36	14.1
Private	66	3.36	3.37	0.84	6.96

Notes: Sales are in 1 million tons.

Table 5: Summary Statistics of Firm Size by Size Quartiles

	Firm Size Category			
	1	2	3	4
	(0,2180]	(2180, 4860]	(4860,9232]	>9232
Mean size	1396	3106	7115	14181
Std Dev	556	654	1357	5875

Notes: Firm size is measured by the total cubic meters (m^3) of all the furnaces the firm operates.

Since our dataset covers only the majority of production and sales, we make additional assumptions to align the observed data with aggregate production and sales. Specifically, we introduce a representative buyer 0 in each market who also purchases from local firms, as well as a competitive fringe firm 0 as the outside option in each market.[7] We normalize the mean utility of the outside option to zero and define the set of available options in

[7]See the Appendix for more details on the market shares of firm 0. We also exclude international steel firms from our model since imports constitute a negligible portion of domestic consumption. For instance, in 2017, imports accounted for only 1.35% of domestic consumption.

market n as $\mathcal{J}_n$.

Each consumer selects an option $j \in \mathcal{J}_n$ to maximize their utility. The logit demand model implies that firm j's sales in market n are given by:

$$q_{jn} = \mu_n \times s_{jn}(p_j, p_{-j}), \tag{2}$$

where μ_n denotes the market size of market n, and $s_{jn}(p_j, p_{-j})$ represents firm j's market share:

$$s_{jn}(p_j, p_{-j}) = \frac{\exp(\xi_{jn} + \alpha p_j + \beta \tau_{jn})}{1 + \sum_{j' \in \mathcal{J}_n} \exp(\xi_{j'n} + \alpha p_{j'} + \beta \tau_{j'n})}.$$

For estimation, we calibrate the market size μ_n based on the output levels of downstream industries that are the primary consumers of steel. Aggregating sales across all markets yields the total sales of firm j:

$$Q_j = \sum_n q_{jn}(p_j, p_{-j}). \tag{3}$$

3.2 Supply

A total of F steel groups engage in Bertrand price competition, with each group may operate multiple firms and selling in multiple markets. Each firm group f selects a vector of posted prices to maximize its short-run total profit across all its products[8]:

$$\begin{aligned} \max_{\{p_j\}_{j \in \mathcal{J}_f}} \quad & \sum_{j \in \mathcal{J}_f} \Big(p_j - MC_j\Big) Q_j(p_j, p_{-j}) \\ \text{s.t.} \quad & Q_j(p_j, p_{-j}) \leq \overline{Q}_j \end{aligned} \tag{4}$$

where each firm j faces a capacity constraint $\overline{Q}_j$, under which it either equates marginal revenue to marginal cost or "prices to capacity" (Kalnins et al., 2017).[9]

We assume that steel production follows a Leontief technology:

$$Q_j = \min\{\beta_{1j} M_{1j}, \beta_{2j} M_{2j}, \beta_{3j} M_{3j}, \beta_{vj} V_j\} \exp(\omega_j + e_j). \tag{5}$$

saying that plant j produces steel using three major raw material and energy inputs—iron ore M_{1j}, coke M_{2j}, and coal M_{3j}—each entering production in fixed proportions. The term

[8] In our sample, 85% of the SOEs are either directly publicly listed or subsidiaries of a publicly listed parent firm, alleviating concerns about their profit maximization objectives in this industry.

[9] An alternative approach to incorporating capacity constraints is to model a hockey-stick-shaped cost function, as in Ryan (2012). However, similar to Miller and Osborne (2014), we found it challenging to estimate the shape parameters in our setting.

V_j captures other unobserved inputs (from the researcher's perspective) in a composite manner, including unobserved costs or shadow costs of inefficiencies. The term ω_j represents firm-specific heterogeneity in production (the logarithm of total factor productivity, TFP), while e_j denotes an i.i.d. error term.

The Leontief specification captures key characteristics of steel production. Capital (blast furnace) serves as a capacity constraint, while the number of workers required to operate the furnace remains relatively fixed. Additionally, the quantities of intermediate inputs—such as iron ore, coke, and coal—are carefully calculated to match the furnace specifications, entering production in fixed proportions. Finally, the composite term $\omega_j + e_j$ reflects variations in the yield rate.

Leveraging our rich production dataset, we allow for substantial firm heterogeneity by permitting the engineering parameters β to vary across firms, incorporating unobserved cost factors V_j, and accounting for productivity differences through ω_j.

The optimality condition for a Leontief production function requires that:

$$\beta_{1j} M_{1j} = \beta_{2j} M_{2j} = \beta_{3j} M_{3j} = \beta_{vj} V_j.$$

Thus, under capacity constraints, firm j's marginal cost is given by:

$$MC_j = \frac{\sum_{l=1}^{3} P_{lj} M_{lj} + P_{vj} V_j}{Q_j} = \frac{\sum_{l=1}^{3} \frac{P_{lj}}{\beta_{lj}} + \frac{P_{vj}}{\beta_v}}{\exp(\omega_j + e_j)}, \tag{6}$$

where P_{lj} represents the firm-specific unit cost of iron ore, coke, and coal, respectively, and P_{vj} represents the firm-specific unit cost of the unobserved input V_j. The second equality follows from the Leontief optimality condition and highlights that marginal cost is negatively correlated with productivity heterogeneity.

4 Estimation

This section outlines our estimation strategy for the logit demand model using aggregate sales data and the production function, leveraging input and output prices and quantities.

4.1 Demand Estimation

Our sales data is aggregated at the destination-region level by firm. For each firm, we observe its posted price p_j in 2017, its distance to markets τ_{jn}, and its region-specific sales

Q_{jr}, where $r \in$ {N, NE, E, CS, SW, NW}.

Market Size Calibration We assume that downstream consumers exhibit inelastic demand for steel, meaning total sales in each market equal its market size. However, we do not observe total sales in each individual province μ_n; instead, we observe only regional sales, denoted as $\mu_r = \sum_{n \in \mathcal{N}_r} \mu_n$. To recover province-specific steel sales μ_n, we employ an input-output accounting equation:

$$\mu_n = \sum_i \gamma_i X_{ni},$$

where X_{ni} serves as a proxy for industry i's output level within province n. Possible proxies include industry total value added in car manufacturing and railway construction. The parameter γ_i captures steel usage per unit of output in industry i.

Aggregating these province-level input-output relationships to the regional level yields the following regression model for estimating the parameters γ:

$$\mu_r = \gamma' \sum_{n \in \mathcal{N}_r} \mathbf{X}_n + \zeta_r,$$

where $\mathbf{X}_n$ is the vector of downstream industry output in market n and ζ_r is a region-specific residual.

Once we obtain region-specific residuals $\widehat{\zeta}_r$, we allocate them to provinces within each region proportionally to the deterministic component of each province's steel consumption. This allocation follows:

$$\widehat{\mu}_n = \widehat{\gamma}' \mathbf{X}_n + \widehat{\zeta}_n,$$

where the provincial residuals are computed as:

$$\widehat{\zeta}_n = \frac{\widehat{\gamma}' \mathbf{X}_n}{\sum_{n' \in \mathcal{N}_r} \widehat{\gamma}' \mathbf{X}_{n'}} \widehat{\zeta}_r.$$

By construction, our calibrated provincial market sizes $\widehat{\mu}_n$ ensure that the sum of province-level sales within each region aligns with observed regional sales.

Demand Parameter Estimation We now describe how to estimate the parameters of the logit demand model. Before proceeding, we need to address a few implementation issues. First, because our sales data is aggregated at the destination-region level by firm, we assume that the unobserved desirability of firm j's product is only firm-region-specific, denoted as

$\xi_{jr(n)}$. Second, our estimation problem may suffer from typical price endogeneity, meaning the unobserved desirability $\xi_{jr(n)}$ and price p_j might be correlated. A common approach is to use cost shifters as instruments for output price. However, the reported unit cost of iron ore and coal in our data includes transportation costs, which may still correlate with the firm-region unobserved desirability $\xi_{jr(n)}$. To control for such correlations, we assume that the unobserved desirability of firm j's product can be decomposed as:

$$\xi_{jr(n)} = \xi_j + \xi_{r(n)} + \widetilde{\xi}_{jr(n)}, \tag{7}$$

where the decomposition separates transportation-related factors, which are captured by the firm-specific effect ξ_j and the region fixed effect $\xi_{r(n)}$. We assume that the residual firm-region desirability $\tilde{\xi}_{jr}$ is uncorrelated with the unit cost of iron ore and coal, i.e., $Z_j \perp \tilde{\xi}_{jr}$.

Furthermore, we use the residual desirability and the average firm-to-province distance within the corresponding region (τ_{jr}) to construct an additional moment condition. Therefore, we define the following moment conditions for estimation:

$$E\left[\widehat{\tilde{\xi}}_{jr}(\alpha,\beta)\cdot\begin{pmatrix} z_{\text{ore},j} \\ z_{\text{coal},j} \\ \tau_{jr} \end{pmatrix}\right] = 0, \tag{8}$$

where $\widehat{\tilde{\xi}}_{jr}(\alpha,\beta)$ is obtained by equating the observed market shares from our data with those implied by our model for a given parameter (α,β).

