Output Quality, Productivity, and Demand: Evidence from the Chinese Steel Industry*

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September 5, 2023

Abstract

Unobserved *objective* output quality differences present a challenge in understanding the magnitude and effect of firms' productivity and demand on performance, because producing higher-quality products incurs higher costs but provides greater consumption benefits. Using a unique panel that contains an index of scientific output quality from the Chinese steel-making industry, we decompose firm heterogeneity in TFPQ into fundamental productivity and the costs of producing objective output quality; similarly, we decompose demand residual (traditionally labeled as quality or product appeal) into fundamental demand and the consumption benefits of objective output quality. We find that about half of the benefits created by objective quality are offset by the cost of producing it. The difference in fundamental productivity is much smaller than that of fundamental demand across firms and over time. More importantly, while fundamental productivity is a strong predictor of firms' quality choice, fundamental demand is only weakly correlated with output quality, highlighting the necessity of separating quality from the other two. In our application to the 2008 global financial crisis, we demonstrate that employing TFPQ and demand residual to assess productivity and demand tends to overstate the impact of productivity while underestimating the influence of demand on shaping firm and industry performance, at the presence of a negative quality shock in demand, and vice versa.

Keywords: *output quality, productivity, demand, revenue productivity growth*

JEL classification: *D24, L11, L15, O47.*

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*The authors thank Jo Van Biesebroeck, Ulrich Doraszelski, Kevin Fox, James Harrigan, Paul Grieco, Yao Luo, Mark Roberts, Yingjun Su, and Daniel Xu for their insightful comments. The paper also benefited from discussions with participants in the 2019 University of Hong Kong Workshop on Firm Dynamics in Industrial Organization and Trade, the 2019 Economic Measurement Group workshop at the University of New South Wales, the 2021 Comparative Analysis of Enterprise Data Conference, and seminars at Monash University and Jinan University. All errors are the authors' responsibility.

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1 Introduction

Productivity and demand are two main sources of heterogeneity across firms. The literature has demonstrated their importance and potentially distinct roles in determining firm turnover (Foster, Haltiwanger, and Syverson, 2008), growth (Pozzi and Schivardi, 2016), investment (Kumar and Zhang, 2019), and trade participation (Roberts, Yi Xu, Fan, and Zhang, 2018). However, the presence of variances in unobserved *objective* output quality could cast challenges in the comprehension of firm heterogeneity in productivity and demand. On the one hand, producing products with high objective quality incurs higher costs. These costs, if not observed, will confound fundamental productivity heterogeneity that stems from technological and managerial differences. On the other hand, premium-quality products generate higher consumption benefits, thereby complicating the essence of fundamental demand which is rooted in sales networks, marketing endeavors, and customer base/tastes.[1] As a result, objective output quality, as an important dimension of unobserved heterogeneity across firms and over time, presents a challenge in understanding the magnitude firms' heterogeneity in fundamental productivity and demand and their effects on firm performance.

This paper investigates the heterogeneity of firms' *objective* output quality and their fundamental productivity and demand, as well as their relationships and distinct contribution to the growth of firms and industry. Leveraging a unique panel that contains an index of scientific output quality at the firm level from the Chinese steel-making industry, we explicitly document the production costs of quality and disentangle these costs from a firm's fundamental productivity. Simultaneously, the direct quality measure helps isolate the demand-enhancing effect of objective quality from the firm's fundamental demand.[2] Such a decomposition gives us clean measures of fundamental productivity and demand that are not confounded with endogenous objective quality differences.

Our analysis is built upon a panel of steel-making firms at the monthly frequency from 2007 to 2014 in China. As a key feature, this data set contains a direct measure of objective and scientific output quality at the firm level, in addition to detailed information on output prices and quantities of inputs and output. The quality measure is based on the share of outputs

[1] Both objective product quality and firm fundamental demand (e.g., sales network, marketing effort, and custom base/tastes) are demand-enhancing. The concept of "product appeal" estimated as demand residual (i.e., market share after controlling for prices) in the literature contains both, due to data limitation. In contrast, we distinguish the effect of objective quality from that of fundamental demand, because they have different determining factors and play different roles in firm performance, as shown in Section 5. Throughout the paper, we refer "quality" as objective quality rather than demand residual, except mentioned otherwise.

[2] In a slight abuse of terminology, we use output quality and objective output quality interchangeably in this paper, whenever it does not cause a confusion.

that are produced following three different quality standards, namely, international, national, and enterprise standards, in descending order. The quality measure demonstrates a substantial variation across firms and over time. This variation serves as a critical source of identification, allowing us to distinguish the impact of quality on production efficiency from that of fundamental productivity. While the former is directly observed in our data, the latter is controlled by a proxy function integrated into our production function estimation, drawing from methodologies like Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2015). Likewise, when estimating demand, the availability of observable quality significantly simplifies the task of discerning the quality-driven benefits from those stemming from fundamental demand. Furthermore, this observability also simplifies the choice of instrumental variables for the prices. If quality was treated as a part of the unobserved demand residual, then commonly employed cost-related variables might not be adequate instrumental variables for output prices because quality variations would influence the production cost.

After controlling for objective quality, we find that the difference in fundamental productivity is much smaller than that of fundamental demand: the interquartile range of fundamental demand (1.060) is more than five-fold of that of productivity (0.180). The large variation of fundamental demand presumably may arise from firms' active investment in demand-enhancing activities such as advertising and marketing, while the variation of productivity may be due to differences in firms' technology, R&D investment, and managerial capability as widely documented in the literature. More importantly, while productivity is a strong positive predictor of firms' quality choice, fundamental demand is only weakly correlated with output quality. This result highlights the importance of separating objective quality from fundamental productivity and demand, especially when objective output quality is endogenously determined by other factors besides fundamental productivity and demand.

The weak correlation between objective output quality and fundamental demand highlights their differences as distinct aspects of firm heterogeneity, although both of them might be welfare-enhancing. The objective output quality is endogenously chosen by the firm and is determined in the production process. The supply of quality increases production costs directly, because producing higher quality may require better (or specialized) equipment and additional refinement processes in the steel-making industry. According to our estimation, increasing output quality by 1 percent reduces steel output quantity by about 0.507 percent, holding production inputs fixed. This is comparable to the quality-quantity tradeoff found by Grieco and McDevitt (2017) in the healthcare industry. Hence, producing high-quality products involves a higher marginal cost, and it is welfare-enhancing only when the cost effect of quality is lower than its consumption benefit. In contrast, the fundamental demand of a firm does not affect the production process or marginal cost of production directly. It is the firm's advantage in the output market determined by its demand-enhancing investment, such as sales network building, advertisement, and marketing. Therefore, the traditional analysis in a vast literature that estimates demand functions and interprets the estimated demand residual (usually labeled as output quality or product appeal) as a proxy of output quality (e.g., Schott, 2004; Hallak, 2006; Khandelwal, 2010; Hallak and Schott, 2011; Feenstra and Romalis, 2014) or demand advantage (Jaumandreu and Yin, 2014) masks the difference between the two and is silent on their distinct roles in firm and industry growth.

While output quality is negatively associated (correlation coefficient: -0.136) with TFPQ which embodies cost of quality, it is indeed positively correlated (correlation coefficient: 0.444) with fundamental productivity. This result reconciles the positive productivity-quality association implied by Kugler and Verhoogen (2009, 2012) with the negative correlation between TFPQ and demand residual as a proxy of quality documented in the more recent literature (e.g., Orr, 2022; Forlani, Martin, Mion, and Muûls, 2023; Eslava, Haltiwanger, and Urdaneta, 2023). That is, although producing quality is costly (implying a negative pressure in the association between TFPQ and quality), after controlling for such cost, the fundamental productivity and quality are still positively correlated.

We explore the impact of firm heterogeneity in fundamental productivity and demand, as well as endogenous quality, on firms' sales performance. We find that both fundamental productivity and demand improve revenue, but they take effect through different channels. Higher fundamental productivity reduces prices but increases output quantity, with elasticities of -0.518 and 1.025, respectively. Higher fundamental demand increases both prices and output quantity, with elasticities of 0.363 and 0.261, respectively. Consistent with the literature (Kugler and Verhoogen, 2012; Feenstra and Romalis, 2014; Hottman, Redding, and Weinstein, 2016; Atkin, Khandelwal, and Osman, 2019)[3], firms producing higher output quality enjoy higher revenues with an elasticity of 0.427. It is contributed by a positive effect of quality on prices (0.564) and a negative effect on output quantity (-0.137).[4] Even with quality heterogeneity, revenue-based productivity (i.e., TFPR) is still a natural measure of firms' overall performance, which combines the effects of fundamental productivity, fundamental demand, and the benefits of quality net of its production

[3]Of course, in these literature output quality is measured as demand residual due to data lamination, which in principle contains both the objective output quality and fundamental demand.

[4]The seemingly surprising negative effect of quality on output quantity partly arises from the quality production costs: producing higher-quality products increases the marginal cost of production and consequently the price which reduces quantity sales.

costs. In our application, the variation of TFPR is mainly driven by fundamental demand, followed by fundamental productivity. The role of quality in the variation of TFPR is more muted because of the offsetting costs and benefits of quality.

We decompose the growth of industrial TFPR during the 2008 global financial crisis to demonstrate the distinct roles of output quality, fundamental productivity and demand in influencing industry performance. We show that output quality may reinforce or mitigate the TFPR growth, because output quality changes may not align with fundamental productivity and demand depending on the nature of the economic shocks. Specifically, during 2007-2010, the Chinese steel-making industry suffered a large economic shock that reduced international demand for steel and intrigued an unprecedented government stimulus plan to boost domestic demand. This constitutes a negative but mild quality shock in demand. The industry average output quality dropped but only slightly, presumably because the stimulated domestic market buffered the loss of high-end steel demand in the export market. At the same time, the overall firm performance as measured by TFPR actually increased by 6.98 percentage points from 2007 to 2010. This is mainly driven by the increases in fundamental demand (6.84 percentage points) and fundamental productivity (0.45 percentage points), which are more significant than that of output quality.

After the financial crisis, the export demand started to recover but the domestic demand growth decelerated due to the slowed growth of domestic downstream industries which usually demand low-quality steel. These opposite trends resulted in a positive and significant quality shock in demand. The average steel quality produced by the industry increased by 3.04 percentage points from 2010 to 2014. During this period, the overall performance of firms as measured by TFPR increased by 4.27 percentage points. This reflects the total effects of the growth in fundamental demand (6.41 percentage points), fundamental productivity (-3.63 percentage point), and the net effect of the benefits and costs of quality improvement (1.50 percentage points). Notably, in contrary to the crisis-stimulus period where the growth of quality offsets the growth of fundamental productivity and demand, output quality growth in the post-crisis period is in line with the growth of fundamental demand but against fundamental productivity growth.

Such detailed decomposition in the presence of quality shocks suggests an important implication regarding the traditional measures of productivity and demand. Without teasing out objective quality, the quantity-based productivity and demand residual confound the production costs and demand benefits of output quality, respectively. When these metrics are used to gauge productivity and demand, they tend to overstate the role of productivity and underestimate the role of demand in shaping firm and industry performance, especially when faced with a negative quality shock in demand, and vice versa.

Our analysis contributes to the literature on the determinants of the growth of firms and industrial dynamics. On the one hand, the literature traditionally emphasizes the role of productivity (e.g., Jovanovic, 1982; Hopenhayn, 1992; Ericson and Pakes, 1995; Melitz, 2003). In particular, using the data from the US steel industry, Collard-Wexler and De Loecker (2015) find that industrial productivity and growth can be improved dramatically via technological improvement as well as technology-induced resource allocation across producers. On the other hand, a growing literature shows that demand is equally, if not more, important for firm turnover and growth (Foster, Haltiwanger, and Syverson, 2008; Pozzi and Schivardi, 2016; Roberts, Yi Xu, Fan, and Zhang, 2018; Kumar and Zhang, 2019). Recently, Jiang and Zhang (2022) further show that firms can actively invest in demand-enhancing activities (e.g. advertisement and marketing) to improve their demand and consequently their growth and long-term performance. Nonetheless, in this literature, the productivity and demand measures confound the their fundamental components with variations stemming from objective output quality. Our paper decomposes these traditional measures into their fundamental elements and objective output quality. By doing so, we unveil the distinct and crucial role of output quality in comprehending the advantages that firms enjoy in terms of productivity and demand, ultimately influencing industry-level performance.

The paper also contributes to the large literature on the measurement of product quality and its applications. Recognizing the unobserved output quality differences, the literature traditionally uses unit prices or demand residual as a proxy of output quality (e.g., Kugler and Verhoogen, 2009; Bastos and Silva, 2010; Khandelwal, 2010). This approach has been widely adopted in different fields to understand important questions. For example, it is shown that product quality largely determines the direction of trade among countries (Hallak and Schott, 2011), how countries specialize in production (Schott, 2004), and terms of trade (Feenstra and Romalis, 2014). Our results show that this approach is appropriate when output quality is perfectly correlated with the firm fundamental demand. However, quality choices may be endogenously influenced by factors such as fundamental productivity, capital stock, and input prices, whose movement and heterogeneity may not necessarily align with fundamental demand. In this case, although quality and fundamental demand may be both welfare-enhancing, confounding them in demand residual masks their different cost implications and distinct roles in firm and industry growth.

