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TECHNICAL PROGRESS AND THE SHARE OF LABOR INCOME

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Abstract

Changes in the labor share of national income affect inequality (Piketty 2014). This paper aims at investigating the relationship between the labor share and technical progress, based on provincial data of the People's Republic of China (PRC) from 1978 to 2012. Our main empirical results show that technical progress in the PRC had been mostly capital biased, contributing to the fast rises in income inequality in the PRC. However, the employment proportion of state-owned enterprises seems to have played a role in offsetting this negative effect, helping contain inequality. In recent years, both effects have become more significant and larger in absolute terms.

JEL Classification: D33, E25, L32, O33

Contents

1. INTRODUCTION

At the aggregate level, national income equals the sum of compensations to labor and capital. Thus, inequality of per capita income as measured by the Gini coefficient can be expressed as a weighted sum of concentration indexes of labor and capital inputs where the weights are simply the labor share and capital share. For given concentrations of wage and capital, national inequality becomes a function of labor or capital share. Because labor is generally more evenly distributed than capital, a rise or fall in the labor share implies a fall or rise of income inequality.

Recently, a growing literature points to the stylized fact of declining labor share globally. For example, Karabarbounis and Neiman (2013) found that among the 59 countries with at least 15 years of data between 1975 and 2012, 42 exhibited downward trends in the labor share. Also, labor share in Germany and France had been falling almost continuously since the early 1980s after rising sharply in the wake of the two oil price shocks in the 1970s (Blanchard 1997; Bentilola and Saint-Paul 1998; Rowthorn 1999; Caballero and Hammour 1997). A similar trend has also been observed in developing countries since the early 1990s. As mentioned earlier, the declining labor share means worsening income distribution (Piketty 2014). To understand this declining trend, it is crucial to identify and analyze the determinants of the labor share.

One of the most important determinants of factor share is technical progress. Unless technical change is neutral, it will cause variations in the labor or capital share. For example, capital-biased technical progress will induce more capital investment, replacing labor by capital and causing declines in the labor share (see Acemoglu 2002, 2003; Caselli 2007). The contrary holds when labor-biased technology change prevails.

In this paper, we examine the relationship between technical progress and labor share in the People's Republic of China (PRC). Although previous papers have studied this relationship using global data and data from developed economies, it remains worthwhile exploring this relationship for the PRC. On the one hand, the PRC is the largest developing economy; thus, changes in the PRC's labor share will have a significant impact on global labor share or global inequality. According to the National Bureau of Statistics of China, the labor share had been decreasing during 1978–2012, especially after the 1990s when it declined from 61% in 1990 to around 46% in 2007 (Bai and Qian 2010). Such dramatic declines must have contributed to fast rises in the PRC's income inequality (Wan 2007, 2008). On the other hand, the PRC's labor market is far from complete. State-owned enterprises (SOEs) still shoulder the responsibility of maintaining social stability, partly by providing employment. Even today, the market share of the PRC's SOEs is still significant. Thus, although technical progress is expected to be biased toward capital in the PRC, its effect on the labor share may be offset by the presence of SOEs.

Based on the PRC's provincial data over the period from 1978 to 2012, this paper first explores the nature and measures the extent of technical progress using the supply-side normalized Constant Elasticity of Substitution production function system of Klump et al. (2007). We then estimate the impacts of factor-biased technical progress on the labor share, paying special attention to the role of SOEs. It is found that technical progress in the PRC had been mostly capital-biased, contributing to the fast rises in income inequality in the PRC. However, the presence of SOEs seems to have played a role in offsetting this negative distributive effect, helping contain inequality. In recent years, both effects became more significant and larger in absolute terms.

The rest of the paper is organized as follows. Section 2 presents literature review. In section 3, an indicator of capital-biased technical progress is proposed, which is built on the supply-side normalized CES production function system. In section 4, we discuss data and empirical method. Section 5 provides estimation results. Finally, section 6 concludes.

2. LITERATURE REVIEW

The determinants of labor share have been explored extensively. They include economic growth (Raffalovich et al. 1992), structural transformation (Serres 2001; Morel 2005), and globalization (Diwan 2000, 2001; Jaumotte and Tytell 2007; Decreuse and Maarek 2015). The effects of economic growth and structural transformation on labor share are widely accepted. Regarding globalization, Harrison (2002), using country-level data from 1960 to 1997, finds that it actually reduces labor share. He argues that the bargaining power of capital became stronger than that of labor in the globalizing era, resulting in declines of the labor share.

Institutional forces matter too as factor shares of income are partly determined by changes in the relative position of capital and labor. For example, Bentolina and Saint-Paul (2003) show that labor unions affect labor's bargaining power. As another example, Bai and Qian (2010) attribute changes in factor share of income in the PRC to changes in the labor market, which had experienced increasing monopoly power and various reforms in the state-owned sectors.

Regarding the relationship between capital-biased technical progress and labor share, Acemoglu (2003) takes technology progress as an endogenous variable and points out that capital-biased technical progress affects labor share of income. Young (2004) develops a Real Business Cycle model incorporating capital-biased technical progress. His dynamic stochastic general equilibrium model explains seasonal changes in labor share of income in the United States. However, the relationship between capital-biased technical progress and labor share in the PRC is not yet examined in the literature, and this paper aims at filling this gap.

