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

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Abstract

This paper studies how the geography of supply and demand shapes market power in China's steel industry. Using novel data, we estimate an equilibrium model that incorporates spatial demand variation and firm heterogeneity in location, product quality, production technology, and cost efficiency. We use the model to quantify how downstream demand shifts and alternative merger designs affect welfare under frictions central to industrial policy. Welfare effects depend critically on merger design: regionally bounded mergers led by efficient firms generate much larger gains than nationally coordinated consolidation centered on large incumbents. The 2018–2024 merger wave realized only a small share of potential gains.

Key Words: Spatial Differentiation, Capacity Misalignment, Market Power, Merger Analysis, Sales Aggregation
JEL Classification: G34, L13, L61, R12

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1 Introduction

Steel is a crucial input in a wide range of industries, including construction, automotive, and general manufacturing. China is the world's largest producer and consumer of steel, accounting for nearly half of global output. Despite its scale, the industry is characterized by intense competition and persistent inefficiencies.

A common measure of market power–the concentration ratio of the top firms–suggests that China's steel industry is far more fragmented than those of major producers such as the United States and Japan. However, steel is costly to transport and markets are largely regional, making simple concentration ratios a potentially misleading measure of market power. The regional mismatch between capacity and market demand in China further complicates interpretation. A quarter of China's steel production is concentrated in Hebei, a northern province surrounding Beijing, while a substantial share of downstream demand lies in the Yangtze River Delta, a coastal region in eastern China.

China's steel industry is currently undergoing a major restructuring, shaped by changes in economic policy and shifting regional demand. The current spatial configuration of capacity–largely the legacy of earlier investment booms and growth patterns–no longer aligns well with the evolving needs of downstream industries. Recognizing these problems, government policy documents repeatedly emphasize the urgency of restructuring and have promoted mergers and acquisitions (M&A) as a key policy instrument for improving industry performance. In 2016, the State Council issued a top-level strategic plan "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.[1]

Several frictions complicate the implementation of this strategy. First, most of M&A activity in China's steel industry in the past has been directed by the government and typically involved large firms acquiring smaller rivals, potentially introducing a scale bias favoring large incumbents over smaller but more efficient producers. Second, local protectionism shapes whether consolidation occurs primarily within regions or at the national level.[2] Provincial governments often prefer "regional" mergers that preserve local capacity rather than cross-regional consolidation that might relocate production and control. Third, ownership restrictions can limit the ability of private firms to acquire state-owned enterprises.

[1] 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, while also promoting cross-regional and cross-ownership consolidation to improve industry efficiency and global competitiveness.

[2] There is extensive literature discussing the presence of local protectionism in China; see, for example, Bai, Du, Tao, and Tong (2004), Barwick, Cao, and Li (2021), Fang, Li, and Wu (2024).

Understanding the trade-offs created by these frictions is central to designing an effective policy. Yet we still know very little about how these frictions jointly affect market structure, costs, and welfare in China's industry.

This paper addresses this gap by developing a structural equilibrium model that combines firm heterogeneity—capturing differences in quality and cost efficiency—with the geographic distribution of supply and demand. This framework allows us to evaluate market power, quantify the efficiency consequences of different consolidation patterns, and assess the welfare implications of alternative policy regimes that govern mergers. We can also use this framework to evaluate the M&A that, in fact, occurred after 2017.

Our empirical model embeds rich firm heterogeneity and the spatial distribution of steel producers in a setting with market-specific downstream demand. On the demand side, downstream users–such as automobiles and appliance manufacturers and construction firms–choose among suppliers in a standard logit framework, where choices are driven by product quality, price, and transportation costs. Our strategy exploits the structure of the model and the granularity of the regional sales data to recover demand parameters and implied markups. 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, steel conglomerates (enteprise groups) operate a portfolio of furnaces and sets prices posted in multiple markets. Each furnace employs a team of workers and produces steel using a Leontief technology that combines iron ore, coke, and coal. Using detailed data on input and output prices and quantities, we estimate production functions that capture firm heterogeneity along multiple dimensions, including input costs, output quality, input-specific efficiency, yield rates, and unobserved cost efficiency. We find that a substantial share of this heterogeneity is driven by unobserved cost efficiency, which is strongly correlated with product quality. Moreover, conditional on product quality and geographic location, private firms are systematically more cost-efficient than state-owned firms. This distinction is central to merger analysis, as the magnitude of cost savings depends on the degree to which firm-level heterogeneity is transferable between merging entities.

Using the estimated model, we conduct counterfactual exercises to evaluate the reorganization of the steel industry, a central priority of China's industrial policy. We also use the framework, which incorporates rich geographic heterogeneity in both supply and demand, to quantify how regional market outcomes respond to recurrent shifts in downstream demand—a pervasive feature of China's ongoing structural transformation. Because capacity constraints may bind, computing the Bertrand equilibrium is challenging, given the large number of products and the potential for multiple binding constraints. We address this chal-

lenge by proposing a novel nested algorithm that avoids directly solving a high-dimensional system of equations. In the outer loop, we update the set of products with binding capacity constraints; in the inner loop, we compute profit-maximizing prices by iterating on the pricing first-order conditions given the current set of binding and nonbinding constraints. The algorithm is fast and robust.

First, we examine a range of merger scenarios that differ in the identity of the leading firm—most efficient versus largest—and in the constraints imposed by geography and ownership. We account for three channels through which mergers affect market outcomes: increased market power, reductions in iron ore prices, and improvements in unobserved cost efficiency. Our simulations show that mergers led by firms selected on efficiency rather than size generate substantially larger average cost reductions. Relaxing ownership restrictions further amplifies these efficiency gains, with the greatest cost savings occurring when both ownership and geographic constraints are removed.

Interestingly, mergers restricted to occur within regions tend to deliver larger average cost reductions than cross-regional or purely within-ownership mergers. Regional mergers allow smaller, but more efficient firms to lead consolidation while limiting the expansion of large, less efficient incumbents. From a welfare perspective, mergers that significantly increase market power without corresponding efficiency improvements tend to reduce welfare. In contrast, more restrictive merger regimes—such as regional or within-ownership mergers—can curb excessive market power and support welfare gains when combined with efficiency-based selection of the acquiring firm.

Our most favorable scenario in terms of total welfare combines both regional and ownership restrictions with efficiency-based selection of merger leaders. In this case, a modest increase in market power, together with a 12.5% reduction in costs, leads to a 26.7% increase in markups, a 4% reduction in price, and an 8.6% increase in sales. These changes generate a 37.9% rise in variable profits and a 14.4% gain in consumer surplus—-the largest among our counterfactual scenarios—-yielding an overall welfare improvement of 24.1%. Moreover, the concentration ratio of the top 10 firms reaches 61.1%, in line with the official consolidation targets. Expanding slightly the set of regional firms that can lead efficiency-based M&A in our counterfactual exercises results in even greater welfare gains, especially through increases in consumer surplus.

Second, we use our model to analyze the welfare implications of the actual M&A activity that occurred in the steel industry between 2018 and 2024. During this period, a total of 21 mergers and acquisitions consolidated the 118 firms in our sample into 64 enterprise groups or conglomerates, down from 86 in 2017. How well did these realized M&As perform relative to the hypothetical mergers described in the previous exercise? Overall, the M&A

activity between 2018 and 2024 captured less than a quarter of the welfare improvement generated under our most favorable hypothetical scenario—cross-region, within-ownership consolidation—and resulted in only modest gains in concentration ratios relative to the increase under this hypothetical scenario.

Baowu Steel—the world's largest steel producer—played an important role in the consolidation of the industry between 2018 and 2024. Baowu is a central state-owned enterprise under the control of China's State Assets Supervisory Administration Commission of the State Council and has been at the center of recent government consolidation efforts in the industry. In the context of our model, we simulate the gains from Baowu's M&A activity and compare them to those we estimate from all realized M&As during the period. Next, we reallocate the same targets that were acquired by Baowu to the most efficient firm among the three largest regional firms by size. We also experiment with further restricting acquiring firms to be the most efficient among the three largest regional state-owned firms. We find that the M&A involving Baowu was the source of approximately 60% of the welfare gains from all M&As in the steel industry; moreover, it maximized the potential gains from these M&As relative to the two alternative scenarios when post-consolidation cost reductions are realized through input cost reductions or knowledge transfer.

Third, we examine how shifts in downstream demand propagate across geographic markets and reshape equilibrium outcomes, highlighting the role of shifting demand in the evaluation of industry reorganization. We focus on the construction sector, which accounted for 45% of total steel consumption in 2017. The slowdown in real-estate activity dating from 2020 has sharply reduced steel demand. To quantify the implications, we combine observed changes in completed floor space in 2023 with our model estimates to compare new steel demand by province. In total, predicted steel demand fell 3.6%. The resulting demand shock is highly uneven across regions: the northern region experiences a modest 1% increase in demand, while other areas face declines ranging from 0.16% to 10.50%. In response, firms cut output across the board, which stabilized prices. Importantly, demand changes affect regions asymmetrically. In the Southwest and East, where firms sell most of their output within the region, the downstream contraction is almost fully passed through to local steel producers. In contrast, in other regions the decline in steel demand does not translate proportionally into reduced production. Firms in the North, Central South, and Northwest experience disproportionately larger sales losses than the rate of downstream decline in their home markets. By comparison, although the Northeast faces a 9.21% decline in local demand, firms in that region experience only a 5.95% reduction in sales, reflecting the fact that most of their output is sold to other regions.

Although this exercise focuses on the construction sector, it illustrates a broader point:

evaluating supply-side reforms requires accounting for shifts in the spatial distribution of demand. As China's industrial structure evolves—for example, through the expansion of automobiles and robotics or the contraction of the real estate sector—downstream demand for steel reallocates across regions, often substantially. The effectiveness of supply-side reorganization therefore depends critically on how supply adjusts to these demand shifts. More generally, because supply-side reforms are a common policy instrument across industries in contemporary China, the incorporation of demand reallocation is central to their design and evaluation. Our results provide a disciplined framework for such analysis.

Related Literature Our work is related to several strands of empirical research. First, it contributes to the literature on the steel industry that has focused primarily on productivity measurement using production-function methods. For example, Collard-Wexler and De Loecker (2015) study the effects of minimill technologies on productivity in the US steel industry, while Brandt, Jiang, Luo, and Su (2022) study productivity differences by ownership types in the Chinese steel industry. See also, e.g., Zhang (2019) and Su and Zhang (2024). An exception is Li, Li, and Zhang (2025), who estimate both a representative consumer demand system and a production function, but abstract from spatial differentiation and strategic interactions among firms. Our paper also integrates the production approach with the demand approach (Berry, 1994; Berry, Levinsohn, and Pakes, 1995) to study market power within an equilibrium framework. We explicitly incorporate spatial variations in downstream demand, which depends on product quality, distance, and price, together with firm supply that varies along multiple dimensions. By explicitly modeling strategic interactions among geographically dispersed firms, we can analyze the effects of mergers and demand shifts in a setting that reflects the spatial realities of the steel market, enabling a more comprehensive analysis of mergers and providing guidance for industrial policy.

Second, this paper belongs to a growing empirical literature on spatial differentiation and market power. For example, McManus (2007) examine nonlinear pricing among spatially differentiated coffee shops, while Houde (2012) study competition in the gasoline market. Miller and Osborne (2014) study spatial differentiation and price discrimination in the U.S. cement industry. Coşar, Grieco, and Tintelnot (2015) study how borders and distance affect wind turbine installations in Denmark and Germany. Our paper is the first to investigate the geography of market power in the steel industry. Building on models of Bertrand competition with spatial differentiation, we explore how merger effects interact with a range of institutional and geographic frictions.

Third, this paper contributes to the research on the welfare effects of horizontal mergers. Classic studies such as Nevo (2000) on breakfast cereals, Berry and Jia (2010) on the

airline industry, Fan (2013) on newspapers, Collard-Wexler (2014) on the cement market, Igami and Uetake (2020) on the hard disk drive industry, and Elliott, Houngbonon, Ivaldi, and Scott (2024) on telecommunications have advanced our understandings of mergers across industries; see Asker and Nocke (2021) for an excellent survey of this literature. However, none of these analyses explicitly address how frictions to consolidation–such as scale biases, local protectionism, and ownership restrictions–shape market outcomes. To our knowledge, our paper is the first to examine these issues, offering new insights into one of the most consequential industrial policy arenas in the world's largest steel market. Moreover, by explicitly accounting for capacity constraints in our merger analysis, this paper connects to the empirical literature on capacity investment and its implications for market outcomes (see, e.g., Ryan (2012), Ching, Hayashi, and Wang (2015), Zahur (2025), and Miller, Osborne, Sheu, and Sileo (2025)).

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.