The paper is related to the growing literature on the understanding of firm productivity when firms may produce goods of different quality levels. Earlier literature remains silent on the role of (objective) output quality in measuring production capability and firm performance due to data limitations.[5] Foster, Haltiwanger, and Syverson (2008) recognize the importance of quality, and they avoid the unobserved quality problem by focusing on establishments producing physically homogeneous products. In the context of differentiated products, a broader literature implicitly assumes that output quality can be perfectly represented by output price or the estimated demand residual, and hence it is a tradition to use revenue-based productivity to resolve the problem of unobserved output quality (e.g., Melitz, 2000). However, revenue-based productivity masks the distinct roles of firm heterogeneity in output quality and fundamental demand and productivity. Using a measure of scientific quality that is directly recorded in the data, we contribute by separating the production costs and consumption benefits of output quality from fundamental productivity and demand.

Although our analysis is built upon the direct observation of objective quality in the Chinese steel-making industry, our result regarding cost of quality aligns and contributes to the emerging literature analyzing the negative relationship between quantity-based productivity and "product appeal". Jaumandreu and Yin (2014), Roberts, Yi Xu, Fan, and Zhang (2018), Forlani, Martin, Mion, and Muûls (2023), and Eslava, Haltiwanger, and Urdaneta (2023) document a robust negative correlation between quantity-based productivity and demand residual across manufacturing firms in various countries (e.g, China, Belgium, and Colombia). At the firm-product level, Orr (2022) and Caselli, Chatterjee, and Li (2023) demonstrate a similar strong negative relationship using data of Indian manufacturers and Mexican manufacturers, respectively. These studies imply that firms face additional marginal costs to manufacture products with high quality, which is approximated by residual demand when objective quality is unobserved. However, it is unclear how well demand residual can represent output quality in characterizing potential cost rising from producing high objective quality. Our research takes a step forward by providing direct evidence of the marginal costs tied to quality using a measure of objective quality. In this context, our analysis aligns closely with the work of Grieco and McDevitt (2017), who explore the quality-quantity trade-off within the healthcare sector, employing proxies for quality to separate quality's cost impact from fundamental productivity. Furthermore, our analysis shares a kinship with the research of Atkin, Khandelwal, and Osman (2019), who reveal a reverse correlation between quantity productivity and quality productivity among rug-makers in Egypt, drawing insights from data that include direct quality assessments. Overall, these papers provide support and external validation of our

[5] See, for example, Olley and Pakes (1996); Klette and Grillches (1996); Levinsohn and Petrin (2003); Gandhi, Navarro, and Rivers (2011); De Loecker and Warzynski (2012); Ackerberg, Caves, and Frazer (2015).

findings in broader applications using different methodologies.

Finally, the paper is also related to the literature on firm endogenous quality choice, especially on the relationship between quality and advantages in productivity and demand. Consistent with the literature (e.g., Kugler and Verhoogen, 2009, 2012), we find a strong association between (objective) quality and fundamental productivity. On the demand side, the literature typically argues that firms with a larger market (fundamental demand) have a stronger incentive to improve quality (e.g., Shaked and Sutton, 1987; Hallak, 2006; Berry and Waldfogel, 2010; Feenstra and Romalis, 2014), yet the evidence is limited due to the lack of objective quality data. The objective quality data from the Chinese steel-making industry, however, demonstrates a weak or even negative correlation with firm fundamental demand, suggesting that the movements of quality and fundamental demand are not necessarily aligned as conjectured by the literature.

In the rest of the paper, Section 2 introduces the background and motivational data patterns. Section 3 develops a framework of endogenous quality choices and demonstrates the components of the TFPR measure. Section 4 describes the estimation strategy and estimation results. Section 5 analyzes the sources of firm heterogeneity. Section 6 evaluates their contributions to the growth of aggregate revenue productivity in the presence of output quality shocks. Section 7 checks the robustness of our main results by allowing for variable markups and examining the validity of the quality measure. We conclude in Section 8.

2 Background and Data

The analysis uses monthly, firm-level data from the Chinese steel-making industry from 2007 to 2014. This section describes the background and key variables, as well as the stylized facts that motivate this study.

2.1 Background

2.1.1 Steel production process

Steel manufacturing is the process of producing steel using iron ore as the major input. The process involves a few stages. First, iron ore is transformed into pig iron in a blast furnace (ironmaking). Then, the molten pig iron and recycled steel scrap are used to produce steel (steelmaking), which is typically further refined and cast into steel products — slab, billet, and bloom. The process is highly capital-intensive. Furnaces or converters are the major capital used in production, depending on the actual process. The most popularly used process is basic oxygen steelmaking, which uses converters. In the alternative electric arc furnaces process, it uses an electric arc furnace instead of a converter and it uses electricity instead of coal as energy. Basic oxygen steelmaking is the major, dominant process used for producing steel in China.

We focus on the latter stages of steelmaking, namely, using pig iron to produce steel products. This focus serves the purpose of this paper due to several considerations. First, the difference in the quality of the major input (pig iron) is minimum across firms and over time, which allows us to focus on output quality without dealing with input quality differences. Second, the quality of steel is mainly determined in this stage, by adding alloy elements and removing unwanted impurities and gases. Third, focusing on the latter stages of steelmaking saves us from considering vertically-integrated production (ironmaking and steelmaking), which may affect productivity according to Brandt, Jiang, Luo, and Su (2022).[6]

2.1.2 Steel quality

Although seemingly homogeneous, Steel varies largely in quality. The quality of steel should be seen as an inherently quantifiable attribute, which is used to determine the ability of the steel to perform its designed function without limitation due to internal flaws or large variances in microstructure or homogeneity. The quality of steel is the summation of how well it meets its specified chemistry, its cleanliness or the degree to which it is free of impurities, the homogeneity of its microstructure, its grain/carbide size, and, in some instances, whether it meets the specified physical and mechanical requirements.[7] These requirements and properties include corrosion resistance, thermal expansion, thermal conductivity, electrical resistivity, hardness, tensile strength, elongation, and elastic modulus. They largely depend on the content of alloys and impurities. Adding specific alloys, such as manganese, titanium, chromium, and aluminum, can change the properties of steel and increase its quality. Limiting dissolved gases, such as nitrogen and oxygen, and ingrained impurities in the steel is also important to ensure the quality of the products cast from the liquid steel.

In principle, higher-quality steel involves higher production costs. The higher cost is associated with the better equipment needed in the production process, additional refinement stages, as well as finer control processes in all aspects of production and refinement. For example, cooling in the casting process relies particularly on perfectly controlled airflows, which are vital for the quality and characteristics of the steel produced. To this end, efficient and robust air compressors are often

[6] Brandt, Jiang, Luo, and Su (2022) use a data set from the Chinese Iron and Steel Association to study the productivity differences in vertically-integrated Chinese steel facilities over three years, without considering the output quality differences.

[7] Cited from a white paper by Natoli Engineering Company, Inc. Accessed on November 5, 2018, via: http://www.samedanltd.com/uploads/pdf/white_paper/b6a0511aa60220d1761f17415fb59ad0.pdf.

required to produce high-quality steel.[8] Moreover, reducing dissolved gases, such as nitrogen and oxygen, and ingrained impurities also requires extra stages in refining, which increases production costs. Finally, although heat treatment is not a determinant factor for the quality of steel, it must be carried out properly to ensure success.

2.1.3 The Chinese steel industry

China's steel production plays an important role in the domestic economy, as well as in the global steel markets. In 2016, China produced about half of the steel in the world in volume. China was also the largest exporter of steel and accounted for 16.1 percent of global steel exports in 2017, according to "World Steel Statistics (2018)" by the World Steel Association. In our data, about 10 percent of steel output was exported on average during the sample period. In the domestic market, the major demand for steel products comes from downstream industries, including construction, machinery and equipment, automobiles, energy, shipbuilding, electronics, railways, and containers. Among these industries, the first four contribute the most, accounting for 85 percent of the total demand in 2017. The construction industry (including real estate and infrastructure) contributed 53 percent; machinery and equipment, 19 percent; automobiles, 8 percent; and energy, 4.6 percent.

On average, the quality of export steel is higher than that produced for the domestic market. This is because, on the one hand, steel for export is usually made in compliance with the international quality standard to be competitive in the global market; on the other hand, domestic steel demand is dominated by the construction industry, which has relatively lower quality requirements relative to other downstream industries. In our data, the correlation between the share of exports and the quality of steel at the industrial level is 0.53.

As a result, the disproportional fluctuation in the international demand and domestic demand for steel influence the quality and quantity of steel produced. During our data period, the Chinese steel-making industry suffered a large economic shock caused by the 2008 global financial crisis and it induced an unprecedented stimulus plan by the Chinese government. Due to the global financial crisis, foreign demand (i.e., exports) for Chinese steel products shrank sharply by 25 percent from 2007 to 2010 in our data. To buffer the shock, the Chinese government initiated an unprecedented fiscal and monetary stimulus plan, the *Four Trillion Stimulus Plan*, in November of 2008. Following the plan, the central government of China injected RMB 4 trillion (USD 570 billion, or about 11 percent of gross domestic product) into the economy in two years. The effect is even larger considering the matching investment from local governments and private investors.

[8] Source: https://man-es.com/process-industry/solutions/iron-steel.

The stimulus plan mainly targeted public infrastructure, real estate, and the rebuilding of areas ravaged by the Great Sichuan earthquake. Overall, more than 80 percent of the stimulus package was distributed to construction-related development.[9] This caused prosperity in the construction sector. The strong growth in the downstream sectors created large domestic demand for steel products. This led to an increase in domestic sales (by 55 percent) as well as total sales (by 47 percent) and large investment in capacity across the steel-making industry from 2007 to 2010. The large capacity investment was incurred by the excess credit with the expectation of long-last prosperity of the domestic demand.

However, after 2010, the growth trend of export and domestic sales was exchanged. The export demand started to recover and experienced steady growth afterward until the end of our data period as the global economy gradually recovered from the crisis. The export volume in 2014 almost doubled that in 2010. By contrast, domestic demand decelerated due to the slowdown of growth in its major domestic downstream industries. The output quantity sold to the domestic market decreased by over 12 percent from 2010 to 2014 in our data. Nonetheless, the firm-level production capacity still increased by about 7 percent in the same period. As a result, the capacity built before and over the post-crisis period quickly became redundant and this consequently led to a loss of production efficiency.

2.2 Data

The analysis uses a new, monthly-frequency panel of major steelmakers in China from 2007 to 2014. The data set comes from a large data service company in China, which receives data on the basic variables from the Chinese Iron and Steel Association. The company also collects additional information from first-hand surveys of the major steel-making firms. One key feature of the data is that it reports detailed information on the quality levels of firm output, in addition to output prices, the quantity of inputs and output, and other firm identity and financial information from the firms' balance sheets. After cleaning up missing variables, the data set covers the 73 largest steel producers in China, which produced about 50 percent of the country's total steel output, or 22 percent of the world's steel output, in 2010.

[9]Specifically, public infrastructure development, including railway, road, irrigation, and airport construction, took up the biggest portion – RMB 1.5 trillion (USD 214 billion), or nearly 38 percent of the total package. Another 25 percent of the total package, or about RMB 1 trillion (USD 143 billion), went to reconstruction works in regions ravaged by the 8-magnitude Sichuan earthquake in May 2008. Around 400 billion (USD 57 billion or 10 percent of the package) was distributed to real estate to build and improve public housing. Rural development, including building public amenities and providing safe drinking water, was allocated RMB 370 billion (USD 53 billion or about 9.3 percent of the package). Source: https://en.wikipedia.org/wiki/Chinese_economic_stimulus_program. Accessed on July 14, 2021.

Output quantity and prices are conventionally defined, as tons of steel and price per ton of steel, respectively. Following the literature, we normalize the firm-level prices and revenue by the industry output price index (i.e., the average output price weighted by firm revenue).[10] Because we focus on the final stage of producing steel products, namely, using pig iron and recycled scrap steel to produce steel products, the major input is the tonnage of pig iron and recycled scrap steel. The labor input is the number of workers, and capital is the tonnage of the basic oxygen furnace, both of which are measured as the amount actually utilized in the production process.

Such detailed input-output data provide us with two obvious advantages in the analysis. First, because the inputs are in physical quantities, input price heterogeneity (as highlighted in Ornaghi, 2006; Grieco, Li, and Zhang, 2016, 2022) does not affect our estimation and measures of productivity. Second, the detailed input and output data at least partly mitigate the usual criticism of heterogeneity in input utilization in manufacturing industries in the production function estimation. Of course, the actual number of working hours and working intensity may vary (even conditional on the utilized number of workers and capital). In addition, besides capital and labor, there may be other (unobserved) inputs with changing utilization rates. All these unobserved factors are captured by the estimated productivity, implying potentially lower levels of productivity when firms face overcapacity problems in the post-crisis period.

2.2.1 Output quality index

What makes this data set unique is that it enables us to compute a scientific, objective output quality index at the firm level. Chinese manufacturing firms (including steel-making firms) follow three levels of quality standards in the production process, in descending order: international, national, and enterprise standards. The international standard is the so-called "foreign advanced standard" in China, as developed by the International Organization for Standardization, International Electrotechnical Commission, Pacific Area Standards Congress, and other international and regional forums. It represents the highest quality standard required in steel production in China and is recognized worldwide. The national standard is developed by the Standardization Administration of China or the corresponding industry (which must be registered and filed with the Standardization Administration of China) and applied domestically. It is sometimes referred to as the industrial standard or "GB standards" in China. The lowest level, the enterprise standard, is developed and applied by individual firms, and it is only implemented within the firm. In the steel-making industry, the three levels of standards differ substantially in their requirements for

[10] Alternatively, we can deflate the prices and revenue by national inflation rates. Our main results are robust.

the steel's physical and chemical properties, as well as impurity content. We use the example of widely produced carbon structural steel to demonstrate the quality difference between the international and national standards in Appendix Table A1.