3. MEASURE OF CAPITAL-BIASED TECHNICAL PROGRESS

3.1 Indicators of Capital-Biased Technical Progress

According to Acemoglu (2002, 2003, and 2007), capital-biased technical progress can be defined as follows. Using *Y* to denote output, a production function with factor-augmented technologies can be written as follows:

$$Y = F(A_t, N_t, B_t, K_t) \tag{3.1}$$

where A_t and B_t denote labor-augmented and capital-augmented technologies, respectively. K_t represents capital and N_t represents labor. Based on (3.1), capital-biased technical progress can be expressed as

$$Tech = \frac{\partial\left(\frac{F_K}{F_N}\right)}{\partial\left(\frac{B}{A}\right)} \tag{3.2}$$

Intuitively, $Tech$ measures to what extent technical progress affects the ratio of marginal returns to capital over marginal productivity to labor. When $Tech$ is positive, technical progress is capital-biased; otherwise, it is labor-biased.

Following the conventional wisdom, we apply the CES production function to model technical progress:

$$Y = \left[(1-\alpha)(A_t N_t)^{\frac{\sigma-1}{\sigma}} + \alpha(B_t K_t)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{3.3}$$

where α denotes the extent of capital intensity, and σ represents the substitution elasticity of capital to labor. Thus, capital-biased technical progress can be expressed as

$$Tech = \frac{\alpha}{1-\alpha}\left(\frac{K_t}{N_t}\right)^{-\frac{1}{\sigma}} \frac{\sigma-1}{\sigma}\left(\frac{B_t}{A_t}\right)^{-\frac{1}{\sigma}} \tag{3.4}$$

In this case, for given capital and labor, when σ is larger than 1, a positive value of $Tech$ implies capital-biased technology change, and vice versa. When σ is equal to 1, technical progress is neutral.

Next, we apply the normalized supply-side system approach proposed by Klump et al. (2007) to estimate the substitution elasticity σ. This approach has proven to be quite robust by Leon-Ledesma et al. (2010). Specifically, the normalized supply-side system can be described as follows:

$$\begin{aligned} ln\left(\frac{Y_t}{\overline{Y}}\right) = ln(\xi) + \frac{\sigma}{\sigma-1} ln\Bigg\{ &(1-\alpha)\left[\frac{N_t}{\overline{N}} exp\left[\left(\bar{t}\frac{\gamma_N}{\lambda_N}\right)\left(\frac{t}{\bar{t}}\right)^{\lambda_N} - 1\right]\right]^{\frac{\sigma-1}{\sigma}} \\ &+\alpha\left[\frac{K_t}{\overline{K}} exp\left[\left(\bar{t}\frac{\gamma_N}{\lambda_N}\right)\left(\frac{t}{\bar{t}}\right)^{\lambda_N} - 1\right]\right]^{\frac{\sigma-1}{\sigma}} \Bigg\} \end{aligned} \tag{3.5}$$

$$\begin{aligned} ln(w_t) = ln(1-\alpha) + ln\left(\frac{\overline{Y}}{\overline{N}}\right) + \frac{\sigma-1}{\sigma} ln(\xi) - \frac{\sigma-1}{\sigma} ln\left(\frac{Y_t/\overline{Y}}{N_t/\overline{N}}\right) \\ + \frac{\sigma-1}{\sigma}\left[\left(\bar{t}\frac{\gamma_N}{\lambda_N}\right)\left(\frac{t}{\bar{t}}\right)^{\lambda_N} - 1\right] \end{aligned} \tag{3.6}$$

$$\begin{aligned} ln(r_t) = ln\alpha + ln\left(\frac{\overline{Y}}{\overline{K}}\right) + \frac{\sigma-1}{\sigma} ln(\xi) - \frac{\sigma-1}{\sigma} ln\left(\frac{Y_t/\overline{Y}}{K_t/\overline{K}}\right) \\ + \frac{\sigma-1}{\sigma}\left[\left(\bar{t}\frac{\gamma_K}{\lambda_K}\right)\left(\frac{t}{\bar{t}}\right)^{\lambda_K} - 1\right] \end{aligned} \tag{3.7}$$

Where t indexes time, ξ denotes the adjustment coefficient so that $\xi\bar{Y} = Y_0$, $\bar{N} = N_0$, $\bar{K} = K_0$, $\bar{t} = t_0$. γ_K and γ_N denote the growth rate of capital and labor productivity, and λ_K and λ_N represent the curvature of capital and labor productivity, respectively. In this system, the growth rate of factor productivity is set as the Box-Cox growth rate. Thus, (3.5)-(3.7) constitutes the complete normalized supply-side system, from which we can estimate σ, γ, λ, and α.

With the estimated α and σ, the index of capital-biased technology D_t can be estimated as follows:

$$D_t \equiv \frac{1}{\varepsilon_t}\frac{\partial \varepsilon_t}{\partial(B_t/A_t)}\frac{d(B_t/A_t)}{dt} = \frac{\sigma-1}{\sigma}\frac{A_t}{B_t}\frac{d(B_t/A_t)}{dt} \tag{3.8}$$

where

$$\varepsilon_t = \frac{\partial Y/\partial K}{\partial Y/\partial N} = \frac{\alpha}{1-\alpha}\left(\frac{B_t}{A_t}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{N_t}{K_t}\right)^{\frac{1}{\sigma}} \tag{3.9}$$

$$A_t = \frac{Y_t}{N_t}\left[\frac{w_t N_t}{(1-\alpha)(w_t N_t + r_t K_t)}\right]^{\frac{\sigma}{\sigma-1}} \tag{3.10}$$

$$B_t = \frac{Y_t}{K_t}\left[\frac{r_t K_t}{\alpha(w_t N_t + r_t K_t)}\right]^{\frac{\sigma}{\sigma-1}} \tag{3.11}$$

where ε_t represents the ratio of marginal labor to capital productivity. Thus, $\frac{\partial \varepsilon_t}{\partial(B_t/A_t)}$ measures to what extent B_t/A_t affects ε_t. Consequently, the index of capital-biased technology D_t captures the impact of technical progress $\left(\frac{d(B_t/A_t)}{dt}\right)$ on the relative marginal productivity (ε_t). Finally, the inverse of ε_t can be used to normalize the impact for comparison between regions. In short, when D_t is positive, implying that technical progress results in the increase of relative marginal productivity, the technology progress is capital-biased; otherwise, it is labor-biased.

