



# Market structure, resource allocation, and industry productivity growth: Firm-level evidence from China's steel industry

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## ABSTRACT

Regional monopoly limits market reforms from improving cross-firm resource allocative efficiency, but little empirical evidence is available from developing countries. This paper provides rich evidence that regional monopoly may hinder the expansion of more productive firms, using the Chinese iron and steel sector as a case. Drawing on a comprehensive panel dataset comprising 11,136 iron and steel firms in China from 1998 to 2009, we demonstrate that market reforms in China's steel industry enhance competition at the national level, but do not effectively improve resource reallocation within provinces. Despite a decline in the market share of the top 10 largest steel enterprises from 80% to 50% between 1998 and 2009, resource reallocation only contributes to 14% of industry-level total factor productivity (TFP) growth, amounting to one-sixth of the contribution from within-firm productivity growth. Furthermore, the effects of resource reallocation within provinces are significantly lower compared to those observed between provinces, suggesting that market fragmentation or frictions hinder the expansion of more productive firms within the same province. These findings underscore the importance of eliminating regional monopoly for developing countries undergoing market reforms to enhance resource allocative efficiency.

## 1. Introduction

Developing countries' economies often are characterized by inefficiencies in resource allocation and low productivity levels, which generally are caused by inadequate institutional arrangements, poor enforcement of contracts and property rights, and information frictions (Balassa, 1988; Bhagwati, 1971). However, in the course of these countries' economic development, if policy makers can launch market reforms by eliminating institutional barriers; liberalizing labor, capital, and product markets; investing in better infrastructure; and promoting an economy characterized by increased competition, aggregate productivity should rise. The notion that developing countries — with the right set of policies — can achieve aggregate productivity growth by reallocating resources from less- to more-efficient firms has been examined thoroughly in the literature on resource misallocation and market reforms (Asker, Collard-Wexler, & Loecker, 2014; Baily, Hulten, & Campbell, 1992; Bartelsman, Haltiwanger, & Scarpetta, 2013; Foster, Haltiwanger, & Krizan, 2001; Foster, Haltiwanger, & Syverson, 2008; Hsieh & Klenow, 2009; Olley & Pakes, 1996; Restuccia & Rogerson, 2017).

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Unfortunately, not all market reforms end up producing the intended higher aggregate productivity increases through improvement of resource allocation efficiency across firms. For the manufacturing industry (as a whole), Hsieh and Klenow (2009) showed that resource misallocation in India worsened during the 1987–1994 period when a policy that limited firms' entry into the manufacturing industry was being abolished. Brandt, Biesebroeck, Johannes, and Zhang (2012) found that within-sector resource reallocation contributed to only 4% of aggregate productivity growth in the Chinese manufacturing industries between 1998 and 2007. Bartelsman et al. (2013) also found that resource misallocation worsened in many Eastern European nations during their transitions to market economies in the 1990s, and that in the case of many of the region's manufacturing industries, gains in resource allocation efficiency were absent or (at best) modest. Other studies that focused on Southern Europe, Latin America, and Africa reported similar results (Gopinath, Kalemli-Özcan, Karabarbounis, & Villegas-Sanchez, 2017; Kalemli-Özcan & Sørensen, 2016; Oberfield, 2013; Sandleris & Wright, 2014).

While the absence of improvements in resource allocation in the face of market reforms is well-documented in many countries, the precise reason why market reforms are not promoting more efficient resource reallocation across firms and yielding higher productivity levels is not always readily apparent. Recent research has identified market monopoly power as an important factor that could undermine the impact of market reforms on resource reallocation (Hopenhayn, 2014; Restuccia & Rogerson, 2013, 2017). Considering that “a producer with monopoly power may produce less than the efficient level, but charge a higher markup” (Restuccia & Rogerson, 2017, 154), market reforms that promote the free flow of resources across firms may fail to improve resource allocation efficiency because monopoly power held by the dominant firm might limit more-productive smaller firms from expanding their production. However, less attention has been paid to understanding how resource allocation across firms responds to market reforms when markets are fragmented by the existence of local monopolies, a phenomenon commonly observed in developing economies.

This paper aims to investigate whether regional monopolies may affect resource allocation across firms when marketization reforms facilitate nationwide competition, using China's iron and steel industry as a case for the period 1998–2009. We started by measuring resource reallocation at the industry level in response to China's market reforms, using the Melitz and Polanec (2016) approach. We compared the estimated contribution of resource reallocation to aggregate productivity growth at the industry level with that of within-firm productivity growth to identify the importance of improving cross-firm resource reallocation efficiency during the reform period. Then, we decomposed the resource reallocation effect into its “within-province” and “between-province” components. Note that steel products sold in more remote markets face more intense competition due to higher transportation costs, which weaken the advantage of more productive firms. If the ‘within-province’ component is found to be smaller than the ‘between-province’ component, it may imply that resource reallocation effects increase with the distance of sales. This observation contradicts the expected impact of market reforms on resource reallocation across firms. Such a scenario suggests the presence of potential non-market factors, including market segregation and local market monopolies, which act as hindrances to resource reallocation across firms within each province. Finally, we conducted a set of regression analyses to establish the link between the within-province resource reallocation effects and the strength of the regional monopoly, measured by the markup of iron and steel firms.

We used data from China's iron and steel industry for several reasons. First, in the most general terms, the iron and steel industry provides a quasi-natural experimental context for us to test the theoretical hypotheses. Specifically, the nation's iron and steel industry has been the focus of its domestic market reforms since the late 1990s (Holloway, Roberts, & Rush, 2010; Tang, 2010), so this makes it (meeting the first requirement) a case that allows us to study the impact of market reforms on resource reallocation across firms. In addition, vertically integrated technology dominates steel production in China and exhibits increasing returns to scale (Brandt, Jiang, Luo, & Su, 2022; Sheng & Song, 2012). Because of this, it was easy for large firms in many provinces (that historically were distributed across the country under the centrally planned economy) to obtain (or strengthen) local monopoly power during the reform period when the national market was starting to become more competitive.<sup>1</sup> Finally, iron and steel products are relatively homogeneous (Collard-Wexler & Loecker, 2015) and, on a per ton basis, relatively low value and sensitive to transportation costs. This characteristic of the industry makes it possible for us to use demand elasticity (or the firm's markup) as a proxy for the sample firms' monopoly power, considering that iron and steel products from different firms (i.e., large vs. small or state-owned enterprises [SOEs] vs. non-SOEs) tend to be perfect substitutes and independent of preferences (Syverson, 2004). In this sense, firms only compete for price in the market, which is determined by production and/or sales costs.

The paper contributes to the literature in two ways. First, we are the first to offer comprehensive empirical evidence that regional monopolies resulting from market reforms may hinder resource reallocation across firms, even when these reforms lead to increased competition in the national market. In particular, we extend the literature (Hopenhayn, 2014; Restuccia & Rogerson, 2013, 2017) by showing that local monopoly power held by a small number of dominant firms may cause market fragmentation and limit more-productive firms from expanding. This provides an alternative explanation as to why market reforms may fail to deliver intended resource reallocation effects in many developing countries. Second, in the context of a large, important industry (namely, China's iron and steel industry), we empirically identified the role of regional monopolies and their effects on resource reallocation across firms in developing countries. Syverson (2004, 2007) found that a monopolistic market structure could restrict resources from being reallocated from less- to more-efficient, dominant firms in the U.S. concrete industry. Collard-Wexler and Loecker (2015) found that market monopolies of large, vertically integrated steel firms could dampen resource allocation effects in the U.S. steel industry. Despite the empirical evidence obtained in developed countries, little evidence has been found on the role of local market monopoly power in affecting cross-firm resource reallocation in developing countries. We address the research gap by demonstrating that the monopoly

<sup>1</sup> This feature of market structure is particularly salient in a developing economy such as China, where local protectionism is rampant, often making markets regionally fragmented (see Brandt, Jiang, Luo, & Su, 2022; Sheng & Song, 2012; Wu, 2000; Xu, 2002).

power of a dominant firm in the local market can undermine the resource reallocation effects within provinces in China's steel industry.

The rest of the paper is organized as follows. Section 2 summarizes the characteristics of China's iron and steel industry and the market reforms in the industry since the late 1990s. Section 3 describes the data and the empirical strategies used to test the hypotheses. Section 4 discusses the empirical results, and Section 5 provides several robustness checks. Section 6 concludes the paper.

## 2. China's iron and steel industry: market reforms and regional monopoly

The iron and steel industry in China is one of the nation's key pillars of economic growth. In 2017, China's iron and steel industry produced 711 million metric tons of pig iron, 832 million metric tons of crude steel, and 33 million tons of alloy products. This production level accounted for more than half of global iron and steel production. The industry also has strong backward and forward industrial linkages. Iron and steel producers generate demand for upstream industries such as iron ore/coal mining and energy. For example, to produce the industry's output level, the industry consumed 1.15 billion tons of iron ore (China Steel Development Research Institute (CSDRI, various issues), 2023). The industry also provided inputs for downstream industries, such as construction, machinery and equipment, automobiles, shipbuilding, etc. Apart from feeding domestic demand, China's steel production also took the lead in global steel trade. According to World Steel Association (2018), China's steel exports accounted for 16.1% of global steel exports in 2017. The industry also accounted for around two-thirds of global iron ore trade (China Steel Development Research Institute (CSDRI, various issues), 2023).

While originally (through the 1980s) a key sector of the economy that was heavily planned, a decade-long effort at market reform starting in the late 1990s changed the course of the Chinese iron and steel industry's development, enabling the industry to achieve two decades of double-digit annual growth. Historically, the iron and steel industry in China strictly followed the central government's planning (Fisher-Vanden, 1998; Jefferson, 1990), yielding low efficiency. These SOEs were still responsible for producing over 80% of the industry's output in 1996. However, in 1998, a two-stage reform was initiated to introduce modern management systems and new forms of ownership into the country's iron and steel firms. Under these reforms, all SOEs were categorized into two groups: "key" firms and "local" firms. In the first stage, between 1998 and 2000, most "key" firms were turned into publicly listed companies, while the vast majority of small- and medium-size "local" firms remained unchanged (Movshuk, 2004; Wu, 2000).<sup>2</sup> During the second reform stage after 2000, "local" firms gradually were privatized. Simultaneously, both private and foreign direct investments were encouraged as part of the industry's reform package (Kim, Lee, Kim, & Lee, 2006). By the end of the reforms in 2008, the industry had become more market-oriented, with the output share of private firms accounting for >60% of the industry's total output (CSDRI, various years).

The market reforms fundamentally changed the industry's operational environment, resulting in positive levels of within-firm technology progress. Fig. 1 shows the changes in the total number of firms (Panel [A]), total employment (Panel [B]), total output (Panel [C]), and total assets (Panel [D]) between 1998 and 2014. During the 1998–2008 reform period, although total employment remained almost unchanged, the total number of firms, total output, and total assets increased substantially. This implies that the industry's average labor productivity increased as market competition intensified. Simultaneously, the increase in total assets (or the average capital-labor ratio) also suggests an increase in technology/innovation and equipment/capital investment. Consequently, the average vertical integration (VI) ratio for steel production in China—one of the most important indicators of production technology in vertically integrated steel firms—increased from around 40% to >99% between 1998 and 2009.<sup>3</sup>

Apart from promoting within-firm productivity growth, market reforms in China's iron and steel industry also were expected to improve the allocative efficiency of resources among firms. However, empirical evidence remains elusive on this. On one hand, although the industry suffered from a sharp decline in average profits, fixed-asset investments continued to build within the local regions over time.<sup>4</sup> In particular, most of the investments were targeted at low-end, old-technology products (such as rebar, wire rods, and plates) that already were in oversupply. Consequently, as China's overall production of crude steel soared from 115 million tons in 1998 to 512 million tons in 2008, the excess supply of crude steel reached 160 million tons (around 24% of the total production capacity).

