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Abstract

We study productivity differences in vertically-integrated Chinese steel facilities using a unique data set that provides equipment-level information on material inputs

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and output in physical units and equipment size for each of the three main stages in the steel value chain, i.e., sintering, pig-iron making, and steel making. We find that private vertically-integrated facilities are more productive than provincial state-owned (SOEs) facilities, followed by central SOEs. This ranking lines up with our productivity estimates in the two downstream production stages, but central SOEs outperform in sintering, most likely because of their superior access to higher quality raw materials. The productivity differential favoring private facilities declines with their size, turning negative for facilities larger than the median. These patterns are linked with equipment-level TFP in private firms as size expands, and the internal configuration of vertically-integrated facilities, which reflect the greater constraints facing private firms. Increasing returns to scale at the stage and facility level partially offset these costs and rationalize firms' choice on larger vertically-integrated facilities.

Key Words: Total Factor Productivity, Vertically-Integrated, Steel, SOEs, Private, China

JEL Classifications: D24 L11 L23 L61

1 Introduction

Increases in productivity are an important source of economic growth for firms, industries and countries. Researchers have documented sizeable and persistent productivity differences between producers and identified their elimination as a potentially important source of productivity growth.[1] Understanding the sources of these differences requires obtaining accurate measures of productivity, which is often hindered by issues of endogeneity and measurement.[2] Even if these problems can be addressed, identifying the sources of these differences is handicapped by the fact that productivity analysis is usually carried out at the aggregate firm level. In contrast, production activity of firms often involves vertically integrated operations carried out in multiple production units in which technologies and productivity likely differ by stage of production. Aggregate data and analysis miss this dimension, effectively ignoring questions related to how firms configure their production operations and then their link with performance.

In the context of China's vertically integrated steel producers, this paper investigates the sources of productivity differences between production facilities through the lens of their internal structure. As far as we know, this paper is one of the first to investigate these kinds of links.[3] By fact of its size - the sector now produces half of the world's steel - China's steel industry is important both domestically and internationally. The sector also remains heavily state-dominated. A recent literature documents sizeable productivity differences between

[1]See for example, Syverson (2004) and Hsieh and Klenow (2009).

[2]De Loecker and Goldberg (2014) show how the absence of producer-level input and output prices, for example, leads to the estimation of revenue-based productivity measures that can reflect aspects other than the true efficiency of the producer.

[3]There is a literature looking at links between productivity and vertical integration of firms, in which the degree of vertical integration is endogenous. See for example, Hortaçsu and Syverson (2007), Forbes and Lederman (2010), Atalay et al. (2014), Natividad (2014) and Li et al. (2016). In this context, production technologies can still differ by stage of production, and aggregation of productivity across these stages remains an issue.

firms and sectors in China that appear tied to ownership and the regulatory environment.[4] State-owned enterprises (SOEs) often enjoy better access to capital, technology, inputs and human resources, but are also tasked with non-economic objectives and typically operate under softer-budget constraints.

Drawing on a unique data set that provides equipment (hereafter used interchangeably with machines and furnaces) level input and output information in physical terms by stage of production, we estimate production functions separately for the three main stages in steel's value chain (sintering, pig-iron making and steel making).[5] The use of input and output in physical units eliminates price biases in the estimation (Li et al. (2017)). Following Domar (1961), we then integrate our productivity estimates for each stage into estimates for integrated facilities, using as weights either the estimated elasticities of material inputs in pig-iron making and steel making or the ratio of the value of sinter and pig-iron to steel. The richness of our data allows us to measure the efficiency of producers at the integrated facility level, and more important, to decompose differences in performance by ownership type into process (stage) level differences, thereby providing new insight into the internal dimensions of complex industrial operations.

We find that private facilities are on average 7.4 percent more productive than central state-owned facilities, and 1.1 percent higher relative to provincial state-owned facilities. With value-added in the steel industry 25 to 30 percent of the gross output, these modest productivity differences translate into sizeable differences in profitability. These differences do not capture the full story however. First, productivity advantages enjoyed by private facilities in downstream production stages (iron-making and steel making) are partially offset by their 10.8 percent lower productivity upstream in sintering. Likely underlying this gap

[4] See for example Hsieh and Klenow (2009), Hsieh and Song (2015), Brandt (2015) and Berkowitz et al. (2017).

[5] Our estimation builds on the control function approach introduced by Olley and Pakes (1996) and Levinsohn and Petrin (2003), and developed further by Ackerberg et al. (2015) and Gandhi et al. (2017).

is central state-owned facilities' superior access to higher quality raw material.[6] Back of the envelope calculations suggest that eliminating the premium of central state-owned facilities in sintering would raise the premium of private facilities at the facility level by an additional 4.1 percentage points, and to 11.5 percent overall. Second, the productivity premium of private facilities declines with their size, and actually turns negative for facilities larger than the median. Private facilities smaller than the median size are 24.7 percent more productive than central state-owned facilities, and 4.9 percent more than provincial state-owned facilities.

These patterns are linked with equipment-level TFP in private firms as size expands, and the configuration of production facilities of private firms when they build larger integrated facilities. In all three stages, we find equipment level TFP of private firms declines relative to SOEs as equipment size expands. Moreover, when building larger facilities, private firms install larger machines/furnaces, but ones that are systematically smaller in size on average than those in state-owned facilities of comparable size. Although operating a portfolio of smaller units may have its advantages when demand is uncertain, the decision of private firms to install relatively smaller machines/furnaces in larger steel-making facilities also reflects the constraints they face, including tighter regulatory hurdles, higher costs of capital, and difficulty in accessing higher quality raw materials and human resources. In the cross-section, this results in higher labor input and spreads their scarce human capital more thinly over a larger number of units to the detriment of productivity. Our study suggests that the productivity premium of private facilities would be significantly higher if these constraints were removed. Significantly larger productivity premiums of privatized SOEs for whom these constraints may be less binding provides support for this view.[7]

The remainder of the paper is organized as follows. Section 2 provides background and

[6]Controlling for raw material quality would likely reduce the productivity advantage we find for SOEs.

[7]Estimation of the productivity premium of private sector firms in an unconstrained environment requires carrying out counterfactuals in the context of a dynamic model. Such an exercise is the planned focus of future work.

context on China's steel sector and industrial policy spanning the period of our analysis. Section 3 describes the data and presents key facts that help guide the empirical analysis. We provide an empirical approach to identify multi-stage productivity in section 4, followed by a discussion on productivity differences and their underlying sources in section 5. We discuss potential biases resulting from measurement errors in section 6 and conclude in section 7.

2 Background and Context

2.1 China's Steel Sector

By the late 1990s, two decades of double-digit annual growth had made China the world's largest steel producer. In 2015, China produced 803.8 million metric tons of crude steel, accounting for 49.6 percent of the world's total production.[8] Several features of China's steel sector figure prominently in our analysis and distinguish it from that in other countries.[9]

First, the sector is state-dominated. Although the role of the private sector has expanded over time, nearly half of industry output continues to be produced by state-owned firms. In addition, 8 out of the top 10 firms in 2015 were state-owned.[10] Restrictions on foreign firm entry and M&A activity have also severely limited the role of foreign-invested enterprises in China's steel sector.

Second, concentration ratios in the domestic industry are low. Despite having half of the worlds' 10 largest steel producers, the production share of the four largest steel producers in China in 2015 was only 19 percent, compared to shares of 65 percent, 78 percent, and

[8]Data source: Steel Statistical Yearbook 2018. World Steel Association.

[9]For additional background and analysis of China's steel sector since the late 1970s, see Song and Liu (2012).

[10]Data Source: Top 100 Global Steel Producers (2011-2016). https://www.kaggle.com/drubal/top-100-global-steel-producers-20112016.

83 percent in the U.S., EU, and Japan, respectively.[11] Low concentration ratios have been accompanied by chronic problems of excess capacity in the sector.

Third, the activity of steel firms in China is largely directed to the production of lower quality steels such as rebar, wire rods and plates for the rapidly expanding domestic market. In 2015, for example, 90 percent of output was sold domestically, nearly two-thirds of which were lower quality products.[12] Domestic firms appear to be heavily protected, and in 2015 imports represented only 1.2 percent of domestic consumption. In sharp contrast, China's steel sector is highly dependent on iron ore imports, and in 2013 two-thirds of the iron ore used was imported.[13] China's iron ore imports also represent two-thirds of global iron ore imports.[14]

Finally, in contrast to the prominent role of electric arc furnaces and the rapid diffusion of mini-mill technology in the U.S. and other countries, steel in China is primarily produced using blast furnaces together with basic oxygen furnaces in vertically integrated facilities. This reflects both limited access to scrap materials domestically and a pronounced policy tilt towards larger furnaces and facilities. Less than 10 percent of China's steel is currently produced using electric arc furnaces.[15] In the U.S. and other countries, the adoption of mini-mill technology has been an important source of industry-wide productivity gains.[16]

[11] Based on authors' calculations using data from Top 100 Global Steel Producers (2011-2016). https://www.kaggle.com/drubal/top-100-global-steel-producers-20112016. The CR4 ratio for the U.S. is based on data from Top Steelmakers in 2017. World Steel Association.

[12] Although exports were only 10 percent of total domestic production, they presented more than a fifth of total world exports. Data source: China Steel Yearbook 2016, 2017. China Iron and Steel Association. Steel Statistical Yearbook 2018. World Steel Association.

[13] Data source: China Steel Yearbook 2016, 2017. China Iron and Steel Association.

[14] Data source: Steel Statistical Yearbook 2018. World Steel Association.

[15] Data source: Steel Statistical Yearbook 2018. World Steel Association.

[16] For the U.S., see Collard-Wexler and De Loecker (2015). Hendel and Spiegel (2014) documents the source of productivity improvement in the context of a single Israeli steel mini-mill.

2.2 Chinese Industrial Policy

A major objective of Chinese industrial policy has been the development of domestic capabilities in sectors identified as key or strategic. Originally, this was largely limited to more mature sectors such as steel, electrical machinery, autos, etc., but more recently has come to include newly emerging technologies such as AI, electric vehicles, renewable energy, biotechnology, etc. In these efforts, central government leadership in identifying key sectors and technologies, concentration of innovation resources in large SOEs, and more recently, the promotion of "indigenous" innovation figure prominently (Brandt and Rawski (2019)). Preferential access to land and finance, subsidies, as well as strict restrictions on the form of participation of foreign firms have been important policy instruments.[17]

"Made in China 2025" (MIC, 2015), a program announced in 2015, forms the centerpiece of China's present industrial policy, but has direct links with the 2006 "National Medium-to Long-Term Plan for the Development of Science and Technology" (Cao et al. (2006)) and the 2010 "Decision of the State Council on Accelerating the Fostering and Development of Strategic Emerging Industries" (Strategic 2010). MIC offers a detailed, ten-year agenda for innovation and upgrading in ten industries, complete with timetables for achieving precise technical benchmarks.

China's steel sector has consistently been one of the key targets of China's industrial policy. Major policy documents for the sector include "Development Policies for the Iron and Steel Industry" (2005), "Blueprint for the Adjustment and Revitalization of the Steel Industry" (2009) and "Planning for the Adjustment and Upgrading of the Iron and Steel Industry 2016-2020". Facing chronic excess capacity, these documents lay out plans for both

[17] There is now a small but growing empirical literature on the impact of these and related policies. See, for example, Haley and Haley (2013) and Kalouptsidi (2017) in the case of subsidies; Berkowitz et al. (2017) on the role of access to finance; and Aghion et al. (2015) on the use of subsidies combined with cheap loans, tax holidays, and tariffs, etc. Li et al. (2015) and Liu (2018) try to rationalize these policies in the context of inter-sector linkages, especially upstream-downstream, and market imperfections.

technology upgrading and improvement, and industry restructuring and consolidation.

3 Data and Descriptive Evidence

3.1 Steel Production Technology

Vertically-integrated steel production involves a complex series of individual processes that use coal as the primary energy source and iron ore as the basic raw material (Ahlbrandt et al. (1996)). A steel facility integrates production carried out in four major stages along the production chain: sintering, pig-iron making, steel making and steel rolling (see Figure 1). Sintering is basically a pre-treatment process that transforms iron ore fines into a high quality burden called sinter for use in the iron-making facility - the blast furnace. The principle of sintering involves the heating of iron ore fines along with flux and coke fines or coal to produce a semi-molten mass that solidifies into porous pieces of sinter with the size and strength characteristics necessary for feeding into the blast furnace. It is basically an agglomeration process achieved through combustion.[18] Sinter, together with coke, pulverized coal and limestone are then fed into the top of a blast furnace, while hot air is injected from below, setting off a chemical reaction throughout the furnace as the material moves downward.[19] The molten pig-iron from the blast furnace along with oxygen and fuel are then fed into a basic oxygen furnace to produce steel, which is called primary steel making. Modern steel making can also incorporate a secondary steel making process, which involves refining of the crude steel.[20] The semi-finished steel produced in vertically-integrated firms is finally shaped into sheets, bars, wire, and tube steel of desired thickness and uniformity

[18] http://ispatguru.com/the-sintering-process-of-iron-ore-fines-2/

[19] https://en.wikipedia.org/wiki/Blast-furnace

[20] In this process, alloying agents are added, the level of dissolved gases in the steel is lowered, and inclusions are removed or altered chemically to ensure that high-quality steel is produced. http://en.wikipedia.org/wiki/Steelmaking

