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

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Abstract

Unobserved objective output quality complicates the analysis of firm productivity and demand because higher-quality products entail higher costs but offer greater consumption benefits. Using a panel of firms with output quality data, we decompose quantity-based productivity into fundamental productivity and the costs of quality, and separate the demand residual into fundamental demand and quality benefits. Fundamental demand accounts for most revenue variation, whereas quality's revenue-enhancing benefits are largely offset by its costs. During the 2008 global financial crisis, shifts in quality diverged from changes in fundamental productivity and demand, highlighting the role of quality in assessing firm and industry performance.

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1 Introduction

Productivity and demand are two fundamental sources of firm heterogeneity, playing distinct roles in shaping firm turnover (Foster et al., 2008), growth (Pozzi and Schivardi, 2016), investment (Kumar and Zhang, 2019), and international trade (Roberts et al., 2018). However, understanding firm heterogeneity in productivity and demand is complicated by the presence of unobserved *objective* output quality. Producing high-quality products typically incurs higher costs, which, if unobserved, can mask true productivity differences driven by technological or managerial factors. Simultaneously, premium-quality products enhance consumer utility and increase demand, which can confound market-driven demand shifters such as marketing efforts and customer base.

This paper investigates firm-level heterogeneity in productivity and demand, disentangling their roles from firms' *objective* output quality and evaluating their distinct contributions to firm and industry growth. Leveraging a unique panel dataset from the Chinese steelmaking industry—which includes a firm-level index of scientifically measured output quality—we directly quantify the production costs associated with quality. This enables us to decompose the traditionally studied quantity-based productivity (TFPQ, as in Foster et al., 2008) into two distinct components: the costs of quality and a measure of fundamental productivity driven by technology. Simultaneously, the direct quality measure allows us to isolate the demand-enhancing effects of objective quality from a firm's market-driven fundamental demand (e.g., factors arising from marketing and customer base)—two elements typically conflated under the broader concept of "product appeal" (e.g., Eslava et al., 2024). This dual decomposition yields clean measures of both fundamental productivity and fundamental demand, free from confounding by endogenous variations in objective quality.

Our analysis is based on a panel of steelmaking firms in China, with a monthly frequency from 2007 to 2014. As a key feature, this dataset includes a direct measure of objective, scientific output quality at the firm level, in addition to detailed information on output prices and the quantities of inputs and outputs. The quality measure is based on the output shares produced under three different quality standards—international, national, and enterprise standards—in descending order. Output quality shows substantial variation across firms and over time, highlighting the importance of distinguishing the production costs of quality from fundamental productivity and discerning the quality-driven benefits from those stemming from fundamental demand.[1]

Our analysis reveals several important insights. First, after accounting for output quality differences, fundamental demand exhibits much larger dispersion than fundamental productivity, with a standard deviation of 1.013 compared to 0.157 for productivity. The large demand heterogeneity likely stems from firms' inherent customer base and investments in demand-enhancing activities, such as advertising and marketing, whereas differences in productivity are driven by factors like technological and managerial capabilities. Notably, although productivity strongly predicts a firm's quality choice, fundamental demand exhibits a weak negative correlation with output quality.

Second, producing higher output quality directly raises production costs, as it often requires specialized equipment and longer production processes, such as additional refinement in steelmaking. Our estimates indicate that a 1% increase in output quality reduces steel output quantity by approximately 0.429%, holding inputs and productivity fixed. This echoes the quality-quantity trade-off observed in other industries, such as healthcare (Grieco and McDevitt, 2017) and rug-making (Atkin et al., 2019). In contrast, fundamental demand does not directly affect production costs but reflects a firm's market advantage. Although the literature often uses demand residuals as proxies for output quality (e.g., Schott, 2004; Hallak, 2006; Khandelwal, 2010; Hallak and Schott, 2011; Feenstra and Romalis, 2014), we show that using the estimated demand residual—which combines output quality and fundamental demand—as a proxy for quality significantly biases the estimated production costs of quality toward zero. These results highlight the distinct cost

[1] This observability also simplifies the choice of instrumental variables for prices. If quality were treated as part of the unobserved demand residual, then commonly employed cost-related variables might not serve as adequate instrumental variables for output prices because quality variations would influence production costs.

implications of objective quality improvements versus market-driven demand fluctuations.

Third, the costs of producing quality lead to a negative correlation between output quality and TFPQ (correlation coefficient: -0.136), whereas output quality is positively correlated with fundamental productivity (correlation coefficient: 0.471). This finding reconciles the positive productivity-quality relationship suggested by Kugler and Verhoogen (2009, 2012) with the negative correlation between TFPQ (as a productivity measure) and demand residual (as a quality measure) reported in recent studies (e.g., Jaumandreu and Yin, 2014; Roberts et al., 2018; Orr, 2022; Forlani et al., 2023; Eslava et al., 2024; Caselli et al., 2025). Because quality production raises costs and lowers TFPQ, controlling for these costs is essential to reveal the underlying productivity-quality relationship.

Fourth, fundamental demand emerges as the primary driver of firm revenue, surpassing productivity and output quality. The fundamental demand of firms in the top 5-percentile revenue group is over four logarithmic units higher than that of the bottom 5-percentile group, whereas variations in fundamental productivity and output quality across revenue levels are comparatively modest. Interestingly, these firm heterogeneity factors influence revenue through distinct channels: fundamental demand drives revenue growth by increasing both prices and output; fundamental productivity does so by reducing prices and boosting output; and output quality primarily raises revenue through higher prices, albeit at the cost of reduced output due to the quality-quantity trade-off.

Finally, quality adjustments over time do not necessarily align with shifts in productivity and demand. As a result, they can either reinforce or counteract TFPR growth. The 2008 global financial crisis led to a sharp decline in international demand, prompting a large-scale government stimulus to support the domestic economy. This resulted in reduced demand for high-end export steel, though domestic expansion partially offset this. Consequently, average quality declined slightly, but overall TFPR rose by 7.78 percentage points, driven primarily by an increase in fundamental demand (8.00 points) and a modest gain in productivity (0.22 point). In the post-crisis period, export demand recovered, but domestic demand growth decelerated due to slower expansion in downstream industries that primarily consume lower-quality steel. This created a positive quality shock, raising the average industry output quality by 3.81 points. TFPR increased by 6.24 points, reflecting gains from fundamental demand by 7.44 points, an offset from declining productivity by -3.37 points, and a net effect (2.17 points) of the benefits and costs from quality growth. Therefore, unlike the crisis period, in which quality growth dampened gains in productivity and demand, post-crisis quality growth aligned with demand expansion but opposed productivity gains.

This paper contributes to the broader literature on measuring and understanding unobservable firm heterogeneity, especially the importance of demand. Existing research has recognized the challenges of productivity measurement due to data limitations, particularly the unobserved quality and prices of inputs and outputs (e.g., Klette and Grillches, 1996; Foster et al., 2008; De Loecker, 2011; De Loecker et al., 2016; Hahn, 2024). In the context of differentiated products, prior studies often assume that output quality can be captured by output prices or estimated demand residuals (e.g., Melitz, 2000), making revenue-based productivity a common approach to addressing the issue of unobserved quality. Recent studies have explored the demand- and cost-side components of revenue-based productivity, highlighting the role of demand in shaping firm growth and size differences (e.g., Pozzi and Schivardi, 2016; Eslava et al., 2024). Nonetheless, these components confound variations in output quality with other sources of firm heterogeneity. Using a direct measure of scientific output quality from the data, we disentangle the effects of technology-driven fundamental productivity and market-driven fundamental demand on firm revenue, isolating them from quality-related influences. Our findings reveal that fundamental demand, rather than quality or productivity, is the primary driver of firm size differences.

In the rest, Section 2 introduces the background and data. Section 3 develops a framework of endogenous quality choices and decomposes the TFPR measure. Section 4 describes the estimation strategy and presents the estimation results. Section 5 analyzes the distinct impact of individual components of firm heterogeneity on revenue. Section 6 evaluates their contributions to the growth of aggregate revenue productivity in the presence of quality shocks. We conclude in Section 7.

2 Background and Data

Production Process and Quality of Steel

Steel manufacturing is the process of producing steel using iron ore as the major input. The process involves two major 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—slabs, billets, and blooms. We focus on the latter stage of steelmaking. This focus serves the purpose of this paper for several considerations. First, the quality difference in the major input (pig iron) is minimal across firms and over time, allowing us to focus on output quality without the need to account for input quality differences. Second, the quality of steel is mainly determined at this stage by adding alloy elements and removing unwanted impurities and gases. Third, focusing on the latter stage of steelmaking spares us from considering vertically integrated production (ironmaking and steelmaking), which may affect productivity, as noted by Brandt et al. (2022).[2]

Although seemingly homogeneous, steel varies significantly in quality. Quality determines steel's ability to perform its designed function without limitations due to internal flaws or large microstructural variations. An index of steel quality is the summation of how well it meets its specified chemistry, its cleanliness, its grain/carbide size, and whether it meets the specified

[2] Brandt et al. (2022) study productivity differences in vertically integrated Chinese steel facilities using a dataset from the Chinese Iron and Steel Association for three years, without considering output quality differences.

physical and mechanical requirements.[3] 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 alter steel's properties and improve its quality. Limiting dissolved gases, such as nitrogen and oxygen, and ingrained impurities is also important to ensure the quality of the products cast from liquid steel.

In principle, higher-quality steel involves higher production costs. These higher costs are associated with the better equipment required in the production process, additional refinement stages, and finer control across all aspects of production and refinement. For example, cooling in the casting process relies heavily on precisely controlled airflows, which is vital for the quality and characteristics of the steel produced. To this end, robust air compressors are often required to produce high-quality steel. Moreover, reducing dissolved gases, such as nitrogen and oxygen, and ingrained impurities also requires additional refining stages, which increase production costs.

The Chinese Steel Industry

China's steel production is crucial for its domestic economy and the global markets. China produced nearly half of the world's steel by volume and was the largest steel exporter, accounting for 16% of global exports in 2017. Domestically, steel demand is driven primarily by construction, machinery, and automobiles, which together accounted for 80% of total demand in 2017. On average, the quality of exported steel is higher than that produced for the domestic market. This is partly because exported steel typically meets international quality standards to remain competitive globally. Additionally, domestic steel demand is largely driven by the construction industry (which accounts for more than half of total demand), which has relatively lower quality requirements than other downstream sectors. In our data, the correlation between the export

[3] Cited from a white paper by Natoli Engineering Company, Inc. Accessed on November 5, 2018.

share and steel quality at the industry level is 0.53.

Fluctuations in international and domestic steel demand significantly impact the quality and quantity of steel produced. The Chinese steel industry experienced a major shock from the 2008 global financial crisis, which sharply reduced foreign demand for Chinese steel by 25% from 2007 to 2010. In response, the Chinese government launched the *Four Trillion Stimulus Plan* in November 2008, injecting RMB 4 trillion (USD 570 billion, or about 11% of GDP) into the economy over two years. Over 80% of the stimulus targeted construction-related projects, including public infrastructure, real estate, and rebuilding efforts after the 2008 Great Sichuan earthquake.[4] This stimulus significantly boosted the construction sector, driving substantial domestic steel demand. Between 2007 and 2010, domestic steel sales rose by 55% and capacity investment surged across the industry, fueled by abundant credit and expectations of sustained domestic demand growth.

However, after 2010, export and domestic sales trends reversed. Export demand recovered steadily as the global economy rebounded, with export volumes in 2014 nearly doubling those of 2010. In contrast, domestic demand slowed due to reduced growth in major downstream industries. From 2010 to 2014, domestic sales dropped by over 12% in our data, whereas firm production capacity still grew by about 7%. Consequently, the capacity built during and immediately after the post-crisis period quickly became redundant, leading to a decline in production efficiency. The opposite trends in exports and domestic sales also led to a rise in industry-level average output quality.

Data

Our analysis uses a monthly panel of 51 major Chinese steelmakers from 2007 to 2014, sourced from a data service company in China that collects data from the Chinese Iron and Steel Association

[4]Source: https://en.wikipedia.org/wiki/Chinese_economic_stimulus_program. Accessed on July 14, 2021.

and through direct firm surveys. These firms accounted for half of China's steel production and 22% of global output in 2010. The data include information on output prices, output quantities, input quantities, and financial information from firm-level balance sheets. Output prices and quantities are defined conventionally as tons of steel and price per ton.[5] Specifically, the output price at the firm level is defined as $P_{jt} = \frac{R_{jt}}{Q_{jt}}$, where R_{jt} is the total revenue of the firm and Q_{jt} is the total quantity (in tonnage) of steel produced by the firm. On the input side, the major intermediate inputs are pig iron and recycled scrap steel, measured in physical units (tonnage). 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 quantity and utilization information offers two obvious advantages for our analysis. First, input quantities in physical terms avoid biases from unobserved input price heterogeneity, a concern often referred to as "input price bias" in the literature (e.g., Ornaghi, 2006; De Loecker et al., 2016; Grieco et al., 2016, 2022). Second, incorporating input utilization data helps mitigate a common issue in production function estimation: unobserved variation in input utilization. Although some unobserved factors—such as fluctuations in labor work intensity—may still exist, they are absorbed in the productivity estimates, which are likely to be lower during periods of overcapacity, such as after the financial crisis.