We provide a numerical algorithm for computing $\widehat{\tilde{\xi}}_{jr}(\alpha,\beta)$, which follows the standard fixed-point iteration approach in Berry (1994); Berry et al. (1995). [10] Specifically, for each parameter pair (α,β), we solve for the unobserved quality term ξ_{jr} by iterating on the contraction mapping:

$$\xi^{(t+1)} = \xi^{(t)} + \log s - \log s(\xi^{(t)};\alpha,\beta),$$

until convergence. Here, $s(\xi;\alpha,\beta)$ represents the model-implied firm-region market shares, which are computed by aggregating firm-level demand across locations: $Q_{jr} = \sum_{n\in\mathcal{N}_r} q_{jn}(p_j, p_{-j})$, and defining firm-region market shares as: $s_{jr}(\xi;\alpha,\beta) = \frac{Q_{jr}}{\sum_{rj'} Q_{j'r}}$. The fixed-point iteration ensures consistency between the observed and predicted market shares, and the estimated residual $\widehat{\tilde{\xi}}_{jr}(\alpha,\beta)$ is obtained by regressing the solved ξ_{jr} on firm- and region-fixed effects.

[10] Since all firms in our data operate within their capacity constraints and have constant marginal costs, the contraction mapping applies well using the observed shares. Miller and Osborne (2014) accommodates a nonlinear cost function and offers an efficient algorithm for solving the model for each combination of parameters and unobserved heterogeneity.

4.2 Recovering Marginal Costs

From the price competition model in Equation 4, the optimal pricing strategy for each firm $j \in \mathcal{J}_f$ satisfies the following first-order condition:[11]

$$Q_j + \sum_{j' \in \mathcal{J}_f} (P_{j'} - MC_{j'}) \frac{\partial Q_{j'}}{\partial P_j} = 0.$$

Collecting the first-order conditions across all J firms, we obtain the pricing system:

$$\mathbf{Q} - \Delta(\mathbf{P} - \mathbf{MC}) = \mathbf{0},$$

where $\mathbf{Q}$, $\mathbf{P}$, and $\mathbf{MC}$ are vectors representing firm output, firm price, and marginal cost, respectively. The $J \times J$ matrix Δ is defined as:

$$\Delta_{jk} = \begin{cases} -\frac{\partial Q_k}{\partial P_j}, & \text{if } k, j \in \mathbf{J}_f, \\ 0, & \text{otherwise.} \end{cases}$$

where the own-price and cross-price derivatives $\frac{\partial Q_k}{\partial P_j}$ is calculated as follows:

$$\frac{\partial Q_k}{\partial P_j} = \begin{cases} \sum_n \alpha \mu_n (1 - s_{kn}) s_{kn}, & \text{if } j = k, \\ -\sum_n \alpha \mu_n s_{kn} s_{jn}, & \text{if } j \neq k, \end{cases}$$

where s_{kn} and s_{jn} denote the predicted market shares of firms k and j in market n, derived from the demand system, and μ_n represents the market size of n, calibrated from the regional level input-output relationships.

In summary, we estimate marginal costs by inverting the first-order conditions:

$$\mathbf{MC} = \mathbf{P} - \Delta^{-1}\mathbf{Q}.$$

All terms on the right-hand side are either observed or estimated.

4.3 Production Function Estimation

Our production data, spanning 2009 to 2017, is at the firm level and includes input and output prices and quantities. To account for firm heterogeneity, we allow production function

[11] All firms in our 2017 sales data operate within their capacity constraints. This approach can be adapted to cases where some firms are constrained and price to capacity.

parameters to vary across firms. Taking the logarithm of the production function involving iron ore, $Q_j = \beta_{1j} M_{1j} \exp(\omega_j + e_j)$, yields the following expression: $\log Q_{jt} - \log M_{1jt} = \log \beta_{1j} + \omega_{jt} + e_{jt}$, where the time subscript is included.

In the first step, we classify firms into four size groups (averaged across years) and allow β_{1j} to vary by size group. We then estimate these coefficients using ordinary least squares:

$$\log Q_{jt} - \log M_{1jt} = \log \beta_{1\kappa(j)} + \omega_{jt} + e_{jt}, \tag{9}$$

where $\kappa(j) \in \{1, 2, 3, 4\}$ and the left-hand side represents the logarithm of the yield rate. We can estimate firm-level total factor productivity (TFP) as:

$$\widehat{\omega_{jt} + e_{jt}} = (\log Q_{jt} - \log M_{1jt}) - \log \widehat{\beta}_{1\kappa(j)}.$$

Additionally, we compute the engineering coefficients for coke and coal as:

$$\beta_{2jt} = \widehat{\beta_{1\kappa(j)}} \times \frac{M_{1jt}}{M_{2jt}}, \quad \beta_{3jt} = \widehat{\beta_{1\kappa(j)}} \times \frac{M_{1jt}}{M_{3jt}}.$$

using the optimality condition for the Leontief production function.

Having obtained these production function coefficients, we infer the unobserved component in the marginal cost, i.e., the unobserved input V from the cost function (6), using estimated marginal costs from the demand system and the production function parameters:

$$\underbrace{\frac{P_{vjt}}{\beta_{vjt}}}_{\substack{\text{unobserved component} \\ MC^u_{jt}}} = \underbrace{\exp(\widehat{\omega_{jt} + e_{jt}})\widehat{MC_{jt}}}_{\text{TFP-neutral marginal cost}} - \underbrace{\sum_{l=1}^{3} \frac{P_{ljt}}{\widehat{\beta}_{ljt}}}_{\substack{\text{observed input cost} \\ MC^o_{jt}}}. \tag{10}$$

We denote the observed and unobserved components of marginal cost as MC^o_{jt} and MC^u_{jt}, respectively. Consequently, the estimated marginal cost from firm's price optimization can be decomposed into observed input costs and unobserved cost factors.

Additional Extrapolation While our demand data includes 118 firms, production information is available for only 62. To address missing input price and quantity data, we construct proxies using firms with complete information. Specifically, we estimate proxy prices based on firms in the same region and size category. Additionally, we infer the unobserved cost component MC_V from firms within the same region-size group. Using these imputed values, along with the estimated marginal cost $\widehat{MC_{jt}}$ and technical coefficients $\widehat{\beta}_{ljt}$, we recover firm productivity estimates $\widehat{\omega_{jt} + e_{jt}}$.

5 Estimation Results

5.1 Demand Estimates

To examine the relevance of the input prices with the endogenous steel price, we present the results from the first stage regressions in Table 6. The findings indicate that both the iron ore and the coal prices are positively correlated with the steel price, and the coefficients are statistically significant. In Column (4), We further include the distance to the closest iron ore mine, seaport, and river port in the regression considering that the transport costs may also influence the steel price. However, Column (4) shows that these factors are not statistically significant. This insignificance is likely because the calculation of the input prices incorporates the transportation cost, thereby absorbing their potential influence on steel prices. As a result, we only include iron ore and coal prices as instruments for steel price in the demand estimation.

We estimate the demand model by leveraging the granularity of the sales data of 2017 and present the estimated coefficients in Table 7.[12] In addition to the results for the full model in Column (4), we also estimate a simple logit model that excludes buyer-seller distance and a demand model that does not account for endogeneity. Column (2) indicates a significant downward bias in the price coefficient (α) when buyer-seller distance is excluded from the model, leading to a biased price elasticity. Additionally, failing to address the endogeneity issue biases the price coefficient upward, as shown in Column (3). Therefore, the subsequent analysis will be based on the estimates in Column (4).

The estimated coefficients on price (α) and distance (β) have negative signs as expected. Economically, sourcing one ton of steel from a location 1,000 kilometers farther away incurs on average a highway transportation cost (including miscellaneous fees) of 500 CNY. The demand estimates suggest that the marginal value of a travel distance of 1,000 kilometers is equivalent to 2,408 CNY (-3.022/1.255*1000 CNY), more than fourfolds of the average transportation cost. This may reflect the loss of utility resulting from supply chain uncertainties related to long-distance sourcing, which could affect the timely use of steel in production. A home bias preference associated with local protectionism is another likely explanation. To investigate how the estimated model fits the data, we generate firm-level market shares using the estimated model in each region and compare the generated moments with the data. Table A6 indicates that our model in general effectively captures the average market share in each regional market.

Using the estimated coefficients for the demand model, we calculate firms' own-price

[12] We only use the 2017 sales data for the estimation due to the lack of information on firms' regional sales in previous years.

elasticity both in the overall domestic markets and within each regional market as well.

Own- and cross-price elasticity The own-price elasticity of demand of firm j in all destination markets is defined as $\frac{\partial Q_j}{\partial p_j}\frac{p_j}{Q_j}$. From the model above, the own- and the cross-price elasticity of demand are characterized as follows:

$$\begin{aligned}\frac{\partial Q_j}{\partial p_j}\frac{p_j}{Q_j} &= \alpha p_j \frac{\sum_n \mu_n s_{jn}(1-s_{jn})}{\sum_n \mu_n s_{jn}}, \\ \frac{\partial Q_j}{\partial p_k}\frac{p_k}{Q_j} &= -\alpha p_k \frac{\sum_n \mu_n s_{jn} s_{kn}}{\sum_n \mu_n s_{jn}} \quad \text{if } k \neq j\end{aligned}$$

where s_{jn} and s_{kn} are the respective predicted market shares of firm j and k in market n.

Elasticity of distance The elasticity of distance of firm j in each destination market n is defined as $\frac{\partial Q_{jn}}{\partial \tau_{jn}}\frac{\tau_{jn}}{Q_{jn}}$. From the model above, the elasticity of distance is characterized as follows:

$$\frac{\partial Q_{jn}}{\partial \tau_{jn}}\frac{\tau_{jn}}{Q_{jn}} = \beta(1-s_{jn})\tau_{jn},$$

where τ_{jn} is the distance between firm j and the center of market n, measured in 1,000 kilometers.