3.2 Data

To obtain the index of capital-biased technology of (3.8), the parameter of capital intensity α and the substitution elasticity of capital to labor σ must be estimated, using the supply-side normalized CES production function system (3.5)–(3.7). These require data on output, capital stock, labor input, labor income, and capital income, which are all available from the National Bureau of Statistics. Our data cover the period 1978–2012 for 28 provinces in the PRC, excluding Tibet, Hainan, and Chongqing (included in Sichuan province).

Capital Stock

Capital stock is estimated using the perpetual inventory method. First, we estimate the initial real capital stock using the following equation:

$$K_0 = I_1/(g+\delta) \tag{3.12}$$

where K_0 is the initial capital stock, I_1 is the capital investment in the first period deflated by the price index of fixed asset investment, g is the growth rate of capital investment, and δ denotes the rate of capital depreciation.

We use provincial fixed capital formation to measure capital investment, which is available from 1952 onward. Following Hall and Jones (1999), we average the growth rate of real fixed capital formation in the first 10 years (1953–1963) and use this average value as the growth rate of capital investment. The depreciation rate is set to be 5%. Note that our empirical modeling results are robust to different depreciation rates.

Next, we iterate each year's real capital stock using the following perpetual inventory method equation:

$$K_{t+1} = I_{t+1} + (1-\delta)K_t \tag{3.13}$$

Thus, we obtain a complete data set of real provincial capital stock for 1952–2012. The nominal capital stock is obtained by multiplying the real capital stock by the price index of fixed asset investment.

Labor Input

We use the number of employees as the proxy of labor input, with data from China Statistical Yearbooks.

Labor and Capital Income

The National Bureau of Statistics (various years) provides annual data on the labor income (NI) and capital income (CI) for each province and each sector. We sum up provincial capital and labor income to obtain the provincial aggregate capital and labor income.

There are two other components in provincial gross domestic product (GDP): net taxes on production (NT), or indirect tax, and depreciation (DE). The latter can be viewed as part of capital income. The indirect tax, following Lu et al. (2008), is proportionally shared between labor and capital. Thus, we have the following estimation of labor income and capital income:

$$wN = NI + \frac{NI}{NI + CI + DE} NT \tag{3.14}$$

$$rK = DE + \frac{CI + DE}{NI + CI + DE} NT \tag{3.15}$$

3.3 Estimation Results

To estimate the system of (3.5)-(3.7) as seemingly unrelated regression (SUR), we employ the feasible generalized nonlinear least squares (FGNLS) method. As Klump et al. (2007) pointed out, the results are only sensitive to different starting values of σ, since the system has a singularity at $\sigma = 1$.

We used different starting values of σ for the nonlinear system estimation. It turns out that for various starting values of $\sigma < 1$, the estimation always converges to the same point for each province. However, for starting values that are greater than 1, the estimation converges to a different point. However, the sums of squared residual are found to be always smaller in the earlier case.

Table 1 presents the estimation results. It is clear that the elasticities of substitution in most provinces are smaller than 1. The provincial index of capital-biased technology progress are then computed and presented in Figure 1. It shows that the index is positive in most cases, confirming that the technical progress is mostly capital-biased.

The same results are obtained when estimations are undertaken using data subsamples for 1978–1992 and 1993–2012, respectively. The first subsample starts with the year of reform initiation and opening up and ends with the year of Deng Xiaoping's southern tour. The second sample mirrors the period with deepened reforms and fast economic growth. The estimation results for the two periods are quite similar, as shown in Figure 2.

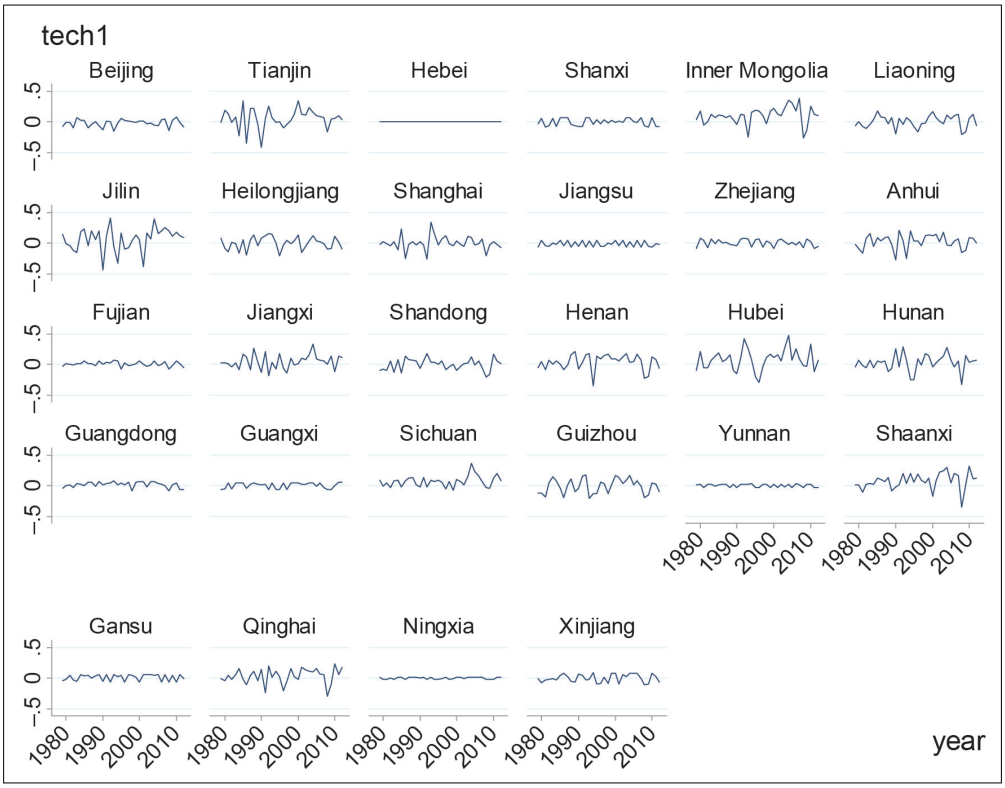
Table 1: Estimates of Substitution Elasticity