What makes this dataset unique is its detailed reporting on firm output quality, which enables us to construct an objective, scientific output quality index at the firm level. Chinese manufacturing firms, including those in steelmaking, adhere to a hierarchy of quality standards in production, organized in descending order: international, national, and enterprise standards. The international standard, often called the "foreign advanced standard" in China, is developed by organizations such as the International Organization for Standardization (ISO), International Electrotechnical

[5] Following Foster et al. (2008), we adjust the firm-level prices and revenue using an industry output price index constructed as the revenue-weighted geometric mean price across all firms in each period. Alternatively, we can deflate prices and revenue using national inflation rates, and our main results remain robust.

Commission (IEC), and Pacific Area Standards Congress, among others. This standard represents the highest quality benchmark in China and is recognized globally. The national standard is developed by the Standardization Administration of China or a relevant industry body, with registration required by the Standardization Administration of China. This standard, sometimes referred to as the industrial or "GB standard" in China, is applied domestically. The enterprise standard, the lowest tier, is developed by individual firms for internal use only and is not intended to meet broader regulatory standards. In the steel industry, these three levels of standards vary significantly in their specifications for the physical and chemical properties of steel, including permissible impurity content.[6]

In our analysis, the steel quality index of a firm is defined as the weighted average of the three quality index numbers, with weights equal to the shares of the physical output produced under each of the three quality standards. Formally, for firm j in period t, the quality index is calculated as $\xi^0_{jt} = \alpha_H S_{Hjt} + \alpha_M S_{Mjt} + \alpha_L S_{Ljt}$, 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.[7] $Q_{jt} = Q_{Hjt} + Q_{Mjt} + Q_{Ljt}$ is the total output quantity.[8] 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 use the index numbers $\alpha_H = 1.5$, $\alpha_M = 1$, and $\alpha_L = 0.5$.[9] As a result,

[6] We illustrate the quality distinctions between the international and national standards using the example of the widely produced carbon structural steel in Appendix Table A1.

[7] This definition follows exactly the regulation in the steelmaking 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.

[8] Although we can compute the firm-level output prices, we do not observe separate prices for each quality tier within a firm. This limits our ability to analyze multi-product firm behavior at the firm-product level, because we cannot estimate separate demand functions for each quality tier without further assumptions. In Appendix C, we outline how a framework of multi-product firms can be approximated by a firm-level model without losing the key empirical insights related to the distinct roles of fundamental productivity and demand as well as the costs and benefits of quality that this paper seeks to highlight. In the context where suitable firm-product level output price and quantity data are available, researchers can estimate a model of multi-product firms directly without approximation to investigate the demand and cost heterogeneity both within and across firms, by applying the approaches in the recent development of the literature (e.g., De Loecker et al., 2016; Orr, 2022; Dhyne et al., 2022; Valmari, 2023; Caselli et al., 2025).

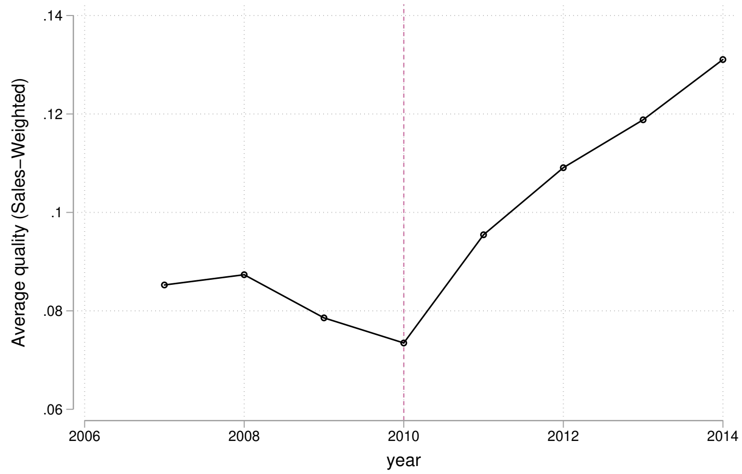
[9] In Appendix D, we test the robustness of our results by using a different set of index numbers estimated flexibly following the insight of Atkin et al. (2019). The estimated quality index numbers are close to the industry practice, and our results are robust.

the output quality index ranges from 0.5 to 1.5. If the quality index is 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, conversely, it means that all products of this firm are produced following the enterprise standard and are at 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 the firm produces steel of higher average quality.

This output quality index reveals important patterns.[10] First, there is substantial heterogeneity in quality. The quality gap between the 90th and 10th percentiles represents 66% of the maximum possible difference. Second, although higher-quality products tend to command higher prices, price is an imperfect measure of quality. The modest correlation between output price and quality (0.165 after controlling for firm- and time-fixed effects) highlights that using price as a proxy for quality may be misleading. Third, the relationship between quality and productivity varies depending on the chosen productivity metric. Quality is positively associated with revenue per worker but negatively associated with quantity produced per worker, as shown in Appendix Table A3. This suggests that although higher quality can increase revenue, a quality-quantity trade-off exists. Finally, the average industry-level quality index fluctuates significantly over time, responding strongly to major economic shocks. Figure 1 shows the evolution of the sales-weighted average quality index. Between 2007 and 2010, the average quality declined, consistent with reduced exports due to the 2008 global financial crisis and increased domestic demand driven by stimulus policies. From 2010 to 2014, the average quality rose significantly, reflecting slowing domestic demand and a steady recovery in export sales.

[10]See Appendix A for a more detailed discussion.

Figure 1: Evolution of average quality



3 Modeling Firm Heterogeneity

This section presents a model of firm heterogeneity, incorporating differences in fundamental productivity and demand with endogenous quality choices. The model accounts for the trade-offs between the benefits and costs of producing higher quality. Its purpose is to provide a conceptual foundation, illustrating how traditionally measured TFPR, TFPQ, and demand residuals capture distinct components of firm heterogeneity when output quality is treated as a separate dimension.

A Theoretical Framework

Each firm produces a single product and competes monopolistically in a vertically differentiated industry. We allow a firm's output price to influence the aggregate price index, but abstract away from direct strategic interactions among firms. Firms endogenously choose objective quality and quantity to maximize profits, given production technology, consumer preferences, and demand conditions. The key trade-off faced by each firm is that, although high-quality products induce higher demand, producing them requires more resources and lowers output quantity.

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 has a constant elasticity of substitution (CES) preference for the quality-adjusted 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 and t is time. The consumer values both the physical quantity (Q_{jt}) and objective quality (ξ_{jt}) of a product, in the form of a quality-adjusted quantity $\tilde{Q}_{jt} \equiv \xi_{jt} Q_{jt}$, given subjective consumer taste (ρ_{jt}). A 1-percent increase in product quality raises the consumer's valuation of the product by 1 percent, holding the physical quantity fixed. We refer to this as the *consumption benefits of objective quality.* Apart from objective quality, the subjective consumer taste, ρ_{jt}, may affect the consumer's evaluation of product j. ρ_{jt} can be serially correlated, and it may be correlated with product prices and objective quality ξ_{jt}. Although both ξ_{jt} and ρ_{jt} boost demand, they differ fundamentally: ξ_{jt} is a product characteristic that raises variable production costs, whereas ρ_{jt} is a consumer taste that does not directly affect them.[11]

Given the consumer's total expenditure I_t and output price P_{jt}, the implied demand function is:

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

where $\phi_{jt} = \ln \rho_{jt} + \ln \left(\frac{I_t}{\sum_j [P_{jt}/(\rho_{jt}\xi_{jt})]^{1-\sigma}} \right)^{\frac{1}{\sigma-1}}$ is referred to as the *fundamental demand.* It is a function of consumer taste ρ_{jt} and an expenditure index $\frac{I_t}{\sum_j [P_{jt}/(\rho_{jt}\xi_{jt})]^{1-\sigma}}$ which does not vary across j. Although the elasticity of substitution, σ, is assumed to be constant, this does not necessarily imply a constant price elasticity of demand or a fixed markup across firms.[12]

[11]The distinction between objective quality ξ_{jt} and subjective consumer taste ρ_{jt} is related to, but not identical with, the concepts of vertical and horizontal differentiation. Specifically, subjective taste ρ_{jt}—and thus the fundamental demand ϕ_{jt} in (2)—contains two main sources of demand variation: horizontal differentiation and consumers' subjective perceptions of product quality. The latter may arise from factors such as branding and marketing, which shape consumers' assessment of quality and their willingness to pay. In this paper, we disentangle objective product quality (ξ_{jt}) from other demand shifters (e.g., ρ_{jt}) embedded in fundamental demand (ϕ_{jt}).

[12]For example, a lower price of firm j's product, P_{jt}, affects its demand through two channels: the substitution

Our model highlights the distinction between objective quality (ξ_{jt}) and fundamental demand (ϕ_{jt}). Although both factors enhance demand, only objective quality directly affects production costs. In contrast, fundamental demand does not, because it captures broader demand shifters such as customer taste and macroeconomic market conditions. Due to data limitations, the empirical literature (e.g., Melitz, 2000) often combines these two components, treating their sum as the demand residual to approximate output quality or overall demand. In contrast, our approach moves beyond this simplification, enabling further investigation into the distinct roles of objective product quality and fundamental demand, particularly in understanding their impact on production costs.

Production technology. In period t, firm j produces Q_{jt} units of a single product j of objective quality ξ_{jt}, using labor L_{jt}, capital K_{jt}, and materials M_{jt}. The production function is

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

where the quantity-based productivity A_{jt} captures any unexplained variation in output conditional on inputs (e.g., TFPQ in Foster et al., 2008). v_{jt} is an unexpected i.i.d. shock with a zero mean, unobserved by the firm when making its input and output decisions. The Leontief function implies that there is no substitution between materials and the capital-labor composition. This reflects the feature of the production technology in the steelmaking industry — the relationship between output and materials is characterized by a 45-degree line as shown in Appendix Figure A2.[13]

effect, where the consumer switches from rival firms to firm j due to the lower price, and the income effect, where the decrease in the aggregate price index enables the consumer to purchase more of firm j's product. As a result, the price elasticity of demand, $\frac{\partial \ln Q_{jt}}{\partial \ln P_{jt}}$, and the corresponding markup can vary across firms, even under a constant σ. This point is also documented in the literature (e.g., Feenstra and Ma, 2007).

The constant elasticity of substitution, σ, remains identifiable even when allowing for variable markups. Our demand estimation, specified in (2), uses time fixed effects to absorb the aggregate price index. This allows us to identify σ from relative demand shifts in response to price changes, purging the influence of income effects. A detailed discussion is provided in Appendix B.

Of course, the elasticity of substitution, σ, may not be constant and could potentially vary with the level of output quality. To assess this possibility, we conduct a robustness check, as detailed in Appendix D, where we allow σ to depend on output quality. The results indicate that the effect of output quality on σ is both economically and statistically insignificant in this context. Moreover, the key parameter estimates of our model remain robust.

[13] Crucially, this 45-degree linear relationship holds consistently across different quality levels, meaning that the

Atkinson and Luo (2024) use a similar Leontief function to model the production technology of electricity generation plants. Our approach carries over if the production function is more flexible.

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:

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

The TFPQ, A_{jt}, depends on the fundamental productivity (ω_{jt}) and costs of quality ($\xi_{jt}^{-\alpha_\xi}$):

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

The fundamental productivity (ω_{jt}) is primarily driven by the technological efficiency of converters, workers' skills, working intensity, and managerial capability that are not captured by the observed inputs. ω_{jt} evolves according to an AR(1) process with i.i.d. productivity shock ϵ_{jt+1}:[14]

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

The cost of quality, $\xi_{jt}^{-\alpha_\xi}$, is another factor that drives the variation in TFPQ. Given fundamental productivity, producing a high-quality product incurs additional costs. For example, producing higher-quality steel requires additional refinement stages, better equipment, and finer process control, as explained in Section 2. These activities require additional inputs and increase production costs, as discussed by Atkin et al. (2019), who model quality production with additional inputs. Instead of modeling quality production directly, we model such costs of quality, $\xi_{jt}^{-\alpha_\xi}$, as a part

Leonfief feature is a fundamental feature conditional on quality rather than being driven by cross-quality differences.

[14]As a robustness check, we included output quality in the evolution process: $\omega_{jt+1} = g_0 + g_1\omega_{jt} + g_\xi \ln \xi_{jt} + \epsilon_{jt+1}$. We found that g_ξ is insignificant: -0.003 (s.e.=0.005). This suggests that output quality influences TFPQ through the quality production costs (i.e., $\xi_{jt}^{-\alpha_\xi}$) rather than through the fundamental productivity evolution process.

of A_{jt} in the spirit of Grieco and McDevitt (2017).[15] We expect $\alpha_\xi > 0$, implying a trade-off between output quality and quantity.

Static output quantity decision. Although output quality ξ_{jt} is dynamically determined at the end of period $t-1$, the output quantity decision is static.[16] At the beginning of each period t, the firm chooses output quantity to maximize its period profit conditional on its state s_{jt}:[17]

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

where the state $s_{jt} = (\xi_{jt}, \omega_{jt}, \phi_{jt}, K_{jt}; \psi_t)$. Here, ψ_t collects the time-specific aggregate factors that influence firm profit (e.g., iron ore price P_{Mt}, wage rate P_{Lt}, and the industrial level aggregate price index).[18] The expectation of revenue takes the ex post production shock, v_{jt}, and any unexpected demand shocks into account. The implied optimal output quantity decision is $Q_{jt} = Q^*(\xi_{jt}, \omega_{jt}, \phi_{jt}, K_{jt}; \psi_t)$.