The steel quality index of a firm is defined as the weighted average of a set of quality index numbers using the shares of the physical quantity of output produced under each of the three quality standards. Formally, for firm j in period t, the quality index is calculated as $\xi_{jt}^0 = \alpha_H S_{Hjt} + \alpha_M S_{Mjt} + \alpha_L S_{Ljt}$, where $S_{Hjt} = \frac{Q_{Hjt}}{Q_{jt}}$, $S_{Mjt} = \frac{Q_{Mjt}}{Q_{jt}}$, and $S_{Ljt} = \frac{Q_{Ljt}}{Q_{jt}}$ are the quantity shares of output produced following the international standard, national standard, and enterprise standard, respectively, in descending order of quality.[11] $Q_{jt} = Q_{Hjt} + Q_{Mjt} + Q_{Ljt}$ is the total output quantity, which equals the sum of quantities produced following different quality standards. α_H, α_M, and α_L are the index numbers assigned to each of the three quality standards. In the steel industry, it is the norm to choose the index numbers as $\alpha_H = 1.5$, $\alpha_M = 1$, and $\alpha_L = 0.5$.[12] As a result, the output quality index ranges from 0.5 to 1.5. If the quality index equals 1.5, it means that all products produced by this firm follow the international quality standard and are of the highest quality level. If the quality index equals 0.5, by contrast, it means that all products of this firm are produced following the enterprise standard and are of the lowest quality level. If the firm produces steel with a mix of two or three standards, the quality index is between 0.5 and 1.5. A higher quality index means that the firm produces steel of higher average quality.

2.2.2 Features of output quality

This subsection presents the patterns of the output quality and its relationship to key variables across firms and over time, which motivate the empirical analysis. In particular, we find substantial heterogeneity of quality. The 90th-10th percentile difference in quality is around 0.66, or about 2.6 times of its standard deviation. Because the range of quality is normalized to be 1 (from 0.5 to 1.5), the interdecile range implies that the quality difference between the 90th and 10th percentiles equals 66 percent of the maximum quality difference.

Output quality and prices. In our data, firms producing high-quality products sell at higher prices. The correlation between these two variables is positive (0.165, significant at the 1 percent

[11] This definition follows exactly the regulation in the steel-making industry in China. For more details, refer to the decree *"Cleaner Production Standard–Iron and Steel Industry"*, which is part of the *"Environmental Protection Industry Standard of the People's Republic of China (HJ/T189-2006)"* issued in 2006 by the Ministry of Ecology and Environment. The book (in Chinese) compiled by Chen (2003) from the *China Iron and Steel Association* also provides a detailed explanation of these quality index numbers.

[12] In Section 7.2, we test the robustness of our results by using a different set of index numbers estimated flexibly following the insight of Atkin, Khandelwal, and Osman (2019). The estimated quality index numbers are close to the industry practice and our results are robust.

level).[13] Table 1 reports a positive association between output prices and the quality index (both in logarithm) in regressions after controlling for fixed effects and firm characteristics, including the firms' market share as a proxy for market power. The results suggest that a 1-percent increase in the output quality index is associated with a higher output price by about 0.343 percent (the fifth column). The positive association is intuitive. First, higher quality promotes demand, allowing firms to charge higher prices. Second, higher quality incurs a higher cost in production, which also drives up prices.[14]

Table 1: Relationship between output quality and output prices

	(1)	(2)	(3)	(4)	(5)
	log(P)	log(P)	log(P)	log(P)	log(P)
Output quality	0.294***	0.352***	0.350***	0.356***	0.343***
	(0.035)	(0.035)	(0.035)	(0.035)	(0.034)
Market share					11.631***
					(0.637)
Firm FE	Y	Y	Y	Y	Y
Year-month FE		Y	Y	Y	Y
Capital capacity (log)			Y	Y	Y
Avg. converter size (log)				Y	Y
Observations	4,070	4,070	4,070	4,025	4,025
Adjusted R^2	0.429	0.467	0.467	0.466	0.509

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Output quality and productivity. Our data reflect that output quality is a firm characteristic that is fundamentally different from productivity. How output quality is related to productivity depends on how productivity is defined. Column (1) in Table 2 shows that output quality is negatively related to labor productivity measured by quantity (i.e., tons of steel) produced per worker. This suggests a trade-off between quality and quantity: higher quality output is more costly to produce. This is consistent with the findings in Column (3): the quantity of output is lower for higher quality conditional on major input variables (labor and capital) and fixed

[13]The correlation is computed in logarithm after removing firm and time fixed effects. Removing firm fixed effects is necessary to control for the impact of any time-invariant factors, such as frictions from geographic differences, institutions, or market power, which may lead to cross-sectional differences.

[14]Nonetheless, this does not mean that output price is a perfect measure of output quality. As will be demonstrated in Section 3, many factors can systematically influence output prices, although these factors are not directly related to output quality. Indeed, the regression results in Table 1 show that market share (market power), capital capacity (firm size), and fixed effects (consumer taste, demand, and input factors) all help to explain the variation of output prices. In addition, as evidence specific to this industry, Appendix Figure A1 shows that the over-time changes in output (steel) prices are largely influenced by the variation in input (iron ore) prices. These dramatic changes in iron ore prices (e.g., fluctuation by over 50 percent within a year) are not driven by different levels of quality of iron ore. Instead, they are mainly due to changes in competition and bargaining outcomes in the international market for iron ore. In the same vein, it can reasonably be inferred that cross-firm differences in output prices may be also driven by (unobservable) heterogeneity in input prices (iron ore) across firms. This is consistent with the observation in Table 1 that a large part of the variation in output prices is left as unexplained (i.e., adjusted R^2 = 0.550), even when the regression controls for a key set of observable variables.

effects. Such a relationship is the key to identify the cost associated with producing high quality from unobservable fundamental productivity, which is formally investigated in Section 4.2. When productivity is measured in revenue terms, nonetheless, Column (2) shows that it is positively related to output quality. This is because the higher quality output can sell at a higher price (Table 1), which offsets and dominates the cost effect of quality. Such a positive effect of quality is also observed in the relationship between revenue and output quality in Column (4). Overall, the comparison implies that an appropriate measure of productivity should take both the benefit and cost effects of quality into account.

Table 2: Relationship between output quality and labor productivity

	(1) Quantity/worker	(2) Revenue/worker	(3) logQ	(4) logR
Output quality	-0.131***	0.214***	-0.189***	0.162***
	(0.041)	(0.056)	(0.032)	(0.034)
Firm FE	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
Labor (log)			Y	Y
Capital capacity (log)			Y	Y
Avg. converter size (log)			Y	Y
Observations	4,035	3,951	3,991	3,909
Adjusted R^2	0.693	0.600	0.933	0.926

Standard errors in parentheses

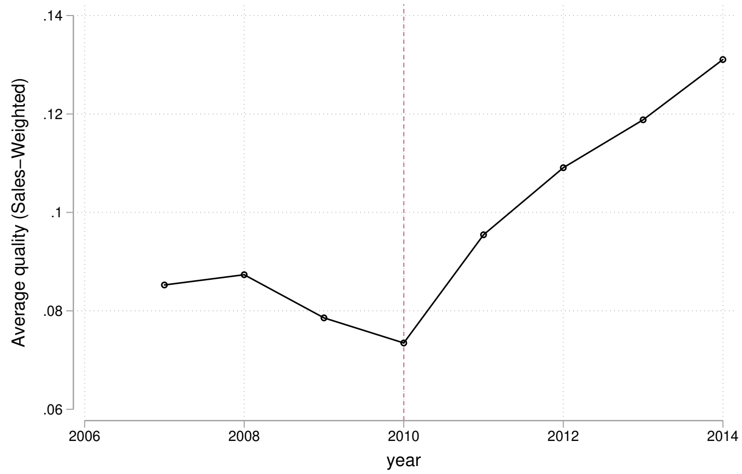
* $p < .10$, ** $p < .05$, *** $p < .01$

Evolution of output quality. The average quality index at the industry level fluctuates significantly over time, showing strong responses to large economic shocks. Figure 1 plots the evolution of the (industrial-level) quality index in terms of the sales-weighted average. From 2007 to 2010, sales-weighted average quality decreased. This is consistent with the decline in exports (typically of high-quality steel) caused by the 2008 global financial crisis and the increase in domestic demand (typically of low-quality steel) caused by the stimulus policy. From 2010 to 2014, the average quality increased substantially because of the slowdown of domestic demand and the steady growth of export sales. Overall, the disproportional response of output quality to large economic shocks emphasizes the importance of accounting for quality when evaluating productivity growth.

3 Modeling of Firm Heterogeneity

The unique data on the objective quality of output allow us to separate costs of quality, benefits of quality, fundamental productivity, and fundamental demand from each other. Utilizing this advantage, this section introduces a model of endogenous quality choices that depend on fun-

Figure 1: Evolution of average quality



damental productivity and fundamental demand, taking into account the benefits and costs of producing higher quality. The model shows that revenue productivity (TFPR) is still a natural measure of firms' overall performance even with endogenous quality heterogeneity and TFPR can be decomposed into the contribution of costs of quality, benefits of quality, fundamental productivity, and fundamental demand. We also illustrate what the traditional concepts, TFPQ and demand residual, actually capture in the presence of output quality heterogeneity.

3.1 Endogenous Quality-Quantity Decisions

In the model, each firm produces a single product and competes monopolistically in an industry of vertically differentiated products.[15] Firms endogenously choose objective quality and quantity to maximize profits, given production technology, consumer preferences for quality, and demand conditions. The key trade-off faced by each firm is that, while high-quality products induce higher demand, producing them costs resources and lowers the physical quantity of output.

Preference for quality and quantity. There are J vertically-differentiated products in the market, each produced by a firm $j \in \{1, 2, ..., J\}$. A representative consumer is endowed with a constant elasticity of substitution (CES) preference for both the quality and quantity of these products:

$$U = \left[\sum_j \rho_{jt}^{\frac{\sigma-1}{\sigma}} \left(\xi_{jt} Q_{jt}\right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where σ is the elasticity of substitution across the products. Q_{jt} is the physical quantity and

[15]Steel-making firms may produce steel products following one, two, or three quality standards, as shown in Section 2.2.1. We use the sales-weighted average to aggregate products of different quality levels to the firm level.

ξ_{jt} is the objective product quality produced by firm j in period t.[16] That is, the consumer values both the quantity and objective quality of the products, given consumer preference. We define $\tilde{Q}_{jt} \equiv \xi_{jt} Q_{jt}$ as quality-adjusted quantity. Thus, a 1-percent increase in product quality provides a 1-percent increase in the consumer's valuation of the product, holding the physical quantity of the product fixed. We refer to this as the *consumption benefit of objective quality.* Apart from objective product quality, consumer taste (embodied with consumer preferences and any idiosyncratic preference shocks that are not directly related to objective product quality), ρ_{jt}, may affect the consumer's subjective evaluation of product j and consequently influence the consumer's utility. ρ_{jt} can be serially correlated and it may be also correlated with product prices and objective quality ξ_{jt}. The difference between ξ_{jt} and ρ_{jt} is that, while ξ_{jt} is a product characteristic that affects variable production cost, ρ_{jt} represents consumer taste, which does not influence the variable cost of production directly.

Given the consumer's total expenditure I_t and output prices P_{jt}, the consumer's utility maximization problem implies the following demand function:

$$\ln Q_{jt} = -\sigma \ln P_{jt} + (\sigma - 1) \ln \xi_{jt} + (\sigma - 1)\phi_{jt}, \tag{2}$$

where $\phi_{jt} = \rho_{jt} + \ln \left(\frac{I_t}{\sum_j [P_{jt}/(\rho_{jt}\xi_{jt})]^{1-\sigma}} \right)^{\frac{1}{\sigma-1}}$ is referred to as the *fundamental demand.* It depends on consumer taste ρ_{jt} and an expenditure index $\frac{I_t}{\sum_j [P_{jt}/(\rho_{jt}\xi_{jt})]^{1-\sigma}}$, which depends on macroeconomic conditions and does not vary across j. The demand elasticity, σ, is assumed to be constant, implying a constant markup in our setting. In Section 7.1, we extend the demand model to allow the markup to vary by the output quality level and show that our main results are robust.

The traditional CES demand function in the empirical literature (e.g., Melitz, 2000) does not distinguish the objective quality ($\ln \xi_{jt}$) and fundamental demand (ϕ_{jt}), and refers their sum (i.e., $\ln \xi_{jt} + \phi_{jt}$, adjusted by $\sigma - 1$) as demand residual to represent output quality. Although this is a convenient approximation of overall demand conditions faced by the firm, it masks the role of objective product quality in shaping the firm production capability. Specifically, due to the nature of I_t and ρ_{jt}, fundamental demand ϕ_{jt} contains several demand shifters such as consumer preferences, idiosyncratic preference shocks, and macroeconomic market conditions. These shifters are not components of firm production capability, and they do not affect the (variable) production costs as output quality does. Using demand residual as a proxy of output quality may understate the role of quality in affecting production costs. For these reasons, we model objective quality ξ_{jt}

[16] Empirically, ξ_{jt} may not be the same as the output quality index ξ^0_{jt} in the data due to differences in measurement scale. We allow for such a possibility in the analysis in Section 4.1.

and fundamental demand ϕ_{jt} separately. Empirically, we use the data on the scientific quality index to separate the objective quality (ξ_{jt}) from fundamental demand (ϕ_{jt}) and show that they are fundamentally different in Section 4. We refer to output quality as objective output quality rather than demand residual throughout the paper, except when stated otherwise.

