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Non-neutral technology, firm heterogeneity, and labor demand☆

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ABSTRACT

In firm-level panel data, labor share exhibits large cross-sectional differences and a declining trend over time. This study examines the role of non-Hicks neutral technology differences across firms and over time in explaining these patterns. The non-Hicks neutral technology allows for differential factor-augmenting efficiencies for capital, labor, and material, and it has direct implications on labor shares. Estimated using firm-level production data and variation in input prices, evidence from the Chinese steel industry affirms the large heterogeneity of the non-Hicks neutral technology across firms, and its change over time is also highly non-Hicks neutral toward saving labor. The non-Hicks neutral technology explains over 50 percent of the 5.01-percentage points decline in labor share in the sample period, mainly due to the evolution of heterogeneous non-Hicks neutral technology and the resulting reallocation effect.

1. Introduction

The large cross-sectional heterogeneity of and decline in labor share have been a global phenomenon in the past four decades. In addition to the well-established large variation in labor share across firms, the literature documents a significant decline in labor share in many countries and industries, using both macro data (Karabarbounis and Neiman, 2014; Harrison, 2005; Rodriguez and Jayadev, 2010) and micro data (Kehrig and Vincent, 2017; De Loecker and Eeckhout, 2017). Most of the global decline, as stated in Karabarbounis and Neiman (2014), *"is attributable to within-industry changes rather than to changes in industrial composition."*

This paper provides micro evidence on how firm-level technology heterogeneity and its evolution over time have contributed to the heterogeneity of and decline in the within-industry share of labor, using data from the Chinese steel industry. To my knowledge, this is the first paper to examine the decline of labor share and the role of non-Hicks neutral technology in driving such changes in a development context.

This paper begins by documenting the large heterogeneity and radical decrease of the labor share in sales among the steel-making firms in China. The 90th/10th percentile difference in labor share in sales within each year is the lowest in 2004 at 7.5 percentage points and the highest in 2001 at 10.9 percentage points, or as the share of value added the lowest in 2007 at 39.7 percentage points and the highest in 2000 at 54.2 percentage points. From 2000 to 2007, the aggregate labor share in sales dropped by 5.01 percentage points, and the decline occurred for firms of all sizes. The largest 20 percent of firms, whose labor share drops by 5.4 percent, contributed the most to the decline. The heterogeneity and radical decrease of labor share cannot be explained by the contemporaneous mild change in input prices, given the reasonable range of substitutability across inputs in this industry.

This study explores the importance of the non-Hicks neutral technology in driving the decline in labor share and shaping the cross-sectional variation in labor share across firms in the Chinese steel industry. Defined as a multidimensional productivity measure, the non-Hicks

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neutral technology allows for differential factor-augmenting efficiencies for capital, labor, and material in a gross production function. It has direct implications for the firm's labor share: adopting a technology with high labor-augmenting efficiency, for instance, increases the marginal output of labor more than that of other inputs, which is labor-saving (labor-using) if inputs are gross complements (substitutes).

The role of non-Hicks neutral technology in driving the decline in labor share is crucial to understand the growth of developing countries in the modern economy. The structural change literature in development economics has identified the process of economic growth for a developing country as employment moving out from agriculture to manufacturing industries, and then to service industries (Lewis, 1954; Baumol, 1967; Kongsamut et al., 2001; Acemoglu and Guerrieri, 2008; Ngai and Pissarides, 2007). If developing countries can adopt labor-saving technologies in manufacturing industries in particular, the same type of cross-sector transition of employment as happened in the history of developed countries may not occur. Consequently, recognizing non-neutral technical differences to understand the path of economic development is important. While a few studies have examined non-neutral technological differences in developed countries (e.g. Doraszelski and Jaumandreu, 2017; Oberfield and Raval, 2014), this is the first to examine such differences and their implication on labor share in a developing economy to my knowledge.

I estimate the firm-time-specific non-Hicks neutral technology, using firm-level production data and variation in input prices. In the model, firms choose labor and material statically to maximize period profit and choose investment dynamically to maximize expected long-term payoff. The non-Hicks neutral technology influences labor share by changing the factor demand for labor, material, and capital investment differently. The estimation uses the idea that firms' optimal input choices contain useful information on the non-neutrality nature of technology; hence, the input ratios and input price ratios can be used as a proxy for the non-Hicks neutral technology in the production function estimation. Specifically, the first order conditions regarding the optimal labor and material choices identify the relative size of the three efficiencies, which can then be used to reduce the three-dimensional unobserved efficiencies in the production function into one dimension. The resulting production function can be estimated similarly as Olley and Pakes (1996).

The estimation results show large cross-sectional technology heterogeneity across firms even within this relatively narrowly defined industry, which has direct implications on firm heterogeneity in labor share. Within each year, the interquartile range is between 2.55 and 3.13 for capital efficiency, and between 2.06 and 2.25 for labor efficiency. The dispersion of material efficiency is smaller, but it is still economically substantial with the within-year interquartile range between 0.30 and 0.46. This implies an advantage of 30–58 percent for the 75th percentile material efficiency relative to the 25th percentile. The three factor-augmenting efficiencies are positively correlated, with mediocre correlation coefficients of 0.08–0.49. This scenario implies that substantial variations emerge in technological non-neutrality across firms: some firms are better at managing labor, while others may excel at using material or capital. Moreover, this cross-sectional heterogeneity of the non-Hicks neutral technology shows no evident converging trend, suggesting that the variation of labor share is a persistent feature across firms.

The non-Hicks neutral nature of technology is also important over time. In the sample period, Chinese steel makers experienced strong labor-saving technology changes. Labor efficiency grew much faster (39.95 percent) than capital efficiency (27.16 percent) and material efficiency (4.80 percent). This scenario implies an annual growth rate of total factor productivity (TFP), the expenditure-weighted average of the three factor-augmenting efficiencies, of 10.54 percent. This technology change is labor saving given that the inputs are gross complements, with the elasticity of substitution estimated at 0.49.

I conduct two counterfactual experiments to evaluate the contribution of the non-Hicks neutral technology on labor share. The first analysis validates that, if technology differences were Hicks neutral across firms and over time, the labor demand in 2007 would have been much higher, given the same factor prices. This scenario explains 51 percent of the 5.01-percentage points decline in labor share. This result complements Oberfield and Raval (2014): both studies contend that the non-Hicks neutral technology contributes substantially to the decline of labor share. Oberfield and Raval (2014) infer the contribution of technology as a residual after taking out the contribution of input price changes; I approach this question more directly by estimating the non-Hicks neutral technology from input-output data and input price variation. The second analysis evaluates the relative contribution of the cross-sectional heterogeneity and over-time changes in the non-Hicks neutral technology on labor share. The findings verify that both the over-time change and cross-sectional heterogeneity of the non-Hicks neutral technology play important roles: the former accounts for 43 percent of the total contribution of the non-Hicks neutral technology on the decline of labor share in the sample period; the latter contributes 57 percent.

The dynamic Olley-Pakes decomposition confirms that the decline of labor share is mainly due to the continuing firms, which experienced the fastest labor-saving technology change. Among all sources, reallocation of production to more labor-saving incumbent firms plays the most important role, explaining approximately 3.28 percentage points of the 5.01-percentage points decline in labor share. Within-firm changes explain 1.26 percentage points of the decline, and firm entry and exit together has a much smaller net effect.

This paper contributes to the recent literature on the determinants of the declining labor share worldwide. Various explanations have been proposed to explain this trend at the macro level. For instance, Karabarbounis and Neiman (2014) attribute it to the relative decline in capital prices, Piketty and Zucman (2014) to pure capital accumulation, and Elsby et al. (2014) to offshoring of labor-intensive tasks. Using firm-level data, De Loecker and Eeckhout (2017) argue that the rising markup since 1980 could explain the contemporaneous decline in labor share in the United States. Kehrig and Vincent (2017) attribute the decline to the reallocation of market share toward less labor-using hyper-productive manufacturing plants. This paper contributes to this line of literature by providing direct micro evidence that the non-Hicks neutral technology change over time at the firm level could be a powerful engine that drives down the labor share. In this sense, the micro evidence echos the macro finding that emphasizes the role of labor-augmenting technological change in driving the decline in labor share (e.g. Lawrence, 2015).

The paper also provides micro-founded evidence on the non-Hicks neutral technological change, contributing to the literature which shows aggregate labor-saving technology change in developed countries (e.g. Gollop and Roberts, 1981; Klump et al., 2007; León-Ledesma et al., 2010; Jin and Jorgenson, 2010).[1] Acemoglu (1998, 2002) proves the possibility of non-Hicks neutral technology change[2] in a dynamic balanced growth model, and Hanlon (2015) provides empirical evidence on directed technology change at the product level, lending support to the key predictions in Acemoglu (2002). This paper contributes to this literature by directly estimating the production function with non-Hicks neutral technology change using firm-level data, and by allowing for more flexibility in the technology evolution process.

The paper extends the large literature that estimates the Hicks neutral technology across firms (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015). This Hicks neutral productivity

[1] Some early studies include Gollop and Jorgenson (1980), Jorgenson et al. (1985), Gollop et al. (1987), David and Van de Klundert (1965), Kalt (1978), Diamond et al. (1978), Sato (1970). Refer to Klump et al. (2007) for a review.

[2] Acemoglu (1998, 2002) uses the term *directed technology change* instead.

difference has proved to be a useful indicator to predict the first-order performance of firms (for example, profitability, trade participation, and entry/exit). However, it plays a less important role in explaining the second-order ratios, such as relative input usage and labor share, because it affects the marginal products of all inputs symmetrically. The finding that technology is non-Hicks neutral fills this gap: firms have different comparative advantages in using different inputs—some firms are better at managing labor and others are better at using capital and material—resulting in different labor shares even when they face the same input prices.

Several recent studies develop and estimate the models of the non-Hicks neutral technology using micro data. Brambilla et al. (2016) identify and estimate a Cobb-Douglas production function with firm-time-specific random coefficients on labor share in addition to the time-specific capital and material efficiencies. They find a systematic link between the choice of export destinations and technology differences across firms. Raval (2017) estimates a value-added constant elasticity of substitution (CES) production function with capital- and labor-augmenting efficiencies and finds that labor augmenting productivity differences are more persistent and more highly correlated with size and exports than capital augmenting productivity differences. Using plant-level panel data for the U.S. automobile industry, Van Biesebroeck (2003) estimates a production function with firm-time-specific labor-saving efficiency and fixed-effect Hicks-neutral efficiency, based on parametric inversion to recover unobserved productivity. Doraszelski and Jaumandreu (2017) extend this work by further allowing the Hicks-neutral efficiency term to be firm-time-specific, and estimate a gross CES production function with labor-augmenting efficiency in addition to Hicks-neutral efficiency. Using panel data from Spain, they deduce that technological change is biased, with both its labor-augmenting and its factor-neutral components causing output to grow by approximately 1.5 percent per year. In this paper, I extend Doraszelski and Jaumandreu (2017) by further allowing the additional material-augmenting efficiency to be flexibly estimated. This scenario relaxes the assumption in their paper that capital and material efficiencies always grow at the same rate, which is a testable empirical question.[3] The introduction of material efficiency is economically important given the large material share in the total input expenditure and the potential differential ability of firms to utilize the material. My estimation shows that capital efficiency and material efficiency not only play different roles in production decision, they also differ largely in their dispersion, with an interquartile range of 3.10 versus 0.36 in 2007, respectively. They have a positive correlation of 0.49.

The magnitude of the elasticity of substitution among inputs largely determines how non-Hicks neutral technological change affects labor share. It also determines the key predictions of many economic models, such as Acemoglu (2002) for balanced growth path, Mankiw (1995) for differences in international factor returns, and Blanchard (1997) for change in income shares. My micro-based estimation asserts that the elasticity of substitution is less than one, consistent with most estimates using macro data (e.g., Antràs, 2004; Klump et al., 2007, and see León-Ledesma et al. (2010) for a review). The magnitude is also similar to the estimates in several recent studies that use firm-level data (Chirinko et al., 2011; Raval, 2017). Moreover, I claim that the estimated elasticity of substitution is substantially lower after controlling for non-neutral technology at the firm level, echoing Antràs (2004) who uses macro data.

The next section introduces the data and background for this study. Section 3 describes the estimation approach and results. Section 4 reports the heterogeneity and evolution of the non-Hicks neutral technology. Section 5 quantifies the contribution of non-Hicks neutral on the decline of labor share and the relative contribution of the heterogeneity and evolution of the non-Hicks neutral technology. Section 6 concludes this paper.

2. Data and facts

2.1. Data

Two panel data sets are matched for the empirical application. The main data source is a rich, firm-level annual survey of industrial firms in China, which was collected through annual surveys of manufacturing enterprises and maintained by the China National Bureau of Statistics. The panel is unbalanced and covers two types of manufacturing firms: all state-owned enterprises (SOEs), and non-SOEs whose annual sales are greater than 5 million RMB (approximately US $650,000). The data set contains information on firm-level annual revenue, input expenditures, wage rate, detailed firm characteristics (for example, age, ownership, and location), and many other financial variables. For a detailed description of the data set, refer to Feenstra et al. (2011), and Brandt et al. (2012, 2014).

The main data are supplemented by using localized input and output prices as proxy for firm-level prices for the steel industry. The supplementary data set is from the China Economic Information Network, which reports province-level price indexes for inputs and outputs for the steel industry. Given that the steel industry in China has very organized local markets for inputs and outputs, and steel makers are relatively concentrated in the same area in each province (usually close to main mines or ports), firms in the same area share very close prices of inputs and outputs for the same products. Thus, province-level prices represent firm-level prices well.[4] Section 4.2 will discuss the influence of potential measurement errors in factor prices, and provide further evidence that the results in this paper are not driven by potential measurement errors in prices.

I further examine the sources of variation in input prices across firms, which play an important role in identifying the non-Hicks neutral technology. Time, space, and firm size all drive the differences of input prices across firms. From 2000 to 2007, the average wage rate almost doubled in this industry, and the material price index increased from 95 to 169. The output price index also increased from 102 to 131. The spatial difference is large too. The province average wage rates in this industry ranged from 9,150 RMB in the poor Gansu province to 23,955 RMB in the rich Guangdong province. For the material price index, the lowest is in Guangxi Province (93.5) and highest in Chongqing Province (224). The average output price index also varies substantially from 92 in Qinghai Province to 164 in Guangxi Province. Finally, firm size has a mild positive correlation with wage rage, material prices, and output prices, with the correlation coefficients at 0.13, 0.02, and 0.04 respectively. Hence, in general, time and space are relatively more important factors that drive the price differences, and firm size plays a mild role.

This paper focuses on the steel industry in China for several reasons. First, reasonable data are available on input prices, which are necessary to estimate the non-Hicks neutral technology. Second, there was rapid technology change in this industry driven by government policy as will be discussed in Section 2.4. We can thus identify the changes in the level of technology and non-neutrality even with relatively short panels. Finally, the large dispersion of geographic and other economic

[3] Doraszelski and Jaumandreu (2017) also discuss the possibility of introducing the third-dimension of productivity in the extension, similar to what I discuss in this paper. They suggest a solution based on the first-order condition of static capital choice when capital is flexibly adjustable, or assuming a time trend of capital efficiency in the presence of capital adjustment friction.

[4] However, the use of localized output prices to represent the firm-level prices does lead to a limitation in the estimation. It implies that no product differentiation or heterogeneity emerges in markups within each location leading to dispersion in firm prices.

Table 1
Heterogeneity and declining of labor share in sales (%).

Year	Firm size group[a]					All groups
	0–20	20–40	40–60	60–80	80–100	
2000	8.08[b]	6.19	4.75	4.67	8.75	8.40
2001	7.31	6.39	5.61	4.62	7.34	7.17
2002	7.71	5.40	4.52	3.90	6.95	6.74
2003	6.61	4.85	4.23	3.60	5.71	5.58
2004	6.51	4.40	3.57	3.23	4.29	4.23
2005	6.42	4.79	3.92	3.22	3.61	3.63
2006	6.29	4.73	3.88	3.52	3.74	3.76
2007	6.46	4.76	3.89	3.29	3.35	3.39
Changes	−1.62	−1.43	−0.86	−1.38	−5.40	−5.01

[a] Firms are divided into five groups by firm size defined by sales, year by year, with each group having 20% of firms within each year.
[b] All means are revenue-weighted.

characteristics of Chinese steel firms can be used to investigate the non-neutral technological heterogeneity across firms.

Given that investment is not directly reported in the data. I recover investment using the observed data on capital stock and capital depreciation. After dropping observations with extreme variable values and missing lagged variables necessary for estimation, the sample contains 24,565 observations from 2000 to 2007. Appendix G provides more details about the sample construction, and Appendix H presents the variable definitions. Table A1 provides summary statistics for the main variables used in the estimation.