Province	ξ	σ	α	Province	ξ	σ	α
Beijing	0.970***	0.942***	0.557***	Shandong	1.060***	0.899***	0.451***
	(–0.016)	(–0.009)	(–0.004)		(–0.015)	(–0.025)	(–0.007)
Tianjin	0.911***	0.659***	0.518***	Henan	1.019***	0.794***	0.354***
	(–0.015)	(–0.015)	(–0.008)		(–0.021)	(–0.014)	(–0.006)
Hebei	1.074***	1.000***	0.411***	Hubei	0.998***	0.613***	0.343***
	(–0.021)	(–0.001)	(–0.006)		(–0.021)	(–0.011)	(–0.012)
Jiangxi	0.971***	0.963***	0.473***	Hunan	0.993***	0.810***	0.297***
	(–0.014)	(–0.011)	(–0.007)		(–0.018)	(–0.018)	(–0.007)
Inner Mongolia	0.958***	0.632***	0.373***	Shandong	1.152***	0.964***	0.394***
	(–0.015)	(–0.014)	(–0.007)		(–0.020)	(–0.007)	(–0.004)
Liaoning	0.993***	0.809***	0.493***	Guangxi	1.080***	0.973***	0.325***
	(–0.009)	(–0.014)	(–0.005)		(–0.027)	(–0.012)	(–0.007)
Jilin	0.978***	0.667***	0.336***	Guizhou	0.955***	0.896***	0.327***
	(–0.019)	(–0.024)	(–0.012)		(–0.023)	(–0.016)	(–0.010)
Heilongjiang	1.015***	0.911***	0.450***	Yunnan	1.101***	0.985***	0.382***
	(–0.018)	(–0.019)	(–0.008)		(–0.023)	(–0.004)	(–0.006)
Shanghai	0.921***	0.782***	0.593***	Shanxi	0.950***	0.722***	0.350***
	(–0.022)	(–0.008)	(–0.006)		(–0.019)	(–0.048)	(–0.008)
Jiangsu	0.964***	0.974***	0.439***	Gansu	0.968***	0.971***	0.391***
	(–0.018)	(–0.005)	(–0.004)		(–0.013)	(–0.006)	(–0.004)
Zhejiang	1.065***	0.958***	0.462***	Qinghai	0.961***	0.852***	0.342***
	(–0.018)	(–0.011)	(–0.006)		(–0.02)	(–0.010)	(–0.006)
Anhui	1.015***	0.853***	0.349***	Ningxia	0.997***	0.992***	0.408***
	(–0.017)	(–0.020)	(–0.007)		(–0.015)	(–0.006)	(–0.004)
Fujian	1.157***	0.968***	0.365***	Xinjiang	1.088***	0.956***	0.352***
	(–0.023)	(–0.007)	(–0.005)		(–0.015)	(–0.021)	(–0.006)
Jiangxi	1.011***	0.769***	0.321***	Sichuan	0.900***	0.735***	0.333***
	(–0.017)	(–0.020)	(–0.008)		(–0.016)	(–0.009)	(–0.008)

Note: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

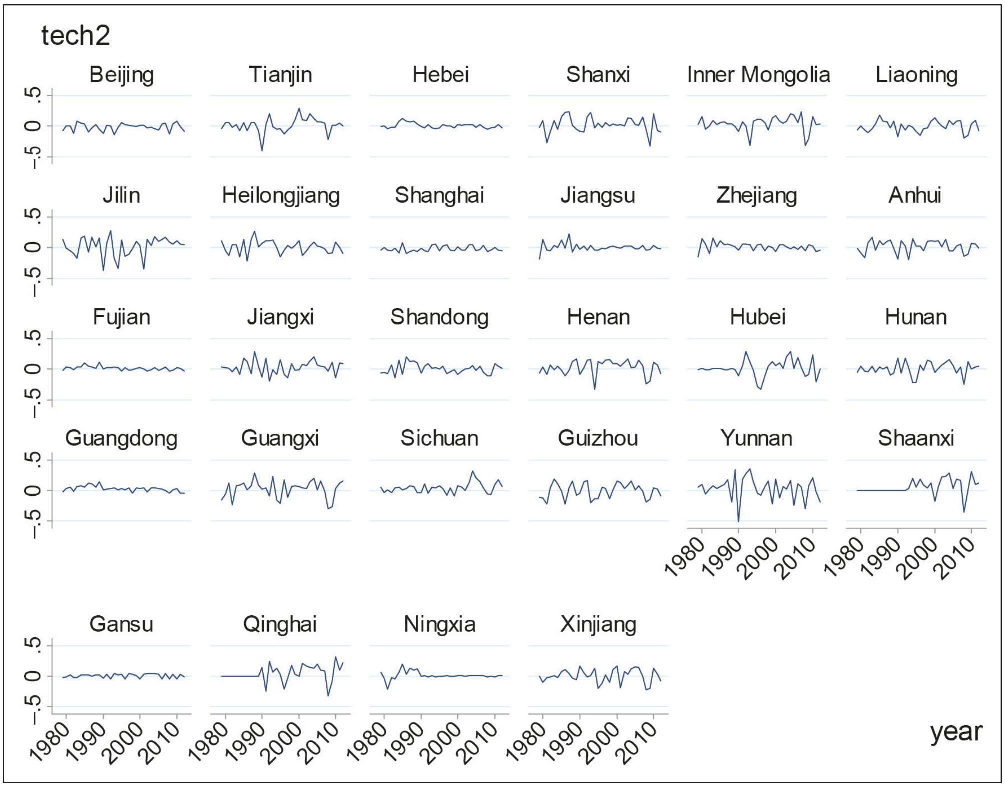
Source: Authors.