Dynamic output quality decision. At the end of period t, the firm observes state s_{jt} and chooses the quality for period $t+1$ to maximize its long-run firm value. This quality choice

[15] Our production function setup can be interpreted in two ways closely aligned with the existing literature. First, it can be interpreted as the production of "quality-adjusted" output using standard inputs (K_{jt} and L_{jt}), expressed as $\xi_{jt}^{\alpha_\xi} Q_{jt} = e^{\omega_{jt}} K_{jt}^{\alpha_k} L_{jt}^{\alpha_\ell}$. This approach embeds quality directly into the production function, capturing the trade-off between quality and quantity as in Grieco and McDevitt (2017). Second, our framework is also consistent with the literature that treats quantity production and quality production as distinct processes (e.g., Atkin et al., 2019), recognizing that firms must use resources to produce output quality. 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: $\lambda_{jt} = \lambda(\xi_{jt}) = 1 - \xi_{jt}^{-\frac{\alpha_\xi}{\alpha_k + \alpha_\ell}}$, with $0 < \xi_{jt}^{-\frac{\alpha_\xi}{\alpha_k + \alpha_\ell}} < 1$. As a result, by accounting for the actual labor and capital used in the production of quantity, $Q_{jt} = e^{\omega_{jt}} [(1-\lambda(\xi_{jt}))K_{jt}]^{\alpha_k} [(1-\lambda(\xi_{jt}))L_{jt}]^{\alpha_\ell} = e^{\omega_{jt}} \xi_{jt}^{-\alpha_\xi} K_{jt}^{\alpha_k} L_{jt}^{\alpha_\ell}$.

[16] The empirical measure of output quality in Section 2 is constructed based on the contemporaneous quantity shares of different quality tiers. This may introduce a correlation between the contemporaneous demand shocks and the quality measure, because fluctuations in demand may influence the observed product mix and, consequently, the calculated quality index. We explicitly allow for such a correlation in the demand estimation in Section 4.

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

[18] Here, P_{Mt} and P_{Lt} are assumed to vary by time but not across firms. In the empirical estimation, we use input quantities measured in physical terms to estimate the production parameters in Section 4, thereby avoiding the "input price bias" highlighted in the literature. Firm-level variation in input prices, if any, can still complicate the use of a proxy-based approach for production estimation. The detailed strategy for addressing this challenge, closely aligned with De Loecker et al. (2016), is outlined in Section 4.

is dynamic because adjusting quality requires time, similar to capital investment, and involves adjustment costs that depend on the firm's current quality level and state, such as its capital stock. Denote the adjustment costs as $C(\xi_{jt}, \xi_{jt+1}; K_{jt})$, which is convex in the change in quality.

The firm's dynamic quality choice problem is characterized by the following Bellman equation:[19]

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

The transition from state s_{jt} to s_{jt+1} reflects the evolution of fundamental productivity, demand, capital stock, and other state variables, as well as the endogenous quality choice.[20] The firm faces a trade-off: improving quality from ξ_{jt} to ξ_{jt+1} enhances future value but entails production and adjustment costs that depend on the size of this quality gap. We denote the implied optimal quality decision as $\xi_{jt+1} = \xi^*(\xi_{jt}, \omega_{jt}, \phi_{jt}, K_{jt}; \psi_t)$.

The optimal quality and production decisions have three important implications. First, optimal quality relies on a set of variables rather than on fundamental productivity alone, implying that quality and fundamental productivity are two distinct dimensions of firm heterogeneity. Second, the demand residual from the demand function (2) is unlikely to be a perfect measure of output quality because the choice of output quality depends on factors including fundamental productivity, capital stock, and input prices, in addition to fundamental demand. Finally, the optimal decision of Q_{jt} provides a proxy to control for the unobserved ω_{jt}, which will be used in Section 4 to estimate the production function. To see this, substituting the choice Q_{jt} into (4), the optimal labor demand is a function of state variables: $L_{jt} = L^*(\xi_{jt}, \omega_{jt}, \phi_{jt}, K_{jt}; \psi_t)$.

[19] Although the quality choice model presented in the paper assumes that output quality is predetermined, following the tradition in the literature, our empirical estimation strategy is also consistent with an alternative framework in which output quality and quantity are determined simultaneously. In particular, even if output quality is determined by the share of contemporaneous output quantity chosen by multi-product firms—as in our construction of the empirical quality measure in Section 2—our instrumental variable approach in Section 4 remains valid and consistent, since contemporaneous quality is not used as an instrument.

[20] The evolution of productivity and demand is specified in (6) and (12), respectively, whereas the capital evolution process is standard and is abstracted away for expository purposes.

Revenue Productivity and Its Components

We define TFPR from the revenue function, $R_{jt} = P_{jt}Q_{jt} = \left\{\exp(\text{TFPR}) K_{jt}^{\alpha_k} L_{jt}^{\alpha_\ell} e^{v_{jt}}\right\}^{\frac{\sigma-1}{\sigma}}$, following Melitz (2000).[21] Combining (2) and (4) to derive the revenue function and using the definition of TFPR above, we obtain:

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

This implies that fundamental productivity, fundamental demand, and output quality all contribute to TFPR. Nonetheless, the benefits of quality are partially offset by the costs of quality — increasing output quality by 1 percent only improves TFPR by $(1 - \alpha_\xi)$ percent, holding other factors fixed.

Without accounting for output quality separately, the **quantity-based productivity** (**TFPQ** in Foster et al., 2008) essentially measures the quantity of output in physical units per input composite. It coincides with A_{jt} in the production function (4):

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

In industries with homogeneous products (i.e., $\xi_{jt} = \xi$), as in Foster et al. (2008), TFPQ is the same as 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 costs of quality. In this case, even if firms have the same fundamental productivity, the measured TFPQ may differ if firms produce outputs of different quality levels. Because quality and fundamental productivity are expected to be positively correlated, TFPQ may understate the dispersion of fundamental productivity.

[21] This definition avoids the scale bias caused by $\frac{\sigma-1}{\sigma}$; thus, it is directly comparable to TFPQ in the literature.

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

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

Note that we have adjusted the demand residual by $(\sigma - 1)$ to make it comparable to TFPQ. Although 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 the differences between objective quality and fundamental demand as different aspects of firm heterogeneity. Table 1 summarizes these key measures and clarifies their different components.

Table 1: Components of key measures

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

4 Output Quality, Productivity, and Demand

This section recovers firms' fundamental demand and fundamental productivity by estimating demand and production functions after explicitly accounting for the role of objective quality.

Demand Estimation

We estimate the demand function to recover firms' fundamental demand (ϕ_{jt}), controlling for objective output quality. This requires addressing two challenges when estimating the demand function (2). The first challenge is the scaling of the quality index. As discussed in Section 2, the recorded scientific quality measure (ξ^0_{jt}) is an index, which may not directly correspond to the benefits of quality in the model, i.e., ξ_{jt} in the utility function (1), due to different choices of measurement scales. To account for this discrepancy, we empirically model the benefits of quality as a function of the recorded index: $\xi_{jt} = \exp(\gamma \xi^0_{jt})$, where the parameter γ adjusts the scale of the scientific quality index to align it with its conceptual role in the model.

The second challenge involves addressing potential endogeneity in demand estimation. Directly estimating equation (2) poses a problem because the unobserved term ϕ_{jt} may correlate with output prices and quality. For instance, persistent demand shocks, which are observable to firms but not to researchers, could create such correlations. To address this issue, we decompose the term $(\sigma - 1)\phi_{jt}$ in (2) into three components: a firm-specific fixed effect (ϕ_j), a time-specific fixed effect (ϕ_t), and an unobserved error term (e_{jt}). The firm-specific fixed effect captures persistent factors, such as product-specific tastes and customer base, whereas the time-specific fixed effect accounts for time-varying factors, such as macroeconomic shocks.

Although this decomposition reduces endogeneity, e_{jt} may still correlate with prices and quality if it is persistent. To address this issue, we assume that e_{jt} follows an autoregressive process:

$$e_{jt} = \rho_0 + \rho_1 e_{jt-1} + \nu_{jt}, \tag{12}$$

where ν_{jt} is an i.i.d. idiosyncratic shock uncorrelated with prior variables before period t.

Taking these adjustments into account, we rewrite the empirical demand function as:

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

where e_{jt} is serially correlated as specified in (12).

We estimate the demand function and demand evolution parameters via the generalized method of moments (GMM), with moment conditions $E(\nu_{jt} Z^D_{jt}) = 0$. Here $\nu_{jt} = e_{jt} - \rho_0 - \rho_1 e_{jt-1}$ and e_{jt} and e_{jt-1} are treated as functions of observable variables according to (13). Z^D_{jt} is a set of instrumental variables including $k_{jt}, p_{jt-1}, q_{jt-1}, \xi^0_{jt-1}$ as well as the firm and year-month fixed effects. These variables are correlated with the price, quality, and quantity in period t. In particular, capital stock shifts the marginal cost and correlates with the output price. Meanwhile, they are uncorrelated with the idiosyncratic shock ν_{jt} which is realized in period t. This makes them valid instrumental variables. Further robustness checks using different IVs are reported in Appendix Table D.

Table 2: Estimates of demand function parameters

	(1) OLS	(2) IV	(3) GMM, AR(1)
σ	0.627***	1.980***	1.829***
	(0.015)	(0.050)	(0.109)
$\gamma(\sigma - 1)$	0.033	0.516***	0.549**
	(0.033)	(0.059)	(0.235)
ρ_1			0.739***
			(0.020)
Year-month FE	YES	YES	YES
Firm FE	YES	YES	YES
Observations	4,070	4,034	3936

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 2 presents the parameter estimates for (13). As our main result, Column (3) reports the GMM estimates with moment conditions $E(\nu_{jt} Z^D_{jt}) = 0$, utilizing an AR(1) process of the error term e_{jt}. The elasticity of substitution σ is estimated to be 1.829, a value comparable to those reported for other industries in the literature (e.g., Broda and Weinstein, 2006; Atkin et al., 2019). This implies that the elasticity of demand with respect to output quality, $(\sigma - 1)$, is 0.829. This result highlights the significant role of the benefits of quality in shaping demand: a 1 percent increase in output quality, ξ_{jt}, leads to a 0.829 percent increase in demand, holding other factors constant. Additionally, the estimated coefficient $\gamma(\sigma - 1)$ is 0.549, allowing us to calculate the scale-adjustment parameter as $\gamma = 0.549/(1.829 - 1) = 0.662$. Using these parameter estimates, we construct the measures of output quality and fundamental demand based on their respective definitions: $\xi_{jt} = \exp(\hat{\gamma}\xi^0_{jt})$ and $\phi_{jt} = (\hat{\phi}_j + \hat{\phi}_t + \hat{e}_{jt})/(\hat{\sigma} - 1)$. These estimates are used in the production estimation in Section 4. For comparison, Column (1) presents estimates from ordinary least squares (OLS), whereas Column (2) shows the result from an instrumental variable (IV) approach that uses capital stock as an IV for price but without assuming the AR(1) structure of the error term e_{jt}. As anticipated, the OLS estimates in Column (1) significantly underestimate the value of σ, whereas the IV estimates in Column (2) align closely with our main findings.

Production Estimation

We recover firm fundamental productivity by estimating the production function after explicitly accounting for the costs of quality. We use a control function approach, building on Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015). Based on the optimal firm decisions outlined in Section 3, labor input (ℓ_{jt}) is assumed to be a monotonic function of fundamental productivity (ω_{jt}), conditional on fundamental demand (ϕ_{jt}), capital stock (k_{jt}), output quality (ξ_{jt}), and a time dummy (ψ_t). Inverting this relationship leads to a control function for fundamental productivity: $\omega_{jt} = \omega(\xi_{jt}, \ell_{jt}, k_{jt}, \phi_{jt}; \psi_t)$. Note that ℓ_{jt} and k_{jt} are the utilized number of workers and capital stock (i.e., the utilized volume of converters), respectively.

As a result, the logarithm of the production function (4) can be written as:

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

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

where the lowercase letters represent variables in logarithm, and v_{jt} is the i.i.d. unexpected shock. All the variables on the right-hand side (other than v_{jt}) are observable or already estimated. In the second equality, $h(\xi_{jt}, \ell_{jt}, k_{jt}, \phi_{jt}; \psi_t) \equiv \alpha_k k_{jt} + \alpha_\ell \ell_{jt} - \alpha_\xi \ln \xi_{jt} + \omega(\xi_{jt}, \ell_{jt}, k_{jt}, \phi_{jt}; \psi_t)$. We specify $h(\cdot)$ as a polynomial function of degree three. Given that 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 $\epsilon_{jt+1} = \omega_{jt+1} - g_0 - g_1\omega_{jt}$.

Finally, we estimate the parameters via GMM using moment conditions: $\mathrm{E}(\epsilon_{jt} Z_{jt}^C) = 0$, where $Z_{jt}^C = (k_{jt}, \ell_{jt-1}, \hat{h}_{jt-1}, p_{Mt-1}, \xi_{jt-1}, \xi_{jt-1}^2, \xi_{jt-1}^3)$ and p_{Mt-1} is the iron ore price in period $t-1$. These instrumental variables, determined in period $t-1$, are uncorrelated with the productivity shock ϵ_{jt} which is realized in period t.

The observed output quality resolves the challenge of identifying the costs of quality from fundamental productivity. As reflected by (14), the relationship between output quantity and output quality identifies the costs of quality after controlling for inputs and fundamental productivity proxied by the observable variables. Furthermore, incorporating observed output quality in our analysis effectively addresses the input price bias highlighted by De Loecker et al. (2016), who emphasize that it is essential to control for unobserved input quality or price variation to achieve a consistent production estimate. They underline that input and output quality are positively correlated and propose using proxies for output quality (such as output prices and market share) to account for input price variations driven by differences in input quality. In our estimation, we explicitly incorporate output quality in both the production function and the productivity control function. By doing this, we effectively controlled for input price and quality heterogeneity following the same insight of De Loecker et al. (2016). In addition, we further minimize potential input price bias by measuring both inputs and outputs in physical quantities rather than monetary terms.