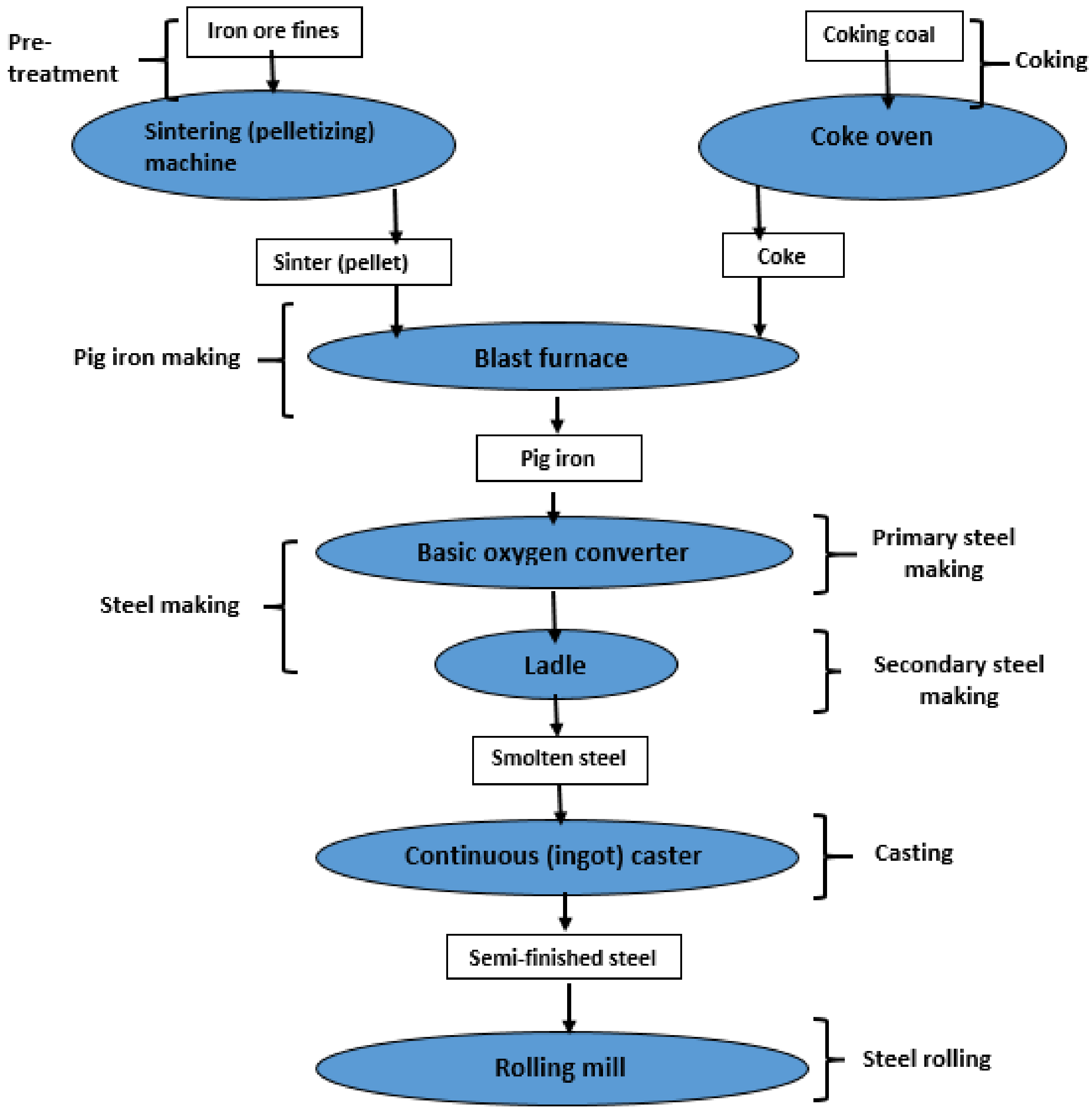

Figure 1: Steel Technology of Integrated Facilities

through a metal forming process in rolling mills.[21]

Technologically, larger blast furnaces are more efficient as they incur smaller heat losses and enable more efficient heat recovery.[22] However, larger furnaces require higher-grade iron ore. The use of low-grade ore in larger blast furnaces increases energy intensity, generates more waste, and may even shorten the life expectancy of the blast furnaces. Larger basic oxygen furnaces also have clear technological advantages. The utilization of automatic control and monitoring systems improves energy efficiency. In addition, the use of hybrid blowing technology helps to reduce the consumption of material inputs while better design and maintenance of refractory linings contribute to longer life expectancies of the furnaces.[23]

3.2 Data

We construct a unique monthly-level data set on the facilities of vertically-integrated firms in the Chinese steel industry from January 2009 to October 2011.[24] Over this period, production of reporting firms in our sample represents sixty percent of the total steel output in China.[25] The reported data are in the form of equipment-level information on inputs and outputs in physical units for each of the three major stages of production (sintering, pig iron making and steel making). Input information includes key material inputs, standardized energy consumption, number of workers, size of equipment (capacity) and utilization

[21] https://en.wikipedia.org/wiki/Rolling-(metalworking)

[22] http://ietd.iipnetwork.org/content/blast-furnace-system

[23] See Yu (2001) and Wang et al. (2006) for more details.

[24] The underlying data are collected by the Chinese Iron and Steel Association (CISA) as part of regular data collection efforts from all firms with annual steel production over 1 million tons.

[25] Our data covers most of the production of the SOEs and in upwards of a third of private firms. Missing is the production of smaller non-member private firms, and more important, the output of some member private firms. Notable omissions include Shandong Rizhao Steel, with an annual production capacity of 10 million tons. Also excluded are facilities run by the headquarters of Baosteel, a central SOE that is generally acknowledged to be the most technically advanced steel firm in China.

rates.[26] These data are supplemented by information on ownership, year of establishment and location.

Our analysis centers on the first three major stages of production, i.e. sintering, pig-iron making and steel making, and excludes steel rolling. We do so for several reasons. First, finished rolled steel products can be highly differentiated, and differ in value added, final usage, and price. Output however is only reported in physical terms. Second, we only have data on total production of rolled products at the firm level rather than the product or the plant level. The input information is similarly aggregated across products and plants. And third, while the main purpose of sintering and pig-iron making is to meet the immediate consumption needs of the next stage in the production chain, firms often sell or hold inventory in semi-finished steel for later use. Therefore, between steel making and rolling, there is a dynamic dimension to decision-making that our data cannot capture. Despite this omission, we still capture a high percentage of the activity in the sector. In an average steel firm, the total value-added generated by the three stages under our consideration is more than double that of the rolling stage, or nearly seventy percent overall.[27]

Steel production in China is a highly vertically-integrated activity. We are able to link equipment across stages and thereby identify vertically-integrated facilities. At the sinter-iron-steel level, we compiled data on 136 fully vertically-integrated facilities, operated by 59 firms.[28] Figure 2 provides an illustration of the make-up of a typical firm in our sample: Each firm may operate multiple integrated facilities; in addition, at each stage in the value chain, a firm may operate multiple production units, i.e. sintering machines, blast furnaces

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[26]For steel rolling, we only have aggregate firm level information.

[27]We base these calculations on a 2015 report by the China Mingsheng Bank, "Research on the Steel Industry and Suggestions on Development Strategy".

[28] We lose observations from a small number of firms and integrated facilities because of missing data. At the stage level, we have complete data on 70 firms in sintering, 71 in iron making, and 68 firms in steel making.

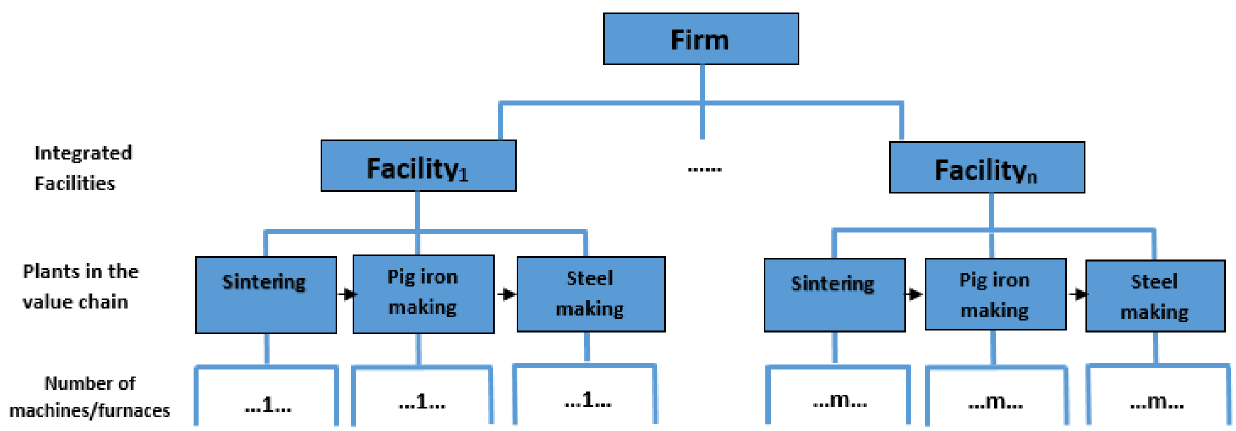

Figure 2: Structure of Integrated Facilities

or basic oxygen furnaces, respectively.

3.2.1 Ownership

We categorize firms by three basic types of ownership: central SOEs, provincial SOEs and private firms. Central SOEs are under the direct supervision of the State-owned Assets Supervision and Administration Commission (SASAC). We also define firms that have been merged into central SOEs as central state-owned. Provincial SOEs are under the direction of provincial or regional SASACs. Private firms in our sample include joint-ventures (JVs), wholly owned foreign firms and privatized SOEs.[29]

Column (1) of Table 1 provides a breakdown of ownership for our sample, which is skewed in favor of state-owned firms, at the equipment level by stage of production and by integrated facility. In each of the three stages of production, between seventy and eighty percent of machines/furnaces are state-owned. State-owned firms are also consistently the source of eighty percent of total production, with the remainder coming from private firms. Within the state sector, provincial SOEs have the largest market share. From a policy perspective, central SOEs are strategically more important and the major beneficiaries of policy choices at the national level.

3.2.2 Size

Steel firms span a wide range of sizes at both the equipment and integrated facility level. By industry convention, we measure the size of a sintering machine by its effective area; size of a blast furnace by its effective volume; and the size of basic oxygen furnace by its tonnage. We define the size of an integrated facility as the total size of basic oxygen furnaces within the facility. These size measures directly reflect production capacity.

Panels A to C of Table 1 provide summary data on equipment size for each stage of

[29] Privatized SOEs were the product of restructuring efforts in the state sector in the late 1990s and early 2000s.

production by ownership. A clear ranking emerges: On average, machines/furnaces of central state-owned facilities are the largest, followed by those of provincial state-owned and then private facilities. A typical private machine/furnace is only 60 percent of the size of a central state-owned machine/furnace. The average size of a private pig-iron furnace, for example, is 699 cubic meters compared to 1230 for a furnace of a central state-owned facility. Note also in columns (4) and (5) the wide range of equipment sizes within each ownership group. Panel D of Table 1 provides comparable information at the integrated facility level. Central SOEs operate the largest facilities, which on average are more than twice as large as those of the private facilities (301 tons versus 131 tons), and a third larger than the facilities of provincial SOEs (301 tons versus 227 tons).

In Table 2, we break down integrated facilities into size quartiles and report for each quartile the total number of facilities by ownership and their respective shares of total steel production. Almost half of the facilities in central SOEs are in the largest size quartile: they produce 14.1 percent of total steel, and make up the largest share of total production by central state-owned facilities. The number of facilities of provincial SOEs is fairly evenly distributed throughout the quartiles, but those in the largest size quartile play a dominant role in total steel production. In sharp contrast with the state-owned facilities, only a single private integrated facility lies in the largest size group. Most private facilities are smaller in size than the sample median. In terms of the total production of private facilities however, the integrated facilities in the third quartile are the most important, and produce 37 percent of the steel by private facilities.

3.2.3 Internal Configuration of Integrated Facilities

As part of a single integrated facility, firms will typically operate multiple production units, e.g. sintering machines, blast furnaces or basic oxygen furnaces, in each stage of production. In Table 3 we report the average number of machines/furnaces and their average size for each stage of production by ownership and facility size. As before, we break down

Table 1: Summary Statistics of Equipment and Facility Size by Ownership

Panel A: Sintering (Machine)					
	(1) Number	(2) Mean	(3) Std. Dev	(4) Min	(5) Max
Total	343	156	127	24	853
Central	56	204	161	24	853
Provincial	203	158	127	24	550
Private	84	122	84	24	360
Panel B: Pig Iron Making (Blast Furnace)					
	(1) Number	(2) Mean	(3) Std. Dev	(4) Min	(5) Max
Total	490	1016	926	128	5500
Central	92	1230	1046	200	4038
Provincial	249	1127	1036	128	5500
Private	149	699	460	179	2680
Panel C: Steel Making (Basic Oxygen Furnace)					
	(1) Number	(2) Mean	(3) Std. Dev	(4) Min	(5) Max
Total	342	95	62	12	300
Central	68	123	66	30	260
Provincial	209	93	63	12	300
Private	65	72	39	30	180
Panel D: Integrated Facility					
	(1) Number	(2) Mean	(3) Std. Dev	(4) Min	(5) Max
Total	136	218	185	30	990
Central	26	301	212	30	840
Provincial	77	227	190	30	990
Private	33	131	96	40	540

Notes: The size of a sintering machine is measured by its effective areas in m^2; the size of a blast furnace is measured by its effective volume in m^3; the size of a basic oxygen furnace is measured by its tonnage. Facility size is measured by the total size of basic oxygen furnaces (steel making) within the facility.

Table 2: Number and Production Share of Integrated Facilities by Size

Panel A: Size Distribution of Integrated Facilities					
	(1) 1st quartile Number	(2) 2nd quartile Number	(3) 3rd quartile Number	(4) 4th quartile Number	(5) Total Number
Central	3	6	5	12	26
Provincial	16	21	18	22	77
Private	13	11	8	1	33
Total	32	38	31	35	136
Panel B: Output Share by Integrated Facilities Size					
	(1) 1st quartile Output Share	(2) 2nd quartile Output Share	(3) 3rd quartile Output Share	(4) 4th quartile Output Share	(5) Total Output Share
Central	1.1%	1.5%	2.9%	14.1%	19.5%
Provincial	5.8%	11.6%	14.3%	30.9%	62.5%
Private	4.3%	4.6%	6.7%	2.4%	18.0%
Total	11.1%	17.6%	23.8%	47.5%	100.0%

Notes: Facility size is measured by the total size of basic oxygen furnaces (steel making) within the facility. The size of a basic oxygen furnace is measured by its tonnage. The size quartiles are calculated over the facility-month observations in the whole sample and are defined as follows: <90, [90,160), [160,300) and ≥ 300. Output is measured in tons of steel.

integrated facilities into size quartiles. As a general rule, the number of machines/furnaces used in each stage increases with the facility quartile. The increase however is less than proportional to the increase in the facility size, implying an increase in average machine/furnace size with the size of the integrated facility. For central state-owned facilities, the number of sintering machines and blast furnaces actually falls with facility size. For steel, they increase, but less rapidly than they do in either provincial state-owned or private facilities. This behavior gives rise to systematic differences in the number of machines/furnaces and their size in each stage of production as the size of the integrated facility increases. In particular, central state-owned facilities consistently operate the smallest number and largest machines/furnaces in each size category, followed by provincial state-owned and then private facilities. Alternatively, when private firms build larger integrated facilities, they do so using more machines/furnaces of smaller average size compared to SOEs.[30]

The Nature of Internal Configuration A firm's choice with respect to the internal configuration of their operations reflects both supply and demand side factors. In the Appendix, we sketch out an illustrative model that captures influences on the size and number of equipment a firm operates and possible tradeoffs. We abstract in the model from decisions on total investment in production capacity, that is, we take investment in production capacity as given.