Production technology. In each period t, firm j produces quantity Q_{jt} of a single product (indexed by j as well) of objective quality ξ_{jt}, using labor L_{jt}, capital K_{jt}, and intermediate materials M_{jt}. The production function is

$$Q_{jt} = \min\{M_{jt}, A_{jt} K_{jt}^{\alpha_k} L_{jt}^{\alpha_\ell}\}, \tag{3}$$

where A_{jt} captures the unexplained variation of output conditional on inputs, in the spirit of quantity-based productivity (e.g., TFPQ in Foster, Haltiwanger, and Syverson, 2008). The Leontief functional form implies that there is no substitution between materials and the composition of labor and capital, while labor and capital (modeled in a Cobb-Douglas form) are substitutable for each other. This reflects the feature of the production technology in the steel-making industry as shown in Appendix Figure A2 – the relationship between output and intermediate materials is characterized by a 45-degree line. Atkinson and Luo (forthcoming) use a similar Leontief function to model the production technology of electricity generation plants. Our analysis carries over if the production function has a form that is generally used in the literature.

Given the Leontief production functional form, the optimal production plan implies that the firm always chooses materials to match the Cobb-Douglas composition of labor and capital. As a result, the production function that is relevant to our empirical analysis is:

$$Q_{jt} = A_{jt} K_{jt}^{\alpha_k} L_{jt}^{\alpha_\ell}. \tag{4}$$

In our context, the quantity-based productivity, A_{jt}, depends on two key components:

$$A_{jt} = e^{\omega_{jt}} \xi_{jt}^{-\alpha_\xi}. \tag{5}$$

The first component in (5), ω_{jt}, represents the (logarithm) *fundamental productivity*, which is largely driven by the unobserved technology of machinery, the skill of workers, working intensity, and the capability of the management team that is not captured by the observed inputs. Assume that ω_{jt} evolves according to an AR(1) process:

$$\omega_{jt+1} = g_0 + g_1\omega_{jt} + \epsilon_{jt+1}, \tag{6}$$

where ϵ_{jt+1} is an i.i.d. productivity shock. The firm observes the current fundamental productivity when making production decisions. It is worth noting that although output quality ξ_{jt} is not modelled as a part of the evolution process of productivity ω_{jt}, these two are still related because the optimal quality choice depends on the level of fundamental productivity.[17]

The second component in (5), $\xi_{jt}^{-\alpha_\xi}$, represents the cost of producing output with higher objective quality. Given fundamental productivity, a firm producing a higher objective quality product may incur additional production costs. For example, producing steel of higher quality requires additional refinement stages, better equipment, and finer process control in all stages of production, as explained in Section 2.1.2. These activities need additional inputs and increase the cost of production, as discussed by Atkin, Khandelwal, and Osman (2019) who explicitly model quality production using additional inputs (e.g., labor and capital). Instead of modeling the production of quality directly, we model such production cost of quality, $\xi_{jt}^{-\alpha_\xi}$, as a part of A_{jt} in the spirit of Grieco and McDevitt (2017).[18] We expect α_ξ to be positive, implying a tradeoff between quality and quantity of output in the production process.

Static output quantity decision. While we treat the choice of quality as a dynamic decision, the output quantity decision is static. The timing of events is as follows. The level of quality in period t has been decided in the end of period $t-1$. Conditional on that, a firm chooses output quantity to maximize its profit in period t, given the demand and production conditions. Specifically, at the beginning of each period t, the firm j observes its state $s_{jt} = (\xi_{jt}, \omega_{jt}, \phi_{jt}, K_{jt}; \psi_t)$.[19] Here ψ_t collects the time-specific aggregate factors that influence firm profit (e.g., iron ore prices and wage

[17]In addition, as a robustness check, when we included output quality (or its lag) in the evolution process, the impact was insignificant. This suggests that output quality influences the quantity-based productivity A_{jt} through the cost of producing a higher quality of output (i.e., $\xi_{jt}^{-\alpha_\xi}$) rather than fundamental productivity.

[18]In fact, our production setup, $Q_{jt} = e^{\omega_{jt}}\xi_{jt}^{-\alpha_\xi}K_{jt}^{\alpha_k}L_{jt}^{\alpha_\ell}$, aligns with the tradition of modelling the quantity production and quality production separately. To see this, assume that a fraction (denoted as λ_{jt}) of capital and labor are required to produce quality level ξ_{jt}; the rest $(1-\lambda_{jt})$ fraction of capital and labor are used in the production of output quantity Q_{jt}. Suppose that λ_{jt} is an increasing function of the level of quality: $\lambda_{jt} = \lambda(\xi_{jt}) = 1 - e^{-\frac{\alpha_\xi}{\alpha_k+\alpha_\ell}\xi_{jt}}$, with $\alpha_\xi > 0$. As a result, by accounting for the actual labor and capital used in the production of quantity, $Q_{jt} = e^{\omega_{jt}}[(1-\lambda(\xi_{jt}))K_{jt}]^{\alpha_k}[(1-\lambda(\xi_{jt}))L_{jt}]^{\alpha_\ell} = e^{\omega_{jt}}\xi_{jt}^{-\alpha_\xi}K_{jt}^{\alpha_k}L_{jt}^{\alpha_\ell}$.

[19]For simplicity, we assume that the firm observes fundamental demand ϕ_{jt} ahead of the quantity decision, although the aggregate price index $\sum_j [P_{jt}/(\rho_{jt}\xi_{jt})]^{1-\sigma}$ contained in ϕ_{jt} is also endogenously determined in market equilibrium. This assumption is consistent with the conventional wisdom of rational expectation and it is a valid assumption especially when the number of firms in the industry is reasonably large.

rates). The firm chooses the quantity of output to maximize period profit:[20]

$$\begin{aligned}\pi(\xi_{jt}, \omega_{jt}, \phi_{jt}, K_{jt}; \psi_t) &= \max_{Q_{jt}} \{P_{jt}Q_{jt} - P_{Mt}M_{jt} - P_{Lt}L_{jt}\} \\ \text{subject to:} & \quad (2),\ (4),\ \text{and } M_{jt} = Q_{jt},\end{aligned} \tag{7}$$

where P_{Mt} and P_{Lt} are the time-varying prices of the intermediate input (i.e., iron ore) and labor, respectively.[21] We denote the implied optimal decisions on quantity as $Q_{jt} = Q^*(\xi_{jt}, \omega_{jt}, \phi_{jt}, K_{jt}; \psi_t)$.

Dynamic quality decision. In the end of each period t, the firm observes its state s_{jt} and chooses the quality of output of period $t+1$ (i.e., ξ_{jt+1}) to maximize the long-run firm value. The choice of quality level is dynamic because the change of quality involves an adjustment cost that depends on the current level of quality. We denote the adjustment cost as $C(\xi_{jt}, \xi_{jt+1})$, which is convex in the absolute changes in quality, $|\xi_{jt+1} - \xi_{jt}|$. The firm's dynamic problem is characterized by the following Bellman equation, in which firms choose the quality of output, after recognizing how the current choice will influence future firm value:

$$V(s_{jt}) = \max_{\xi_{jt+1}} \{\pi(s_{jt}) - C(\xi_{jt}, \xi_{jt+1}) + \delta E(V(s_{jt+1}|s_{jt}))\}. \tag{8}$$

The transition of the state from s_{jt} to s_{jt+1} is subject to the evolution processes of fundamental productivity, capital stock, and other state variables. While the productivity evolution is specified in (6), the capital evolution process is standard and is abstracted away for demonstration purpose.[22] The trade-off presented in the dynamic problem is that while enhancing quality may improve both present profit and the firm's future value, the firm incurs adjustment costs to materialize this change, depending on the quality gap between the current level ξ_{jt} the proposed level for the next period ξ_{jt+1}. We denote the implied optimal quality decision as $\xi_{jt+1} = \xi^*(\xi_{jt}, \omega_{jt}, \phi_{jt}, K_{jt}; \psi_t)$.[23]

The optimal decisions described above have three important implications. First, the optimal objective quality of output relies on a set of variables rather than fundamental productivity exclusively, implying that output quality and fundamental productivity are two fundamentally different dimensions of firm heterogeneity. Observing only one of them does not fully reveal the

[20] Given the state variables and quality, according to (4), choosing Q_{jt} is equivalent to choosing L_{jt}. Thus, L_{jt} does not appear in the choice variable set.

[21] Although the direct material input of steel-making is pig iron, we approximate price of pig iron by the price of iron ore. This is because iron ore is the main input in the production process of iron-making, which provides the main input (pig iron) in the steel-making procedure. Thus, we use the price of pig iron and the price of iron ore exchangeably in this paper.

[22] Our empirical model does not depend on estimating a specific evolution process of capital stock.

[23] We assume there exists an interior solution. In general, the optimal choice of quality will not be infinite in the presence of adjustment costs. The firm will not choose the lowest quality level either if there exists a net benefit of quality, as we show empirically in Section 4.2.

other, because they are unlikely to be perfectly correlated. Their correlation may change over time and they may respond to fundamental demand (ϕ_{jt}) differently, depending on how capital stock (K_{jt}) and factor prices (ψ_t) vary across firms and over time. Also, the quality choice depends on the previous quality choice, due to adjustment costs of quality. This lends us a way to use the lag of output quality as a relevant instrumental variable for the current output quality in the estimation of production function in Section 4.2.

Second, the demand residual from the demand function (2) is unlikely to be a perfect measure of the objective output quality. According to the optimal decisions from (7), the choice of output quality depends on factors including fundamental productivity, capital stock, and input prices, in addition to fundamental demand. If the characteristics of these factors are different (as documented by Pozzi and Schivardi, 2016, for the case of productivity and demand), the variation of output quality is not necessarily aligned with that of fundamental demand, as we confirm in Section 4.3. As a result, the revenue-based productivity (as in Melitz, 2000) confounds the production capability with fundamental demand that may arise from consumers' subjective preferences, idiosyncratic shocks, and macroeconomic market conditions, which do not represent objective output quality.

Finally, the optimal decision of Q_{jt} provides a proxy to control for the unobserved ω_{jt} in the production function estimation. To see this, plugging the choice Q_{jt} into (4), the optimal labor demand is a function of state variables: $L_{jt} = L^*(\xi_{jt}, \omega_{jt}, \phi_{jt}, K_{jt}; \psi_t)$. In Section 4.2, we assume that the labor demand function is monotonic in ω_{jt} conditional on other state variables, including fundamental demand (ϕ_{jt}) and output quality (ξ_{jt}), and invert it to obtain a proxy for ω_{jt} in the spirit of Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2015).

3.2 Revenue Productivity and Its Components

Built on the framework of the previous subsection, we first demonstrate TFPR as a valid measure of firm performance with quality differences, in the spirit of Melitz (2000). We show that TFPR captures four components: fundamental productivity, fundamental demand, cost of quality, and benefit of quality. Then, we show what TFPQ and demand residual used in the literature capture exactly when there is quality heterogeneity.

We adopt the approach in Melitz (2000) to define TFPR directly from: $R_{jt} = P_{jt}Q_{jt} = \left\{\exp(\text{TFPR}) K_{jt}^{\alpha_k} L_{jt}^{\alpha_\ell}\right\}^{\frac{\sigma-1}{\sigma}}$, where P_{jt} and R_{jt} are the output price and revenue of firm j in period t, respectively.[24] Combining (2) and (4) to derive the revenue function and using the definition of TFPR above, we obtain:

$$\text{TFPR}_{jt} = \underbrace{\omega_{jt}}_{\text{fundamental productivity}} - \underbrace{\alpha_\xi \ln \xi_{jt}}_{\text{cost effect of quality}} + \underbrace{\ln \xi_{jt}}_{\text{benefit effect of quality}} + \underbrace{\phi_{jt}}_{\text{fundamental demand}} \tag{9}$$

This equation implies that fundamental productivity, fundamental demand, and output quality all contribute to TFPR. Nonetheless, the role of output quality is partially offset by its cost – increasing output quality by 1 percent only improves TFPR by $(1 - \alpha_\xi)$ percent, holding all other factors fixed.

Without accounting for output quality separately, the **quantity-based productivity** (**TFPQ**, as referred by Foster, Haltiwanger, and Syverson, 2008) essentially measures the quantity of output in physical units per input composite. It coincides with A_{jt} in production function (4). Hence it is defined as:

$$\text{TFPQ}_{jt} = \underbrace{\omega_{jt}}_{\text{fundamental productivity}} - \underbrace{\alpha_\xi \ln \xi_{jt}.}_{\text{cost effect of quality}} \tag{10}$$

In industries with homogeneous products (i.e., $\xi_{jt} = \xi$), as in Foster, Haltiwanger, and Syverson (2008), TFPQ is the same as the firm's fundamental productivity ω_{jt}. However, in industries with vertically differentiated products, as is the case for most industries, TFPQ no longer measures fundamental productivity. Instead, it is a combination of fundamental productivity and the cost effect of quality. In this case, even if firms have the same fundamental productivity, the measured TFPQ may still differ if the firms produce outputs of different quality levels due to the heterogeneity in other dimensions.[25] Because quality and fundamental productivity are usually positively correlated, TFPQ tends to understate the dispersion of fundamental productivity.

Finally, the demand residual is defined from the demand function (2). That is,

$$\text{Demand Residual}_{jt} = \underbrace{\ln \xi_{jt}}_{\text{benefit effect of quality}} + \underbrace{\phi_{jt}}_{\text{fundamental demand}} . \tag{11}$$

Note that we have adjusted demand residual by $(\sigma - 1)$ to make it conceptually comparable to TFPQ. While the literature usually treats demand residual as product appeal or perceived quality, it essentially contains the objective quality and fundamental demand. In this paper, we emphasize

[24] This definition avoids the scale bias caused by $\frac{\sigma-1}{\sigma}$ and thus is directly comparable to the traditionally used quantity-based productivity (i.e., TFPQ).