We estimate an average price elasticity of -4.26 in the domestic steel market (see Table A7), which aligns with values reported in the existing literature. For comparison, the average own-price elasticity of cars by year ranges from -4.23 to -5.78 in Grieco et al. (2024), while Berry et al. (1995) estimate own-price elasticities for car models in 1990 between -3.09 and -6.76. Similarly, the firm-level elasticity of concrete varies from -2.84 to -3.75 across specifications in Miller and Osborne (2014).[13] Table 8 further emphasizes the role of geography in understanding steel demand. On average, firms face less elastic demand in their home markets, and price elasticity within each regional market generally increases with proximity to suppliers. Additionally, the elasticity of distance in Table 9 shows that demand is highly elastic in distance and becomes increasingly elastic as the seller-buyer distance grows. This result highlights the importance of the shipping distance in shaping the steel market demand.

[13] Li et al. (2025) report a lower elasticity of -1.83, estimating steel demand under a constant price elasticity specification without accounting for spatial heterogeneity in demand and strategic interactions among firms.

Table 6: Regressions of Steel Price on IVs

Variables	(1) steel price	(2) steel price	(3) steel price	(4) steel price
ore price	4.662***		2.447***	2.129***
	(0.522)		(0.594)	(0.802)
coal price		2.320***	1.673***	1.752***
		(0.222)	(0.265)	(0.345)
mine				4.60e-07
				(4.86e-07)
river				0.00634
				(0.140)
sea				0.0393
				(0.135)
Constant	0.525*	1.251***	0.423	0.475*
	(0.288)	(0.178)	(0.264)	(0.285)
Observations	204	204	204	204
R-squared	0.283	0.351	0.401	0.405

Notes: Mine, sea, and river represent the distances (in 1,000 kilometers) from a steel firm to the nearest iron ore mine, seaport, and river port, respectively. These data are based on the authors' calculations.

Table 7: Demand Estimates

Coefficients	(1) OLS-logit	(2) IV-logit	(3) OLS-logit	(4) IV-logit
α	-0.751***	-5.076***	-0.920***	-1.255***
	(0.243)	(1.088)	(0.092)	(0.064)
β			-2.546***	-3.022***
			(0.237)	(0.138)
Number of firms	118	118	118	118

Notes: Standard errors are reported in parentheses.

5.2 Production Function and TFP Estimates

Table 10 presents the estimation results for the production function (equation 9), based on firm-level input and output data from 2009 to 2017.[14] Firms in size category 1 serve as the reference group. These estimates allow us to recover the technical coefficients for iron ore (β_{1k}) across the four size groups, as well as firm-level TFP estimates (see Table A11). Since

[14]Firm size category follows the size quartiles presented in Table 5.

Table 8: Estimates of Own Price Elasticity by Region

	Destination Region					
Supply Region	North	Northeast	East	Central South	Northwest	Southwest
North	-4.07	-4.18	-4.11	-4.11	-4.15	-4.15
Northeast	-4.07	-3.83	-4.06	-4.06	-4.18	-4.18
East	-4.75	-4.79	-4.54	-4.66	-4.76	-4.70
Central South	-4.74	-4.85	-4.67	-4.53	-4.82	-4.66
Northwest	-4.77	-5.01	-5.00	-4.77	-4.28	-4.57
Southwest	-4.90	-4.61	-5.03	-4.59	-4.59	-4.44

Each cell entry represents the average own-price elasticity of firms from the row region selling in the column region. This value is calculated using the own-price elasticities of firms operating within each province of the respective region.

Table 9: Elasticity of Distance by Region

	Destination Region					
Supply Region	North	Northeast	East	Central South	Northwest	Southwest
North	-1.23	-3.03	-3.00	-4.26	-3.97	-5.01
Northeast	-2.54	-1.46	-4.04	-6.15	-6.04	-6.91
East	-2.51	-4.07	-1.54	-3.38	-5.40	-5.09
Central South	-3.07	-5.89	-2.46	-2.28	-4.41	-3.48
Northwest	-4.37	-7.80	-7.22	-5.93	-2.68	-4.04
Southwest	-5.71	-7.84	-4.50	-2.99	-3.84	-1.79

Each cell entry represents the average elasticity distance of firms from the row region selling in the column region. This value is calculated using the distance elasticities of firms operating within each province of the respective region.

we allow the technical coefficients for coke and coal to be firm-time specific to account for allocative errors in the Leontief optimality condition, these coefficients are computed using the estimates in Table 10. We then report the mean values of these coefficients for each firm size category in Table 11.

Table 10 shows that the coefficients for firm sizes 3 and 4 are significantly positive, with the coefficient for size 4 being larger than that for size 3. This suggests that larger firms benefit from a technical efficiency premium in the use of iron ore. The efficiency in coke use exhibits a consistent size premium, as indicated by the estimates associated with β_2 in Table 11. However, for both iron ore and coke efficiency, the size premium remains relatively small. In contrast, coal efficiency (β_3) follows a reversed pattern across firm sizes, suggesting that larger firms are more energy-intensive. Additionally, the recovered TFP

estimates show only slight dispersion, with firms at the 90th percentile being merely 7% more productive than those at the 10th percentile. Given that firm TFP in this Leontief production process primarily reflects how firms manage the use of raw materials, it likely overlooks other, potentially more significant, differences in firm efficiency.

Table 10: Production Function with Iron Ore (In Log)

	(1)
VARIABLES	$\log Q_{jt} - \log M_{1jt}$
$firmsize2$	0.00414
	(0.00408)
$firmsize3$	0.0152***
	(0.00409)
$firmsize4$	0.0256***
	(0.00410)
Constant	-0.539***
	(0.00289)
Observations	619
R-squared	0.072

Table 11: Input Coefficients by Firm Size Category

	Firm Size Category			
	1	2	3	4
β_1	0.583	0.585	0.592	0.598
β_2	2.526	2.666	2.655	2.789
β_3	7.619	7.297	7.138	6.890

5.3 Marginal Cost and Markup

After recovering the marginal cost at the firm level, we calculate Lerner's index $\frac{P-MC}{P}$ as a measure of firm markup. The average markup is 0.241 and ranges from 0.153 to 0.334 (see Table A12), illustrated by Figure 3. Our markup estimates align with values reported in the existing literature. For comparison, the median markup of cars by year ranges from 0.185 to 0.325 in Grieco et al. (2024), while Berry et al. (1995) estimate an average markup of 0.239 for car models in 1990. Miller and Weinberg (2016) estimate an average markup of

0.34 in the U.S. brewing industry.[15]

Following Equation 10, we calculate TFP-neutral marginal cost and further decompose it into an observed input cost (MC^o) attributed to the use of the three primary inputs - iron ore, coke, and coal - and an unobserved component (MC^u) due to the unobserved composite input and constraint. Table 12 presents the summary statistics of the decomposed marginal costs. The average firm marginal cost is 2,649.8 Chinese Yuan (CNY hereafter) or 366.10 USD. However, there is a noticeable variation, as firms at the 90th percentile incur 44% higher costs than those at the 10th percentile. In addition, the TFP-neutral marginal cost differs only slightly from the estimated marginal cost. While the observed input cost accounts for two-thirds of the total marginal cost, they explain only a small fraction of the differences in total marginal cost (see Table A13). In contrast, the unobserved component in marginal cost accounts for the majority of the variation in the estimated marginal cost; the standard deviations of the two stay at similar magnitudes.

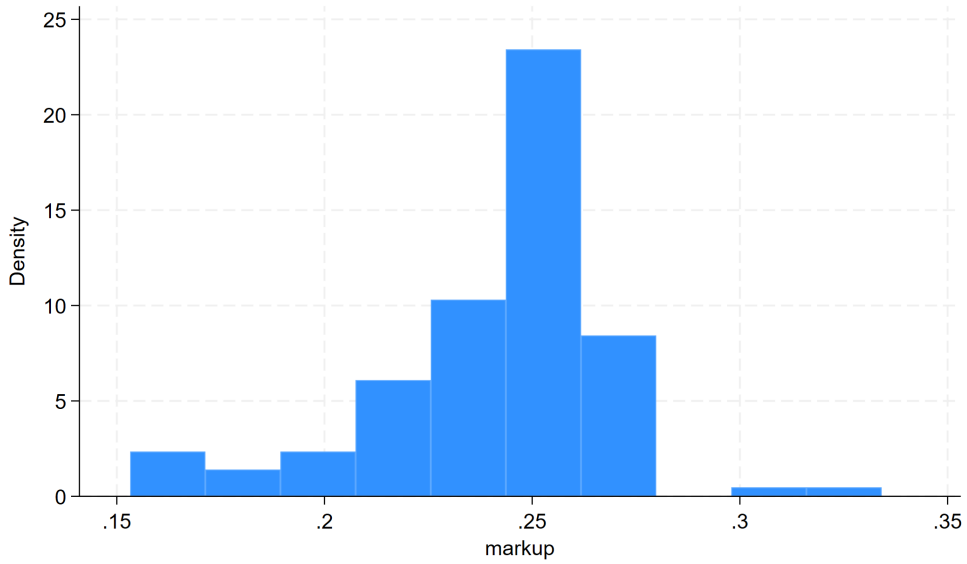
To explore the factors that drive the cost difference, we run regressions of the unobserved component in marginal cost on various firm characteristics and summarize the results in Table 13. Column (1) shows that the coefficient on product quality is positive and significant, with this factor alone explaining 20% of the variation in this unobserved component.[16] Scatter plots of MC^u against product quality in Figure 4 further illustrate the strong positive relationship between the two. In addition, Column (2) shows that larger firm size is associated with lower costs. This result remains robust after controlling for region and ownership fixed effects (Column (3)) and when replacing firm size category dummies with a more precise measure of firm size—firm capacity (Column (4)).[17] In particular, doubling firm capacity leads to a cost reduction of 229.2 CNY, holding other conditions constant, which corresponds to 8.6% of the average marginal cost. Furthermore, both Columns (3) and (4) suggest that private firms on average are more cost-efficient than their state-owned counterparts after controlling for firm size and location. Overall, product quality, ownership, firm size (or capacity), and region fixed effects combined explain 40-50$\%$ of the total variations in the unobserved component in marginal cost. The residuals from the above regressions associated with unobserved firm characteristics explain the remaining portion

[15] Our estimates also suggest an average price-cost margin (P/MC) of 1.32 in 2017 for the major Chinese steel firms, higher than the estimate in Brandt et al. (2017) that the price-cost margin in 2007 for broader coverage of firms in the smelting and processing of ferrous metals industry is 1.14.