Increasing returns to scale in equipment (furnace) size provide firms clear incentives to achieve their desired production capacity using larger equipment (furnaces).[31] As they try to expand however, private firms face much more severe constraints compared to SOEs. Foremost are central government regulations, which make it very difficult for private sector

[30] To examine this relationship more fully, we estimate Poisson regressions of the number of equipment in each stage of an integrated facility on log facility size and log size interacted with our ownership dummies for each individual stage. We estimate related regressions for log equipment size on facility size, results of which are reported in the Appendix.

[31] Estimates of return to scale are reported in Section 5.1.

firms to obtain the permission required to build larger facilities. These kinds of hurdles have increased with problems of excess capacity in the industry. Firms often try to circumvent these restrictions by carrying out a series of smaller projects that use smaller equipment (furnaces).

Better human capital and higher quality raw materials are needed to take full advantage of the new technology embodied in larger equipment (furnaces). Private sector firms are disadvantaged vis-*à*-vis SOEs in both respects, thereby reducing the returns to installing equipment (furnaces) of larger size.[32] The same is true with respect to the cost of finance, which makes it more difficult for private firms to mobilize the funds needed to make the investments associated with larger equipment (furnaces).

Demand-side considerations and profitability may also factor in, but in the opposite direction. In the face of demand shocks, it is costly for firms to shut down (start up) furnaces; moreover, these costs are increasing in the size of the equipment. This makes it much more difficult for a firm with a large furnace to adjust to demand shocks in the short run. By contrast, firms with smaller units can adjust production more efficiently by simply suspending operations in a subset of their furnaces rather than by shutting down their entire operations. In principle, this logic should apply equally to private firms and SOEs. Differences in the weight on profit maximization in the firm's objectives however may make such behavior more common in the case of private sector firms.

[32] Human capital and new technology associated with larger machines and furnaces are considered complementary to each other, a feature we discuss more in detail in Section 5.3. Firms choose the size of furnaces by maximizing the discounted value of expected future profits, which depends on expected future environments including the possibilities of accumulating human capital. Although private firms may be constrained by human capital in the short-run, they may still have incentives to use equipment of larger size if they can accumulate enough human capital over time to match with newer technology.

Table 3: Internal Configuration of Integrated Facilities by Size

Sintering (Machine)						
		(1)	(2)	(3)	(4)	(5)
Ownership	Variables	Total	1st quartile	2nd quartile	3rd quartile	4th quartile
Central	Number of Machines	1.98	1.89	2.38	2.50	1.63
	Average Size	274	104	95	222	416
Provincial	Number of Machines	2.41	1.77	2.22	2.41	2.91
	Average Size	186	117	141	225	236
Private	Number of Machines	2.12	1.71	2.31	2.09	5.00
	Average Size	129	74	147	151	360
Iron Making (Blast Furnace)						
		(1)	(2)	(3)	(4)	(5)
Ownership	Variables	Total	1st quartile	2nd quartile	3rd quartile	4th quartile
Central	Number of Furnaces	2.32	2.48	2.28	2.13	2.38
	Average Size	1938	435	985	1902	2768
Provincial	Number of Furnaces	2.66	1.99	2.84	2.59	2.90
	Average Size	1423	633	809	1770	2145
Private	Number of Furnaces	2.82	1.85	3.29	3.56	3.00
	Average Size	707	482	614	828	2680
Steel Making (Basic Oxygen Furnace)						
		(1)	(2)	(3)	(4)	(5)
Ownership	Variables	Total	1st quartile	2nd quartile	3rd quartile	4th quartile
Central	Number of Furnaces	2.44	1.37	1.83	2.26	3.08
	Average Size	127	48	87	94	180
Provincial	Number of Furnaces	2.56	1.49	2.21	3.09	3.09
	Average Size	94	46	67	81	152
Private	Number of Furnaces	1.90	1.09	2.00	2.69	3.00
	Average Size	75	54	79	84	180

Notes: Facility size is measured by the total size of basic oxygen furnaces (steel making) within the facility. The size quartiles are calculated over the facility-month observations in the whole sample and are defined as follows: <90, [90,160), [160,300) and ≥ 300. The size of a sintering machine is measured by its effective areas in m^2; the size of a blast furnace is measured by its effective volume in m^3; the size of a basic oxygen furnace is measured by its tonnage.

4 Estimating Total Factor Productivity of Integrated Facilities

This section describes a framework for estimating total factor productivity of multiple-stage production systems. Section 4.1 discusses the timeline of firms' decision. Section 4.2 presents the theoretical framework and the methodology to construct productivity for integrated facilities. Section 4.3 explains the details of our estimation procedure.

4.1 Description of Decision-Making

Firms make choices regarding investment and production. At the beginning of each year, a firm observes its state, which includes observable variables that affect their input access, output market, and borrowing/regulatory constraints that depend on ownership. Based on its initial state, the firm chooses its targeted level of total production to maximize current profit. This production must then be allocated among integrated facilities and machines/furnaces in each stage to minimize its total production cost. During the year, the firm carries out the production plan and generates final outputs. At the end of the year, the firm decides on investment, which depends on the current state. This decision has dynamic implications: first, larger machines/furnaces are less flexible with respect to input choice and potentially more costly to maintain/adjust, which affects the expected payoff when there is uncertainty in the input and output market; and second, larger machines/furnaces enjoy the benefits of increasing returns to scale. Moreover, the choice of investment (i.e., the size of the facility, and its internal configuration) may be limited by various constraints (e.g. tighter regulatory hurdles, access to finance, human capital, raw materials, etc) that depend on ownership.

Since we have a short panel, we leave the investigation of the full industry dynamics for future research. This paper centers on productivity differences by facility ownership related to facilities' internal configuration. Here we take advantage of the monthly frequency of our data at the facility level and focus on the monthly production of facilities. At the beginning of each month, each facility observes its stock of capital and labor and then the productivity of its individual machines/furnaces. Based on these observables, the facility decides intermediate inputs for its individual machines/furnaces. Note that the facility obtains its intermediate inputs used in a downstream stage from production in the previous stage. Following convention, we assume that intermediate input choices are monotone with respect to productivity in each corresponding stage. At the end of this month, the facility decides on the number of workers and maintaining/utilizing certain machines/furnaces in the next month.

4.2 A Model of Multiple-Stage Production

In each period t, an integrated facility (facility "i") engages in three major stages of production, i.e., sintering (stage "1"), pig iron making (stage "2") and steel making (stage "3"). Along this production chain, output in each stage serves as the key material input for the subsequent downstream production stage. Each stage (plant) may involve a single or multiple machines/furnaces j. For simplicity, we omit i and t in the description of the model.

A complete production process is described as below:

$$\begin{cases} Y_{1j_1} = \min\{e^{\omega_{1j_1}} L_{1j_1}^{\alpha_1} K_{1j_1}^{\beta_1}, \gamma_1 R_{1j_1}\} e^{\epsilon_{1j_1}}, \\ Y_{2j_2} = e^{\omega_{2j_2}+\epsilon_{2j_2}} L_{2j_2}^{\alpha_2} K_{2j_2}^{\beta_2} R_{2j_2}^{\gamma_2}, \\ Y_{3j_3} = e^{\omega_{3j_3}+\epsilon_{3j_3}} L_{3j_3}^{\alpha_3} K_{3j_3}^{\beta_3} R_{3j_3}^{\gamma_3}, \end{cases} \tag{1}$$

where

$$\sum_{j_1} Y_{1j_1} = \sum_{j_2} R_{2j_2},$$
$$\sum_{j_2} Y_{2j_2} = \sum_{j_3} R_{3j_3},$$
$$Y_3 = \sum_{j_3} Y_{3j_3},$$

and R_{1j_1} represents crude iron ore fine, Y_{1j_1} and R_{2j_2} denote sinter, Y_{2j_2} and R_{3j_3} pig iron, and Y_{3j_3} denotes the final product steel.[33] Our measure of capital K_{sj_s} is the capacity of the equipment j in stage s, $s = 1, 2, 3$, and L_{sj_s} is the corresponding number of employees. Productivity ω_{sj_s} is Hicks-neutral. Moreover, output from different machines/furnaces within a stage are perfect substitutes. As sintering is an agglomeration process that reshapes iron ore to the size and strength necessary for pig-iron making, this stage of production is assumed Leontief in materials.[34]

Our model reflects several important properties of production in the steel industry. First, inputs in different stages are not perfect substitutes, an assumption that is implicitly imposed

[33]Strictly speaking, iron ore fed into the furnace is a mixture of 75% sinter, 15% pellets and 10% lump iron ore. Since we have limited information on the latter two, we abstract from their role in the first stage and use total tonnage of the mixture in the second stage. Provided that the proportions are constant, this simplification produces consistent estimates except for the intercept in the second-stage production function.

[34]Substitution may exist between raw iron ore and labor (capital), mostly likely due to the quality of iron ore. However, we do not have information on the raw iron ore used in sintering. As we discuss more fully below, our inability to control for raw material differences likely results in a lower bound estimate of productivity of private firms in sintering relative to SOEs. In pig iron making and steel making, taking furnace size as given, a Leontief production function in materials may better describe the production technology because materials are used in fixed proportions in the production process based on engineering designs. However, the share of material inputs in production changes with furnace size, suggesting that a Leontief production function in materials likely fails to capture the potential substitutability. We provide estimation results using Leontief production functions in the Appendix.

in the standard firm-level production function. Second, upstream inputs, namely, labor and capital, contribute to the entire production chain through their role as intermediate material providers. Ignoring these features may result in biased estimates of input elasticity, and thus, estimates of returns to scale and TFP.

To see this more clearly, consider as a counterpart to our production function process the standard aggregate (log) production function for firm i at time t. We omit subscripts i and t for simplicity.

$$y_3 = \tilde{\omega} + \alpha \tilde{l} + \beta \tilde{k} + \tilde{\epsilon},$$

where $\tilde{l}$ is the logarithm of total labor input and equal to $\log(L_1+L_2+L_3)$, and $\tilde{k}$ is $\log(\tilde{K}_1+\tilde{K}_2+\tilde{K}_3)$, the logarithm of total capital input measured in value terms. In the case of labor, the aggregate production function implicitly assumes that the contribution of labor input to output is of the form of $(L_1+L_2+L_3)^{\alpha}$, which implies that what matters to production is the total amount of labor input and not the allocation of labor across production stages. Labor inputs in each stage are perfectly substitutable with firms able to move workers freely across stages at no expense of output. In contrast, our multi-stage specification allows the role of labor to differ by stage. For example, the contribution of labor is of the form of $(L_1^{\alpha_1\gamma_2\gamma_3} L_2^{\alpha_2\gamma_3} L_3^{\alpha_3})$ in the case in which each stage operates a single machine/furnace. Moreover, the elasticity coefficients are asymmetric, reflecting the sequential nature and relative importance of these inputs.

Another advantage of the above production system is that it allows intuitive calculation of facility-level return to scale and aggregation of stage productivity. First, we calculate the facility-level return to scale, defined as the ratio between the percentage change in output and the associated proportional change in inputs. Multiplying each capital and labor term in production process (1) by a positive constant a leads to new amounts of outputs

$$\begin{cases} Y_{1j_1}(a) = a^{\alpha_1+\beta_1} Y_{1j_1}, \\ Y_{2j_2}(a) = a^{\alpha_2+\beta_2} a^{(\alpha_1+\beta_1)\gamma_2} Y_{2j_2}, \\ Y_{3j_3}(a) = a^{\alpha_3+\beta_3} a^{[(\alpha_2+\beta_2)+(\alpha_1+\beta_1)\gamma_2]\gamma_3} Y_{3j_3}. \end{cases}$$

Note that $a^{\alpha_s+\beta_s}$, where $s = 1, 2, 3$, is due to the proportional changes in the current stage capital and labor. This proportional change propagates into the next stage and has a proportional effect on its output, as well. Therefore, the facility-level returns to scale (RS) is characterized by the sum of the capital and labor elasticities in each stage of production weighted by the material input elasticities:

$$RS = (\alpha_1 + \beta_1) \cdot \gamma_2\gamma_3 + (\alpha_2 + \beta_2) \cdot \gamma_3 + (\alpha_3 + \beta_3). \tag{2}$$

The propagation effects on the outputs in the downstream stage deserve some attention. Outputs from the upstream stage are intermediate inputs in the immediate downstream stage. In principle, the firm could change intermediate input use by different proportions in downstream furnaces. However, due to the homogeneity of the production functions, it is optimal for the firm to apply the same proportional change to each furnace.[35]

Second, we follow Domar (1961) to construct an estimate for facility-level productivity by aggregating productivity across the three stages. In particular, we define facility-level productivity as a weighted sum of stage productivity, i.e.,

$$\omega = \tilde{\omega}_1 \cdot \gamma_2\gamma_3 + \tilde{\omega}_2 \cdot \gamma_3 + \tilde{\omega}_3. \tag{3}$$

[35] This can be seen clearly by solving the following optimization problem. $R_{j_s}(a) = \arg \max_{R_{j_s}, j_s=1,2,\ldots,J} \sum_{j_s} e^{\omega_{j_s}} K_{j_s}^{\alpha_s} L_{j_s}^{\beta_s} R_{j_s}^{\gamma_s}$ s.t. $\sum_{j_s} R_{j_s} = a * \sum_{j_{s-1}} Y_{j_{s-1}}$. Solving the above problem, we obtain that $R_{j_s}(a) = a * R_{j_s}$. A detailed proof is available in the Online Appendix.

We measure stage-level productivity $\tilde{\omega}_s$ by the weighted average productivity across machines/furnaces of stage s, $s = 1, 2, 3$, using the deterministic parts of the production function as weights. Intuitively, the facility-level productivity ω reflects the sum of productivity in each stage of production weighted by its importance in the production chain using elasticities. Alternatively, we can use the value shares of pig iron and sinter out of the total value of steel as the corresponding weights.[36]

The facility-level productivity reflects how efficiency variations in each stage propagate into later stages. We now describe the intuition using the case in which each stage only involves a single machine/furnace. Applying the Leontief first-order condition for sintering, we proceed with the following (log) production system:

$$y_3 = \omega + \alpha_1\gamma_2\gamma_3 l_1 + \alpha_2\gamma_3 l_2 + \alpha_3 l_3 + \beta_1\gamma_2\gamma_3 k_1 + \beta_2\gamma_3 k_2 + \beta_3 k_3 + \epsilon,$$

where $\omega \equiv \omega_3 + \gamma_3\omega_2 + \gamma_2\gamma_3\omega_1$ and $\epsilon \equiv \epsilon_3 + \gamma_3\epsilon_2 + \gamma_2\gamma_3\epsilon_1$ are facility-level productivity and facility-level noise, respectively.