2.2. Heterogeneity and declining of labor share

The investigation of technological non-neutrality across firms and over time is motivated by two facts observed in the firm-level data. First, labor share displays large heterogeneity across firms in the steel industry in China. The 90th/10th percentile difference of labor share in sales within each year is the lowest in 2004 at 7.5 percentage points and the highest in 2001 at 10.9 percentage points, with the industry mean labor share in sales being 8.4 percent in 2000.[5]

In Table 1, the sample is divided into five groups of equal number of observations according to sales within each year, and the average labor share in sales is shown for each year-size group. A large dispersion of labor share exists across firms of different sizes, with labor share displaying a slight U-shape in firm size. On average for 2007, the mean labor share for the smallest 20 percent of the firms is 6.46 percent, which is almost twice as much as that for the second largest group, which has the lowest labor share (3.35 percent). When using labor share in value added, the pattern is similar; it is omitted here to save space.

Second, the labor share features a substantial declining trend during the data period. From 2000 to 2007, the industry average labor share in sales decreases by 5.01 percentage points, from 8.40 to 3.39 percent. This declining trend is shared by firms of all size groups, with the largest group experiencing the strongest decline by 5.4 percentage points and the medium group showing the least decline by 0.86 percentage point. When measured by labor share in value added, the pattern is similar and it is omitted here to save space.

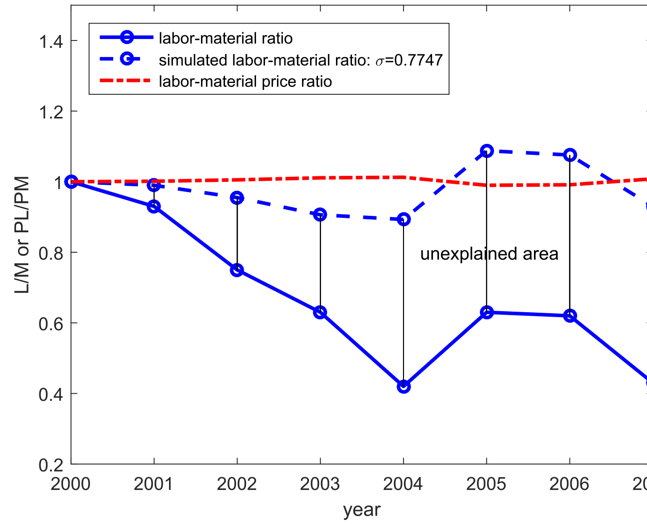


Fig. 1. Evolution of the labor-material ratio and relative price in the Chinese steel industry, 2000–2007.

2.3. Technological non-neutrality and labor demand: a first glance

The heterogeneity of input prices across firms and over time would unlikely explain the large cross-sectional heterogeneity and sharp decline in labor share. Fig. 1 and Table 2 examine the relationship between input and input price ratios, and show that input price heterogeneity is insufficient to explain the heterogeneity and movement in the input ratios. Fig. 1 plots the movements of the mean labor-material price and labor-material ratios from 2000 to 2007, with the value of the initial year normalized to be one. The labor-material price ratio increases slightly during this period, by approximately 9 percent in total in the seven years. By contrast, the mean labor-material ratio decreases sharply by 51 percent during the same period. The small change of input price ratio would unlikely explain such a sharp drop in the labor-material ratio given that the estimated elasticity of substitution is mostly less than or close to one (Chirinko et al., 2011; Raval, 2017; Antràs, 2004; Klump et al., 2007; León-Ledesma et al., 2010; Chirinko et al., 2011). Fig. 1 further plots the simulated average labor-material ratio for 2000–2007, choosing 2000 as the base year. The simulated labor-material ratio is computed on the basis of the observed price changes and the largest estimate of the elasticity of substitution, 0.775, as reported in Table 2 assuming the Hicks-neutral technology.[6] The predicted change in the labor-material ratio is much smaller than that observed in the data, leaving a large gap that cannot be explained by input price changes. This gap is consistent with a labor-saving non-Hicks neutral technology change over time.

[5] The low labor share in revenue is typical in China, with the average labor share in revenue being only 5.5 percent for the entire manufacturing sector in China during the same period. The high material inputs share (approximately 80 percent in revenue) and low wage rate were the main factors contributing to the low labor share in China. The declining labor share is also a common feature in the manufacturing sector in China, with the labor share in revenue declining from nearly 7% to 5% from 2000 to 2007, which shares a similar pattern in the steel industry to be discussed later. The share of labor in value added displays a similar pattern of large cross-sectional variation in the steel industry: its 90th/10th percentile difference is the lowest in 2007 at 39.7 percentage points and the highest in 2000 at 54.2 percentage points, with the industry mean labor share in valued added being 36.1 percent in 2000.

[6] The simulated average labor-material ratio for the year 2004, for instance, is computed as.

$$\left(\frac{L}{M}\right)_{2004} = \left(\frac{L}{M}\right)_{2000}\left[1-\sigma\left(\triangle\frac{P_L}{P_M}/\frac{P_L}{P_M}\right)\right],$$

where σ is the elasticity of substitution and $\triangle\frac{P_L}{P_M}/\frac{P_L}{P_M}$ is the percentage change in the labor-material price ratio from 2000 to 2004. The simulated labor-material ratios for other years are similarly computed.

Table 2
Input prices and input ratio: reduced-form regression.[a]

Variable	OLS				Random effect	Fixed effect
	(1)	(2)	(3)	(4)		
σ	0.775	0.760	0.761	0.737	0.573	0.490
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy		Yes	Yes	Yes	Yes	Yes
Age			Yes	Yes	Yes	Yes
Ownership			Yes	Yes	Yes	
Sigma-u[b]					0.7128	0.8124
Sigma-e					0.4137	0.4137
Rho					0.748	0.794
R-squared	0.274	0.295	0.297	0.314	0.311[c]	0.297[c]

[a] Dependent variable: labor-material ratio; independent variables: labor-material price ratio and other control variables. Standard errors are reported in parentheses.
[b] Sigma-u: the between-group variance in fixed and random coefficient models; sigma-e: the within-group variance. rho: fraction of variance due to between-groups variance.
[c] Overall R-squared in the fixed and random coefficient models.

Table 2 provides further evidence on that the input price ratio can only explain a small portion of the variation in the input ratio. We take the widely used CES production function as an example to illustrate the idea. If technology is Hicks neutral and labor and material are flexibly chosen to minimize costs, the input and input price ratios have a simple relationship,

$$\ln \frac{labor\ quantity}{material\ quantity} = -\sigma \ln \frac{wage\ rate}{material\ price} + constant + \xi.$$

Here σ is the elasticity of substitution. I suppressed the subscript for firm and year for all variables to simplify the notation. ξ contains the measurement error or any unobserved efficiency differences that are not Hicks neutral. The elasticity of substitution, σ, can be identified from the variation of input price ratios, under the assumption that ξ is uncorrelated with input price ratios. On the basis of this equation, I use the logarithm of the labor-material ratio as the dependent variable and run a series of ordinary least square regressions (OLS), with the logarithm of the labor-material price ratio as the major independent variable. The results are reported in the first four columns in Table 2. These regressions differ from one another in the additional covariates that are controlled for. The R-squared, as reported in the last row, is the major interest. Even after controlling for firm characteristics such as ownership, age, and year dummy, input prices together can only explain less than 30 percent of the variation in the input ratio. Similar results are found in fixed effect and random effect models, as shown in the last two columns in Table 2. Moreover, in contrast to the U.S. case in which increasing markup drives down the labor share since 1980s (De Loecker and Eeckhout, 2017), the markup in the steel industry in China in fact decreased during the sample period due to rising input prices and intensified competition. These results corroborate that some other factors are responsible for the large variation in the labor-material ratio.

The non-neutral technology provides a natural explanation for these observations. With the non-neutral technology, firms differ not only in their absolute level of efficiency, but also in their relative efficiency ratios. The former determines the absolute level of inputs used, or the size of factor demand; the latter determines the relative amount of the input used, or the composition of factor demand. More specifically, the relative factor efficiency differentials among firms imply a different marginal products of factors among firms, which leads to different input ratios among firms even when their input prices are the same. This paper estimates the effect of the non-Hicks neutral technology on labor demand and labor share based on a structural model that allows for flexible non-Hicks neutral technological heterogeneity, across firms and over time.

2.4. Historical background for the technology change

This subsection reviews the historical background of technology upgrading in the Chinese steel industry during the data period. We also provide some background on the layoff of workers in Chinese state-owned enterprises and show that it is unlikely to drive the radical decline in labor share as observed in the data.

2.4.1. Technology-enhancing policy and firms' technology investment

By the end of 1990s, although some firms in China had adopted the advanced BOF steel making process (Basic oxygen Furnace) and continuous casting technology, most firms were still using the old technology such as open-hearth process, molded casting, and blooming mill process. The size of key equipment (e.g. furnace) also varies substantially. The very heterogeneous production process led to large cross-sectional differences in input efficiencies in this industry.

Following the nationwide policy that aimed at enhancing technology improvement in all industries in China in 1997, the steel industry launched a large-scale technology upgrading movement starting 1999. The government gave strong incentives to encourage firms to upgrade their outdated technology via means such as direct subsidy and access to loans. Investment in technology upgrading, as the share of total investment in this industry, increased sharply to over 40 percent in 1999 from about 25 percent in 1980s.[7] In 1999, the industry invested approximately 25 billion RMB in technology upgrading, and this number rose to over 57 billion in 2002. The government further strengthened this policy in 2003 by announcing a complete list of outdated technology and equipment that should be terminated, and encouraged steel makers (especially large- and medium-size ones) to upgrade their technology and equipment. Consequently, the technology upgrading investment increased to nearly 100 billion in 2003, and remained high in subsequent years.

Since 1990s, China's steel industry made a major breakthrough in six key technologies and general technologies. This includes the continuous casting technology, blast furnace injection pulverized coal technology, blast furnace longevity technology, bar and wire continuous rolling technology, slag splashing technology and comprehensive energy saving technology for process adjustment. These technologies were then widely utilized by Chinese steel makers following their large investment in technology upgrading. Among them, the continuous casting

[7] Refer to page 141 of "China's Steel Industry: 50 Years of History" (in Chinese) by Zhifu Guo etc., Metallurgical Industry Press, September 1999.

technology has the most significant impact on productivity. The average continuous casting ratio increased from 86.97 in 2000 to 97.51 in 2005, according to *"China Steel Statistics"* 2000–2006 and an expert report from World Bank.[8]

The technology upgrading during this period has three features. First, the old and low-efficiency technology was replaced by more advanced ones, and small-size equipment (for example, furnace) was replaced by larger and more efficient ones. Second, automation was widely adopted together with the new technology, as well as in many other firms without replacing their core production equipment. The automation had the potential to save a substantial amount of labor. Third, the internet and information technology were gradually introduced into the production and management process in the steel-making firms. These changes together potentially can have a large impact on firms' efficiency in using capital, labor, and intermediate inputs.

The wide use of continuous casting technology, together with technology improvement in other dimensions such as automation and adoption of internet and information technology in the production process, led to a large efficiency improvement of Chinese steel makers, as measured by different efficiency indicators popularly used in the industry. For example, according to the *"China Steel Statistics"*, the comprehensive energy consumption per ton of steel on average decreased from 0.92 to 0.74 ton of standard coal from 2000 to 2005. The average utilization factor of blast furnace increased from 2.15 to 2.62 ton of iron per cubic meter of blast furnace per day, and the utilization factor of converter increased from 31.80 to 37.01 ton of steel per cubic meter of converter per day during the same period. The comprehensive yield also increased from 92.48 percent in 2000 to 95.61 percent in 2005.

2.4.2. Layoff in state-owned enterprises (SOE)

One possible explanation of the declining labor share, and as a result the labor-saving technology change as estimated later in this paper, might be the layoff of SOE workers due to the reform of SOEs starting in the mid-1990s, as discussed in Naughton (2007). In this discussion we show that layoff is unlikely to drive the declining labor share and the pattern of technology change.

The large-scale reform and layoff of SOE workers first started in early 1990s, and continued throughout the whole 1990s. The peak of layoff happened during 1998–2000, with about 2.137 million SOE workers being laid off in all industries in three years (especially in 1998 and 1999). The reform and layoff of SOE workers were induced by the large financial losses arising from low productivity and excess workers in SOE firms, which placed heavy financial burden to the government to cover the SOE losses. The layoff mainly happened in industries that suffered big losses, including coal mining, textile, machinery, and military products according to the *"China Labor Yearbook"*. The textile industry was chosen as the experimental field prior to the massive layoff in other industries.

The impact of the reform and especially layoff was minimum in the steel industry during our data period (2000–2007). The major reason is that 2000–2010 was the golden time for Chinese steel industry, due to the boom of Chinese economy and especially the boom of investment in housing and infrastructure. The steel prices were at a relatively high level, and steel makers (both SOEs and non-SOEs) were in general making good profits. Consequently, there was very low pressure to reform and layoff workers in this industry. In fact, the problem of this industry did not emerge until after 2010, when the long-term impact of the 2007 financial crisis emerged and the effect of China's fiscal stimulation policy faded away.

Moreover, the facts from the data also suggest that layoff should not be a big issue during the data period in the steel industry. First, the average number of workers per all-time SOE firm actually increased during the data period, suggesting that the SOE layoff reform did not have a substantial impact in the steel industry. Second, the average number of workers needed to produce 1 million RMB revenue decreased by similar percentage for both SOEs and non-SOEs. From 2000 to 2007, this number decreased by 66 percent for all-time private firms, and 68 percent for all-time SOEs. Finally, the estimated labor productivity for private firms grew substantially as well, at an annualized rate of 25%. Given that private firms are not subject to layoff policy shocks, this result further supports that the SOE layoff policy should not have been the main driving force of the estimated improvement of labor productivity.

The historical background suggests that there may be substantial upgrading of technology in this industry following the technology-enhancing policy and its resulting massive technology investment. This paper explores how the potential technology upgrading contributes to the decline of labor share in this industry.

3. Empirical model

This section proposes a method to estimate the production function with non-Hicks neutral technology and reports the basic estimation results.

3.1. Model setup

This subsection sets up a descriptive model of firms' production and investment decisions. The purpose is to present the model components and clarify the basic assumptions that form the basis for estimating the production function.

Production function. The production function for firm j at time t is CES with non-Hicks neutral technology and non-constant returns to scale,

$$Q_{jt} = \left\{ [\exp(\omega_{jt}^0)K_{jt}]^\gamma + [\exp(\nu_{jt}^0)L_{jt}]^\gamma + [\exp(\mu_{jt}^0)M_{jt}]^\gamma \right\}^{\frac{\kappa}{\gamma}}, \quad (1)$$

where Q_{jt} denotes the output and K_{jt}, L_{jt} and M_{jt} denote capital, labor, and material inputs, respectively. ω_{jt}^0, ν_{jt}^0 and μ_{jt}^0 represent capital-augmenting efficiency, labor-augmenting efficiency, and material-augmenting efficiency, respectively. They are observed by firms at the time of production but not by researchers, and they are the focus of this paper. Parameter γ captures the elasticity of substitution, which equals $\frac{1}{1-\gamma}$. The production function may have non-constant returns to scale, as captured by the parameter κ. The output is observed subject to an i.i.d. normal measurement error or unobserved productivity shocks (to both firms and researchers), $\varepsilon_{jt} \sim N(0, \sigma_\varepsilon^2)$; hence researchers only observe $Y_{jt} = Q_{jt}\exp(\varepsilon_{jt})$.

The firm-time-specific productivity measure allows for the study of the cross-sectional heterogeneity and evolution of non-neutral technology over time, and its implication on labor share across firms and over time. In particular, when the efficiency ratio $(\omega_{jt}^0 : \nu_{jt}^0 : \mu_{jt}^0)$ differs across firms for a given date t, the ratio of the marginal products of capital, labor, and material will be asymmetric across firms. So there is non-neutral technology heterogeneity across firms, leading to variation of labor share across firms. Similarly, when the efficiency ratios $(\omega_{jt}^0 : \nu_{jt}^0 : \mu_{jt}^0)$ change over time t, technology change will affect the marginal products of different inputs asymmetrically, leading to a non-neutral technology change over time and change of labor share over time. The production function with non-neutral technology in Eq. (1) accommodates several traditional concepts of neutral technology as its special cases. When $\omega_{jt}^0 - \nu_{jt}^0$ and $\omega_{jt}^0 - \mu_{jt}^0$ are both constant for all j and t, the production function degenerates to a Hicks neutral technology (Hicks, 1932). When both ω_{jt}^0 and μ_{jt}^0 are constant for all j and t but

[8] http://siteresources.worldbank.org/INTEAPREGTOPENVIRONMENT/Resources/ReportSteel&Iron20080104CN.pdf. Last accessed on May 2, 2019 (in Chinese).

ν_{jt} is not, the technology is Harrod neutral (labor-augmenting, Harrod, 1939). When both ν_{jt}^0 and μ_{jt}^0 are constant for j and t but ω_{jt} is not, the technology is Solow neutral (capital-augmenting, Solow, 1960; Jorgenson, 1966). As a result, the three traditional concepts of technology are all special cases of and nested in Eq. (1).

We represent the non-neutrality nature of the technology, by using three efficiency ratios. $\omega_{jt}^0 - \mu_{jt}^0$, the capital-material efficiency ratio, measures the non-neutrality of capital efficiency relative to material efficiency. Similarly, the labor-material efficiency ratio, $\nu_{jt}^0 - \mu_{jt}^0$, measures the non-neutrality of labor efficiency relative to material efficiency. $\omega_{jt}^0 - \nu_{jt}^0$ measures the capital-labor efficiency ratio. The three efficiency ratios completely describe the non-neutrality of technology.