[16] Product quality is the perceived valuation of the firm's product (ξ_j) from the demand estimation after teasing out the potential effect of the firm's proximity to the nearest river ports, seaports, and iron ore mines.

[17] To deal with potential measurement errors in the reported capacity data, firm capacity is calculated using the sales divided by the firm-level capacity utilization rate. For firms lacking information on capacity utilization, we use the average capacity utilization rate of the firms in the same size category and the same geographic location as a proxy.

Figure 3: Distribution of Firm Markups



of the cost variations and serve as a critical margin of firm efficiency, which we use in the subsequent merger analysis as the extent of cost savings depends on the transferability of firm-level heterogeneity.

Table 12: Summary Statistics of the Marginal Costs

	MC	TFP-neutral MC	MC^o	MC^u
mean	2649.8	2671.9	1802.4	869.5
Std Dev	471.2	483.1	111.7	466.6
p10	2253.1	2267.0	1713.4	527.6
p50	2485.8	2507.8	1791.8	718.6
p90	3245.0	3295.3	1948.7	1444.5

Notes: Observed input cost $MC^o = \sum_{j=1}^{3} P_{ji_kt}/\widehat{\beta}_{jk}$; TFP-neutral $MC = \exp(\widehat{\omega_{i_kt} + e_{i_kt}})\widehat{MC_{i_kt}}$; unobserved component MC^u = TFP-neutral $MC - MC^o$.

Table 13: Unobserved Component in Marginal Cost and Firm Characteristics

VARIABLES	(1) MC^u	(2) MC^u	(3) MC^u	(4) MC^u
product quality	136.4***	177.7***	170.7***	218.6***
	(24.93)	(28.48)	(27.08)	(28.10)
$firmsize2$		-155.2	-152.7	
		(101.5)	(93.73)	
$firmsize3$		-294.2**	-434.0***	
		(115.4)	(107.1)	
$firmsize4$		-391.0***	-518.7***	
		(134.7)	(126.7)	
private			-350.0***	-378.5***
			(127.0)	(121.4)
provincial			-86.23	-191.0
			(125.7)	(117.2)
age			0.342	0.819
			(1.838)	(1.756)
logcap				-229.2***
				(39.74)
Constant	766.5***	923.4***	1,468***	4,676***
	(42.82)	(75.53)	(160.3)	(596.2)
Observations	118	118	118	118
Adjusted R-squared	0.198	0.248	0.426	0.474
Region FE	NO	NO	YES	YES

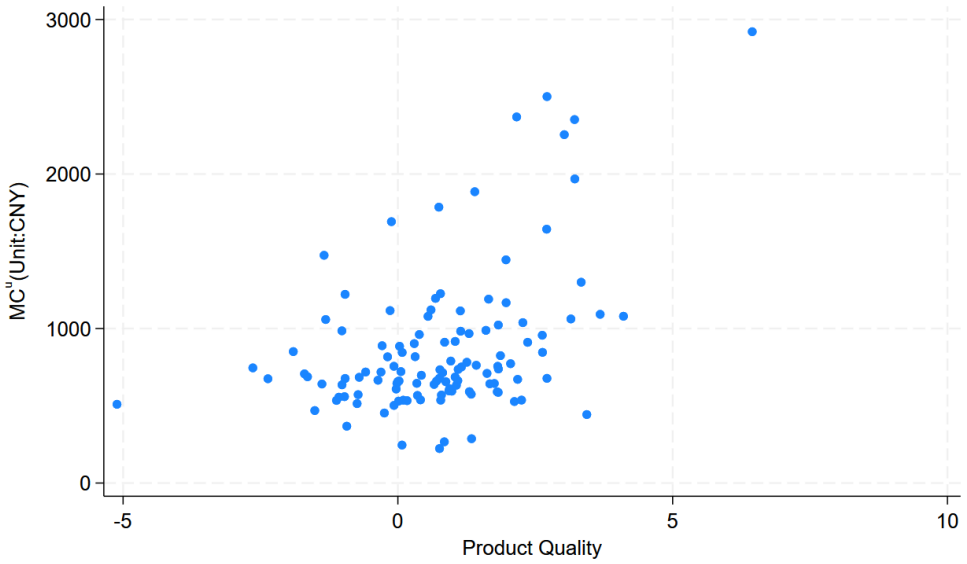
Notes: Firmsize2, firmsize3, and firmsize4 are firm size dummies. Private and provincial are ownership dummies for the private and the provincial state-owned firms respectively. Central SOEs are the reference group. logcap captures firm capacity in logarithm.

6 Counterfactual Analysis

6.1 Merger Analysis

The Chinese central government has long regarded mergers and acquisitions ($M\&A$) as a crucial policy tool for reducing excess capacity and enhancing industry performance. On September 19, 2016, the State Council issued a top-level strategic plan titled "Guiding Opinions on Promoting Mergers, Reorganizations, and Handling Zombie Enterprises in the Steel Industry," specifying that by 2025, approximately 60% to 70% of China's steel production would be concentrated within roughly ten major steel groups. The goal of increasing

Figure 4: Unobserved Component in MC and Product Quality



market concentration was repeatedly emphasized in several subsequent policy documents. Following the policy initiatives, a significant number of $M\&A$ events have taken place. Notably, from 2018 to 2024, these activities have reduced the number of steel groups in our sample from 87 to 64. This section aims to evaluate and compare the effects of mergers on firm markups, market equilibrium, and welfare across various counterfactual merger scenarios.

Our considerations are based on the following three criteria in relation to the three key frictions confronting the Chinese steel industry - local protectionism, ownership restriction, and scale bias. First, we consolidate firms both nationwide and within regional boundaries. Second, we consider mergers within and across ownership types, i.e., state-owned and private. Third, for each merger case, we select a leading firm either as the largest firm by size within the scope defined by criteria 1 and 2 or as the most efficient among the top three largest firms. Here, we define firm efficiency as the residuals in the regression of the unobserved component in marginal cost MC^u on the firm characteristics described in column (4) of Table 13. The combination of these three criteria yields eight merger scenarios, as illustrated in Table 14. Since we account for existing ownership structures, including cross-regional groups, whenever the identified regional leading firms belong to the same existing group, the newly merged regional firms are treated as a single cross-regional entity. This explains why regional mergers result in slightly fewer groups than the total number of regions.

For each counterfactual scenario, we examine the merger outcomes with and without

Table 14: Counterfactual Designs

Experiment	Leader	Scope	Ownership	# of Groups
1	Efficiency	Nationwide	Across	1
2	Size	Nationwide	Across	1
3	Efficiency	Nationwide	Within	2
4	Size	Nationwide	Within	2
5	Efficiency	Regional	Across	4
6	Size	Regional	Across	5
7	Efficiency	Regional	Within	10
8	Size	Regional	Within	10

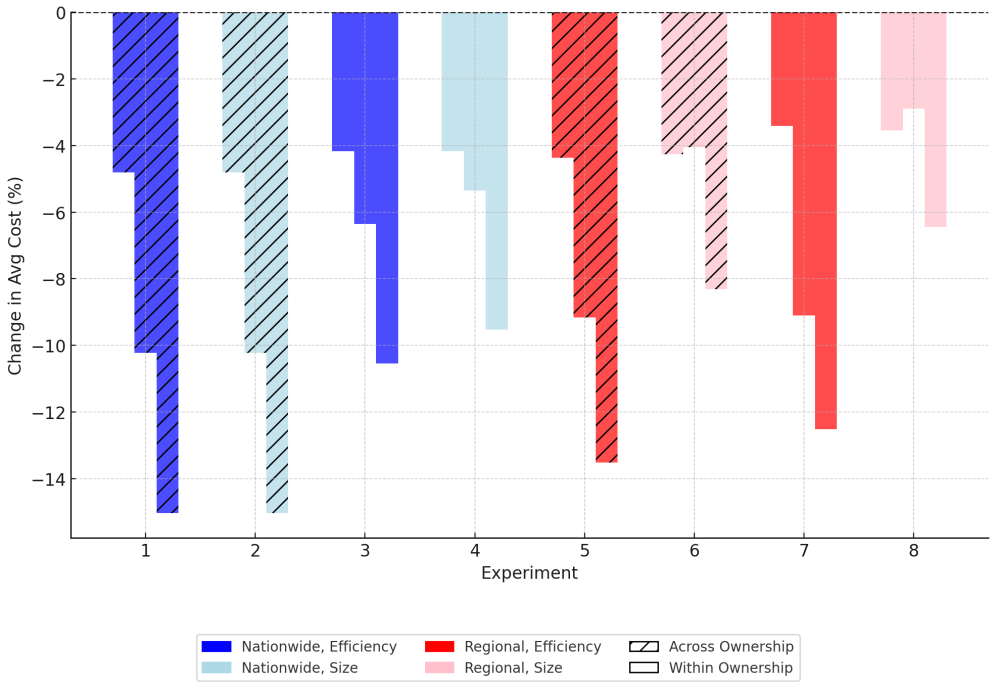
accounting for cost gains induced by mergers. Specifically, we consider two sources of cost gains: 1) Iron ore cost reduction. Firms are allowed to source iron ore at the lowest available price within their newly merged group. This lowest price is identified as the minimum unit cost paid by any firm within the same group, excluding transportation-related costs. We then recalculate each firm's marginal cost using the sum of this minimum price and its transportation-related costs.[18] 2) Efficiency improvement. Firms within each consolidated group are permitted an efficiency gain by adopting the efficiency level of their group's leading firm, defined above as the residual from the unobserved component in cost MC^u. Marginal costs for each firm are then recalculated using these newly assigned efficiency levels. This improvement can be attributed to the potential learning effects within the newly merged group and the transfer of advanced managerial knowledge from the leader firm to its subsidiaries after the merger. In the counterfactual analysis, we also consider the combined cost gains from the two sources mentioned above.