4.3 Estimation Approach

In this section, we develop a modified control function approach to estimate the production system of vertically-integrated steel facilities. This approach is based on Olley and Pakes (1996) and relies on a production unit's choice on intermediate inputs to control for unobserved productivity (Levinsohn and Petrin (2003)). A major advantage of our data is that it contains equipment-level information on inputs and output, which allows estimating production functions by stage-equipment and the calculation of equipment-level productivity estimates.[37]

[36]The derivation of the alternative weights is described in the Appendix.

[37]We abstract from firms' entry/exit decisions since they are not prominent in the data. We also do not take into account monthly entry/exit decisions on machines/furnaces, but these could be dealt with in a manner similar to Olley and Pakes (1996). Effectively, we can estimate the probability that a machine/furnace

We adapt the control function approach to allow for interdependence across stages within the facility. To this end, we allow the optimal intermediate input demand function of a machine/furnace to depend on not only its own state capital and labor, but also the amount of production required in the subsequent stages of production. For simplicity, we omit subscript i in the description of our approach. The demand functions of intermediate inputs of the three production stages $\phi_{st}(\cdot)$, $s = 1, 2, 3$, are as follows:

$$e_{1j_1t} = \phi_{1t}(k_{1j_1t}, l_{1j_1t}, \omega_{1j_1t}, k_{2t}, l_{2t}, n_{2t}, \omega_{2t}, k_{3t}, l_{3t}, n_{3t}, \omega_{3t}), \tag{4}$$

$$e_{2j_2t} = \phi_{2t}(k_{2j_2t}, l_{2j_2t}, \omega_{2j_2t}, k_{3t}, l_{3t}, n_{3t}, \omega_{3t}), \tag{5}$$

$$e_{3j_3t} = \phi_{3t}(k_{3j_3t}, l_{3j_3t}, \omega_{3j_3t}), \tag{6}$$

where k_{st},l_{st},ω_{st} are the average capital, labor and TFP of stage s, $s = 2, 3$, and n_{st} the total number of machines/furnaces of stage s. We use energy input to control for unobserved TFP in sintering ω_{1j_1t} and pig iron making ω_{2j_2t}, and use scrap steel input to control for unobserved TFP in steel making ω_{3j_3t}.

Following Ackerberg et al. (2015), we assume that $\phi_{st}(\cdot)$ is strictly monotone in ω_{sj_st} conditioning on (k_{sj_st}, l_{sj_st}), and for sintering and pig iron making, on the information of downstream stages as well. In addition, the scalar unobservability condition also holds in our setting due to the timing assumptions of firms' input choices, so we can invert the above relationships to control for the unobserved productivity. To proceed, we first invert the demand function of steel making (6), estimate the production function of this stage, and obtain estimates of average TFP $\widehat{\omega}_{3t}$. After we plug the estimated $\widehat{\omega}_{3t}$ into the intermediate input demand function for pig iron making, the only remaining unobservable in the demand function (5) is productivity ω_{2j_2t}. We then invert the demand function (5) to obtain a control function for productivity ω_{2j_st} and estimate the stage-2 production function. Next, we plug both the estimated productivity of pig iron making $\widehat{\omega}_{2t}$ and steel making $\widehat{\omega}_{3t}$ into the

shuts down and use it as a control in our production function estimation.

intermediate input demand function of sintering (4) and estimate the production function of sintering.

Equations (7), (8), and (9) provide the control functions for steel making, pig iron making and sintering.

$$\omega_{3j_3t} = \phi_{3t}^{-1}(k_{3j_3t}, l_{3j_3t}, e_{3j_3t}), \tag{7}$$

$$\omega_{2jt} = \phi_{2t}^{-1}(k_{2j_2t}, l_{2j_2t}, e_{2j_2t}, k_{3t}, l_{3t}, \widehat{\omega}_{3t}), \tag{8}$$

$$\omega_{1jt} = \phi_{1t}^{-1}(k_{1j_1t}, l_{1j_1t}, e_{1j_1t}, k_{2t}, l_{2t}, \widehat{\omega}_{2t}, k_{3t}, l_{3t}, \widehat{\omega}_{3t}). \tag{9}$$

Our first-step estimating equation for each individual stage is then given by the equation below, which expresses output y as a semiparametric function of $(k_{sj_st}, l_{sj_st}, e_{sj_st}, r_{sj_st})$ and of the information of downstream stages in the case of stage 1 sintering and stage 2 pig iron making.

$$y_{sj_st} = \alpha_s l_{sj_st} + \beta_s k_{sj_st} + \gamma_s r_{sj_st} + \phi_{st}^{-1}(\cdot) + \epsilon_{sj_st}.$$

As usual, we collect the deterministic terms and denote them as $\Phi_{st}(\cdot) \equiv \alpha_s l_{sj_st} + \beta_s k_{sj_st} + \gamma_s r_{sj_st} + \phi_{st}^{-1}(\cdot)$. Note that for stage $s = 1$, the same analysis follows by leaving out r_{1j_1t} due to the Leontief technology.

Ackerberg et al. (2015) argue that it may take longer to adjust capital and labor input use optimally than intermediate inputs, which include materials and energy. Since our data are on a monthly basis and include large SOEs that face significant hiring and firing costs, labor is likely to be fixed or quasi-fixed. Therefore, it is reasonable to assume that the demand for intermediate inputs depends on productivity and the predetermined capital and labor input. The advantage of using energy inputs as control variables is two-fold: first, energy input is measured in terms of standardized coal, which addresses the issue of potential bias resulting from quality differences in inputs; and second, using energy input for the control function throughout the first two stages keeps our estimation consistent. We approximate

$\Phi_{st}(\cdot)$ by a high order polynomial and use OLS regression for estimation. We also include ownership dummies ($Downership$), time dummies (Dt) and province dummies ($Dprovince$) in the regression. In pig-iron making, we adjust material input r by the percentage of pure ore content to control for quality variation. Basic oxygen furnaces (steel making) differ significantly in the share of steel that goes through secondary refining. One of the major goals of secondary refining is to remove impurities from the molten steel, so the intensity of secondary refining potentially reflects the quality of pig iron used in steel making. To control for input quality in steel making, we also include in the first stage a dummy to capture whether furnaces carry out secondary refining ($Dsecond_{sj_st}$) and then the share of steel that goes through secondary refining ($second_{sj_st}$).

In the second step, we estimate the parameters $\theta \equiv (\alpha, \beta, \gamma) \in \Theta$ by GMM, which exploits a Markov assumption on the TFP and the timing of input choices. Θ denotes the parameter space. In particular, we assume that TFP of each equipment j in stage s follows a first-order Markov process:

$$\omega_{sj_st} = g(\omega_{sj_s,t-1}) + \xi_{sj_st},$$

which says that the current productivity shock consists of an expected term predicted by productivity at $t-1$ ($\omega_{sj_s,t-1}$) plus a deviation from the expectation, often referred to as the "innovation" component (ξ_{sj_st}). Note that ω_{sj_st} is identified up to θ from the first step after taking out measurement error and unanticipated shocks from output. We regress ω_{sj_st} on a linear function of $\omega_{sj_s,t-1}$ to obtain $g(\omega_{sj_s,t-1})$.[38] Denote $\omega_{sj_st}(\theta) \equiv \widehat{\Phi_{st}}(\cdot) - \alpha l_{sj_st} - \beta k_{sj_st} - \gamma r_{sj_st}$. For a given θ, $g(\cdot)$ can be estimated and thus ξ_{sj_st} (up to θ) is obtained. The latter

[38]The results are robust to higher order polynomials.

is used to construct the moment conditions:

$$E[(\xi_{sj_st}(\theta)+\epsilon_{sj_st})\begin{pmatrix} l_{sj_s,t-1} \\ l_{sj_st} \\ k_{sj_st} \\ r_{sj_s,t-1} \\ \Phi_{sj_s,t-1}(k_{sj_s,t-1}, l_{sj_s,t-1}, r_{sj_s,t-1}) \end{pmatrix}]=0.$$

Since the capital stock is a state variable at t, it should be orthogonal to the innovation shock on productivity at t. We use current labor (l_{sj_st}) as an instrument for itself because of its dynamic feature, and also include labor at $t-1$ as an additional instrument. And we use lagged material input $r_{sj_s,t-1}$ as an instrument for r_{sj_st}. As pointed out by Gandhi et al. (2017), the use of $\xi_{sj_st}+\epsilon_{sj_st}$ rather than ξ_{sj_st} alone in the moment condition is more general. We search over the parameter space Θ to find $\hat{\alpha}$, $\hat{\beta}$ and $\hat{\gamma}$ that minimize the above moment conditions.

We use the GMM procedure to identify separately production function coefficients for each individual stage s in a backward order as described above, $s=3,2,1$. As is commonly done, we also add firms' age to the production function to control for potential systematic differences in technology resulting from the learning-by-doing process.[39] In steel making, we allow the status of secondary refining ($Dsecond_{sj_s,t-1}$) and the share of secondary refining ($second_{sj_s,t-1}$) to enter the productivity evolution process since secondary refining technology may potentially impact the law of motion of productivity.

Compared with a commonly used aggregate revenue production function, our procedure has several advantages. First, our setup properly captures the characteristics of the vertically-integrated production chain. Second, the use of input and output in physical units in our estimation helps eliminate price biases, and allows us to recover true productions

[39] Ideally we want to use a machine/furnace's age to capture this process. Lacking this information, we use the firm's age.

coefficients.[40] Third, our GMM estimates correct for any endogeneity bias due to the potential relationship between input usage and unobserved productivity. Finally, disaggregated information on inputs and output by stage of production allows us to estimate accurately a multi-stage production system.

Measurement Errors The use of input and output measured in physical units helps avoid potential biases introduced by heterogeneous prices, which could reflect for example market power, misallocation, etc. But measures in physical terms can have flaws too, and may not capture potential quality differences in output, capital vintage, raw materials, or in the facility's human capital. The number of employees that we use to measure labor abstracts from differences in workers' skill level. Similar issues arise in our use of equipment capacity as our measure for the capital stock. In Section 6, we return to these issues and provide several robustness checks for possible biases stemming from these sources.

5 Main Results

5.1 Production Function Coefficients

Table 4 presents estimates of the production functions for sintering, iron making and steel making, the three major production stages along the value chain for steel. For each stage of production, we report results using both OLS and GMM. For sintering, the coefficients are only provided for labor and capital, and not for materials, reflecting the assumed Leontief technology. The elasticities are largest for materials, followed by capital and labor. Of the three stages, sintering is the most capital intensive, followed by pig-iron and steel making.

[40] For a detailed discussion of the biases encountered when using sales and expenditure data, see De Loecker and Goldberg (2014).

Table 4: Production Functions

	(1)	(2)	(3)	(4)	(5)	(6)
	sintering		iron making		steel making	
VARIABLES	ols	gmm	ols	gmm	ols	gmm
l	0.212***	0.188***	0.149***	0.182***	0.0582***	0.0525***
	(0.00842)	(0.0133)	(0.00552)	(0.00190)	(0.00442)	(0.00174)
k	0.811***	0.878***	0.353***	0.449***	0.154***	0.129***
	(0.00647)	(0.000979)	(0.00553)	(0.000886)	(0.00374)	(0.00281)
m			0.534***	0.437***	0.746***	0.878***
			(0.00564)	(0.00505)	(0.00483)	(0.00295)
age	-0.00125***	-0.000516	-0.000435**	-0.000288	-0.000442***	-0.000564*
	(0.000300)	(0.00168)	(0.000176)	(0.000538)	(0.000102)	(0.000327)
Observations	6,386	6,386	8,082	8,082	8,485	8,485
R-squared	0.830		0.919		0.927	
Ownership FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Returns to Scale	1.02	1.07	1.04	1.07	0.96	1.06
	(0.048)	(0.013)	(0.024)	(0.005)	(0.026)	(0.003)

Note: Standard errors of production function coefficients using GMM estimation and returns to scale from both OLS and GMM are computed via bootstrap of 1,000 replications clustered by facility.

Weights for Returns to Scale and TFP Construction In order to construct facility-level returns to scale, we need to integrate the sum of the capital and labor elasticities in each stage of production weighted by the material input elasticities. For the construction of facility-level TFP, we can use either the elasticity of material inputs in each stage or value shares to integrate estimates of stage-level TFP into an aggregate measure of TFP at facility level. In Table 5 we report the two sets of weights for each stage of production. As we move downstream, the contribution of stage-level production to facility-level returns to scale and efficiency increases: The weight on sintering is 0.38 compared to weights of 0.88 and 1.0 on iron-making and steel production, respectively. Our two sets of weights are also fairly similar in magnitude and deliver similar estimates of TFP. The subsequent analysis is based on the TFP estimates weighted by the elasticities.

Returns to Scale Our OLS estimates suggest increasing returns to scale in sintering (1.02) and iron making (1.04), and decreasing returns to scale in steel making (0.96). In contrast, our GMM estimates imply increasing returns to scale in each stage of production.[41] The sum of the input elasticity is slightly larger for sintering (1.07) and iron making (1.07) than for steel making (1.06). These differences are reflected at the facility level (see equation (2) in section 4.2), where we find increasing returns to scale of 1.14 based on the GMM estimates, and 0.99 using the OLS estimates.[42] At the facility-level, the OLS estimates suggest slight decreasing returns to scale due to the fact that the final stage production offsets the advantages of increasing returns to scale in the first two stages. In contrast, the facility-level estimate from GMM is larger than the returns to scale in the individual

[41]We replicate the OLS and GMM estimation for steel making for a thousand bootstrapped samples, and find that the mean of the returns to scale from GMM is statistically larger than the returns to scale from the OLS. The difference between OLS and GMM for sintering and pig iron making is not statistically significant, however both sets of estimates imply increasing returns to scale.

[42]The standard error for the estimate of the returns to scale calculated from the GMM estimates at the facility level is 0.008.

stages, suggesting that the three stages contribute to overall increasing returns in a mutually reinforcing way. Therefore, the OLS estimates can lead to misleading conclusions about the features of steel technology. Our facility-level estimate based on the GMM procedure is also larger than several recent estimates for the industry, notably, an estimate of 1.03 by Collard-Wexler and De Loecker (2015) for the US, and 1.07 for China by Sheng and Song (2012).[43] The increasing returns to scale at both the equipment- and facility-level provide incentives for steel firms to build larger facilities and install larger machines/furnaces to take advantage of falling long-run average costs.