During this same time frame, many studies found that the market reforms significantly improved the market share of "local" firms in China's iron and steel industry (Kim et al., 2006; Sheng & Song, 2012; Wu, 2000). Many of these newly entered private firms or privatized SOEs were small and, thus, not well-equipped with modern technology compared with the "key" firms. As additional evidence, Brandt, Jiang, Luo, and Su (2022) also found that no significant difference in productivity existed for private/privatized "local" firms in terms of ownership, even in recent years. Thus, such a change in the industrial structure implies that resource misallocation across firms worsened during the reform period.

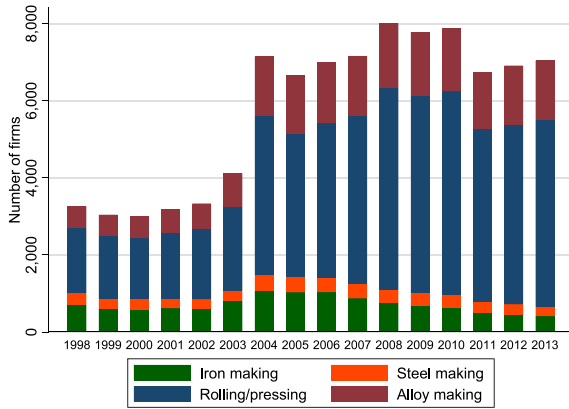
Three distinct features of China's iron and steel industry are useful in understanding the changes in resource allocation efficiency within the industry. First, China's steel production relies on the use of vertically integrated facilities, compared with electric arc

<sup>2</sup> In general, "key" firms are big firms that are directly controlled by the central government and provincial or municipal authorities. "Local" firms are younger and smaller in size and are controlled by local governments (Steinfeld, 1998).

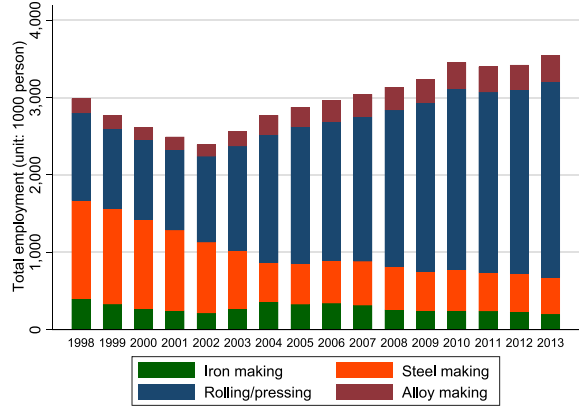
<sup>3</sup> The vertical ratio is technical terminology that is defined as the proportion of pig iron directly used for crude steel production. In practice, it is used to measure the efficiency of a vertical-integrated steel mill.

<sup>4</sup> According to a report by China Daily (August 1, 2013), in the first half of 2013, the profit of the 86 largest steel mills was a mere 2.27 billion Yuan (about US\$ 0.33 billion), with an average profit margin of 0.13%. This is in sharp contrast to the two-digit rate of return earned in many other industries.

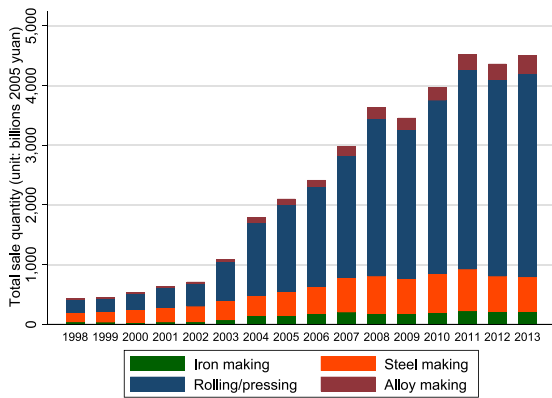
(A) Number of Firms



(B) Total Number of Employed Workers  
(unit: 1000 persons)



(C) Total Sales  
(unit: billions yuan at 2005 price)  
(unit: billions yuan at 2005 price)



(D) Total Asset Value in real term  
(unit: billions yuan)

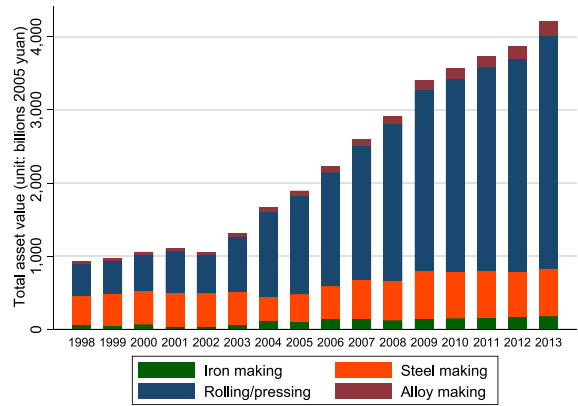


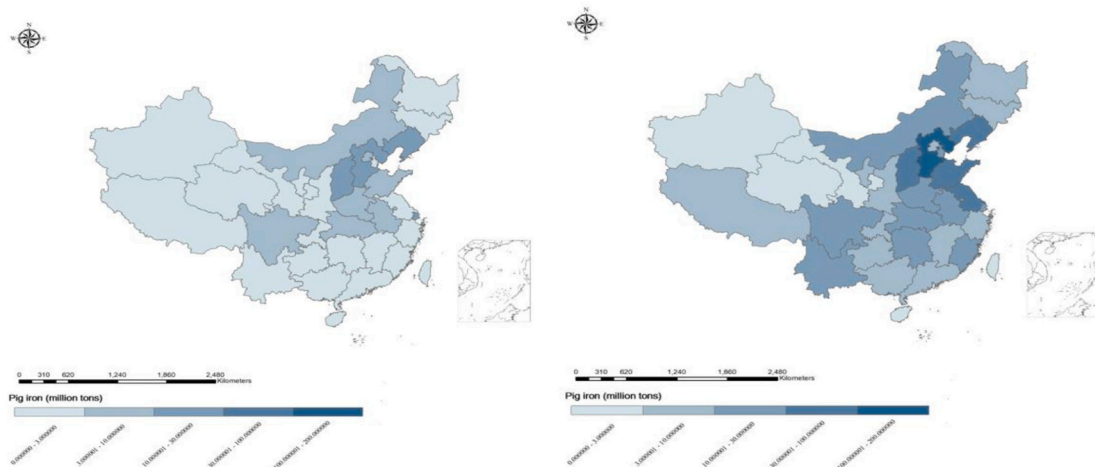
Fig. 1. China’s Iron and Steel Industry: 1998–2013.

Source: the data are obtained from China Iron and Steel Statistical Yearbook, various years, which is available at the CEIC database.

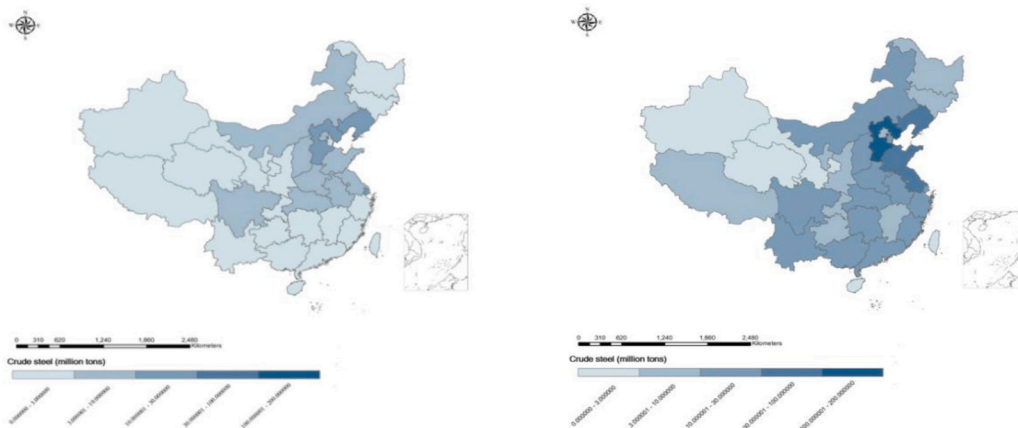
furnaces and mini-mill technology in the U.S. and other developed countries. This production technology enables China’s iron and steel firms to obtain market monopoly power more easily by expanding operational scale because the production is characterized by increasing returns to scale. Second, most iron and steel firms in China produce homogeneous and low-end products because of the downstream demand coming mainly from the construction industry. For example, in 2017, the construction industry (including the real estate and infrastructure sub-industries) contributed 53% of the nation’s total domestic demand for steel products. Given that steel products are close substitutes, iron and steel firms in China must compete over price. Third, as a legacy of the centrally planned era, both “key” and “local” steel firms are sparsely distributed geographically across regions. In fact, most “key” firms usually command particular advantages given their connection to local governments, thereby restricting free market access and mergers and acquisitions (M&As) activities in the local market.

Given the three aforementioned distinct features, market reforms in China’s iron and steel industry have reduced the overall concentration ratio at the industry level, but strengthened regional monopoly by “key” firms in local regions (Holloway et al., 2010; Tang, 2010). Fig. 2 shows the change in production of pig iron, crude steel, and alloy products across the provinces between 1998 and 2009. The output share of the top 10 largest steel enterprises in China in 2009 declined to 50% (from 80% in 1998) compared with shares of 65%, 78%, and 83% in the U.S., EU, and Japan, respectively (Brandt, Jiang, Luo, & Su, 2022). This implies that the nation’s market reforms reduced the industry’s average concentration ratio nationwide. However, when taking a closer look at provincial-level

### Panel (A) pig iron production: 1998 vs. 2009



### Panel (B) crude steel production: 1998 vs. 2009



### Panel (C) finished steel production: 1998 vs. 2009

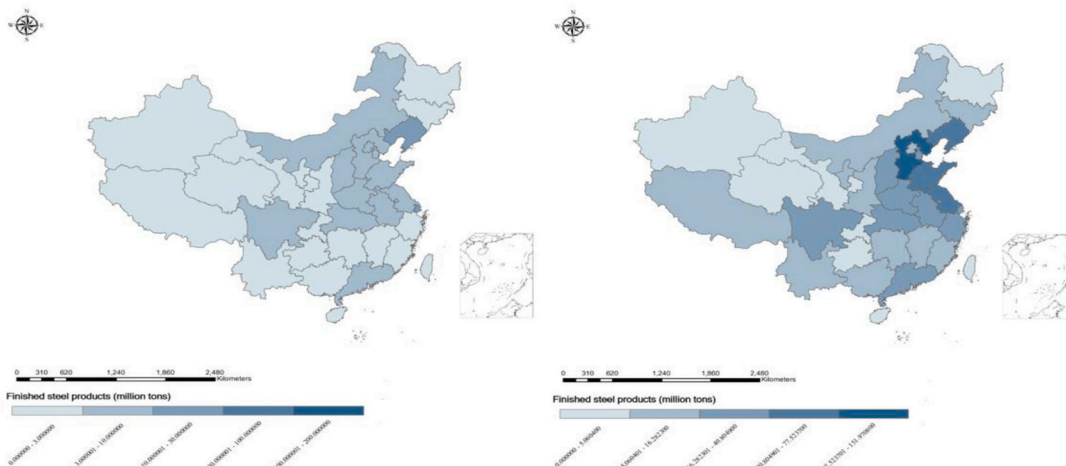


Fig. 2. Distribution of pig iron, crude steel and finished steel production in China.

markets, the proportion of top steel producer's output share in each province increased to >60% of the local market, a concentration ratio that is comparable to that of the rest of the world. According to this analysis, the distinct market structure in China has incentivized the bigger key steel manufacturers to expand their production, often irrationally, to gain an advantage over their smaller competitors (Fung, 2009), leading to the oversupply problem. (See Fig. 2.)