We report the percentage changes in the average marginal costs for the different counterfactual scenarios in Figure 5. Table A14 presents the corresponding marginal cost estimates, along with the average marginal cost under a scenario that accounts for actual M&A activities from 2018 to the present. Holding other dimensions constant, mergers directed by leader firms selected based on efficiency rather than size result, on average, in greater cost reductions (scenarios 3 vs. 4, 5 vs. 6, and 7 vs. 8). Additionally, removing ownership restrictions allows firms to achieve larger cost-efficiency improvements following mergers (scenarios 1 vs. 3, 2 vs. 4, 5 vs. 7, and 6 vs. 8). However, we observe differential effects when removing geographic boundaries. For instance, mergers occurring within regions and ownership types yield larger average cost reductions compared to mergers across geographic boundaries (scenario 3 vs. 7). This occurs because within-region mergers enable

[18] We regress the observed total unit cost paid by firms on their proximity to the nearest seaports, river ports, and iron ore mines, and subsequently collect the residuals and predicted values. This method decomposes the iron ore unit cost into transportation-unrelated and transportation-related components.

smaller yet more efficient private firms to lead the merged groups. Overall, firms experience the most significant cost improvements when both geographic and ownership restrictions are removed, as indicated by the first and second clusters in Figure 5. Specifically, when firms benefit from cost synergies stemming from both lower input prices and enhanced efficiency, average marginal costs decrease by approximately 15%. This is followed by within-region mergers across ownership types, with an average marginal cost reduction of 13.5%, and within-region mergers within ownership types, achieving a cost decrease of 12.5%.

Figure 5: Percentage Changes in the Average Marginal Costs



Notes: In each cluster, the 1st bar represents the percentage change associated with lower ore prices, the 2nd bar with lower efficiency, and the 3rd bar with both.

Since firms' capacity is fixed in the short run, those expanding production following mergers and subsequent cost adjustments may encounter binding capacity constraint.[19] Therefore, for each experiment described above, we incorporate the updated ownership and marginal cost structures into a Bertrand competition model with capacity constraints. Holding demand fixed, we then solve the model (4) to determine the new equilibrium prices and sales.[20]

[19]There is a small but growing literature that incorporates capacity constraints in demand estimation. For example, Ching et al. (2015) estimate demand under capacity constraints in the Wisconsin nursing home market in 1999 and assess the impact of relaxing these constraints. Similarly, Miller and Osborne (2014) model capacity constraints using a hockey-stick-shaped cost function that depends on capacity utilization following Ryan (2012).

[20]We present in Appendix B.2 the computational steps used to solve the model.

We present the simulation results in Table 15 corresponding to the counterfactual scenarios described above, without marginal cost adjustments and with cost adjustments due to iron ore cost reduction, and efficiency improvement combined with the iron ore cost reduction.

The percentage change in firm markups ranges from 10.9% to 43.5% across counterfactual scenarios without cost adjustments but with strengthened market power. When the entire industry is consolidated into a single group (excluding fringe firms), the average market price increases by 15.9%, while sales accounted for by the newly configured group decline by 28.4%. Nevertheless, total variable profits increase by 17.4%. The enhanced market power significantly reduces consumer surplus by 38%, more than offsetting the profit gain and resulting in a net welfare loss of 15.4%. If firms realize substantial cost-efficiency improvements following the merger, the average markup for the consolidated group can rise by as much as 61.4%. Variable profits increase further, and the efficiency gains reduce the loss in consumer surplus. These combined effects yield a net welfare gain of 16.7%.

Our simulation results suggest that a welfare gain can be achieved if firms experience sufficient post-merger cost efficiency improvements. The magnitude of this gain depends on the interplay between enhanced market power and efficiency gains. The most prominent welfare improvement among our designed experiments occurs when mergers take place within regions and ownership types and, in particular, are guided by the most efficient leader firms (experiment 7). A modest increase in market power and a strong cost reduction of 12.5% lead to a markup increase of 26.7%, which coincides with a price reduction of 4% and a sales expansion of 8.6%. The 37.9% increase in variable profit and a consumer surplus gain of 14.4%—the highest consumer surplus gain among the designed counterfactual scenarios—jointly contribute to an overall welfare improvement of 24.1%. In addition, the CR10 reaches 61.1%, aligning with the policy goal.

Figure 6 presents scatter plots of consumer surplus and firm profits (in CNY). The color coding illustrates three possible merger outcomes: blue represents mergers that solely increase market power, red indicates mergers that also reduce iron ore prices, and green signifies mergers that lower both iron ore prices and unobserved components in marginal cost MC^u. For comparison, filled shapes correspond to the actual market structure by the end of 2024, while the star marks our 2017 data. Notably, experiments 1 and 2 yield identical outcomes because the largest Chinese steel firm is also the most efficient among the top firms by size. A few notable patterns emerge from this figure. First, when market power effects dominate, there is a negative monotonic relationship between firm profits and consumer surplus. However, nonmonotonicities appear if firms achieve substantial cost reductions through lower iron ore prices and improved efficiency (green). Second, experiments 3

and 5 highlight the trade-off between allowing nationwide mergers versus cross-ownership mergers. Although experiment 5 focuses solely on regional mergers, cross-ownership mergers can generate gains in both consumer surplus and firm profits. On one hand, regional mergers limit the growth of market power, thus imposing fewer harms on consumers. On the other hand, some private firms thrive under regional mergers because, despite their efficiency, they only rank among the top firms locally. Finally, experiments 4 and 6 show the opposite outcome when the leading firm is determined primarily by its size.