5.2 Productivity Differences in Integrated Facilities

5.2.1 Productivity Differences by Ownership

We present estimates of facility-level productivity differentials by ownership in Table 6. Column (1) shows that private integrated facilities are on average 7.4 percent more productive than the facilities in central SOEs, and are 1.1 percent more productive relative to provincial SOEs. The magnitude of the private ownership premium in steel is small by comparison with Hsieh and Song (2015)'s recent estimate of 33 percent for 2007 for the manufacturing sector, but more in line with Berkowitz et al. (2017), who find an average 8.2 percent productivity premium of private firms relative to SOEs between 2003 and 2007.[44] With value added in

[43]Possibly underlying these differences is some combination of the estimation of an aggregate production function, and in the case of Sheng and Song (2012), estimation of a revenue production function. The latter is necessary because of the lack of firm-level price information. De Loecker and Goldberg (2014) point out that variation in both output and input prices in a revenue production function likely results in a downward bias in production function coefficients and therefore a lower returns to scale. Collard-Wexler and De Loecker (2015) construct firm-level input and output deflators, and thus effectively estimate a production function in physical terms.

[44]Differences in these estimates may come from several sources: First, estimation of a value-added versus gross-output production function. Although both value-added and gross-output based TFP indices provide a measure of technological change, the two will not necessarily be the same (Balk (2009)). Second, differences in

Table 5: Weights for Returns to Scale and TFP Aggregation

	(1)	(2)	(3)
	Weight 1 Elasticity	Weight 2 Value Share	
Sintering	$\hat{\gamma}_2 * \hat{\gamma}_3$	Mean	Std Dev
	0.38	0.52	0.16
Iron making	$\hat{\gamma}_3$	Mean	Std Dev
	0.88	0.82	0.05
Steel making	1	1	

Notes: $\hat{\gamma}_2$ is the estimated elasticity of material input (iron ore) in iron-making production function. $\hat{\gamma}_3$ is the estimated elasticity of material input (iron) in steel-making production function.

assumptions relating to the underlying production technology, e.g., Cobb-Douglas versus CES versus translog, may result in differences in estimated TFP and our productivity ranking. And third, some estimates may only reflect within-sector variation, while others capture both within and between sector differences in TFP.

the steel sector 25-30 percent of gross output, even modest productivity differences of the sort we estimate translate into significant differences in profitability by ownership, which have wider implications.

5.2.2 The Larger, the Better?

We documented systematic differences in the size of integrated facilities by ownership: SOEs in general operate much larger facilities. The scatter plot of TFP against facility size in Figure 3 demonstrates a slight negative relationship between the two for the full sample and a more pronounced negative relationship for private facilities. To examine this relationship more systematically, we add facility size to the regression of TFP on firm ownership, and also run regressions on facility size that include interaction terms of ownership dummies with facility size. Estimates are provided in Table 6 columns (2) and (3), and confirm the results of Figure 3. On average, TFP falls with facility size, as indicated by column (2) of Table 6. The productivity premium of private facilities relative to facilities of central SOEs also drops by almost half, to 3.8 percent. Moreover, private facilities now become 1.1 percent less productive than provincial state-owned facilities. Examining the size effect by ownership, we see that size appears to have a small positive effect on TFP for central state-owned facilities. In sharp contrast, for private firms, and slightly less so for provincial SOEs, productivity of integrated facilities declines with size. The coefficient on the interaction term for private facilities implies that with a doubling in size, their productivity declines by 14.7 percent relative to central state-owned facilities. This has the effect of reducing the productivity premium of these facilities relative to central state-owned facilities at larger sizes. When facility size is above the median, TFP of private facilities falls below that of central state-owned facilities. We observe the same pattern in the comparison between private and provincial state-owned facilities.

Table 6: Productivity Differences by Ownership and Size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Facility	Facility	Facility	Sintering	Sintering	Sintering	Iron Making	Iron Making	Iron Making	Steel Making	Steel Making	Steel Making
Variables	logtfp	logtfp	logtfp	logtfp	logtfp	logtfp	logtfp	logtfp	logtfp	logtfp	logtfp	logtfp
logsize		-0.0479	0.0434		-0.0903***	-0.118***		-0.0338***	-0.0346		-0.0529***	-0.0212
		(0.0319)	(0.0467)		(0.0232)	(0.0339)		(0.00849)	(0.0228)		(0.00585)	(0.0151)
PrivateXlogsize			-0.147			-0.0225			-0.0552			-0.0679**
			(0.0933)			(0.0663)			(0.0349)			(0.0329)
ProvincialXlogsize			-0.108*			0.0504			0.0116			-0.0327**
			(0.0633)			(0.0459)			(0.0245)			(0.0162)
Private	0.0743	0.0382	0.802*	-0.108**	-0.144***	-0.0512	0.0612***	0.0429*	0.393*	0.0615***	0.0316**	0.331**
	(0.0631)	(0.0728)	(0.462)	(0.0518)	(0.0485)	(0.318)	(0.0207)	(0.0221)	(0.235)	(0.0152)	(0.0156)	(0.138)
Provincial	0.0633	0.0490	0.633*	-0.0930**	-0.115***	-0.360	0.0222	0.0158	-0.0622	0.0155	-0.00630	0.147*
	(0.0516)	(0.0543)	(0.360)	(0.0446)	(0.0408)	(0.231)	(0.0194)	(0.0196)	(0.176)	(0.00947)	(0.00993)	(0.0791)
Constant	-0.113**	0.141	-0.357	0.0342	0.471***	0.608***	-0.0842***	0.146**	0.151	-0.0420***	0.204***	0.0544
	(0.0481)	(0.187)	(0.273)	(0.0372)	(0.113)	(0.165)	(0.0218)	(0.0651)	(0.165)	(0.00874)	(0.0299)	(0.0749)
Observations	3,440	3,440	3,440	8,728	8,728	8,728	11,836	11,836	11,836	8,510	8,510	8,510
R-squared	0.022	0.036	0.051	0.015	0.043	0.046	0.020	0.033	0.038	0.048	0.151	0.162
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Central state-owned facilities and their machines/furnaces are the omitted group. Private and provincial indicate ownership dummies. The size of a sintering machine is measured by its effective areas in m^2; the size of a blast furnace is measured by its effective volume in m^3; the size of a basic oxygen furnace is measured by its tonnage. Facility size is measured by the total size of basic oxygen furnaces (steel making) within the facility. Standard errors are clustered by machines/furnaces for stage-level analysis and by facility for facility-level analysis, but not corrected for the sampling error in constructed productivity.

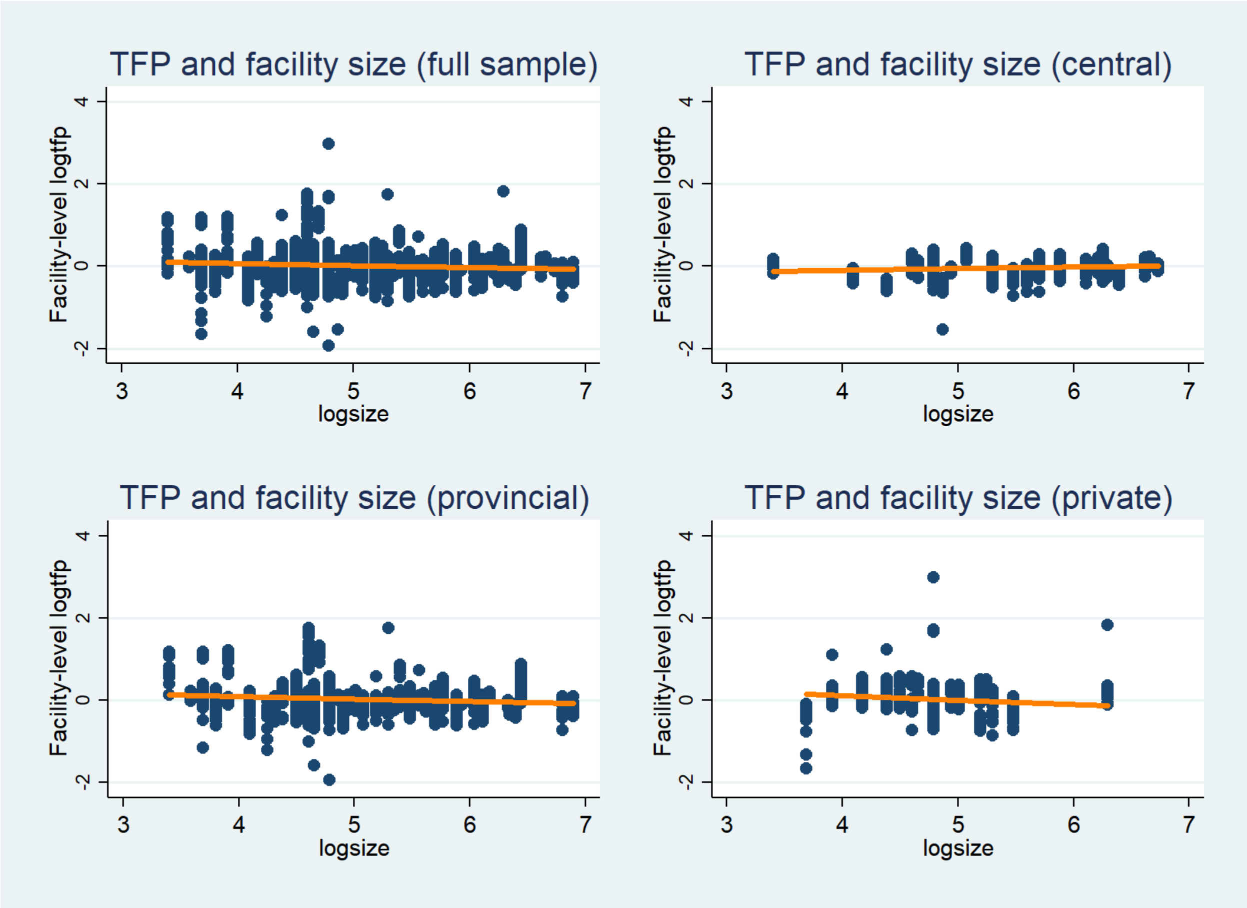

Figure 3: Facility-level TFP and Size of Integrated Facilities

Notes: By industry convention, facility size is measured by the total size of basic oxygen furnaces (steel making) within the facility; the size of a basic oxygen furnace is measured by its tonnage. Each plot represents a facility-month observation.

5.3 Productivity Differences: A Further Look

This section takes advantages of our unique data to rationalize the productivity differences that we identified above. Our analysis centers on two key questions: Where in production is the premium coming from? Why does TFP decline with size for private firms in particular?

Productivity Differences by Stage of Production To examine the sources of the observed productivity differences, we first study the effect of ownership on equipment-level productivity. In columns (4), (7) and (10) of Table 6, we report estimates of productivity by ownership for each stage of production. Estimates are obtained from simple OLS regressions of the log of equipment-level TFP on ownership dummies that control for the effect of seasonality with the use of monthly dummies. In columns (5), (8) and (11), we report results that also control for the size of equipment. In these regressions, equipment of central state-owned facilities are our omitted category. In both pig-iron making and steel-making, private facilities have a productivity advantage over central state-owned facilities of 6.1 percent and 6.2 percent, respectively. The premium of private facilities in both stages is slightly smaller in comparison with provincial state-owned facilities. In sharp contrast, the productivity ordering by ownership is reversed for sintering: Sintering machines of central state-owned facilities are 10.8 percent more productive than private facilities, and 9.3 percent more productive than provincial state-owned facilities. Clearly, the ordering of productivity by ownership at the facility level follows that found in pig-iron making and steel making. This implies that the sizeable productivity disadvantage of private facilities in sintering is more than offset by their superiority in the two downstream stages of production.

What might help to explain the reversal in the productivity ranking in the case of sintering? A regular supply of iron ore is critical to the running of sintering machines. SOEs, especially central SOEs, typically enjoy privileged access to iron ore.[45] Central SOEs source

[45] Interview with a steel consultant at Shanghai Securities Research Institute in December, 2014.

imported iron ore through long-term contracts directly with the importers, which enable them to build up inventories of iron ore when prices are relatively low. In principle, sourcing difficulties might force private facilities to operate their sintering machines at lower rates of capacity utilization, which then show up as lower productivity. Data on capacity utilization however reveal only modest differences by ownership in the case of sintering.[46] Nonetheless, private facilities' use of lower quality iron ore might hold the key to the differences we observe in productivity in sintering.[47]

In general, domestic iron ore is of much lower quality than imported ore and contains a higher proportion of impurities.[48] This is reflected, for example, in the silica content of the iron ore, a chemical substance that lowers the quality of sinter and also adversely affects the production process. For domestic iron ore, the silica content ranges from 6.5 to 12 percent. By contrast, imported iron ore is more homogeneous in pure ore content, and contains only 4 percent silica.[49] Over the three-year period between 2009 and 2011, steel firms of all ownership in China relied heavily on imported ore, however private firms used two-thirds more domestic iron ore than did SOEs: 33.3 percent versus 20 percent.[50] Data for 2010 and 2011 indicate that rich ore fines - a measure of the quality of crude ore used in sintering - make up 60.1 percent and 62.8 percent of total crude iron ore processed in central SOEs in these two respective years, compared to 47.5 and 46.2 percent in private firms, a difference of 12.6 and 16.6 percentage points, respectively.

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[46] Capacity utilization is measured here as the ratio of operating days to total calendar days minus scheduled maintenance days. Private facilities actually operate slightly more intensively than central state-owned facilities by 1.8 percentage points.

[47] Factors influencing sintering process. July 8, 2013. http://ispatguru.com/factors-influencing-sintering-process/

[48] See Gao (2006) for more details.

[49] The information on iron ore fines is based on data in Yu (2004).

[50] Data on iron ore are reported on an annual basis and cover two-thirds of the firms in the production data.

Sintering is positioned at the very beginning of the value chain and entails the production of high quality burden out of crude iron ore fines. The use of lower grade domestic iron ores by private facilities necessitates additional processing in order to produce the iron ore of the desired quality for pig-iron production. This ties up the processing equipment longer and requires additional labor inputs, both of which translate directly into the lower equipment productivity we observe.[51] Depending on the substitution possibilities between labor, capital and iron ore quality, inclusion of iron ore in the production function would likely reduce the premium of SOEs over private firms in TFP in sintering.

Productivity Differences and Internal Configuration As discussed in Section 3.2.3, when private firms build facilities with larger capacity, they install larger machines/furnaces, but more of them and of lower average machine/furnace size compared to SOEs. This difference is especially sharp as the size of integrated facilities grows larger, e.g., in the third-quartile for pig iron making. This pattern may help explain the falling productivity premium of private integrated facilities.

To identify the role of larger equipment size in explaining productivity differences by ownership, we add to the previous regressions an interaction term between equipment size and our ownership dummies.[52] The reported estimates in Table 6 suggest that equipment-level TFP declines with equipment size. Moreover, equipment-level TFP in private facilities declines relative to state-owned facilities as equipment size expands in all three production stages, with the effect more pronounced in pig-iron and steel making.