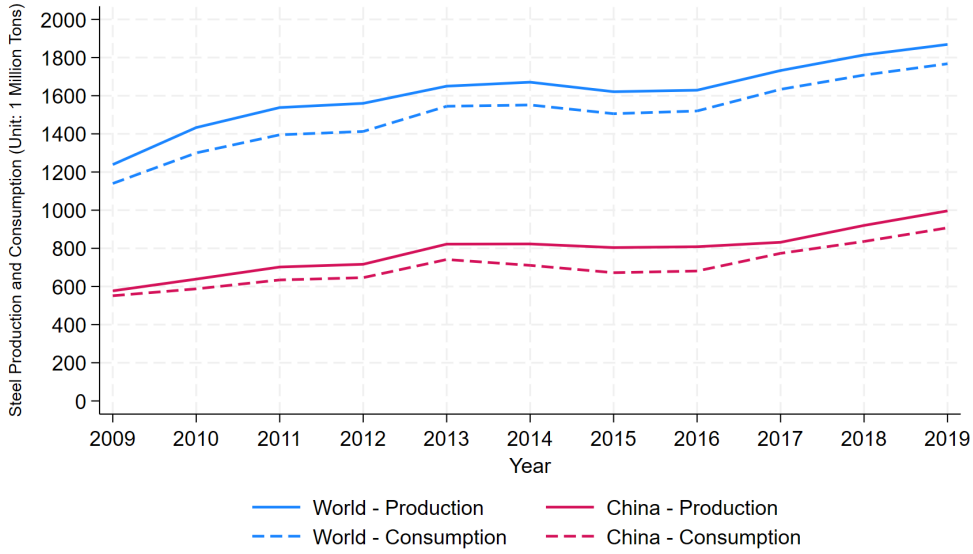
2 Background and Data

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), which benefit from well-developed sea and river ports, facilitating iron ore imports, and are located 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



Note: 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.

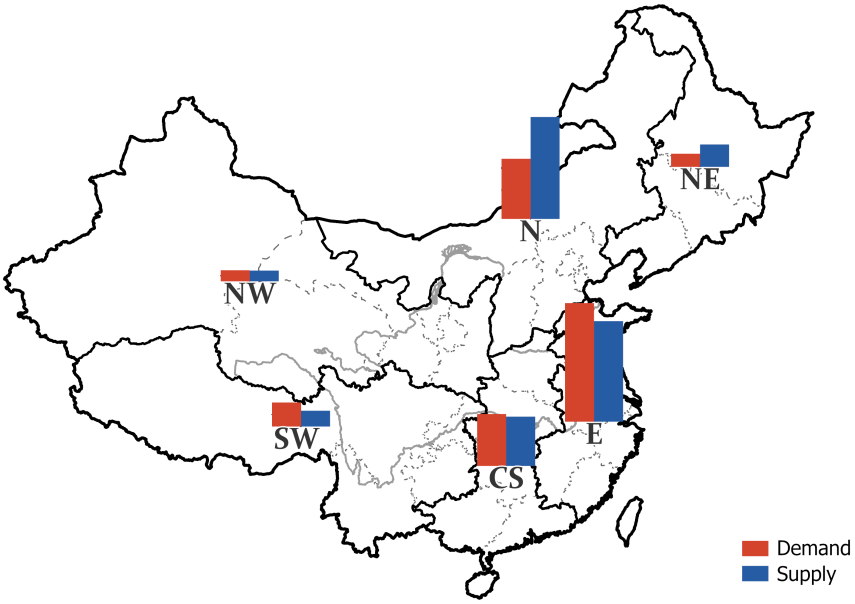
2.2 Data

Steel Sales Our primary data on steel sales are for 2017 and is sourced from a steel consulting service company in China, which compiles information from the Chinese Iron and Steel Association and collected through proprietary firm surveys. The dataset encompasses 86 major steel groups in China that operate 118 steel firms distributed in six geographic regions of China: North (N), Northeast (NE), East (E), Central South (CS), Southwest (SW) and Northwest (NW).[3] See Table A2 in the Appendix for the geographic distribution of the sample firms. Steel sales of these firms, measured in tonnage, represent 56.3% of total domestic sales in 2017, and their exports 44.2% of China's steel exports.[4] The sales data also provide a regional breakdown of sales of each firm. We observe steel flows from these 118 major steel firms to China's six geographic regions and the export market. Each geographic region encompasses several provinces, illustrated by Figure 2.

[3]An "enterprise group" in China is similar to a conglomerate, and typically consists of a parent company and subsidiaries under its control. Among the 86 steel groups, 74 operate a single steel firm, and the remaining 12 groups have a total of 44 firms under their control.

[4]We calculate total domestic sales using output of finished steel products minus export. Inventories are small compared to domestic sales and exports. 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 export figures. See more details on the sample coverage in Table A1.

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.

Steel Production We have detailed firm-level information from 2009 and 2017 on the prices and quantities of steel inputs and output. 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.[5] The input data include key material and energy inputs, number of workers, furnace size (capacity), and utilization rates. For iron ore, we have separate data on imported and domestic-sourced ore.

Steel trade flow Table 1 provides the breakdown of steel sales by firms in each region to each of the six regional markets plus exports. The last row and column of the table report each region's shares of domestic demand and supply. In general, the largest fraction of steel firms' sales are to their home markets with much smaller sales to more distant markets. The role of own-market sales varies significantly however. Firms in the Southwest supply almost

[5]The integration of the sales and the input-output datasets provides complete information for 62 firms, which account for 72% of total sales in the sales data. We develop a method in Section 4.3 to address the gap between the production and sales data.

exclusively in the home market (93.2%), while those in the Northeast sell only a third of their steel in their home region. Overall, cross-regional flows comprise a significant portion of steel sales, notably from the Northeast and the North to the other regions. While the North produces 33.9% of total steel output, the region only consumes 20.1%. In contrast, the most important steel consumer, the East, absorbs (39.4%) of the steel produced, but contributes only 33.4% of the output. Note also that China's steel output is consumed primarily in the domestic market, with exports accounting for 7.2% of total sales in 2017.

Market structure Table A3 reports the number of firms selling steel in each regional market, together with a breakdown by firm location. Regional markets are highly contested. Even in the smaller markets in the Northeast, Northwest, and Southwest—markets representing only 4.4%, 8.0%, and 3.7% of total final demand—there are 63, 74, and 61 firms selling steel, respectively. Table A3 further reveals that firms sell primarily in their home regions and are less likely to ship steel to distant markets. Consistent with these patterns, average firm market shares are low in all regions, however firms command significantly higher market shares in their home markets (see Table A4).

Table A5 summarizes the regional and national market shares of the four largest (CR4) and ten largest firms (CR10) based on firm-level and group-level sales, respectively. Based on group-level sales, for example, CR4 is only 16.61%, and CR10 is 27.36%. The concentration ratio in China is substantially lower than that in the 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 are notable regional disparities. The Northeast and Northwest exhibit the highest market concentration, and the East the lowest. This regional variation is also evident in Table A6, where the most dominant firm in the Northeast and Northwest holds 16.92% and 13.42% of the market share, respectively, compared to 4.67% in the East.

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) of the State Council. Firms that have been merged into central SOEs are also classified as central state-owned. Provincial SOEs fall under the direction of provincial or municipal SASACs. Table A7 indicates that SOEs account for 60% of the overall steel sales in the sample, of which the 13 central SOEs contribute approximately one-third

[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.

and the 39 provincial/municipal SOEs the other two-thirds. Private firms dominate in number, but only supply 40% of all steel.

Firm Size Firms vary significantly in size. Table A7 shows that firms at the 90th percentile sell twelve times more steel than those at the 10th percentile. The differences are slightly smaller within each ownership category. Table A8 reports the mean and standard deviation for each size quartile, with firms in the largest quartile on average nine times larger than those in the smallest.

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

		Destination Region							
		N	NE	E	CS	SW	NW	Export	All
Supply	N	55.1%	1.7%	24.4%	8.8%	2.3%	2.9%	4.8%	33.9%
	NE	8.0%	35.4%	29.2%	11.5%	0.3%	0.4%	15.1%	7.5%
	E	2.0%	0.8%	78.6%	9.9%	1.9%	0.3%	6.5%	33.4%
	CS	4.7%	0.5%	17.7%	66.5%	5.8%	2.0%	2.8%	16.4%
	SW	0.6%	0.0%	2.2%	3.1%	93.2%	0.6%	0.4%	5.3%
	NW	3.3%	0.2%	3.9%	5.2%	24.4%	62.1%	0.9%	3.6%
	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 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.

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 $n \in \{0, 1, 2, \ldots, N\}$, with $n = 0$ denoting the export market. 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.

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 (Berry,

1994; Berry et al., 1995). 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.

Since our data do not cover all 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, and 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 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:

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

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 in principle operating 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:

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

[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. In 2017, imports accounted for only 1.35% of domestic consumption.

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, Froeb, and Tschantz, 2017).[8]

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 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.[9] 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, i.e., steel output per unit of intermediate input.

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 nega-

[8] 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.

[9] These characteristics also preclude us from using the production function approach for markup estimation advocated by Hall (1986) and further developed by Loecker and Warzynski (2012).

tively 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 $r \in \{\text{N, NE, E, CS, SW, NW}\}$.

For estimation, we calibrate the market size μ_n using the output levels of downstream industries that are the primary consumers of steel. While the sales data are observed at the firm–destination–region level, the demand model is specified at the firm–province level. Accordingly, we aggregate model-implied firm-level demand across provinces within each region to align model predictions with the sales data:

$$Q_{jr} = \sum_{n \in \mathcal{N}_r} q_{jn}(p_j, p_{-j}). \tag{7}$$

By modeling demand at the province level and microfounding firm–region sales, the framework captures rich spatial variation in downstream demand across provinces while remaining consistent with the level of aggregation in the data.

Market Size Calibration We assume that downstream consumers purchase steel from either one of the sampled firms or the competitive fringe, so that total sales in each market equal the market size. However, we do not observe total sales in each individual province μ_n, and only observe regional sales, denoted $\mu_r = \sum_{n \in \mathcal{N}_r} \mu_n$. 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 the total output of major downstream industries.[10] The parameter γ_i captures steel

[10] In our estimation, we use total output data, measured in physical units, from building construction, railway and highway construction, power generation, car manufacturing, and shipbuilding, along with aggregate

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 may suffer from typical price endogeneity and the possibility that unobserved desirability $\xi_{jr(n)}$ and price p_j are correlated. A common approach is to use cost shifters as instruments for output price. However, the reported unit cost of imported iron ore and coal in our data includes transportation costs, which may still correlate with the firm-region unobserved desirability $\xi_{jr(n)}$.[11] To control for such correlations, we assume that the unobserved desirability of firm j's product can be decomposed as:

$$\xi_{jr(n)} = \xi_j + \xi_{r(n)} + \widetilde{\xi}_{jr(n)}, \tag{8}$$

regional sales data from 2005 to 2018. We report the estimation results in Table A9.

[11] Considering that variations in iron ore prices may also reflect differences in iron ore quality—which, in turn, affect output quality—we use the unit cost of imported iron ore as an instrument, as imported iron ores are generally more homogeneous and of higher quality than domestic ones.

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:

$$E\left[\widehat{\tilde{\xi}}_{jr}(\alpha,\beta)\cdot\begin{pmatrix} z_{\text{ore},j} \\ z_{\text{coal},j} \\ \tau_{jr} \end{pmatrix}\right] = 0, \tag{9}$$

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) and Berry et al. (1995).[12] 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.[13] Here, $s(\xi;\alpha,\beta)$ denotes the model-implied firm–region market shares. These shares are constructed by aggregating firm-level demand across locations as in (7), and are defined as

$$s_{jr}(\xi;\alpha,\beta) = \frac{Q_{jr}}{\sum_{j'} Q_{j'r}}.$$

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.

[12] 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.

[13] See Appendix B.1 for the proof of the contraction mapping.

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:[14]

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

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.

[14] 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.

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.[15] To account for firm heterogeneity, we allow production function 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 based on capacity and allow β_{1j} to vary by size group. We then estimate these coefficients using ordinary least squares:

$$\log Q_{jt} - \log M_{1jt} = \log \beta_{1\kappa(j)} + \omega_{jt} + e_{jt}, \tag{10}$$

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:

$$\underbrace{\frac{P_{vjt}}{\beta_{vjt}}}_{\substack{\text{unobserved component} \\ MC^u_{jt}}} = \underbrace{\exp(\widehat{\omega_{jt} + e_{jt}})\widehat{MC_{jt}}}_{\text{TFP-neutral marginal cost}} - \underbrace{\sum_{l=1}^{3} \frac{P_{ljt}}{\widehat{\beta}_{ljt}}}_{\substack{\text{observed input cost} \\ MC^o_{jt}}}. \tag{11}$$

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.

[15] We calculate the average iron ore price at the firm level by combining the costs of both imported and domestic iron ores.

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

We estimate the demand model using the granular sales data from 2017 and report the OLS estimates in column (3) of Table 2.[16] For comparison, we estimate a simplified logit specification that excludes buyer–seller distance and report the corresponding OLS results in column (1). As expected, the estimated price coefficients (α) in both specifications are negative. However, omitting buyer–seller distance leads to a downward bias in the estimated price coefficient.