Table 15: Merger Simulation Results

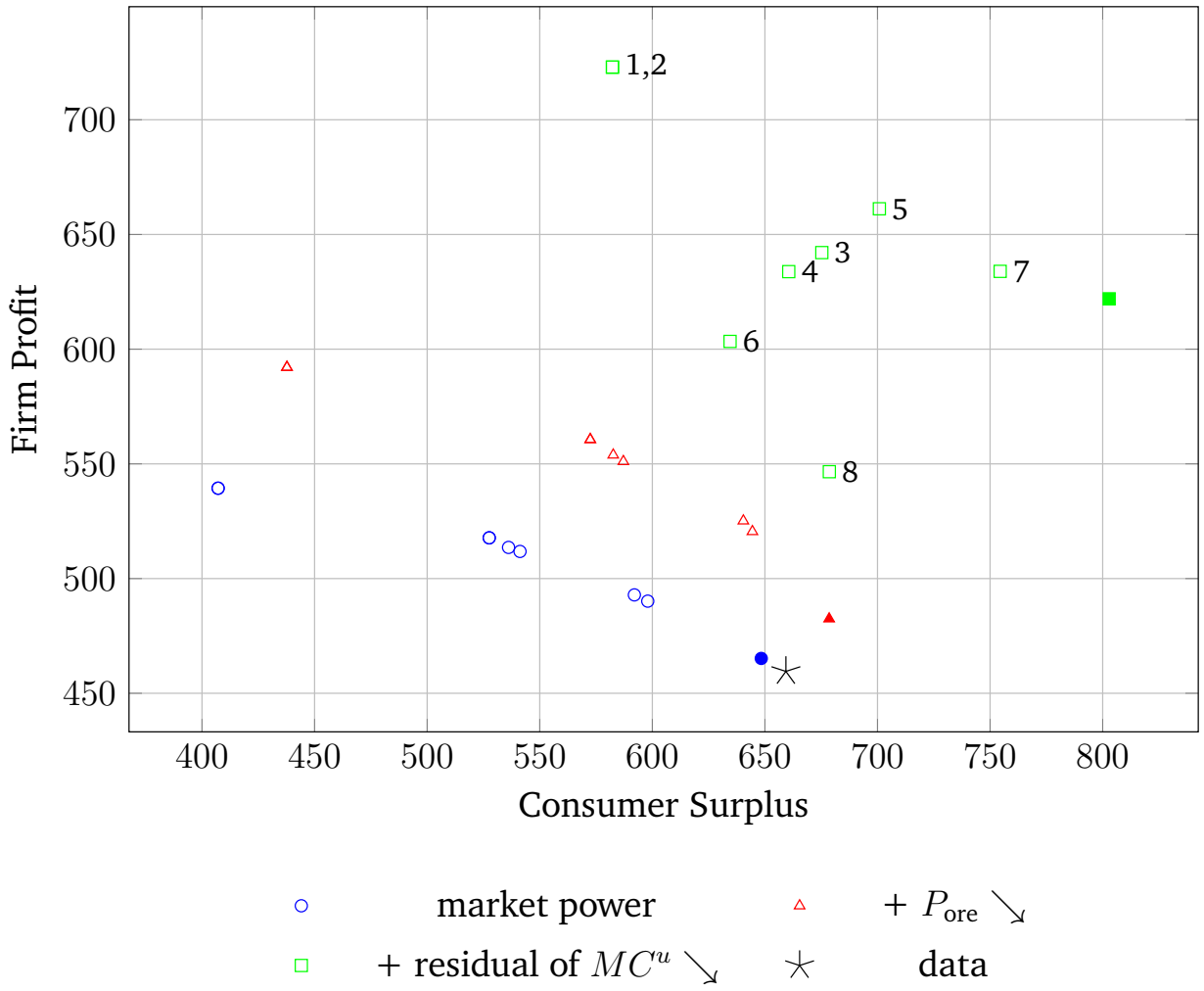
Experiment	Effects	Δ MC	Δ Price	Δ Sales	Δ Markup	Δ Profit	Δ CS	Δ Welfare	CR10
1	Mp	0.0%	15.9%	-28.4%	43.5%	17.4%	-38.2%	-15.4%	40.3%
1	MpPo	-4.8%	13.8%	-24.4%	52.0%	28.8%	-33.6%	-8.0%	42.5%
1	MpPoMc	-15.0%	5.6%	-7.6%	61.4%	57.3%	-11.7%	16.7%	52.0%
2	Mp	0.0%	15.9%	-28.4%	43.5%	17.4%	-38.2%	-15.4%	40.3%
2	MpPo	-4.8%	13.8%	-24.4%	52.0%	28.8%	-33.6%	-8.0%	42.5%
2	MpPoMc	-15.0%	5.6%	-7.6%	61.4%	57.3%	-11.7%	16.7%	52.0%
3	Mp	0.0%	7.3%	-13.7%	21.5%	12.7%	-20.0%	-6.6%	48.6%
3	MpPo	-4.2%	4.7%	-8.7%	26.9%	22.0%	-13.2%	1.3%	51.4%
3	MpPoMc	-10.5%	0.1%	1.6%	32.8%	39.7%	2.4%	17.7%	57.1%
4	Mp	0.0%	7.3%	-13.7%	21.5%	12.7%	-20.0%	-6.6%	48.6%
4	MpPo	-4.2%	4.7%	-8.7%	26.9%	22.0%	-13.2%	1.3%	51.4%
4	MpPoMc	-9.5%	0.8%	0.2%	31.4%	37.9%	0.2%	15.7%	56.4%
5	Mp	0.0%	7.8%	-12.9%	22.9%	11.8%	-18.7%	-6.2%	49.0%
5	MpPo	-4.4%	5.1%	-7.8%	28.8%	20.5%	-11.6%	1.6%	51.9%
5	MpPoMc	-13.5%	-1.0%	3.8%	39.2%	43.9%	6.3%	21.7%	58.4%
6	Mp	0.0%	7.4%	-12.3%	21.9%	11.4%	-17.9%	-5.9%	49.3%
6	MpPo	-4.3%	4.8%	-7.3%	27.6%	19.9%	-10.9%	1.7%	52.1%
6	MpPoMc	-8.3%	2.1%	-2.6%	31.7%	31.3%	-3.8%	10.6%	54.8%
7	Mp	0.0%	3.5%	-6.1%	10.9%	6.7%	-9.3%	-2.7%	52.8%
7	MpPo	-3.4%	1.2%	-1.5%	14.5%	13.3%	-2.3%	4.1%	55.4%
7	MpPoMc	-12.5%	-4.0%	8.6%	26.7%	37.9%	14.4%	24.1%	61.1%
8	Mp	0.0%	3.7%	-6.8%	11.4%	7.3%	-10.2%	-3.0%	52.4%
8	MpPo	-3.6%	1.3%	-1.9%	15.2%	14.3%	-2.9%	4.2%	55.2%
8	MpPoMc	-6.4%	-0.8%	1.7%	17.8%	18.9%	2.9%	9.5%	57.2%
Actual	Mp	0.0%	0.4%	-1.0%	1.2%	1.2%	-1.6%	-0.5%	33.8%
Actual	MpPo	-1.6%	-0.8%	1.9%	2.8%	5.0%	2.9%	3.8%	36.0%
Actual	MpPoMc	-9.7%	-5.0%	12.5%	16.1%	34.9%	21.8%	27.2%	44.4%

Notes: Mp corresponds to the scenario without marginal cost adjustment, MpPo with iron ore cost reduction, and MpPoMc with both the iron ore cost reduction and efficiency improvement.

6.2 Shifting Downstream Demand

The rapidly growing construction sector in China has made itself the most important domestic consumer of steel. Using the size of the floor space in completed buildings in 2017

Figure 6: Consumer Surplus vs. Firm Profits (Billion CNY)



and the estimates in Column (3) of Table A5, we find the construction sector accounted for 45% of the total steel consumption in the same year.[21] However, the slowdown of the real estate sector - in particular after the Pandemic - resulted in a shrinking demand for steel by the construction sector. For example, the size of the floor space in completed buildings declined by 8% nationwide in 2023 compared to 2017. However, the change rate varies significantly by province. To capture the resulting change in steel demand, we use the actual change in the size of the floor space in completed buildings in 2023 and the estimates in Column (3) of Table A5 to calculate the new demand for steel in the respective province. We feed the new demand into the previously estimated structural model and simulate the new equilibrium prices and sales at the firm level. We report the simulation results of the equilibrium prices and the sales in Table 16 and the domestic trade flows before and after the demand shock in Tables 17 and 18.

The demand shock affects the six geographic markets asymmetrically. The Northeast and Southwest experience the most significant declines in steel demand. However, in absolute terms, the East suffers the most severe decline, as it accounted for 42.5% of total domestic steel demand in 2017—the largest share, driven by its strong regional economic performance in China. In response to the negative demand shock, firms universally scale back production, yet prices remain stable, as shown in Table 16. Our results indicate that trade flow patterns persist, as the shares of firm sales to each destination region remain stable. In the Southwest, where firms sell more than 90% of their steel within the region, the 10.5% downstream decline is almost fully passed through to local steel firms. A similar pattern is observed in the East. However, in other regions, the decline in steel demand does not fully translate into a proportional reduction in production. Instead, firms in the North, Central South, and Northwest experience an asymmetrically greater loss in sales than the rate of downstream decline in their home markets. Additionally, spatial demand variation can mitigate the slowdown effect on local firms. For instance, while the Northeast faces a 9.21% decline in demand, Northeast firms see only a 5.95% reduction in sales, as more than 60% of their sales occur in other regions.

7 Conclusion

This paper examines market power in the Chinese steel industry by incorporating the geographic distribution of producers and spatial variations in downstream demand into a structural demand and supply framework. Using detailed industry data, we estimate key

[21] This figure likely underestimates the share of steel consumption attributed to the construction sector due to the steel used in buildings currently under construction and new projects initiated during the year.

Table 16: Effects of Shifting Demand from the Construction Sector

	Demand (million tons)			Average Price (CNY)			Average Firm Sales (million tons)		
Region	2017	Simulation	Change	2017	Simulation	Change	2017	Simulation	Change
N	210.60	212.72	1.01%	3274.70	3274.84	0.00%	3.74	3.68	-1.61%
NE	45.91	41.68	-9.21%	3248.8	3247.93	-0.028%	6.23	5.86	-5.95%
E	413.00	393.73	-4.67%	3657.78	3657.91	0.00%	6.08	5.81	-4.42%
CS	180.81	180.52	-0.16%	3663.88	3663.76	0.00%	4.41	4.36	-1.07%
NW	38.59	38.34	-0.63%	3682.53	3684.37	0.050%	4.31	4.18	-3.14%
SW	83.87	75.07	-10.50%	3686.08	3684.46	-0.044%	3.86	3.45	-10.60%

Table 17: Domestic Steel Trade Flows (2017)

	Destination Region						
Supply Region	North	Northeast	East	Central South	Northwest	Southwest	All
N	57.9%	1.8%	25.6%	9.2%	3.0%	2.4%	18.8%
NE	9.4%	41.7%	34.4%	13.6%	0.5%	0.4%	5.1%
E	2.1%	0.8%	84.1%	10.6%	0.4%	2.0%	18.8%
CS	4.8%	0.5%	18.2%	68.4%	2.1%	6.0%	8.2%
NW	3.3%	0.2%	3.9%	5.2%	62.7%	24.7%	2.2%
SW	0.6%	0.0%	2.2%	3.1%	0.6%	93.5%	3.2%
Other	21.4%	4.7%	42.2%	19.2%	3.9%	8.6%	43.7%
All	21.6%	4.7%	42.5%	18.6%	4.0%	8.6%	100.0%

[1] The figure in each cell of the region-to-region matrix represents the percentage of steel from the sample firms in each region or from firm 0 (row) sold to each destination region (column).
[2] The last row presents the shares of total steel demand contributed by each region.
[3] The last column presents the shares of steel provided by each region.