Two additional pieces of evidence indicate the existence of market fragmentation and regional monopoly in China's iron and steel industry. First, we observed substantial steel price dispersion across provinces, which persisted during the period 1998–2009. Between 1998 and 2009, the variance in the coefficients of average prices of all steel products increased, while round steel and line steel products' prices remained constant. For products as homogeneous as crude steel, the existence of a substantial price dispersion across provinces, along with a rapid increase in supply, clearly indicates the existence of regional market segregation.

Second, we used data from 86 major steel firms registered with the China Iron and Steel Association in 2008 to calculate the average sales radius for each firm (Fig. 3). On one hand, most steel firms serve local consumers located within a radius of 200 km from the selling entity (or within a province). On the other hand, within each province, large and small steel firms coexist. Large and small firms' sales radius overlap, with small firms usually distributed at the edge of large firms' sales radius. The two findings above offer further support for the observation that China's national iron and steel market actually comprises a set of fragmented markets and regional monopolies.

The characteristics of a regional monopoly has been viewed as an important factor that could undermine the role of market reforms in facilitating expansion at more-productive steel firms. However, to the best of our knowledge, neither formal modeling nor systemic empirical examinations have been conducted to identify the role of regional monopolies in affecting resource reallocation across firms and how they contribute to aggregate productivity growth. We attempt to overcome this shortcoming in the next section.

### 3. Data and empirical strategy

In this section, we present the data and methodology used for examining the empirical relationship between the resource reallocation effects and monopoly power of firms in local markets. A theoretical model is also provided in Appendix A to describe how regional monopolies may affect resource reallocation efficiency across firms.

#### 3.1. Data collection and firm-level TFP estimates

The data used in the present study mainly came from the Chinese Industrial Enterprise Database (CIED) provided by China's National Bureau of Statistics (NBS). The data cover the 1998–2009 period.<sup>5</sup> Iron and steel firms in the study were defined as those registered with the industry and engage in "smelting and pressing of ferrous metals" (namely, Category 32 of the two-digit Chinese Industrial Classification [CIC] Code). The set of the included firms includes four four-digit sub-sectors based on the steel production process: sintering/iron making; steel making; rolling and pressing; and alloy making.<sup>6</sup> The CIED database includes all state-owned and private enterprises above a designated output (those with annual sales of at least RMB 5 million).

Using these data provided a large sample base upon which to reflect on how China's iron and steel firms grew during the sample period. Dropping the observations with incomplete information left us with a sample of 33,778 firm-year observations. The sample ranged from 1654 firms in 1998 to 4929 firms in 2009.

The summary statistics on the major variables are listed in Table 1. The firms included in our sample account for >90% of the total number of firms in China's iron and steel industry. The combined output and asset shares accounted for around 96% of the total output/asset shares of the nation. Compared with the data used in the literature, our sample was more representative because it covered not only all SOEs, including both large and small firms, but also many private firms, which helped alleviate any potential selection bias problem.

The output and intermediate input quantities at the firm level were derived by dividing total sales revenue and expenditures on the intermediate inputs by the corresponding firm-level product and intermediate input prices, respectively. Firm-level product and intermediate input prices were estimated using product-level price data collected at the factory gate (see below). *Capital* was defined as a firm's net fixed assets deflated by the industry-level price index for investments specific to the iron and steel industry. *Labor* was defined as the number of employees (*zaigang* workers, which exclude redundant workers such as those laid off or already retired). The level of human capital (or labor quality) was adjusted by taking into account the sample firms' average wages.

We collected detailed product prices for both the outputs and intermediate inputs from the price surveys conducted by the National Development Research Center (NDRC). The NDRC price database provides the monthly prices for all manufacturing and mining products measured at the factory gate in 130 major cities between 1989 and 2012. For this study's purposes, we matched these price data with the top three products of each firm and their major inputs. Data on the weights for price aggregation were collected from the internal reports for representative firms of the China Iron and Steel Association by region.

<sup>5</sup> Although the global financial crisis started in 2008, it is not until late 2009 that the iron and steel industry in China was affected when the total output of the industry dropped because of the slack in demand (Fung, 2009).

<sup>6</sup> Steel manufacturing is the process of producing steel using iron ore and coking coal as the major input. The process involves four steps: the first is iron making, or iron ore is transformed into pig iron in a blast furnace; the second is steel making, or the molten pig iron and recycled steel scrap are fed into a converter to produce steel; the third and fourth step is rolling/pressing, which refers to when the output crude steel is refined and cast into steel products such as slab, billet and bloom, or other alloy products.

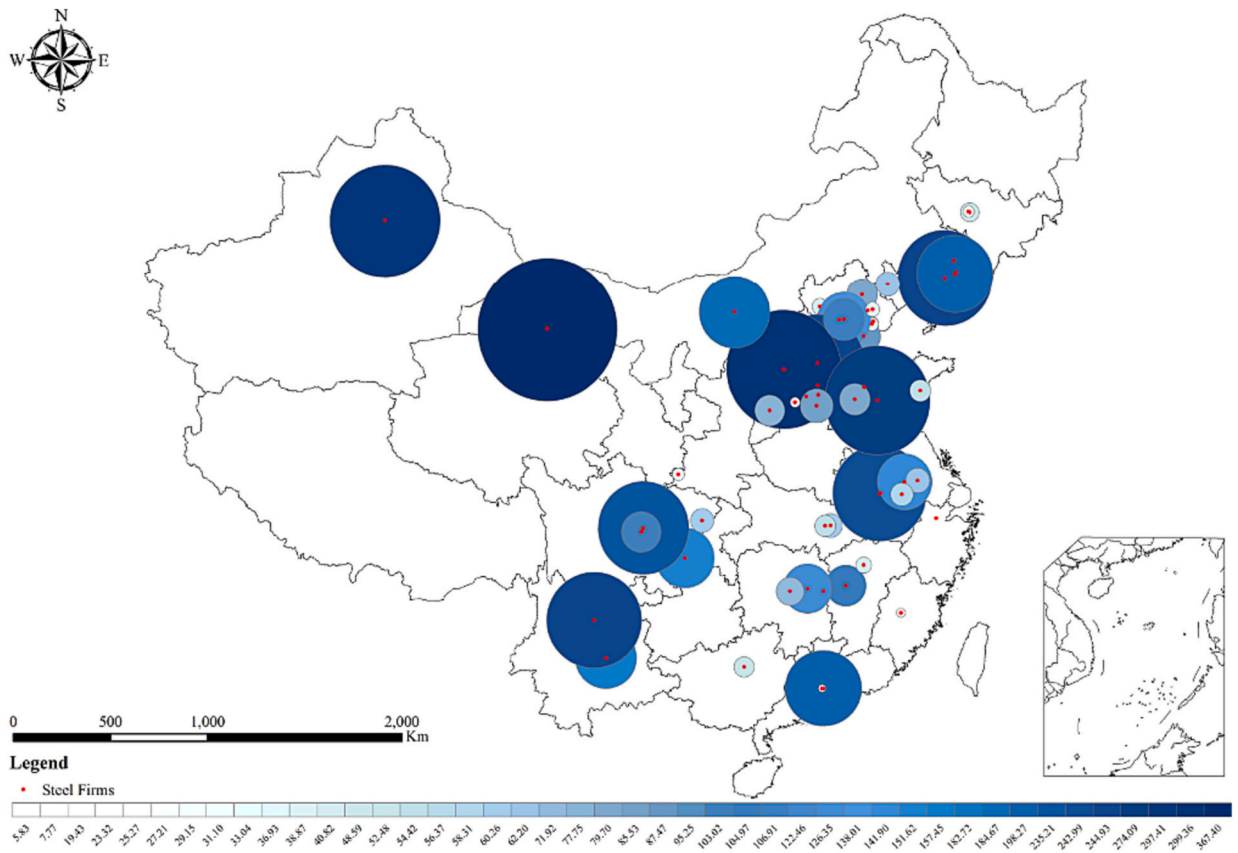


Fig. 3. The Sales Radius of Major Chinese Iron and Steel Firms: 2008.  
 Source: Authors' calculations using data from China Iron and Steel Association in 2008, China.

**Table 1**  
The Summary Statistics on China’s Iron and Steel Firms between 1998 and 2009.

	Sintering/Iron making	Steel making	Rolling/pressing	Alloy making	Average
Output value at current price (billion yuan)	1.691 (9.054)	17.442 (63.528)	4.610 (29.335)	0.885 (2.456)	4.046 (27.173)
Employment (person)	405.19 (1356.49)	3384.70 (12,752.82)	602.92 (3544.13)	201.02 (382.65)	633.00 (4066.04)
Workers’ annual wage (1000 yuan)	10.21 (17.91)	14.39 (14.40)	14.89 (22.43)	11.19 (11.95)	13.28 (19.63)
Fixed asset value (billion yuan at 2000 price)	0.337 (1.773)	7.430 (35.595)	1.661 (15.196)	0.154 (0.801)	1.433 (14.233)
Intermediate inputs (billion yuan)	1.292 (7.287)	13.096 (43.446)	3.589 (21.840)	0.665 (1.910)	3.116 (19.814)
Export value (million yuan)	36.439 (405.323)	834.087 (7037.639)	284.553 (3410.599)	82.243 (582.477)	232.190 (3080.286)
Entity share of SOEs (%)	26.13 (41.66)	30.14 (47.52)	19.71 (37.58)	21.03 (39.02)	21.67 (39.33)
Number of observations	6882	2275	25,581	9081	43,819

Source: Authors’ calculations using the China Industrial Enterprise Database.