Figure 1: Index of Capital-Biased Technology (Whole Sample)



Source: Authors.

Figure 2: Index of Capital-Biased Technology (Split Sample)



Source: Authors.

4. THE TECHNICAL PROGRESS – LABOR SHARE RELATIONSHIP

In this section, we estimate the impact of biased technical progress on the labor share. We follow the modeling strategy of Decreuse and Maarek (2015), which focuses on the effect of globalization on the labor share. We simply extend their model by adding the index of biased technical progress as the key variable:

$$S_{it} = \alpha_0 + \beta_1 Tech_{i,t-1} + \theta' X_{i,t-1} + \eta_t + \mu_i + u_{it} \qquad (4.1)$$

where i indexes province and t indexes year. S_{it} denotes the labor share, $Tech$ represents capital-biased technical progress, X contains control variables. η and μ represent year and provincial fixed effects, respectively. u is the usual white noise term. In (4.1), all independent variables are lagged to alleviate possible endogeneity. β measures the effect of capital-biased technical progress on the labor share, and we expect β to be negative.

The following control variables are considered. First, cross-sectional variations in the labor share are related to distortions in the factor markets. Bai and Qian (2010) argue that the main causes of factor market distortion in the PRC are government behavior (as measured by government expenditure over GDP) and the presence of SOE in terms of their proportion in total employment, both of which are included in (4.1).

Second, globalization indicators of trade (% of GDP) and foreign direct investment or FDI (% of GDP) are controlled in (4.1). FDI may induce higher labor share via increased competition. It may also help lower the labor share due to labor productivity improvement induced by FDI-related technology changes (Decreuse and Maarek 2015). Intuitively, importing labor-intensive goods erodes the labor share while exporting labor-intensive goods can increase the labor share (Jaumotte and Tytell 2007). However, as pointed out by Melitz (2003), exports in general may help improve aggregate productivity by increasing the market share of more productive firms, resulting in lower labor share.

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Labor Share	980	0.583	0.107	0.272	0.928
Index of Biased Technology 1	952	0.024	0.107	–0.434	0.474
Index of Biased Technology 2	952	0.017	0.106	–0.503	0.351
SOE Employment Proportion	946	0.704	0.136	0.207	0.917
Secondary GDP Proportion	980	0.454	0.087	0.190	0.812
Government Expenditure/GDP	980	0.154	0.073	0.049	0.612
Trade/GDP	974	0.245	0.459	0.000	3.824
FDI/GDP	822	0.028	0.039	0.000	0.322
Education	979	0.006	0.007	0.000	0.035
GDP per capita	980	7.352	1.076	5.156	10.296
Capital-Output Ratio	980	1.132	0.660	0.474	5.128

FDI = foreign direct investment, GDP = gross domestic product, SOE = state-owned enterprise.

Source: CNBS' Annual Industrial Survey.

Other control variables include human capital (measured by number of university students over population), which directly affects labor income and, thus, labor share and economic growth, which raises demand for labor but also increases labor cost and profits (Raffalovich et al. 1992). To capture the effect of structural transformation on the labor share, the manufacturing share in GDP is included. Since capital intensity captures the extent of factor endowment, defined as capital-output ratio, it is also controlled in our model. All nominal variables are appropriately deflated. Table 2 presents the summary statistics.

5. EMPIRICAL RESULTS

5.1 Baseline Results

Table 3 presents estimation results for the baseline model (4.1). All regressions include year and province fixed effects. Standard errors are clustered at the provincial level to alleviate possible serial correlation.