Table 18: Domestic Steel Flows (Simulation)

	Destination Region						
Supply Region	North	Northeast	East	Central South	Northwest	Southwest	All
N	59.6%	1.6%	25.3%	8.2%	3.1%	2.2%	19.1%
NE	10.2%	39.9%	35.7%	13.3%	0.5%	0.4%	5.0%
E	2.3%	0.8%	83.9%	10.7%	0.4%	1.9%	18.5%
CS	4.9%	0.4%	17.4%	69.8%	2.1%	5.4%	8.3%
NW	3.4%	0.2%	3.9%	5.0%	64.3%	23.3%	2.2%
SW	0.7%	0.0%	2.3%	3.5%	0.6%	92.9%	2.9%
Other	22.2%	4.4%	41.1%	20.3%	4.0%	8.0%	43.9%
All	22.6%	4.4%	41.8%	19.2%	4.1%	8.0%	100.0%

[1] The figure in each cell of the region-to-region matrix represents the percentage of steel from the sample firms in each region or from firm 0 (row) sold to each destination region (column).
[2] The last row presents the shares of total steel demand contributed by each region.
[3] The last column presents the shares of steel provided by each region.

economic parameters and assess how the spatial distribution of market power influences market outcomes. Our counterfactual analyses highlight the impact of shifting downstream demand and evaluate potential mergers under different market frictions.

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Online Appendix to "The Geography of Market Power: Evidence from the Chinese Steel Industry"

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A Additional Figures and Tables

A.1 Sample Coverage

Column (1) of Table A1 presents the percentage of steel supply from the sample firms located in each region; Column (2) presents the percentage of total steel supply from each region using the data on total steel output at the provincial level. Column (3) presents the share of the total omitted supply contributed by each region, while Column (4) presents the share of the total omitted demand contributed by each region. The North and the East account for the largest shares of the missing supply. While the omitted supply and demand are close to being balanced in most regions, the omitted firms in the North appear to be the net provider of steel, in particular to the exporting market. The comparison between the shares in missing supply and demand suggests that the omitted firms from our sample mostly sell in their home regions, supporting our assumption that they are located close to demand. In addition, we rely on domestic market information for demand estimation. Therefore, using the sample data will not likely lead to important estimation bias.

Table A1: Regional share of steel supply: sample vs aggregate data

	(1)	(2)	(3)	(4)
	Sample supply	Aggregate supply	Missing supply	Missing demand
North	18.35%	33.90%	34.87%	19.5%
Northeast	5.60%	7.48%	4.20%	4.2%
East	18.62%	33.40%	33.14%	38.4%
Central South	7.79%	16.40%	19.29%	17.4%
Southwest	2.95%	5.27%	5.19%	7.9%
Northwest	2.08%	3.56%	3.33%	3.6%
Export				9.0%

A.2 Data description

Table A2 provides the location distribution of sample firms; Tables A3 and A4 provide a detailed breakdown of the average and maximal market shares across regional markets.

Table A2: Firm Distribution by Firm Location

Region	Province	Number of Firms
East	Anhui	2
East	Fujian	1
East	Jiangsu	13
East	Jiangxi	3
East	Shandong	8
East	Shanghai	1
East	Zhejiang	2
Central South	Guangdong	3
Central South	Guangxi	2
Central South	Henan	6
Central South	Hubei	3
Central South	Hunan	4
Central South	Yunnan	1
North	Hebei	34
North	Inner Mongolia	1
North	Shanxi	8
North	Tianjin	6
Northeast	Heilongjiang	1
Northeast	Jilin	1
Northeast	Liaoning	6
Northwest	Gansu	1
Northwest	Qinghai	1
Northwest	Shaanxi	2
Northwest	Sichuan	4
Northwest	Xinjiang	1
Southwest	Chongqing	1
Southwest	Guizhou	2
	Total	118

Table A3: Breakdown of the average market shares across regional markets

		Destination Region							
		N	NE	E	CS	SW	NW	Export	All domestic
Supply Region	N	1.03%	0.30%	0.28%	0.26%	0.21%	0.60%	0.67%	0.38%
	NE	0.28%	5.66%	0.52%	0.47%	0.06%	0.16%	1.68%	0.64%
	E	0.10%	0.19%	1.24%	0.46%	0.24%	0.11%	0.88%	0.63%
	CS	0.14%	0.10%	0.23%	1.67%	0.41%	0.43%	0.25%	0.45%
	SW	0.09%	0.01%	0.05%	0.27%	4.30%	0.23%	0.08%	0.40%
	NW	0.08%	0.03%	0.07%	0.16%	1.27%	7.01%	0.14%	0.44%

Each figure represents the average market share in each regional market (column), broken down by selling firms' geographic location (row).

Table A4: Breakdown of the maximal firm market share across regional markets

		Destination Region							
		N	NE	E	CS	SW	NW	Export	All domestic
Supply Region	N	3.42%	1.92%	1.43%	1.70%	1.18%	4.17%	2.14%	1.58%
	NE	1.12%	16.92%	1.82%	2.12%	0.11%	0.29%	6.61%	2.18%
	E	0.53%	2.03%	4.67%	2.60%	1.26%	0.74%	5.45%	2.28%
	CS	0.43%	0.22%	1.16%	6.87%	1.03%	1.86%	0.74%	1.50%
	SW	0.09%	0.02%	0.13%	0.53%	7.74%	0.46%	0.08%	0.85%
	NW	0.11%	0.06%	0.13%	0.33%	3.89%	13.42%	0.19%	0.93%

Each figure represents the maximal firm market share in each regional market (column), broken down by selling firms' geographic location (row).

A.3 Demand Estimation

We estimate equation 7 using provincial-level output data on the primary downstream industries for steel and present the estimation results in Table A5.[22] For market size calibration at the provincial level, we use the estimates from Column (3), as this model accounts for nearly all variations in regional steel use.

To investigate how the estimated model fits the data, we generate firm-level market shares using the estimated model across regions and compare the generated moments with the data. Table A6 shows that our model in general effectively captures the average market share in each regional market. In addition, we present in Table A7 the own-price elasticity at the firm level based on the demand estimates.

A.4 Production Function Estimation

Table A8 summarizes the firm-time specific technical coefficients for coke and coal. We then calculate the per-ton use of the three primary inputs (iron ore, coke, and coal) and present the results in Table A9. The estimates for coal indicate greater heterogeneity in the use of the energy input. The correlation analysis suggests that the use of the two raw materials is positively correlated, whereas they both exhibit a negative association with the energy input. Table A11 summarizes the TFP estimates based on the production function for iron ore, suggesting small variations.

[22] We compile provincial-level output data on the primary downstream industries for steel from 2005 to 2018, drawing from various issues of China's provincial steel yearbooks.

Table A5: Input - Output Coefficients for Steel Demand

VARIABLES	(1) steel	(2) steel	(3) steel
floor space	68.99***	68.14***	51.99***
	(12.52)	(14.48)	(9.775)
power	-0.310	-0.227	0.706**
	(0.221)	(0.243)	(0.344)
road	9.615	18.08	22.11
	(38.56)	(90.01)	(43.84)
rail	11.36***	18.63***	5.390**
	(4.280)	(5.956)	(2.643)
auto	3.762**	3.911*	2.565
	(1.888)	(2.272)	(1.872)
ship	2.465**	2.193	1.517*
	(1.197)	(1.452)	(0.789)
Observations	84	84	84
Adj R-squared	0.853	0.834	0.971
Year FE	NO	YES	YES
Region FE	NO	NO	YES

Notes: Steel is measured by tonnage, floor space is completed buildings measured by 1,000 square meters, road is newly constructed highways in kilometers, rail is newly constructed operating length in meters, auto is units of cars, ship is newly completed total tonnage of ships, power is power generation equipment measured by kilowatt.

Table A6: Average Market Share in Each Regional Markets: Model vs Data

	Data	Model
	Mean	Mean
East	0.57%	0.57%
Central South	0.60%	0.60%
North	0.61%	0.61%
Northeast	0.90%	0.90%
Northwest	0.93%	0.93%
Southwest	0.76%	0.76%

Table A7: Estimates of Own Price Elasticity of Demand

	(1)
mean	-4.26
p10	-5.03
p50	-4.07
p90	-3.80

Table A8: Distribution of the Technical Coefficients on Coke and Coal

	β_2	β_3
Mean	2.659	7.237
Std Dev	0.243	1.331
P10	2.346	5.988
P90	2.962	9.026

Table A9: Per-Ton Use of Inputs by Firm Size Category

	Firm Size Category			
	1	2	3	4
$1/\beta_1$	1.715	1.708	1.689	1.672
$1/\beta_2$	0.401	0.378	0.378	0.361
$1/\beta_3$	0.137	0.142	0.142	0.147

For coke and coal, we report the mean values of the reciprocal of the coefficients for each firm size category.

Table A10: Correlation between the technical coefficients (β) on different Leontief inputs

	Ore	Coke	Coal
Ore	1		
Coke	0.339	1	
Coal	-0.190	-0.577	1

Table A11: Dispersion of TFP

	Std Dev	90:10 ratio
Firm TFP	0.035	1.072

Note: The TFP estimates are calculated using the estimated production function for iron ore.

Table A12: Total marginal cost and firm markup

Variable	Obs	Mean	Std. dev.	Min	Max
Markup	118	0.241	0.0283	0.153	0.334

Table A13: Marginal Costs

	(1)	(2)
VARIABLES	MC	TFP-neutral MC
MC^o	1.174***	1.127***
	(0.376)	(0.388)
Constant	533.2	641.4
	(679.3)	(699.9)
Observations	118	118
R-squared	0.077	0.068

Notes: Observed input cost $MC^o = \sum_{l=1}^{3} P_{ljt}/\widehat{\beta}_{ljt}$; TFP-neutral $MC = \exp(\widehat{\omega_{jt} + e_{jt}})\widehat{MC_{jt}}$.

A.5 Merger Analysis

We report the average marginal costs for the different counterfactual scenarios in Table A14, which also reports the average marginal cost corresponding to the scenario that incorporates the actual mergers occurring between 2018 and the present day.