3.2. Empirical strategy

Our empirical strategy contained three steps. The first was to estimate the firm-level Cobb-Douglas production function by using the semi-parametric estimation technique and calculate the firm-level TFP, which is defined as the residual of total output minus capital, labor and intermediate inputs, multiplied by their respective marginal contribution (or their output elasticities). Using the regression method to estimate firm-level TFP has long been discussed in the literature (Akerberg, Benkard, Berry, & Pakes, 2007; Collard-Wexler & Loecker, 2015; Levinsohn & Petrin, 2003; Olley & Pakes, 1996). Here, two issues need to be addressed to help describe our approach. The first is that we corrected for potential price variations across firms and over time for both the outputs and inputs, which reduced the effects from different output and input structures on output prices across firms and over time. The second issue that we sought to account for was the potential correlation between capital use and unobserved productivity level, which, in principle, helps resolve the endogeneity problem in the estimation of production functions.<sup>7</sup>

The estimated firm-level TFP is then used to calculate aggregate industry-level TFP, the within-firm productivity effect and the resource reallocation effect across firms and their average annual growth rates in China’s iron and steel industry in response to market reforms during the 1998–2009 period. In the standard OP estimation, industry-level TFP equals the weighted average of firm-level TFP. It can be decomposed into two components, including unweighted average firm-level TFP and the sum of the covariance between firm-level productivity and the firm’s output share:

$$\Omega_t = \bar{\omega}_t + \sum_i (\omega_{it} - \bar{\omega}_t)(s_{it} - \bar{s}_t) \tag{1}$$

$$\Delta \Omega_t = \Delta \bar{\omega}_t + \Delta \sum_i (\omega_{it} - \bar{\omega}_t)(s_{it} - \bar{s}_t) \tag{1'}$$

where  $\Omega_t$  is industry-level productivity,  $\omega_{it}$  is firm-level productivity, and  $s_{it}$  is the total output share of firm  $i$ .  $\bar{\omega}_t$  and  $\bar{s}_t$  are the unweighted means of firm-level productivity and the firm’s output share, respectively.  $\Delta$  represents average year-to-year change. The decomposition result obtained from (1) and (1') will inform the analysis of how resource reallocation may contribute to industry-level TFP and its growth relative to within-firm technology progress.

In the second step, we split the whole iron and steel market into in-local (or within-province) and remote (between-province) markets. By using the approach proposed by Melitz and Polanec (2016) and Collard-Wexler and Loecker (2015), we decompose the industry-level resource reallocation effects, measured by using the sum of firm-level size-productivity covariance, into within-province and between-province components, such that:

$$\Omega_t = \bar{\Omega}_t(\phi) + \sum_k [\Omega_{kt}(\phi) - \bar{\Omega}_t(\phi)][s_{kt}(\phi) - \bar{s}_t(\phi)] \tag{2}$$

in which  $\bar{\Omega}_t(\phi)$  is the unweighted productivity of type  $\phi$  firms across its  $k$  provinces,  $\Omega_{kt}(\phi)$ , and  $\bar{s}_t(\phi)$  is the average output share of type  $\phi$  firms across its  $k$  provinces,  $s_{kt}(\phi)$ . Thus, the aggregate productivity of type  $\phi$  firms in province  $k$ ,  $\Omega_{kt}(\phi)$ , can be decomposed into the unweighted productivity of type  $\phi$  firms in province  $k$  and the covariance between these firms’ size and productivity (or “within-province” decomposition):

$$\Omega_{kt}(\phi) = \bar{\omega}_{ikt}(\phi) + \sum_{i \in k} [\omega_{ikt}(\phi) - \bar{\omega}_{kt}(\phi)][s_{ikt}(\phi) - \bar{s}_{kt}(\phi)] \tag{3}$$

<sup>7</sup> The detailed procedures that we used to estimate the firm-level TFP based on the sector-level production function (thus the firm-level TFP) are provided in Appendix B.



in which  $\overline{\omega_{ikt}}(\phi)$  is the unweighted productivity of firm  $i$  in province  $k$  at time  $t$  by type  $\phi$ ,  $\omega_{ikt}(\phi)$ , and  $\overline{s_{kt}}(\phi)$  is the average output share of firm  $i$  in group  $k$  at time  $t$   $s_{ikt}(\phi)$  and  $\sum_i s_{ikt}(\phi) = 1$ . Both Eqs. (2) and (3) can be written in growth form such as:

$$\Delta\Omega_t = \Delta\overline{\Omega}_t(\phi) + \Delta\sum_k [\Omega_{kt}(\phi) - \overline{\Omega}_t(\phi)][s_{kt}(\phi) - \overline{s}_t(\phi)] \tag{2'}$$

$$\Delta\Omega_{kt}(\phi) = \Delta\overline{\omega}_{ikt}(\phi) + \Delta\sum_{i \in k} [\omega_{ikt}(\phi) - \overline{\omega}_{kt}(\phi)][s_{ikt}(\phi) - \overline{s}_{kt}(\phi)] \tag{3'}$$

In comparing the resource reallocation effect and its change over time between firms obtained from (2), (2'), (3) and (3'), we retrieved the change in resource reallocation effect in space. If the within-province resource reallocation effect is relatively larger than that of the between-province effect, the market is deemed more competitive (and vice versa).

In addition, we also defined the group (or  $\phi$ ) by using ownership (i.e., SOEs vs. non-SOEs) (rather than province) to examine how resources shift between and within firms with different types of ownership. In doing so, we had an a priori expectation that SOEs typically are viewed as dominant firms in the local market. This exercise allowed us to test this idea empirically and seek supportive evidence for the presence (or not) of the nature of the monopoly power of the dominant firm(s).

In the third step, we examined the relationship between the within-province resource reallocation effect and average firm-level markup because the impact of a regional market monopoly as measured by average firm-level markup, decreases as the sales distance expands beyond the provincial level. To test this hypothesis, we regressed the within-province resource reallocation effect on average firm-level markup while controlling for other potential determinants, such that

$$COV_{rst} = \alpha + \beta MKP_{rst} + \gamma Z_{rt} + u_s + v_t + \varepsilon_{rst} \tag{4}$$

in which  $COV_{rst}$  denotes the within-province OP covariance, and  $r$ ,  $s$ , and  $t$  denote province, sector, and year, respectively.  $MKP_{rst}$  is the average markup of steel firms in province  $r$  at year  $t$ , which captures the degree of monopolistic competition.  $Z_{rt}$  represents a set of control variables.

In these regressions, we added control variables to account for the factors that could affect cross-firm resource reallocation beyond factors associated with firms' regional monopoly power. These factors included the number of iron and steel firms by sector in the local market, a firm's average export share, and the average level of fixed-asset investment within the province (e.g., Jefferson, 1990). The purpose of adding these variables was to account for the impact from the sector-level market concentration level, each firm's export orientation, and vintage effects, respectively, on cross-firm resource reallocation within the local market. In addition, we also accounted for the provincial cluster effects ( $u_s$ ) and included a year dummy ( $v_t$ ), which takes 1 for the period after China's accession into the WTO.

Finally, when estimating the coefficient of interest,  $\beta$ , in Eq. (4), We also employed an instrumental variables (IV) approach to address the potential concern of reverse causality. This is important because resource misallocation could potentially exacerbate the monopoly power. In implementing the IV approach, we used two different instrumental variables. One is the maximum sale distance of the top steel firm in each province, a variable that seeks to exploit the exogenous variation in a firm's location distance to the market. The other variable, following Syverson (2004), is the total housing area under construction, which is relevant because rapid growth in the construction industry (as well as the level of public infrastructure investment in a region's downstream industries) can drive market demand for iron and steel products (Fung, 2009; Holloway et al., 2010; Tang, 2010). For example, in 2008, the construction industry consumed about 55% of China's steel (Fung, 2009). Both instruments are associated with firms' local monopoly power, but are not related directly to size-productivity covariance.

#### 4. Empirical results

In this section, we will discuss the results obtained by applying the empirical strategy to the data described in Section 4. The results are presented in Tables 2–6.

##### 4.1. Industry TFP growth and resource reallocation

As discussed in Section 4, industry-level TFP growth can be decomposed into within-firm productivity growth and resource reallocation effect. As shown in Table 2, annual industry-level TFP growth during the 1998–2009 period was, on average, 5.34% per year. Differing from the previous literature (e.g. Brandt et al., 2012), our estimate of industry-level TFP growth also include the impact of firms' entry and exit.<sup>8</sup> According to our analysis, within-firm productivity growth accounts for 86% of overall annual industry-level TFP growth (or 4.59% per year). The resource reallocation effect, as measured by annual growth in OP covariance, was 0.74% per year and accounted for only 14% of overall annual industry-level TFP growth. Moreover, our findings are consistent with the results of Brandt et al. (2012), who observed limited resource reallocation effects in the Chinese manufacturing industries between 1998 and

<sup>8</sup> Our estimates of annual total factor productivity (TFP) growth, based on gross output, in the Chinese iron and steel industry exceed those reported in prior literature for manufacturing sectors (e.g., Brandt et al., 2012). This difference can be attributed to three factors: the distinct characteristics of the iron and steel industry, the rapid turnover of firms during the sampled period, and the specific composition of the sample. A comprehensive analysis of this matter is elaborated in Appendix B.

**Table 2**  
Contribution of Resource-Reallocation to the Industry-level TFP Growth (%): 1998–2009.

	TFP Growth	Unweighted Average	OP Covariance
1998–2001	4.55	2.13	2.42
2002–2005	8.38	6.76	1.61
2006–2009	2.88	4.27	–1.39
1998–2009	5.34	4.59	0.74

Note: We adopt the OP (Olley & Pakes, 1996) to measure the contribution of resource reallocation to TFP growth. Results from alternative approaches (i.e. FHK and BHC) are reported in Appendix C.

**Table 3**  
Decomposition of TFP Growth and Its Components by Sectors (%): 1998–2009.

	TFP Growth	Unweighted Average	OP Covariance
Sinister/iron making	5.74	4.28	1.46
Steel making	4.35	4.02	0.33
Rolling/pressing	4.56	4.32	0.24
Alloy making	4.50	3.68	0.82

Note: “Sinister/iron making” refers to China Industry Classification (CIC) Code 3210; “Steel making” refers to CIC 3220; “Rolling/pressing” refers to CIC 3230; “Alloy making” refers to CIC 3240.

**Table 4**  
Comparing the Resource-Reallocation Effects across Regions: Between-province vs. Within-province (%): 1998–2009.

	Between Province			Within Province		
	TFP	Unweighted Average	OP Covariance	TFP	Unweighted Average	OP Covariance
Sinister/iron making	5.74	4.67	1.07	4.67	4.28	0.39
Steel making	4.35	4.11	0.24	4.11	4.02	0.09
Rolling/pressing	4.56	5.37	–0.81	5.37	4.32	1.04
Alloy making	4.50	4.13	0.37	4.13	3.68	0.45

Note: “Sinister/iron making” refers to China Industry Classification (CIC) Code 3210; “Steel making” refers to CIC 3220; “Rolling/pressing” refers to CIC 3230; “Alloy making” refers to CIC 3240. “Within province” refers to resource reallocation within province, while “Between province” refers to resource reallocation effects between provinces.

**Table 5**  
Comparing the Resource-Reallocation Effects across Ownerships: Between ownership vs. Within ownership (%): 1998–2009.

	Between SOEs/Non-SOEs			Within SOEs			Within Non-SOEs		
	TFP	Ave	COV	TFP	Ave	COV	TFP	Ave	COV
Sinister/iron making	5.74	4.47	1.26	3.35	4.33	–0.98	5.6	4.11	1.49
Steel making	4.35	4.61	–0.26	4.6	4.49	0.11	4.62	4.33	0.29
Rolling/pressing	4.56	4.65	–0.08	4.28	4.86	–0.59	5.01	4.12	0.89
Alloy making	4.50	4.78	–0.29	5.06	3.76	1.31	4.51	3.42	1.09

Note: “Sinister/iron making” refers to China Industry Classification (CIC) Code 3210; “Steel making” refers to CIC 3220; “Rolling/pressing” refers to CIC 3230; “Alloy making” refers to CIC 3240. “Within SOEs” refers to resource reallocation among SOEs, “Within Non-SOEs” refers to resource reallocation among non-SOEs, and “Between SOEs/Non-SOEs” refers to resource reallocation between SOEs and non-SOEs.