[25] Firms may choose to produce output of different quality levels even if they have the same fundamental productivity, because quality choice also depends on other factors such as capital stock, factor prices, and fundamental demand, as shown in Section 3.1.

the differences between objective quality and fundamental demand in terms of their heterogeneity, reaction to large economic shocks, as well as their distinct contributions to firm performance measured by TFPR. Table 3 summarizes these key measures and clarifies the different components they capture.

Table 3: Components of key measures

	TFPR	TFPQ	Demand Residual
Fundamental productivity (ω)	✓	✓	
Fundamental demand (ϕ)	✓		✓
Production cost of quality ($\alpha_\xi \ln \xi$)	✓	✓	
Consumption benefit of quality ($\ln \xi$)	✓		✓

4 Output Quality, Productivity, and Demand

This section recovers firm fundamental productivity and demand by estimating demand and production functions after taking the role of objective quality explicitly into account. We first describe the estimation procedure, estimation results, and characteristics of recovered firm-level fundamental productivity and demand. Then, we highlight the role of quality in the measurement of fundamental productivity and demand via a series of comparisons.

4.1 Fundamental Demand

We recover firm fundamental demand (i.e., ϕ_{jt}) by estimating the demand function after controlling for the objective output quality. The data record an index of scientific quality, ξ^0_{jt}, as discussed in Section 2, which affects consumer utility. However, ξ^0_{jt} itself may not directly reflect the consumption benefit of quality in the model (i.e., ξ_{jt} in the utility function (1)), due to the choice of the quality measurement scale in the data. That is, ξ^0_{jt} may not equal to ξ_{jt} exactly. To allow for such a possibility, we model ξ_{jt} as a function of the quality index in the data: $\xi_{jt} = \exp(\gamma \xi^0_{jt})$, where the parameter γ adjusts the scale of the scientific quality index. Plugging this function into (2) yields the estimating equation:

$$\ln Q_{jt} = -\sigma \ln P_{jt} + \gamma(\sigma - 1)\xi^0_{jt} + (\sigma - 1)\phi_{jt}. \tag{12}$$

In the estimation, we decompose $(\sigma - 1)\phi_{jt}$ into a firm fixed effect ϕ_j, a time fixed effect ϕ_t, and a random term e_{jt}. The firm fixed effect captures any persistent firm factors (that is distinct from the objective quality) such as a taste specific to firm j's product; the time fixed effect captures time factors (that differ from the objective quality) such as macroeconomic shocks and allows for serial correlation of the demand residual; the random term e_{jt} represents unobserved shocks or i.i.d measurement errors. Thus, the above equation can be rearranged as follows:

$$\ln Q_{jt} = -\sigma \ln P_{jt} + \gamma(\sigma - 1)\xi_{jt}^0 + \phi_j + \phi_t + e_{jt}. \tag{13}$$

Although we control for the time and firm fixed effects in identifying the key coefficient of objective quality (i.e., γ) using the within-firm variation of objective quality, this does not mean that all the persistence or across-firm variation in the demand residual are captured only by the fundamental demand (i.e., ϕ_{jt}). In fact, the both the persistence and across-firm variation of ξ_{jt}^0 and ϕ_{jt} are separately identified, because objective quality (and thus its persistence and across-firm variation) is directly observed.[26]

Because the unobserved shock e_{jt} may be correlated with the output price, we estimate (13) using a panel data instrumental variable (IV) approach. We use the firm's capital stock as an instrumental variable for the output price in the main result. Capital stock directly shifts marginal cost and thus, it is correlated with the price but not the unobserved demand shock e_{jt}. Therefore, it serves as an appropriate instrumental variable for the endogenous price.

Table 4: Estimates of demand function parameters

	(1) OLS	(2) IV
σ	0.627***	1.980***
	(0.015)	(0.050)
$\gamma(\sigma - 1)$	0.033	0.516***
	(0.033)	(0.059)
Year-month FE	YES	YES
Firm FE	YES	YES
Observations	4,070	4,034

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

The estimation results of our main specification (13) are reported in Table 4. As a comparison, we also report the results based on ordinary least squares (OLS). In the panel data IV estimation, the elasticity of substitution $\sigma = 1.980$, which is close to that reported in the literature (e.g., Broda and Weinstein, 2006; Atkin, Khandelwal, and Osman, 2019). The implied coefficient of output

[26] To be precise, once the coefficients in (13) are estimated, we construct the fundamental demand according to its definition, $\phi_{jt} = \frac{\phi_j + \phi_t + e_{jt}}{\sigma - 1} = \frac{\ln Q_{jt} + \sigma \ln P_{jt} - \gamma(\sigma-1)\xi_{jt}^0}{\sigma - 1}$, conditional on the observation of objective quality, which varies across firm and over time.

quality ξ_{jt} in (2), $(\sigma - 1)$ as the elasticity of demand with respect to quality, equals 0.980. This suggests a significant impact of quality on demand: a 1 percent increase in quality, ξ_{jt}, increases demand by 0.980 percent, holding other factors fixed.[27] As expected, the OLS estimation gives qualitatively similar results, but it substantially underestimates the demand elasticity of prices. Finally, the estimated coefficient, $\gamma(\sigma - 1)$, is 0.516, implying the scale-adjustment parameter as $\gamma = 0.516/(1.980 - 1) = 0.527$.

After the estimation, we compute output quality and fundamental demand according to their definitions as $\xi_{jt} = \exp(\hat{\gamma}\xi^0_{jt})$ and $\phi_{jt} = (\hat{\phi}_j + \hat{\phi}_t + \hat{e}_{jt})/(\hat{\sigma} - 1)$, respectively. As conjectured in Section 3.1, output quality and fundamental demand display significantly different patterns. We summarize their differences and relationship to key variables in Section 4.3 after estimating the production function.

Remark: There are two main identification assumptions in the above estimation. First, the idiosyncratic demand shock e_{jt} is uncorrelated with the output quality index ξ^0_{jt} in (13) in the main result. To ensure the robustness of our estimate against this assumption, we show that the results are similar when we use various alternative instrumental variables to control for potential correlation between e_{jt} and ξ^0_{jt}. This is reflected in Columns (1)-(4) of Appendix Table A2,

The second identification assumption is that, after explicitly including quality index (ξ^0_{jt}) into the estimating equation and controlling for firm fixed effect (ϕ_j) and time fixed effect (ϕ_t), the remaining idiosyncratic component (e_{jt}) of fundamental demand, although may be correlated with output prices, is uncorrelated with instrumental variables (IVs). The related literature that estimates demand functions similar to (13) usually uses cost shifters as IVs. Cost shifters will not be appropriate IVs if quality influences cost but is treated as a part of the error term. In our context, we leverage the advantage of our data to control for quality directly (as opposed to leaving it as an error component) in estimating (13). Thus, the assumption that cost shifters, such as capital stock in our analysis, are uncorrelated with the error term e_{jt} is more likely to hold in our case. Nonetheless, even if this assumption does not hold, our main result is still robust, as demonstrated in the following two alternative estimation approaches.

The first alternative approach is to recognize that, although e_{jt} may be correlated with contemporaneous capital stock, it is less likely to be correlated with lagged capital stock. In a robustness check using 3rd-6th lags of capital stock (i.e., lagged by quarter of the year) as instrumental

[27] The impact of quality on demand is not exactly equal to the consumption benefit of quality (in terms of consumer utility, as reflected by ξ_{jt} in the utility function (1)). Although the former intrinsically arises from the latter but is also influenced by the elasticity of demand.

variables, we find that the estimate is quantitatively similar, as shown in Column (5) of Appendix Table A2. The results using other lag lengths of capital as IVs are also similar as long as the length of the lags are within a reasonable range (e.g., 12 months). We omit these results in the table to save space.

The second alternative approach is to assume that fundamental demand evolves following an auto-regression evolution process $\phi_{jt} = \rho_0 + \rho_1 \phi_{jt-1} + \upsilon_{jt}$, where υ_{jt} is an innovation term that is observed to the firm and not to researchers. We estimate the demand function and the evolution process jointly. Specifically, we solve ϕ_{jt} and ϕ_{jt-1} from (12) and substitute them into the evolution process in order to compute the innovation term υ_{jt}. We use 1st-3rd lagged capital stock and quality as well as their interactions as instrumental variables to construct moment conditions and estimate the parameters via GMM. The estimated demand elasticity and the benefit of objective quality on demand are close to our main result, as shown in Column (6) of Appendix Table A2.

4.2 Fundamental Productivity

We recover firm fundamental productivity by estimating the production function after accounting for the cost of quality. Specifically, we estimate the production function using a proxy approach, following the insight of Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2015). According to the optimal firm decisions in Section 3.1, we assume that labor input is a monotonic function of fundamental productivity ω_{jt}, conditional on capital stock k_{jt}, fundamental demand ϕ_{jt}, quality ξ_{jt}, and a time dummy ψ_t. Thus, we invert this relationship to writing fundamental productivity as $\omega_{jt} = \omega(\xi_{jt}, \ell_{jt}, k_{jt}, \phi_{jt}; \psi_t)$, where ℓ_{jt} and k_{jt} are the utilized number of workers and capital (i.e., the volume of converters), in logarithm, respectively.[28] Then, the logarithm of the production function (4) is written as:

$$q_{jt} = \alpha_k k_{jt} + \alpha_\ell \ell_{jt} - \alpha_\xi \ln \xi_{jt} + \omega(\xi_{jt}, \ell_{jt}, k_{jt}, \phi_{jt}; \psi_t) + v_{jt}, \tag{14}$$

where the lowercase letters represent variables in logarithm, and v_{jt} is an i.i.d. measurement error. All the variables on the right-hand side (other than the error term v_{jt}) are either observable or estimated. We summarize all the components other than the error term in (14) as a function $h(\cdot)$:

$$q_{jt} = h(\xi_{jt}, \ell_{jt}, k_{jt}, \phi_{jt}; \psi_t) + v_{jt}, \tag{15}$$

[28] The estimation results are robust if alternative proxies are used, as shown in Appendix B.

where $h(\xi_{jt}, \ell_{jt}, k_{jt}, \phi_{jt}; \psi_t) \equiv \alpha_k k_{jt} + \alpha_\ell \ell_{jt} - \alpha_\xi \ln \xi_{jt} + \omega(\xi_{jt}, \ell_{jt}, k_{jt}, \phi_{jt}; \psi_t)$. We specify $h(\cdot)$ as a polynomial function of degree three and control for ψ_t using a time dummy. Given that the measurement error v_{jt} is uncorrelated with the right-hand-side variables, we estimate (15) using an OLS regression and denote the fitted value as $\hat{h}_{jt}$. In turn, we have $\omega_{jt} = \hat{h}_{jt} + \alpha_\xi \ln \xi_{jt} - \alpha_k k_{jt} - \alpha_\ell \ell_{jt}$ and, by substituting it into (6), we obtain the idiosyncratic productivity shock $\epsilon_{it+1} = \omega_{jt+1} - g_0 - g_1 \omega_{jt}$. Finally, we estimate the parameters via the generalized method of moments. Specifically, the moments are:

$$\mathrm{E}(\epsilon_{jt} Z_{jt}) = 0, \tag{16}$$

where Z_{jt} is a set of instrumental variables including $k_{jt}, \ell_{jt-1}, m_{jt-1}, \hat{h}_{jt-1}, \xi_{jt-1}$, and ξ^2_{jt-1}, which by assumption are uncorrelated with the productivity shock ϵ_{jt}.

Remark: In the related literature, the challenge of disentangling the impacts of fundamental productivity and cost of quality is that both factors influence production efficiency while remaining as unobservable sources of heterogeneity to researchers. Although the literature has used residual demand estimated from the demand function as a proxy of output quality in analyzing the relationship between TFPQ and output quality (e.g., Jaumandreu and Yin, 2014; Orr, 2022; Forlani, Martin, Mion, and Muûls, 2023; Eslava, Haltiwanger, and Urdaneta, 2023), it remains an open question how well demand residual can represent output quality in characterizing the potential cost of quality.

In our analysis, the task of identifying quality-related costs from fundamental productivity is facilitated by the observability of output quality in our dataset. As reflected by (14), the variation of output quantity with respect to the observed output quality, after controlling for the inputs as well fundamental productivity which is proxied by the observable variables, identifies cost of quality. Yet, this identification hinges upon several assumptions that are supported by our underlying model in Section 3.1. First, the control function of fundamental productivity is effectively achieved through the specified proxy function, as outlined in (14). Second, regarding the evolution of fundamental productivity, the innovation term ϵ_{jt} in period t is unobservable to the firm in period $t-1$. Consequently, this term is uncorrelated with the instrumental variables in $t-1$ employed in the moment conditions presented in (16). Third, the selection of output quality exhibits persistence due to adjustment costs as discussed in Section 3.1, thus enabling ξ_{jt-1} to function as a suitable instrumental variable for ξ_{jt}.