To address potential endogeneity concerns, we re-estimate the model using input prices, i.e., iron ore and coal prices, as IVs for steel prices. Table 3 reports the first-stage results, showing that both input prices are positively and significantly correlated with steel prices. In column (4), we include distances to the nearest iron ore mine, seaport, and river port to account for price variation related to transport cost differences. None of the distance variables are statistically significant, likely because input prices already incorporate transportation costs and thus absorb their influence on steel prices. Consequently, we only use iron ore and coal prices as instruments for steel prices in demand estimation.

The IV estimation results are reported in columns (2) and (4) of Table 2. Comparing the two IV specifications reveals a larger downward bias in the price coefficient when the buyer–seller distance is excluded than in the corresponding OLS comparison, resulting in a more biased price elasticity. Consistent with the OLS results, the estimated coefficients on price (α) and distance (β) are both negative. Importantly, failing to address price endogeneity biases the price coefficient upward. For this reason, all subsequent analysis is based on the estimates reported in column (4).

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

[16] We restrict the estimation to 2017 because firm-level regional sales data are unavailable for earlier years.

CNY. 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 four times the average cost of highway transportation. 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 an alternative explanation.

To investigate how well 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 A10 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 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 A11), which aligns with values reported in the existing literature. For comparison, the firm-level elasticity of concrete varies from -2.84 to -3.75 across specifications in Miller and Osborne (2014).[17] For cars, the average own-price elasticity ranges from -4.23 to

[17] Li et al. (2025) report a lower elasticity of -1.83, estimating steel demand under a constant price elasticity

-5.78 in Grieco, Murry, and Yurukoglu (2024), while Berry et al. (1995) estimate own-price elasticities for car models in 1990 between -3.09 and -6.76. Table 4 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 distance to suppliers. Table 5 shows that demand is highly elastic in distance and becomes increasingly elastic as the seller-buyer distance grows. This result highlight the importance of shipping distance in shaping the steel market demand.

Table 2: Demand Estimates

	(1)	(2)	(3)	(4)
Coefficients	OLS-logit	IV-logit	OLS-logit	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 6 presents the estimation results for the production function (equation 10), based on firm-level input and output data from 2009 to 2017.[18] 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 A15). Since 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 6. We then report the mean values of these coefficients for each firm size category in Table 7.

Table 6 shows that the coefficients for firm sizes 3 and 4 are significantly positive, with the coefficient for size 4 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 7. However, for both iron ore and coke efficiency, the size premium remains relatively small. In contrast, coal efficiency (β_3) follows a reverse pattern across firm sizes, suggesting that larger firms are more energy-intensive. Additionally, the recovered TFP estimates show only

specification without accounting for spatial heterogeneity in demand and strategic interactions among firms.

[18] Firm size categories follow the size quartiles presented in Table A8.

Table 3: 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 4: 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

Notes: 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.

slight dispersion, with firms at the 90th percentile 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 5: 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

Notes: 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.

Table 6: 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

Notes: Firmsize2, firmsize3, and firmsize4 are firm size dummies.

Table 7: 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 the Lerner index $\frac{P-MC}{P}$ as a measure of firm markup. The average markup is 0.24 and ranges from 0.15 to 0.33 (see Table A16), illustrated by Figure 3. Our markup estimates align with values reported in the existing literature. For comparison, the implied Lerner index in the U.S. steel industry ranges from 0.17 to 0.29 over 1963–2002, based on the markup estimates for blast furnace producers reported in Collard-Wexler and De Loecker (2015). These values are remarkably consistent with our estimates (see also De Loecker, Eeckhout, and Unger (2020)). In addition, 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.[19]

Following Equation 11, 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 8 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 noticeable variation, with firms at the 90th percentile incurring 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 A17). 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 associated with the cost difference, we decompose the estimated unobserved component of marginal cost by regressing it on firm characteristics, the results from which are summarized in Table 9. 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.[20] 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

[19] 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, Van Biesebroeck, Wang, and Zhang (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.

[20] 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.

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)).[21] 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 capture the remaining cost variation and represent a key dimension of firm efficiency. These regressions serve as a decomposition exercise, allowing us to estimate cross-firm differences in costs and efficiency that may be transferable through M&A activity and are therefore central to the gains we quantify from mergers. While the effects of some controls, such as state ownership, firm size, and region, are arguably persistent and plausibly exogenous, concerns remain regarding the endogeneity of product quality. In particular, product quality may be correlated with firms' unobserved efficiency: firms with lower unobserved marginal costs may systematically produce higher-quality products. In the absence of a credible instrumental variable, we assess the potential implications of this bias through a robustness analysis reported in Appendix A.5, examining how sensitive the counterfactual market outcomes are to potential bias in the quality coefficient. We find that the resulting changes in key economic outcomes are modest in magnitude.

Table 8: 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 $MC - MC^o$.

[21] 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

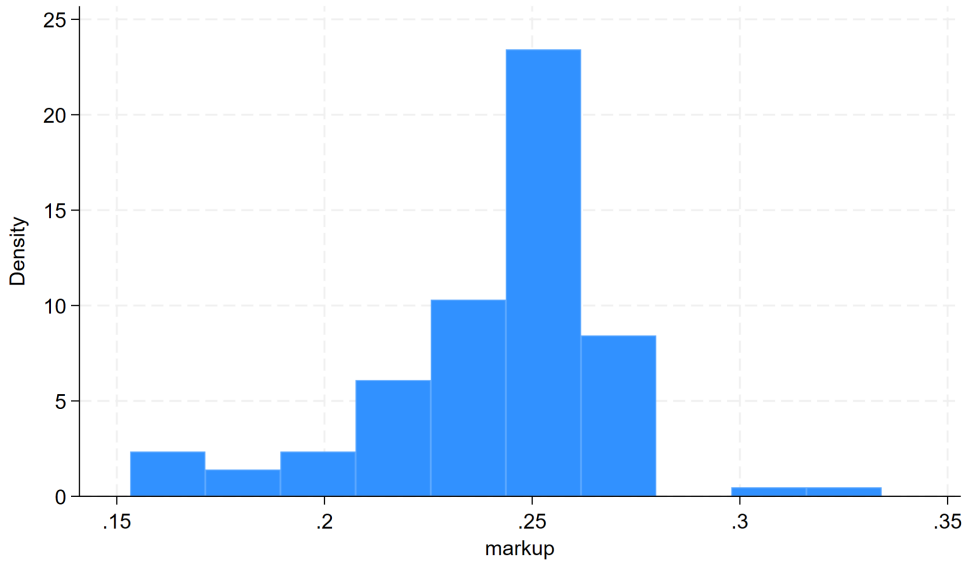
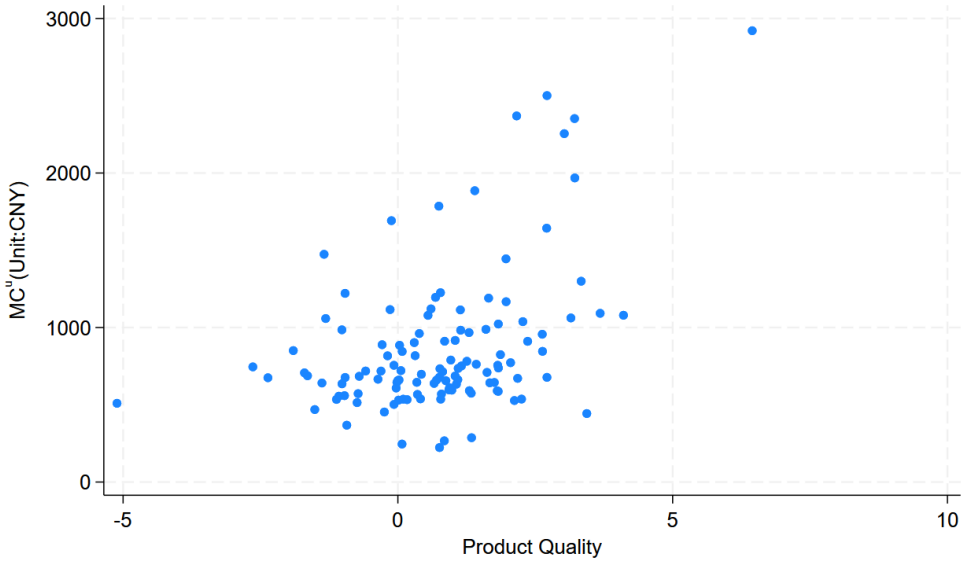


Figure 4: Unobserved Component in MC and Product Quality



6 Counterfactual Analysis

In this section, we use the estimated model to quantify the equilibrium consequences of consolidation and geographic demand shifts in China's steel industry. The Chinese central government has long viewed M&As as a key policy instrument for reducing excess capacity

Table 9: 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.

and improving 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 market concentration was repeatedly emphasized in several subsequent policy documents. Consistent with this agenda, a substantial wave of mergers between 2018 and 2024 reduced the number of steel groups in our sample from 86 to 64.[22]

[22]We identify 21 consolidation cases involving 27 acquired and merged firms. Most merger cases occur within both region and ownership (10 cases), while cross-region mergers within the same ownership group account for 5 cases. Cross-ownership mergers are relatively rare, with only 1 within-region case and 5 cross-

We first study a set of full consolidation counterfactuals under defined scopes that correspond to three key frictions in the Chinese steel industry: local protectionism, ownership restrictions, and scale bias. These exercises provide benchmark outcomes that clarify the trade-offs associated with each friction. Next, we examine the aggregate effect of the realized M&A activities over 2017-2024. In this context, we also simulate the effect of those mergers involving the world's largest steel producer, Baowu Steel, and compare it with two alternative designs that restrict mergers to within regions. We then turn to a separate set of counterfactuals that examine how regional demand and supply respond to shifts in demand across regions, further illustrating the geographic distribution of market power. More broadly, this exercise underscores the importance of accounting for shifting demand when evaluating industry reorganization.

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 model (4) to determine the new equilibrium prices and sales. Because firms' capacity is fixed in the short run, those expanding production following M&As and subsequent cost adjustments may encounter binding capacity constraints.[23] Appendix B.3 describes the computational steps used to solve the model.[24]

6.1 Full Consolidation Counterfactuals under Defined Scopes

In this section, we evaluate and compare the effects of mergers on firm markups, market equilibrium, and welfare across various counterfactual consolidation scenarios under defined scopes.

Counterfactual Designs Our first set of counterfactual experiments is based on hypothetical designs that follow 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

region cases. For consolidation cases carried out by cross-region enterprise groups, we define an M&A as cross-regional when the newly consolidated firms are located in regions distinct from that of the acquiring group's headquarters.

[23] 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).

[24] See Liu and Luo (2026) for a formal characterization of the Bertrand–Nash equilibrium in a multimarket, multiproduct oligopoly under capacity constraints.

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.[25] The combination of these three criteria yields eight merger scenarios, as illustrated in Table 10.[26]

Table 10: Counterfactual Designs

Experiment	Leader	Scope	Ownership
1	Efficiency	Nationwide	Cross
2	Size	Nationwide	Cross
3	Efficiency	Nationwide	Within
4	Size	Nationwide	Within
5	Efficiency	Regional	Cross
6	Size	Regional	Cross
7	Efficiency	Regional	Within
8	Size	Regional	Within

For each counterfactual scenario, we first examine outcomes driven solely by the enhanced pricing power resulting from the ownership change, and then consider two additional sources of cost gains. First, we allow for 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.[27] Second, we allow for efficiency improvement. 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 9.[28] Firms within each consolidated group are permitted an efficiency gain by adopting the efficiency level of their group's leading firm, defined above as

[25] We also experiment with selecting the most efficient firm among the top five largest firms, the results for which we report Table A20 in the Appendix.

[26] In the cross-ownership (within-ownership) and regional merger scenarios, the number of resulting regional firms is fewer than the maximum because the pre-existing ownership structures in the 2017 baseline already include cross-regional corporate groups. When regional leading firms involved in different mergers belong to the same corporate group, the corresponding merged entities are aggregated and treated as a single cross-regional firm. Thus, the regional mergers result in slightly fewer groups than the total number of regions, as shown in Table 11.

[27] 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. Alternatively, one can model the iron ore price as a function of total iron ore purchases, following Fan (2013). With more detailed data on iron ore transactions, a structural approach similar to Gowrisankaran, Nevo, and Town (2015) could be employed to estimate the bargaining game between steel firms and iron ore mines, enabling the prediction of post-merger input prices.

[28] Recall that we model and estimate substantial firm heterogeneity arising from differences in engineering parameters, productivity, and unobserved cost components. The engineering parameters and productivity

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.