Table 3: Estimates of the production function and productivity evolution process

	α_ξ	α_k	α_ℓ	g_0	g_1
Estimate	0.429***	0.749***	0.142***	-0.011*	0.976***
Standard error	(0.167)	(0.033)	(0.046)	(0.006)	(0.006)

Table 3 reports the estimates of the production function and productivity evolution process. The estimated parameters for capital ($\alpha_k = 0.749$) and labor ($\alpha_\ell = 0.142$) reflect the high capital-to-labor intensity characteristic of the steelmaking industry. These findings align with those of Brandt et al. (2022), who report that the capital coefficient in Chinese sintering, pig-iron making, and steelmaking industries is approximately three to five times larger than the labor coefficient. Considering the monthly frequency of our data, the estimated productivity persistence parameter ($g_1 = 0.976$) translates to an annual persistence of 0.747. This value falls within the range reported in the literature, where yearly productivity persistence typically ranges from 0.6 to 0.8 (e.g., Baily et al., 1992; Roberts and Supina, 2000; Ábrahám and White, 2006; Foster et al., 2006, 2008).

The results highlight a significant cost effect associated with producing higher-quality output. Specifically, the estimated parameter α_ξ indicates that a 1 percent increase in output quality reduces output quantity by 0.429 percent, holding fundamental productivity, capital, and labor constant. This structural estimate aligns with the empirical patterns observed in Appendix Table A3, which demonstrates that higher-quality producers achieve lower output quantities for a given amount of inputs. Overall, our results reveal that approximately half of the demand benefits provided by improved quality are offset by the costs of quality in the Chinese steelmaking industry.

Our findings on the costs of quality align closely with the emerging literature documenting a negative relationship between quality and quantity across diverse industries and countries using various methodologies. Grieco and McDevitt (2017) find a trade-off between the number of patients treated and the quality of care in healthcare. Atkin et al. (2019) reveal an inverse correlation between quantity productivity and quality productivity among Egyptian rug-makers using direct quality assessments. More broadly, this result corroborates the robust negative relationship between quantity-based productivity and "product appeal" (demand residual) documented by Jaumandreu and Yin (2014), Roberts et al. (2018), Forlani et al. (2023), Orr (2022), Eslava et al. (2024), and Caselli et al. (2025) across manufacturing firms in Belgium, China, Colombia, India, and Mexico.[22] These studies rely on demand residuals as a proxy for quality when quality data

[22]In our context, the correlation coefficient between TFPQ and the demand residual is 0.29. This correlation is not negative as reported by the literature, likely because our TFPQ measurement is based on physical quantities

are unavailable.

Our analysis contributes to this literature by providing direct evidence on the costs of quality. Without quality data, the traditional literature based on quality proxies is likely to underestimate the costs of quality. To document this, we follow the traditional literature in estimating the demand function without using direct output quality data, employing capital stock as an instrumental variable for output price. The derived demand residual is then treated as a proxy for output quality in the production function estimation, following the same methodology outlined in Section 4. Despite obtaining estimates of demand and production parameters similar to our main results, this approach fails to capture the substantial production costs of quality. As reported in Appendix Table A4, the estimated parameter of costs of quality is $\alpha_\xi = 0.013$ (s.e., 0.038), which is insignificant economically and statistically. This failure to detect the costs of quality may stem from two key issues: (1) the mismeasurement of output quality when using demand residual as a proxy, and (2) bias introduced in the estimation of demand and production function parameters. To isolate these two potential causes, we conduct an additional analysis using the proxy measures of output quality, but the same demand and production parameters estimated from our model that incorporates direct quality data. The results confirm that mismeasurement of output quality alone still fails to detect the production costs of quality.[23] The detailed results and implementation are presented in Appendix Table A5.

of output and inputs. This approach effectively removes heterogeneity in material prices, wage rates, and capital utilization, which are often unobserved in standard TFPQ measures. However, this correlation remains significantly lower than the 0.47 correlation between fundamental productivity and output quality. This comparison supports the same underlying implication in the literature: firms producing higher-quality products incur additional production costs, which dampens the observed correlation between TFPQ and the demand residual relative to that between fundamental productivity and output quality.

[23]This is intuitive — output quality affects the marginal cost of production, whereas fundamental demand may mainly come from the inherent customer base and the effort of marketing (as a kind of fixed cost), which may not increase the marginal cost of production.

Output Quality, Productivity, and Demand as TFPR Components

The concept of TFPR has been central to the study of firm and industry performance. In recent years, increasing attention has been paid to the distinction between TFPQ and demand heterogeneity as key components of TFPR. Building on this foundation, our estimation results allow us to further investigate technology-driven fundamental productivity and market-driven fundamental demand, separating them from the costs and benefits of output quality, respectively. This subsection examines the implications of this detailed decomposition, shedding light on the distinct roles of these components.

Our findings reveal that output quality and fundamental demand are distinct dimensions of firm heterogeneity. First, quality and fundamental demand are weakly negatively correlated (correlation coefficient: -0.05).[24] This suggests that the movements of quality and demand are not necessarily aligned, as conjectured by the literature (e.g., Shaked and Sutton, 1987; Hallak, 2006; Berry and Waldfogel, 2010; Feenstra and Romalis, 2014). Second, the dispersion of fundamental demand is approximately six times greater than that of quality. This disparity highlights the large variability of market conditions firms face compared to their quality differentiation. Third, producing high-quality output incurs higher production costs, whereas higher demand — driven by factors such as customer base expansion or marketing effort — does not necessarily raise production costs, as examined in Section 4. This underscores the distinct cost implications of quality improvements versus market-driven demand fluctuations.

Our findings also highlight the importance of accounting for the costs of quality in reconciling the

[24] This relationship is further confirmed in Appendix Figure A3b. The negative relationship likely stems from segmented, quality-dependent markets in the steel industry, where the market size or customer base (fundamental demand) for high-quality steel is smaller than that for lower-quality steel. We demonstrate this point by highlighting the conceptual differences between output quality and fundamental demand (e.g., customer base) in a model with quality-differentiated products in Appendix C . Empirically, this does not imply that higher quality reduces firm demand. By explicitly accounting for both output quality and fundamental demand in the demand function, our estimates in Table 2 demonstrate that higher quality increases sales quantities when price and fundamental demand are held constant.

seemingly conflicting results in the literature. Although studies such as Kugler and Verhoogen (2009, 2012) suggest a positive relationship between productivity and quality, more recent research has documented a negative correlation between TFPQ (as a productivity measure) and demand residual (as a quality proxy) (e.g., Jaumandreu and Yin, 2014; Orr, 2022; Forlani et al., 2023; Eslava et al., 2024). On the one hand, our findings show that more productive firms indeed tend to choose higher-quality steel, as evidenced by the positive correlation (coefficient: 0.471) between fundamental productivity and output quality after controlling for firm fixed effects and time fixed effects.[25] On the other hand, producing high-quality products incurs substantial costs, resulting in a negative correlation (coefficient: -0.136) between TFPQ and output quality.

This finding carries significant implications for the relationship between output prices and productivity. In the steelmaking industry, the correlation between output prices and fundamental productivity is positive (coefficient: 0.229) after controlling for firm fixed effects and time fixed effects. This contrasts with the results of Foster et al. (2008), who document a negative correlation in homogeneous-product industries where more efficient firms reduce prices by passing along their cost savings. In quality-differentiated industries, more productive firms tend to leverage their efficiency to produce higher-quality products, which incur higher costs and thus higher prices. As a result, the correlation between fundamental productivity and output prices may be positive, reflecting the role of endogenous quality choices and the costs of quality, in addition to the cost-saving channel highlighted by Foster et al. (2008), in shaping price-productivity relationships.

Table 4: Variance-covariance Decomposition of TFPR

var(TFPR)	var(ω)	var($\ln\tilde{\xi}$)	var(ϕ)	2cov(ω, $\ln\tilde{\xi}$)	2cov($\ln\tilde{\xi}$, ϕ)	2cov(ω, ϕ)
1.143	0.025	0.010	1.027	0.014	-0.010	0.077

Note 1: $\ln\tilde{\xi} = (1-\alpha_\xi)\ln\xi$ represents the net effect of the benefits and costs of quality.
Note 2: The covariances are multiplied by 2, so that the sum of variances of covariances of the components of TFPR equals the variance of TFPR.

By accounting for both the costs and benefits of quality alongside the effects of fundamental

[25]This pattern is also demonstrated in Appendix Figure A3a.

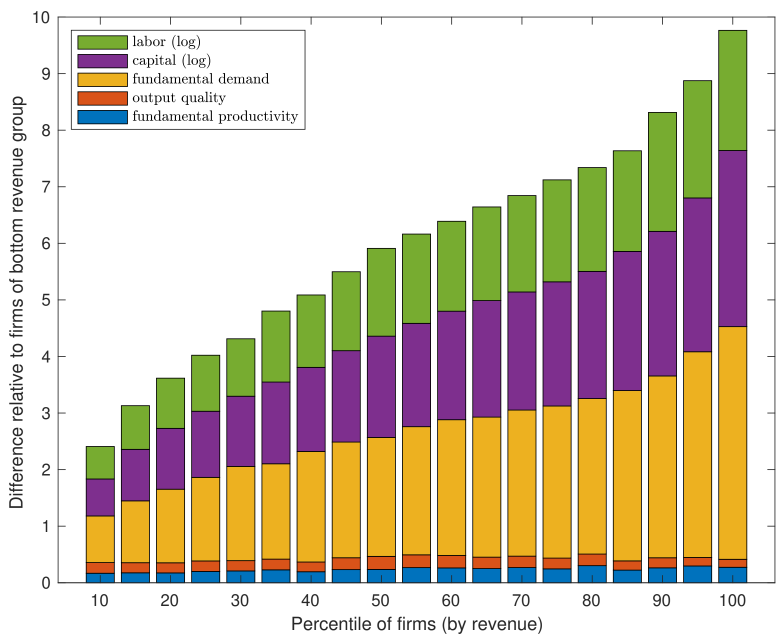
productivity and demand, TFPR is a natural measure of firms' overall performance despite the different roles of these individual components. Table 4 decomposes the variance of TFPR into its elements: fundamental productivity (ω), fundamental demand (ϕ), and the net effect of quality's benefits and costs ($\ln \tilde{\xi}$). The results indicate that variation in TFPR is predominantly driven by fundamental demand, which exhibits the greatest dispersion (standard deviation: 1.013). In contrast, fundamental productivity shows significantly less variability (standard deviation: 0.157). The positive covariance between fundamental productivity and demand further amplifies TFPR dispersion by 0.077. The net effect of output quality contributes modestly to TFPR dispersion due to the offsetting impact of quality's benefits and costs, although the dispersion of output quality itself (variance: 0.03) is comparable to that of fundamental productivity. Moreover, the positive covariance between the net effect of quality and fundamental productivity contributes to the dispersion of TFPR, which is largely offset by the negative covariance between the net effect of quality and fundamental demand.

The substantial heterogeneity in fundamental demand across firms likely reflects differences in marketing investment, customer base, geographic factors, and other market-driven elements. A Shapley–Owen variance decomposition (i.e., Shorrocks et al., 2013) shows that firm fixed effects explain 82% of the variation in fundamental demand, whereas time fixed effects and idiosyncratic demand shocks account for only 4% and 14%, respectively. This highlights that fundamental demand is predominantly shaped by firm-specific characteristics. The result aligns with recent evidence on the central role of marketing in driving firm growth. For instance, Jiang and Zhang (2024) document substantial heterogeneity in firms' marketing investments and show that these differences are a key source of variation in demand and sales.

5 Firm Heterogeneity and Revenue

The literature has a long tradition of using unobservable firm heterogeneity to explain firm behavior and performance (e.g., Jovanovic, 1982; Hopenhayn, 1992; Ericson and Pakes, 1995; Melitz, 2003; Collard-Wexler and De Loecker, 2015). More recently, Pozzi and Schivardi (2016) emphasized the distinct roles of demand and productivity in shaping firm outcomes. This section extends the literature by disentangling the effects of fundamental productivity and fundamental demand on firm revenue, after separately accounting for quality-related influences.

Figure 2: Firm heterogeneity (by revenue group)



We begin by analyzing how different dimensions of firm heterogeneity vary across firm sizes. Note that Section 3 implies the following revenue production function in logarithm:

$$r_{jt} = \frac{\sigma-1}{\sigma}\omega_{jt} + \frac{\sigma-1}{\sigma}(1-\alpha_\xi)\ln\xi_{jt} + \frac{\sigma-1}{\sigma}\phi_{jt} + \frac{\sigma-1}{\sigma}\alpha_k k_{jt} + \frac{\sigma-1}{\sigma}\alpha_\ell \ell_{jt}. \tag{16}$$

This equation helps evaluate the contribution of each revenue component – including fundamental productivity, demand, the net effect of quality, capital, and labor – to firm size differences. In Figure 2, we categorize firm-year observations into 20 equally sized percentile groups based on revenue. The figure presents the average characteristics of each revenue group relative to those of the bottom 5-percentile revenue group. The figure reveals systematic differences across various dimensions of firm heterogeneity. Firms in higher revenue groups tend to have significantly greater fundamental demand. Notably, firms in the top 5-percentile revenue group have a fundamental demand exceeding that of the bottom 5-percentile group by over 4 logarithmic units. This gap is larger than that in labor (about 2 logarithmic units) and capital stock (around 3 logarithmic units). In contrast, variations in fundamental productivity and output quality are more modest across revenue groups. Firms in the top 5-percentile group exhibit only about 27% higher fundamental productivity and 14% higher output quality than firms in the bottom 5-percentile group. Overall, unobservable heterogeneity (i.e., combining fundamental productivity, fundamental demand, and output quality) is as important as observable heterogeneity (i.e., combining capital stock and labor) in explaining firm size differences in revenue. Among all these factors, fundamental demand emerges as the dominant driver of firm size variation.