2007. Specifically, they found that within-sector resource reallocation contributed to only 4% of the aggregate productivity growth. Our study provides further evidence of the constrained resource reallocation within the iron and steel industry, highlighting the importance of understanding the limited impact of resource reallocation on productivity growth.

Our results also demonstrate clear declining trends in resource reallocation effects throughout the sampled time frame. When we split the whole period into three subperiods—1998–2001, 2002–2005, and 2006–2009—annual growth in OP covariance (a measure of resource reallocation effects) declined from 2.42% a year during the period 1998–2001 to –1.39% a year during the period 2006–2009. In contrast, over the same period, annual within-firm productivity growth increased from 2.13% to 4.27% per year, indicating rapid technology progress. Such trends are somewhat surprising because market reforms during this period led to a substantial increase in the privatization of steel and iron industry firms, as well as the marketization level in the industry. In other words, during a time when the resource reallocation effect was deteriorating, China was in the middle of implementing a set of market reforms

**Table 6**  
Market Monopoly Power and the Resource Reallocation Effect within Provinces: 1998–2009.

	Sales Radius (IV1)		Construction Area (IV2)	
	Fixed Effect	Fixed Effect with IV	Fixed Effect	Fixed Effect with IV
	(1)	(2)	(3)	(4)
Dependent variable: within-province covariance (ln)				
Average firms' markup	−0.344* (0.132)	−0.999*** (0.145)	−0.474** (0.137)	−1.468*** (0.533)
Total crude steel production (ln)	−0.015 (0.014)	−0.028** (0.013)	0.000 (0.008)	0.004 (0.008)
Export share of output	−0.003 (0.307)	−0.123 (0.330)	−0.010 (0.286)	−0.173 (0.152)
Number of steel firms	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Fixed asset investment (ln)	0.008** (0.002)	0.004*** (0.001)	0.010** (0.002)	0.009*** (0.003)
Constant	0.191 (0.085)	–	0.102 (0.048)	–
Dummy for WTO accession	Yes	Yes	Yes	Yes
Province*Sector FE	Yes	Yes	Yes	Yes
Province*Sector cluster effects	Yes	Yes	Yes	Yes
Number of observations	933	933	1059	1059
R-squared	0.036	–	0.060	–
Number of province X sector	99	99	117	117

Note: Robust standard errors in parentheses, \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . The first-stage F-test for IV are 57.97 and 14.45 respectively. The first-stage results for FEIV models are reported in Table C1 of Appendix C.

that elicited a reduction in market share of SOE firms in the industry, from 80% in 1996 to 40% in 2008. Simultaneously, the market share of the top 10 largest firms in the industry fell from 80% in 1998 to 50% in 2009. In such an environment, one might have expected to see a more positive resource allocation effect resulting from the relatively rapid levels of within-firm technological progress.

Our analysis is also clear in showing that the pattern of productivity changes is not confined to the overall/aggregated sector. In examining the four subsectors of China's iron and steel industry, the results do not indicate a significant positive resource reallocation effect in any subsector. As shown in Table 3, the OP covariance term grows at the rate of <1% per year in three out of the four subsectors, which is far less than the 3.68–4.32%-per-year growth found in annual within-firm productivity. Although the OP covariance term in the sintering/iron-making subsector increases slightly (1.46% a year), its contribution to sub-sectoral-level TFP growth remains relatively small (only about 25%).

#### 4.2. Resource reallocation between and within province

Could the unintended resource reallocation effect due to market reforms in China's iron and steel industry during the 1998–2009 period be related to regional market monopoly? To answer this question, we decomposed the industry-level resource reallocation effect into two components: the *within-province* and *between-province* effects. As discussed before, the purpose of doing this is to test the hypothesis: The presence (or absence) of a local market monopoly can be shown by comparing the within-province resource reallocation effects with the between-province resource reallocation effects. If there was a nationwide competitive iron and steel market, the resource relocation effect would be larger in the local market, where firms' sales price is more likely to be determined by their productivity. Thus, we expect *between-province* resource reallocation effects to be lower than *within-province* resource reallocation effects.

Table 4 shows the decomposition results for the four subsectors. As shown in Column (3) of Table 4, in three out of the four subsectors, resource reallocation *between provinces* positively contributes to industry-level TFP growth. However, and relevant to our results, the magnitude of these TFP shifts is small. On average, the change in the OP covariance *between provinces* only accounts for 5.52%, 8.22%, and 18.64% of industry-level TFP growth in the sintering/iron making, steel-making, and alloy-making sectors, respectively. Such results are consistent with what should be expected. The between-province effect should be small, considering that transportation costs would be expected to undermine the impact from productivity growth of more-productive steel firms and keep them from being able to expand their market share into more remote regions.

Interestingly, despite there being small *between-province* productivity effects, the *within-province* resource reallocation effects generally are not significantly larger than the *between-province* resource reallocation effects. Specifically, in the case of the sintering/iron-making and steel-making sectors, the *within-province* resource reallocation effect is 36.45% and 37.5% of the already small *between-province* resource reallocation effect, respectively. As for alloy making, the *within-province* and *between-province* resource reallocation effects are 0.45% and 0.37% per year, respectively, i.e., similar in magnitude. The findings on the insignificant *within-province*

resource reallocation effect relative to the *between-province* resource reallocation effect contradict the hypothesis that a nationwide competitive market exists. Therefore, based on this finding, one begins to hypothesize that either market fragmentation characterizes China's iron and steel market and/or dominant firms impose monopoly power within provinces (which, in turn, could limit more-productive firms from expanding into local markets).<sup>9</sup>

In the literature, iron and steel market fragmentation usually is attributed to local protectionism associated with the presence of large SOEs and the privileges that they enjoy, including prioritized access to various resources and close ties with local governments (Brandt, Jiang, Luo, & Su, 2022; Sheng & Song, 2012). According to the literature, SOEs are significant in generating GDP growth, employment, and tax revenue, thereby contributing to improving the performance indicators that are important to local policy makers. However, because SOEs share the same administrative system as local governments and state-owned banks, they historically have enjoyed preferential treatment in land use and bank loans compared with their private counterparts (Song & Liu, 2012). Given the difference in the economic status between SOEs and non-SOEs compared with local governments, it may be hypothesized that local protectionism could help SOEs establish their market power.

To investigate the potential link between resource reallocation effects and market structure caused by SOEs' presence in China's local markets, we further classified the iron and steel firms by ownership and decomposed the industry-level resource reallocation effect into components among SOEs and non-SOEs, and between the two types of firms. We expect that resource reallocation should be larger among non-SOEs rather than among SOEs (and also somewhat higher between SOEs and non-SOEs). This expectation is confirmed in our empirical results. As shown in Table 5, the average annual change in OP covariance terms between SOEs and non-SOEs is estimated to range from  $-0.08$  to  $-0.29\%$  in three out of the four subsectors (including steel, rolling and pressing, and alloy production). When examining average annual change in OP covariance terms among non-SOEs, it is clear that they are all positive. Similarly, the average annual change in OP covariance terms among non-SOEs is also much larger than those among SOEs. Because both SOEs and non-SOEs have experienced similar within-productivity growth during the reform period, our findings suggest that SOEs, which have been shown to receive local protection (and, thus, command local monopoly power), are less likely to be part of a process that allows resource reallocation across firms in response to productivity shocks. In addition, the presence of locally supported SOEs also may limit other more-productive firms from being able to expand.

#### 4.3. Regional monopoly and resource reallocation

The decomposition analysis above shows that low levels of resource reallocation effect at the industry level may derive from the fact that weak resource reallocation exists within provinces. We also showed that weak resource reallocation within provinces could be related to SOEs' reluctance to participate in (or allow) resource reallocation, and there was a lack of interaction between SOEs and non-SOEs during the reform period. However, no direct evidence so far indicates a link between low resource reallocation effects within a province and large and dominant SOEs' monopoly power in the local market. In this section, we further examined the relationship between within-province OP covariance and firms' monopoly strength in the local market, both visually (see Fig. 4 and the discussion below) and by the estimated coefficient from the fixed effect model with instrumental variables.

We start by illustrating the relationship between the within-province OP covariance and dominant firms' local monopoly power for the four subsectors by province and over time. In this analysis, we measured the local market monopoly power of firms by using the average markup of steel firms for each province.<sup>10</sup> As shown in Fig. 4, the within-province OP covariance is correlated negatively with the average markup of steel firms. Consistent with the prediction from Proposition 2 (above), our findings imply that resources are reallocated across iron and steel firms relatively slowly in the provinces where dominant firms have relatively strong market power.

We further performed regressions to examine the relationship between the within-province OP covariance and average markup of steel firms formally. Table 6 reports the regression results from the fixed effect (FE) and fixed effect with instrumental variables (FEIV) regressions. From the baseline fixed effect regressions, as reported in Columns (1) and (3), we found a significant negative relationship between firms' local monopoly power and the within-province resource reallocation effect in China's overall iron and steel industry.<sup>11</sup> Our preferred FEIV regressions confirm the results, as shown in Columns (2) and (4). The estimated coefficients for the average firm-level markup also are negative and significant at the 1% level after taking into account the effect from other control variables. In particular, the results obtained from the FEIV regressions are  $-1.00$  and  $-1.47$ , respectively, which are much smaller than those obtained from the FE regressions ( $-0.34$  and  $0.47$ ), suggesting that omitted variables may be correlated negatively with steel firms' market power.

The findings associated with the regression in Columns (2) and (4) imply that a 1% increase in average firm-level markup is associated with a reduction in within-province resource reallocation of 1.00 to 1.47%. Such a finding is consistent with our theoretical model's prediction that the monopoly power held by a market's dominant firm might limit more-productive firms from expanding their production. The finding, which is consistent with the finding by Syverson (2004) in the U.S. concrete industry, suggests that the noncompetitive market structure that exists in some local markets in China is an important factor that is undermining the impact of the

<sup>9</sup> The only exception is the rolling/pressing industry, which by its very nature is dominated by many small- and medium-sized firms.

<sup>10</sup> We define the variable as the ratio of primary sales revenue to primary sales costs for the four subsectors, following the approach of Collard-Wexler & Loecker, 2015. For a detailed explanation of the methodology used to derive this mark-up as a measure of the monopoly power of local firms, please refer to Collard-Wexler & Loecker, 2015.

<sup>11</sup> Note that in Table 6, we utilize two instrumental variables, each applied in a separate fixed effects regression, as demonstrated in Columns (1) and (3). Additionally, we employ fixed effects alongside an instrumental variable regression, as illustrated in Columns (2) and (4).