Several channels help to explain the above observation. First, larger furnaces and sintering machines utilize newer technologies, which firms only master with experience. Zhu et al.

[51] In iron- and steel-making, however, our production function estimation already factors in the quality of the key material inputs. In fact, controlling for input quality changes only slightly the magnitudes of productivity differentials.

[52] Note that in these regression we may be picking up the systematic (and unobserved) correlation between the size of the equipment and overall number of equipment the firm is running.

(2010) document that large furnaces fail to achieve their expected production efficiency when they initially go into operation because of firms' limited technological capabilities. Firms such as Baosteel, widely regarded as China's most advanced steelmaker, invest heavily in R&D, human resources, etc, to better align the firms' technological capability with these new technologies. Li (2011) and Yang et al. (2011) discuss the learning-by-doing effects in pig iron making for Baosteel and in steel making for Masteel, respectively. The decline in TFP with equipment size in all ownership categories likely reflects less experience associated with newer technologies.[53] Later adoption of newer technologies by private firms, in turn, may help explain the sharper decline in TFP with furnace size for these firms.

Second, larger furnaces and sintering machines require better human capital both on the shop floor and in management, exactly the areas in which private firms face constraints. Ahlbrandt et al. (1996) argue in the context of the US steel industry that for any given level of technology, the best performing plants are those with the most capable production workers. More generally, new technology and human capital are highly complementary.[54] Li (2011) points out, for example, that by design larger blast furnaces are more advanced in their technology (e.g. energy saving and environmental friendly), and also more demanding in the role of advanced management systems.[55] In larger furnaces, workers must also control the size, shape and temperature of the burdens fed into furnaces within much finer tolerances, thereby putting a premium on higher quality shop-floor workers.[56] Large furnaces also require

[53] However, our short panel cannot effectively show such learning-by-doing effect.

[54] Giorcelli (2019) finds that management and new machines were complementary using data on Italian firms in the context of Productivity Program, a part of Marshall Plan.

[55] Larger blast furnaces require managers to adopt modern management procedures, such as "PDCA", i.e. Plan, Do, Check and Action. As large blast furnaces also generate huge amounts of data, management and analysis of data are critical for operating and control of large and modern blast furnace. See "High Capacity Iron Making with Large, Modern Blast Furnaces", International Conference on Emerging Trends in Metals & Minerals Sector. New Delhi, 5 September 2014.

[56] In addition, in larger furnaces, the production process must be more carefully monitored to ensure that

additional care and maintenance: A temporary breakdown lasting a single minute can result in substantial costs.

Much lower levels of human capital in private facilities may contribute to the more rapid drop-off in TFP as equipment size rises.[57] A growing literature documents the effect of ownership on a firms' ability to access resources and capital. Drawing on a sample of private enterprises in China, Garnaut et al. (2012) argue that private firms are not only financially constrained, but are also constrained with respect to human capital.[58] Iskandar (2015) uses the World Bank 2012 survey data to provide evidence that private firms are constrained in their ability to hire skilled and trained labor. The steel industry is no exception. In China's steel sector 18.7 percent of SOE employees had a college degree or higher compared to only 7.2 percent in private firms. The percentage of skilled labor in SOEs was almost two and a half times higher than in private firms (4.7 versus 2 percent).[59]

Larger sintering machines and furnaces embody newer technologies that are highly complementary with the human capital endowments of SOEs, e.g. more talented and experienced managers and more highly skilled workers. Smaller machines and furnaces using earlier vintage technologies are much less demanding in this regard, and thus more compatible with the managerial talent, organizational capabilities and skill sets of private firms. Lower levels

slag is removed almost immediately because of the greater risk that it might clog the furnace as pressure inside the furnace increases (Yao (2014)).

[57]In our regressions, we are not able to control for human capital differences. Since human capital in private firms is lower than SOEs, including human capital would likely raise the TFP premium of private firms. The effect of the size premium by ownership depends on the ratio of human capital in SOEs to private firms by furnace size, which we do not have information on.

[58]The four surveyed cities include Beijing, Chengdu, Chengde and Wenzhou.

[59]The figures are based on the authors' calculation using the 2004 Industrial Survey Data. We define high skilled labor as the total number of technicians and high-skilled workers. Several studies have also shown that state-owned firms in China have deep human resource reserves (e.g. Peng and Heath (1996); Tan (2003)).

of human capital in private firms likely increase the time needed to digest and fully exploit the potential of new technology. Further, the greater number of machines/furnaces at larger private facilities spreads scarce managerial resources even thinner, thereby lowering the productivity of these private facilities.

6 Discussion

This section examines how measurement errors in capital and output might affect our main analysis.

6.1 Measurement Error in Capital

The use of production capacity as our measure of firm capital has its advantages, but may still not fully capture differences in capital intensity between firms.[60] For example, investment costs per unit of capacity, which we assume are constant, might increase with equipment size.[61] The potential bias results from two sources. First, the positive correlation between capacity and unit investment cost leads to an upward bias in capital coefficients. Second, estimated productivity contains the unit price of capacity. Other things equal, the overestimate of the capital stock in private facilities would lead to a downward bias in the productivity differentials that we found in pig-iron and steel making.

To see this more clearly, we express production as a function of price-adjusted capital k^*, where k^* is the product of capacity k, our capital measure in the baseline estimation, and

[60] One shortcoming of capital stock measures in value terms is that they include investments in pollution abatement equipment, which are not separately identified in the data. While these investments are good for the environment, they do not likely augment productivity. Firms that invest more in pollution control, all else equal, will likely have lower TFP. The use of capital measures in physical (capacity) terms is not susceptible to these biases.

[61] We extract the information on investment costs of steel plants by size from an internal report prepared by the Chinese Metallurgy Planning Institute in August 2016 per the authors' request.

the unit capacity price, p.

$$\begin{aligned} y_i &= \alpha l_i + \beta k_i^* + \gamma r_i + \omega_i + \epsilon_i \\ &= \alpha l_i + \beta k_i + \gamma r_i + \beta p_i + \omega_i + \epsilon_i \end{aligned}$$

In our baseline model, we treat unit capacity price p as measurement error, so our estimated productivity is equal to $\hat{\beta} p_i + \hat{\omega}_i$. Since unit capacity price p is positively correlated with capacity k, this leads to a potential upward bias in the estimated parameter on capital β. Our estimates of productivity ownership differentials are also likely to be biased because our measure of productivity $(\hat{\beta} p_i + \hat{\omega}_i)$ includes the unobserved unit capacity price. Consider the estimated productivity differential between private and central state-owned facilities, i.e., $\hat{\beta}(p_i^{private} - p_i^{central}) + (\hat{\omega}_i^{private} - \hat{\omega}_i^{central})$. The first term reflects capacity price differences, and the second measures the true difference in productivity. As private facilities systematically operate smaller equipment than central state-owned facilities, the unit capacity price of private machines/furnaces is generally lower. Consequently, the first term of the productivity differential is negative, which gives rise to a downward bias in the estimated productivity premium of private firms at the equipment level compared to central state-owned facilities.

We use the price information on investment of basic oxygen furnaces (steel making) to adjust capital in this particular stage of production, and re-estimate the production function for steel making using this adjusted capital measure. The estimated coefficients are reported in Table 7. Compared to the baseline estimation, using the adjusted capital generates a lower coefficient for capital, as predicted. We report the corresponding productivity differentials in Table 8. The productivity premium of private furnaces over central state-owned furnaces rises slightly from 6.2 percent to 6.4 percent when we base our estimates on the price-adjusted capital.

Table 7: Production Function: Robustness Check

	(1)	(2)
	Steel Making	
	Non-Adjusted	Price-Adjusted
Variables	GMM	GMM
l	0.0525***	0.0520***
	(0.00174)	(0.00174)
k	0.129***	0.0920***
	(0.00281)	(0.00258)
m	0.878***	0.885***
	(0.00295)	(0.00252)
age	-0.000564*	-0.000582*
	(0.000327)	(0.000339)
Observations	8,514	8,514
Ownership FE	YES	YES
Province FE	YES	YES
Time FE	YES	YES

Note: Standard errors of GMM estimation are computed via bootstrap of 1,000 replications clustered by facility.

Table 8: Ownership Premium of Productivity in Steel Making: Robustness Check

	(1)	(2)
Variables	Non-Adjusted logtfp	Price-Adjusted logtfp
Private	0.0615***	0.0641***
	(0.0152)	(0.0153)
Provincial	0.0155	0.0147
	(0.00947)	(0.00937)
Constant	-0.0420***	-0.0413***
	(0.00874)	(0.00861)
Observations	8,510	8,510
R-squared	0.048	0.052
Time FE	YES	YES

Notes: Furnaces of central state-owned facilities are the omitted group. Provincial and private are ownership dummies. Standard errors are clustered by furnace.

Independent of furnace size, systematic differences may also exist in the costs per unit of capacity between private and state-owned facilities. In general, we expect private firms to be more cost sensitive, and for them to be successful in finding ways to build furnaces of any size at lower cost, and thus enjoy lower per unit cost of capacity relative to SOEs. This source of measurement error would further underestimate productivity premiums of private facilities. Similar to our discussion about the bias generated by ignoring the increasing unit cost of capacity with equipment size, there will be an effect coming through our estimate of the elasticity for capital, and our estimate of the capital stock of these private facilities. Additional information on capacity cost by ownership is needed to estimate the magnitude of this bias.

6.2 Measurement Error in Output

In our data, output is measured in physical units, obscuring output quality differences between facilities. In principle, this could bias our productivity comparisons. Let y^* measure quality-adjusted output, defined as a function of observed output y and X, a vector of output quality measures. f is a general production function and is stage-specific but time-invariant.

$$y_i^*(y_i, X_i) = f(l_i, k_i, r_i) + \omega_i + \epsilon_i \tag{10}$$

Assuming that y and the quality components are additively separable

$$y_i^* = y_i + \delta(X_i) \tag{11}$$

Substituting equation (11) into equation (10), we obtain our baseline production function.

$$y_i = f(l_i, k_i, r_i) + (\omega_i - \delta(X_i)) + \epsilon_i \tag{12}$$

This makes explicit that estimated productivity $\omega_i - \hat{\delta}(X_i)$ also incorporates output quality.

Table 9: Output Quality Differences by Ownership

	(1)	(2)	(3)
Variables	Sintering Grade Stability	Iron Making Premium Grade	Steel Making Secondary
Private	-10.56**	1.354	-39.54***
	(4.243)	(3.935)	(7.873)
Provincial	-2.481	-5.717	-26.77***
	(1.929)	(3.689)	(6.698)
Constant	90.79***	65.92***	56.25***
	(1.716)	(3.365)	(6.113)
Observations	8,728	11,836	8,510
R-squared	0.027	0.018	0.093
Time FE	YES	YES	YES

Notes: All quality measures are in percentage points. Secondary denotes the share of steel that goes through secondary steel refining and provides an important piece of evidence on the quality of steel. Standard errors are clustered by machines/furnaces.

Table 10: Quality-Adjusted Ownership Premium of Facility-level Productivity

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	logtfp	logtfp	logtfp	logtfp	logtfp	logtfp
logsize			-0.0479	-0.0687**	0.0434	0.0238
			(0.0319)	(0.0317)	(0.0467)	(0.0509)
PrivateXlogsize					-0.147	-0.137
					(0.0933)	(0.0901)
ProvincialXlogsize					-0.108*	-0.110*
					(0.0633)	(0.0641)
Private	0.0743	0.0847	0.0382	0.0530	0.802*	0.765*
	(0.0631)	(0.0665)	(0.0728)	(0.0712)	(0.462)	(0.449)
Provincial	0.0633	0.0724	0.0490	0.0652	0.633*	0.660*
	(0.0516)	(0.0512)	(0.0543)	(0.0537)	(0.360)	(0.365)
Constant	-0.113**	-0.0478	0.141	0.257	-0.357	-0.237
	(0.0481)	(0.111)	(0.187)	(0.201)	(0.273)	(0.287)
Observations	3,440	3,440	3,440	3,440	3,440	3,440
R-squared	0.022	0.027	0.036	0.049	0.051	0.063
sinter quality	NO	YES	NO	YES	NO	YES
iron quality	NO	YES	NO	YES	NO	YES
steel quality	NO	YES	NO	YES	NO	YES
Time FE	YES	YES	YES	YES	YES	YES

Notes: Central state-owned facilities are the omitted group. Provincial and private are ownership dummies. Standard errors are clustered by facility.

Table 9 reports output quality comparisons across ownership: On average, private firms produce lower quality sinter and steel but higher shares of premium grade pig iron compared to SOEs.[62]

To see how these differences in output quality affect productivity differentials by ownership, we re-estimate the facility-level productivity differentials by adding as controls the quality measure of each output. Table 10 shows that the productivity premium of private facilities relative to central state-owned facilities increases slightly from 7.4 percent to 8.5 percent once we control for output quality. On the other hand, the premium relative to provincial state-owned facilities remains more or less the same. In short, the premium of private firms cannot be attributed to quality differences in the output they produce.

7 Conclusion

This paper is one of the first to study the underlying sources of productivity differences by firms' ownership structure through the lens of firms' internal configuration. The new data set that we construct provides equipment-level information on inputs and output in physical units for each stage in the value chain of vertically-integrated facilities. We find that private integrated facilities are on average 7.4 percent more productive than central state-owned facilities, and 1.1 percent relative to provincial state-owned facilities. This ranking lines up with our productivity estimates in the two downstream production stages, but central state-owned facilities outperform in sintering, most likely because of their use of higher quality raw materials. Back of the envelope calculations suggest that eliminating the premium of central state-owned facilities in sintering would raise the premium of private facilities at the facility level by an additional 4.1 percentage points, or to 11.5 percent overall.

[62]We have information on the stability rates of sinter and shares of premium iron, important quality measures of sinter and pig iron. Shares of secondary steel making provide evidence on the quality of steel. Steel mills carry out secondary refining to produce higher quality steel. See detailed description at https://www.steel.org/∼/media/Files/AISI/Making%20Steel/Article%20Files/learning_2ndrefining.pdf

Table 11: Productivity Differences by Ownership: Privatization

	(1)	(2)	(3)	(4)
Variables	Facility logtfp	Sintering logtfp	Iron Making logtfp	Steel Making logtfp
Privatized	0.141*	0.0281	0.0739***	0.0948***
	(0.0799)	(0.0643)	(0.0255)	(0.0155)
New private	0.0307	-0.241***	0.0514**	0.0365*
	(0.0741)	(0.0550)	(0.0220)	(0.0208)
Provincial	0.0633	-0.0930**	0.0222	0.0156
	(0.0516)	(0.0446)	(0.0194)	(0.00947)
Constant	-0.113**	0.0333	-0.0843***	-0.0419***
	(0.0481)	(0.0372)	(0.0218)	(0.00874)
Observations	3,440	8,728	11,836	8,510
R-squared	0.029	0.037	0.021	0.063
Time FE	YES	YES	YES	YES

Notes: Central state-owned facilities and their machines/furnaces are the omitted group. New private, privatized and provincial are ownership dummies. Standard errors are clustered by facility for facility-level analysis and by machines/furnaces for stage-level analysis.