Table 5: Revenue variation decomposition: contribution of firm heterogeneity

	ω	$\ln \xi$	ϕ	ℓ	k	Total
Contribution (percentage points)	3.70	1.25	57.39	4.51	33.49	100.00

We also perform a variance decomposition of revenue to quantify the contribution of each component in (16) in explaining revenue variation. Following the approach of Eaton et al. (2004) and Hottman et al. (2016), we regress each component (x_{jt}) on total revenue using the specification: $x_{jt} = \beta_0^x + \beta_1^x r_{jt} + \epsilon_{jt}^x$, where coefficient β_1^x represents the contribution of component x on the variance of revenue. By OLS properties, this decomposition allocates the covariance terms between revenue components equally across them, implying that $\beta_1^\omega + \beta_1^\xi + \beta_1^\phi + \beta_1^k + \beta_1^\ell = 1$. The results in Table 5 show that the variation in fundamental demand, presumably driven by firm-specific characteristics in the output market such as customer base, marketing investment, and geographic factors, explains the largest share of revenue variation (around 57%), surpassing even the significant contribution of capital stock (about 33%). Finally, although the contribution of fundamental productivity is relatively small (3.70%), it remains comparable to that of labor.[26] The impact of output quality is modest (1.25%) because a large part of the quality's revenue-enhancing benefits is offset by its production costs. In the absence of quality costs, the contribution of quality would be similar to that of fundamental productivity.

Nonetheless, each factor affects revenue differently through pricing and quantity channels. These patterns are implied by our structural model in Section 3 and verified by estimating a panel-data fixed-effects model that controls for year-month fixed effects and observable firm characteristics, as reported in Appendix Table A6. Both fundamental productivity and demand are positively associated with revenue. However, they impact revenue through different mechanisms. Conditional on other factors, higher fundamental productivity decreases prices but boosts output. In contrast, higher fundamental demand raises both prices and outputs. Notably, although higher output quality also increases revenue, its mechanism differs from that of productivity and demand: quality raises prices but reduces output. These results align with the growing literature on the effects of productivity and demand on firm performance (Foster et al., 2008; Pozzi and Schivardi, 2016; Roberts et al., 2018; Kumar and Zhang, 2019; Jiang and Zhang, 2024) and contribute by decomposing traditional metrics into finer dimensions of firm heterogeneity.

Overall, these firm-level results highlight the substantial contribution of TFPR to revenue and the distinct roles of its individual components. In the next section, we use the 2008 global financial crisis as a case study to examine TFPR growth in the Chinese steel industry and its driving forces.

[26] Labor's contribution is smaller than that of capital stock, although the labor differences across revenue groups in Figure 2 are similar to that of capital stock. This is because of lower labor elasticity to output ($\alpha_\ell = 0.14$), which is only one-fifth of capital's elasticity ($\alpha_k = 0.75$).

6 Quality Shocks and Aggregate TFPR Growth

This section empirically examines how output quality, alongside fundamental productivity and demand, contributes to aggregate revenue productivity (TFPR) growth at the industry level, particularly during periods of significant economic shocks when quality growth may not align with shifts in these demand and production fundamentals.

The Chinese steelmaking industry around the 2008 global financial crisis provides an excellent case for this purpose. During our data period, the steelmaking industry experienced a significant economic shock due to the global financial crisis and the unprecedented stimulus plan implemented by the Chinese government as a response. The shock caused substantial 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 the demand residual, as proxies for productivity and demand, respectively, can be biased by embodied output quality. To do so, 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) in Table 6.

The crisis-stimulus period (2007–2010). During this period, industry-level TFPR increased by 7.78 percentage points, primarily driven by a substantial rise in fundamental demand (contributing 8.00 percentage points), alongside a modest gain in fundamental productivity (0.22 percentage points) and a decline in output quality (–0.78 percentage points). This reduction in quality is consistent with the trend depicted in Figure 1. As noted in Section 2, the decline reflects a shift in demand composition: foreign demand for high-quality steel contracted, whereas the domestic demand, predominantly for lower-quality products, rose, spurred by the Chinese government's Four Trillion Stimulus Plan. This decline in quality contrasts with the rising demand and productivity; however, it also reduces the production costs of quality, represented by $-\alpha_\xi \ln \xi_{jt}$,

Table 6: Decomposition of aggregate revenue productivity growth (percentage points)

	Crisis-Stimulus Period (2007-2010)	Post Crisis Period (2010-2014)
TFPR ($\omega - \alpha_\xi \ln \xi + \ln \xi + \phi$)	7.78	6.24
contributed by TFPQ	0.56	-5.01
—Fundamental productivity (ω)	0.22	-3.37
—Costs of quality ($-\alpha_\xi \ln \xi$)	0.33	-1.64
contributed by demand residual	7.22	11.25
—Benefits of quality ($\ln \xi$)	-0.78	3.81
—Fundamental demand (ϕ)	8.00	7.44

thereby partially offsetting its adverse effect on TFPR. As a result, the overall impact of quality, given by $(1-\alpha_\xi)\ln \xi_{jt}$, remains limited.

The modest role of output quality contrasted sharply with the significant contribution of the demand residual, the traditional proxy for quality. Although the demand residual, primarily driven by fundamental demand, accounted for the largest share of TFPR growth, the contribution of output quality was negative. Similarly, TFPQ overstates the production-side contribution during this period by including quality-related costs.

The post-crisis period (2010–2014). After 2010, export demand began to recover and grew steadily as the world gradually recovered from the global financial crisis. Meanwhile, domestic steel demand decelerated amid a slowdown in major downstream industries as the effects of China's stimulus plan gradually faded. Consequently, the aggregate quality of steel grew strongly in this period by 3.81 percentage points. The aggregate fundamental demand increased by 7.44 percentage points as the export market began to recover in the post-crisis period. Nonetheless, fundamental productivity declined significantly by 3.37 percentage points.

Notably, without distinguishing between output quality and fundamental demand, the demand residual grew by 11.25 percentage points, which is significantly higher than the growth in output quality (3.81 percentage points). The demand residual also grew significantly differently from fundamental demand, because output quality improved substantially in the post-crisis period. This is in sharp contrast to the crisis-stimulus period, when the demand residual mainly captures growth in fundamental demand because output quality growth was mild. The comparison further suggests the distinct roles of output quality and fundamental demand in driving TFPR growth. Finally, TFPQ reflects a growth of -5.01 percentage points, significantly understating the productivity growth as measured by fundamental productivity (-3.37 percentage points).

Overall, fundamental demand is a stronger driver of TFPR growth compared with fundamental productivity, after controlling for output quality. The improvement of output quality, however, does not necessarily align with that of fundamental demand or fundamental productivity. Consequently, the conventional proxies of demand or productivity may understate or overstate their contributions to TFPR growth, depending on the nature of the quality shock.

7 Conclusion

Unobserved output quality complicates the assessment of firms' productivity and demand advantages, as higher-quality products involve higher production costs but greater demand benefits. Large shocks, such as the 2008 financial crisis and fiscal stimulus policies, disproportionately affect demand across different quality levels, further obscuring the evaluation of firm capability growth.

This paper examines firm heterogeneity in output quality, productivity, and demand using a unique panel with an index of scientific output quality from the Chinese steel industry. The objective quality measure enables us to decompose TFPQ into fundamental productivity and the costs of quality, and to separate demand residual into fundamental demand and the benefits of quality. We find that approximately half of quality's benefits are offset by the costs of producing quality. Fundamental demand accounts for the largest share of revenue variation, followed by productivity, whereas quality's impact remains modest due to its high production costs. Using the shocks of the 2008 global financial crisis and China's stimulus policies, we document that output quality can amplify or dampen changes in revenue productivity because its growth may diverge from fundamental productivity and demand, depending on the nature of economic shocks. Moreover, TFPQ and demand residual, by conflating costs and benefits of quality, may significantly bias evaluations of productivity and demand contributions to firm performance. Nonetheless, even after accounting for quality, fundamental demand continues to play a dominant role in the growth of firm revenue productivity, highlighting the importance of future research on its underlying drivers, such as marketing investment, customer base, and geographic factors.

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Appendices

A Output Quality Characteristics

This appendix presents the patterns of the output quality and its relationship to key variables.

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 level).[27] Table A2 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 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).[28] The positive association is intuitive. First, producing higher quality incurs larger costs (i.e., costs of quality), which drives up prices. Second, higher quality also promotes demand, allowing firms to charge higher prices.

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 A3 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 effects. Such a relationship is the key to identifying the costs of quality associated with producing high-quality products from unobservable fundamental productivity, which is formally investigated in Section 4. When productivity is measured in revenue terms, nonetheless, Column (2) shows that it is positively related to output quality. This is because higher-quality output can sell at a higher price (Table A2). This effect offsets and dominates the costs of quality. Such a positive effect of quality is also observed in the relationship between revenue and output quality in Column (4).

B Derivation of CES Demand Function From Utility Function

This section has three purposes. First, it provides a detailed derivation of the CES demand function (2) from the representative consumer utility function (1). Second, it demonstrates that the constant elasticity of substitution may not be equal to the price elasticity of demand when firm size is non-negligible, and thus does not preclude variable markups across firms. Finally, it clarifies that our empirical strategy of estimation is consistent with the potential variable demand elasticity and markups. We assume that there is no strategic interaction between individual firms

[27]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.

[28] Nonetheless, this does not mean that output price is a perfect measure of output quality. As 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 A2 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 changes over time in output (steel) prices are largely influenced by the variation in input (iron ore) prices. These dramatic changes in iron ore prices (e.g., fluctuations of 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.

and that a firm's price choice impacts other firms only by changing the aggregate price index.

Deriving the CES demand function. We start from the constant elasticity of substitution (CES) preference of the representative consumer, (1):

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

where σ is the constant elasticity of substitution across the products.

Given the consumer's total expenditure (I_t) and output prices, the consumer maximizes her utility according to the following problem:

$$\begin{aligned} &\max_{Q_{jt}} \left[\sum_j \rho_{jt}^{\frac{\sigma-1}{\sigma}} \left(\xi_{jt} Q_{jt}\right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \\ &\text{subject to:} \quad \sum_j P_{jt} Q_{jt} = I_t. \end{aligned} \tag{B.2}$$

The Lagrangian function is written as:

$$\mathcal{L} = \left[\sum_j \rho_{jt}^{\frac{\sigma-1}{\sigma}} \left(\xi_{jt} Q_{jt}\right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} + \lambda (I_t - \sum_j P_{jt} Q_{jt}), \tag{B.3}$$

where λ is the Lagrangian multiplier.

The first-order condition with respect to Q_{jt} is:

$$\left[\frac{(\rho_{jt}\xi_{jt})^{\sigma-1}}{Q_{jt}} \right]^{\frac{1}{\sigma}} \left[\sum_j \rho_{jt}^{\frac{\sigma-1}{\sigma}} \left(\xi_{jt} Q_{jt}\right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{1}{\sigma-1}} = \lambda P_{jt}. \tag{B.4}$$

Take the ratio of the above equation for any two products i and j to obtain:

$$\frac{P_{it}}{P_{jt}} = \left(\frac{\rho_{it}\xi_{it}}{\rho_{jt}\xi_{jt}} \right)^{\frac{\sigma-1}{\sigma}} \left(\frac{Q_{jt}}{Q_{it}} \right)^{\frac{1}{\sigma}}. \tag{B.5}$$

That is, for any product i, we have

$$Q_{it} = \left(\frac{\rho_{it}\xi_{it}}{\rho_{jt}\xi_{jt}} \right)^{\sigma-1} \left(\frac{P_{jt}}{P_{it}} \right)^{\sigma} Q_{jt}. \tag{B.6}$$

Substituting this relationship into the budget constraint, we obtain:

$$I_t = \sum_i P_{it} Q_{it} = Q_{jt} P_{jt}^{\sigma} \sum_i \left[\left(\frac{\rho_{it}\xi_{it}}{\rho_{jt}\xi_{jt}} \right)^{\sigma-1} P_{it}^{1-\sigma} \right]. \tag{B.7}$$

Solve for Q_{jt} from the above equation and take logarithm to obtain the demand function (2):

$$\ln Q_{jt} = -\sigma \ln P_{jt} + (\sigma - 1)\ln \xi_{jt} + (\sigma - 1)\phi_{jt}, \tag{B.8}$$

where $\phi_{jt} = \ln \rho_{jt} + \ln \left(\frac{I_t}{\sum_j [P_{jt}/(\rho_{jt}\xi_{jt})]^{1-\sigma}} \right)^{\frac{1}{\sigma-1}}$.

Price elasticity of demand. Next, we demonstrate that the constant elasticity of substitution (σ) is not equal to the price elasticity of demand $\frac{\partial Q_{jt}}{\partial P_{jt}} \frac{P_{jt}}{Q_{jt}}$ when firm size is non-negligible.