Demand. Firms face monopolistic competition in the output market, and they are price takers in the labor and material inputs markets.[9] The demand function for firm $j's$ output has constant demand elasticity

$$Q_{jt} = \Phi_{jt} P_{jt}^{\eta}, \tag{2}$$

where P_{jt} is the output price endogenously chosen by the firm, and η is the constant demand elasticity. Φ_{jt} is a time-specific demand shifter observed by the firm before choosing labor and material in each period. Φ_{jt} is further decomposed to be a time dummy Φ_t common to all firms, an unexpected i.i.d. shock ξ_{jt}^D, and the effects of other observed firm characteristics, such as firm size, age, and ownership. Assume that Φ_{jt} can be written in the following form:

$$\begin{aligned} \ln\ \Phi_{jt} &= \Phi_t + \alpha_{size} * \textit{firm size} + \alpha_{age} * \textit{firm age} \\ &\quad + \alpha_{own} * \textit{firm ownership} + \xi_{jt}^D. \end{aligned}$$

Productivity evolution process. The productivity vector $(\omega_{jt}^0, \nu_{jt}^0, \mu_{jt}^0)$ evolves following a vector auto regression process VAR(1),[10]

$$\begin{aligned} \omega_{jt}^0 &= \rho_{\omega 0} + \rho_{\omega\omega}\omega_{jt-1}^0 + \rho_{\omega\nu}\nu_{jt-1}^0 + \rho_{\omega\mu}\mu_{jt-1}^0 + \xi_{jt}^{\omega}, \\ \nu_{jt}^0 &= \rho_{\nu 0} + \rho_{\nu\omega}\omega_{jt-1}^0 + \rho_{\nu\nu}\nu_{jt-1}^0 + \rho_{\nu\mu}\mu_{jt-1}^0 + \xi_{jt}^{\nu}, \\ \mu_{jt}^0 &= \rho_{\mu 0} + \rho_{\mu\omega}\omega_{jt-1}^0 + \rho_{\mu\nu}\nu_{jt-1}^0 + \rho_{\mu\mu}\mu_{jt-1}^0 + \xi_{jt}^{\mu}. \end{aligned} \tag{3}$$

Here all $\rho's$ are parameters and $(\xi_{jt}^{\omega}, \xi_{jt}^{\nu}, \xi_{jt}^{\mu})$ are the productivity shocks, which are i.i.d. across firms and over time, to corresponding efficiencies. Note that the efficiencies can have an impact on each other in the next period.

Production and investment decisions. Firms make two decisions each period: production decisions and investment decisions. At the beginning of each period, firms choose their own labor and material statically to maximize period profits, observing technology, capital, input prices, and demand status.

$$\begin{aligned} \max_{L_{jt}, M_{jt}} \quad & \left\{ P_{jt}Q_{jt} - W_{jt}L_{jt} - P_{Mjt}M_{jt} \right\} \\ s.t. \quad & Q_{jt} = \left\{ [\exp(\omega_{jt}^0)K_{jt}]^{\gamma} + [\exp(\nu_{jt}^0)L_{jt}]^{\gamma} + [\exp(\mu_{jt}^0)M_{jt}]^{\gamma} \right\}^{\frac{\kappa}{\gamma}}, \\ & Q_{jt} = \Phi_{jt}P_{jt}^{\eta}, \end{aligned}$$

where W_{jt} and P_{Mjt} are the wage rate and material price for firm j at time t, respectively. The output price, P_{jt}, is endogenously determined by the market clearing condition for the differentiated product for firm j at time t. The assumption of static labor choices, aside from the material decisions, is fairly plausible in China compared with other countries. Several practical reasons emerge. First, the labor market in China is very competitive due to the high volume of labor supply in the market, which favors firms. Second, generally there is a lack of effectively-enforced laws and regulations to protect workers in China. Third, labor unions in China are very weak and, in most of the cases, they are controlled by firms. These factors together result in much lower hiring and firing costs in China, compared with developed countries, where the labor policies and unions generally favor workers.

For expositional purpose, I denote $\omega_{jt} = \omega_{jt}^0 - \mu_{jt}^0$, $\nu_{jt} = \nu_{jt}^0 - \mu_{jt}^0$, and $\mu_{jt} = \kappa\mu_{jt}^0$. Then the optimal labor and material demands are determined by the associated first-order conditions,

$$\begin{aligned} & \kappa \frac{1+\eta}{\eta} \Phi_{jt}^{\frac{-1}{\eta}} Q_{jt}^{\frac{1}{\eta}} \left\{ [\exp(\omega_{jt})K_{jt}]^{\gamma} + [\exp(\nu_{jt})L_{jt}]^{\gamma} + M_{jt}^{\gamma} \right\}^{\frac{\kappa}{\gamma}-1} \\ & \quad \times \exp(\mu_{jt}) \exp(\gamma\nu_{jt}) L_{jt}^{\gamma-1} = W_{jt}, \end{aligned} \tag{4}$$

$$\begin{aligned} & \kappa \frac{1+\eta}{\eta} \Phi_{jt}^{\frac{-1}{\eta}} Q_{jt}^{\frac{1}{\eta}} \left\{ [\exp(\omega_{jt})K_{jt}]^{\gamma} + [\exp(\nu_{jt})L_{jt}]^{\gamma} + M_{jt}^{\gamma} \right\}^{\frac{\kappa}{\gamma}-1} \\ & \quad \times \exp(\mu_{jt}) M_{jt}^{\gamma-1} = P_{Mjt}. \end{aligned} \tag{5}$$

The endogenous variables are L_{jt} and M_{jt}, and the exogenous variables are $\omega_{jt}, \nu_{jt}, \mu_{jt}, W_{jt}, P_{Mjt}, K_{jt}$, and Φ_{jt}. To simplify the analysis, I further assume that the production and demand functions satisfy regular conditions such that there is a unique interior solution to Eqs. (4) and (5). The optimal input demands for labor and material, as a result, are functions of the state variables, $L_{jt}^* = L(\omega_{jt}, \nu_{jt}, \mu_{jt}, W_{jt}, P_{Mjt}, K_{jt}, \Phi_{jt})$ and $M_{jt}^* = M(\omega_{jt}, \nu_{jt}, \mu_{jt}, W_{jt}, P_{Mjt}, K_{jt}, \Phi_{jt})$. Accordingly, the labor share in sales also depends on the state variables, including non-Hicks neutral technology, input prices, demand factor, and capital stock. The capital stock may not be optimal due to friction or any other form of distortions.

Investment (in logarithm), i_{jt}, is chosen dynamically to maximize the expected firm value, given current state $(\omega_{jt}, \nu_{jt}, \mu_{jt}, k_{jt}, P_{Mjt}, W_{jt})$. So the optimal investment function can be written as a nonparametric function $i_{jt} = i(\omega_{jt}, \nu_{jt}, \mu_{jt}, k_{jt}, P_{Mjt}, W_{jt})$. In the empirical application, investment is defined as gross active investment, which includes the purchase and selling of assets. Consequently, it could be positive or negative. The investment has very few inactive observations (less than 0.2 percent).[11] Fig. A1 in Appendix presents the distribution of investment-to-capital ratio.

3.2. Estimation

The parameters of interest include the production parameters (κ, γ), the demand elasticity η, the parameters in the productivity evolution process $(\rho_0, \rho_{\omega}, \rho_{\nu}, \rho_{\mu})$, and the firm-time-specific non-neutral productivity measure $(\omega_{jt}^0, \nu_{jt}^0, \mu_{jt}^0)$. The model parameters are estimated using data on output quantity and prices, material quantity and prices, wage rate, number of workers, book value of capital stock, and investment. The identification is straightforward. First, the demand parameters are separately identified in the demand function. To estimate the production parameters, the usual transmission bias caused by the correlation between the unobserved productivity and input choices is present, because firms observe their productivity before choosing labor and material inputs, as in Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015). The new challenge is that we

[9] The price-taker assumption in the labor and material inputs market does not preclude that firms may still have different wage rates and material prices due to factors such as transportation costs, as discussed in Grieco et al. (2016).

[10] Extending the VAR process to a Markov process is straightforward. Given the short panel we have in the empirical analysis (eight years), I assume the first-order VAR process. Extending this assumption further to allow for a more general Markov process with higher order is also possible.

[11] Among all the observations, 69.75 percent have positive investment, 30.07 percent have negative investment, and 0.18 percent have zero investment (45 of 24,565).

have multi-dimensional unobserved factor efficiencies arising from the general non-Hicks neutral technology. The key source of variation to identify the production function with non-Hicks neutral technology is the variation in input prices and input usage ratios. Given the demand parameters, the variation in input prices and input usage ratios identifies the relative size of the three efficiencies, as shown in the first order conditions regarding firms' optimal labor and material choices. This scenario allows us to reduce the original production function with multi-dimensional unobserved efficiencies into one with one-dimensional unobserved efficiency, which is readily identified following Olley and Pakes (1996).

Specifically, multiplying both sides of the first-order conditions in Eqs. (4) and (5) by L_{jt} and M_{jt}, respectively, and dividing both sides by $P_{jt}Q_{jt}$ yields the first-order conditions in "share form":

$$\frac{\kappa\frac{1+\eta}{\eta}\exp(\gamma\nu_{jt})L_{jt}^{\gamma}}{\left\{[\exp(\omega_{jt})K_{jt}]^{\gamma}+[\exp(\nu_{jt})L_{jt}]^{\gamma}+M_{jt}^{\gamma}\right\}}=S_{Ljt}^{*}, \tag{6}$$

$$\frac{\kappa\frac{1+\eta}{\eta}M_{jt}^{\gamma}}{\left\{[\exp(\omega_{jt})K_{jt}]^{\gamma}+[\exp(\nu_{jt})L_{jt}]^{\gamma}+M_{jt}^{\gamma}\right\}}=S_{Mjt}^{*}, \tag{7}$$

where $S_{Ljt}^{*}\equiv\frac{W_{jt}L_{jt}}{P_{jt}Q_{jt}}$ and $S_{Mjt}^{*}\equiv\frac{P_{Mjt}M_{jt}}{P_{jt}Q_{jt}}$ are the shares of labor and material in revenue. One advantage of the share-form first-order condition is that the demand shifter, Φ_{jt}, and the scaled material efficiency, μ_{jt}, are absorbed in labor share and material share. Therefore, we can solve for the two efficiency ratios, ω_{jt} and ν_{jt}, directly from the share-form first-order conditions if $\gamma\neq 0$.[12]

$$\nu_{jt}=\frac{1}{\gamma}\ln\frac{S_{Ljt}^{*}}{S_{Mjt}^{*}}+\ln\frac{M_{jt}}{L_{jt}}, \tag{8}$$

$$\omega_{jt}=\frac{1}{\gamma}\ln\frac{S_{Kjt}^{*}}{S_{Mjt}^{*}}+\ln\frac{M_{jt}}{K_{jt}}=\frac{1}{\gamma}\ln\left(\frac{\kappa\frac{1+\eta}{\eta}}{S_{Mjt}^{*}}-\frac{S_{Ljt}^{*}}{S_{Mjt}^{*}}-1\right)+\ln\frac{M_{jt}}{K_{jt}}. \tag{9}$$

Where $S_{Kjt}^{*}=\kappa\frac{1+\eta}{\eta}-S_{Ljt}^{*}-S_{Mjt}^{*}$ is the revenue elasticity of capital, although it may not optimally correspond to the capital costs due to potential capital adjustment friction or other distortions in the capital market. The intuition of these two equations is straightforward. Given that the labor-material ratio depends on input prices and the labor-material efficiency ratio, the latter can be recovered from the variation in labor-material ratio and expenditure share ratio. A similar idea applies to the capital-material efficiency ratio, except that the capital share is replaced by the implied revenue elasticity of capital, which may be subject to distortions. The idea of exploiting the first-order conditions of profit maximization in the production function estimation is widely used in the literature (e.g., Van Biesebroeck, 2003; Gandhi et al., forthcoming; Doraszelski and Jaumandreu, 2013; Grieco et al., 2016; Oberfield and Raval, 2014).[13]

Given that output is observed with noise, $Y_{jt}=Q_{jt}\exp(\varepsilon_{jt})$, replacing ω_{jt} and ν_{jt} in the production function by Eqs. (8) and (9) yields

$$lnY_{jt}=\mu_{jt}+\frac{\kappa}{\gamma}ln\left(\kappa\frac{1+\eta}{\eta}\right)+\kappa lnM_{jt}-\frac{\kappa}{\gamma}lnS_{Mjt}^{*}+\varepsilon_{jt}. \tag{10}$$

This equation reduces the original three-dimensional unobserved productivity measure to be one-dimensional, so it can be estimated using the standard approaches, such as Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015), by using investment or other proxies for μ_{jt}.

First-stage estimation. We use investment as the proxy for the augmented material efficiency μ_{jt} in Eq. (10), following Olley and Pakes (1996), Ackerberg et al. (2015), Aw et al. (2011), and Zhang (2017). Firms' dynamic decisions imply the following capital investment function: $i_{jt}=i(\omega_{jt},\nu_{jt},\mu_{jt},k_{jt},P_{Mjt},W_{jt})$. Given that the input prices and wage rate may be persistent over time, the estimation allows them to have an impact on firms' dynamic capital investment decisions. The investment function is strictly monotonic in μ_{jt} conditional on $(\omega_{jt},\nu_{jt},k_{jt},P_{Mjt},W_{jt})$.[14] Therefore, the investment function can be inverted to solve for the scaled material efficiency, $\mu_{jt}=\mu(i_{jt},\omega_{jt},\nu_{jt},k_{jt},P_{Mjt},W_{jt})$. Replacing $\omega_{jt}=\omega_{jt}(m_{jt},k_{jt},\frac{S_{Ljt}^{*}}{S_{Mjt}^{*}},S_{Mjt}^{*})$ and $\nu_{jt}=\nu_{jt}(m_{jt},l_{jt},\frac{S_{Ljt}^{*}}{S_{Mjt}^{*}})$ in the $\mu(\cdot)$ function by Eqs. (8) and (9), the unobserved scaled material efficiency μ_{jt} is recovered as a nonparametric function of the observed variables, $\mu_{jt}=\mu\left(i_{jt},l_{jt},m_{jt},k_{jt},P_{Mjt},W_{jt},\frac{S_{Ljt}^{*}}{S_{Mjt}^{*}},S_{Mjt}^{*}\right)$. Replacing μ_{jt} in Eq. (10) by the above equation leads to the first-stage estimation equation:

$$\ln Y_{jt}=\underbrace{\phi(i_{jt},l_{jt},m_{jt},k_{jt},P_{Mjt},W_{jt},\frac{S_{Ljt}^{*}}{S_{Mjt}^{*}},S_{Mjt}^{*})}_{\phi_{jt}\equiv\mu_{jt}+\frac{\kappa}{\gamma}\ln(\kappa\frac{1+\eta}{\eta})+\kappa\ln M_{jt}-\frac{\kappa}{\gamma}\ln S_{Mjt}^{*}}+\varepsilon_{jt} \tag{11}$$

In the empirical exercise, I parameterize the function $\phi(\cdot;\alpha)$ as a polynomial function up to third order, with α being the polynomial parameters. I also control for firm age, ownership, and a full set of time dummies in the estimation. By assumption, the right-hand-side variables are uncorrelated with the measurement error ε_{jt}. This equation then can be estimated using nonlinear least squares or generalized method of moments (GMM). The estimation separates the measurement error from the prediction term in (11), denoted as $\widehat{\varepsilon_{jt}}$ and $\widehat{\phi_{jt}}$ separately. From the definition of ϕ_{jt} in Eq. (11), the scaled material efficiency can be recovered as a function of observables up to unknown parameters (κ,γ,η),

$$\mu_{jt}=\widehat{\phi_{jt}}+\frac{\kappa}{\gamma}\ln S_{Mjt}^{*}-\kappa\ln M_{jt}-\frac{\kappa}{\gamma}\ln\left(\kappa\frac{1+\eta}{\eta}\right). \tag{12}$$

Given Eqs. (8) and (9) and the relationship between $(\omega_{jt},\mu_{jt},\nu_{jt})$ and $(\omega_{jt}^{0},\mu_{jt}^{0},\nu_{jt}^{0})$, the original non-Hicks neutral technology measure $(\omega_{jt}^{0},\mu_{jt}^{0},\nu_{jt}^{0})$ can be recovered as follows:

$$\omega_{jt}^{0}=\omega_{jt}+\mu_{jt}^{0}=\frac{1}{\kappa}\widehat{\phi_{jt}}+\frac{1}{\gamma}\ln\left(\kappa\frac{1+\eta}{\eta}-S_{Ljt}^{*}-S_{Mjt}^{*}\right)-\ln K_{jt}-\frac{1}{\gamma}\ln\left(\kappa\frac{1+\eta}{\eta}\right), \tag{13}$$

$$\nu_{jt}^{0}=\nu_{jt}+\mu_{jt}^{0}=\frac{1}{\kappa}\widehat{\phi_{jt}}+\frac{1}{\gamma}\ln S_{Ljt}^{*}-\ln L_{jt}-\frac{1}{\gamma}\ln\left(\kappa\frac{1+\eta}{\eta}\right), \tag{14}$$

$$\mu_{jt}^{0}=\frac{1}{\kappa}\mu_{jt}=\frac{1}{\kappa}\widehat{\phi_{jt}}+\frac{1}{\gamma}\ln S_{Mjt}^{*}-\ln M_{jt}-\frac{1}{\gamma}\ln\left(\kappa\frac{1+\eta}{\eta}\right). \tag{15}$$

[12] This condition naturally excludes the Cobb-Douglas production function, which is well known not to accommodate factor-augmenting efficiencies.