We also find that the productivity premium of private facilities declines with facility size, and actually turns negative for vertically-integrated facilities larger than the medium. Some of the decline in the productivity premium of private facilities with size may arise from less experience with newer technologies. This behavior also likely reflects choices of private firms when they decide to build larger integrated facilities, most notably, the fact that they install a larger number of smaller units, i.e. sintering equipment and furnaces, to achieve the desired level of capacity. In this paper we suggest a number of constraints responsible for these choices, which spreads their scarce human resources more thinly over a larger number of units, and lowers their relative productivity. Our analysis suggests that the productivity advantage of private facilities would be significantly higher if the constraints were removed.

Support for this conjecture comes in the form of the estimated premium of privatized SOEs for whom constraints are less binding. A product of ownership reforms between the late 1990s and 2005, privatized SOEs operate 13 out of the 33 private integrated facilities and are the source of one-third of the steel production of private firms, or 7 percent of the total steel production. We divide private firms into privatized SOEs and new private firms and re-estimate productivity differentials, which we report in Table 11. We observe pronounced differences, and at the facility level privatized SOES are 14.1 percent more productive than central SOEs and 7.8 percent more than provincial SOEs. Much of the premium enjoyed by private firms is a product of the superiority of privatized SOEs. Privatized SOEs outperform other firms in all individual stages, including in sintering in which an average private firm has enormous disadvantage compared to central SOEs.

These results are important in two important respects. First, they suggest that privatized SOEs are likely less constrained than newly established private firms. Privatized SOEs, for example, may be able to leverage the network of the former SOEs to help access key raw materials, finance as well as human capital. Second, these results imply that private firms would perform even better than SOEs if they were less constrained. Our earlier estimates likely represent a lower bound of the return to changes that would put private firms on an equal footing with SOEs.

Finally, in this paper we have focused largely on the constraints facing private firms in their choice of plant size. As discussed in the end of Section 5.3, there are also advantages to having a portfolio of plants with smaller average size. In order to examine these trade-offs more carefully, we need to build and estimate a structural dynamic model that looks at the role of both demand and supply side considerations in the firm's choices. This entails incorporating into a dynamic model of investment the various constraints that we identified facing firms of different ownership type. We also need to model the demand side, fluctuations in which likely shape firms' decisions on internal configuration. Access to several more years of firm level data will facilitate model identification by providing data that spans both booms and busts in China's steel market.

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A Online Appendix

A.1 Production allocation across machines/furnaces

Lemma A.1. *It is optimal for a firm to apply a same proportional change in intermediate inputs across different machines/furnaces j in production stage s, i.e., $R_{j_s}(a) = a * R_{j_s}$, where $a > 0$.*

Proof. Let

$$Y = \max_{R_1, R_2, ..., R_J} \quad \sum_{j_s=1}^{J} b_{j_s} * (R_{j_s}^{\gamma_s}) \tag{13}$$

$$\text{subject to} \quad \sum_{j_s=1}^{J} R_{j_s} = \sum_{j_{s-1}=1}^{J'} Y_{j_{s-1}}, \tag{14}$$

where $b_{j_s} = e^{\omega_{j_s}} K_{j_s}^{\alpha_s} L_{j_s}^{\beta_s}$, $j_s = 1, 2, ..., J$, and $\sum_{j_{s-1}=1}^{J'} Y_{j_{s-1}} \equiv R$. Consider the Lagrangian function

$$L = \sum_{j_s=1}^{J} b_{j_s} * (R_{j_s}^{\gamma_s}) + \lambda(R - R_1 - R_2 - ... - R_J)$$

The first order conditions with respect to $R_1, R_2, ..., R_J$ are as follows:

$$b_1 \gamma_s R_1^{\gamma_s - 1} = \lambda,$$

$$b_2 \gamma_s R_2^{\gamma_s - 1} = \lambda,$$

$$...$$

$$b_J \gamma_s R_J^{\gamma_s - 1} = \lambda.$$

Therefore $b_1 R_1^{\gamma_s-1} = b_2 R_2^{\gamma_s-1} = ... = b_J R_J^{\gamma_s-1}$, and as a result,

$$R_2 = (\frac{b_1}{b_2})^{\frac{1}{\gamma_s-1}} R_1,$$
$$R_3 = (\frac{b_1}{b_3})^{\frac{1}{\gamma_s-1}} R_1,$$
$$...$$
$$R_J = (\frac{b_1}{b_J})^{\frac{1}{\gamma_s-1}} R_1.$$

Substitute $R_2, R_3, ...R_J$ into the constraint $\sum_{j_s=1}^{J} R_{j_s} = R$, and we get the expression of R_1:

$$R_1 = \frac{R}{\frac{b_1}{b_1}^{\frac{1}{\gamma_s-1}} + \frac{b_1}{b_2}^{\frac{1}{\gamma_s-1}} + \frac{b_1}{b_3}^{\frac{1}{\gamma_s-1}} + ... + \frac{b_1}{b_J}^{\frac{1}{\gamma_s-1}}} \equiv \theta_1 R. \tag{15}$$

Similarly, we get the expressions of R_{j_s}, $j_s = 2, 3, ..., J$:

$$R_{j_s} = \frac{R}{\frac{b_j}{b_1}^{\frac{1}{\gamma_s-1}} + \frac{b_j}{b_2}^{\frac{1}{\gamma_s-1}} + \frac{b_j}{b_3}^{\frac{1}{\gamma_s-1}} + ... + \frac{b_j}{b_J}^{\frac{1}{\gamma_s-1}}} \equiv \theta_{j_s} R.$$

Based on the definition of b_{j_s}, θ_{j_s} is fixed given K_{j_s}, L_{j_s} and ω_{j_s}. Therefore, when the intermediate input changes by a constant positive proportion a, $R_{j_s}(a) = \theta_{j_s} * a * R = a * R_{j_s}$. □

Corollary A.1.1. *Suppose that intermediate inputs R is produced in the upstream production stage using a Leontief technology with capital and labor elasticities α_{s-1} and β_{s-1}. Then firm-level returns to scale (RS) is characterized by the sum of the capital and labor elasticities in each stage of production weighted by the material input elasticities, i.e., $RS = (\alpha_{s-1} + \beta_{s-1})\gamma_s + (\alpha_s + \beta_s)$.*

Proof. By plugging the expressions of R_{j_s} derived in Lemma A.1 into the objective function

(13), we get

$$\begin{aligned} Y_s &= b_1 R_1^{\gamma_s} + b_2 R_2^{\gamma_s} + ... + b_J R_J^{\gamma_s} \\ &= R^{\gamma_s}(b_1\theta_1^{\gamma_s} + b_2\theta_2^{\gamma_s} + ... + b_J\theta_J^{\gamma_s}) \end{aligned}$$

Therefore, augmenting all inputs by the same proportion a ($a > 0$) leads to a new amount of production:

$$\begin{aligned} Y_s(a) &= R(a)^{\gamma_s}(b_1\theta_1^{\gamma_s} + b_2\theta_2^{\gamma_s} + ... + b_J\theta_J^{\gamma_s})a^{\alpha_s+\beta_s} \\ &= a^{(\alpha_{s-1}+\beta_{s-1})\gamma_s} R^{\gamma_s}(b_1\theta_1^{\gamma_s} + b_2\theta_2^{\gamma_s} + ... + b_J\theta_J^{\gamma_s})a^{\alpha_s+\beta_s} \\ &= a^{(\alpha_{s-1}+\beta_{s-1})\gamma_s+(\alpha_s+\beta_s)} Y_s \end{aligned}$$

□

A.2 Nature of Internal Configuration: A Heuristic Model

Our empirical results link the decline in the productivity premium of private firms as facility size increases to the internal configuration of firms. In light of the fact that steel production exhibits increasing returns to scale at both the equipment and facility level, why are private integrated facilities on average much smaller than their state-owned counterparts, as are the machines/furnaces they operate throughout the value chain?

Below we sketch out an illustrative model that captures the tradeoffs and the nature of a firm's choices with respect to the size and number of equipment they operate. We abstract here from decisions on total investment in production capacity, that is, we take investment in production capacity as given, and analyze firms' choice with respect to the size of machines/furnaces to achieve this goal. Although smaller size has its advantages, the choice also reflects more severe constraints private firms face as they try to expand in the form of tighter regulatory hurdles, access to finance, human capital, etc.

Setup Consider a firm that plans to increase its iron making capacity by $1000m^3$.[63] It has two options: Build a single $1000m^3$ furnace (option 1) or build two identical $500m^3$ furnaces (option 2). Installation occurs in period 1 and production in period 2. The firm faces uncertainty in demand in period 2, and with probability p, faces high demand, which we denote by state (H), and with probability $1-p$ faces demand that is low, which we denote by state (L).

Payoff The payoff of option 1 (2) is $\pi_{1H}(\pi_{2H})$ in state H and $\pi_{1L}(\pi_{2L})$ in state L. Since iron making is expected to enjoy increasing returns to scale, we assume that $\pi_{1H} > \pi_{2H}$. Firms face short-run fluctuations in demand, with the time (and therefore costs) to start up or shut down a furnace increasing with size.[64] This makes it much more difficult for a large furnace to adjust to demand shocks in the short run. By contrast, firms with several smaller units can adjust production more efficiently by simply suspending operations in a subset of

[63]In practice, firms make capacity decisions in terms of m^3 rather than tonnage. However, the production capacity in terms of tonnage of two $500m^3$ is not necessarily equal to that of a single $1000m^3$.

[64]Larger blast furnaces require more thorough inspections and the replacement of key components before they can be safely restarted. The entire process typically takes in upwards of two to four weeks, and entails sizeable costs. On this point, see Chen (2016).

Table A1: Total Cost Per Unit of Capacity

Panel A: Iron Making (Blast Furnace)	
Size (m^3)	Cost per m^3 (unit:1 Million RMB)
450-999	0.36
1000-2499	0.39
2500-4000	0.415
>4000	0.475
Panel B: (Steel Making) Basic Oxygen Furnace	
Size (tonnage)	Cost per ton (unit:1 Million RMB)
≤50t	2.65
60-80	3.35
100-120	4.15
150-180	4.65
200-250	5.15
≤300	5.75

Notes: Data Source: Chinese Iron and Steel Association. 1 US Dollar = 6.89 RMB.

their furnaces. This production flexibility of smaller furnaces implies that in low states $\pi_{2L} > \pi_{1L}$.

Investment cost A sizeable investment is required to install an integrated facility. The investment cost of a single large machine/furnace is also substantially larger than multiple smaller machines/furnaces with equal total capacity. In Table A1, we report the investment cost per unit of capacity by furnace size.[65] Installing two $500m^3$ furnaces rather than a single furnace of $1000m^3$ saves 4.35 million US dollars, or 7-8% of total investment. Since investment costs per unit of capacity (c) increase with furnace size, i.e. $c_1 > c_2$, the total investment cost under option 1 is higher than that under option 2, $f_1 = 1000 * c_1 > f_2 = 500 * 2 * c_2$.

Expected payoffs under two options

$$v_1 = p\pi_{1H} + (1-p)\pi_{1L} - f_1$$

$$v_2 = p\pi_{2H} + (1-p)\pi_{2L} - f_2$$

The firm's optimal internal configuration realizes the highest payoff. The firm chooses to build a $1000m^3$ furnace if and only if the following condition is satisfied:

$$\frac{\pi_{2L} - \pi_{1L} + f_1 - f_2}{\pi_{2L} - \pi_{1L} + \pi_{1H} - \pi_{2H}} < p \tag{16}$$

Intuitively, if the benefit of economies of scale is large enough to offset the higher cost in building a larger furnace, and the probability of a high state is sufficiently high, then it is optimal for the firm to build a single plant rather than two smaller plants.

Several other considerations also factor into a firm's size choice, which we examine below.

[65] The figures are based on an internal report prepared by the Chinese Metallurgy Planning Institute in August 2016 for the authors.

A.2.1 Regulatory Constraints

Rapid expansion of China's steel sector the last two decades has been accompanied by an unexpected and unwelcomed outcome: massive excess capacity. A major objective of China's central government is to limit excess capacity, and more important, to restructure the industry around a small number of SOEs under its direct supervision. Central government permission is essential for expanding capacity, and very difficult for private firms to obtain. Private firms that undertake large expansions risk drawing public attention and becoming a target of upper-level regulatory agencies.

Collusion with local governments is a popular strategy of private firms to circumvent regulatory restrictions and reduce the possibility of detection. A well-known example is Tieban Steel, a private firm in Jiangsu province that wanted to expand its capacity by 8.4 million tons. Tieben took advantage of a regulatory loophole and split the expansion into 22 sub-projects.[66] Tieben ultimately failed, and its owner was imprisoned, but the case illustrates the influence of regulatory constraints on the size of units private firms decide to build.

The regulatory constraints that firms face building larger plants can be captured by an additional cost (E) to the regular investment cost. In our model, the total investment cost now becomes $\tilde{f}_1 = f_1 + E$, and all else equal, the LHS of equation (16) increases to $\frac{\pi_{2L}-\pi_{1L}+\tilde{f}_1-f_2}{\pi_{2L}-\pi_{1L}+\pi_{1H}-\pi_{2H}}$. If these costs are sufficiently high, the firm will find it optimal to install two $500m^3$ furnaces rather than a single 1000 m^3 furnace.

A.2.2 Capital Constraints

In theory, increasing returns to scale provide firms a strong motive to install larger machines/furnaces. However, it is well documented that private firms in China are discriminated

[66] See Jian (2014) for more details of the Tieban Incident.

against in the credit market, and face a higher cost of capital.[67] Hence, private firms face a trade-off between enjoying lower long-run average costs after bearing the immediate higher investment cost and making less-costly investments, but incurring higher average costs. The financing constraints likely steer private firms towards smaller machines/furnaces.

Credit constraints can be captured by a wedge ($\tau > 1$) in the per unit investment costs of constrained and the unconstrained firms, leading to an increase in the differences in the total investment costs under the two investment options. That is, $\tilde{f}_1 - \tilde{f}_2 = 1000 * \tau * (c_1 - c_2) > f_1 - f_2$, which drives up the LHS of equation (16). All else equal, the larger the wedge, our model predicts that firms are more likely to install two $500m^3$ furnaces.