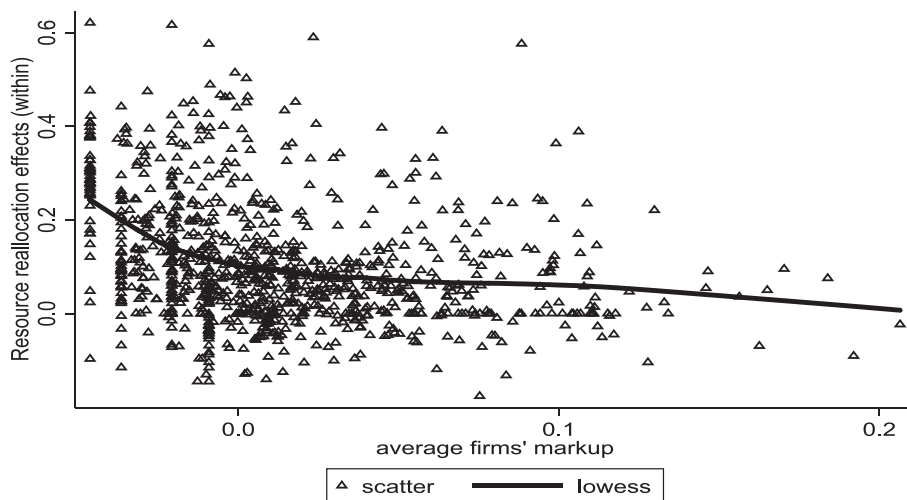


Fig. 4. Relationship between the Within-province Resource Reallocation Effect and Firms' Local Monopoly Power: 1998–2009.

Note: The vertical axis denotes the within-province OP covariance used to measure the resource reallocation effects within provinces, while the horizontal axis denotes the average firms' mark-up at the province level used to measure the local monopoly power.

Source: Authors' calculations.

market reforms on resource reallocation in China's iron and steel industry.

To sum up, in this section, we empirically demonstrated that market reforms in China's iron and steel industry have not delivered the intended resource reallocation effects across firms during the 1998–2009 period. In fact, resource reallocation worsens over time despite the fact that the reforms significantly increased privatization and marketization levels, as well as facilitated within-firm productivity growth. According to the findings, the within-province resource reallocation effect is particularly weak. The measured within-province effect generally is smaller compared with the between-province resource reallocation effect. Finally, our results also show that the weak within-province resource reallocation effect is likely to be related to the local monopoly power of the dominant firm(s) in local markets.

## 5. Robustness check

In this section, we conduct several sensitivity tests to assess the robustness of our empirical results. Firstly, there might be concerns regarding the relationship between our findings on the weak resource reallocation effect in China's iron and steel industry during the market reform period and the OP decomposition method that we utilized. Nishida, Petrin, and Polanec (2013) demonstrated that different decomposition methods employed by analysts yield distinct measures of the resource reallocation effect. To address this concern, we re-evaluated the resource reallocation effect using two other widely used approaches: the BHC approach, proposed by Baily et al. (1992), and the FHK approach, proposed by Foster et al. (2001, 2008). The decomposition of industry-level TFP growth obtained from employing the BHC and FHK approaches confirms our finding that the resource reallocation effect remains weak in comparison to within-firm productivity growth during the reform period (refer to Table C2 in Appendix C).

Secondly, the measures we employed for product prices may play a significant role in influencing the estimation of the resource reallocation effect among firms, as firms often make input/output decisions based on profitability rather than productivity growth. While our main analysis utilized the quantity-based TFP measure, we also conducted additional analyses using alternative approaches, such as the revenue-based TFP measure, to ensure the robustness of our findings. The results obtained from the revenue-based TFP measure are generally consistent with our initial findings, with the exception that the resource reallocation effect at the industry level during the sample period appears slightly larger. This outcome aligns with the existing literature, which suggests that firms are more inclined to allocate resources in response to profit shocks rather than productivity shocks, despite the strong positive correlation between the two indicators in the long run.

Thirdly, the decisions made by firms regarding entry and exit may have asymmetric impacts on resource reallocation among firms. From 1998 to 2009, the average annual rates of firm entry into and exit from China's iron and steel industry were 16% and 33%, respectively. While we considered the influence of firms' entry and exit in our main analysis, we did not differentiate between entering, exiting, and ongoing firms. To assess the sensitivity of our results to this assumption, we conducted a separate examination of the impact of market reforms on resource reallocation, specifically focusing on firms entering or exiting.

On average, the net impact of firms' entry and exit contributed to approximately 1% of TFP growth at the industry level. However, our study reveals that the average TFP level of entering firms is not only lower than that of incumbent firms but also lower than that of exiting firms, particularly after 2002. This finding aligns with the observations of Brandt et al. (2012), who noted that "firms entering at a slightly lower productivity level" and that "entrants have below-average productivity, particularly in their first year" (p. 346). These results suggest that the rapid expansion of the iron and steel industry through a high influx of new firms does not significantly contribute to TFP growth. Finally, by employing the methodology proposed by Melitz and Polanec (2016), we demonstrate that the effects of market reforms on resource reallocation, specifically for continuing firms, closely align with our original findings. This confirms the consistency between our previous examination of the impact of market reforms on resource reallocation effects across all firms and the specific focus on continuing firms in this analysis.

Fourthly, we evaluate the robustness of our original findings by examining how variations in resource reallocation effects across different geographical areas align with our results when alternative measures or definitions are utilized to define the local market. To address this, we investigate the impact of using regions instead of provinces to define the local market in the iron and steel industry in China. We divided the market into seven regions, namely northeast, north, northwest, east, south, middle, and southwest, based on the definitions outlined in the state plan from the national strategy for market integration of steel production.

As indicated in the descriptive statistics presented earlier in the paper, the market concentration level within each region experienced an average decline of 10 to 20% during the reform period (1998–2009), suggesting relatively higher competitiveness in both within-region and between-region markets. When utilizing these new regional divisions, the data indicate that the within-region resource reallocation effect is significantly larger than the between-region resource reallocation effect when comparing the effects within and between regions (refer to Table C3 in Appendix C). This finding generally aligns with our theoretical prediction (Proposition 1 in Appendix A) that resource reallocation effects across firms will decrease in a remote yet competitive market.

Fifthly, our regression results in Section 4.3 could potentially be sensitive to using the average firm-level markup by sub-sectors at the provincial level as the sole measure of regional monopoly. To address this concern, we also consider alternative measures of market monopoly power and conduct the regressions anew.

To mitigate this issue, we explore the use of the total markup of all steel firms in all four sub-sectors at the provincial level, as well as the markup of the largest firm, as alternative measures of market monopoly power. Additionally, we adopt the approach proposed by Loecker, and Jan, and Frederic Warzynski. (2012) to estimate firm-level markup and repeat our analysis.

Consistent with the results obtained using the average firm-level markup by sub-sector as the measure of regional monopoly, the markup of firms measured by employing alternative methods exhibits a negative association with the within-province size-productivity covariance. This suggests that our findings are robust and not reliant on any specific measure of monopoly power.

Overall, the evidence supports the robustness of the negative relationship between market power firms and within-province resource reallocation effects in China's iron and steel industry. This finding holds true across various alternative measures of firm productivity and markup, output prices, considerations of firms' entry and exit, different levels of regional aggregation, and alternative regression methods.

## 6. Concluding remarks

Policy makers in developing countries have implemented market reforms with the aim of enhancing resource allocation efficiency among firms, thereby fostering overall total factor productivity (TFP) growth. It is widely believed that through market reforms, more-productive firms would have the opportunity to expand their output in a competitive or privatized market, driven by accelerated within-firm productivity growth. This assumption suggests that such reforms would lead to an overall improvement in aggregate productivity.

However, an increasing body of literature investigating the reallocation of resources across firms has uncovered perplexing evidence that market reforms may not yield the intended effects on resource allocation. This presents a puzzling phenomenon, as it challenges the conventional understanding that market reforms would effectively drive resource reallocation across firms.

In this paper, we provide an explanation as to why market reforms might not enhance resource allocation efficiency in a more competitive market overall, particularly when local monopoly power becomes stronger. To illustrate this point, we use China's iron and steel industry as a case study. Our analysis reveals that the regional market monopolies of locally dominant firms act as a constraint on more-productive firms, impeding their ability to expand their output. As a result, market reforms aimed at enhancing overall market competitiveness may not achieve the desired resource reallocation effects in response to within-firm productivity growth within the local market. Consequently, there is a possibility that this could lead to a decline in overall resource reallocation efficiency. By utilizing firm-level data from China's iron and steel industry during the reform period of 1998–2009, our study provides evidence indicating that the within-province market monopoly, especially that of the local dominant firm, hampers the efficient reallocation of resources from less-efficient steel firms to more efficient ones.

Finally, the monopoly power of dominant firms in local markets has been identified as one of the factors contributing to the issue of over-capacity in steel production. Our findings provide insights into the paradox of an oversupply of low-end iron and steel products despite the Chinese market becoming more competitive due to market reforms. This phenomenon has been widely observed in various industries during the reform period of 1998–2009, such as the concrete and energy sectors (European Chamber, 2016; Lin, Liu, & Fredrich, 2016; Shi, Rioux, & Galkin, 2018), and it is also applicable to other developing countries undergoing market reforms.

These findings highlight the importance of prioritizing policies that eliminate regional protection and market segregation. By doing so, it becomes possible to facilitate more efficient resource reallocation across regions under market reforms. This policy implication holds significant relevance not only for China but also for other developing nations in the process of implementing market reforms.

**Data availability**

Data will be made available on request.

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**Appendix A. A Theoretical Resource Reallocation Model in a Monopolistic Competitive Market**

In this appendix, we developed a monopolistic competition model to show how regional market monopoly may affect cross-firm resource reallocation effects (measured by using productivity-size covariance). The purpose is to provide a theoretical lens through which one can link regional market monopoly to the resource reallocation effects through introducing the price elasticity, and provide an identification condition that one can use to detect market monopoly impact and guide the empirical study.

We start with supposing that the industry comprises  $N$  firms, and each firm,  $i$ , produces one type of good using log-linear production technology, such that

$$Q_i = A_i I_i^\alpha \tag{A1}$$

in which  $Q_i$  is firm  $i$ 's output and  $A_i$  is its TFP.  $I_i$  is the variable input used in production, which can be defined either as a single input, such as labor, or a composite input of labor, capital, and other intermediate inputs. The symbol  $\alpha$  is the elasticity of output with respect to the variable input, such that  $\alpha \in (0, +\infty)$ .<sup>12</sup>

To organize production, firms need to pay both a sunk cost,  $\bar{C}$ , and a variable cost,  $C'_i = W_i I_i$ , in which  $W_i$  is the input price. Moreover, we assumed that the variable cost is proportional to input use and that factor markets are competitive. From these assumptions, it should be clear that all firms pay the same market price for inputs,  $\bar{W}$ , such that  $W_i = \bar{W}$ . Thus, the total cost of production,  $C_i$ , is defined as:  $C_i = C'_i + \bar{C} = \bar{W} I_i + \bar{C}$ . On the demand side, the utility function is assumed to take the form of a constant elasticity of substitution (CES) function,  $U = [\sum_i \theta_i^{1-\rho} Q_i^\rho]^{1/\rho}$ . For simplicity, we did not distinguish between large and small iron and steel firms in our model to maintain the generality of the model prediction (An extension can be done easily). Following from this assumption, the utility maximization problem can be written as:

$$\max_U \left[ \sum_i \theta_i^{1-\rho} Q_i^\rho \right]^{1/\rho} \quad \text{s.t.} \quad \sum_i P_i Q_i = M \tag{A2}$$

in which  $M$  is total expenditures, and  $P_i$  and  $Q_i$  are the price and output of firm  $i$ .  $\theta_i$  is the adjustment coefficient for consumption of a particular product, and the elasticity of substitution  $\rho < 1$  implies that the firms' products are substitutes.