Table 3: Baseline Results

Labor Share$_{i,t}$	(1)	Labor Share$_{i,t}$	(2)
Index of Biased Technology 1$_{i,t-1}$	–0.148***	Index of Biased Technology 2$_{i,t-1}$	–0.159***
	(–0.021)		(–0.021)
SOE Employment Proportion$_{i,t-1}$	0.028	SOE Employment Proportion$_{i,t-1}$	0.026
	(–0.113)		(–0.114)
Secondary GDP Proportion$_{i,t-1}$	–0.676***	Secondary GDP Proportion$_{i,t-1}$	–0.678***
	(–0.201)		(–0.200)
Government Expenditure/ GDP$_{i,t-1}$	–0.284**	Government Expenditure/ GDP$_{i,t-1}$	–0.252*
	(–0.137)		(–0.136)
Trade/GDP$_{i,t-1}$	–0.012	Trade/GDP$_{i,t-1}$	–0.010
	(–0.012)		(–0.013)
FDI/GDP$_{i,t-1}$	0.173	FDI/GDP$_{i,t-1}$	0.147
	(–0.204)		(–0.206)
Education$_{i,t-1}$	–1.309	Education$_{i,t-1}$	–0.951
	(–2.295)		(–2.201)
GDP per capita$_{i,t-1}$	–0.001	GDP per capita$_{i,t-1}$	–0.004
	(–0.101)		(–0.100)
Capital-output Ratio$_{i,t-1}$	0.000	Capital-output Ratio$_{i,t-1}$	0.000
	(–0.035)		(–0.034)
Provincial Fixed Effect	YES	Provincial Fixed Effect	YES
Year Fixed Effect	YES	Year Fixed Effect	YES
N	766	N	766
R^2	0.748	R^2	0.751

FDI = foreign direct investment, GDP = gross domestic product.

Notes:

1) Index of Biased Technology 1 is estimated using the whole sample; Index of Biased Technology 2 is estimated using the split sample.

2) Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: Authors.

In column (1) of Table 3, we use the index of capital-biased technology estimated using the whole data sample of 1978–2012. The result shows that in general, capital-biased technical progress reduces the labor share. A 1-percentage-point increase in the index of capital-biased technology leads to approximately 0.15 percentage point decrease in the labor share. This impact confirms our prior expectation that capital-biased technology will increase the marginal output of and return to capital relative to labor, which reduces the labor income share. This negative relationship is a robust-to-different measure of biased technology. Using the index estimated using the split samples of 1978–1992 and 1993–2012, similar results are found, as column (2) demonstrates.

Turning to control variables, government expenditure is found to reduce labor share. A possible explanation lies in the capital-biased government expenditure on infrastructure investment and industrial support. The manufacturing share in GDP also depresses the labor share. This is reasonable as the manufacturing sector is more capital intensive than the agriculture and service sectors. With the development of the manufacturing sector, the share of the agriculture sector declines, so does the labor income share. The impacts of other control variables are insignificant, including globalization indicators, GDP per capita, human capital, and capital intensity. The insignificance of the coefficient of SOE employment proportion will be further explored below.

5.2 The Effects of State-Owned Enterprises

In Table 3, we do not find a significant impact of SOE employment proportion on the labor share. This is not consistent with the finding of Bai and Qian (2010), who show a significant and positive relationship, without controlling biased technical progress. Therefore, the reason for the insignificance may lie in the inclusion of the biased technology index. It is possible that the effect of SOE on the labor share has been absorbed by biased technical progress.

It is well recognized that the operating efficiency of the PRC’s SOEs is lower than non-SOEs, while non-SOEs are faced with credit constraint. Song et al. (2011) argue that non-SOEs can undo credit constraint through internal saving and capital accumulation, leading to the downsizing of SOEs. As a consequence, the capital income share will increase as non-SOEs adopt relatively more capital-biased technologies. In this case, the correlation between the SOE variable and the index of capital-biased technology is negative, and thus it became positively correlated with the labor share.

More importantly, SOEs have soft budget constraints and also share the social responsibility to provide jobs to maintain social stability (Lin and Tan 1999; Kornai et al. 2003). On the other hand, compared with non-SOEs, the trade union of SOEs is larger and better organized, which helps protect labor income. Therefore, it is expected that in those regions where SOE proportions are higher, the effect of capital-biased technical progress on job replacement, and thus on the labor share, might be weakened.

To explore the role of the SOE variable in the relationship between capital-biased technical progress and labor income share, we extend model (4.1) by adding the interaction between *SOE* and *Tech*:

$$S_{it} = \alpha_0 + \beta_1 Tech_{i,t-1} + \beta_2 Tech_{i,t-1} \times SOE_{i,t-1} + \theta' X_{i,t-1} + \eta_t + \mu_i + u_{it} \qquad (5.1)$$

We expect the coefficient of the interaction (β_2) to be positive.

Table 4 presents the estimation results of model (5.1). Column (1) uses the index estimated with the whole sample, and column (2) uses the estimates based on the split samples. Consistent with prior expectation, the coefficient of the interactive term is positive and significant. The results are robust-to-different measures of capital-biased technical progress. Once the interaction is controlled, the absolute value of the coefficient of capital-biased technical progress becomes much larger. This suggests that, if there are no SOEs in the economy, a 1% point increase in the index of capital-biased technology will lead to approximately 0.52 percentage point decrease in the labor share. Evaluated at the sample mean of *SOE*, the SOEs offset the negative effect of capital-biased technical progress on the labor share by roughly 0.352%, which is quite significant.