[13] More papers use similar first-order conditions of labor and material in other scenarios. For instance, Epple et al. (2010) develop a procedure to estimate the housing supply function using the first-order condition of the indirect profit function maximization; De Loecker (2011), De Loecker and Warzynski (2012), and De Loecker et al. (2012) use the first-order condition of labor and/or material choice of profit maximization to estimate firm-level markup.

[14] The invertibility condition is generally satisfied. Basically we want to show that the investment function is strictly increasing in μ_{jt}, conditional on $(\omega_{jt},\nu_{jt},k_{jt},P_{Mjt},W_{jt})$. Consider an increase in μ_{jt} by $\Delta\mu_{jt}$. It is equivalent to an increase in μ_{jt}^{0} by $\frac{1}{\kappa}\Delta\mu_{jt}$ because $\mu_{jt}=\kappa\mu_{jt}^{0}$. Note that $\omega_{jt}=\omega_{jt}^{0}-\mu_{jt}^{0}$ and $\nu_{jt}=\nu_{jt}^{0}-\mu_{jt}^{0}$. Conditioning on $(\omega_{jt},\nu_{jt},k_{jt},P_{Mjt},W_{jt})$ requires that both ω_{jt}^{0} and ν_{jt}^{0} also increase by the same amount, $\frac{1}{\kappa}\Delta\mu_{jt}$, as μ_{jt}^{0}. So the invertibility condition here is equivalent to the condition that "when capital, labor, and material efficiencies all increase by the same amount (i.e. a Hicks-neutral technology change), investment increases strictly", which is the same condition as in Olley and Pakes (1996).

Second-stage estimation. Using the VAR(1) assumption on the factor-augmenting efficiencies defined in Eq. (3), the i.i.d. productivity shocks $(\xi^{\omega}_{jt}, \xi^{\mu}_{jt}, \xi^{\nu}_{jt})$ in the productivity evolution process can be recovered, with $(\omega^0_{jt}, \mu^0_{jt}, \nu^0_{jt})$ and their lags being replaced by Eqs. (13)–(15). In addition, the demand shock (ξ^D_{jt}) can be recovered from the demand function as

$$\xi^D_{jt} = \ln Q_{jt} - (\eta * \ln P_{jt} + \Phi_t + \alpha_{size} * \textit{firm size} + \alpha_{age} * \textit{firm age} + \alpha_{own} * \textit{firm ownership}). \quad (16)$$

Denote $\xi_{jt} = (\xi^{\omega}_{jt}, \xi^{\mu}_{jt}, \xi^{\nu}_{jt}, \xi^D_{jt})$. The resulting moment condition is

$$E(Z'_{jt}\xi_{jt}) = 0,$$

where the matrix $Z_{jt} = (Z^{\omega}_{jt}, Z^{\mu}_{jt}, Z^{\nu}_{jt}, Z^D_{jt})$ contains instrumental variables associated with the evolution process for each of the factor-augmenting efficiency and demand functions.

The parameters governing the evolution process of the efficiencies, all $\rho' s$, are naturally identified by their corresponding lag terms $(\omega^0_{jt-1}, \nu^0_{jt-1}, \mu^0_{jt-1})$, which are the best IVs to identify the $\rho' s$ given other parameters. To make use of this idea to improve estimation efficiency, I concentrate out all the $\rho' s$ in the GMM estimation, and let the optimizer in GMM to iterate only on $(\kappa, \gamma, \eta, \alpha_{size}, \alpha_{age}, \alpha_{own})$ plus year effects. Given all these parameters, the $\rho' s$ are estimated within each iteration using linear least squares. The IVs are chosen as follows:

$$Z^{\omega}_{jt} = Z^{\mu}_{jt} = Z^{\nu}_{jt} = \left(S^*_{Mjt-1}, \ln(\frac{P_{Mjt}}{P_{Ljt}}), 1\right),$$

$$Z^D_{jt} = \left(\ln(W_{jt}), \ln(P_{Mjt}), k_{jt}, \text{firm age, firm ownership, year fixed effects}\right).$$

The parameter estimates are in general robust to different choices of reasonable instrumental variables. I collect all the model parameters (including $\rho' s$) in θ. θ can then be estimated by minimizing a sample version of the above moment conditions using GMM,

$$\hat{\theta} = \min_{\theta}\left(\frac{1}{N}\sum_{j,t} Z'_{jt}\varepsilon_{jt}\right)' W \left(\frac{1}{N}\sum_{j,t} Z'_{jt}\varepsilon_{jt}\right). \quad (17)$$

All the parameters are estimated using iterated GMM using the variance-covariance matrix of the moments estimated from the previous iteration to approximate the optimal weighting matrix W in each iteration. Then the original level of factor-augmenting efficiencies, $(\omega^0_{jt}, \nu^0_{jt}, \mu^0_{jt})$, can be recovered accordingly from Eqs. (13)–(15). The Standard error of the parameter estimates can be constructed using bootstrapping.

Measurement error in shares. Sometimes the input shares, S^*_{Ljt} and S^*_{Mjt}, may be measured with errors. In particular, they may contain the same measurement errors as in the revenue, because the input shares in the data are calculated as the ratio of the input expenditures to sales. Specifically, the observed input shares in the data are defined as follows: $S_{Ljt} \equiv \frac{W_{jt}L_{jt}}{P_{jt}Y_{jt}} = S^*_{Ljt}\exp(-\epsilon_{jt})$ and $S_{Mjt} \equiv \frac{P_{Mjt}M_{jt}}{P_{jt}Y_{jt}} = S^*_{Mjt}\exp(-\epsilon_{jt})$. Here $\epsilon_{jt} \sim N(0, \sigma^2_{\epsilon})$ is the i.i.d. measurement error or unobserved productivity shocks in output. The first-stage estimation Eq. (11) must be slightly adjusted to address this issue, by replacing S^*_{Ljt} and S^*_{Mjt} by their observed counterparts,

$$\ln Y_{jt} = \underbrace{\phi(i_{jt}, l_{jt}, m_{jt}, k_{jt}, P_{Mjt}, W_{jt}, \frac{S_{Ljt}}{S_{Mjt}}, \ln S_{Mjt} + \varepsilon_{jt})}_{\phi_{jt} \equiv \mu_{jt} + \frac{\kappa}{\gamma}\ln(\kappa\frac{1+\eta}{\eta}) + \kappa \ln M_{jt} - \frac{\kappa}{\gamma}\ln S^*_{Mjt}} + \varepsilon_{jt} \equiv \widetilde{\phi}(\cdot, \varepsilon_{jt}). \quad (18)$$

Note that the error ε_{jt} is canceled out in the ratio $\frac{S_{Ljt}}{S_{Mjt}}$. In Appendix I, I prove that the function $\widetilde{\phi}(\cdot, \varepsilon_{jt})$ is strictly increasing in ε_{jt} under mild conditions. Given the strict monotonicity condition, Imbens and Newey (2009) show that the structural function $\widetilde{\phi}(\cdot)$ is nonparametrically identified upon normalization of the distribution of ϵ_{jt}, given existence of an instrumental variable (IV) for the endogenous variable (S_{Mjt} in our case). They also propose a two-step series estimator to estimate the function structurally and do inference. Torgovitsky (2016) develops a semiparametric minimum distance independence estimator based on IV when the function $\widetilde{\phi}(\cdot, \varepsilon_{jt})$ is parameterized, which does not require normalization of the scale of the error term.

In the empirical exercise, I parameterize the function $\phi(\cdot)$ as a polynomial function $\phi(\cdot) = \phi(\cdot; \alpha)$ up to third order except for the argument S^*_{jt}, which is taken as linear to simplify the empirical implementation. Here α denotes the set of polynomial parameters. This simplification allows solving for the i.i.d. shock term ε_{jt} analytically, so that a standard GMM can be applied.[15] Given the polynomial approximation, we can solve for the error term, ε_{jt}, from Eq. (18) as follows:

$$\varepsilon_{jt} = \left[\ln Y_{jt} - \phi(i_{jt}, l_{jt}, m_{jt}, k_{jt}, P_{Mjt}, W_{jt}, \frac{S_{Ljt}}{S_{Mjt}}, S_{Mjt}; \hat{\alpha})\right] / (1 + \alpha_{S_M}), \quad (19)$$

where α_{S_M} is the parameter of S_{Mjt} in the function $\phi(\cdot, \varepsilon_{jt})$. Then the polynomial parameter α can be estimated using GMM based on moment conditions, $E\left(Z'_{1jt}\varepsilon_{jt}\right) = 0$. Here Z_{1jt} is the set of instrumental variables including all polynomial terms of $(1, i_{jt}, l_{jt}, m_{jt}, k_{jt}, P_{Mjt}, W_{jt}, \frac{S_{Ljt}}{S_{Mjt}}, S_{Mjt-1})$ up to third order, which are uncorrelated with the error term ε_{jt} by assumption. Here the lagged material-revenue share S_{Mjt-1} is used as the IV for S_{Mjt}. The expenditure share ratio $\frac{S_{Ljt}}{S_{Mjt}}$ is uncorrelated with the error term, because ε_{jt} is canceled out in the ratio. The estimate of the error term ε_{jt}, denoted as $\hat{\varepsilon}_{jt}$, can be computed from Eq. (19). Accordingly the estimate of ϕ_{jt} and the model-predicted material and labor shares can be calculated by $\widehat{\phi_{jt}} = \ln Y_{jt} - \hat{\varepsilon}_{jt}$, $\hat{S}^*_{Mjt} = S_{Mjt}\exp(\hat{\varepsilon}_{jt})$, and $\hat{S}^*_{Ljt} = S_{Ljt}\exp(\hat{\varepsilon}_{jt})$. Replacing S^*_{Ljt} and S^*_{Mjt} by $\hat{S}^*_{Ljt}$ and $\hat{S}^*_{Mjt}$, the second stage estimation carries on exactly.[16]

The estimation results reported in the rest of the paper are based on the refined estimation. We also tested the sensitivity of our estimation results to the size of measurement errors by manually adding additional disturbance in revenue (and as a result labor and material shares). The estimation results are very similar and all of our main results are robust. To save space, we omit these tables here and they are available upon request.

3.3. Empirical results

I estimate the model using an unbalanced panel of firms from the steel industry in China from 2000 to 2007. The estimates of the production parameters and evolution process of the factor-augmenting efficiencies are reported in Table 3. The return to scale is close to one ($\kappa = 0.961$), indicating that technology in this industry has almost constant returns to scale. The estimated elasticity of substitution, which is defined as $\frac{1}{1-\gamma}$, equals 0.489. This is close to the firm-level estimates in Chirinko et al. (2011) with common factor-augmenting efficiencies across firms (0.4), and in Raval (2017) with heterogeneous factor-augmenting efficiencies (0.5). However, it is lower than that estimated

[15] Alternatively, we can allow for a more flexible functional form of $\phi(\cdot; \alpha)$ in S^*_{Mjt} at the cost of a more complicated estimator. In this case, Simulated GMM or the two-stage estimator developed in Torgovitsky (2016) can be applied. Or alternatively, we can use local linear estimator in the first stage given the nonparametric identification result.

[16] In the empirical estimation, we also deal with outliers with negative revenue elasticity of capital, which by assumption should be positive. We assume that these outliers are caused by measurement errors on output, which has been estimated in the first stage, and adjust the elasticity accordingly. Specifically, I calculate the expected measurement error generating the negative elasticity and remove it from the corresponding revenue. We then use the error-free revenue to calculate labor and material shares, which ensure positive capital elasticity used to recover capital efficiency in Eq. (13).

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

Parameter	Estimates	Standard error
κ	0.961	0.000
γ[a]	−1.045	0.058
Capital efficiency: ω_{jt}^0		
$\rho_{\omega\omega}$	0.523	0.008
$\rho_{\omega\nu}$	0.074	0.011
$\rho_{\omega\mu}$	0.126	0.051
$\rho_{\omega 0}$	−2.260	0.083
Labor efficiency: ν_{jt}^0		
$\rho_{\nu\omega}$	−0.038	0.004
$\rho_{\nu\nu}$	0.841	0.005
$\rho_{\nu\mu}$	0.235	0.023
$\rho_{\nu 0}$	0.525	0.037
Material efficiency: μ_{jt}^0		
$\rho_{\mu\omega}$	−0.007	0.001
$\rho_{\mu\nu}$	0.012	0.002
$\rho_{\mu\mu}$	0.611	0.007
$\rho_{\mu 0}$	0.186	0.012

[a] The implied elasticity of substitution is $\frac{1}{1-\gamma} = 0.489$, with bootstrapped standard error 0.014.

Table 4
Estimates of the demand function.

Parameter	Estimates	Standard error
η	−3.587	0.001
Size effect[a]	0.705	0.004
Age	0.079	0.016
SOE	0.028	0.025
Year effect	Yes	–
Constant	Yes	–

[a] The firm size is measured by capital stock, log(K).

Table 5
Correlation: Efficiencies and input ratio.

Correlation type	Correlation		
Among efficiencies	$(\omega_{jt}^0, \nu_{jt}^0)$ 0.301	$(\omega_{jt}^0, \mu_{jt}^0)$ 0.489	(ν_{jt}^0, μ_{jt}^0) 0.077
Efficiency and firm size	(lnq, ω_{jt}^0) 0.032	(lnq, ν_{jt}^0) 0.495	(lnq, μ_{jt}^0) 0.127
Efficiency ratio and input ratio	$(\omega_{jt}^0 - \mu_{jt}^0, \ln\frac{K}{M})$ −0.456	$(\nu_{jt}^0 - \mu_{jt}^0, \ln\frac{L}{M})$ −0.947	$(\omega_{jt}^0 - \nu_{jt}^0, \ln\frac{K}{L})$ −0.516

using aggregate data in general. For example, Klump et al. (2007) estimate an elasticity of substitution at 0.51 under factor-augmenting efficiency using aggregate U.S. data from 1953 to 1998. Antràs (2004) estimates it at 0.80 under factor-augmenting efficiency, and 0.94–1.02 under the Hicks-neutral efficiency assumption, also using aggregate U.S. data from 1948 to 1998. The less-than-one elasticity of substitution in our estimation suggests that inputs are gross complements to each other, which is the key for predicting many firm behaviors. For example, it implies that labor-augmenting technology change is labor-saving and that firms using a technology with higher labor-augmenting efficiencies employ less labor.

A comparison with Table 2 also shows that omitting the non-neutrality feature of technology will cause a substantial upward bias in the estimates of elasticity of substitution. This is due to the potential correlation between the omitted non-neutral technology and input price ratios. Assuming Hicks neutral technology, the OLS estimates of elasticity of substitution in Table 2 range from 0.737 to 0.775, which is more than 50 percent higher than that estimated in the full model when non-neutral technology is allowed. This result is consistent with Antràs (2004), who also estimates a lower elasticity of substitution after controlling for factor-augmenting efficiency using aggregate data from the United States. The random effect and fixed effect models in Table 2 partially correct for the omitted variable bias, because the unobserved labor-material efficiency ratio is persistent over time as will be shown later in this paper. As a result, the estimates from these two models are closer to the structural estimate. In the random effects model, the elasticity of substitution is 0.573, which is just slightly higher than that estimated in the full model. In the fixed effect model, the estimated elasticity (0.490) is statistically the same to that derived in the full model.

The factor-augmenting efficiencies are persistent over time. Nearly 52 percent of the capital efficiency can be carried over to the next period ($\rho_{\omega\omega} = 0.523$). The persistence parameters for labor and material efficiency are even higher, at 84 percent for labor efficiency and 61 percent for material efficiency. The strong persistence of factor-augmenting efficiencies advocates that the heterogeneity of the non-neutral technology across firms could be an important firm characteristic that potentially influences firm activities persistently. The estimate also suggests a generally positive cross effect among the three efficiencies. For instance, higher labor and material efficiencies contribute to higher next-period capital efficiency, and higher labor efficiencies contribute to higher next-period material efficiency as well. The only exception is that capital efficiency may have a negative but small impact on next-period labor and material efficiencies in this industry in the data period.

Table 4 reports the demand parameters, which are jointly estimated with the production parameters. The demand elasticity is $\eta = -3.587$ in this industry. This scenario means that a 1 percent increase in output price ceteris paribus will reduce the firm demand significantly by approximately 3.6 percent. It implies a gross markup of nearly 39 percent for the steel firms. Given that steel industry is very capital intensive with large fixed costs, the margin of the industry is much lower than the markup. In the regression, I also control for firm size, firm age, year effect, and ownership. The results corroborate that larger and older firms have a higher demand. State-owned enterprises (SOE) have no significant impact on demand, other things being equal.