According to the demand function, the price elasticity of demand is written as:

$$\frac{\partial Q_{jt}}{\partial P_{jt}} \frac{P_{jt}}{Q_{jt}} = \frac{\partial \ln Q_{jt}}{\partial \ln P_{jt}} = -\sigma + (\sigma - 1)\frac{\partial \phi_{jt}}{\partial \ln P_{jt}}, \tag{B.9}$$

where $\phi_{jt} = \ln \rho_{jt} + \ln \left(\frac{I_t}{\sum_j [P_{jt}/(\rho_{jt}\xi_{jt})]^{1-\sigma}} \right)^{\frac{1}{\sigma-1}}$ contains P_{jt}. Thus, $(\sigma - 1)\frac{\partial \phi_{jt}}{\partial \ln P_{jt}}$ is not zero and the price elasticity of demand $\frac{\partial Q_{jt}}{\partial P_{jt}} \frac{P_{jt}}{Q_{jt}}$ may vary by firm. In fact, the model predicts that larger firms have more inelastic demand. To see this, we explicitly express $\frac{\partial \phi_{jt}}{\partial \ln P_{jt}}$ as:

$$\frac{\partial \phi_{jt}}{\partial \ln P_{jt}} = \frac{(\rho_{jt}\xi_{jt})^{\sigma-1} P_{jt}^{1-\sigma}}{\sum_i (\rho_{it}\xi_{it})^{\sigma-1} P_{it}^{1-\sigma}}. \tag{B.10}$$

Using the budget constraint relationship (B.7), we have:

$$\frac{\partial \phi_{jt}}{\partial \ln P_{jt}} = \frac{(\rho_{jt}\xi_{jt})^{\sigma-1} P_{jt}^{1-\sigma}}{\sum_i (\rho_{it}\xi_{it})^{\sigma-1} P_{it}^{1-\sigma}} = \frac{P_{jt}Q_{jt}}{Q_{jt}P_{jt}^{\sigma} \sum_i \left[\left(\frac{\rho_{it}\xi_{it}}{\rho_{jt}\xi_{jt}} \right)^{\sigma-1} P_{it}^{1-\sigma} \right]} = \frac{R_{jt}}{I_t}. \tag{B.11}$$

That is,

$$\frac{\partial Q_{jt}}{\partial P_{jt}} \frac{P_{jt}}{Q_{jt}} = -\sigma + (\sigma - 1)\frac{R_{jt}}{I_t}. \tag{B.12}$$

Recalling that I_t is the budget, $\frac{R_{jt}}{I_t}$ is the market share of firm j in period t. Because $\sigma > 1$, the above equation suggests that a firm's price elasticity of demand varies in market share: firms with larger market shares are associated with more inelastic demand. This point is also documented in the literature (e.g., Feenstra and Ma, 2007).

Note that the above derivation and relationship apply regardless of the number of firms in the market. When there are a large number of firms in the market and each firm has a small market share, the price elasticity of demand for each firm is approximately equal to σ. In our context, the interquartile range (IQR) of market share is approximately 1.8 percent. This implies a negligible variation in the price elasticity of demand, with an IQR of approximately 0.018 based on our estimate of σ.

Implication on our empirical estimation strategy. Although we assume constant elasticity of substitution, our empirical strategy of estimating the demand and production functions does not require a constant price elasticity of demand (or a constant markup) across firms. We articulate this point as follows.

In the demand estimation outlined in Section 4, we focus on estimating (2), particularly the elasticity of substitution σ. Note that the industry-level price index, $\frac{I_t}{\sum_j \left[\frac{P_{jt}}{\rho_{jt}\xi_{jt}}\right]^{1-\sigma}}$, is common across all firms in the industry (i.e., varying by time but not by firm). Consequently, time fixed effects in the demand estimation absorb the industry-level price index. As a result, σ can be identified through cross-sectional comparisons. To illustrate, consider a two-firm case (firms 1 and 2). If firm 1 experiences an exogenous price change, this affects its demand both directly through σ and indirectly by altering the aggregate price index. However, the change in the aggregate price index also impacts firm 2's demand. Since the time fixed effects control for shifts in the aggregate price index (effectively canceling out the influence of the industry-wide price level), the relative change in demand between the two firms provides the identifying variation for σ.

In the production estimation described in Section 4, the key assumption is the invertibility of the proxy function used to approximate unobserved fundamental productivity. The complexity arising from a variable price elasticity of demand (and thus a variable markup) is that the markup should, in principle, be part of the control variables in the proxy function. However, because in equilibrium the variable markup can be expressed as a function of market share, as shown in (B.12), which is essentially determined by the state variables, we can control for it by explicitly including the state variables, ξ_{jt}, ϕ_{jt}, k_{jt}, and a set of time dummies, in the proxy function. In particular, these variables include the estimated fundamental demand ϕ_{jt}, which is the key driving force of market share (revenue) as documented in Section 5. As a result, our empirical estimation strategy in Section 4 is consistent with the potential variable markups.

C Approximating a Model of Multi-product Firms

Because our focus is to understand firm-level heterogeneity, our model setup in Section 3 assumes that each firm produces a single product, although the firm-level output is aggregated from steel complying with three quality standards. In principle, one can view the steel complying with three quality standards as three different products, each with its own demand (in a potentially segmented market) and production functions. Nonetheless, our data do not contain firm-product level output prices, limiting our ability to estimate the demand function at the product level. The lack of firm-product-level input data also poses further challenges in estimating the production function at the firm-product level. In this section, we discuss the conditions under which the firm-level model in Section 3 serves as an approximation to an underlying multi-product firm model, while preserving the core insights of our analysis—such as the distinct roles of fundamental productivity and demand, as well as the production costs and consumption benefits of quality.

For expository purposes, we suppress the subscript for firm and time. There are three products, indexed by $i = \{1, 2, 3\}$, produced by the firm.[29] Following the notation of the demand function (2) in Section 3, we assume each of the three products has a demand function:

$$\ln Q_i = -\sigma \ln P_i + (\sigma - 1)\ln \xi_i + (\sigma - 1)\phi_i, \tag{C.1}$$

where $\sigma > 1$ is the elasticity of substitution parameter.

Here ξ_i represents a quality value for product i and remains constant across both time and firms. To align with the empirical implementation described in Section 4, we define the quality values as

$$\xi_1 = e^{\gamma\alpha_L}, \quad \xi_2 = e^{\gamma\alpha_M}, \quad \xi_3 = e^{\gamma\alpha_H}, \tag{C.2}$$

[29] We do not use L, M, H as in Section 2 to avoid confusion with labor L and material M used in this section.

where $\alpha_L = 0.5$, $\alpha_M = 1$, and $\alpha_H = 1.5$ are fixed quality index numbers, following the notation in Section 2, and γ is a flexible scale parameter that adjusts these fixed index numbers to the corresponding quality values used in consumer utility in Section 3. The inclusion of the parameter γ serves an empirical purpose: it rescales the industry's quality indices $(\alpha_L, \alpha_M, \alpha_H)$ to align them with the conceptual role of quality in the model.

In contrast, the fundamental demand ϕ_i can vary by firm, time, and product. Importantly, the correlation between the quality value ξ_i and fundamental demand ϕ_i can be flexible. For example, quality may be negatively associated with fundamental demand if the market size (customer base) embodied in the fundamental demand for lower-quality products is larger than that for high-quality products.

The firm's production technology is described by a transformation function:

$$\left\{\frac{Q_1}{A_1} + \frac{Q_2}{A_2} + \frac{Q_3}{A_3}\right\} = F(L, M, K), \tag{C.3}$$

where $A_i = e^{\omega}\xi_i^{-\alpha_\xi}$, following the setup in (5), denotes the TFPQ of product i. As in the main model, TFPQ depends on the firm's fundamental productivity (ω), which is common across products, and the cost of quality $(\xi_i^{-\alpha_\xi})$, which varies across products. Here, L, M, and K denote firm-level inputs, and $F(\cdot)$ is a general input aggregator.

While Cairncross et al. (2025) and Khmelnitskaya et al. (2025) show that a transformation function can be derived from individual product-level production functions under certain assumptions—such as differentiability and homogeneity of $F(\cdot)$,[30] we instead model the firm's production technology directly through the transformation function in (C.3). This specification represents the frontier of the firm's production possibility set for given inputs and allows for a broader range of input aggregators $F(\cdot)$ without requiring differentiability or homogeneity assumptions. These features make it compatible with the functional form of $F(\cdot)$ adopted in our empirical implementation in Section 3.

Intuitively, (C.3) states that the firm transforms inputs L, M, K into outputs Q_1, Q_2, Q_3, with the marginal rate of transformation between any two outputs depending on their TFPQ levels

[30] These papers obtain a firm-level transformation function with a Constant Elasticity of Substitution (CES) output aggregator, $\left\{\left[\frac{Q_1}{A_1}\right]^{\frac{1}{\delta}} + \left[\frac{Q_2}{A_2}\right]^{\frac{1}{\delta}} + \left[\frac{Q_3}{A_3}\right]^{\frac{1}{\delta}}\right\}^{\delta}$. Our specification is an analog with $\delta = 1$. Such a restriction is useful in driving the approximation (i.e., (C.5) and (C.19)) of the multi-product firm framework by a firm-level model, which is the focus of our analysis.

Whether δ is equal to 1 or not is an empirical question. If $\delta = 1$, the marginal rate of transformation of any two outputs, for example outputs 1 and 2, will only depend on their relative productivity difference, A_1/A_2; if $\delta \neq 1$, the marginal rate of transformation also depends on their relative production scale Q_1/Q_2. When firm-product level output price and quantity data are available, researchers can utilize this intuition to estimate the value of δ, as proposed by Caselli et al. (2025) and Khmelnitskaya et al. (2025).

Of course, with $\delta = 1$, our empirical estimate of α_ℓ and α_k in Section 4 suggests a decreasing return to scale and consequently implies diseconomies of scope in producing multiple products within the same firm, based on the result in Khmelnitskaya et al. (2025). In our context, this outcome may be plausible due to production process inflexibility and the need for specialized equipment in the steel industry. High-quality steel requires much tighter control over temperature, alloying, and impurities, and facilities often dedicate specific production lines, furnaces, or continuous casters to such outputs. When a firm attempts to produce both high- and low-quality grades, the same equipment must be frequently adjusted or repurposed, which increases downtime for cleaning, calibration, and maintenance. Moreover, it may reduce yields due to contamination risks (e.g., traces of impurities from low-grade batches compromising high-quality steel). In addition, since we use utilized capital as the measure of K_{jt} in the production model, shared inputs—as a source of economies of scope emphasized by Cairncross et al. (2025) and Khmelnitskaya et al. (2025)—are already controlled for. As a result, joint production can be less efficient than specialization across separate firms, thereby giving rise to diseconomies of scope.

(A_i). Since $A_i = e^{\omega}\xi_i^{-\alpha_\xi}$, this implies that outputs are technologically substitutable once adjusted for the cost of producing outputs with different quality levels.

In what follows, we show that a firm-level model as in our empirical equations (2) and (4) can be an approximation of a multi-product firm model with individual product-level demand functions and a firm-level transformation function described above.

Approximating the production side. Substituting $A_i = e^{\omega}\xi_i^{-\alpha_\xi}$ into (C.3) and define $Q = \sum_{i=1,2,3} Q_i$. After some algebra, we have:

$$Q = A \times F(L, M, K), \tag{C.4}$$

where $A \equiv e^{\omega}\left[\frac{Q_1}{Q}\xi_1^{\alpha_\xi} + \frac{Q_2}{Q}\xi_2^{\alpha_\xi} + \frac{Q_3}{Q}\xi_3^{\alpha_\xi}\right]^{-1}$.

Replacing ξ_i by its corresponding quality index numbers described in (C.2), we have:

$$\begin{aligned}
\left[\frac{Q_1}{Q}\xi_1^{\alpha_\xi} + \frac{Q_2}{Q}\xi_2^{\alpha_\xi} + \frac{Q_3}{Q}\xi_3^{\alpha_\xi}\right] &= \left[\frac{Q_1}{Q}e^{\alpha_\xi\gamma\alpha_L} + \frac{Q_2}{Q}e^{\alpha_\xi\gamma\alpha_M} + \frac{Q_3}{Q}e^{\alpha_\xi\gamma\alpha_H}\right] \\
&\approx e^{\left\{\alpha_\xi\gamma\frac{Q_1}{Q}\alpha_L + \alpha_\xi\gamma\frac{Q_2}{Q}\alpha_M + \alpha_\xi\gamma\frac{Q_3}{Q}\alpha_H\right\}} \\
&= e^{\alpha_\xi\gamma\xi^0} \\
&= \xi^{\alpha_\xi}.
\end{aligned} \tag{C.5}$$

where $\xi = e^{\gamma\xi^0}$ and $\xi^0 = \frac{Q_1}{Q}\alpha_L + \frac{Q_2}{Q}\alpha_M + \frac{Q_3}{Q}\alpha_H$ as defined in the main text of the paper. The second equation is an empirical approximation that is appropriate when the variance of $(\alpha_\xi\gamma\alpha_L, \alpha_\xi\gamma\alpha_M, \alpha_\xi\gamma\alpha_H)$ with associated share $(\frac{Q_1}{Q}, \frac{Q_2}{Q}, \frac{Q_3}{Q})$ is small.[31]

Therefore, the transformation function can be written as:

$$Q = A \times F(L, M, K), \tag{C.6}$$

where $A \approx e^{\omega}\xi^{-\alpha_\xi}$. That is, (C.6) is corresponding to our firm-level production function (4). In particular, Q is the firm-level total physical output quantity of steel in tonnage; L, M, K are the inputs at the firm level; ω is the firm-level fundamental productivity; ξ, as a firm-level quality index, is a function of quality numbers weighted by the quantity shares. Notice that ξ is a continuous function of quantity shares, although ξ_1, ξ_2, and ξ_3 are constant. Because the values of ξ_1, ξ_2, and ξ_3 are in ascending order, a higher quantity share of product 3, for example, implies a higher value of quality at the firm level.