Table 11: Simulation Results for the Full Consolidation Counterfactuals

Experiment	Effects	# of Groups	ΔMC	ΔPrice	ΔSales	ΔMarkup	ΔProfit	ΔCS	ΔWelfare	CR10
1	Mp	1	0.0%	15.9%	-28.4%	43.5%	17.4%	-38.2%	-15.4%	40.3%
1	MpPo	1	-4.8%	13.8%	-24.4%	52.0%	28.8%	-33.6%	-8.0%	42.5%
1	MpPoMc	1	-15.0%	5.6%	-7.6%	61.4%	57.3%	-11.7%	16.7%	52.0%
2	Mp	1	0.0%	15.9%	-28.4%	43.5%	17.4%	-38.2%	-15.4%	40.3%
2	MpPo	1	-4.8%	13.8%	-24.4%	52.0%	28.8%	-33.6%	-8.0%	42.5%
2	MpPoMc	1	-15.0%	5.6%	-7.6%	61.4%	57.3%	-11.7%	16.7%	52.0%
3	Mp	2	0.0%	7.3%	-13.7%	21.5%	12.7%	-20.0%	-6.6%	48.6%
3	MpPo	2	-4.2%	4.7%	-8.7%	26.9%	22.0%	-13.2%	1.3%	51.4%
3	MpPoMc	2	-10.5%	0.1%	1.6%	32.8%	39.7%	2.4%	17.7%	57.1%
4	Mp	2	0.0%	7.3%	-13.7%	21.5%	12.7%	-20.0%	-6.6%	48.6%
4	MpPo	2	-4.2%	4.7%	-8.7%	26.9%	22.0%	-13.2%	1.3%	51.4%
4	MpPoMc	2	-9.5%	0.8%	0.2%	31.4%	37.9%	0.2%	15.7%	56.4%
5	Mp	4	0.0%	7.8%	-12.9%	22.9%	11.8%	-18.7%	-6.2%	49.0%
5	MpPo	4	-4.4%	5.1%	-7.8%	28.8%	20.5%	-11.6%	1.6%	51.9%
5	MpPoMc	4	-13.5%	-1.0%	3.8%	39.2%	43.9%	6.3%	21.7%	58.4%
6	Mp	5	0.0%	7.4%	-12.3%	21.9%	11.4%	-17.9%	-5.9%	49.3%
6	MpPo	5	-4.3%	4.8%	-7.3%	27.6%	19.9%	-10.9%	1.7%	52.1%
6	MpPoMc	5	-8.3%	2.1%	-2.6%	31.7%	31.3%	-3.8%	10.6%	54.8%
7	Mp	10	0.0%	3.5%	-6.1%	10.9%	6.7%	-9.3%	-2.7%	52.8%
7	MpPo	10	-3.4%	1.2%	-1.5%	14.5%	13.3%	-2.3%	4.1%	55.4%
7	MpPoMc	10	-12.5%	-4.0%	8.6%	26.7%	37.9%	14.4%	24.1%	61.1%
8	Mp	10	0.0%	3.7%	-6.8%	11.4%	7.3%	-10.2%	-3.0%	52.4%
8	MpPo	10	-3.6%	1.3%	-1.9%	15.2%	14.3%	-2.9%	4.2%	55.2%
8	MpPoMc	10	-6.4%	-0.8%	1.7%	17.8%	18.9%	2.9%	9.5%	57.2%

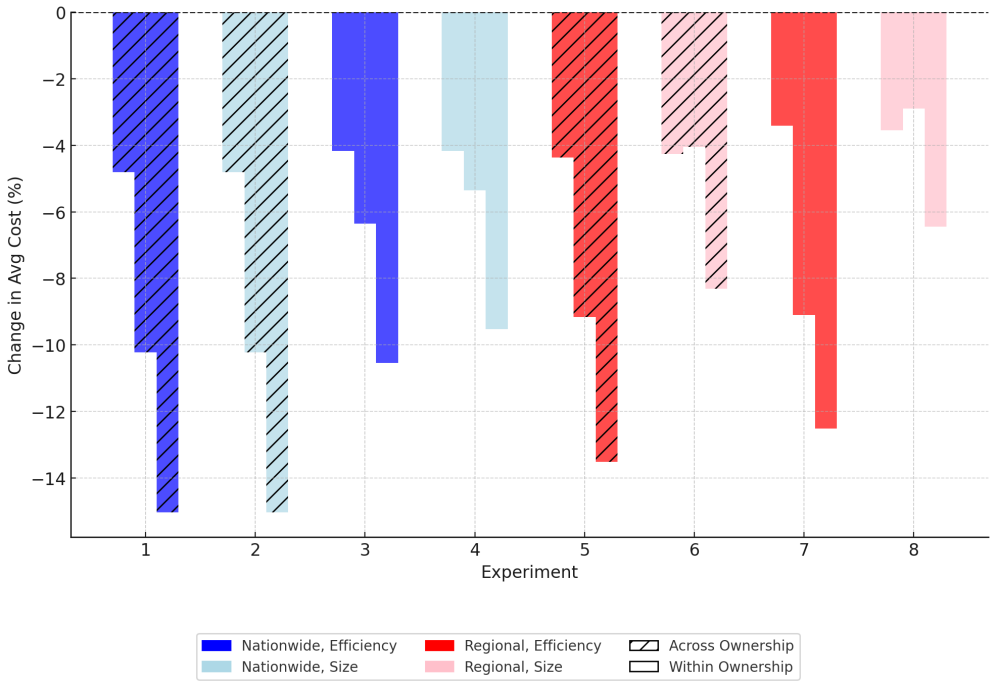
Notes: Mp corresponds to the scenario without marginal cost adjustment, MpPo with iron ore cost reduction, and MpPoMc with both the iron ore cost reduction and efficiency improvement.

Marginal Costs Table 11 reports the results of the counterfactual exercises, and Figure 5 reports the percentage changes in average marginal costs across the same set of counterfactual scenarios. 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

differences are largely determined by machine specifications and are therefore relatively fixed. In contrast, the unobserved component of marginal cost captures factors such as managerial efficiency, operational practices, and organizational know-how, which are more readily transferable across firms. This motivates us to reassign marginal cost residuals in alternative merger configurations.

vs. 4, 5 vs. 7, and 6 vs. 8). However, we do not observe the same when removing geographic boundaries. Rather, 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 smaller but 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.

Markup and Welfare 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

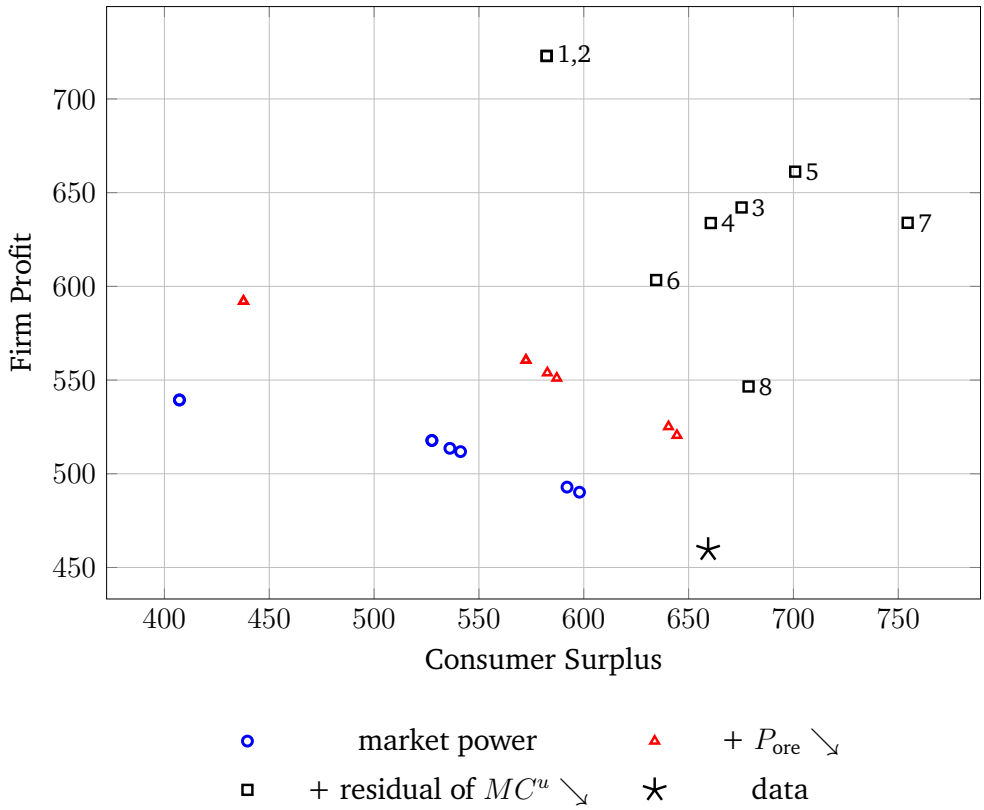
enhanced market power significantly reduces consumer surplus by 38%, more than offsetting the profit gain and resulting in a net welfare loss of 15.4%. Allowing for substantial cost-efficiency improvements following the merger, the average markup for the consolidated group can rise by as much as 61.4%. Variable profits increase further, with the efficiency gains compensating for the loss in consumer surplus. These combined effects yield a net welfare gain of 16.7% under experiment 1.

Our simulation results suggest that welfare gains 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 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%, coinciding 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. As illustrated by Table A20 in the Appendix, expanding the set of firms from which to select the most efficient increases welfare gains considerably, especially through increases in consumer surplus.

Consumer Surplus and Firm Profit 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 associated with the consolidated market structure, 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, 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.

Several 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, non-monotonicities 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 the one hand, regional mergers limit the growth of market power, thus imposing fewer costs on consumers. On the other

Figure 6: Consumer Surplus and Firm Profits



Notes: Consumer surplus and firm profits are reported in billion CNY. For the blue and red shapes, the first position represents Experiments 1 and 2, the second represents Experiments 3 and 4, and each subsequent position corresponds to a distinct experiment.

hand, some private firms thrive under regional mergers because they only rank among the top firms locally and not nationally. Finally, experiments 4 and 6 show the opposite outcome when the leading firm is determined primarily by its size.

Regional Winners and Losers The counterfactuals highlight significant differences in the distribution of welfare gains between producers and consumers depending on how M&A occurs. To examine how regional gains are apportioned, we next break down the welfare outcomes by region for experiments that feature the largest cost gains (nationwide merger experiment 1) and the highest welfare improvements (regional merger experiments 5 and 7). Counterfactuals 1, 5, and 7 examine efficiency-led mergers. Counterfactual 1 merges all firms nationwide across ownership types, while Counterfactuals 5 and 7 consider regional mergers across and within ownership types, respectively.

Figure 7 illustrates regional percentage changes in firm profits when post-merger cost gains are fully realized (MpPoMc). First, the nationwide merger experiment 1 has a substantial aggregate effect, raising national average firm profits by 57.3 percent. Profitability

increases significantly in all regions, with relatively modest regional differences emerging. Second, restricting mergers to within regions yields markedly smaller profit increases overall and wider regional heterogeneity. The smallest gains are in North and Northeast, and the largest in Northwest and Southwest. Recall that Northwest and Southwest are the most inland regions and are further from major demand centers; moreover, these two regions are largely self-sufficient in steel production, as shown in Table 1. Consequently, within-region mergers allow smaller but more efficient firms to emerge as leaders of the consolidated entities, disproportionately benefiting firms in Northwest and Southwest.

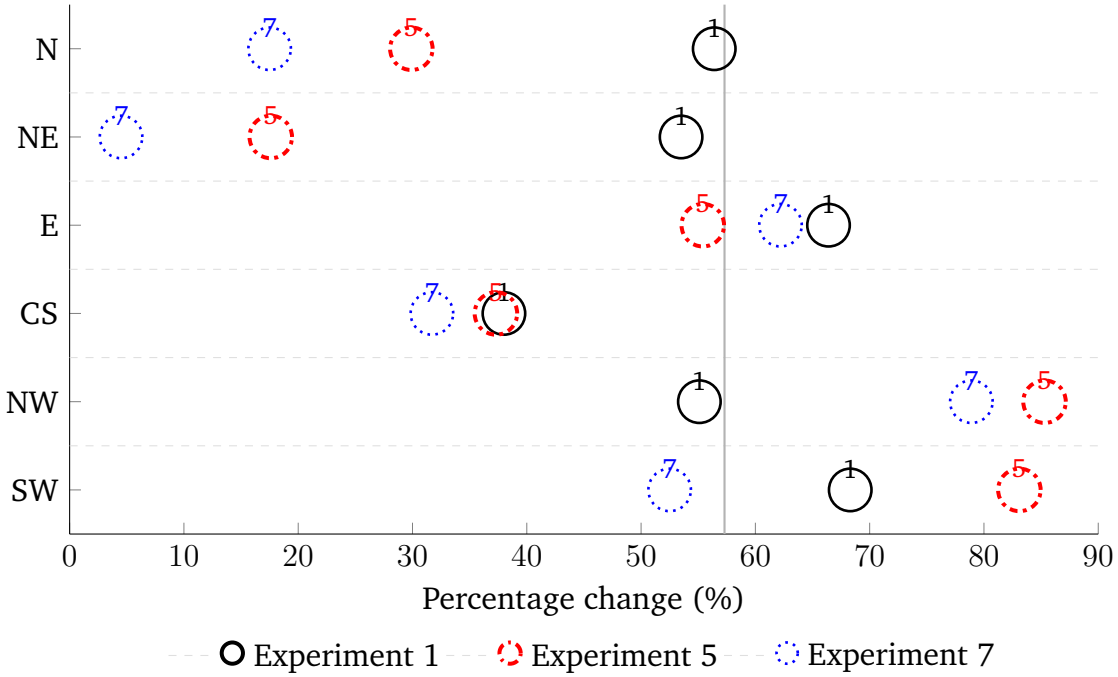
Table A19 reports detailed regional outcomes between experiments. When mergers occur across ownership types and across the country (i.e., Experiment 1) and post-merger cost gains are fully realized (i.e., MpPoMc), the Northeast experiences the highest welfare gain of 24.2%, followed by the North. These net steel-supplying regions benefit substantially from profit gains. In contrast, although profit gains are also pronounced in the East and the Southwest—the net steel-consuming regions—these gains are partly offset by consumer surplus losses, resulting in smaller welfare improvements than in the Northeast and the North. When regional mergers are considered (i.e., Experiments 5 and 7), regions such as the Northwest and Southwest, followed by the East, experience large welfare gains, driven by both strong profit growth and a reversal of consumer surplus losses. In contrast, Central South exhibits more moderate gains, while the North and Northeast show only limited welfare improvement.