Table 4: The Effects of State-Owned Enterprises

Labor Share$_{i,t}$	**(1)**	**Labor Share$_{i,t}$**	**(2)**
Index of Biased Technology 1$_{i,t-1}$	–0.553***	Index of Biased Technology 2$_{i,t-1}$	–0.520***
	(–0.160)		(–0.173)
Index of Biased Technology 1$_{i,t-1}$* SOE Employment Proportion$_{i,t-1}$	0.569***	Index of Biased Technology 2$_{i,t-1}$* SOE Employment Proportion$_{i,t-1}$	0.489**
	(–0.215)		(–0.217)
SOE Employment Proportion$_{i,t-1}$	0.032	SOE Employment Proportion$_{i,t-1}$	0.032
	(–0.110)		(–0.114)
Secondary GDP Proportion$_{i,t-1}$	–0.660***	Secondary GDP Proportion$_{i,t-1}$	–0.669***
	(–0.194)		(–0.196)
Government Expenditure/GDP$_{i,t-1}$	–0.285**	Government Expenditure/GDP$_{i,t-1}$	–0.259*
	(–0.140)		(–0.141)
Trade/GDP$_{i,t-1}$	–0.013	Trade/GDP$_{i,t-1}$	–0.011
	(–0.012)		(–0.013)
FDI/GDP$_{i,t-1}$	0.193	FDI/GDP$_{i,t-1}$	0.157
	(–0.210)		(–0.211)
Education$_{i,t-1}$	–0.837	Education$_{i,t-1}$	–0.836
	(–2.260)		(–2.199)
GDP per capita$_{i,t-1}$	–0.004	GDP per capita$_{i,t-1}$	–0.008
	(–0.099)		(–0.098)
Capital-output Ratio$_{i,t-1}$	0.000	Capital-output Ratio$_{i,t-1}$	0.000
	(–0.034)		(–0.034)
Provincial Fixed Effect	Y	Provincial Fixed Effect	Y
Year Fixed Effect	Y	Year Fixed Effect	Y
N	766	N	766
R^2	0.748	R^2	0.751

FDI = foreign direct investment, GDP = gross domestic product.

Notes:

1) Index of Biased Technology 1 is estimated using the whole sample; Index of Biased Technology 2 is estimated using the split sample.

2) Standard errors in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

Source: Authors.

5.3 Further Robustness Check

So far, we have presented empirical results that support a priori expectation on the relationship between technical progress and the labor share, as well as the role that the PRC's SOEs play in this relationship. Our results are robust-to-different estimates of capital-biased technology. In what follows, we further explore the robustness of the results in two other directions. First, we consider potential measurement errors. Second, we investigate the relationship for different time intervals.

5.3.1 Measurement Errors

We mainly consider possible measurement errors of the *SOE* variable. In sections 5.1 and 5.2, we used employment proportion as a proxy of SOE presence. In Table 5, we redo Tables 3 and 4 using its fixed asset proportion to represent the presence of SOE. The results remain robust to different measures of capital-biased technology: capital-biased technical progress depresses labor income share, and SOEs help offset such effects and contribute to equity.

Table 5: Robustness Check for Measurement Error

	Index of Biased Technology 1		**Index of Biased Technology 2**	
Labor Share$_{i,t}$	**(1)**	**(2)**	**(3)**	**(4)**
Index of Biased Technology$_{i,t-1}$	–0.148***	–0.336***	–0.158***	–0.327***
	(–0.021)	(–0.080)	(–0.021)	(–0.090)
Index of Biased Technology$_{i,t-1}$* SOE Fixed Asset Proportion$_{i,t-1}$		0.327***		0.296**
		(–0.117)		(–0.130)
SOE Fixed Asset Proportion$_{i,t-1}$	–0.031	–0.040	–0.027	–0.032
	(–0.054)	(–0.052)	(–0.054)	(–0.052)
Secondary GDP Proportion$_{i,t-1}$	–0.623***	–0.606***	–0.628***	–0.615***
	(–0.170)	(–0.163)	(–0.168)	(–0.164)
Government Expenditure/GDP$_{i,t-1}$	–0.276**	–0.281**	–0.241**	–0.245**
	(–0.108)	(–0.112)	(–0.106)	(–0.110)
Trade/GDP$_{i,t-1}$	–0.009	–0.010	–0.007	–0.007
	(–0.011)	(–0.011)	(–0.012)	(–0.012)
FDI/GDP$_{i,t-1}$	0.160	0.167	0.138	0.143
	(–0.176)	(–0.177)	(–0.176)	(–0.174)
Education$_{i,t-1}$	–2.235	–2.027	–1.839	–1.852
	(–2.446)	(–2.369)	(–2.354)	(–2.328)
GDP per capita$_{i,t-1}$	–0.002	–0.006	–0.005	–0.009
	(–0.096)	(–0.094)	(–0.095)	(–0.093)
Capital-output Ratio$_{i,t-1}$	–0.014	–0.011	–0.013	–0.013
	(–0.041)	(–0.039)	(–0.040)	(–0.039)
Provincial Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES
N	781	781	781	781
R^2	0.737	0.741	0.740	0.742

FDI = foreign direct investment, GDP = gross domestic product.

Notes:

1) Index of Biased Technology 1 is estimated using the whole sample; Index of Biased Technology 2 is estimated using the split sample.

2) Standard errors in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

Source: Authors.

5.3.2 Different Time Intervals

Next, we estimate the regression models for different time periods: 1978–1992 and 1993–2012. Table 6 presents the results with *Tech* estimated using the whole sample, while Table 7 reports results with *Tech* estimated using the split samples. Clearly, for most regressions, previous results are found to hold.

A more interesting finding is that, the coefficients of *Tech* and its interaction with *SOE* are more significant and larger in absolute terms in the more recent period of 1993–2012. This is rather intuitive, as the wage income before 1992 was mostly set by the government, rather than the firm's profit maximization consideration, resulting in weak correlation between capital-biased technical progress and the labor income share. For the same reason, the PRC's SOEs did not play an important role in reducing the negative effect of capital-biased technical progress on the labor share. The contrary occurred after Deng Xiaoping's south tour in 1992. The tour drove the PRC's rapid development of the manufacturing sector, with faster accumulation of capital along with enhanced capital-biased technical progress.