Since steel products usually are viewed as relatively homogeneous goods in the market, we assumed that the products coming from different firms are imperfect substitutes only because of the difference in product prices due to spatial competition exists across firms, and firms differ in their factories' distances from their final consumption markets, as explained in Syverson (2004). Specifically, because steel products are low value-added in wholesale markets, industrial consumers usually are sensitive to sales prices quoted by firms from different locations. In this sense, the shipment cost is not negligible because it adds more to the market price as the transportation distance increases. To incorporate this characteristic into the model, we assumed that the sale of steel products by each firm is subject to an iceberg transaction cost, i.e., to sell one unit of steel product to a distant place, the firm must ship  $\tau_i \geq 1$  unit of product, with  $\bar{\tau} \geq 1$ .

For there to be no arbitrage opportunity, the output price of firm  $i$  must be equal to  $P_i = \tau_i P$  and  $P = \frac{M}{Q}$ , in which  $P = [\sum_{i=1}^n P_i^\rho]^{1/\rho}$  is the market price and  $Q = \sum_i Q_i$  is the total output, such that  $P_i = \frac{\tau_i M}{Q}$ . Normalizing the unit expenditure, we derived the demand for each firm  $i$ 's product from (A2) as

$$Q_i = M \theta_i P_i^{-\varepsilon} \tag{A3}$$

in which  $\varepsilon = \tau_i^{-\frac{\rho}{1-\rho}} / \delta_i$  is the price elasticity of demand  $(\partial Q_i / \partial P) / (Q_i / P)$ , which is a function of distance to market and is measured by iceberg transaction costs  $\tau_i$  and market structure  $\delta_i$ . Generally, three factors jointly determine the price elasticity of demand – including

<sup>12</sup> Where  $\alpha < 1$  represents a decreasing return to scale,  $\alpha = 1$  constant return to scale, and  $\alpha > 1$  increasing return to scale.

transportation distance, unit transportation/transaction costs, and market monopoly power – and it usually is  $>1$ .

If firms have no monopoly power in the local market ( $\delta_i = 1$ ), the price elasticity of demand ( $\epsilon$ ) is likely to be lower the longer the shipping distance is between producers and consumers, such that  $\frac{\partial \epsilon}{\partial \tau} < 0$ , as the transportation costs will add to the sales prices. However, if there is market segregation ( $\delta_i > 1$ ), firms' monopoly power will change the distribution of demand elasticity across space. Specifically, the price elasticity of demand ( $\epsilon$ ) will decrease in the local market, as we have  $\frac{\partial \epsilon}{\partial \delta_i} < 0$ , but the impact from firms' monopoly power will be offset by increased transportation costs in more remote markets. Thus, price elasticity of demand under the assumption of a market monopoly power's presence could be lower in the local market than in the remote market.

Combining production and consumption, the firms' profits equal total revenue minus total costs:

$$\pi_i = P_i Q_i - \bar{W} I_i - \bar{C} \tag{A4}$$

In equilibrium, free entry condition drives firms' economic profit down to zero. Substituting (1) and (3) into (4), and taking the first order condition of (4), we have

$$I_i^\alpha = \left[ \alpha \left( 1 - \frac{1}{\epsilon} \right) (M\theta_i)^{\frac{1}{\epsilon}} \bar{W} A_i^{1-\frac{1}{\epsilon}} \right]^{\frac{\alpha \epsilon}{\alpha + \epsilon - \alpha \epsilon}} \tag{A5}$$

Combining (1) and (5), firms' output can be written as

$$Q_i = A_i I_i^\alpha = \left[ \alpha \left( 1 - \frac{1}{\epsilon} \right) (M\theta_i)^{\frac{1}{\epsilon}} \bar{W} \right]^{\frac{\alpha \epsilon}{\alpha + \epsilon - \alpha \epsilon}} A_i^{\frac{\epsilon}{\alpha + \epsilon - \alpha \epsilon}} \tag{A6}$$

Taking the logarithms of (6), we have the logarithm of the firm's output (or scale) being written as

$$\ln Q_i = B + \frac{\epsilon}{\alpha + \epsilon - \alpha \epsilon} \ln A_i \tag{A7}$$

in which  $B = \frac{\alpha \epsilon}{\alpha + \epsilon - \alpha \epsilon} \ln \left[ \alpha \left( 1 - \frac{1}{\epsilon} \right) (M\theta_i)^{\frac{1}{\epsilon}} \bar{W} \right]$ . If the idiosyncratic technological shock affects a firm's total factor productivity (TFP) randomly, we can assume that firms' productivity in logarithm takes the form of a normal distribution, such that  $\ln A_i \sim \mathcal{N}(\mu, \sigma^2)$  and  $E[(\ln A_i)^2] = \sigma^2 + \mu^2$ ; thus, we have

$$\ln Q_i \sim \mathcal{N} \left( B + \frac{\epsilon}{\alpha + \epsilon - \alpha \epsilon} \mu, \left( \frac{\epsilon \sigma}{\alpha + \epsilon - \alpha \epsilon} \right)^2 \right).$$

The resource reallocation effects, expressed as the covariance of the logarithm of firm size and productivity (when  $\alpha = 1$ , or constant return to scale), can then be written as:

$$COV[\ln Q_i, \ln A_i] = E[\ln Q_i \ln A_i] - E[\ln Q_i] E[\ln A_i] = \epsilon \sigma^2 \tag{A8}$$

**Proposition 1.** *The resource reallocation effects, as measured by size-productivity covariance, increase with price elasticity of demand ( $\epsilon$ ) and decrease with the transportation distance ( $\tau_i$ ) if firms operate in a competitive market.*

**Proof.** Taking the first order condition of (8) with respect to  $\epsilon$ , we have  $\frac{\partial COV[\ln Q_i, \ln A_i]}{\partial \epsilon} = \sigma^2 > 0$ . Moreover, if there is no monopoly power, the elasticity of demand  $\epsilon$  is only determined by transportation costs and thus likely to decline with the shipping distance between producers and consumers. QED

An implication from the above proposition is that in the absence of market monopolies, firms will increase their output in response to an idiosyncratic technology shock (that raises within-firm productivity), yet the extent of the output response to productivity shock will decrease with the distance over which their output must be sold. This result exists because increased transportation costs erode more-productive firms' production cost advantages in remote markets. As a result, the resource reallocation effects become smaller in the remote market, even under the assumption of a competitive market. However, if a market monopoly power exists, the situation will change.

**Proposition 2.** *The resource reallocation effect, as measured by the size-productivity covariance, decreases with a firm's markup (or monopoly power,  $\delta_i$ ) in local markets that dominant firms monopolize.*

**Proof.** From (3), we have  $\frac{\partial \epsilon}{\partial \delta_i} < 0$ . Substituting this into (8), we have  $\frac{\partial COV[\ln Q_i, \ln A_i]}{\partial \delta_i} < 0$ . Since the monopoly power of firms are usually stronger in the local market, resource reallocation effects are more likely to be weakened by firms' monopoly power in the local market. QED



Proposition 2 shows that the resource reallocation effect will be undermined by the presence of a firm’s monopoly power, particularly the power that the firm exerts in the local market. On one hand, dominant firms will restrict their output in response to productivity shocks to maximize their profits. On the other hand, dominant firms’ local monopoly power will limit more-productive, but relatively smaller, firms from expanding. However, both effects should be much stronger in the local market, considering that the role of dominant firms’ market power in affecting resource reallocation effects across all the local firms will be weakened by increased transportation costs in more remote markets.

Based on the above discussion, we arrived at two testable hypotheses: a) In a competitive market, resource reallocation effects within provinces will be larger than those between provinces, and b) if a dominant firm monopolizes the local market (thereby limiting more-productive firms from expanding), the resource reallocation effects in the local market should be associated negatively with firms’ average markup (as they are dominating the local market).

**Appendix B. Estimating firm-level total factor productivity**

This appendix provides a brief description on how firm-level total factor productivity is measured based on the gross output model when using the regression method.

*B.1. Output and input price correction*

To estimate firm-level productivity, we need to derive quantities of output and inputs from data on revenue and expenditures. In doing so, firm-specific prices for output and inputs need to be constructed to deflate the corresponding values. By assuming input allocation across products have the same share as output, Collard-Wexler and Loecker (2015) suggest using the average of product prices with product-specific sales share as weights to approximate firm-level output prices. This is a simple method, but it is biased due to the strong assumption of proportional allocation of all inputs to different outputs.

We propose to use a transitive Fisher index to aggregate product-specific prices using real output of each firm as weights. Specifically, we assume firms at each time period are independently observed. A direct Fisher index between any two observations can be written as

$$P_{it,ks}^F = \left( \sum_j p_{jt} q_{ijt} / \sum_j p_{js} q_{ijs} \right)^{1/2} \left( \sum_j p_{jt} q_{kjs} / \sum_j p_{js} q_{kjs} \right)^{1/2} \tag{B1}$$

where  $p_{jt}$  and  $p_{js}$  are the price of product  $j$  at time  $t$  and  $s$ , and  $q_{ijt}$  and  $q_{kjs}$  are the quantity of product  $j$  manufactured by firms  $i$  and  $k$  at time  $t$  and  $s$ . Now, choosing a firm at any time as a base ( $bb$ ), the EKS formula (Eltető & Köves, 1964; Szulc, 1964) is used to derive the transitive price index,  $P_{it,bb}$ , of firm ( $i$ ) at time  $t$  relative to the base as follows

$$P_{it,bb} = \prod_{ks} P_{it,ks}^F P_{ks,bb}^F \tag{B2}$$

Defining  $Q_{it}^j = R_{it}^j / P_{it,bb}$ , output quantity can be written as.

$$\frac{R_{it}^j}{P_{it,bb}} = F_{\omega}^j(L_{it}, K_{it}) \exp(\omega_{it}^j) \tag{B3}$$

where  $R_{it}^j$  is the revenue of firm  $i$ ’s product  $j$   $k$  at time  $t$  while  $Q_{it}^j$  is the corresponding quantity.  $\omega_{it}$  is firm-level productivity.  $L_{it}$  and  $K_{it}$  are labor and capital inputs respectively.

A similar method can be applied to derive price deflators for various inputs. Following Collard-Wexler and Loecker (2015), we group all inputs into three categories: labor, capital and intermediate inputs. For labor, the number of workers (or hours worked)  $L_{it}$  at the firm level are observed but quality differences need to be accounted for. We use the firm-level average wage ( $W_{it}$ ) to construct a quality adjustment index and combine it with the number of workers to account for differences in workers’ skills across firms. For capital, we use firm-level financial information to estimate their financial costs ( $r_{it}$ ) for investment to correct the capital stock series.

There are many intermediate inputs used in steel firms, and these can be quite different across firms using different production technologies. To simplify the comparison, we group them into four categories: fuel and electricity, coking coal, iron ores and scrap steel, and others. Firm-specific price indexes ( $P_{it,bb}^M$ ) for intermediate inputs, relative to the same base, are estimated using Eqs. (B2) and (B3). Prices for each group of intermediate inputs are calculated using commodity prices, while the shares of each group of intermediate input in total expenditure are used as weights.

Finally, assuming a Cobb-Douglas production technology, we estimate the production function using our constructed output and input price deflators and revenue and expenditure data as follows

$$\ln\left(\frac{R_{it}^j}{P_{it,bb}}\right) = \beta_l \ln\left(\frac{L_{it}}{W_{it}}\right) + \beta_k \ln\left(\frac{K_{it}}{r_{it}}\right) + \beta_m \ln\left(\frac{M_{it}}{P_{it,bb}}\right) + \omega_{it} + \varepsilon_{it} \tag{B4}$$

where lower case indicates the logarithm of deflated variables.  $\varepsilon_{it}$  is residual, which is used to absorb measurement errors in output and prices.