6.2 Counterfactual Evaluation of Observed Consolidation

In the next set of experiments, we incorporate all M & A involving the sample firms that occurred between 2018 and 2024 in the 2017 ownership structure of the China steel industry, and examine the aggregate effects of these M & A on the industry. We consider two sources of cost gains that arise from consolidation. First, iron ore cost reduction: newly consolidated firms are allowed to source iron ore at the lowest available price within their newly formed group. Second, efficiency improvement: we allow knowledge to transfer from acquiring firms to acquired firms. Moreover, when the acquiring entity is a business group, we allow knowledge to transfer from the most efficient of the top three largest pre-existing subsidiaries within the group to the newly consolidated firms. The simulated market outcomes are reported in Table 12.

Markup and Welfare Consider the scenario in which post-merger cost efficiencies are fully realized (MpPoMc). On average, realized M&A activities reduce marginal costs by

Figure 7: Regional Winners and Losers across Merger Experiments



Notes: Circles indicate regional percentage changes in firm profit under MpPoMc. Numbers inside the circles identify the experiment: 1 (black), 5 (red), and 7 (blue). The vertical line denotes the national firm profit increase under Experiment 1 relative to the actual setting in Year 2017.

2.6% through input cost savings and efficiency improvements, a smaller gain than in the full-consolidation counterfactuals considered above. Markups rise by 5.5%, and the implied welfare gain is 5.3%, less than one-quarter of the welfare improvement generated under our most favorable hypothetical scenario—cross-region, within-ownership consolidation. Although concentration, as measured by CR10, rises from 27% to 36%, it remains well below the stated policy target of 60%.

Regional Winners and Losers The regional breakdown in Table A22 reveals pronounced heterogeneity in the effects of realized M&A activity. Welfare gains are largest in regions with the most significant consolidation: the Southwest experiences a welfare increase of 14.7%, followed by the Northeast and the East, with gains of 9.0% and 6.3%, respectively. These welfare improvements are attributed to important gains in profit and consumer surplus in these regions. In particular, profits rise by 32.3% for Southwest producers, and by about 12% in both the East and the Northeast. In contrast, the central south suffers a slight welfare loss of 0.1%, with the producers in the region experiencing a profit loss of 1.7%.

6.3 Consolidation Configurations of the Baowu Steel Group

In this section, we focus exclusively on the Baowu Group, a central state-owned enterprise under the supervision of China's State-owned Assets Supervision and Administration Commission of the State Council. Baowu is also the world's largest steel producer, accounting for roughly 13% of China's total crude steel production in 2024, with steelmaking capacity exceeding that of the entire United States.[29] Baowu maintains a broad geographic presence throughout China except in the Northeast region and was involved in five within-ownership consolidations over 2017-2024, including three within-region transactions and two cross-region transactions. These activities account for 38.6% of the newly consolidated capacity in our sample over the same period.

We consider three scenarios involving Baowu. First, to isolate the M&A effects attributable to Baowu, we incorporate into the 2017 benchmark ownership structure only those M&A cases led by Baowu between 2018 and 2024. Second, we construct an alternative consolidation scenario in which the most efficient firm among the top three largest regional firms acquires in each region the same targets that were taken over by Baowu between 2018 and 2024. Third, we modify this alternative scenario by restricting the acquiring entities to be the most efficient SOEs among the top three largest regional state-owned firms, thereby reflecting an alternative SOE-led consolidation process. In each scenario, we continue to allow for two sources of cost gains post-consolidation—iron ore cost reduction and efficiency improvement—as described in the previous section.

Markup and Welfare From Table 12, Baowu's consolidation activity generates a welfare gain of 3.5% when post-merger cost reductions are fully realized (MpPoMc), accounting for roughly 60% of the welfare gains from all M&As in the steel industry. This finding underscores Baowu's central role in the industry's consolidation process.

Comparing the effects of Baowu-led consolidation with the alternative regional designs, Table 12 indicates that welfare gains are highest under the actual Baowu M&A scenario when post-merger input cost reduction or knowledge transfer occurs. This reflects larger average cost reductions among newly acquired firms in the Baowu Group than in the alternative designs. By contrast, when no post-merger cost gains materialize, the regional merger designs yield smaller welfare losses, owing to lower concentration and associated market power. Overall, welfare differences between these scenarios remain modest.

Regional Winners and Losers The regional breakdown of the simulation results in Table A22 reveals more pronounced and asymmetric differences in regional outcomes across sce-

[29] The percentage is calculated based on data from the World Steel Association.

narios. Figure 8 illustrates regional percentage changes in firm profits when post-merger cost gains are fully realized (MpPoMc). Profit changes range from -1.2% in the Northwest and the Northeast to 27.3% in Southwest. Restricting mergers to within regions leads to markedly smaller profit gains in the East, but substantially larger gains in the Southwest. Notably, these two regions accounted for approximately 84% of the steel capacity Baowu newly consolidated during 2018 and 2024. As before, within-region consolidation enables smaller yet more efficient firms to emerge as leaders of the consolidated entities, disproportionately benefiting firms in the Southwest.

Table A22 reports additional results on consumer surplus and welfare across the three scenarios. The alternative regional M&A design generates higher welfare gains in the Southwest — by 2.1 percentage points relative to the actual Baowu scenario—but leads to welfare losses of approximately 4 percentage points in the East. This pattern arises because firms in the Southwest benefit from larger efficiency gains when learning from a more efficient regional leader than under the actual design, whereas firms in the East can only learn from a less efficient leader. Moreover, firms in these two regions are dominant market players locally; as a result, switching to regional mergers produces sizable welfare effects.

Table 12: Simulation Results for Actual and Baowu Consolidation

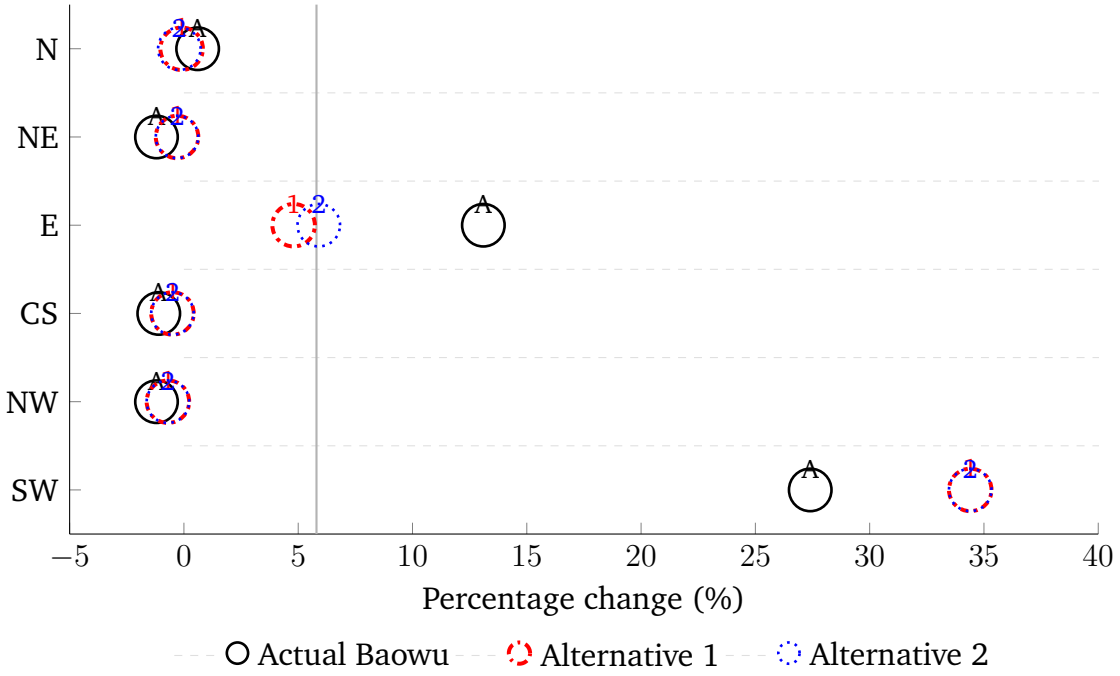
Experiment	Effects	ΔMC	ΔPrice	ΔSales	ΔMarkup	ΔProfit	ΔCS	ΔWelfare	CR10
Actual	Mp	0.0%	0.4%	-1.1%	1.3%	1.4%	-1.8%	-0.5%	33.7%
Actual	MpPo	-0.8%	-0.1%	-0.1%	2.1%	2.7%	-0.2%	1.0%	34.5%
Actual	MpPoMc	-2.6%	-1.1%	2.1%	5.5%	8.0%	3.3%	5.3%	36.0%
Baowu	Mp	0.0%	0.2%	-0.7%	0.6%	0.8%	-1.1%	-0.3%	30.3%
Baowu	MpPo	-0.2%	0.0%	-0.2%	0.9%	1.5%	-0.3%	0.4%	30.8%
Baowu	MpPoMc	-1.3%	-0.4%	1.2%	3.2%	5.8%	1.9%	3.5%	32.0%
Alternative1	Mp	0.0%	0.1%	-0.2%	0.2%	0.3%	-0.4%	-0.1%	29.3%
Alternative1	MpPo	-0.1%	0.0%	0.0%	0.4%	0.6%	0.0%	0.3%	29.5%
Alternative1	MpPoMc	-0.8%	-0.2%	0.4%	2.4%	3.4%	0.7%	1.8%	29.9%
Alternative2	Mp	0.0%	0.1%	-0.2%	0.2%	0.3%	-0.4%	-0.1%	29.3%
Alternative2	MpPo	-0.1%	0.0%	0.0%	0.4%	0.6%	0.0%	0.3%	29.5%
Alternative2	MpPoMc	-0.9%	-0.2%	0.5%	2.6%	3.7%	0.7%	2.0%	29.9%

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.

6.4 Shifting Downstream Demand

The rapidly growing construction sector in China has become the most important domestic steel consumer. Using the size of the floor space in completed buildings in 2017 and estimates in Column (3) of Table A9, the construction sector accounted for 45% of total steel

Figure 8: Regional Winners and Losers across Baowu M&A Experiments



Notes: Circles indicate regional percentage changes in firm profit under MpPoMc. Numbers inside the circles identify the experiment: Actual Baowu M&A (black), Alternative 1 (red), and Alternative 2 (blue). The vertical line denotes the national firm profit increase resulting from the actual Baowu M&A between 2018 and 2024, relative to the 2017 baseline.

consumption in the same year.[30] The collapse of the real estate sector after 2020 reduced steel demand by the construction sector. Between 2017 and 2023, floor space in completed buildings declined by 8% nationwide in 2023, which reduced steel demand nationally by 3.6%.

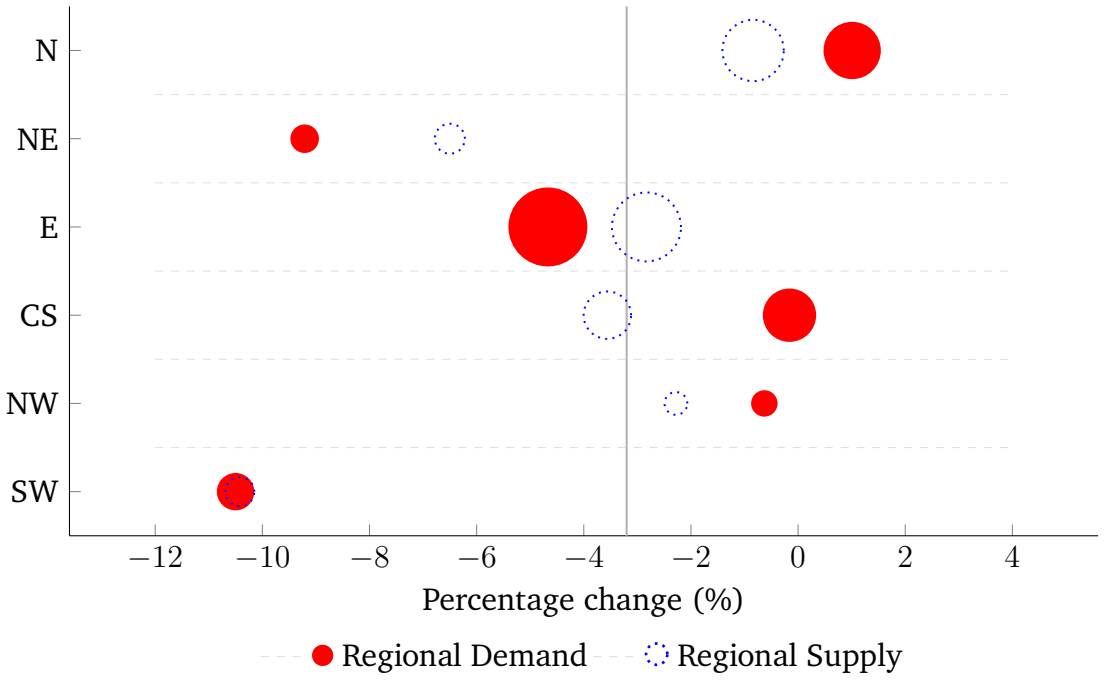
The change in the construction sector's steel demand varies significantly by province. To capture these differences, we use the actual change in the size of the floor space in completed buildings in 2023 and the estimates in Column (3) of Table A9 to calculate the new demand for steel in each province. We then resimulate the new equilibrium prices and sales at the firm level using the new estimates of steel demand. We report the simulation results of the equilibrium prices and the sales in Table A25 and the domestic trade flows after the demand shock in Table A26.