Approximating the demand side. We illustrate the firm-level demand function (2) is an approximation of the individual product demand functions in this setting under the assumption of profit maximization.

Specifically, the firm maximizes the profit, subject to the demand functions (C.1) and transforma-

[31] Consider a random variable x, which takes values of $\alpha_\xi\gamma\alpha_L$, $\alpha_\xi\gamma\alpha_M$, and $\alpha_\xi\gamma\alpha_H$ with probability $(\frac{Q_1}{Q}, \frac{Q_2}{Q}, \frac{Q_3}{Q})$ respectively. The second-order Taylor expansion implies that an approximation: $E(e^x) = e^{E(x)}(1 + \frac{1}{2}Var(x))$. As a result, $E(e^x) \approx e^{E(x)}$ if $Var(x)$ is sufficiently small. In our application, after estimating the model, we compute the variance of a variable taking values of $(\hat{\alpha}_\xi\hat{\gamma}\alpha_L, \hat{\alpha}_\xi\hat{\gamma}\alpha_M, \hat{\alpha}_\xi\hat{\gamma}\alpha_H)$ with associated share $(\frac{Q_{j1t}}{Q_{jt}}, \frac{Q_{j2t}}{Q_{jt}}, \frac{Q_{j3t}}{Q_{jt}})$ for each firm j that produces all three products in period t. We find that these variances are indeed small: the median is 0.011, and the maximum is 0.019. For comparison, the corresponding values of $e^{E(x)}$ have a median of 1.100 across these observations. This confirms that the variance is negligible relative to the magnitude of $e^{E(x)}$, validating the approximation.

tion function (C.3):

$$\max_{Q_1,Q_2,Q_3,M,L} \sum_{i=1,2,3} P_i Q_i - P_M M - P_L L.$$

Plugging in the demand functions, the Lagrangian function can be written as:

$$\mathbb{L} = \sum_{i=1,2,3} Q_i^{1-\frac{1}{\sigma}} \xi_i^{\frac{\sigma-1}{\sigma}} e^{\frac{\sigma-1}{\sigma}\phi_i} - P_M M - P_L L - \lambda \left[\left\{ \frac{Q_1}{A_1} + \frac{Q_2}{A_2} + \frac{Q_3}{A_3} \right\} - F(L, M, K) \right] \tag{C.7}$$

The first-order condition with respect to Q_i is:

$$\frac{\partial \mathbb{L}}{\partial Q_i} = \frac{\sigma - 1}{\sigma} P_i - \frac{\lambda}{A_i} = 0. \tag{C.8}$$

Take the ratio of any of the two first-order conditions to obtain:

$$\frac{P_i}{P_j} = \frac{A_j}{A_i}, \tag{C.9}$$

where $i \neq j = 1, 2, 3$.

Since $A_i = e^{\omega} \xi_i^{-\alpha_\xi}$, we have:

$$\frac{P_i}{P_j} = \left[\frac{\xi_i}{\xi_j} \right]^{\alpha_\xi}. \tag{C.10}$$

Based on the above equation, we define

$$\tilde{P} \equiv \frac{P_i}{\xi_i^{\alpha_\xi}}, \quad i = 1, 2, 3, \tag{C.11}$$

where $\tilde{P}$ can be viewed as a quality-adjusted price index which is a constant for all the three products produced by the same firm.

Write the demand function (C.1) equivalently as:

$$Q_i = \left[\frac{P_i}{\xi_i^{\alpha_\xi}} \right]^{-\sigma} \xi_i^{(\sigma-1)-\alpha_\xi \sigma} e^{(\sigma-1)\phi_i}. \tag{C.12}$$

Plug the price index (C.11) into the above equation to obtain:

$$Q_i = \tilde{P}^{-\sigma} \xi_i^{(\sigma-1)-\alpha_\xi \sigma} e^{(\sigma-1)\phi_i}. \tag{C.13}$$

Sum over the above equation for all three products to obtain

$$Q \equiv \sum_{i=1,2,3} Q_i = \left[\tilde{P} \right]^{-\sigma} \left[\sum_{i=1,2,3} \xi_i^{(\sigma-1)-\alpha_\xi \sigma} e^{(\sigma-1)\phi_i} \right], \tag{C.14}$$

Note that in the above equation, Q is the total quantity – the same as we defined and used in the empirical setup. Similarly, as in our empirical setup, we define a firm-level price index as the average of prices weighted by quantity shares:

$$P \equiv \frac{\sum_{i=1,2,3} P_i Q_i}{Q}, \tag{C.15}$$

which is usually considered as unit price.

Substituting (C.11) into the above equation, we have the following:

$$\tilde{P} = \frac{P}{\sum_{i=1,2,3} \frac{Q_i}{Q} \xi_i^{\alpha_\xi}}. \tag{C.16}$$

Plug the above equation into (C.14) to obtain:

$$Q = P^{-\sigma} \left[\sum_{i=1,2,3} \frac{Q_i}{Q} \xi_i^{\alpha_\xi} \right]^{\sigma} \left[\sum_{i=1,2,3} \xi_i^{(\sigma-1)-\alpha_\xi \sigma} e^{(\sigma-1)\phi_i} \right]. \tag{C.17}$$

Replacing ξ_i by its corresponding quality index numbers described in (C.2) and following the similar spirit of approximation as conducted in (C.5), we have:[32]

$$\begin{aligned}
& \left[\sum_{i=1,2,3} \xi_i^{(\sigma-1)-\alpha_\xi \sigma} e^{(\sigma-1)\phi_i} \right] && \text{(C.18)} \\
= & \left[\sum_{i=1,2,3} e^{(\sigma-1)\phi_i} \right] \left\{ \sum_{i=1,2,3} \xi_i^{(\sigma-1)-\alpha_\xi \sigma} w_i \right\} \\
= & \left[\sum_{i=1,2,3} e^{(\sigma-1)\phi_i} \right] \left\{ e^{[(\sigma-1)-\alpha_\xi \sigma]\gamma \alpha_L} w_1 + e^{[(\sigma-1)-\alpha_\xi \sigma]\gamma \alpha_M} w_2 + e^{[(\sigma-1)-\alpha_\xi \sigma]\gamma \alpha_H} w_3 \right\} \\
\approx & \left[\sum_{i=1,2,3} e^{(\sigma-1)\phi_i} \right] e^{\left\{ [(\sigma-1)-\alpha_\xi \sigma]\gamma \alpha_L w_1 + [(\sigma-1)-\alpha_\xi \sigma]\gamma \alpha_M w_2 + [(\sigma-1)-\alpha_\xi \sigma]\gamma \alpha_H w_3 \right\}} \\
\approx & \left[\sum_{i=1,2,3} e^{(\sigma-1)\phi_i} \right] e^{\left\{ [(\sigma-1)-\alpha_\xi \sigma]\gamma \xi^0 \right\}} \\
= & \left[\sum_{i=1,2,3} e^{(\sigma-1)\phi_i} \right] \xi^{\left\{ [(\sigma-1)-\alpha_\xi \sigma] \right\}} && \text{(C.19)}
\end{aligned}$$

where $\xi = e^{\gamma \xi^0}$, $\xi^0 = \frac{Q_1}{Q}\alpha_L + \frac{Q_2}{Q}\alpha_M + \frac{Q_3}{Q}\alpha_H$ as defined in the main text of the paper. Note that $w_i \equiv \frac{e^{(\sigma-1)\phi_i}}{\sum_{i=1,2,3} e^{(\sigma-1)\phi_i}}$ is a weight, and the last approximation is valid when this weight is

[32] Similar to the explanation in Footnote 31, the first approximation is valid when the variance of $\left[((\hat{\sigma}-1) - \hat{\alpha}_\xi \hat{\sigma})\hat{\gamma}\alpha_L,\ ((\hat{\sigma}-1) - \hat{\alpha}_\xi \hat{\sigma})\hat{\gamma}\alpha_M,\ ((\hat{\sigma}-1) - \hat{\alpha}_\xi \hat{\sigma})\hat{\gamma}\alpha_H \right]$ with associated probability (w_1, w_2, w_3) is small. While (w_1, w_2, w_3) are not directly observed, they can be approximated by the quantity shares $\left(\frac{Q_1}{Q}, \frac{Q_2}{Q}, \frac{Q_3}{Q}\right)$ as explained in Footnote 33. For each firm in each period producing all three products, we compute the variance of this variable and find that it is indeed small. Across these observations, the median variance is 0.0001 and the maximum is 0.0002. For comparison, the corresponding values of $e^{E(x)}$ have a median of 1.001. Thus, the variance is negligible relative to the magnitude of $e^{E(x)}$, validating the approximation.

approximately the same as the quantity weight $\frac{Q_i}{\sum_{i=1,2,3} Q_i}$. In our application, these weights are close and the approximation is appropriate.[33]

Substitute (C.5) and (C.19) into (C.17), we obtain:

$$Q = P^{-\sigma}\xi^{\sigma-1}e^{(\sigma-1)\phi}, \tag{C.20}$$

where $\xi = e^{\gamma\xi^0}$, $\xi^0 = \frac{Q_1}{Q}\alpha_L + \frac{Q_2}{Q}\alpha_M + \frac{Q_3}{Q}\alpha_H$ as defined in the main text of the paper, and

$$\phi \equiv \ln\left[\sum_{i=1,2,3} e^{(\sigma-1)\phi_i}\right]^{\frac{1}{\sigma-1}}. \tag{C.21}$$

Take the logarithm of (C.20) to obtain:

$$\ln Q = -\sigma \ln P + (\sigma-1)\ln\xi + (\sigma-1)\phi. \tag{C.22}$$

This aggregated (firm-level) demand function corresponds to our empirical demand function (2). In particular, Q is the firm-level physical quantity of output; P is the firm-level unit price defined accordingly in (C.15); ϕ is the firm-level fundamental demand specified in (C.21); $\xi = e^{\gamma\xi^0}$ and $\xi^0 = \frac{Q_1}{Q}\alpha_L + \frac{Q_2}{Q}\alpha_M + \frac{Q_3}{Q}\alpha_H$ as defined in the main text of the paper.

Finally, we impose assumptions on the underlying firm-product-level demand shocks ϕ_{jit}, in order to provide foundation to support the assumption that the firm-level fundamental demand ϕ_{jt} follows an AR(1) process as assumed in Section 4.

Specifically, by reintroducing the full index notation consistent with the demand function (2) and following the derivation in Appendix B, the firm-product-level demand shock for product i, firm j, and time t can be written as:

$$\phi_{jit} = \ln\rho_{jit} + \ln\left(\frac{I_{it}}{\sum_j \left[P_{jit}/(\rho_{jit}\xi_i)\right]^{1-\sigma}}\right)^{\frac{1}{\sigma-1}},$$

where ϕ_{jit} represents the consumer taste for product i, and I_{it} is the total expenditure allocated to product i, consistent with the setup in Section 3.

Assume that the firm-product-specific taste parameter can be multiplicatively separated as:

$$\rho_{jit} = \psi_{jt} \times \psi_i,$$

where ψ_{jt} is a firm-time-specific component and ψ_i is a product-specific component. Under this

[33] To see this point, note that (C.13) implies that the quantity share can be written as $s_i \equiv Q_i/\sum_i Q_i = e^{(\sigma-1)\phi_i}\xi_i^{(\sigma-1)-\alpha_\xi\sigma}/\sum_i(e^{(\sigma-1)\phi_i}\xi_i^{(\sigma-1)-\alpha_\xi\sigma})$, $i = 1, 2, 3$. These shares are close to the demand shares $w_i = e^{(\sigma-1)\phi_i}/\sum_i e^{(\sigma-1)\phi_i}$ when the term $((\sigma-1)-\alpha_\xi\sigma)$, which captures the net effect of quality on demand, is small. To see this, let $x_i \equiv e^{(\sigma-1)\phi_i}$ and $\kappa_i \equiv \xi_i^{(\sigma-1)-\alpha_\xi\sigma}$, where κ_i is computable from the estimated model. Then $w_i = x_i/\sum_i x_i$, while the observed quantity share can be written as $s_i = \kappa_i x_i/\sum_i(\kappa_i x_i)$. From this identity, we obtain $w_i = (s_i/\kappa_i)/\sum_i(s_i/\kappa_i)$, showing that w_i can be recovered directly from the data and the estimated parameters. We then compare the weight vector (w_1, w_2, w_3) with (s_1, s_2, s_3) by computing the absolute differences $\Delta = (|w_1 - s_1|, |w_2 - s_2|, |w_3 - s_3|)$ for each firm j producing all three products in period t. Across all such firm-year observations, the differences are very small: the median difference is only 0.23%, with a maximum of 0.69%. This confirms that using (s_1, s_2, s_3) as an approximation to (w_1, w_2, w_3) is accurate in our application.

assumption, the firm-product-level demand shock becomes:

$$\phi_{jit} = \ln \psi_{jt} + \ln \psi_{it},$$

where

$$\psi_{it} = \left(\frac{I_{it}}{\sum_j \left[P_{jit}/(\psi_{jt}\xi_i) \right]^{1-\sigma}} \right)^{\frac{1}{\sigma-1}},$$

which varies only by product i and time t.