Table 5 summarizes the basic correlations among the three efficiencies. First, the three factor-augmenting efficiencies are positively correlated with each other. The correlation between labor and capital efficiencies is 0.301. The other two correlation coefficients are 0.489 and 0.077. That the correlations among the three efficiencies are substantially different from perfect correlation implies that the heterogeneity of non-neutral technology across firms is substantial. Some firms may have advantage in one factor-augmenting efficiency, but may have disadvantage in others. Second, the labor efficiency is strongly positively correlated with firm size, with a correlation coefficient of 0.495. Capital efficiency and material efficiency are also positively correlated with firm size, but the correlation is much weaker. Moreover, there is a negative correlation between input ratios and corresponding efficiency ratios. This is consistent with the elasticity of substitution being less than one—a factor-augmenting efficiency change reduces the demand for that factor when inputs are gross complements.

4. Non-Hicks neutral technology and labor share

This section examines the heterogeneity of the non-Hicks neutral technology and its evolution over time. It also explores the relative contribution of the three factor-augmenting efficiencies to the cross-sectional variation and decline in labor share observed in the data.

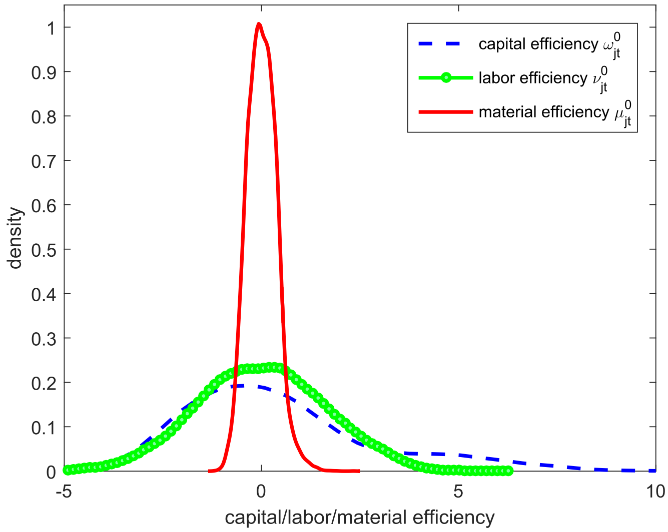


Fig. 2. Heterogeneity of input-specific efficiencies.

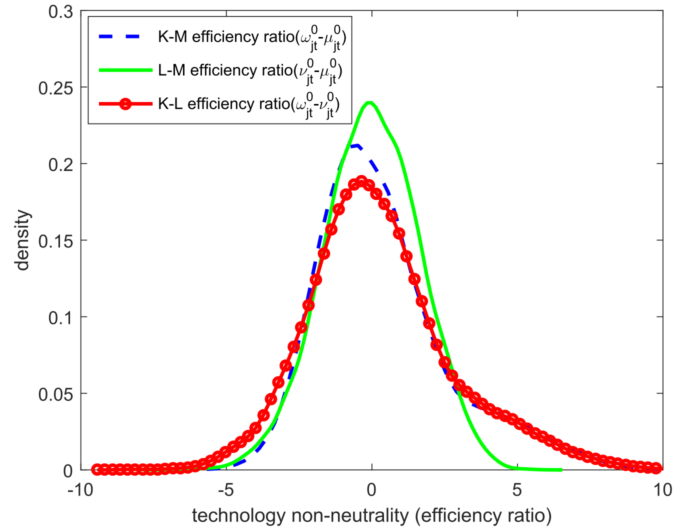


Fig. 3. Heterogeneity of technological non-neutrality.

4.1. Non-Hicks neutral technology: cross-sectional heterogeneity

The non-Hicks neutral technology shows large heterogeneity across firms, especially for the capital- and labor-augmenting efficiencies. Within each year in the sample period, the interquartile range is between 2.55 and 3.13 for capital efficiency, and between 2.06 and 2.25 for labor efficiency. The dispersion of material efficiency is smaller, with the within-year interquartile range between 0.30 and 0.46, implying an advantage of 30–58 percent for the 75th percentile relative to the 25th percentile. This scenario suggests that relative to material efficiency heterogeneity, capital- and labor-augmenting efficiencies are more important sources of technology heterogeneity across firms. However, the variation in material efficiency is economically significant. I plot the kernel density of the recovered factor-augmenting efficiencies, $(\omega^0_{jt}, \nu^0_{jt}, \mu^0_{jt})$ by pooling data from all years together in Fig. 2. The mean is normalized to be zero. The within-year distribution is very similar; it is not reported here to save space.

The substantial heterogeneity of technological non-neutrality emerges across firms too, as measured by the three efficiency ratios, capital-material efficiency ratio $\omega^0_{jt} - \mu^0_{jt}$, labor-material efficiency ratio $\nu^0_{jt} - \mu^0_{jt}$, and capital-labor efficiency ratio $\omega^0_{jt} - \nu^0_{jt}$. The interquartile ranges of the three ratios are 2.69, 2.33, and 2.96, respectively. Fig. 3 plots the kernel density of $\omega^0_{jt} - \mu^0_{jt}$, $\nu^0_{jt} - \mu^0_{jt}$, and $\omega^0_{jt} - \nu^0_{jt}$, by pooling data from all years together. The within-year distributions are very similar, and are not reported here to save space. The large dispersion in the efficiency ratios implies that technological non-neutrality, aside from efficiency levels, is an important source of firm technology heterogeneity. While the level of efficiencies is important in predicting the first-order performance of firms (e.g., level of input demand, profitability, trade participation, and entry/exit), the non-neutrality nature of technology is more salient in explaining the second-order ratios, such as relative input usage and labor share, because it affects the marginal products of all inputs symmetrically. Both sources deserve equally important attention when analyzing firm behaviors such as inputs demand, growth/shrinking, entry/exit, and trade decisions.

The non-Hicks neutral technology is correlated to firm size systematically. As shown in Table 5, all three factor-augmenting efficiencies are positively correlated with firm size, and the correlation is especially strong for labor efficiency. Table 6 presents the mean efficiency levels for firms of different sizes. The size groups are classified in the same way as in Table 1, year by year. The revenue-weighted average labor efficiency of the largest group is about 8.4 times[17] higher than that for the smallest group. Material efficiency in general also increases in firm size, but very slightly. The material efficiency of the group of the largest firms is about 28 percent higher than that for the group of the smallest firms. Comparing the small size-material efficiency correlation with the much larger dispersion of material efficiency cross firms, it is shown that the heterogeneity of material efficiency is not mainly driven by the size of firms, and we should observe a large dispersion of material efficiency even within each size group. Capital efficiency shows an inverse-U shape with respect to firm size. The group of the largest firms has the lowest capital efficiency, which on average is about 67 percent lower than that of the second largest group which has the highest average capital efficiency. The differential correlation between firm size and different factor-augmenting efficiencies again suggests that the heterogeneity of technology across firms is non-Hicks neutral. Large firms in general use technologies that save labor.

4.2. Non-Hicks neutral technology: over-time change

Technology change over time is highly non-Hicks neutral. Table 7 exhibits that labor-augmenting efficiency grew the fastest during the data period, at an annual rate of 39.95 percent on average in this industry. This fast growth of labor efficiency may have arisen from the technology-upgrading incentive policy issued by Chinese government those years, as discussed in Section 2.4, which stipulated large-scale automation and adoption of automatic control in this industry during the data period. Capital and material efficiencies also grew substantially, at rates of 27.16 and 4.80 percent per year, respectively. The differential growth of factor-augmenting efficiencies together implies a total factor productivity growth rate of around 10.54 percent per year, which is defined as the weighted average of the three growth rates using input shares as the corresponding weights.

Fig. 4 plots the evolution of the three efficiency ratios from 2000 to 2007, which represents the non-neutrality of technology. In the figure, the solid dots represent the yearly median, and lines represent the 10th-to-90th percentile range. The three efficiency ratios change dramatically over time, together lending support to a labor-saving non-neutral technology change over time. In particular, the labor-material efficiency ratio grows very quickly, supporting the idea that technology change is non-Hicks neutral toward saving labor relative to material (given that

[17] exp(5.365–3.238) ≃ 8.390.

Table 6
Firm size and non-neutral technology: Dispersion and growth.

Year	Firm size group[a]				
	0–20	20–40	40–60	60–80	80–100
			Labor efficiency: ν_{jt}^0		
Mean[a]	3.238	4.017	4.466	4.963	5.365
Growth rate (%)	19.28	20.32	14.03	19.02	42.35
			Material efficiency: μ_{jt}^0		
Mean	0.543	0.580	0.591	0.600	0.791
Growth rate (%)	4.78	5.38	5.31	4.86	4.77
			Capital efficiency: ω_{jt}^0		
Mean	−4.777	−4.127	−3.844	−3.893	−5.010
Growth rate (%)	15.64	17.50	16.17	15.29	28.51

All means are revenue weighted.
[a] Firms are divided into five groups by firm size defined by sales, year by year, with each group having 20% of the firms within each year.

Table 7
Average annual growth rate of productivity levels (%, revenue-weighted), 2000–2007.

Capital efficiency[a]	Labor efficiency	Material efficiency	Implied TFP[b]
27.16	39.95	4.80	10.54

[a] The average annual growth rate of capital efficiency from 2000 to 2007, x, is obtained by solving the equation $(1+x)^7 \exp(\omega_{jt=2000}^0) = \exp(\omega_{jt=2007}^0)$. Growth rates for labor and material efficiencies are similarly defined.
[b] The implied total factor productivity (TFP) is calculated as the weighted average of the capital, labor, and material efficiencies, using input expenditure share as the weight.

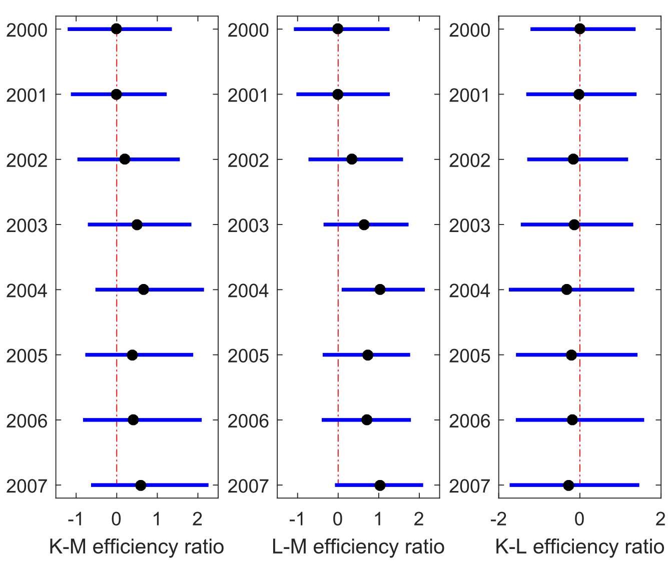


Fig. 4. Non-neutral technology change.

the elasticity of substitution is less than one). The capital-material efficiency ratio increases substantially, suggesting that technology progress saves capital relative to material in the data period. Finally, the capital-labor efficiency ratio decreases substantially in the data period, providing further evidence that technology progress in the Chinese steel industry was non-Hicks neutral from 2000 to 2007. It saved labor more than capital.

The horizontal lines represent the interdecile range of the associated efficiencies. The dots are the corresponding median. The vertical dot-dashed lines represent the median value of the associated efficiency for the first year (2000). The first figure shows that the capital-material efficiency ratio decreased slightly. The second figure shows that, relative to material efficiency, labor efficiency grows substantially. The last figure shows a substantial drop of capital-labor efficiency ratio. In sum, technology change is non-neutral toward saving labor (labor-augmenting).

The labor-saving non-Hicks neutral technology change also displays substantial heterogeneity across firms of different sizes. Table 6 shows that the group of the largest firms have the highest growth rate of labor efficiency on average at the rate of 42.35 percent, relative to only 14.03–20.32 percent for the other four groups of relatively smaller firms. The medium-size group and the second smallest group have the highest growth rates of material efficiency at the rate of 5.31 and 5.38 percent respectively, relative to a slightly lower 4.77–4.86 percent for the other four groups. For capital efficiency, the group of the largest firms has the highest growth rate of 28.51 percent; the other four groups experienced slower growth of capital efficiency at a rate of 15.29–17.50 percent. This result affirms that the evolution of technological non-neutrality is uneven across firms of different sizes: larger firms on average are becoming relatively more and more labor-saving, compared with smaller firms. The differential growth rate of factor-augmenting efficiencies—the overall average and that among different sizes of firms—further suggests that the non-neutral technology is an important feature of firm technology, and must be considered for understanding firm heterogeneity.

To show whether the non-neutral technology has been converging over time, I calculate the interquartile range (IQR) for efficiency levels and efficiency ratios year by year from 2000 to 2007. In general, the non-Hicks neutral technology shows no obvious converging trend during the data period. As shown in the first three columns in Table A2, labor efficiency converges slightly in the first few years, but diverges after 2004. Overall, there is no obvious convergence of labor efficiency as measured by the interquartile range if ignoring 2000. Capital efficiency diverges substantially, with the IQR increasing from 2.75 in 2000 to 3.10 in 2007. The dispersion of material efficiency also becomes even larger, with the IQR increasing from 0.30 in 2000 to 0.36 in 2007.

Table 8
Decomposition of TFP growth and heterogeneity.

	Capital efficiency	Labor efficiency	Material efficiency
Contribution to TFP growth (%)[a]	39.6	17.7	42.7
Contribution to TFP heterogeneity (%)[b]	60.5	4.0	35.5

[a] The contribution of each component is calculated as the growth of each of C_ω, C_ν, and C_μ relative to the growth of TFP from 2000 to 2007.
[b] I first calculate the demeaned C_X and TFP, by subtracting their corresponding yearly mean. The contribution of each C_X to the heterogeneity of TFP is defined as the coefficient of regressing the demeaned C_X on demeaned TFP for each $X \in \{\omega, \nu, \mu\}$.

The last three columns in Table A2 report the IQRs of the efficiency ratios, which measure the non-neutrality of technology. The capital-labor efficiency ratio, as the main source of technological non-neutrality, diverges over time. It further supports the idea that technological non-neutrality, as an important aspect of technology aside from the level of technology, should not be ignored to understand firms' technology differences for predicting firm behavior.

To understand the relative importance of the three factor-augmenting efficiencies in shaping TFP differences, I decompose the TFP growth and heterogeneity into the contribution of capital efficiency, labor efficiency, and material efficiency. By definition, $TFP = C_\omega + C_\nu + C_\mu$, where C_X equals factor efficiency X multiplied by the corresponding factor expenditure share, for all $X \in \{\omega, \nu, \mu\}$. The contribution of C_ω, C_ν, and C_μ to the growth of TFP from 2000 to 2007 is reported in the first row in Table 8. The capital efficiency contributed 39.6 percent to the growth of TFP, labor efficiency contributed 17.7 percent, and material efficiency contributed the most (42.7 percent), although material efficiency itself grew much slower than labor efficiency. The large material share plays a role here: a small change in material efficiency can have a large impact on TFP given the large material expenditure share. Consequently, although material efficiency itself grew slower than labor efficiency, it contributed more to the growth of TFP.

The contribution of individual factor efficiencies to the cross-sectional difference in TFP is reported in the second row in Table 8. The capital efficiency contributed the most (60.5 percent) due to its large cross-sectional heterogeneity. The labor efficiency contributed only 4 percent, while the material efficiency contributed 35.5 percent. Again, the relative expenditure share plays a role here: given the large material share, a small difference in material efficiency can have a large impact on TFP. Consequently, although the cross-sectional heterogeneity of material efficiency is smaller than that of labor efficiency, material efficiency plays a more important role than labor efficiency in driving the cross-sectional difference in TFP.

4.3. Discussion

Factor price measures. As discussed in Section 2, the localized material prices at the province level are used as proxy for firm-level prices. Given that the steel industry in China has very organized local markets for inputs and outputs, and steel makers are relatively concentrated in the same area in each province, firms in the same area share very close prices of inputs and output for the same products. Therefore, we believe that the local market material prices represent firm price well. However, it is likely that other factors, such as transportation costs and market power, may affect the effective material prices faced by individual firms. In this discussion, I argue that it is unlikely that these factors are driving the results.

First, the transportation costs together account for only 5.5 percent in total production costs, according to the *"2007 Business Logistics Survey Report"* based on a yearly survey of the steel makers in China. The reported transportation costs include the total costs for transporting both inputs and outputs. Given the large geographic difference in China, a large portion of the transportation costs may be due to transportation costs between regions. Consequently, within each market (province), the difference in transportation costs among firms should not be too large. This is especially true given the fact that steel makers in China are relatively concentrated in the same area within each province (usually close to main mines or ports). Hence, the difference between the local market price and firms' effective price may not be a big issue.

Second, if market power were the issue, then we would expect that larger firms would have lower input prices. In our estimation, this would bias upward the estimates of material-augmenting efficiency for larger firms. However, the correlation between material efficiencies and firm size (0.13) is small. In fact, it is much smaller than that for labor efficiency, for which we observe the firm-level wage rate. Hence it is unlikely that market power is a big issue.