Figure 9 illustrates percentage changes in regional demand and supply induced by demand shifts in the construction sector. The demand shifts affect 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

[30]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.

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, which helped to maintain prices as shown in Table A25. 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.

Figure 9: Regional Demand and Supply Changes Induced by Demand Shifts



Notes: Red dots indicate percentage changes in demand, and blue open circles indicate percentage changes in total firm sales. Marker size is proportional to total volume in 2017. The vertical line denotes the national demand change in the counterfactual relative to 2017.

7 Conclusion

This paper develops and estimates a structural model of demand and supply in the Chinese steel industry that incorporates the geographic distribution of producers and spatial variation in downstream demand. Using detailed industry data, we estimate key parameters and quantify how the spatial distribution of market power shapes the distribution of surplus across regions and market participants. Our counterfactual analyses evaluate alternative merger designs under distinct institutional frictions and examine how shifts in downstream demand reallocate market power across regions.

Our findings have direct implications for China's ongoing steel-sector restructuring. First, "bigger" is not necessarily "better": welfare gains depend critically on the design of consolidation. Mergers led by more efficient firms and confined within regions generate substantially larger welfare gains than nationally coordinated consolidation centered on large incumbents. Regional consolidation captures efficiency gains while limiting the expansion of market power across geographic markets. In contrast, the realized merger wave between 2018 and 2024, dominated by the state-owned Baowu Group, achieved only a fraction of the attainable welfare gains.

Second, evaluating supply-side reforms requires accounting for shifts in the spatial distribution of demand. Using the construction sector as a focal application, we demonstrate how regional demand shifts propagate across geographic markets and reshape equilibrium outcomes. More broadly, as the geographic locus of demand evolves, the effects of industrial reorganization hinge critically on how supply adjusts to these changes. Future research could explore the dynamic implications of alternative M&A policies, including their effects on entry, exit, and long-run capacity investment across regions.

References

Asker, J. and V. Nocke (2021). Collusion, mergers, and related antitrust issues. In *Handbook of industrial organization*, Volume 5, pp. 177–279. Elsevier.

Bai, C.-E., Y. Du, Z. Tao, and S. Y. Tong (2004). Local protectionism and regional specialization: evidence from china's industries. *Journal of International Economics 63*(2), 397–417.

Barwick, P. J., S. Cao, and S. Li (2021). Local protectionism, market structure, and social welfare: China's automobile market. *American Economic Journal: Economic Policy 13*(4), 112–151.

Berry, S. and P. Jia (2010). Tracing the woes: An empirical analysis of the airline industry. *American Economic Journal: Microeconomics 2*(3), 1–43.

Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile prices in market equilibrium. *Econometrica 63*(4), 841–890.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, 242–262.

Brandt, L., F. Jiang, Y. Luo, and Y. Su (2022). Ownership and productivity in vertically integrated firms: evidence from the chinese steel industry. *Review of Economics and Statistics 104*(1), 101–115.

Brandt, L., J. Van Biesebroeck, L. Wang, and Y. Zhang (2017). Wto accession and performance of chinese manufacturing firms. *American Economic Review 107*(9), 2784–2820.

Cameron, A. C. and P. K. Trivedi (2005). *Microeconometrics: methods and applications*. Cambridge University Press.

Ching, A. T., F. Hayashi, and H. Wang (2015). Quantifying the impacts of limited supply: The case of nursing homes. *International Economic Review 56*(4), 1291–1322.

Collard-Wexler, A. (2014). Mergers and sunk costs: An application to the ready-mix concrete industry. *American Economic Journal: Microeconomics 6*(4), 407–447.

Collard-Wexler, A. and J. De Loecker (2015). Reallocation and technology: Evidence from the us steel industry. *American Economic Review 105*(1), 131–171.

Coşar, A. K., P. L. Grieco, and F. Tintelnot (2015). Borders, geography, and oligopoly: evidence from the wind turbine industry. *Review of Economics and Statistics 97*(3), 623–637.

De Loecker, J., J. Eeckhout, and G. Unger (2020, 01). The rise of market power and the macroeconomic implications*. *The Quarterly Journal of Economics 135*(2), 561–644.

Elliott, J., G. V. Houngbonon, M. Ivaldi, and P. T. Scott (2024). Market structure, investment and technical efficiencies in mobile telecommunications. *Journal of Political Economy 132*(12), 1–16.

Fan, Y. (2013). Ownership consolidation and product characteristics: A study of the us daily newspaper market. *American Economic Review 103*(5), 1598–1628.

Fang, H., M. Li, and Z. Wu (2024). Tournament-style political competition and local protectionism: theory and evidence from china. *Working Paper*.

Gowrisankaran, G., A. Nevo, and R. Town (2015). Mergers when prices are negotiated: Evidence from the hospital industry. *American Economic Review 105*(1), 172–203.

Grieco, P. L., C. Murry, and A. Yurukoglu (2024). The evolution of market power in the us automobile industry. *The Quarterly Journal of Economics 139*(2), 1201–1253.

Hall, R. E. (1986). Market structure and macroeconomic fluctuations. *Brookings Papers on Economic Activity 17*(2), 285–338.

Houde, J.-F. (2012). Spatial differentiation and vertical mergers in retail markets for gasoline. *American Economic Review 102*(5), 2147–2182.

Igami, M. and K. Uetake (2020). Mergers, innovation, and entry-exit dynamics: Consolidation of the hard disk drive industry, 1996–2016. *The Review of Economic Studies 87*(6), 2672–2702.

Kalnins, A., L. Froeb, and S. Tschantz (2017). Can mergers increase output? evidence from the lodging industry. *The RAND Journal of Economics 48*(1), 178–202.

Li, J., S. Li, and H. Zhang (2025). Output quality, productivity, and demand: Evidence from the chinese steel industry. *Working Paper*.

Liu, B. and Y. Luo (2026). Multiproduct multimarket price competition under capacity constraints. *Working Paper*.

Loecker, J. D. and F. Warzynski (2012). Markups and firm-level export status. *American economic review 102*(6), 2437–2471.

McManus, B. (2007). Nonlinear pricing in an oligopoly market: The case of specialty coffee. *The RAND Journal of Economics 38*(2), 512–532.

Miller, N. and M. Weinberg (2016). The market power effects of a merger: Evidence from the us brewing industry. *Econometrica*.

Miller, N. H. and M. Osborne (2014). Spatial differentiation and price discrimination in the cement industry: evidence from a structural model. *The RAND Journal of Economics 45*(2), 221–247.

Miller, N. H., M. Osborne, G. Sheu, and G. Sileo (2025). Technology and market power in the cement industry. *Working Paper*.

Nevo, A. (2000). Mergers with differentiated products: The case of the ready-to-eat cereal industry. *The Rand journal of economics*, 395–421.

Ryan, S. P. (2012). The costs of environmental regulation in a concentrated industry. *Econometrica 80*(3), 1019–1061.

Su, L. and S. Zhang (2024). Import license, misallocation, and aggregate total factor productivity in the chinese steel industry. *The Journal of Industrial Economics 72*(2), 848–867.

Zahur, N. B. (2025). Long-term contracts and efficiency in the liquefied natural gas industry. *Available at SSRN 4222408*.

Zhang, H. (2019). Non-neutral technology, firm heterogeneity, and labor demand. *Journal of Development Economics 140*, 145–168.

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 reports the geographic distribution of sample firms. Table A3 presents the number of firms participating in each regional market, along with a breakdown by firm location. Tables A4 and A6 provide detailed summaries of average and maximum market shares across regions. Table A5 presents the concentration raios.

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: Firm Participation in Regional Markets by 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.

Table A4: 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 A5: 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 A6: 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).

Table A7: Firm Sales by Ownership

Ownership	Firm Number	Mean	Std Dev	10th	90th	Sales Share
Total	118	4.64	4.52	0.84	10.00	100%
Central SOE	13	7.96	6.90	2.53	21.2	19%
Provincial SOE	39	5.7	4.57	0.36	14.1	41%
Private	66	3.36	3.37	0.84	6.96	40%

Notes: Mean, standard deviation, and the 10th and 90th percentiles refer to sales, which are measured in million tons.

Table A8: 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.

A.3 Demand Estimation

We estimate equation 8 using provincial-level output data on the primary downstream industries for steel and present the estimation results in Table A9.[31] 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 A10 shows that our model in general effectively captures the average market share in each regional market. In addition, we present in Table A11 the own-price elasticity at the firm level based on the demand estimates.

A.4 Production Function Estimation

Table A12 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 A13. 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 A15 summarizes the TFP estimates based on the production function for iron ore, suggesting small variations.

[31] 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 A9: 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 A10: 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 A11: Estimates of Own Price Elasticity of Demand

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

Table A12: 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 A13: 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 A14: 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 A15: 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 A16: Summary of firm markup

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

Table A17: 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

A.5.1 Full Consolidation Counterfactual Designs

We report the simulated marginal costs under the full consolidation counterfactuals in Table A18, and the corresponding regional breakdown in Table A19. We also experiment with selecting the most efficient firm among the top five largest firms for corresponding counterfactual designs 1, 3, 5, and 7; we report the results in Table A20.

Table A18: Average Marginal Costs After the Full Consolidation

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

Table A19: Regional Breakdown Results for Full Consolidation Counterfactuals

Effects	Experiment	1	1	1	5	5	5	7	7	7
	Region	Mp	MpPo	MpPoMc	Mp	MpPo	MpPoMc	Mp	MpPo	MpPoMc
ΔProfit	National	17.4%	28.8%	57.3%	11.8%	20.5%	43.9%	6.7%	13.3%	37.9%
	N	18.8%	29.6%	56.4%	12.8%	22.7%	29.9%	7.9%	15.9%	17.5%
	NE	18.3%	31.0%	53.5%	14.2%	21.2%	17.6%	7.0%	7.9%	4.5%
	E	17.6%	26.8%	66.4%	11.8%	17.0%	55.4%	6.7%	10.7%	62.2%
	CS	15.3%	28.5%	38.0%	10.3%	22.0%	37.3%	5.3%	14.7%	31.7%
	NW	13.7%	18.5%	55.1%	8.0%	11.3%	85.3%	3.8%	6.8%	78.9%
	SW	14.9%	41.4%	68.3%	8.8%	31.1%	83.1%	4.5%	22.9%	52.5%
ΔCS	National	-38.2%	-33.6%	-11.7%	-18.7%	-11.6%	6.3%	-9.3%	-2.3%	14.4%
	N	-40.6%	-36.0%	-17.2%	-25.1%	-18.1%	-6.1%	-12.0%	-4.0%	5.8%
	NE	-38.5%	-33.3%	-12.7%	-12.0%	-4.8%	2.8%	-6.5%	-2.2%	5.1%
	E	-38.8%	-35.1%	-10.3%	-18.5%	-12.7%	6.1%	-9.0%	-3.4%	16.2%
	CS	-36.0%	-30.9%	-12.3%	-15.8%	-8.1%	8.2%	-8.8%	-1.3%	13.7%
	NW	-32.4%	-29.4%	-7.1%	-15.3%	-9.8%	28.1%	-9.2%	-3.5%	32.3%
	SW	-36.7%	-28.3%	-5.0%	-15.2%	-2.3%	26.4%	-6.5%	6.4%	26.2%
ΔWelfare	National	-15.4%	-8.0%	16.7%	-6.2%	1.6%	21.7%	-2.7%	4.1%	24.1%
	N	-10.1%	-2.3%	20.6%	-5.6%	2.8%	12.4%	-1.8%	6.2%	11.8%
	NE	-6.9%	2.5%	24.2%	2.5%	9.7%	11.0%	1.1%	3.4%	4.7%
	E	-19.1%	-13.4%	16.6%	-7.9%	-2.3%	23.3%	-3.5%	1.5%	32.3%
	CS	-17.4%	-9.3%	6.0%	-6.4%	2.8%	18.8%	-3.7%	4.5%	20.2%
	NW	-12.4%	-8.6%	19.9%	-5.2%	-0.6%	52.9%	-3.5%	1.0%	52.5%
	SW	-20.0%	-5.8%	18.7%	-7.4%	8.5%	44.8%	-3.0%	11.7%	34.7%

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.