**B.2. Treatment of endogeneity**

However, there is a potential endogeneity concern when using Eq. (B4) to estimate firm-level productivity, since unobserved productivity could be correlated with input use. Several approaches are used in the literature to deal with the endogeneity problem, for example, [Olley and Pakes \(1996\)](#); [Levinsohn and Petrin \(2003\)](#); [Akerberg, Caves, and Frazer \(2015\)](#); [Wooldridge \(2009\)](#).

Following [Akerberg et al. \(2015\)](#) and [Wooldridge \(2009\)](#), we adopt a two-stage procedure in the estimation. Specifically, the first stage is to regress output  $q_{it} = \ln\left(\frac{R_{it}^j}{P_{it,bb}}\right)$  on a flexible function of inputs  $(l_{it}, m_{it}, k_{it})$  (where  $l_{it} = \ln\left(\frac{L_{it}}{W_{it}}\right)$ ,  $m_{it} = \ln\left(\frac{M_{it}}{P_{it,bb}}\right)$  and  $k_{it} = \ln\left(\frac{K_{it}}{r_{it}}\right)$ ) so as to use the information of investment ( $i_{it}$ ) or other external instruments to identify productivity.

$$q_{it} = \varphi_{\varphi,t}(l_{it}, m_{it}, k_{it}, i_{it}) + \varepsilon_{it} \tag{B5}$$

where firm-level productivity is estimated as

$$\omega_{it} = \widehat{\varphi_{\varphi,t}} - f_{\varphi,t}(l_{it}, m_{it}, k_{it}, i_{it}; \beta) \tag{B6}$$

Using Eqs. (B5) and (B6) for productivity estimation requires the use of the process that determines productivity movements over time. In this case, we use an exogenous Markov process such that

$$\omega_{it} = g_{\varphi}(\omega_{i,t-1}, \widehat{X}_{it}) + v_{\varphi it} \tag{B7}$$

where firm-level productivity and its movements vary across different production technologies.

Estimation of the production function coefficients  $\beta$  relies on assumptions about how firms change input use in response to random productivity shocks over time  $v_{\varphi it}$ . When various inputs are assumed to adjust with productivity shocks at different speed, the identification conditions can be quite different. We allow firms to dynamically choose both labor and capital but adjust the use of intermediate inputs only when productivity shocks arrive. This assumption can be summarized in a moment condition as follows

$$E \left[ v_{\varphi it}(\beta) \begin{pmatrix} l_{it} \\ m_{it-1} \\ k_{it} \end{pmatrix} \right] = 0 \tag{B8}$$

The condition in Eq. (B8) is flexible and allows for a variety of production functions with different assumptions about the variability of inputs and the use of instruments.

Our firm-level TFP estimate for China’s iron and steel industry is comparable to the existing literature such as [Brandt et al. \(2012\)](#) and [Sheng and Song \(2012\)](#). While there are some apparent difference between our estimates of aggregate TFP growth and those obtained from [Brandt et al. \(2012\)](#), the difference can be attributed to four possible reasons.

First, although the average TFP estimates for incumbents the manufacturing industry (based on the gross output model) for continuing firms is 2.85% a year in [Brandt et al. \(2012\)](#), there are substantial difference in TFP growth estimates across industries. For the period of 1998–2007, the estimated TFP growth across 4-digit industries in [Brandt et al. \(2012\)](#) exercise ranged from 0.5% to 6.8%. Our estimate of TFP growth for the iron and steel industry fall into the range.

Second, while the estimates for incumbents are on average 2.85% in [Brandt et al. \(2012\)](#), the aggregate estimates at the industry-level when taking into account of firms’ entering and exiting become 4.1% (See Table A.12 in [Brandt et al. \(2012\)](#)). This is because firms’ entry and exit will increase average TFP will generate destructive creation effects as discussed in [Brandt et al. \(p. 346, Brandt et al., 2012\)](#). In our sample, the total number of iron and steel firms increased by around three fold (i.e. from 1426 to 4151) between 1998 and 2009, which contributes to around 1.1% aggregate TFP growth.

Third, most iron and steel firms in China are large in size and heavily equipped and experienced a rapid technology progress in early 2000, which make their TFP growth relatively higher compared to other industries. As is discussed in [Brandt et al. \(2012\)](#), “large Chinese firms are increasing productivity at a higher than average rate”. On average, size of iron and steel firms in China is 4 times larger in employment, 79 times larger in fixed asset and 400 times larger in output value than those of manufacturing firms, it is thus no surprise that estimated average TFP growth is higher in the iron and steel industry. Meanwhile, rapid growth in investment for updating equipment of the iron and steel industry for the sample period may also leads to rapid TFP growth.

Fourth, when calculating the TFP growth rate, we use the average of year-to-year growth (rather than the time-period average) to approximate the growth rate for the whole period, which incorporated the year-to-year fluctuation of TFP into the estimates and thus leads to a higher estimated trend estimate of TFP growth.

**Table B1**  
Production Function Estimates based on the Gross Output Model by Sectors.

	All 4 Sectors				Iron making				Steel making				Rolling/pressing				Alloy making			
	OLS	FE	LP	ACF	OLS	FE	LP	ACF	OLS	FE	LP	ACF	OLS	FE	LP	ACF	OLS	FE	LP	ACF
Dependent variable: real gross output in logarithm																				
Ln_L	0.087*** (0.005)	0.108*** (0.007)	0.075*** (0.002)	0.049*** (0.003)	0.073*** (0.013)	0.100*** (0.015)	0.061*** (0.023)	0.021** (0.009)	0.034*** (0.010)	0.042*** (0.010)	0.026*** (0.002)	0.0090 (0.009)	0.086*** (0.007)	0.110*** (0.010)	0.065*** (0.003)	0.046*** (0.004)	0.088*** (0.009)	0.113*** (0.011)	0.085*** (0.009)	0.037*** (0.008)
Ln_W (Human Capital)	0.038*** (0.004)	0.056*** (0.006)	0.039*** (0.000)	-0.030*** (0.007)	0.041*** (0.010)	0.060*** (0.010)	0.039*** (0.009)	-0.026* (0.015)	-0.009 (0.012)	-0.001 (0.011)	-0.017*** (0.001)	-0.084*** (0.025)	0.032*** (0.006)	0.051*** (0.008)	0.030*** (0.004)	-0.027*** (0.010)	0.052*** (0.009)	0.063*** (0.010)	0.058*** (0.007)	0.018 (0.021)
Ln_K	0.026*** (0.003)	0.033*** (0.003)	0.016*** (0.004)	0.040*** (0.003)	0.030*** (0.006)	0.034*** (0.006)	0.010 (0.122)	0.030*** (0.007)	0.009 (0.007)	0.011 (0.007)	0.017 (0.054)	0.026*** (0.009)	0.030*** (0.0040)	0.040*** (0.005)	0.020*** (0.006)	0.046*** (0.003)	0.017*** (0.004)	0.017*** (0.005)	0.039 (0.031)	0.031*** (0.006)
Ln_M	0.881*** (0.007)	0.844*** (0.010)	0.907*** (0.005)	0.852*** (0.003)	0.879*** (0.016)	0.841*** (0.020)	0.923*** (0.181)	0.881*** (0.007)	0.956*** (0.010)	0.942*** (0.012)	0.955*** (0.064)	0.955*** (0.011)	0.881*** (0.010)	0.838*** (0.016)	0.915*** (0.009)	0.829*** (0.003)	0.879*** (0.011)	0.848*** (0.014)	0.846*** (0.054)	0.873*** (0.006)
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prov. Cluster Multinomial Terms	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.027*** (0.029)	1.199*** (0.044)	- (0.191)	2.102*** (0.191)	1.087*** (0.073)	1.251*** (0.093)	- (0.544)	2.477*** (0.062)	0.730*** (0.072)	0.829*** (0.072)	- (1.014)	1.238 (1.014)	0.996*** (0.046)	1.202*** (0.069)	- (0.258)	2.363*** (0.258)	1.110*** (0.059)	1.283*** (0.078)	- (0.784)	3.678*** (0.784)
Returns to Scale	1.032	1.041	1.037	-	1.023	1.035	1.033	-	0.989	0.993	0.980	-	1.028	1.039	1.029	-	1.035	1.040	1.028	-
Num. of Obs.	43,255	43,255	43,255	32,004	6824	6824	6824	4932	2119	2119	2119	1544	25,379	25,379	25,379	18,936	8933	8933	8933	6592
R squared	0.968	-	-	0.972	0.961	-	-	0.966	0.991	-	-	0.992	0.969	-	-	0.973	0.947	-	-	0.955
Number of firms	11,134	11,134	11,134	11,134	1871	1871	1871	1871	560	560	560	560	6391	6391	6391	6391	2312	2312	2312	2312

Note: following Nishida et al. (2013), we control for workers' average wage to account for change in human capital. Meanwhile, the returns to scale (RTS) for production function is not reported as it will involve multi-polynomial terms.

**Table C1**  
The First-stage Estimation Results for the FEIV Regression.

	FEIV1	FEIV2
Dependent variable: Average firms' markup		
Sales Radium (ln)	0.114*** (0.015)	–
Construction area (ln)	–	–0.006*** (0.002)
Total crude steel production (ln)	–0.013*** (0.003)	0.005* (0.003)
Export share of output	–0.161* (0.083)	–0.166*** (0.017)
Number of steel firms	–0.000 (0.000)	0.000*** (0.000)
Fixed asset investment (ln)	–0.005*** (0.001)	–0.001** (0.000)
Dummy for WTO accession	–0.008* (0.005)	–0.010*** (0.002)
Kleibergen-Paap rk LM statistic	32.12	14.35
Cragg-Donald Wald F statistic	55.12	5.27
Kleibergen-Paap Wald rk F statistic	57.97	14.35

Note: Robust standard errors in parentheses, \*, \*\*, \*\*\* denotes level of significance at 10%, 5% and 1% respectively.

**Table C2**  
The Contribution of Resource Reallocation to the Industry-level TFP Growth: the BHC and FHK approaches.

	TFP Growth	With-firm Growth	RE_Con.	COV	Net EE
BHC	5.70	4.23	–1.04	0.06	2.45
FHK	5.58	4.23	0.14	–	1.21

Note: BHC refers to the approach proposed by Baily et al. (1992), while FHK refers to the approach proposed by Foster et al. (2001), Foster et al., 2008).

**Table C3**  
Comparing the Resource-Reallocation Effect across 7 Regions: Between-region vs. within-region (%): 1998–2009.

	Between Region			Within Region		
	TFP	Unweighted Average	OP Covariance	TFP	Unweighted Average	OP Covariance
Sinister/iron making	5.735	5.166	0.569	5.166	4.276	0.890
Steel making	4.354	4.612	–0.259	4.612	4.021	0.592
Rolling/pressing	4.560	5.128	–0.568	5.128	4.325	0.803
Alloy making	4.499	4.204	0.295	4.204	3.675	0.529
Average	5.337	5.464	–0.128	5.464	4.594	0.870

Note: The seven regions are defined on geographical attributes, which include North-East China, North China, North-West China, East China, South China, Middle China and South-China.

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