The estimation results for the production function and productivity evolution process are presented

Table 5: Estimates of the production function and productivity evolution process

Parameter	Estimate	Parameter	Estimate
α_ξ	0.507^{***}	g_0	-0.011^{*}
	(0.186)		(0.006)
α_k	0.750^{***}	g_1	0.975^{***}
	(0.031)		(0.006)
α_ℓ	0.142^{***}		
	(0.044)		

Standard errors are in parentheses.

in Table 5. The estimates of the capital and labor parameters, $\alpha_k = 0.750$ and $\alpha_\ell = 0.142$, are consistent with the high capital-to-labor intensity in the steel-making industry. This result is similar to estimates reported by Brandt, Jiang, Luo, and Su (2022) who find that the coefficient of capital is about 3-5 times as large as the coefficient of labor in the Chinese sintering, pig-iron making, and steel-making industries. Given that the frequency of our data is monthly, the productivity persistence parameter $g_1 = 0.975$ implies a yearly persistence of 0.752. This value is within the range of estimates in the literature (e.g. Baily, Hulten, Campbell, et al., 1992; Roberts and Supina, 2000; Ábrahám and White, 2006; Foster, Haltiwanger, and Krizan, 2006; Foster, Haltiwanger, and Syverson, 2008), which finds that the productivity persistence coefficient is on the order of 0.6 to 0.8 yearly.

The results demonstrate a significant cost effect of quality. The estimate of α_ξ suggests that a 1 percent increase in output quality reduces output quantity by 0.507 percent, holding fundamental productivity, capital, and labor fixed. This structural estimate echoes the empirical patterns reported in Columns (1) and (3) in Table 2 in Section 2.2.2, which show that the quantity of output is lower for higher quality conditional on major input variables. Overall, our result reflects that about half (i.e., $\alpha_\xi = 0.507$) of the consumption benefit created by quality is offset by the cost of producing the quality in the Chinese steel-making industry.

Although our analysis is built upon the direct observation of objective quality in the Chinese steel-making industry, our result regarding cost of quality is largely consistent with the findings in the emerging literature that documenting the negative relationship between quality and quantity (or between TFPQ and demand residual) across various industries and countries using different estimation methodologies. These papers provide external validation of our result. In particular, our cost of quality estimate is close to the finding in Grieco and McDevitt (2017), who show a trade-off between increasing the number of patients treated and improving the quality of care by health care providers. Our result also echoes the finding in Atkin, Khandelwal, and Osman (2019), who reveal a reverse correlation between quantity productivity and quality productivity among rug-makers in Egypt, drawing insights from data that include direct quality assessments. More broadly, this estimate corroborates the negative relationship between quantity-based productivity and "product appeal" documented in the recent literature. For example, Jaumandreu and Yin (2014), Roberts, Yi Xu, Fan, and Zhang (2018), Forlani, Martin, Mion, and Muûls (2023), and Eslava, Haltiwanger, and Urdaneta (2023) document a robust negative correlation between quantity-based productivity and demand residual in across manufacturing firms in various countries (e.g., China, Belgium, and Colombia). At the firm-product level, Orr (2022) and Caselli, Chatterjee, and Li (2023) demonstrate a similar strong negative relationship using data of Indian manufacturers and Mexican manufacturers, respectively. These papers imply that firms incur costs to manufacture products with high quality, using demand residual as an approximation of quality due to the lack of direct quality measure. Our analysis provides direct evidence to support the cost of quality.

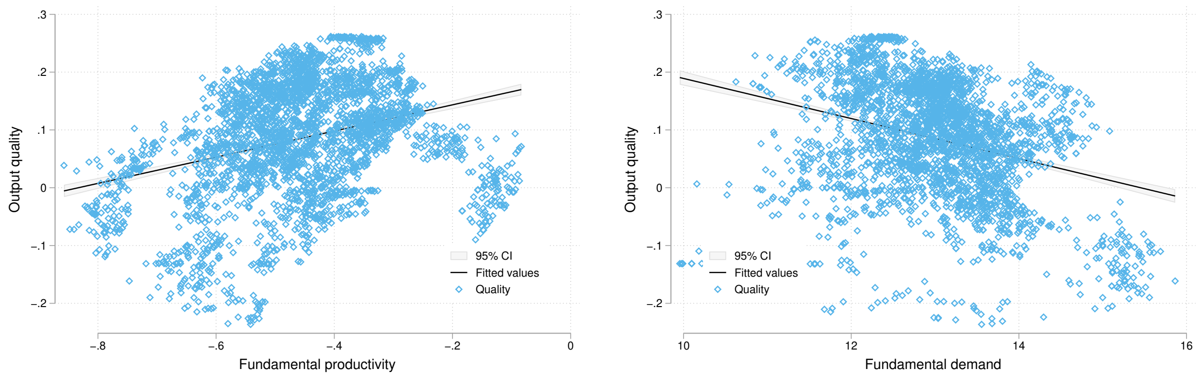
4.3 Output Quality and Fundamental Productivity and Demand: Relationship

This subsection explores how objective output quality is related to fundamental productivity and fundamental demand.

First, fundamental productivity (i.e., ω) is a strong predictor of output quality ($\ln \xi$). The relationship between the two is presented in Figure 2a. The positive association suggests that firms with high fundamental productivity endogenously choose to produce high-quality steel to maximize profit. This result is consistent with the endogenous quality theory in Kugler and Verhoogen (2009, 2012) where prices are used as a proxy for quality in Colombian manufacturing census data. Importantly, our analysis reconciles the positive productivity-quality association implied by Kugler and Verhoogen (2009, 2012) with the negative correlation between TFPQ and demand residual documented in the more recent literature (e.g., Jaumandreu and Yin, 2014; Orr, 2022; Forlani, Martin, Mion, and Muûls, 2023; Eslava, Haltiwanger, and Urdaneta, 2023). That is, although producing quality is costly (implying a negative pressure in the association between TFPQ and quality), after controlling for such cost, the fundamental productivity and quality are positively correlated. Nonetheless, the correlation coefficient between the two (0.444, in Table 6) is far from 1. This implies that there exist other quality determinants whose variations do not align with that of the fundamental productivity, as conjectured in Section 3.1.

This result also has an important implication for the correlation between endogenous output prices and fundamental productivity. Our result shows a positive correlation (0.207) between them.

Figure 2: The relationship between output quality and fundamental productivity and demand



(a) Fundamental productivity and quality (b) Fundamental demand and quality

This is in contrast to Foster, Haltiwanger, and Syverson (2008), who find a negative correlation between output prices and productivity in homogeneous-product industries, where more efficient firms can pass along their cost savings through lower prices.[29] When output quality varies, quality differentiation provides two new channels which drive a positive correlation between fundamental productivity and output prices. The first channel is that higher quality increases production costs and consequently drives up output prices. The second channel is that firms producing high-quality output may charge higher prices because high quality increases demand as we show in the robustness check. Therefore, if more productive firms endogenously choose to produce high-quality products, the correlation between fundamental productivity and output prices can be positive if the effect from the new quality channels dominates the traditional efficiency-price pass-through.

Table 6: Correlation between quality, prices, and productivity

	Fundamental productivity	TFPQ
Quality	0.444***	-0.136***
Price (log)	0.207***	0.126***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Second, fundamental demand (ϕ) is significantly different from objective output quality ($\ln \xi$), in terms of their degrees of dispersion and correlation. As to be shown in Table 9, the interquartile range (IQR) of fundamental demand is more than 5 times larger than the IQR of output quality.[30] This is because they are different aspects of firm heterogeneity that are not necessarily aligned with each other as discussed in Section 3.1.[31] This is also reflected by their (weak) negative

[29]Remind that in homogeneous industries, TFPQ is a precise measure of fundamental productivity, ω.
[30]This difference in IQR is robust even if the firm fixed effect and time fixed effect are excluded from ϕ.
[31]In the presence of adjustment costs, firms may not be able to adjust output quality according to demand shocks

relationship as shown in Figure 2b.[32] Such a negative fundamental demand-quality relationship is potentially due to segmented quality-dependent markets for steel of different levels of quality. That is, the market size (fundamental demand) of high-quality steel may be even lower than that of low-quality steel.[33]

Table 7: Production costs of quality: alternative quality measures

	(1) logQ	(2) logQ	(3) logQ	(4) logQ
Fundamental demand	0.024***	0.024***		
	(0.003)	(0.003)		
Demand residual			0.002	0.000
			(0.003)	(0.003)
Year-month FE		Y		Y
Fundamental productivity	Y	Y	Y	Y
capital (log)	Y	Y	Y	Y
labor (log)	Y	Y	Y	Y
Observations	3,916	3,916	3,916	3,916
Adjusted R^2	0.985	0.984	0.984	0.984

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

More importantly, fundamental demand and output quality also have different influences on the variable production cost. While output quality has a significant negative impact on the quantity output (as captured by the cost of quality) as shown in the production function estimation result in Table 5, fundamental demand has a small, positive influence on the quantity output. The latter is reflected in Table 7. We estimate OLS regressions as analogs of production function (4) in logarithm using either fundamental demand (in the first two columns) or demand residual (in the last two columns) as a replacement of output quality.[34] Furthermore, treating the demand residual as a proxy of output quality (as usually implemented in the literature without observing the actual output quality), Columns (3) and (4) show the impact is insignificant economically and statistically.[35] This is intuitive – output quality affects the marginal cost of production while

timely. However, the documented weak correlation is not driven by time-specific shocks because they (as time effects) are removed in computing the correlation. Instead, the weak correlation is mainly because output quality, as an endogenous choice, relies on factors such as fundamental productivity, capital stock, and input prices, whose variations are not necessarily aligned with that of fundamental demand, as demonstrated in Section 3.1.

[32] This relationship is robust even if the fundamental productivity ω is controlled for.

[33] Nonetheless, this does not mean that the impact of output quality on the firm demand is negative. By separately accounting for output quality and fundamental demand in the demand function, the estimation results in Table 4 show that higher quality increases firms' sales quantity holding price and fundamental demand fixed.

[34] We include the estimated fundamental productivity in the regressions to avoid the endogeneity issue caused by unobservable fundamental productivity.

[35] In an unreported specification, we estimate a version of the production function following the same procedure of Section 4.2 with both output quality and fundamental demand allowed to influence output. We found a result consistent with the pattern of Table 7 – the influences of output quality and fundamental demand are dramatically different qualitatively and quantitatively.

fundamental demand may mainly come from the effort of marketing (as a kind of fixed cost). When confounding them as the demand residual, the positive effect of fundamental demand on output quantity is offset by the negative effect of objective output quality on output quantity (as shown in Table 8 in the next section).

5 Distinct Roles of Firm Heterogeneity on Sales Performance

The literature has a long tradition of using unobservable firm characteristics (e.g., productivity) to explain firm behavior and performance (e.g., Jovanovic, 1982; Hopenhayn, 1992; Ericson and Pakes, 1995; Melitz, 2003). More recently, Pozzi and Schivardi (2016) stress the distinct characteristics of demand and productivity and their impact on firm performance. However, due to the lack of firm-level quality data, the literature usually confounds fundamental productivity and demand with output quality. This may produce biased results on the role of fundamental productivity and demand on firm performance, because the growth of output quality may not align with fundamental productivity and demand, as documented in Section 4.3. In this section, we examine the distinct roles of firm heterogeneity in output quality, fundamental productivity, and fundamental demand on firm revenue, pricing, and quantity sales.

For this purpose, we estimate a panel data fixed effect model, accounting for year-month fixed effects and observable firm characteristics. The results are reported in Table 8. Column (1) shows that both fundamental productivity (measured as ω) and fundamental demand (measured as ϕ) are positively associated with firms' revenue. The elasticity of fundamental productivity is about 0.507, while fundamental demand has a significantly larger elasticity (about 0.624). This difference corroborates the finding of Pozzi and Schivardi (2016), who show that the pass-through of productivity shocks to growth is more incomplete, compared with demand shocks. Nonetheless, fundamental productivity and fundamental demand influence firm revenue through different channels. Columns (2)-(3) of Table 8 show that higher fundamental productivity reduces prices but increases output, with elasticities at -0.518 and 1.025, respectively. In contrast, higher fundamental demand increases both prices and output quantity, with elasticities of 0.363 and 0.261, respectively.

Although output quality also increases firm revenue (with an elasticity of 0.427), its mechanism is different from that of fundamental productivity and demand. Table 8 shows that the revenue-promoting effect of output quality is contributed by a positive effect on output prices (0.564) and a negative effect on output quantity (-0.137). The negative quality-quantity association is the result of two reinforcing forces. On the one hand, it reflects a trade-off between quality and

Table 8: Firm heterogeneity and sales performance

	(1) log(R)	(2) log(P)	(3) logQ
Fundamental productivity	0.507***	-0.518***	1.025***
	(0.024)	(0.024)	(0.048)
Fundamental demand	0.624***	0.363***	0.261***
	(0.005)	(0.005)	(0.010)
Output quality	0.427***	0.564***	-0.137***
	(0.024)	(0.025)	(0.049)
Year-month FE	Y	Y	Y
Capital capacity (log)	Y	Y	Y
Avg. converter size (log)	Y	Y	Y
Observations	3,876	3,876	3,876
Adjusted R^2	0.942	0.596	0.757

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

quantity in the production process, holding all other factors fixed. On the other hand, higher quality increases prices, which contributes to reducing demand. The different mechanisms through which output quality, fundamental productivity, and fundamental demand affect firm revenue performance highlight their distinct nature as aspects of firm heterogeneity.

Combining the effect of fundamental productivity, fundamental demand, and the costs and benefits of higher quality, revenue productivity (TFPR) is still a natural measure of firms' overall performance, despite the different roles of these individual components. The variation of TFPR is mainly driven by firms' fundamental demand. Table 9 shows that the interquartile range (IQR) of fundamental demand is 1.060, which is fairly close to that of TFPR (1.084). In contrast, the dispersion (measured as IQR) of fundamental productivity is merely 0.180. The dispersion of output quality is comparable to that of fundamental productivity. But considering the cost of quality, which is also a component of TFPR, the net effect of quality in driving the TFPR dispersion is even smaller.