Table 6: Subsample Robustness Check for Index of Biased Technology 1

	1978–1992		1993–2012	
Labor Share$_{i,t}$	**(1)**	**(2)**	**(3)**	**(4)**
Index of Biased Technology$_{i,t-1}$	–0.133***	–0.114	–0.157***	–0.539***
	(–0.017)	(–0.250)	(–0.026)	(–0.128)
Index of Biased Technology$_{i,t-1}$* SOE Fixed Asset Proportion$_{i,t-1}$		–0.026		0.551***
		(–0.333)		(–0.173)
SOE Fixed Asset Proportion$_{i,t-1}$	–0.386	–0.386	–0.099	–0.100
	(–0.322)	(–0.323)	(–0.107)	(–0.101)
Secondary GDP Proportion$_{i,t-1}$	–0.219*	–0.218*	–0.416**	–0.407**
	(–0.130)	(–0.130)	(–0.178)	(–0.171)
Government Expenditure/GDP$_{i,t-1}$	–0.078	–0.077	–0.216*	–0.213*
	(–0.172)	(–0.174)	(–0.123)	(–0.125)
Trade/GDP$_{i,t-1}$	–0.044**	–0.044**	0.004	0.003
	(–0.020)	(–0.020)	(–0.014)	(–0.013)
FDI/GDP$_{i,t-1}$	–0.032	–0.035	0.117	0.138
	(–0.394)	(–0.380)	(–0.164)	(–0.164)
Education$_{i,t-1}$	8.958	8.950	–4.037	–3.750
	(–7.078)	(–7.133)	(–2.508)	(–2.449)
GDP per capita$_{i,t-1}$	–0.177***	–0.177***	–0.032	–0.024
	(–0.063)	(–0.063)	(–0.092)	(–0.089)
Capital-output Ratio$_{i,t-1}$	0.052***	0.052***	–0.041	–0.045
	(–0.016)	(–0.016)	(–0.066)	(–0.066)
Provincial Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES
N	228	228	538	538
R^2	0.967	0.967	0.783	0.788

FDI = foreign direct investment, GDP = gross domestic product.

Note: Standard errors in parentheses: * p < 0.1, ** p < 0.05, *** p < 0.01.

Source: Authors.

Table 7: Subsample Robustness Check for Index of Biased Technology 2

	1978–1992		1993–2012	
Labor Share$_{i,t}$	**(1)**	**(2)**	**(3)**	**(4)**
Index of Biased Technology$_{i,t-1}$	–0.137***	–0.262***	–0.159***	–0.514***
	(–0.015)	(–0.094)	(–0.023)	(–0.150)
Index of Biased Technology$_{i,t-1}$* SOE Fixed Asset Proportion$_{i,t-1}$		0.161		0.493**
		(–0.122)		(–0.193)
SOE Fixed Asset Proportion$_{i,t-1}$	–0.526	–0.530	–0.106	–0.099
	(–0.348)	(–0.348)	(–0.110)	(–0.110)
Secondary GDP Proportion$_{i,t-1}$	–0.217*	–0.217*	–0.448**	–0.442**
	(–0.130)	(–0.130)	(–0.177)	(–0.173)
Government Expenditure/GDP$_{i,t-1}$	–0.036	–0.044	–0.174	–0.174
	(–0.152)	(–0.151)	(–0.121)	(–0.124)
Trade/GDP$_{i,t-1}$	–0.037	–0.037	0.006	0.006
	(–0.023)	(–0.023)	(–0.015)	(–0.015)
FDI/GDP$_{i,t-1}$	–0.230	–0.205	0.106	0.115
	(–0.452)	(–0.444)	(–0.166)	(–0.166)
Education$_{i,t-1}$	9.672	9.605	–3.869	–3.835
	(–7.907)	(–7.885)	(–2.450)	(–2.442)
GDP per capita$_{i,t-1}$	–0.179**	–0.182***	–0.025	–0.022
	(–0.070)	(–0.070)	(–0.090)	(–0.088)
Capital-output Ratio$_{i,t-1}$	0.058***	0.057***	–0.035	–0.039
	(–0.017)	(–0.017)	(–0.065)	(–0.066)
Provincial Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES
N	228	228	538	538
R^2	0.967	0.967	0.783	0.787

FDI = foreign direct investment, GDP = gross domestic product.

Note: Standard errors in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

Source: Authors.

6. CONCLUSION

This paper aims at investigating the relationship between technical progress and labor share of income, based on the PRC's provincial data over the period from 1978 to 2012. Two measures of capital-biased technical progress were constructed using a supply-side normalized CES production function system, coupled with feasible generalized nonlinear least square (FGNLS) estimation. Estimation results show that technical progress in the PRC is mostly capital biased. And the capital-biased technical progress depressed the labor income share. Because the increase of the capital share leads to higher inequality (Piketty 2014), such capital-biased technical progress contributes to worsening income distribution and social instability. On the other hand, the PRC's SOEs play a role in providing job security, stabilizing the level of labor income and, thus, reducing the equity-deteriorating effect of capital-biased technical progress. Both effects are more significant and larger in absolute value in the more recent period.

The capital-biased technical progress is perhaps inevitable, as most developing economies, including the PRC, rely on the import and imitation of technology from developed economies, which are relatively more capital intensive. Accordingly, three policy options can be proposed to alleviate the negative effect on the labor share. First, the government shall institute a well-functioning child care program and related benefits. They can help increase fertility and labor force participation in both the short and the long run (Del Boca 2002). Second, capital-saving (labor-biased) technical progress should be promoted, which can increase the demand for labor input. Finally, healthy development of SOEs can also play a role in reducing the inequality effect of capital-biased technical progress, but its operating efficiency must be improved.

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