Finally, as a thought experiment, I check the robustness of the results by estimating several versions of the model after manually introducing additional i.i.d. measurement errors to material and output prices. Given that the transportation costs for inputs and output together account for only 5.5 percent in total production costs, I choose the noise level to each price to be 1, 2, and 5 percent. The estimated patterns of non-Hicks neutral technology and their implications on labor share are reported in Appendix Tables A3 and A4. In general all of the main results are robust and not very sensitive to adding additional i.i.d. shocks to input and output prices.

Labor quality. Another potential explanation of the estimated improvement of labor efficiency could be the potential improvement of labor quality. Although a direct measure of labor quality changes over time is unavailable in the data, labor quality unlikely drives our main results.

If labor quality improvement was substantial, then it is a valid conjecture that wage rate would have increased quickly in this industry, especially given the good market conditions in the steel industry driven by infrastructure and housing investment in China during the data period. However, we did not observe such a pattern. The growth rate of wage rate in the steel industry was about 10 percent each year, which was substantially lower than the country average in manufacturing sector (13.2 percent). The slower growth of wage rate also made it hard for steel makers to attract talent.

In fact, labor quality in the steel industry has been in general very low. In the 2004 Census dataset in China which provides some measures of labor quality in the Chinese Steel Industry,[18] 98.5% of employees did not have a university degree and 94% of employees did not have any technical certificate of any level.[19] The low level of labor quality in the fifth year (out of eight) in our data suggests that the improvement of labor quality, if any, should not be large at least in the first five years in our dataset. Hence, the impact of labor quality, if any, should not

[18] Unfortunately, these labor quality measures are not available in the 2008 census data for this industry, although they are available for some other industries.

[19] Technical certificate is a key certificate of labor skill in this industry, classified into high/medium/low, and no certificate.

Table 9
Contribution of Non-Hicks neutral technology to changes in labor share from 2000 to 2007.

	Data	Counterfactual		
		(1)	(2)	(3)[a]
	Has BTC Has BTH	Remove BTC&BTH	Remove BTH	Remove BTC
Labor share in 2007 (%)	3.39	5.95	4.84	4.50
Contribution to changes in labor share (%)	−5.01	−2.56 (51%)[b]	−1.45 (29%)	−1.11 (22%)

[a] Implied by counterfactuals (1) and (2). Results are similar when conducting an independent counterfactual to remove the effect of BTC.
[b] Share of the decline of labor share explained by each source is reported in the parenthesis.

be substantial in the data period and should not have driven our main results.

More general production function. In our application, we focus on the CES production function, which is widely used in the literature and the simplest way to introduce non-Hicks neutral technology. However, the method can be applied to a more general production function, given some mild conditions. Appendix J provides a discussion.

5. Application: labor share in the Chinese steel industry

The non-Hicks neutral technology asymmetrically affects the marginal output of different inputs, creating a differential effect on firms' optimal choice of labor, material, and capital. Hence it has direct implications on labor share. This section evaluates the contribution of non-Hicks neutral technology to the decline of labor share in the Chinese steel industry based on our structural model. I also conduct a dynamic Olley Pakes decomposition to examine the sources of the changes in labor share and productivity.

5.1. Counterfactuals: contribution of Non-Hicks neutral technology

The steel industry in China experienced fast output growth and a radical decline in labor share in the data period. From 2000 to 2007, the average labor demand per firm decreased by 54 percent, but the average output per firm was more than doubled. Consequently, the labor share in sales decreased by 5.01 percent, from 8.40 percent in 2000 to 3.39 percent in 2007. This section conducts two counterfactual experiments to answer the following two questions. First, what would have been the labor share in this industry, if there were no non-Hicks neutral technology? Second, what is the relative importance of the cross-sectional heterogeneity and over-time change of non-Hicks neutral technology in saving labor? All counterfactuals keep input prices and other state variables fixed to highlight the effect of non-Hicks neutral technology.[20]

The first question is answered in the first counterfactual experiment. To this purpose, I remove non-neutral technology across firms and over time completely in the counterfactual, and assume that all firms have the same factor-augmenting efficiency ratios in all years, $(\omega_0 : \nu_0 : \mu_0)$, which is chosen as the median of the factor-augmenting efficiencies in 2000. Then I construct a counterfactual Hicks-neutral productivity measure, $\widetilde{\omega}_{jt}$, in such a way that given $\widetilde{\omega}_{jt}$, the implied TFP for each observation equals the ones observed in the data. The difference between the predicted labor share and that observed in the data highlights the impact of the non-Hicks neutral technology on labor share. Appendix K provides more details on how we calculate the predicted labor share in the counterfactual.

The results are reported in Table 9. As shown in counterfactual (1), the average labor share would be higher in the counterfactual after removing non-Hicks neutral technology completely, at 5.95 percent in 2007, in contrast to the 3.39 percent in the data. As a result, the non-Hicks neutral technology alone contributes to the decline of labor share by 2.56 percentage points, or 51 percent of the 5.01-percentage points decline in labor share. These results imply that the majority of the declines in labor share was contributed by the non-Hicks neutral technology. Input prices, together with all other factors, explain 49 percent of the total decline of labor share in the sample period.

In the second counterfactual experiment, I evaluate the relative importance of the cross-sectional heterogeneity and over-time change in non-Hicks neutral technology in driving the change of labor share. To do so, I do a similar experiment as above, except that I remove only the non-Hicks neutral technology dispersion across firms within each year, but keep the non-neutral technology change over time. Specifically, within each year t, I assume that all firms have the same factor-augmenting efficiency ratios, $(\omega_{0t} : \nu_{0t} : \mu_{0t})$, which are chosen as the median of the factor efficiency ratios of all firms in year t. Then I construct a counterfactual Hicks-neutral productivity measure, $\widehat{\omega}_{jt}$, in such a way that given $\widehat{\omega}_{jt}$, the implied TFP for each observation equals the ones observed in the data. I do the same for all years, year by year. Within each year, there is no non-Hicks neutral technology heterogeneity across firms. But over time there is still non-neutral technology change. The difference between the predicted labor demand in the counterfactual and that in the data represents the contribution of non-neutral technology dispersion across firms. The contribution of the non-neutral technology change over time can be derived from the difference between the above two counterfactual experiments.

The results are reported in column (2) in Table 9. If no non-Hicks neutral technology heterogeneity emerged across firms, then the average labor share in 2007 would be 4.84 percent in contrast to the 3.39 percent observed in the data. So the non-Hicks neutral technology heterogeneity across firms explains 1.45 percentage points, or 29 percent of the 5.01-percentage points decline in labor share. It accounts for 57 percent of the total contribution of the non-Hicks neutral technology to the decline in labor share. The difference between these two counterfactuals also suggests that the non-Hicks neutral technology change over time contributes 1.11 percentage points, or 22 percent of the 5.01-percentage points decline in labor share. It accounts for 43 per-

[20] The cost, of course, is the difference between the results from the general equilibrium analysis and partial equilibrium analysis. Considering the price adjustment in input market equilibrium, the actual effect on labor demand of non-neutral technology will be smaller than what we predict here, because price adjustment will partly offset this effect. In a similar manner, if we allow firms to adjust their investment in the counterfactual, the estimated effect of non-neutral technology on labor demand will also be smaller. Because the main focus of this paper is to examine the nature of technology, I refrain from the temptation to develop a full general equilibrium model with inputs markets clearing, in order to highlight the impact of technology on labor demand and labor share.

Table 10
Dynamic OP decomposition of labor share and non-Hicks neutral technology.

Variable	Aggregate	Continuing firms		Firm turnover	
		Within growth	Reallocation	Entry	Exit
△labor share (%): sales weighted	−5.01	−1.26	−3.28	−0.17	−0.30
△capital efficiency	1.682	1.100	0.492	0.369	−0.279
△labor efficiency	2.353	0.991	1.191	−0.038	0.219
△material efficiency	0.328	0.400	−0.062	−0.015	0.005
△ implied TFP	0.621	0.530	0.077	0.040	−0.026

cent of the total contribution of the non-Hicks neutral technology to the decline in labor share. Hence the cross-sectional differences and over-time changes in non-Hicks neutral technology are almost equally important in driving the decline of labor share during the sample period.

Of course, the counterfactual results are based on fixed input prices and output level. If the input prices and output level were allowed to adjust, the predicted effect of non-neutral technology on labor demand would be smaller. The actual decline of labor demand and labor share in this case would also depend on the strength of the equilibrium price effects. Given that the main purpose of this paper is to understand the nature of non-neutral technology and its implication on labor demand, this experiment is still meaningful.

5.2. Dynamic Olley Pakes decomposition

This subsection explores the relative importance of firm improvement, reallocation, and entry/exit in driving the decline in labor share, by using a dynamic Olley Pakes (OP) decomposition of the industry's aggregate labor share. Specifically, the analysis decomposes the change in industry aggregate labor share between any two periods (t = 1, 2) into four terms as follows:

$$\triangle S_L = \triangle \overline{S}_{LC} + (cov_{C2} - cov_{C1}) + w_{E2}(S_{LE2} - S_{LC2}) + w_{X1}(S_{LC1} - S_{LX1}), \tag{20}$$

where $w_{Gt} = \sum_{i \in G} w_{it}$ represents the aggregate market share of firm group $G \in \{C, E, X\}$. $cov_{Ct} = \sum_{i \in C}(w_{it|C} - \overline{w}_{t|C})(S_{Lit} - \overline{S}_{Lt|C})$ is the covariance term between market share and labor share for continuing firms. $S_{LGt} = \sum_{i \in G}(w_{it}/w_{Gt})S_{Lit}$ is group $G's$ aggregate labor share. The first term, $\triangle \overline{S}_{LC}$ represents the change in labor share for continuing firms. The second term, $(cov_{C2} - cov_{C1})$, represents the change in the covariance between market share and labor share for continuing firms, which captures the impact of reallocation among continuing firms. The last two terms capture the contributions of entry and exit. A similar decomposition is used in Collard-Wexler and De Loecker (2015) and Melitz and Polanec (2015).

The decomposition results from 2000 to 2007 are reported in the first row in Table 10. The evolution of the sales-weighted labor share is mainly due to the continuing firms. Among all the sources, reallocation contributed 3.28 percentage points, and within-firm changes contributed 1.26 percentage points to the decline of labor share, in contrast to the 5.01-percentage points decline in total labor share at the industry level. By contrast, the net firm turnover in total contributed less than 0.5 percentage point to the decline in labor share, although the industry in the data period experienced substantial firm entry and exit.

The relatively more important contribution of continuing firms—especially through reallocation—can be rationalized by the change in non-Hicks neutral technology. To see this, I decompose the non-Hicks neutral efficiency levels in the same way as labor share, and report the results in the last three rows in Table 10. The continuing firms contributed the largest part to the change of almost all three efficiencies at the industry level. Given that the change is mainly labor-saving, the continuing firms naturally contributed most to the decline in labor share. Reallocation generates more labor-saving technology change relative to within-firm growth (note the large difference in material efficiencies and the large material expenditure share), which explains the relatively greater contribution of reallocation compared with within-firm changes. Moreover, new entrants and exit contributes to a lower gap between labor efficiency and the other two efficiencies, which explains their smaller contribution to labor share compared with other sources. Similarly, the continuing firms contributed the most to the growth of TFP from 2000 to 2007 in this industry. The within-firm growth of TFP contributed 85 percent of the total TFP growth, and the reallocation among continuing firms contributed an additional 12 percent. The net effect of entry and exit is small.

6. Conclusion

The large cross-sectional heterogeneity and decline in labor share have been a global phenomenon over the past four decades. Using firm-level data from the steel industry in China, this paper documented large cross-sectional heterogeneity and radical decline in labor share. From 2000 to 2007, the labor share declined by 5.01 percent and average firm labor demand declined by 54 percent, while output per firm was more than doubled. This large change in labor share and labor demand cannot be explained by the mild change in relative factor prices.

This study examined the role of non-Hicks neutral technology in driving the declining trend and large variation in labor share across firms. It estimated the firm-level non-Hicks neutral technology, and showed large heterogeneity of non-Hicks neutral technology across firms and swift non-Hicks neutral technology change toward saving labor in general. Counterfactual experiments showed that non-Hicks neutral technology explains over 50 percent of the 5.01-percentage points decline in labor share, mainly due to the evolution of heterogeneous non-Hicks neutral technology and the resulting reallocation effect. The cross-sectional differences and over-time changes in non-Hicks neutral technology play almost equally important role in driving these changes.

Appendices

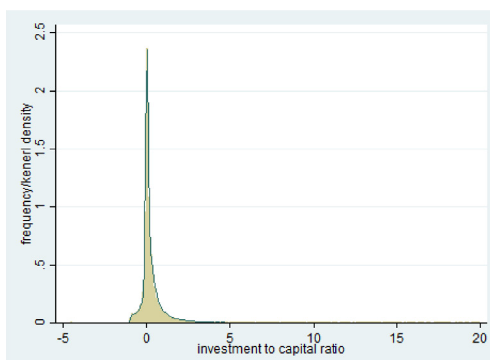
A. Sample construction

The basic data used in the empirical exercise are the firm-level survey data from the Chinese steel industry from 2000 to 2007. I refine this data set by the following treatment:

- Missing and negative values: drop any observation with missing or non-positive value for any of the following variables: number of workers, capital stock, revenue, wage expenditure, intermediate inputs expenditure.
- Firm size: drop any observation when revenue is less than RMB100,000, or the number of workers is fewer than give.
- Factor-revenue share: drop any observation when labor share in revenue is grater than 99 percent, or material share is greater than 99%, or the sum of labor and material shares is less than 10%, or any of them is less than 0.5%, or capital share is less than 0.5%.
- Construction of firm-level investment measure: I define firm-level investment as the gross investment at the firm level during the calendar year in question. The change in investment may be due to purchase of capital stock and selling existing capital stock. As a result, the capital could increase or decrease depending on firms' decisions on buying and selling capital. As this measure is not directly observed in the data set, we construct gross investment at the firm level from year-end capital and capital depreciation observed in the data.

  $$I_{jt} = (year\ end\ capital)_{jt} - (year\ end\ capital)_{jt-1} + (capital\ depreciation)_{jt}.$$

  In this process, I also used the year-end capital in 1999 to ensure that the investment measure is also available for 2000. We then drop the first year of each firm appearing in the data, so that all the observations have investment measure. The histogram and kernel density of the investment-to-capital ratio are reported in Fig. A1. It is shown that the distribution is quite smooth, with zero investment less than 0.5%.After this data cleaning, we have a sample of 24,565 observations from 2000 to 2007. The empirical application is based on this data set. I report the summary statistics of the key variables used in the estimation in Table A1.



This figure shows the histogram and kernel density of the investment-to-capital ratio across firms, pooling all years together. The year-by-year distribution is similar.

Fig. A1 Distribution of the Investment-to-Capital Ratio.

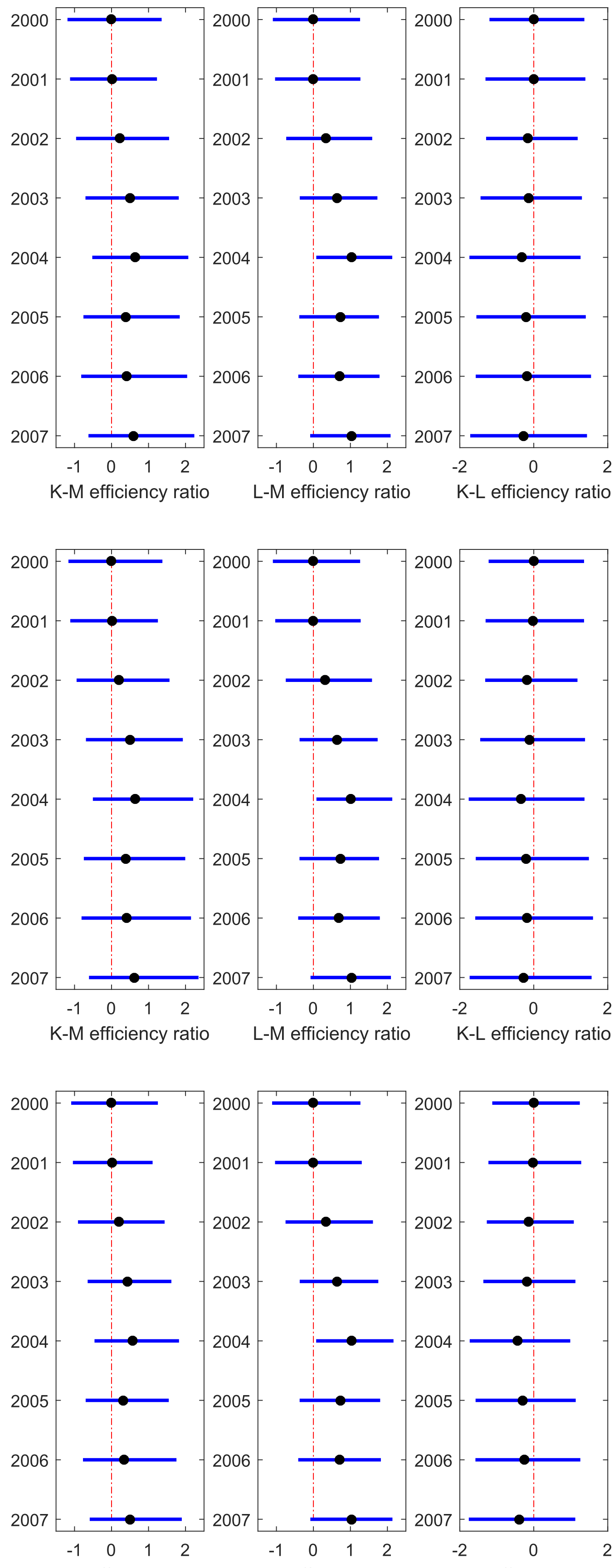


Fig. A2 Non-neutral technology change: 1%, 2.5%, and 5% noise to input and output prices.