A.2.3 Human Capital Constraints

A growing literature documents the effect of ownership on a firms' ability to access resources and capital. Drawing on a sample of private enterprises in China, Garnaut et al. (2012) argue that private firms are not only financially constrained, but are also constrained with respect to human capital.[68] Iskandar (2015) uses the World Bank 2012 survey data to provide evidence that private firms are constrained in their ability to hire skilled and trained labor. The steel industry is no exception. In China's steel sector 18.7 percent of SOE employees had a college degree or higher compared to only 7.2 percent in private firms. The percentage of skilled labor in SOEs was almost two and a half times higher than in private firms (4.7 versus 2 percent).[69]

Larger sintering machines and furnaces embody newer technologies that are highly complementary with the human capital endowments of SOEs, e.g. more talented and experienced managers and more highly skilled workers.[70] Smaller machines using earlier vintage technolo-

[67]See for example, Brandt and Li (2003), Poncet et al. (2010), Guariglia et al. (2011) and Cull et al. (2015).

[68]The four surveyed cities include Beijing, Chengdu, Chengde and Wenzhou.

[69]The figures are based on the authors' calculation using the 2004 Industrial Survey Data.

[70]Several studies have also shown that state-owned firms in China have deep human resource reserves

gies are much less demanding in this regard, and thus more compatible with the managerial talent, organizational capabilities and skill sets of private firms. The ability of a firm to fully leverage the production potential of larger plants and the returns to scale is tied to their human capital. This suggests that a firm facing human capital constraints has a lower $\pi_{1H} - \pi_{2H}$, which increases the likelihood that a firm decides to build two $500m^3$ furnaces through its effect on the LHS of equation (16).

A.2.4 Raw Material Constraints

As is evidenced in Figure A1, the iron ore that smaller furnaces use covers a much wider range of grades than larger furnaces which only use high grade ore. This is a different kind of flexibility that smaller furnaces enjoy than being cheaper to start-up/shutdown in the face of changing demand conditions. For private firms, access to only lower grade iron ores and greater flexibility of smaller furnaces with respect to iron ore choice may predispose them towards smaller units.

In our model, raw material constraints can be reflected in equation (16) in various ways. For example, in a high state, the market may be short of good quality iron ore. When a firm is constrained in their access to higher quality raw materials, the flexibility of the smaller furnaces in raw materials can (partially) offset the economies of scale of larger furnances, help narrow the gap between π_{1H} and π_{2H}, and result in an increase in the LHS of equation (16). In short, a firm facing raw material constraints is more likely to install two $500m^3$ furnaces.

(e.g. Peng and Heath (1996); Tan (2003)).

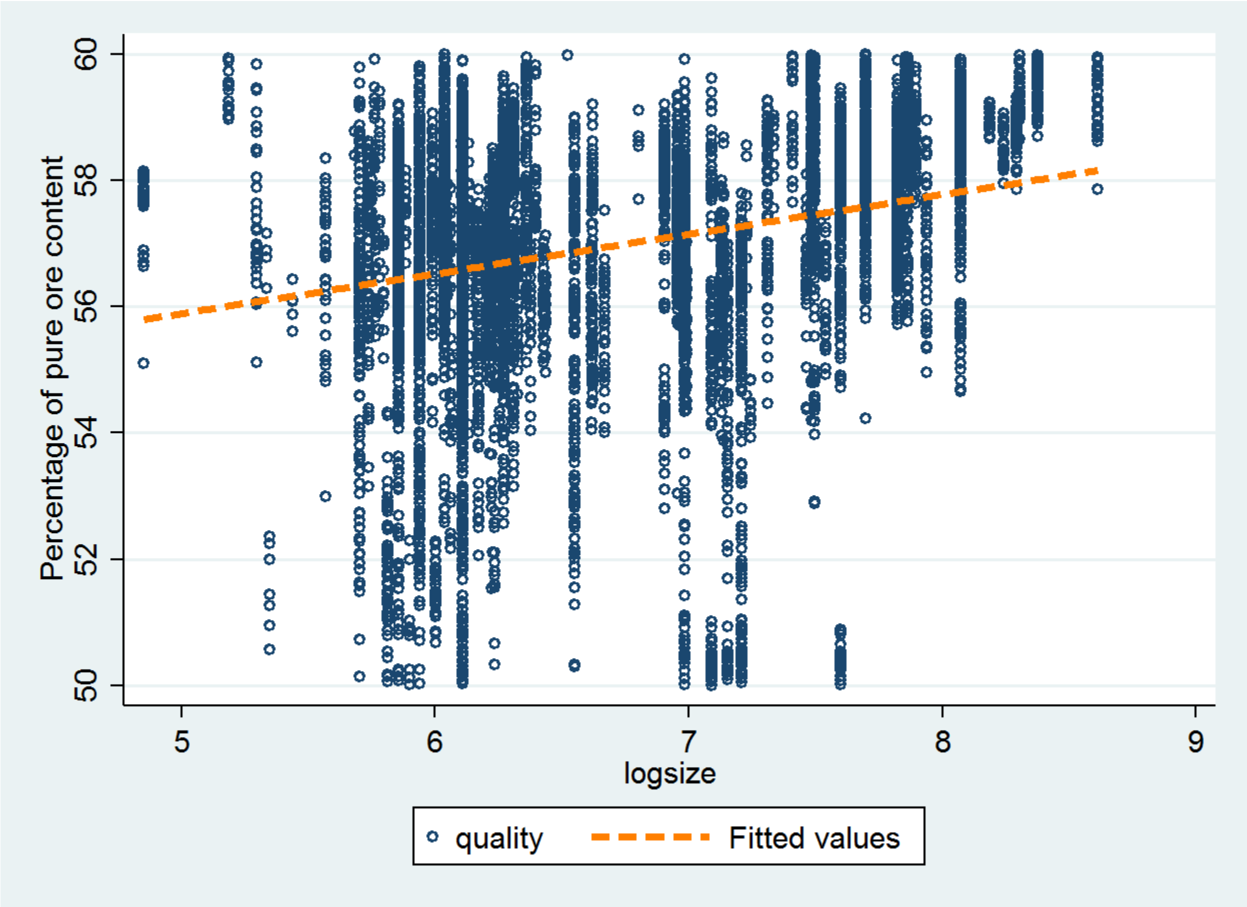

Figure A1: Grade of Iron Ore and Size of Iron-Making Plants (Blast Furnace)

Notes: Blast furnace size is measured by the effective volume of the furnace in cubic meters (m^3).

A.3 Derivation of Alternative Weights

We assume that producers face perfect competition for sinter, pig iron and steel, the prices of which are P_1, P_2 and P_3, respectively. We omit the facility subscript and time subscript t in the following illustration. Iron making (steel making) plants choose labor $L_2(L_3)$ and intermediate material $R_2(R_3)$ to maximize profits, while capital $K_2(K_3)$ is predetermined.[71] The first order conditions with respect to material R_2 and R_3 and the inter-linkage equality equations $Y_1 = R_2$ and $Y_2 = R_3$ imply:

$$\gamma_2 = \frac{P_1 Y_1}{P_2 Y_2}$$
$$\gamma_3 = \frac{P_2 Y_2}{P_3 Y_3}$$

Hence we obtain the alternative weights:

$$\gamma_3 = \frac{P_2 Y_2}{P_3 Y_3}$$
$$\gamma_2 \gamma_3 = \frac{P_1 Y_1}{P_3 Y_3}$$

A.4 Algorithm

As discussed in Ackerberg, Caves, and Frazer (2015), the GMM estimation approach that we take to the finite samples is subject to the convergence of local minimums. To address this concern, we follow a flexible algorithm to set initial values for the objective function. We start from the OLS estimates $\theta_{ols} \equiv (\alpha_{ols}, \beta_{ols}, \gamma_{ols})$ (estimated elasticities for labor, capita and material input respectively), and then we draw 100 random vectors $v \equiv (v_l, v_k, v_r)$ from

[71] Labor could be a dynamic choice too. We examine this more fully in our discussion of the estimation approach.

a uniform distribution ranged from 0.8 to 1.2.[72] We give perturbation to the OLS estimates using the random vectors v and make 100 sets of initial values at $\theta_p \equiv \theta_{ols} \cdot v'$, $p = 1, 2, ..., 100$. For each set of initial values, we obtain an optimal $\hat{\theta}_p$, and we value the objective function using $\hat{\theta}_p$. Finally we pick our estimates of $\tilde{\theta}$ from the minimal values of the objective functions using these 100 different sets of initial values.[73]

[72]We relax the range to (0.7,1.3) and (0.9,1.1) too, and obtained robust estimates.

[73]Ideally, one can expand the number of initial-value sets for robustness check. In our case, the convergence is reached among these 100 sets of values.

Table A2: Number of Equipment and Facility Size by Production Stage

	(1)	(2)	(3)
Variables	Poisson Sintering Number	Poisson Iron Making Number	Poisson Steel Making Number
logsize	-0.199	-0.0106	0.385***
	(0.132)	(0.126)	(0.0880)
PrivateXlogsize	0.556***	0.382**	0.118
	(0.174)	(0.175)	(0.121)
ProvincialXlogsize	0.463***	0.125	-0.0658
	(0.168)	(0.148)	(0.104)
Private	-2.715***	-1.644*	-0.520
	(0.949)	(0.903)	(0.638)
Provincial	-2.264**	-0.519	0.523
	(0.940)	(0.792)	(0.582)
Constant	1.781**	0.896	-1.268**
	(0.775)	(0.678)	(0.495)
Observations	3,440	3,440	3,440
Owner FE	YES	YES	YES
Time FE	YES	YES	YES

Notes: Number is denoted for the number of machines/furnaces used in each stage. Facility size is measured by the total size of basic oxygen furnaces (steel making) within the facility. The size of a basic oxygen furnace is measured by its tonnage. Private and provincial are ownership dummies. Standard errors are clustered by facility.

A.5 Additional Evidence on Internal Configuration

To examine the characteristics of firms' internal configuration more fully, we estimate Poisson regressions of the number of equipment in each stage of an integrated facility on log facility size and log size interacted with our ownership dummies for each individual stage. We estimate related regressions for log equipment size on facility size. Results are presented in Table A2 and Table A3.

Table A3: Average Equipment Size and Facility Size by Production Stage

	(1)	(2)	(3)
Variables	Sintering logsize	Iron Making logsize	Steel Making logsize
logsize	0.718***	0.765***	0.609***
	(0.103)	(0.122)	(0.0788)
PrivateXlogsize	-0.136	-0.287	-0.162
	(0.146)	(0.184)	(0.105)
ProvincialXlogsize	-0.343**	-0.102	0.00835
	(0.138)	(0.139)	(0.0938)
Private	0.507	1.072	0.747
	(0.754)	(0.928)	(0.543)
Provincial	1.624**	0.453	-0.192
	(0.753)	(0.782)	(0.531)
Constant	1.342**	3.032***	1.349***
	(0.573)	(0.702)	(0.448)
Observations	3,440	3,440	3,440
R-squared	0.344	0.536	0.593
Owner FE	YES	YES	YES
Time FE	YES	YES	YES

Notes: Facility size is measured by the total size of basic oxygen furnaces (steel making) within the facility. The size of a sintering machine is measured by its effective areas in m^2; the size of a blast furnace is measured by its effective volume in m^3; the size of a basic oxygen furnace is measured by its tonnage. Private and provincial are ownership dummies. Standard errors are clustered by facility.

Table A4: Production Functions

VARIABLES	(1) sintering ols	(2) sintering gmm	(3) iron making ols	(4) iron making gmm	(5) steel making ols	(6) steel making gmm
l	0.215***	0.187***	0.303***	0.253***	0.341***	0.353***
	(0.00843)	(0.0151)	(0.00706)	(0.00266)	(0.00787)	(0.00301)
k	0.811***	0.871***	0.758***	0.758***	0.562***	0.662***
	(0.00645)	(0.00100)	(0.00478)	(0.000997))	(0.00514)	(0.00151)
age	-0.00115***	-0.000475	-0.000648***	0.000187	-0.000584***	-0.00201*
	(0.000300)	(0.00168)	(0.000217)	(0.000673)	(0.000198)	(0.00121)
Observations	6,389	6,389	9,353	9,353	8,514	8,514
R-squared	0.829		0.825			
Ownership FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES

Note: Standard errors of production function coefficients using GMM estimation are computed via bootstrap of 1,000 replications clustered by facility.

A.6 Leontief Production Function

We present the results based on Leontief production functions in Table A4 and Table A5.

Table A5: Productivity Differences by Ownership and Size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Sintering logtfp	Sintering logtfp	Sintering logtfp	Iron logtfp	Iron logtfp	Iron logtfp	Steel logtfp	Steel logtfp	Steel logtfp
logsize		-0.0825***	-0.110***		-0.00663	-0.0115		-0.0902***	0.0202
		(0.0232)	(0.0340)		(0.0141)	(0.0379)		(0.0236)	(0.0728)
PrivateXlogsize			-0.0224			-0.0873			-0.242**
			(0.0664)			(0.0578)			(0.109)
ProvincialXlogsize			0.0516			0.0240			-0.114
			(0.0466)			(0.0406)			(0.0774)
Private	-0.111**	-0.142***	-0.0495	0.0670**	0.0634*	0.616	0.147***	0.0968*	1.160**
	(0.0513)	(0.0484)	(0.319)	(0.0339)	(0.0370)	(0.391)	(0.0538)	(0.0567)	(0.480)
Provincial	-0.0973**	-0.115***	-0.365	0.0213	0.0200	-0.142	0.0694*	0.0336	0.567
	(0.0444)	(0.0410)	(0.235)	(0.0321)	(0.0328)	(0.296)	(0.0401)	(0.0412)	(0.375)
Constant	0.0367	0.434***	0.572***	-0.120***	-0.0751	-0.0418	-0.159***	0.259**	-0.261
	(0.0368)	(0.113)	(0.166)	(0.0370)	(0.110)	(0.277)	(0.0422)	(0.121)	(0.358)
Observations	8,728	8,728	8,728	11,852	11,852	11,852	8,538	8,538	8,538
R-squared	0.016	0.039	0.043	0.017	0.018	0.024	0.034	0.064	0.078
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Central state-owned facilities and their machines/furnaces are the omitted group. Private and provincial indicate ownership dummies. The size of a sintering machine is measured by its effective areas in m^2; the size of a blast furnace is measured by its effective volume in m^3; the size of a basic oxygen furnace is measured by its tonnage. Facility size is measured by the total size of basic oxygen furnaces (steel making) within the facility. Standard errors are clustered by machines/furnaces for stage-level analysis and by facility for facility-level analysis, but not corrected for the sampling error in constructed productivity.