Table A20: Full Consolidation Counterfactuals with Acquirers Restricted to the Five Largest Firms

Experiment	Effects	ΔMC	ΔPrice	ΔSales	ΔMarkup	ΔProfit	ΔCS	ΔWelfare	CR10
1'	MpPoMc	-15.7%	5.1%	-6.6%	62.2%	59.0%	-10.3%	18.2%	52.5%
3'	MpPoMc	-18.8%	-6.0%	9.9%	42.4%	51.5%	16.9%	31.1%	61.8%
5'	MpPoMc	-15.0%	-1.7%	5.4%	41.9%	47.8%	9.0%	24.9%	59.3%
7'	MpPoMc	-15.2%	-6.2%	12.4%	29.2%	41.7%	21.4%	29.7%	63.2%

Notes: MpPoMc with both the iron ore cost reduction and efficiency improvement.

A.5.2 Counterfactuals Based On Actual and Baowu Consolidation

We present the simulated marginal cost post merger in Table A21, and in Table A22 the regional breakdown results for the actual M&As and the counterfactuals based on Baowu consolidation.

Table A21: Average Marginal Costs Post Merger for Actual and Baowu Consolidation

Experiment	w/o adjustment	Lower ore cost	Higher efficiency	Both
Actual	2649.8	2629.4	2601.0	2580.6
Baowu	2649.8	2643.8	2621.1	2615.1
Alternative1	2649.8	2646.8	2630.2	2627.2
Alternative2	2649.8	2646.8	2627.9	2625.0

Table A22: Regional Breakdown Results for Actual and Baowu Consolidation

Effects	Experiment	Actual			Baowu			Alternative1			Alternative2		
	Region	Mp	MpPo	MpPoMc	Mp	MpPo	MpPoMc	Mp	MpPo	MpPoMc	Mp	MpPo	MpPoMc
ΔProfit	National	1.4%	2.7%	8.0%	0.8%	1.5%	5.8%	0.3%	0.6%	3.4%	0.3%	0.6%	3.7%
	N	1.3%	2.8%	3.7%	0.6%	0.7%	0.6%	0.2%	0.1%	-0.1%	0.2%	0.1%	-0.2%
	NE	1.7%	2.7%	12.2%	0.7%	0.2%	-1.2%	0.2%	0.0%	-0.3%	0.2%	0.0%	-0.3%
	E	1.5%	3.5%	12.4%	1.0%	3.3%	13.1%	0.4%	1.4%	4.8%	0.4%	1.4%	5.9%
	CS	1.2%	0.4%	-1.7%	0.8%	0.3%	-1.1%	0.2%	0.0%	-0.5%	0.2%	0.0%	-0.5%
	NW	1.1%	0.2%	1.0%	0.6%	0.2%	-1.2%	0.3%	0.1%	-0.7%	0.3%	0.1%	-0.7%
	SW	1.3%	5.0%	32.3%	0.9%	2.2%	27.4%	0.6%	2.0%	34.4%	0.6%	2.0%	34.4%
ΔCS	National	-1.8%	-0.2%	3.3%	-1.1%	-0.3%	1.9%	-0.4%	0.0%	0.7%	-0.4%	0.0%	0.7%
	N	-1.0%	1.3%	2.9%	-0.3%	0.1%	0.9%	-0.1%	0.0%	0.0%	-0.1%	0.0%	0.0%
	NE	-2.8%	-0.4%	5.1%	-0.2%	-0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	E	-2.2%	-0.6%	3.9%	-1.6%	-0.3%	3.1%	-0.5%	0.1%	0.7%	-0.5%	0.1%	0.9%
	CS	-1.5%	-1.1%	0.8%	-1.1%	-0.8%	0.3%	-0.2%	-0.1%	0.4%	-0.2%	-0.1%	0.4%
	NW	-1.9%	-1.3%	1.9%	-0.4%	-0.2%	0.5%	-0.2%	-0.1%	-0.1%	-0.2%	-0.1%	-0.1%
	SW	-2.1%	0.5%	6.3%	-1.5%	-0.6%	3.5%	-1.1%	-0.2%	3.4%	-1.1%	-0.2%	3.4%
ΔWelfare	National	-0.5%	1.0%	5.3%	-0.3%	0.4%	3.5%	-0.1%	0.3%	1.8%	-0.1%	0.3%	2.0%
	N	0.2%	2.1%	3.3%	0.2%	0.4%	0.8%	0.1%	0.1%	0.0%	0.1%	0.1%	-0.1%
	NE	-0.3%	1.3%	9.0%	0.3%	0.1%	-0.6%	0.1%	0.0%	-0.1%	0.1%	0.0%	-0.2%
	E	-0.9%	0.9%	6.9%	-0.7%	0.9%	6.6%	-0.2%	0.6%	2.2%	-0.2%	0.6%	2.6%
	CS	-0.5%	-0.5%	-0.1%	-0.4%	-0.4%	-0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	NW	-0.6%	-0.7%	1.5%	0.0%	0.0%	-0.2%	0.0%	0.0%	-0.4%	0.0%	0.0%	-0.4%
	SW	-1.0%	1.9%	14.7%	-0.7%	0.3%	11.3%	-0.5%	0.5%	13.4%	-0.5%	0.5%	13.4%

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.

A.5.3 Robustness Analysis

In the marginal cost regressions (i.e., Table 9), the OLS estimates may suffer from a negative bias due to endogeneity arising from a negative correlation between product quality and firms' unobserved efficiency—firms with lower (unobserved) marginal costs tend to produce higher-quality products. To assess how this bias may affect market outcomes in the counterfactual analyses, we adjust the OLS estimate of product quality from Column (4) of Table 9 upward by 10% and 20%, and use the resulting coefficients to simulate marginal costs under each hypothetical merger design described in Table 10.

Table A23 reports the average firm-level marginal costs across counterfactual scenarios and compares them with those obtained using the baseline OLS marginal-cost estimates. The results suggest that upward adjustments to the OLS quality coefficient reduce marginal costs relative to the benchmark only modestly, and that the cost change is approximately linear in the percentage change of the quality coefficient. We then simulate market equilibrium outcomes using these adjusted cost estimates and present the results in Table A24. We find that the resulting changes in key economic outcomes are positive across the board—except for prices, as expected given the lower marginal costs—and that the magnitudes of these changes are modest.

Table A23: Average Marginal Costs After the Mergers for Robustness Checks

Experiment	Original	up10%		up20%	
	Both	Both	change	Both	change
1	2251.6	2214.7	-1.64%	2175.4	-3.38%
2	2251.6	2214.7	-1.64%	2175.4	-3.38%
3	2370.6	2352.2	-0.78%	2332.3	-1.62%
4	2397.5	2381.9	-0.65%	2364.7	-1.37%
5	2291.6	2263.0	-1.25%	2229.0	-2.73%
6	2429.7	2411.7	-0.74%	2390.0	-1.63%
7	2318.0	2302.2	-0.68%	2283.3	-1.50%
8	2478.9	2466.8	-0.49%	2452.7	-1.06%

Notes: Original represents the experiment based on the original OLS estimates, up10% and up20% are based on the quality coefficient adjusted upward by 10% and 20%, respectively.

Table A24: Simulation Results for Robustness Checks

Experiment	Effects	Coefficient	ΔMC	ΔPrice	ΔSales	ΔMarkup	ΔProfit	ΔCS	ΔWelfare	CR10
1	MpPoMc	Original	-15.0%	5.6%	-7.6%	61.4%	57.3%	-11.7%	16.7%	52.0%
1	MpPoMc	Up10%	-16.4%	4.2%	-5.9%	62.4%	58.7%	-9.2%	18.7%	52.9%
1	MpPoMc	Up20%	-17.9%	3.4%	-5.2%	65.2%	60.7%	-8.2%	20.1%	53.3%
2	MpPoMc	Original	-15.0%	5.6%	-7.6%	61.4%	57.3%	-11.7%	16.7%	52.0%
2	MpPoMc	Up10%	-16.4%	4.2%	-5.9%	62.4%	58.7%	-9.2%	18.7%	52.9%
2	MpPoMc	Up20%	-17.9%	3.4%	-5.2%	65.2%	60.7%	-8.2%	20.1%	53.3%
3	MpPoMc	Original	-10.5%	0.1%	1.6%	32.8%	39.7%	2.4%	17.7%	57.1%
3	MpPoMc	Up10%	-11.2%	-0.4%	2.0%	33.7%	40.3%	3.2%	18.4%	57.4%
3	MpPoMc	Up20%	-12.0%	-0.8%	2.2%	35.1%	41.2%	3.5%	19.0%	57.5%
4	MpPoMc	Original	-9.5%	0.8%	0.2%	31.4%	37.9%	0.2%	15.7%	56.4%
4	MpPoMc	Up10%	-10.1%	0.4%	0.4%	32.5%	38.5%	0.6%	16.2%	56.5%
4	MpPoMc	Up20%	-10.8%	0.0%	0.8%	33.5%	39.1%	1.3%	16.8%	56.7%
5	MpPoMc	Original	-13.5%	-1.0%	3.8%	39.2%	43.9%	6.3%	21.7%	58.4%
5	MpPoMc	Up10%	-14.6%	-1.6%	4.5%	41.1%	44.9%	7.4%	22.8%	58.8%
5	MpPoMc	Up20%	-15.9%	-2.3%	5.2%	43.5%	46.4%	8.7%	24.2%	59.2%
6	MpPoMc	Original	-8.3%	2.1%	-2.6%	31.7%	31.3%	-3.8%	10.6%	54.8%
6	MpPoMc	Up10%	-9.0%	1.7%	-2.0%	32.8%	32.1%	-2.9%	11.5%	55.2%
6	MpPoMc	Up20%	-9.8%	1.0%	-1.0%	33.7%	32.9%	-1.4%	12.7%	55.7%
7	MpPoMc	Original	-12.5%	-4.0%	8.6%	26.7%	37.9%	14.4%	24.1%	61.1%
7	MpPoMc	Up10%	-13.1%	-4.4%	9.0%	27.7%	38.0%	15.1%	24.5%	61.3%
7	MpPoMc	Up20%	-13.8%	-4.8%	9.3%	29.0%	38.5%	15.7%	25.1%	61.5%
8	MpPoMc	Original	-6.4%	-0.8%	1.7%	17.8%	18.9%	2.9%	9.5%	57.2%
8	MpPoMc	Up10%	-6.9%	-1.0%	2.0%	18.7%	19.9%	3.4%	10.1%	57.4%
8	MpPoMc	Up20%	-7.4%	-1.3%	2.4%	19.7%	20.9%	3.9%	10.9%	57.6%

Notes: MpPoMc with both the iron ore cost reduction and efficiency improvement. Original represents the experiment based on the original OLS estimates, up10% and up20% are based on the quality coefficient adjusted upward by 10% and 20%, respectively.

A.6 Shifting Downstream Demand

We present the simulated results of the demand shifts in Table A25 and the resulting regional flows in Table A26.

Table A25: 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 A26: 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.

B Technical Appendix

B.1 Proof of Contraction Mapping

Let $T_{jr}(s)[\xi] \coloneqq \xi_{jr} + \log(s_{jr}) - \log(s_{jr}(\xi))$.

Normalization: $u_{i0n} = \epsilon_{i0n}$, where the outside good's mean utility is set to zero.

Note that $\sum_{j'} \sum_{n \in N_r} \mu_n \frac{\exp(\xi_{j'n} + \alpha p_{j'} + \beta \tau_{j'n})}{1 + \sum_{k' \in J_n} \exp(\xi_{k'n} + \alpha p_{k'} + \beta \tau_{k'n})} = \sum_{n \in N_r} \mu_n$ for all $j' \in J_n$ for all $n \in N_r$. Denote total sales in region r as $M_r \coloneqq \sum_{n \in \mathcal{N}_r} \mu_n$. Then,

$$
\begin{aligned}
s_{jr}(\xi; \alpha, \beta) &= \frac{1}{M_r} \sum_{n \in \mathcal{N}_r} \mu_n s^n_{jr}(\xi; \alpha, \beta) \\
&= \frac{1}{M_r} \Big[\sum_{n \in \mathcal{N}_r} \mu_n \frac{\exp(\xi_{jn} + \alpha p_j + \beta \tau_{jn})}{1 + \sum_{k \in \mathcal{J}_n} \exp(\xi_{kn} + \alpha p_k + \beta \tau_{kn})} \Big] \\
&= \frac{1}{M_r} \Big[\sum_{n \in \mathcal{N}_r} \mu_n \frac{\exp(\xi_{jr} + \alpha p_j + \beta \tau_{jn})}{1 + \sum_{k \in \mathcal{J}_n} \exp(\xi_{kr} + \alpha p_k + \beta \tau_{kn})} \Big],
\end{aligned}
$$

where market share of firm j in province n of region r $s^n_{jr}(\xi; \alpha, \beta) = \frac{\exp(\xi_{jn} + \alpha p_j + \beta \tau_{jn})}{1 + \sum_{k \in \mathcal{J}_n} \exp(\xi_{kn} + \alpha p_k + \beta \tau_{kn})}$. The third equality holds because ξ_s are firm-region specific.[32]

For convenience, we restate the Theorem of Appendix I of Berry et al. (1995).