Table A1
Summary statistics of major variables.

Variable	Notation	Mean	Standard deviation
Revenue	R_{jt}	402,727.90	2,557,351.00
Capital	K_{jt}	158,516.50	1,459,216.00
Employee	L_{jt}	703.32	4341.87
Investment	I_{jt}	0.58	2.03
Labor share	shl_{jt}	0.04	0.04
Material share	shm_{jt}	0.80	0.10
Wage rate	W_{jt}	15.34	17.81
Material price	P_{mjt}	146.28	48.34
Output price	P_{jt}	121.94	15.57
Output quantity	Q_{jt}	3252.06	20,181.63
Material quantity	M_{jt}	2098.86	11,735.85

Table A2
(Non)Convergence of non-Hicks neutral technology: Inter-Quartile Range (IQR).

Year	IQR of efficiency levels			IQR of efficiency ratios		
	ω_{jt}^0	ν_{jt}^0	μ_{jt}^0	$\omega_{jt}^0-\nu_{jt}^0$	$\nu_{jt}^0-\mu_{jt}^0$	$\omega_{jt}^0-\mu_{jt}^0$
2000	2.749	2.253	0.302	2.592	2.361	2.569
2001	2.546	2.153	0.361	2.716	2.301	2.360
2002	2.645	2.149	0.384	2.486	2.330	2.522
2003	2.755	2.064	0.411	2.774	2.096	2.553
2004	2.863	2.078	0.437	3.090	2.049	2.676
2005	2.854	2.145	0.460	2.995	2.155	2.662
2006	3.131	2.188	0.413	3.163	2.197	2.925
2007	3.097	2.142	0.361	3.195	2.173	2.894

Table A3
Basic productivity patterns after adding additional noise to input and output prices.

Panel A—Correlation: Efficiencies and input ratio (corresponding to Table 5)

noise level 1%			noise level 2.5%			noise level 5%		
(ω^0,ν^0)	(ω^0,μ^0)	(ν^0,μ^0)	(ω^0,ν^0)	(ω^0,μ^0)	(ν^0,μ^0)	(ω^0,ν^0)	(ω^0,μ^0)	(ν^0,μ^0)
0.301	0.488	0.075	0.304	0.480	0.077	0.312	0.480	0.074
(lnq,ω^0)	(lnq,ν^0)	(lnq,μ^0)	(lnq,ω^0)	(lnq,ν^0)	(lnq,μ^0)	(lnq,ω^0)	(lnq,ν^0)	(lnq,μ^0)
0.030	0.495	0.122	0.030	0.494	0.122	0.025	0.491	0.116
$(\omega^0-\mu^0,\frac{K}{M})$	$(\nu^0-\mu^0,\frac{L}{M})$	$(\omega^0-\nu^0,\frac{K}{L})$	$(\omega^0-\mu^0,\frac{K}{M})$	$(\nu^0-\mu^0,\frac{L}{M})$	$(\omega^0-\nu^0,\frac{K}{L})$	$(\omega^0-\mu^0,\frac{K}{M})$	$(\nu^0-\mu^0,\frac{L}{M})$	$(\omega^0-\nu^0,\frac{K}{L})$
−0.460	−0.947	−0.521	−0.455	−0.947	−0.513	−0.503	−0.944	−0.558

Panel B—Firm size and non-neutral technology: Dispersion and growth (corresponding to Table 6)

	noise level 1%					noise level 2.5%					noise level 5%				
firm group	0–20	20–40	40–60	60–80	80–100	0–20	20–40	40–60	60–80	80–100	0–20	20–40	40–60	60–80	80–100
labor efficiency															
mean	3.221	3.998	4.445	4.940	5.337	3.250	4.030	4.477	4.975	5.373	3.274	4.062	4.517	5.020	5.410
growth (%)	19.28	20.30	14.03	18.97	42.33	19.24	20.30	14.01	19.04	42.58	19.48	20.48	14.06	19.23	42.86
material efficiency															
mean	0.532	0.568	0.578	0.586	0.771	0.549	0.586	0.595	0.604	0.793	0.486	0.523	0.533	0.542	0.728
growth (%)	4.78	5.37	5.32	4.86	4.75	4.75	5.35	5.34	4.90	4.92	4.74	5.29	5.20	4.92	4.53
capital efficiency															
mean	−4.830	−4.167	−3.890	−3.951	−5.030	−4.514	−3.831	−3.568	−3.627	−4.742	−5.091	−4.500	−4.230	−4.276	−5.445
growth (%)	16.28	16.93	16.35	14.68	28.53	16.15	17.30	16.13	14.22	28.53	17.08	16.22	14.11	12.24	25.27

Panel C—Dispersion of efficiencies and efficiency ratios: Interquartile range

noise level 1%			noise level 2.5%			noise level 5%		
ω_0	ν_0	μ_0	ω_0	ν_0	μ_0	ω_0	ν_0	μ_0
2.836	2.237	0.516	2.917	2.243	0.521	2.532	2.280	0.528
$\omega^0-\mu^0$	$\nu^0-\mu^0$	$\omega^0-\nu^0$	$\omega^0-\mu^0$	$\nu^0-\mu^0$	$\omega^0-\nu^0$	$\omega^0-\mu^0$	$\nu^0-\mu^0$	$\omega^0-\nu^0$
2.653	2.229	2.921	2.738	2.238	2.999	2.356	2.273	2.694

Panel D—Average annual growth rate of productivity levels (%, revenue-weighted), 2000–2007 (corresponding to Table 7)

noise level 1%				noise level 2.5%				noise level 5%			
ω_0	ν_0	μ_0	TFP	ω_0	ν_0	μ_0	TFP	ω_0	ν_0	μ_0	TFP
27.15	39.93	4.79	10.53	27.09	40.14	4.95	10.65	24.00	40.41	4.59	9.79

Notes: The size groups of firms are defined as those in Table 1.

Table A4
Labor share and non-Hicks neutral technology, with additional noise to input and output prices.

Panel A—Decomposition of TFP Growth and Heterogeneity (corresponding to Table 8)

	noise level 1%			noise level 2.5%			noise level 5%		
	Capital Efficiency	Label Efficiency	Material Efficiency	Capital Efficiency	Labor Efficiency	Material Efficiency	Capital Efficiency	Labor Efficiency	Material Efficiency
Contribution to TFP growth (%)	39.65	17.68	42.67	39.03	17.51	43.46	37.68	18.96	43.36
Contribution to TFP heterogeneity (%)	60.3	4.0	35.6	60.6	4.0	35.4	57.0	4.3	38.7

Panel B—Contribution of Non-Hicks neutral technology to changes in labor share from 2000 to 2007 (corresponding to Table 9)

	noise level 1%			noise level 2.5%			noise level 5%		
	Counterfactual			Counterfactual			Counterfactual		
	(1)Remove BTC&BTH	(2)Remove BTH	(3)Remove BTC	(1)Remove BTC&BTH	(2)Remove BTH	(3)Remove BTC	(1)Remove BTC&BTH	(2)Remove BTH	(3)Remove BTC
Labor share in 2007 (%)	5.95	4.84	4.50	5.86	4.78	4.47	5.83	4.77	4.44
Contribution to changes in labor share (%)	−2.56(51%)	−1.45(29%)	−1.11(22%)	−2.47(49%)	−1.39(28%)	−1.08(22%)	2.44(49%)	1.38(28%)	1.06(21%)

Panel B—Dynamic Olley Pakes decomposition of labor share[1] and non-Hicks neutral technology (corresponding to Table 10)

	noise level 1%					noise level 2.5%					noise level 5%				
	aggregate	continuing firms		firm turnover		aggregate	continuing firms		firm turnover		aggregate	continuing firms		firm turnover	
		within	reallocate	entry	exit		within	reallocate	entry	exit		within	reallocate	entry	exit
△K-efficiency	1.681	1.114	0.523	0.358	−0.313	1.678	1.079	0.442	0.388	−0.231	1.506	0.956	0.447	0.379	−0.277
△L-efficiency	2.352	0.989	1.183	−0.037	0.217	2.362	0.994	1.186	−0.039	0.222	2.376	0.997	1.190	−0.034	0.223
△M-efficiency	0.328	0.399	−0.063	−0.014	0.006	0.338	0.403	−0.055	−0.017	0.006	0.314	0.397	−0.076	−0.016	0.009
△TFP	0.620	0.531	0.081	0.039	−0.031	0.629	0.530	0.076	0.042	−0.018	0.584	0.507	0.059	0.041	−0.023

Notes: Labor share decomposition is the same as in Table 10, so it is omitted here.

B. Variable definitions

The major variables used in this paper are defined as follows:

- Revenue (R_{jt}): total sales in year t for firm j.
- Capital stock (K_{jt}): year-end depreciated book value of capital stock in year t for firm j, adjusted by the yearly average utilization rate of capital at the industry level.
- Labor employment (L_{jt}): number of workers employed in year t for firm j.
- Total wage expenditure (TW_{jt}): total expenditure on wages and benefits to workers in year t for firm j.
- Wage rate (W_{jt}): average wage rate for firm j in year t. It is computed by dividing the wage expenditure by labor employment.
- Material expenditure (MV_{jt}): includes all expenditure on intermediate inputs, but not capital equipments or other fixed/long-term investment.
- Capital investment (I_{jt}): constructed using data on capital stock and annual depreciation. It is computed as the difference between the year-end capital stock in years t and t-1, plus yearly depreciation in year t.
- Labor share (S_{Ljt}): the ratio of total wage expenditure to revenue.
- Material share (S_{Mjt}): the ratio of material expenditure to revenue.
- Material price (P_{Mjt}): proxied by the province-level material price index where the firm is located. Because the market for the Chinese steel industry is very organized locally, the province-level material price is very close to firm-level price. The same applies for output prices.
- Material quantity (M_{jt}): the ratio of material expenditure to material price.
- Output price(P_{jt}): proxied by the province-level output price index where the firm is located.
- Output quantity (Q_{jt}): the ratio of revenue to output price.
- Firm age (age_{jt}): defined as the difference between the data year and the year in which the firm started up.
- Firm ownership state-owned enterprise (own_soe_{jt}): a dummy equals 1 if more than 30 percent of the stock share is owned by the state.

C. Monotonicity of $\widetilde{\phi}(\cdot, \varepsilon_{jt})$ in Equation (18)

Theorem 1. (Conditional monotonicity of $\widetilde{\phi}(\cdot, \varepsilon_{jt})$) *The function $\widetilde{\phi}(\cdot, \varepsilon_{jt})$ is strictly increasing in ε_{jt} conditional on data $(i_{jt}, l_{jt}, m_{jt}, k_{jt}, P_{Mjt}, W_{jt}, \frac{S_{Ljt}}{S_{Mjt}}, S_{Mjt})$, if the unexpected productivity shock ε_{jt} is not too large, such that*

1. *When $\gamma < 0$ or $\gamma > \kappa$: $\widetilde{S}^*_{Kjt} > 0$ for all observations, or,*
2. *When $0 < \gamma < \kappa$: $0 < \widetilde{S}^*_{Kjt} < \frac{1+\eta}{\eta}\frac{\kappa}{\kappa-\gamma}$ and $\frac{\partial i_{jt}/\partial\omega_{jt}}{\partial i_{jt}/\partial\mu_{jt}} > 1$ for all observations,*

where $\widetilde{S}^*_{Kjt} \equiv \kappa\frac{1+\eta}{\eta}\exp(\varepsilon_{jt}) - S^*_{Ljt} - S^*_{Mjt}$.

Proof. *From* Equation (10) *we have*

$$\frac{\partial\widetilde{\phi}_{jt}}{\partial\varepsilon_{jt}} = \frac{\partial Y_{jt}}{\partial\varepsilon_{jt}} = \frac{\partial\mu_{jt}}{\partial\varepsilon_{jt}} + 1 - \frac{\kappa}{\gamma}. \tag{C.1}$$

The relationship between μ_{jt} and ε_{jt} is implicitly determined in the capital investment function, from which we recover the augmented material efficiency μ_{jt}. Conditional on the available data $(i_{jt}, l_{jt}, m_{jt}, k_{jt}, P_{Mjt}, W_{jt}, \frac{S_{Ljt}}{S_{Mjt}}, S_{Mjt})$, the capital investment function $i_{jt}= i(\omega_{jt}, \nu_{jt}, \mu_{jt}, k_{jt}, P_{Mjt}, W_{jt})$ defines an implicit function of μ_{jt} with respect to ε_{jt}. Using the implicit function theorem, we have

$$\frac{\partial\mu_{jt}}{\partial\varepsilon_{jt}} = -\frac{\partial i_{jt}/\partial\varepsilon_{jt}}{\partial i_{jt}/\partial\mu_{jt}} = -\frac{\partial i_{jt}/\partial\omega_{jt}}{\partial i_{jt}/\partial\mu_{jt}}\frac{\partial\omega_{jt}}{\partial\varepsilon_{jt}}. \tag{C.2}$$

From Eq. (9), we have

$$\frac{\partial\omega_{jt}}{\partial\varepsilon_{jt}} = -\frac{1}{\gamma}\frac{\kappa\frac{1+\eta}{\eta}}{\kappa\frac{1+\eta}{\eta}\exp(\varepsilon_{jt}) - S^*_{Ljt} - S^*_{Mjt}} = -\frac{1}{\gamma}\frac{\kappa\frac{1+\eta}{\eta}}{\widetilde{S}^*_{Kjt}} \tag{C.3}$$

Combining the above three equations, we have

$$\frac{\partial\widetilde{\phi}_{jt}}{\partial\varepsilon_{jt}} = \frac{1}{\gamma}\frac{\partial i_{jt}/\partial\omega_{jt}}{\partial i_{jt}/\partial\mu_{jt}}\frac{\kappa\frac{1+\eta}{\eta}}{\widetilde{S}^*_{Kjt}} + (1 - \frac{\kappa}{\gamma}). \tag{C.4}$$

Case 1: $\gamma < 0$.

This is the case of the greatest interest, because almost all estimates of the elasticity of substitution in the literature are less than 1. In this case, inputs are gross complements, which implies $\partial i_{jt}/\partial\omega_{jt} < 0$. The reason is that when conditional on μ_{jt} and ν_{jt} together with other data variables in the investment function, $\partial i_{jt}/\partial\omega_{jt}$ actually captures how capital-augmenting efficiency ω^0_{jt} changes investment, while fixing labor efficiency (ν^0_{jt}), material efficiency (μ^0_{jt}) and other state variables. When the inputs are gross complements, this effect is negative. Because $\partial i_{jt}/\partial\mu_{jt}$ is always positive, as shown in Section 3.2, $\gamma < 0$, and $\widetilde{S}^*_{Kjt} > 0$ by assumption, the first term in Eq. (C.4) is positive. And, because $\gamma < 0$ and $\kappa > 0$, the second term in Eq. (C.4), $(1 - \frac{\kappa}{\gamma})$, is also positive. As a result, we have $\frac{\partial\widetilde{\phi}_{jt}}{\partial\varepsilon_{jt}} > 0$ in this case.

Case 2: $\gamma > \kappa$.

Because $\gamma < 1$, this case may happen only when $0 < \kappa < 1$. In this case, inputs are gross substitutes, which implies $\partial i_{jt}/\partial\omega_{jt} > 0$. Because $\gamma > 0$ in this case, the first term in Eq. (C.4) is positive, given that $\widetilde{S}^*_{Kjt} > 0$ by assumption. Also, it is straightforward to see that $(1 - \frac{\kappa}{\gamma})$ is also positive. As a result, we have $\frac{\partial\widetilde{\phi}_{jt}}{\partial\varepsilon_{jt}} > 0$ in this case.

Case 3: $0 < \gamma < \kappa$.

From Eq. (C.4), $\frac{\partial\widetilde{\phi}_{jt}}{\partial\varepsilon_{jt}} > 0$ is equivalent to

$$\frac{1}{\gamma}\frac{\partial i_{jt}/\partial\omega_{jt}}{\partial i_{jt}/\partial\mu_{jt}}\frac{\kappa\frac{1+\eta}{\eta}}{\widetilde{S}^*_{Kjt}} + (1 - \frac{\kappa}{\gamma}) > 0.$$

Given $\widetilde{S}^*_{Kjt} > 0$ and $\gamma > 0$, the above condition is equivalent to

$$\widetilde{S}^*_{Kjt} < \frac{\kappa\frac{1+\eta}{\eta}}{\kappa - \gamma}\frac{\partial i_{jt}/\partial\omega_{jt}}{\partial i_{jt}/\partial\mu_{jt}}.$$

The conditions that $\widetilde{S}^*_{Kjt} < \frac{1+\eta}{\eta}\frac{\kappa}{\kappa-\gamma}$ and $\frac{\partial i_{jt}/\partial\omega_{jt}}{\partial i_{jt}/\partial\mu_{jt}} > 1$ guarantee that this inequality holds. This completes the Proof.