Table 9: Dispersion of quality, productivity, and demand

	TFPR	ω	$\ln\xi$	ϕ	TFPQ	Demand Residual
Interquartile range (IQR)	1.084	0.180	0.156	1.060	0.176	0.997

When decomposing TFPR in a traditional format as TFPQ and demand residual, both of which embody output quality, these components have smaller dispersion compared with these of fundamental productivity and fundamental demand, respectively, as shown in Table 9. This is due to the output quality's positive correlation with fundamental productivity and its negative correlation with fundamental demand. In particular, while firms with higher fundamental productivity tend to produce higher quality steel, the higher quality incurs higher production costs. Such cost of quality, without being accounted for explicitly, is captured as a part of TFPQ and reduces its dispersion. But more importantly, if the cost effect is large enough to offset the positive efficiency-quality association (i.e., the correlation between fundamental productivity and output quality), TFPQ and output quality are negatively correlated. In the case of the steel-making industry in question, the correlation coefficient is -0.136.

Overall, these results from the firm-level analysis reflect the importance of distinguishing output quality from fundamental productivity and demand as distinct aspects of firm heterogeneity. In the following section, we use the 2008 global financial crisis as a case study to evaluate the growth of TFPR and the roles of output quality, fundamental productivity, and fundamental demand in driving the growth of TFPR in the Chinese steel-making industry.

6 Quality Shocks and Aggregate Productivity Growth

The literature (e.g., Foster, Haltiwanger, and Syverson, 2008; Pozzi and Schivardi, 2016) shows that both production side and demand side factors are sources of productivity growth and firm performance. Nonetheless, in the context of quality-differentiated industries, the production side factor (i.e., TFPQ) and demand side factor (i.e., demand residual) as discussed in the literature embody the cost of quality and benefit of quality, respectively. This consequently biases the estimates of their roles in driving revenue productivity growth. This is because the growth of output quality, which is affected by several determinants as discussed in Section 3.1, does not necessarily align with the growth of demand and production side factors especially when firms face large economic shocks.

This section empirically evaluates the contribution of quality as well as fundamental productivity and demand to the growth of aggregate revenue productivity, when output quality varies due to large economic shocks. The Chinese steel-making industry around the 2008 Global Financial Crisis provides an excellent case for this purpose. During our data period, the steel-making industry in China experienced a large economic shock due to the global financial crisis and the induced unprecedented stimulus plan by the Chinese government. The shock caused significant fluctuations in output quality, fundamental productivity, and fundamental demand in the industry. We first examine how these individual components influence aggregate productivity growth measured by TFPR. Then, we illustrate how the contributions of TFPQ and demand residual as proxies of fundamental productivity and demand, respectively, can be biased due to the embodied output quality. We compute the sales-weighted average of each measure and present their growth over the crisis-stimulus period (2007-2010) and the post-crisis period (2010-2014), respectively, in Table 10.

The crisis-stimulus period (2007-2010). During this period, the industrial level TFPR increased by 6.98 percentage points. This is mainly due to a significant increase in fundamental demand (i.e., ϕ) by 6.84 percentage points and a slight increase in fundamental productivity by 0.45 percentage point. However, there was a decline (0.63 percentage) in the average quality, consistent with Figure 1. This is because foreign demand (i.e., exports, representing the demand for high-quality steel) for Chinese steel products decreased, as discussed in Section 2, while the Four Trillion Stimulus Plan initiated by the Chinese government substantially increased the domestic demand, which is on average of low quality. Noticeably, the negative contribution of output quality is opposite to the growth of demand and fundamental productivity in this period. Nonetheless, such quality deterioration also lowered production costs (as reflected as $-\alpha_\xi \ln \xi_{jt}$), which partially alleviated the impact of lowered quality on TFPR. As a result, the overall effect of quality, as measured by $(1 - \alpha_\xi) \ln \xi_{jt}$, is relatively small.

The relatively small contribution of true quality is in sharp contrast to the role of demand residual, which is conventionally understood as a measure of quality. As shown at the bottom of the first column of Table 10, the conventional measure of quality (i.e., demand residual) contributes 89 percent of the drop of TFPR while the actual contribution of quality (i.e., $\ln \xi$) is negative and much smaller. In contrast, the contribution of demand residual is much more in line with that of fundamental demand. In addition, the role of the production side is overstated in comparison between the contributions of TFPQ and fundamental productivity. This is because TFPQ contains the cost of quality which decreased due to the lowered quality level.

The post-crisis period (2010-2014). After 2010, the export demand started to recover and experienced steady growth afterward, as the world gradually recovered from the global financial crisis. Meanwhile, as the effect of the stimulus plan in China gradually faded away, the domestic steel demand decelerated due to the slowdown of growth in its major domestic downstream industries. Consequently, the aggregate quality of steel grew strongly in this period by 3.04 percentage points. The aggregate fundamental demand increased by 6.41 percentage points as the export market began to recover in the post-crisis period. Nonetheless, fundamental productivity declined significantly by 3.63 percentage points, presumably because of overcapacity – the capacity built up during the economic stimulus period (through investment) was much larger than the

Table 10: Decomposition of aggregate productivity growth (percentage points)

	Crisis-Stimulus Period (2007-2010)	Post Crisis Period (2010-2014)
TFPR ($\omega - \alpha_\xi \ln \xi + \ln \xi + \phi$)	6.98	4.27
contributed by		
—Fundamental demand (ϕ)	6.84	6.41
—Fundamental productivity (ω)	0.45	-3.63
—Benefit of quality ($\ln \xi$)	-0.63	3.04
—Cost of quality ($-\alpha_\xi \ln \xi$)	0.32	-1.54
contributed by		
—Demand residual ($\ln \xi + \phi$)	6.21	9.45
—TFPQ ($\omega - \alpha_\xi \ln \xi$)	0.77	-5.17

decreased demand during the post-crisis period. In sum, the contrast suggests that the growth of quality may not align with the growth of fundamental productivity.

It is worth noting that, without distinguishing the output quality and fundamental demand, the conventional measure of demand residual grew dramatically by 9.45 percentage points, which is significantly higher than the growth of output quality (3.04 percentage points). The growth of demand residual is even significantly different from the growth of fundamental demand because output quality grew substantially in the post-crisis period. This is in sharp contrast to the crisis-stimulus period when demand residual largely captures the growth of fundamental demand because the growth of output quality is mild. The comparison further suggests the distinct roles of output quality and fundamental demand in driving TFRP growth. Finally, TFPQ reflects a growth of -5.17 percentage points, significantly understating the productivity growth as measured by fundamental productivity (-3.63 percentage points).

Overall, we find that fundamental demand is a stronger driver of TFPR growth compared with fundamental productivity, after controlling for output quality. The growth of output quality, however, does not necessarily align with the growth of demand or fundamental productivity. If output quality growth is in the opposite direction of demand or fundamental productivity, the conventional proxies of demand or fundamental productivity understate their contributions to TFPR growth and vice versa.

7 Robustness Analysis

7.1 Variable Markups

Our main results assume that the elasticity of demand is constant and thus the implied markups are the same across firms and over time. Nonetheless, it is possible that firms that produce high quality steel also charge high markups. That is, essentially, the demand elasticities (thus markups) can be different across firms and over time. However, given that we follow Melitz (2000) to define TFPR as (9) in Section 3.2, the decomposition of TFPR is robust to the potential markup variation, conditional on the demand and production function parameters. Of course, the demand and production function parameters may be different in the scenario where the variable markups are allowed. In what follows, we show that our main results are robust by estimating a variant of the model with variable markups.

Specifically, while we maintain the other elements of the model, we assume that the demand elasticity is a function of output quality. Thus, the demand function (13) is flexibly written as:

$$\ln Q_{jt} = \sigma_P \ln P_{jt} + \sigma_\xi \ln \xi_{jt} + \sigma_{\xi P} \ln \xi_{jt} \ln P_{jt} + \phi_j + \phi_t + e_{jt}. \tag{17}$$

In order to make the results comparable, we have used the estimated $\hat{\gamma}$ in the main result to define $\ln \xi_{jt} = \hat{\gamma}\xi^0_{jt}$ in the above specification. The demand elasticity, $\sigma_P + \sigma_{\xi P} \ln \xi_{jt}$, depends on output quality ($\ln \xi_{jt}$) as long as $\sigma_{\xi P}$ is non-zero. If $\sigma_{\xi P} = 0$, then the demand model degenerate to our main specification (13).

We use the same method as described in Sections 4.1 and 4.2 to estimate the demand function (17) and the production function (4), respectively. The results are presented in Appendix Table A3. Not surprisingly, there is indeed an impact of output quality on demand elasticity. The estimates suggest that a 1 percent increase in output quality rises the demand elasticity by 1.3 percent (i.e., more inelastic), implying a higher markup. Overall, the standard deviations of the demand elasticities and markups, as a measure of their dispersion, are 0.338 and 1.334, respectively. Nonetheless, the estimates imply a median demand elasticity of -1.602, which is similar to our main results (-1.980), and a median markup of 2.661, which is also similar to our main results (2.020), as suggested by the estimates in Table 4. On the production side, the parameter estimates are quantitatively similar to our main results in Table 5. In particular, the estimate of α_ξ suggests that a 1 percent increase in output quality reduces output quantity by 0.537 percent, holding fundamental productivity, capital, and labor fixed. This is very close to that estimated in our main result in Table 5.

7.2 Flexibly Estimated Quality Index Numbers

In our main results, we follow the industry practice to define the firm-level steel quality index as the average of a set of descending quality index numbers (i.e., $\alpha_H = 1.5$, $\alpha_M = 1$, and $\alpha_L = 0.5$)

weighted by the quantity shares of output produced under each of the three quality standards. In this section, we examine the validity of these quality index numbers in representing the quality differences among the three standards. We show the robustness of our results by estimating the quality index numbers flexibly, following the insight of Atkin, Khandelwal, and Osman (2019).

Specifically, we treat α_H, α_M, and α_L as parameters to be estimated. Similar to Section 2.2, we define the quality index as $\xi_{jt}^0 = \alpha_H S_{Hjt} + \alpha_M S_{Mjt} + \alpha_L S_{Ljt}$, where $S_{Hjt} = \frac{Q_{Hjt}}{Q_{jt}}$, $S_{Mjt} = \frac{Q_{Mjt}}{Q_{jt}}$, and $S_{Ljt} = \frac{Q_{Ljt}}{Q_{jt}}$ are the quantity shares of output produced at the international standard, national standard, and enterprise standard, respectively. Substituting the quality index in (13), we have

$$\ln Q_{jt} = -\sigma \ln P_{jt} + \gamma(\sigma - 1)(\alpha_H S_{Hjt} + \alpha_M S_{Mjt} + \alpha_L S_{Ljt}) + \phi_j + \phi_t + e_{jt}.$$

Without loss of generality, we normalize $\alpha_M = 1$ as a location normalization. Because $S_{Hjt} + S_{Mjt} + S_{Ljt} \equiv 1$, the above equation can be rewritten as:

$$\ln Q_{jt} = -\sigma \ln P_{jt} + \tilde{\alpha}_H S_{Hjt} + \tilde{\alpha}_L S_{Ljt} + \phi_j + \phi_t + e_{jt}. \tag{18}$$

where $\tilde{\alpha}_H = \gamma(\sigma - 1)(\alpha_H - 1)$ and $\tilde{\alpha}_L = \gamma(\sigma - 1)(\alpha_L - 1)$. With a slight abuse of notation, we combine the normalization term with α_M with the fixed effect terms to avoid additional notations. Obviously, the scale of α_H and α_L is not identified separately from γ in this flexible specification. Instead, we can only estimate the combined terms $\tilde{\alpha}_H$ and $\tilde{\alpha}_L$. The sign of $\tilde{\alpha}_H$ and $\tilde{\alpha}_L$ shows the ordinal relationship among α_H, α_M, and α_L, given γ and σ. (18) can be estimated similarly to that in our main results, using the instrumental variable approach to deal with potential endogeneity in output prices and shares of products produced following different standards.

The estimation results are reported in Panel A in Appendix Table A4. In all specifications, we controlled for firm fixed effects. In the OLS estimation, as expected, the elasticity of demand σ is biased due to potential endogeneity problems. In the second column, we use capital stock and the interaction of lagged output shares produced according to international and enterprise standards as instrumental variables for output prices and output shares. In the third column, we further control for year-month fixed effect in addition to the above IV approach. The elasticity of substitution (i.e., $\sigma = 1.935$) from the instrumental variable approach is similar to that in our main results. More importantly, the quality index numbers (Panel B) implied from the estimates are $\hat{\alpha}_H = 1.468$, $\hat{\alpha}_M = 1$ (as normalized), and $\hat{\alpha}_L = 0.468$.[36] They are very close to those used

[36] Because γ and the scale of $\alpha's$ are not separately identifiable, we normalize $\alpha_H - \alpha_L = 1$ in order to make the estimation comparable with those in the industry practice. That is, the difference between the highest and lowest

in the industry. This shows that the quality index numbers used in our main results are indeed consistent with the quality ladder of the three quality standards.

Given the estimated quality index numbers and demand function, we re-calculate the output quality index and re-estimate the production function in the same way as Section 4.2. The output quality index is highly correlated with that used in the main results, with a correlation coefficient of 0.98. We report the production function estimation results in Panel C of Appendix Table A4. Then, we re-compute the productivity measures and report their dispersion (as shown by the interquartile range) in Panel D. Finally, we re-calculate the aggregate growth of TFPR and its decomposition and report them in Panel E. Not surprisingly, all the results are similar to our main results. This supports the validity of the quality index numbers used in practice in the industry and shows that our main results are robust to the alternative index numbers flexibly estimated from the data.