Theorem 1. (BLP) Consider the metric space $(\mathbb{R}^K, d)$ with $d(x, y) = ||x - y||$ (where $||\cdot||$ is the sup-norm). Let $f : \mathbb{R}^K \to \mathbb{R}^K$ have the properties:

1. For all $x \in \mathbb{R}^K$, $f(x)$ is continuously differentiable, with, for all j and k,

$$\partial f_j(x)/\partial x_k \geq 0$$

and

$$\sum_{k=1}^{K} \partial f_j(x)/\partial x_k < 1$$

.

2. $\min_j \inf_x f(x) \equiv x > -\infty$.

[32] Note that in the main text, firm j's market share in market n is denoted as s_{jn} instead. Here, we use a slightly different notation to enhance clarity in the proof.

3. There is a value, $\bar{x}$, with the property that if for any j, $x_j \geq \bar{x}$, then for some k (not necessarily equal to j), $f_k(x) < x_k$.

Then, there is a unique fixed point, x_0, to f in $\mathbb{R}^K$. Further, let the set $X = [\underline{x}, \bar{x}]^K$, and define the truncated function $\hat{f} : X \to X$, as $\hat{f}_j(x) = \min\{f_j(x), \bar{x}\}$. Then, $\hat{f}(x)$ is a contraction of modulus less than 1 on X.

Theorem 2. There exists $\xi_0 \in \mathbb{R}^{JR}$ fixed point of T. Further, there exists $\underline{\xi}, \bar{\xi} \in \mathbb{R}$ such that for $\Xi \coloneqq [\underline{\xi}, \bar{\xi}]^{JR}$, and $\hat{T} : \Xi \to \Xi$ defined as $\hat{T}_j \coloneqq \min\{T_j(\xi), \bar{\xi}\}$, $\hat{T}$ is a contraction map of modulus less than 1 on Ξ.

Proof. (1) Let $\ell t, \ell' t' \in \{1, \ldots, JR\}$ arbitrary. The argument of $s_{\ell t}(\cdot)$ exists within exponentials, so $T(\xi)$ is continuously differentiable since $exp(\cdot)$ is continuously differentiable.

For $\ell t = \ell' t'$,

$$\begin{aligned}
\frac{\partial T_{\ell t}(\xi)}{\partial \xi_{\ell t}} &= 1 - \frac{1}{s_{\ell t}(\xi)} \frac{\partial s_{\ell t}(\xi)}{\partial \xi_{\ell t}} \\
&= 1 - \frac{\sum_{n \in \mathcal{N}_r} \mu_n \frac{\partial s^n_{\ell t}(\xi)}{\partial \xi_{\ell t}}}{\sum_{n \in \mathcal{N}_r} \mu_n s^n_{\ell t}(\xi)} \\
&\geq 0
\end{aligned}$$

since $\frac{\partial s^n_{\ell t}(\xi)}{\partial \xi_{\ell t}} \leq s^n_{\ell t}(\xi)$.

For $\ell t \neq \ell' t'$,

$$\begin{aligned}
\frac{\partial T_{\ell t}(\xi)}{\partial \xi_{\ell' t'}} &= -\frac{1}{s_{\ell t}(\xi)} \frac{\partial s_{\ell t}(\xi)}{\partial \xi_{\ell' t'}} \\
&= -\frac{\sum_{n \in \mathcal{N}_r} \mu_n \frac{\partial s^n_{\ell t}(\xi)}{\partial \xi_{\ell' t'}}}{\sum_{n \in \mathcal{N}_r} \mu_n s^n_{\ell t}(\xi)} \\
&\geq 0
\end{aligned}$$

which holds with equality for $t \neq t'$.

Then,

$$\sum_{r,j} \frac{\partial T_{\ell t}(\xi)}{\partial \xi_{jr}} = 1 - \frac{\sum_{n \in \mathcal{N}_t} \mu_n \left(\frac{\partial s^n_{\ell t}(\xi)}{\partial \xi_{\ell t}} + \sum_{j \neq \ell} \frac{\partial s^n_{\ell t}(\xi)}{\partial \xi_{jt}} \right)}{\sum_{n \in \mathcal{N}_t} \mu_n s^n_{\ell t}(\xi)}$$

Now,

$$\frac{\partial s^n_{\ell t}(\xi)}{\partial \xi_{\ell t}} = \frac{\exp(\xi_{\ell t} + \alpha p_\ell + \beta \tau_{\ell n})(1 + \sum_{k \in \mathcal{J}_n \setminus \{\ell\}} \exp(\xi_{kt} + \alpha p_k + \beta \tau_{kn}))}{(1 + \sum_{k \in \mathcal{J}_n} \exp(\xi_{kt} + \alpha p_k + \beta \tau_{kn}))^2}$$

and

$$\frac{\partial s^n_{\ell t}(\xi)}{\partial \xi_{jr}} = -\frac{\exp(\xi_{\ell t} + \alpha p_\ell + \beta \tau_{\ell n})\exp(\xi_{jt} + \alpha p_j + \beta \tau_{jn})}{(1 + \sum_{k \in \mathcal{J}_n} \exp(\xi_{kt} + \alpha p_k + \beta \tau_{kn}))^2}$$

for $j \neq \ell$.

This implies

$$\frac{\partial s^n_{\ell t}(\xi)}{\partial \xi_{\ell t}} + \sum_{j \neq \ell} \frac{\partial s^n_{\ell t}(\xi)}{\partial \xi_{jt}} = \frac{\exp(\xi_{\ell t} + \alpha p_\ell + \beta \tau_{\ell n})}{(1 + \sum_{k \in \mathcal{J}_n} \exp(\xi_{kt} + \alpha p_k + \beta \tau_{kn}))^2} > 0$$

Therefore, $\sum_{r,j} \frac{\partial T_{\ell t}(\xi)}{\partial \xi_{jr}} < 1$.

(2) Let $jr \in \{11, \ldots, JR\}$ arbitrary. Note that $s_{jr}(\xi) = \exp(\xi_{jr}) D_{jr}(\xi)$ where

$$D_{jr}(\xi) \coloneqq \frac{1}{M_r}\Big[\sum_{n \in \mathcal{N}_r} \mu_n \frac{\exp(\alpha p_j + \beta \tau_{jn})}{1 + \sum_{k \in \mathcal{J}_n} \exp(\xi_{kr} + \alpha p_k + \beta \tau_{kn})}\Big] \tag{A1}$$

Then, $T_{jr}(\xi) = \log(s_{jr}) - \log(D_{jr}(\xi))$. Note that $D_{jr}(\xi)$ is decreasing in every element of ξ. Now, $\lim_{\xi \to -\infty} D_{jr}(\xi) = \frac{1}{M_r} \sum_{n \in \mathcal{N}_r} \mu_n \exp(\alpha p_j + \beta \tau_{jn})$. This implies

$$\begin{aligned}
\inf_{\xi \in \mathbb{R}^{JR}} T_{jr}(\xi) &= \log(s_{jr}) - \lim_{\xi \to -\infty} \log(D_{jr}(\xi)) \\
&= \log(s_{jr}) - \log\Big(\frac{1}{M} \sum_{n \in \mathcal{N}_r} \mu_n \exp(\alpha p_j + \beta \tau_{jn})\Big) \\
&> -\infty
\end{aligned}$$

Let $\underline{\xi}_{jr} \coloneqq \log(s_{jr}) - \log\Big(\frac{1}{M_r} \sum_{n \in \mathcal{N}_r} \mu_n \exp(\alpha p_j + \beta \tau_{jn})\Big)$. Then, $\inf_{\xi \in \mathbb{R}^{JR}} T(\xi) = (\underline{\xi}_{11}, \ldots, \underline{\xi}_{JR})$ so $\underline{\xi} \coloneqq \min_{j,r} \inf_{\xi \in \mathbb{R}^{JR}} T(\xi) > -\infty$.

(3) Let $jr \in \{11, \ldots, JR\}$ arbitrary. Let s_{jr} denote the share of good j in region r observed in the data. Consider $x_{kr} = -\infty$ for all $k \in \{0, \ldots, J\} \setminus \{0, j\}$. Let $\bar{x}_{jr}$ be the value of x_{jr} such that $s_{0r} = s_{0r}(\mathbf{x})$.[33] Let $\bar{\xi} > \max_{j,r} x_{jr}$.

[33] This defines, for each jr, the value of x_{jr} such that, in the case that consumers only consider good jr and the outside good in region r (because all other goods yield $-\infty$ utility), they would buy the same amount of the outside good according to the market share functions as is seen in the data. This is done to satisfy condition 3 of Theorem 1, and follows similar reasoning as the proof of the Lemma in the Appendix of Berry (1994).

Now, suppose that in $\xi \in \mathbb{R}^{JR}$ there exists $jr \in \{11, \ldots, JR\}$ such that $\xi_{jr} \geq \bar{\xi}$. This implies that $s_{0r}(\xi) < s_{0r}$ which implies that $\sum_{k \neq 0} s_{kr}(\xi) > \sum_{k \neq 0} s_{kr}$.[34] This implies that there exists $j' \in \{1, \ldots, J\}$ such that $s_{j'r}(\xi) > s_{j'r}$ which implies that $T_{j'r}(\xi) = \xi_{j'r} + \log\left[\frac{s_{j'r}}{s_{j'r}(\xi)}\right] < \xi_{j'r}$.

Therefore, T satisfies the conditions of Theorem 1, which implies that $\hat{T}$ is a contraction map of modulus less than 1 on Ξ. □

B.2 Standard Errors of the GMM Estimator

Following Cameron and Trivedi (2005)[35], 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.[36] The sample analogue of the moment conditions is $\frac{1}{\sum_r J_r} Z'\xi$.

[34] In the case where $\xi_{kr} = -\infty$ for all $k \in \{0, \ldots, J\} \backslash \{j, 0\}$, as above, having $\xi_{jr} \geq \bar{\xi}$ implies that $s_{0r}(\xi) < s_{0r}$ so $s_{jr}(\xi) > s_{jr}$. Then, this would also be the case if any of the $\xi_{kr} > -\infty$, since consumers are even less likely to substitute away from good k in this case, and would be even more likely to substitute away from the outside good. Mathematically, if $\xi_{kr} = -\infty$ for all $k \in \{0, \ldots, J\} \setminus \{j, 0\}$, then $\bar{\xi}$ sets

$$s_{0r}(\boldsymbol{\xi}) = \frac{1}{M}\sum_{n \in \mathcal{N}} \mu_n \frac{1}{1 + \exp(\xi_{jr} + \alpha p_j + \beta \tau_{jn})} < s_{0r}$$

If one of the $\xi_{kr} > -\infty$, then the term $\exp(\xi_{kr} + \alpha p_k + \beta \tau_{kn})$ would be added to the denominator of the fraction inside the summation, so $s_{0r}(\boldsymbol{\xi})$ would be reduced in this case.

[35] See page 175 for more details.

[36] 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.

$$\widehat{G}|_{\theta=\widehat{\theta}} = \frac{1}{\sum_r J_r} Z' \frac{\partial \xi}{\partial \theta'}|_{\theta=\widehat{\theta}}$$

$$= \frac{1}{\sum_r J_r} \begin{pmatrix} z_{11,1} & z_{21,1} & \cdots & z_{jr,1} & \cdots \\ z_{11,2} & z_{21,2} & \cdots & z_{jr,2} & \cdots \\ z_{11,3} & z_{21,3} & \cdots & z_{jr,3} & \cdots \end{pmatrix} \begin{pmatrix} \frac{\partial \xi_{11}}{\partial \alpha} & \frac{\partial \xi_{11}}{\partial \beta} \\ \frac{\partial \xi_{21}}{\partial \alpha} & \frac{\partial \xi_{21}}{\partial \beta} \\ \vdots & \vdots \\ \frac{\partial \xi_{jr}}{\partial \alpha} & \frac{\partial \xi_{jr}}{\partial \beta} \\ \vdots & \vdots \end{pmatrix},$$

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:

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

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.3 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

$$p_j = \frac{1}{\alpha}\left[\log \overline{Q}_j - \log \sum_n \mu_n \frac{\exp(\beta \tau_{jn} + \xi_{jr})}{1 + \sum_{j'} \exp(\alpha p_{j'} + \beta \tau_{j'n} + \xi_{j'r})}\right] \tag{A2}$$

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

$$\mathbf{P} = \mathbf{MC} + \Delta^{-1}\mathbf{Q} \tag{A3}$$

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 (A2) if $j \in \mathcal{J}_c$ and (A3) 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.