Thus, the firm-level fundamental demand can be written as:

$$\phi_{jt} = \ln \left[\sum_{i=1}^{3} e^{(\sigma-1)\phi_{jit}} \right]^{\frac{1}{\sigma-1}} = \ln \psi_{jt} + \ln \overline{\psi}_t, \tag{C.23}$$

where

$$\overline{\psi}_t = \left[\sum_{i=1}^{3} e^{(\sigma-1)\psi_{it}} \right]^{\frac{1}{\sigma-1}},$$

which depends only on time t.

We assume that the firm-time-specific taste component $\ln \psi_{jt}$ follows an AR(1) process. It then follows that ϕ_{jt}, being the sum of $\ln \psi_{jt}$ and a time-specific term $\ln \overline{\psi}_t$, also follows an AR(1) process with time fixed effects. This structure justifies the empirical implementation in Section 4, where the firm-level fundamental demand ϕ_{jt} is assumed to follow an AR(1) process with both firm and time fixed effects in the estimation of the demand function.

D Robustness Analysis

Additional IVs and Alternative Specifications in Demand Estimation

In our main results, we estimate the demand function (13) via GMM, using $k_{jt}, p_{jt-1}, q_{jt-1}$, and ξ^0_{jt-1} as IVs. These variables are correlated with the explanatory variables in period t but are uncorrelated with the idiosyncratic term ν_{jt}, which is realized in period t in the AR(1) evolution process of the demand shock. This section presents demand estimates using additional instrumental variables and fixed effects specifications to assess the robustness of our results.

Column (1) of Table A7 tests the robustness of our results when using year and month fixed effects instead of the year-month fixed effects used in Table 2, while maintaining the same set of instrumental variables. In Column (2), we expand the IV set by including the lagged average price of rival firms. Column (3) adds industry-level iron ore prices interacted with firm size (proxied by capital stock) to capture differences in input costs across firms of varying sizes, given that our iron ore price data are industry-wide and vary only by time. Column (4) introduces lagged smelting time per converter—an operational statistic influenced by output quality but unrelated to demand—as an additional instrument. Across all these alternative specifications, the estimated demand parameters remain quantitatively similar to our main findings.

Allowing Elasticity of Substitution as a Function of Output Quality

Our analysis assumes that the elasticity of substitution σ is constant. Nonetheless, it is possible that steel of different quality levels may be associated with different elasticities. In this section, we show that our main results are robust by estimating a variant of the model with the elasticity of substitution varying as a function of output quality. Our results show that the demand and production function parameters are qualitatively similar to our main result and that the elasticity of substitution does not vary significantly by quality in our context.

Specifically, while keeping all other elements of the model unchanged, we allow the elasticity of substitution to vary with quality by defining it as: $\sigma = \sigma_P + \sigma_{\xi P} \ln \xi_{jt}$, where σ_P and $\sigma_{\xi P}$ are parameters to be estimated. This modification leads to a more flexible demand function:

$$\ln Q_{jt} = -\sigma_P \ln P_{jt} + \sigma_\xi \ln \xi_{jt} - \sigma_{\xi P} \ln \xi_{jt} \ln P_{jt} + \phi_j + \phi_t + e_{jt}. \tag{D.1}$$

To ensure comparability with our main results, we use the previously estimated $\hat{\gamma}$ to define $\ln \xi_{jt} = \hat{\gamma}\xi^0_{jt}$ in the modified specification. Under this formulation, the elasticity of substitution, given by $\sigma_P + \sigma_{\xi P} \ln \xi_{jt}$, varies with output quality ($\ln \xi_{jt}$) whenever $\sigma_{\xi P}$ is nonzero. If $\sigma_{\xi P} = 0$, the model simplifies to our main specification in (13).

We employ the same estimation method outlined in Section 4 to estimate the demand function (D.1) and the production function (4). The results, presented in Appendix Table A8, indicate that while output quality does have an effect on the elasticity of substitution, this impact is both economically and statistically insignificant. Specifically, a 1 percent increase in output quality is estimated to increase elasticity by only 0.08 percent, implying a marginal shift toward greater inelasticity. More importantly, the parameter estimates for both the demand and production functions remain largely consistent with our main findings in Tables 2 and 3. This robustness check confirms that our primary specification effectively captures the key characteristics without being significantly affected by variations in the elasticity of substitution across quality levels.

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 et al. (2019).

Specifically, we treat α_H, α_M, and α_L as parameters to be estimated. Similar to Section 2, we define the quality index as $\xi^0_{jt} = \alpha_H S_{Hjt} + \alpha_M S_{Mjt} + \alpha_L S_{Ljt}$, 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 into (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 set $\alpha_M = 1$ as a location normalization. Because $S_{Hjt}+S_{Mjt}+S_{Ljt} \equiv 1$, the demand function can be rewritten as:

$$\ln Q_{jt} = -\sigma \ln P_{jt} + \tilde{\alpha}_H S_{Hjt} + \tilde{\alpha}_L S_{Ljt} + \phi_j + \phi_t + e_{jt}, \tag{D.2}$$

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 into 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. (D.2) can be estimated similarly to our main results, using the instrumental variable approach to deal with potential endogeneity in output prices and shares of products produced following different standards.

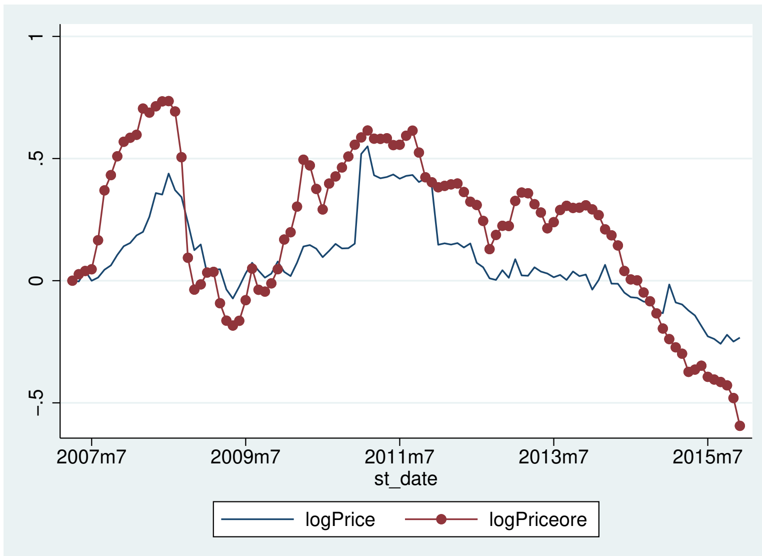
The estimation results are reported in Panel A of Appendix Table A9. In the first column, σ is biased in the OLS estimation. In the second column, we use capital stock and the interaction of lagged output shares produced according to international and enterprise standards as the IVs for output prices and output shares. In the third column, we further control for year-month fixed effects in the IV approach. The estimated elasticity of substitution ($\sigma = 1.935$) from 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 $\hat{\alpha}_L = 0.468$.[34] These values are very close to those used 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 in Section 4. 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 A9. Finally, we re-calculate the aggregate growth of TFPR and its decomposition and report them in Panel D. Not surprisingly, all the results are similar to our main findings. This supports the validity of the quality index numbers used in practice and shows that our main results are robust to the alternative index numbers flexibly estimated from the data.

[34] Because γ and the scale of α's are not separately identifiable, we normalize $\alpha_H - \alpha_L = 1$ to make the estimation comparable with those in industry practice. That is, the difference between the highest and lowest quality index numbers is normalized to be 1, as in 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 the 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 the enterprise standard (α_L) can be similarly calculated. Given $\hat{\sigma}$, the implied scale-adjustment parameter $\hat{\gamma} = 0.391/(\hat{\sigma} - 1) = 0.418$.

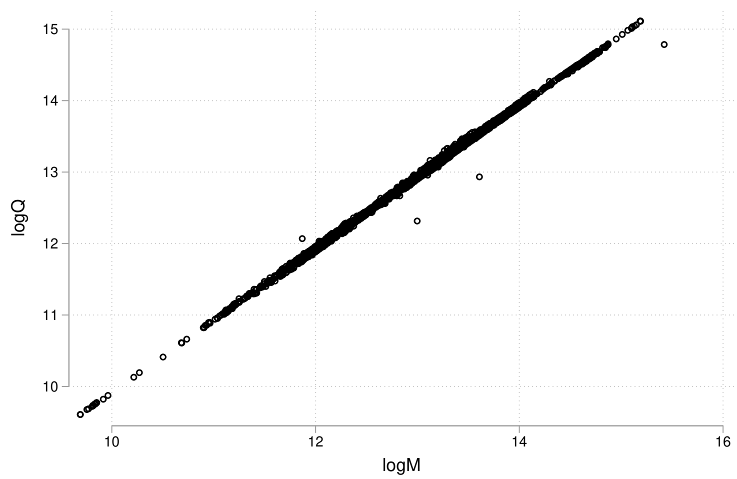
E Additional Figures and Tables

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.

Figure A2: Leontief technology of steel production: quantity of input (pig iron) and output (steel)



This figure provides support for the choice of the Leontief production function in (3), which reflects the characteristics of the production process in the steelmaking 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 in materials explains 99.89% of the variation in 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). Crucially, this 45-degree linear relationship holds consistently across different quality levels, meaning that the Leontief feature is a fundamental feature conditional on quality rather than being driven by cross-quality differences.

Figure A3: The relationship between output quality and fundamental productivity and demand

(a) Fundamental productivity and quality

(b) Fundamental demand and quality

Table A1: National and international 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.

Table A2: Relationship between output quality and output prices

	(1) log(P)	(2) log(P)	(3) log(P)	(4) log(P)	(5) 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

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

Table A3: 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

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

Table A4: Demand and production estimates without using quality data

Parameter	Demand	Parameter	Production
σ	1.805***	α_ξ	0.013
	(0.105)		(0.038)
$\gamma(\sigma-1)$	-	α_k	0.765***
			(0.086)
ρ_1	0.747***	α_ℓ	0.113
	(0.020)		(0.110)
		g_0	-0.027
			(0.017)
		g_1	0.960***
			(0.021)

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$
[1] Capital stock is used as the IV for output price in the demand estimation.
[2] The estimated demand residual from the demand function is used as a proxy of output quality measure in estimating the production function.
[3] Production estimation follows the same procedure as in our main results.

Table A5: Production costs of quality using quality proxies

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

[1] This table reports OLS regression estimates 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 for output quality. The fundamental demand, fundamental productivity, and demand residual are measures constructed from our main model with quality data. The fundamental productivity measure is included in the regressions to avoid the endogeneity issue caused by unobserved production efficiency (i.e., productivity).

Table A6: Firm heterogeneity and channels to affect sales performance

	(1) Revenue	(2) Price	(3) Quantity
Fundamental productivity	0.467***	-0.527***	0.994***
	(0.005)	(0.007)	(0.012)
Fundamental demand	0.454***	0.450***	0.005*
	(0.001)	(0.001)	(0.003)
Output quality	0.155***	0.399***	-0.244***
	(0.003)	(0.004)	(0.006)
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	0.997	0.963	0.983

Revenue, price, and quantity are in logarithm.

Standard errors in parentheses

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

Table A7: Robustness: demand estimates with alternative IVs and specifications

	(1)	(2)	(3)	(4)
σ	1.910***	2.019***	2.762***	1.906***
	(0.133))	(0.154)	(0.421)	(0.132)
$\gamma(\sigma - 1)$	0.537***	0.574***	0.597	0.546**
	(0.267))	(0.268)	(0.465)	(0.266)
ρ_1	0.744***	0.733***	0.766***	0.744***
	(0.020)	(0.020)	(0.021)	(0.020)
Year FE, month FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Observations	3936	3936	3936	3924

Standard errors in parentheses

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

[1] Column (1) uses year fixed effects and month fixed effects (as opposed to year-month fixed effects in the main result) while using the same IVs as in the main results. Column (2) adds the lagged average prices of other firms as an IV. Column (3) includes the industry-level iron ore price interacted with capital stock as an IV to capture differences in input costs across firms of varying sizes (iron ore price data vary only by time). Column (4) adds the lag of smelting time per converter as an IV.

Table A8: Robustness: demand and production estimates with variable elasticity of substitution

Parameter	Demand	Parameter	Production
σ_P	1.789***	α_ξ	0.433***
	(0.110)		(0.006)
σ_ξ	0.515**	α_k	0.777***
	(0.269)		(0.031)
$\sigma_{\xi P}$	-0.076	α_ℓ	0.102**
	(0.449)		(0.045)
ρ_1	0.758***	g_0	-0.016
	(0.017)		(0.006)
		g_1	0.973***
			(0.007)

Standard errors in parentheses

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

Table A9: 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: Aggregate productivity growth					
		2007-2010		2010-2014	
TFPR ($\omega - \alpha_\xi \ln \xi + \ln \xi + \phi$)		7.22		4.73	
contributed by TFPQ		0.75		-5.18	
—Fundamental productivity(ω)		0.39		-3.59	
—Costs of quality ($-\alpha_\xi \ln \xi$)		0.36		-1.59	
contributed by demand residual		6.47		9.91	
—Benefits of quality ($\ln \xi$)		-0.54		2.46	
—Fundamental demand (ϕ)		7.01		7.45	