Table A14: Average Marginal Costs After the Mergers

Experiment	w/o adjustment	Lower ore cost	Higher efficiency	Both
1	2649.8	2522.4	2378.9	2251.6
2	2649.8	2522.4	2378.9	2251.6
3	2649.8	2539.2	2481.2	2370.6
4	2649.8	2539.2	2508.1	2397.5
5	2649.8	2534.1	2407.0	2291.6
6	2649.8	2537.0	2542.4	2429.7
7	2649.8	2559.3	2408.5	2318.0
8	2649.8	2555.6	2573.1	2478.9
Actual	2649.8	2607.1	2435.6	2393.0

B Technical Appendix

B.1 Standard Errors of the GMM Estimator

Following Cameron and Trivedi (2005)[23], the estimated asymptotic variance-covariance matrix of the GMM estimator is given by

$$\widehat{V}_{GMM} = \frac{1}{\sum_r J_r}(\widehat{G}'W\widehat{G})^{-1}\widehat{G}'W\widehat{S}W\widehat{G}(\widehat{G}'W\widehat{G})^{-1},$$

where J_r represents the number of active firms in each regional market r, and $\sum_r J_r$ the total sample size, i.e. the total number of firm-region observations.[24] The sample analogue of the moment conditions is $\frac{1}{\sum_r J_r} Z'\xi$.

$$\begin{aligned}\widehat{G}|_{\theta=\widehat{\theta}} &= \frac{1}{\sum_r J_r} Z' \frac{\partial \xi}{\partial \theta'}|_{\theta=\widehat{\theta}} \\ &= \frac{1}{\sum_r J_r} \begin{pmatrix} z_{11,1} & z_{21,1} & \cdots & z_{jr,1} & \cdots \\ z_{11,2} & z_{21,2} & \cdots & z_{jr,2} & \cdots \\ z_{11,3} & z_{21,3} & \cdots & z_{jr,3} & \cdots \end{pmatrix} \begin{pmatrix} \frac{\partial \xi_{11}}{\partial \alpha} & \frac{\partial \xi_{11}}{\partial \beta} \\ \frac{\partial \xi_{21}}{\partial \alpha} & \frac{\partial \xi_{21}}{\partial \beta} \\ \vdots & \vdots \\ \frac{\partial \xi_{jr}}{\partial \alpha} & \frac{\partial \xi_{jr}}{\partial \beta} \\ \vdots & \vdots \end{pmatrix},\end{aligned}$$

where $\mathbf{z}_{jr}$ and ξ_{jr} denote the instruments and the residual of firm j selling in regional market r. Next, we consider how to derive $\frac{\partial \xi_{jr}}{\partial \alpha}$ and $\frac{\partial \xi_{jr}}{\partial \beta}$. According to the model, we can derive the market share at the firm-region level, as described in the model section, i.e., $s_{jr} = \frac{\sum_{n\in\mathcal{N}_r} \mu_n s_{jn}}{\sum_{n\in\mathcal{N}_r} \mu_n}$, where $s_{jn} = \frac{\exp(\alpha p_j + \beta \tau_{jn} + \xi_{jr(n)})}{1 + \sum_{j'=1}^{J_r} \exp(\alpha p_{j'} + \beta \tau_{j'n} + \xi_{j'r(n)})}$. By the implicit function theorem, we obtain the following derivatives:

[23] See page 175 for more details.

[24] Because our sales data is aggregated at the destination-region level by firm, we assume that the unobserved desirability of firm j's product is only firm-region-specific, denoted as $\xi_{jr(n)}$ or ξ_{jr} interchangeably. For the same reason, J_r captures the number of active firms in each province n within region r.

$$\frac{\partial \xi_{jr}}{\partial \alpha} = -\frac{\frac{\partial s_{jr}}{\partial \alpha}}{\frac{\partial s_{jr}}{\partial \xi_{jr}}},$$
$$\frac{\partial \xi_{jr}}{\partial \beta} = -\frac{\frac{\partial s_{jr}}{\partial \beta}}{\frac{\partial s_{jr}}{\partial \xi_{jr}}}.$$

From $s_{jr} = \frac{\sum_{n \in \mathcal{N}_r} \mu_n s_{jn}}{\sum_{n \in \mathcal{N}_r} \mu_n}$, we obtain the following derivatives:

$$\frac{\partial s_{jr}}{\partial \alpha} = \frac{\sum_{n \in \mathcal{N}_r} \mu_n \frac{\partial s_{jn}}{\partial \alpha}}{\sum_{n \in \mathcal{N}_r} \mu_n},$$
$$\frac{\partial s_{jr}}{\partial \beta} = \frac{\sum_{n \in \mathcal{N}_r} \mu_n \frac{\partial s_{jn}}{\partial \beta}}{\sum_{n \in \mathcal{N}_r} \mu_n},$$
$$\frac{\partial s_{jr}}{\partial \xi_{jr}} = \frac{\sum_{n \in \mathcal{N}_r} \mu_n \frac{\partial s_{jn}}{\partial \xi_{jr}}}{\sum_{n \in \mathcal{N}_r} \mu_n}.$$

Since $s_{jn} = \frac{\exp(\alpha p_j + \beta \tau_{jn} + \xi_{jr(n)})}{1 + \sum_{j'=1}^{J_r} \exp(\alpha p_{j'} + \beta \tau_{j'n} + \xi_{j'r(n)})}$ for $n \in \mathcal{N}_r$, we have

$$\begin{aligned}
\frac{\partial s_{jn}}{\partial \alpha} &= s_{jn} \left(p_j - \frac{\sum_{j'=1}^{J_r} p_{j'} \exp(\delta_{j'n})}{1 + \sum_{j'=1}^{J_r} \exp(\delta_{j'n})} \right), \\
\frac{\partial s_{jn}}{\partial \beta} &= s_{jn} \left(\tau_{jn} - \frac{\sum_{j'=1}^{J_r} \tau_{j'n} \exp(\delta_{j'n})}{1 + \sum_{j'=1}^{J_r} \exp(\delta_{j'n})} \right), \\
\frac{\partial s_{jn}}{\partial \xi_{jn}} &= s_{jn} \left(1 - s_{jn} \right),
\end{aligned}$$

where $\delta_{jn} = \alpha p_j + \beta \tau_{jn} + \xi_{jr(n)}$ for $n \in \mathcal{N}_r$. And

$$\begin{aligned}
\widehat{S}|_{\theta=\widehat{\theta}} =& \frac{1}{\sum_r J_r} \sum_r \sum_{j=1}^{J_r} \begin{pmatrix} \xi_{jr} z_{jr,1} \\ \xi_{jr} z_{jr,2} \\ \xi_{jr} z_{jr,3} \end{pmatrix} \begin{pmatrix} \xi_{jr} z_{jr,1} & \xi_{jr} z_{jr,2} & \xi_{jr} z_{jr,3} \end{pmatrix} \\
=& \frac{1}{\sum_r J_r} \sum_r \sum_{j=1}^{J_r} (\mathbf{z}_{jr}' \xi_{jr})(\xi_{jr} \mathbf{z}_{jr})
\end{aligned}$$

B.2 Finding Bertrand Equilibrium with Potentially Binding Capacity Constraints

Denote the list of products with binding capacity constraints $\mathcal{J}_c$. For any product $j \in \mathcal{J}_c$, its price should satisfy "pricing to capacity," i.e., $Q_j(p_j, p_{-j}) = \overline{Q}_j$, where $\overline{Q}_j$ is the maximum level of production of the firm j. This is equivalent to $\overline{Q}_j = \sum_n \mu_n \frac{\exp(\alpha p_j + \beta \tau_{jn} + \xi_{jr})}{1 + \sum_{j'=1}^{J_r} \exp(\alpha p_{j'} + \beta \tau_{j'n} + \xi_{j'r})}$.

Thus, we can construct an updating rule

$$p_j = \frac{1}{\alpha}\left[\log \overline{Q}_j - \log \sum_n \mu_n \frac{\exp(\beta \tau_{jn} + \xi_{jr})}{1 + \sum_{j'} \exp(\alpha p_{j'} + \beta \tau_{j'n} + \xi_{j'r})}\right] \tag{A1}$$

For any product $j \notin \mathcal{J}_c$, its price should satisfy this FOC $Q_j + \sum_{j' \in \mathcal{J}_f \& j' \notin \mathcal{J}_c} (P_{j'} - MC_{j'}) \frac{\partial Q_{j'}}{\partial P_j} = 0$. Thus, we can construct an updating rule

$$\mathbf{P} = \mathbf{MC} + \Delta^{-1}\mathbf{Q} \tag{A2}$$

We use the following algorithm to find the Bertrand equilibrium with possible binding capacity constraints in counterfactual experiments.

1. initiate $\mathcal{J}_c = \emptyset$
   (a) initiate prices p
   (b) update prices using (A1) if $j \in \mathcal{J}_c$ and (A2) if $j \notin \mathcal{J}_c$
   (c) iterate till prices converge p^*
2. calculate sales and update the constraint set by adding to the old constraint set the most constrained firm:

$$\mathcal{J}_c^{(t+1)} = \mathcal{J}_c^{(t)} \cup \left\{ j^* \mid j^* = \arg\max_{\substack{j \notin \mathcal{J}_c^{(t)} \\ \text{UR}_j \geq 1}} \text{UR}_j \right\},$$

   where $\text{UR}_j = \frac{Q_j(p^*)}{\overline{Q}_j}$ denotes the utilization rate of plant j.
3. iterate until the constraint set $\mathcal{J}_c$ converges.