D. Extension: more general production function

This section shows that the method developed in this paper can be applied to more general production function forms. I will focus on showing the conditions under which the capital-material efficiency ratio and labor-material efficiency ratio, (ω_{jt}, ν_{jt}), can be recovered from observed variables up to parameters.[21]

Suppose the production function is in the flexible form

$$Q_{jt} = F\left[\exp(\omega^0_{jt})K_{jt}, \exp(\nu^0_{jt})L_{jt}, \exp(\mu^0_{jt})M_{jt}\right],$$

which is homogeneous of degree κ. Then it can be rewritten into the transformed form as follows,

$$Q_{jt} = \exp(\mu_{jt})F\left[\exp(\omega_{jt})K_{jt}, \exp(\nu_{jt})L_{jt}, \exp(M_{jt}\right].$$

Here the triple $(\omega_{jt}, \nu_{jt}, \mu_{jt})$ is defined exactly the same as that in the main text. Assuming firms choose material and labor optimally to maximize period profit, we can derive two first-order conditions in share forms:

$$\exp(\nu_{jt})L_{jt}\frac{F_2\left(\exp(\omega_{jt})K_{jt}, \exp(\nu_{jt})L_{jt}, M_{jt}\right)}{F\left(\exp(\omega_{jt})K_{jt}, \exp(\nu_{jt})L_{jt}, M_{jt}\right)} = S^*_{Ljt}, \tag{D.1}$$

$$M_{jt}\frac{F_3\left(\exp(\omega_{jt})K_{jt}, \exp(\nu_{jt})L_{jt}, M_{jt}\right)}{F\left(\exp(\omega_{jt})K_{jt}, \exp(\nu_{jt})L_{jt}, M_{jt}\right)} = S^*_{Mjt}. \tag{D.2}$$

Similarly, the demand shifter and augmented efficiency μ_{jt} are absorbed in the expenditure shares, S^*_{Ljt} and S^*_{Mjt}, both of which are observed in the data subject to i.i.d shocks. There are two unknowns, (ω_{jt}, ν_{jt}), in this two-equation system. In principle we can solve for them uniquely if this two-equation system is not degenerated. This can be guaranteed if the following two conditions are satisfied: (1) $F(\cdot)$ is strictly increasing in all its arguments and strictly concave and (2) $\frac{E^l_{jt\omega}}{E^m_{jt\omega}} \neq \frac{E^l_{jt\nu}}{E^m_{jt\nu}}$, where E^i_{jt} is the output elasticity of input $i \in \{l, m\}$ and $E^i_{jtx} = \frac{\partial E^i_{jt}}{\partial x}$ is the derivative of output elasticity E^i_{jt} with respect to efficiency x. The first condition is quite standard in the literature. The second condition basically ensures that the capital- and labor-augmenting efficiencies affect the output elasticity of inputs differently. In the special case of CES, this condition is just that the elasticity of substitution does not equal one. Given this condition, the idea to solve for ω_{jt} and ν_{jt} from the above share-form first-order conditions is clear. Because ω_{jt} and ν_{jt} affect the output elasticity differently and the output elasticity determines the revenue share of inputs, we can infer ω_{jt} and ν_{jt} from the relative revenue share of labor and material, which are observed in the data subject to i.i.d. shocks. Given these conditions, the labor-material efficiency ratio ν_{jt} can be solved directly by dividing Eq. (D.1) by (D.2). ω_{jt} can be solved by inserting ν_{jt} back into either of the two first-order conditions.

E. Construction of counterfactual Hicks neutral productivity and labor demand

This appendix explains how to perform the two counterfactual experiments to answer the following two questions. First, what is the contribution of non-Hicks neutral technology, inclusive of the cross-sectional heterogeneity and over-time change of non-Hicks neutral technology, on the decline in labor share in this industry from 2000 to 2007? Second, what is the relative importance of the cross-sectional heterogeneity and over-time change of non-Hicks neutral technology in saving labor? To answer these two questions, we first calculate the elasticities of labor share with respect to the efficiencies of capital, labor, and material, as implied by our structural model. Then we calculate the change of the efficiencies when moving from the data to each of the counterfactual scenarios. Finally the contribution of technology changes on labor share can be calculated combining information on the labor share elasticities and change of efficiencies.

[21] The subsequent steps, namely inserting (ω_{jt}, ν_{jt}) into the production function to get an equation similar to Eq. (10) and estimating the parameters based on the resulting equations, are quite straightforward following a similar procedure developed in Olley and Pakes (1996) and applied in Section 3 in this paper. These subsequent steps are omitted here to save space.

Labor share elasticity. The labor share implied by the model is

$$S^*_{Ljt} = \frac{\kappa \frac{1+\eta}{\eta} \exp(\gamma \nu_{0jt}) L^{\gamma}_{jt}}{\left\{[\exp(\omega_{0jt})K_{jt}]^{\gamma} + [\exp(\nu_{0jt})L_{jt}]^{\gamma} + [\exp(\mu_{0jt})M_{jt}]^{\gamma}\right\}}.$$

Or in logarithm,

$$\ln S^*_{Ljt} = \ln(\kappa \frac{1+\eta}{\eta}) + \gamma \nu_{0jt} + \gamma \ln L_{jt} - \ln\left\{[\exp(\omega_{0jt})K_{jt}]^{\gamma} + [\exp(\nu_{0jt})L_{jt}]^{\gamma} + [\exp(\mu_{0jt})M_{jt}]^{\gamma}\right\}.$$

The total differentiation of the log labor share is as follows

$$d\ln S^*_{Ljt} = \gamma d\nu_{0jt} + \gamma d\ln L_{jt} - \frac{1}{A}dA, \tag{E.1}$$

where

$$\begin{aligned}
A &= [\exp(\omega_{0jt})K_{jt}]^{\gamma} + [\exp(\nu_{0jt})L_{jt}]^{\gamma} + [\exp(\mu_{0jt})M_{jt}]^{\gamma} \\
dA &= \{\gamma[\exp(\omega_{0jt})K_{jt}]^{\gamma} d\omega_{0jt} + \exp(\gamma\omega_{0jt})K^{\gamma}_{jt} d\ln K_{jt} + \gamma[\exp(\nu_{0jt})L_{jt}]^{\gamma} d\nu_{0jt} \\
&\quad + \gamma[\exp(\mu_{0jt})M_{jt}]^{\gamma} d\mu_{0jt} + \exp(\gamma\nu_{0jt})L^{\gamma}_{jt} d\ln L_{jt} + \exp(\gamma\mu_{0jt})M^{\gamma}_{jt} d\ln M_{jt} \\
&= B + \exp(\gamma\nu_{0jt})L^{\gamma}_{jt} d\ln L_{jt} + \exp(\gamma\mu_{0jt})M^{\gamma}_{jt} d\ln M_{jt}
\end{aligned}$$

Here $B = \exp(\gamma\omega_{0jt})K^{\gamma}_{jt} d\ln K_{jt} + \gamma[\exp(\omega_{0jt})K_{jt}]^{\gamma} d\omega_{0jt} + \gamma[\exp(\nu_{0jt})L_{jt}]^{\gamma} d\nu_{0jt} + \gamma[\exp(\mu_{0jt})M_{jt}]^{\gamma} d\mu_{0jt}$. A change in factor-augmenting efficiencies affects labor share through a direct effect of efficiencies, and an indirect effect by changing the demand for inputs. We focus on the short-term reaction of labor and material demand, by fixing capital for simplicity.

Using the notation of A, the first order condition with respect to the optimal choice of labor and material can be rewritten as follows,

$$\kappa \frac{1+\eta}{\eta} \Phi_{jt}^{\frac{-1}{\eta}} A^{\frac{\kappa}{\gamma}-1+\frac{\kappa}{\eta\gamma}} \exp(\gamma\nu_{0jt}) L^{\gamma-1}_{jt} = W_{jt},$$

$$\kappa \frac{1+\eta}{\eta} \Phi_{jt}^{\frac{-1}{\eta}} A^{\frac{\kappa}{\gamma}-1+\frac{\kappa}{\eta\gamma}} \exp(\gamma\mu_{0jt}) M^{\gamma-1}_{jt} = P_{Mjt}.$$

After taking logarithm, total differentiation of the first order conditions implies the following equation system

$$d\ln[\kappa \frac{1+\eta}{\eta} \Phi_{jt}^{\frac{-1}{\eta}}] + (\frac{\kappa}{\gamma} - 1 + \frac{\kappa}{\eta\gamma})\frac{1}{A}dA + \gamma d\nu_{0jt} + (\gamma-1)d\ln L_{jt} = d\ln W_{jt},$$

$$d\ln[\kappa \frac{1+\eta}{\eta} \Phi_{jt}^{\frac{-1}{\eta}}] + (\frac{\kappa}{\gamma} - 1 + \frac{\kappa}{\eta\gamma})\frac{1}{A}dA + \gamma d\mu_{0jt} + (\gamma-1)\ln M_{jt} = d\ln P_{Mjt}.$$

Given that A is a function of $d\ln L$ and $d\ln M$, we can solve out $d\ln L$ and $d\ln M$ from the above two-equation linear system. The results are as follows

$$d\ln L_{jt} = \frac{A\left\{d\ln W_{jt} - \gamma d\nu_{0jt} - d\ln[\kappa \frac{1+\eta}{\eta}\Phi_{jt}^{\frac{-1}{\eta}}]\right\} - (\frac{\kappa}{\gamma} - 1 + \frac{\kappa}{\eta\gamma})\left\{B + \frac{A_m}{\gamma-1}\left[d\ln\frac{P_{Mjt}}{W_{jt}} - \gamma(d\mu_{0jt} - d\nu_{0jt})\right]\right\}}{(\frac{\kappa}{\gamma} - 1 + \frac{\kappa}{\eta\gamma})(A_m + A_l) + A(\gamma-1)},$$

$$d\ln M_{jt} = d\ln L_{jt} + \frac{1}{\gamma-1}(d\ln P_{Mjt} - d\ln W_{jt}) - \frac{\gamma}{\gamma-1}(d\mu_{0jt} - d\nu_{0jt}).$$

To simplify the notification, we denoted $A_k = [\exp(\omega_{0jt})K_{jt}]^{\gamma}, A_l = [\exp(\nu_{0jt})L_{jt}]^{\gamma}$, and $A_m = [\exp(\mu_{0jt})M_{jt}]^{\gamma}$. So $A = A_k + A_l + A_m$. The impact of efficiencies of capital, labor, and material on labor and material demand can then be derived by calculating the corresponding partial derivatives, as follows

$$\frac{\partial \ln L}{\partial \omega_0} = \frac{\partial \ln M}{\partial \omega_0} = \frac{-\gamma A_k}{A_m + A_l + \frac{A(\gamma-1)}{(\frac{\kappa}{\gamma}-1+\frac{\kappa}{\eta\gamma})}},$$

$$\frac{\partial \ln L}{\partial \nu_0} = \frac{-\frac{A\gamma}{(\frac{\kappa}{\gamma}-1+\frac{\kappa}{\eta\gamma})} - \frac{\gamma}{\gamma-1}A_m - \gamma A_l}{A_m + A_l + \frac{A(\gamma-1)}{(\frac{\kappa}{\gamma}-1+\frac{\kappa}{\eta\gamma})}}$$

$$\frac{\partial \ln M}{\partial \nu_0} = \frac{\partial \ln L}{\partial \nu_0} + \frac{\gamma}{\gamma-1},$$

$$\frac{\partial \ln L}{\partial \mu_0} = \frac{-A_m\gamma\frac{\gamma-2}{\gamma-1}}{A_m + A_l + \frac{A(\gamma-1)}{(\frac{\kappa}{\gamma}-1+\frac{\kappa}{\eta\gamma})}},$$

$$\frac{\partial \ln M}{\partial \mu_0} = \frac{\partial \ln L}{\partial \mu_0} - \frac{\gamma}{\gamma-1}.$$

Then the elasticity of (log) labor share with respect to the efficiencies of capital, labor, and material can be computed following Eq. (E.1).

$$\frac{\partial \ln S^*_{Ljt}}{\partial \omega_0} = \gamma \frac{\partial \ln L_{jt}}{\partial \omega_0} - \frac{1}{A}\left\{\gamma A_k + A_l \frac{\partial \ln L}{\partial \omega_0} + A_m \frac{\partial \ln M}{\partial \omega_0}\right\}, \tag{E.2}$$

$$\frac{\partial \ln S^*_{Ljt}}{\partial \nu_0} = \gamma + \gamma \frac{\partial \ln L}{\partial \nu_0} - \frac{1}{A}\left\{\gamma A_l + A_l \frac{\partial \ln L}{\partial \nu_0} + A_m \frac{\partial \ln M}{\partial \nu_0}\right\}, \tag{E.3}$$

$$\frac{\partial \ln S^*_{Ljt}}{\partial \mu_0} = \gamma \frac{\partial \ln L}{\partial \mu_0} - \frac{1}{A}\left\{\gamma A_m + A_l \frac{\partial \ln L}{\partial \mu_0} + A_m \frac{\partial \ln M}{\partial \mu_0}\right\}. \tag{E.4}$$

Counterfactual (1): contribution of non-Hicks neutral technology

The first counterfactual experiment evaluates the importance of non-Hikcs neutral technology to labor share. The idea is to ask what would be the labor share if the impact of non-Hicks neutral technology is removed completely. To this purpose, I choose the first year (2000) as the base year and assume that all firms share the same factor-augmenting efficiencies, (ω_0, ν_0, μ_0). (ω_0, ν_0, μ_0) is chosen as the median of $(\omega_{0jt}, \nu_{0jt}, \mu_{0jt})$ in year 2000 ($t = 2000$) estimated in the full model. So the production function in the counterfactual world is

$$Q_{jt} = \exp(\kappa \widetilde{\omega}_{jt})\left\{[\exp(\omega_0)K_{jt}]^\gamma + [\exp(\nu_0)L_{jt}]^\gamma + [\exp(\mu_0)M_{jt}]^\gamma\right\}^{\frac{\kappa}{\gamma}},$$

where $\widetilde{\omega}_{jt}$ is the counterfactual Hicks-neutral productivity. We choose $\widetilde{\omega}_{jt}$ in such a way that the implied TFP in this counterfactual world equals that estimated in the data. Specifically for year $t' = 2007$, $\widetilde{\omega}_{jt'}$ is determined by

$$\widetilde{\omega}_{jt} + (w_k\omega_0 + w_l\nu_0 + w_m\mu_0) = (w_k\omega_{0jt'} + w_l\nu_{0jt'} + w_m\mu_{0jt'}).$$

w_k, w_l, and w_m are the corresponding weights, chosen as the output elasticity with respect to capital, labor, and material inputs respectively. Then under this new technology in the counterfactual, we removed the cross-sectional heterogeneity and over-time evolution of non-Hicks neutral technology. As a result, the difference of labor share in the conterfactual and that in the data represents the contribution of non-Hicks neutral technology on labor share. We use first-order approximation to calculate this contribution, in the following steps.

- Step 1: Calculate the differences of efficiencies from this counterfactual to that in the data as follows (with a little abuse of notation):

  $$D\omega_0 = \omega_{0jt'} - (\widetilde{\omega}_{jt} + \omega_0),$$

  $$D\nu_0 = \nu_{0jt'} - (\widetilde{\nu}_{jt} + \nu_0),$$

  $$D\mu_0 = \mu_{0jt'} - (\widetilde{\mu}_{jt} + \mu_0).$$

- Step 2: Calculate the contribution of non-Hicks neutral technology changes to labor share. In the empirical analysis, we use first-order approximation as follows,

  $$\triangle S_L^{nonHicks} = \frac{\partial S_{Ljt}}{\partial \omega_0} D\omega_0 + \frac{\partial S_{Ljt}}{\partial \nu_0} D\nu_0 + \frac{\partial S_{Ljt}}{\partial \mu_0} D\mu_0.$$

  Note that $\triangle S_L^{nonHicks}$ constitutes the contribution of non-Hicks neutral technology differences across firms and over time on labor share.

Counterfactual (2): Contribution of non-neutral technology dispersion

To isolate the contribution of the cross-sectional heterogeneity from the over-time change of non-Hicks neutral technology, we perform the second counterfactual in which we remove only the cross-firm heterogeneity of non-Hicks neutral technology. Then the difference of labor share between this counterfactual and the data defines the contribution of the cross-sectional differences of non-Hicks neutral technology to labor share; the difference of the labor share between this counterfactual and that in counterfactual (1) above defines the contribution of the over-time changes in non-Hicks neutral technology to labor share.

The solution procedure is very similar to that in counterfactual (1), except that we do the above computation year by year. For each year, we fix the factor-augmenting efficiency ratios at $(\omega_{0t}, \nu_{0t}, \mu_{0t})$, which are the medians of the corresponding efficiencies in year t. Thereafter, we do the above solution procedure for observations in year t only. We repeat this for each year and compute the labor demand for each year when there is no non-neutral technology dispersion across firms within each year, while keeping non-neutral technology change over time.

Table 9 illustrates the counterfactual results.

Appendix F. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jdeveco.2019.06.001

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