8 Conclusion

Unobserved output quality differences present a challenge in understanding the magnitude and effect of firms' advantages in productivity and demand on performance because producing high-quality products incurs higher costs but provides greater consumption benefits. When facing large shocks—such as the 2008 global financial crisis and the resulting unprecedented stimulating policy in China—the demand for different quality levels may change disproportionally. This creates further difficulty in evaluating the growth of firm capability before and after the shocks.

This paper investigates firms' heterogeneity in output quality and fundamental productivity and demand, using a unique panel that contains an index of scientific output quality from the Chinese steel-making industry. The objective quality measure allows us to decompose the traditional TFPQ into the fundamental productivity and the costs of quality; it also allows us to decompose the demand residual (usually labeled as quality or product appeal in the literature) into the fundamental demand and the consumption benefit of quality. We find that about half of the benefits created by quality are offset by the cost of producing quality in the steel industry. There is a small difference in fundamental productivity and a large difference in fundamental demand across firms and over time, after controlling for quality. More importantly, while productivity is a strong predictor of firms' quality choice, fundamental demand is only weakly correlated with

quality index numbers is normalized to be 1, as in the industry practice. Given the estimates of the third column in Panel A, this implies $\gamma * (\sigma - 1) = 0.391$. The implied quality index number for international standard (α_H) is thus $1 + \tilde{\alpha}_H / (\gamma * (\sigma - 1)) = 1.468$, following the definition of $\tilde{\alpha}_H$. The implied quality index number for enterprise standard (α_L) can be similarly calculated. Given $\hat{\sigma}$, the implied scale-adjustment parameter $\hat{\gamma} = 0.391/(\hat{\sigma} - 1) = 0.418$.

output quality, highlighting the necessity of separating quality from the other two.

In the application, we document that the 2008 global financial crisis and the induced unprecedented stimulating policy in China non-negligibly reduced the average quality of steel in the first few years; the quality increased during the post-crisis period following the recovery of high-quality steel export and slow growth of domestic low-quality demand. We show that output quality may reinforce or mitigate the changes in revenue productivity as a measure of firm performance, because the growth of output quality may not align with fundamental productivity and demand depending on the nature of the economic shocks. Furthermore, TFPQ and demand residual—by confounding the production costs and demand benefits of output quality, respectively—substantially bias the evaluation of the contribution of fundamental productivity and demand to firm and industry performance.

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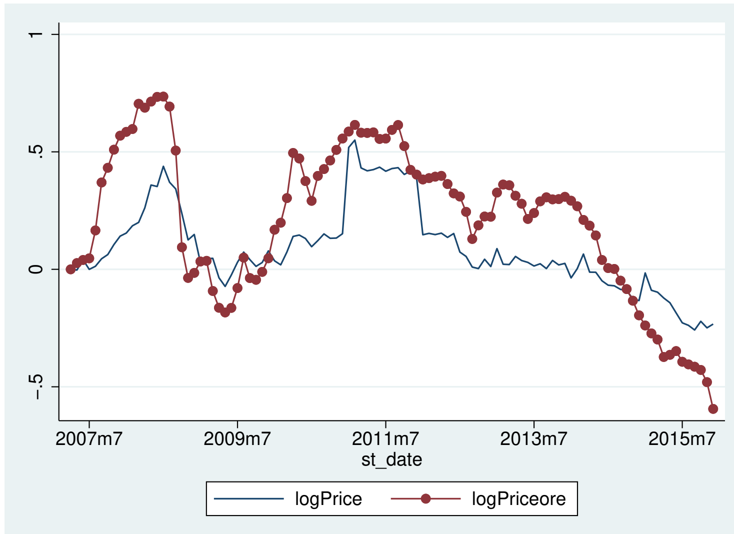
Appendices

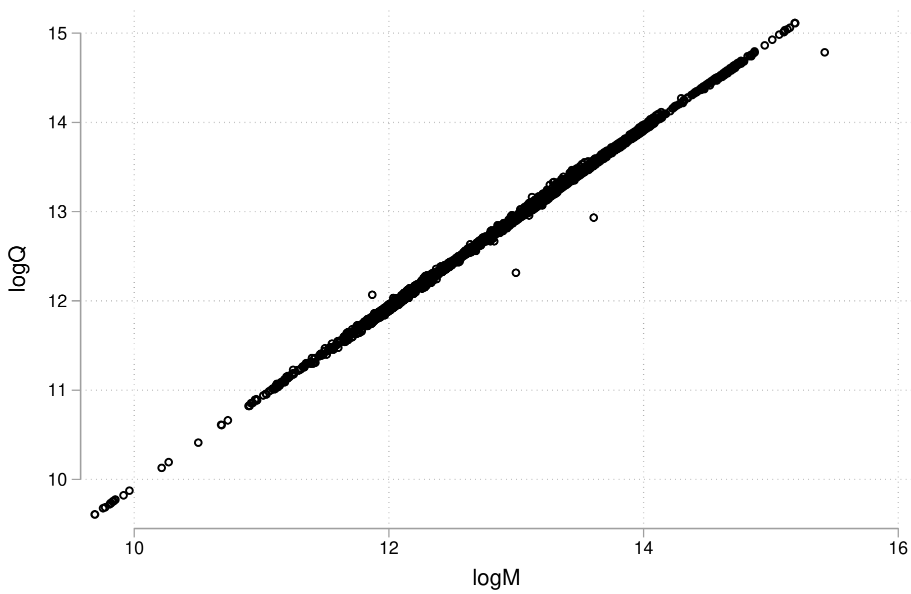
A Appendix Figures and Tables

Figure A1: Co-movement of the iron ore price and steel price in logarithm, normalized



Note: This figure presents the co-movement of prices of steel and iron ore from 2007 to 2014. The vertical axis represents the average prices (in logarithm) at the monthly level, and the horizontal axis is the time (e.g. 2007m7 means July 2007). The average prices of the first month are normalized to be 1 (or 0 in logarithm). The figure shows that the two prices co-move and the steel prices largely reflect the changes in iron ore prices over time. This scenario is consistent with the estimation results in Table 1, which shows that the estimated correlation between steel prices and product quality increases after controlling for the year-month fixed effect.

Figure A2: Leontief technology of steel production: quantities of input (pig iron) and output(steel), tonnage



This figure provides support for the choice of Leontief production in (3) reflects the feature of the production process in the steel-making industry. In our data, the steel output and pig iron input are almost perfectly correlated. The correlation coefficient between these two variables is 1.00. A linear regression of $\ln Q_{jt}$ against $\ln M_{jt}$ shows that the variation of materials explains 99.89 percent of the variation of physical output, with a regression coefficient of 1.00. This suggests that the usage of materials directly determines the quantity of physical output, with little substitution between pig iron material input and other inputs (labor and capital).

Table A1: National and international differences in standards for carbon structural steel

	National (GB/T699-2015)	International (Japan, G4051-2016)
Si(%)	0.17-0.37	0.15-0.35
Mn(%)	0.35-0.65	0.30-0.60
P(%)	$\leq$0.035	$\leq$0.03
S(%)	$\leq$0.035	$\leq$0.035
Cr(%)	$\leq$0.25	$\leq$0.20
Ni(%)	$\leq$0.25	$\leq$0.20
Cu(%)	$\leq$0.25	$\leq$0.30
Yield strength (MPa)	$\geq$ 245	$\geq$ 245
Tensile strength (MPa)	$\geq$ 410	$\geq$ 402
Elongation (%)	$\geq$21	$\geq$28
Impact energy (J)	$\geq$27	$\geq$40

[1] To ensure comparability, we chose the 25mm sample bar size from Type 20 in China and S20C in Japan, which are both carbon structural steel with similar carbon content (0.18-0.23%). Carbon structural steel belongs to the low carbon, low carbon chromium, molybdenum, and nickel case hardening steel. It is widely produced by Chinese steelmakers. It is usually in round bars and flat sections but can be cut to any required size. It is widely used for all industrial applications requiring more wear resistance and strength, such as gears, pins, and rams.

[2] The product is of higher quality if it has fewer impurities (P, S, Cr, and Ni), or higher physical properties (yield strength, tensile strength, elongation, and impact energy).

[3] Data source: https://www.totalmateria.com.

B Robustness of the Demand Estimates

In the main results, we estimated the demand function, (13), using a dynamic panel data approach with capital stock as an instrumental variable for the output price. There are two assumptions for the consistent estimates. First, the unobserved demand shock, e_{jt}, is uncorrelated with the firm's capital stock. Second, the unobserved demand shock is uncorrelated with output quality ξ^0_{jt}. This appendix shows that our results are robust to alternative assumptions.

In Column (1) of Table A2, we show that our results are robust when using lagged capital stock as an instrumental variable for output prices. This relaxes the first assumption above slightly, by allowing the unobserved demand shock, e_{jt}, to be potentially correlated with the current period capital stock (but not the lagged capital stock). To address the possibility that the unobserved demand shock may be correlated with current-period ξ^0_{jt}, we instrument ξ^0_{jt} using its lag in Columns (2)-(4). Specifically, we use ξ^0_{jt-1} and ξ^0_{jt-2} as instrumental variables for ξ^0_{jt} in Columns (2) and (3), while maintaining current-period capital stock as an instrumental variable for the output price. In Column (4), we use the lagged quality index as the instrumental variable for ξ^0_{jt} while using the lagged capital stock as an instrumental variable for the output price. In Column (5), we use 3rd-6th lags of capital stock, which are less likely to be correlated with the current fundamental demand, as instrumental variables for the output price. Finally, in Column (6), we jointly estimate the demand function and the evolution of fundamental demand, which follows an auto-regression process $\phi_{jt} = \rho_0 + \rho_1\phi_{jt-1} + \upsilon_{jt}$, where υ_{jt} is an innovation term that is observed to the firm and not to researchers. In all specifications, our demand estimates are robust qualitatively and quantitatively.

Table A2: Estimates of the demand function: alternative specifications

	(1)	(2)	(3)	(4)	(5)	(6)
σ	2.063***	1.950***	1.933***	2.063***	2.148***	1.435***
	(0.066)	(0.049)	(0.048)	(0.066)	(0.099)	(0.147)
$\gamma(\sigma-1)$	0.545***	0.510***	0.506***	0.554***	0.563***	0.848***
	(0.064)	(0.064)	(0.064)	(0.069)	(0.073)	(0.417)
	(0.062)	(0.058)	(0.057)	(0.062)		
Year-month FE	✓	✓	✓	✓	✓	
Firm FE	✓	✓	✓	✓	✓	
AR(1)						✓
Observations	3937	3938	3841	3937	3507	3717

Standard errors are in parentheses.

Column (1): use lag capital as IV for price; no IV for quality.

Column (2): use capital and lag quality as IV for price and quality.

Column (3): use capital, lag quality, and second order lag quality as IV for price and quality.

Column (4): use lag capital and lag quality as IV for price and quality.

Column (5): use 3rd-6th lags (i.e., lagged by a quarter of the year) of capital and quality as IV for price and quality. Results are robust with other lengths of capital lags.

Column (6): assume AR(1) of fundamental demand: $\phi_{jt} = \rho_0 + \rho_1 \phi_{jt-1} + \upsilon_{jt}$.
The estimated monthly persistence is 0.989, implying yearly persistence of 0.874.

* $p < .10$, ** $p < .05$, *** $p < .01$.

Table A3: Robustness: Demand and production estimates with variable markups

Parameter	Demand	Parameter	Production
σ_P	-1.794***	α_ξ	-0.536***
	(0.045)		(0.018)
σ_ξ	0.610***	α_k	0.731***
	(0.078)		(0.034)
$\sigma_{\xi P}$	1.300***	α_ℓ	0.161***
	(0.404)		(0.048)
		g_0	-0.007
			(0.0006)
		g_1	0.974***
			(0.006)

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table A4: Robustness: Results using estimated quality index numbers

Panel A: Demand function estimates			
	OLS	IV	IV
σ	0.603***	2.387***	1.935***
	(0.017)	(0.069)	(0.048)
$\tilde{\alpha}_H$	0.105***	0.269***	0.184***
	(0.034)	(0.086)	(0.066)
$\tilde{\alpha}_L$	-0.104**	-0.280***	-0.209***
	(0.044)	(0.106)	(0.081)
Time FE			✓
Firm FE	✓	✓	✓
Observations	4,070	3,938	3,896

Panel B: Implied quality index numbers			
	α_H	α_M	α_L
Flexibly estimated (based on last column above)	1.468	1.000	0.468
Industry practice (used in main results)	1.500	1.000	0.500

Panel C: Production function estimates					
	α_ξ	α_k	α_ℓ	g_0	g_1
	0.647***	0.751***	0.140***	-0.011**	0.976***
	(0.237)	(0.031)	(0.044)	(0.006)	(0.006)

Panel D: Dispersion						
	TFPR	ω	$\ln\xi$	ϕ	TFPQ	Demand Residual
Interquartile range	1.132	0.181	0.125	1.094	0.176	0.994

Panel E: Aggregate productivity growth		
	2007-2010	2010-2014
TFPR ($\omega - \alpha_\xi \ln\xi + \ln\xi + \phi$)	7.22	4.73
contributed by		
—Fundamental demand (ϕ)	7.01	7.45
—Fundamental productivity(ω)	0.39	-3.59
—Benefit of quality ($\ln\xi$)	-0.54	2.46
—Cost of quality ($-\alpha_\xi \ln\xi$)	0.36	-1.59
contributed by		
—Demand residual ($\ln\xi + \phi$)	6.47	9.91
—TFPQ ($\omega - \alpha_\xi \ln\xi$)	0.75	-5.18