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Technical change and income inequality in China

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1 | INTRODUCTION

There is a sizable and growing literature, focusing on the determinants of income inequality (e.g. Gottschalk & Smeeding, 2000; Greenwood, Guner, Kocharkov, & Santos, 2014; Lerman & Yitzhaki, 1985; Li, Squire, & Zou, 1998; Piketty & Saez, 2003). And more and more research attention has been directed towards the role of technical change as a major driver of income distribution (Acemoglu, 1998).

The conventional approach to analysing the technology–inequality nexus is to identify and estimate the impacts of technical change on the wage gap between skilled and unskilled labour, typi-cally in terms of the difference in the average income between these two groups of labourers. According to Acemoglu (1998) and Katz and Murphy (1992), new technologies lead to increases in the productivity of skilled workers and their wages, enlarging this wage gap. Krusell, Ohanian, Ríos-Rull, and Violante (2000) argue that improvement in capital-embodied productivity leads to rising demand for equipment and, when equipment is complementary with skilled labour, the wage gap rises. This gap-enlarging finding has been confirmed by many scholars, including Aghion, Howitt, and Violante (2002), Esquivel and Rodrıguez-López (2003), Moore and Ranjan (2005), and Van Reenen (2011). On the contrary, Goldin and Katz (1996) found that this gap was kept in check in the USA despite significant technological progress. Card and DiNardo (2002) concluded that wage inequality measured as the standard deviation of log wages and the 90th and 10th per-centile wage gap was stable in the 1990s in the USA despite advances in computer technology.

However, wage inequality, especially the wage gap between skilled and unskilled labours, is only one component of the overall inequality, notwithstanding its importance. By definition, total inequality can be expressed as a weighted sum of labour income and capital income (CI) inequalities.[1] On the other hand, a driver of income distribution such as technical change may generate different impacts on the overall inequality than its components. For example, an anti-discrimination policy may help narrow the gender gap but may lead to higher wage inequality within male employees at the same time. Similarly, capital-augmenting technical change may enlarge the wage gap between the skilled and unskilled but could meanwhile help reduce inequality within the capitalists, leaving its overall impact on the overall income inequality underdetermined. Clearly, it is insufficient to just analyse the technical change–wage gap nexus if one is interested in the overall income inequality.

To the best of our knowledge, little has been published on the technical change–income inequality relationship, with the exception of Jaumotte, Lall, and Papageorgiou (2013) who found a positive impact of technological progress (defined as the share of ICT capital in total capital stock) on income inequality based on a panel data set of 51 counties over a 23-year period from 1981 to 2003.

This paper represents an early attempt to gauge the impact of technical change on the overall inequality, not just a particular component of inequality. This is achieved by establishing that the labour share of income is negatively correlated with overall inequality as indicated by the popular Gini coefficient, and by modelling the labour share of income as a function of technical change. Based on 1978–2012 provincial panel data from China, the framework of Acemoglu (2002, 2007) will be employed to measure technical change. And the labour share of income will be then regressed on the estimated technical change. The main empirical results show that technical change in China had been mostly capital-biased. It contributed to the successive reductions in China's labour share of income and thus rapid rises in income inequality.

The rest of the paper is organised as follows. Section 2 presents our analytical frameworks, including arguments for establishing the correlation between the labour share of income and technical change and that for measuring technical change. In Section 3, we discuss data and empirical econometric models. Section 4 provides estimation results and discussions. Finally, Section 5 concludes.

2 | ANALYTICAL FRAMEWORKS

2.1 | Inequality, technical change and the labour share of income

To establish the relationship between technical change and inequality, the usual econometric approach would require specifying and estimating model (1):

$$Ine = h(Tech, Z), \tag{1}$$

where *Ine* denotes an inequality indicator, *Tech* denotes technical change, and *Z* denotes control variables. Unfortunately, sufficient observations on inequality are not available from China to permit estimation of the above econometric model.

However, it is still possible to explore the impact of technical change on inequality by analysing the relationship between labour share of income and technical change. This is because the overall inequality as indicated by the popular Gini index can be expressed as a weighted sum of concentration indices of labour and CI, with labour and capital share of income as weights. Thus,

[1] Here, the inequalities are indicated by concentration indices.

as long as CI is more concentrated or more unequal than the labour income, a declining in the labour share of income implies rising inequality, and *vice versa*. One can then gauge the impact of technical change on income distribution by modelling the relationship between technical change and the labour share of income.

Is capital or labour income more concentrated? According to Jacobson and Occhino (2012), the concentration index of CI is always larger than that of labour income in the USA during 1979–2007, with the former ranging from 0.62 to 0.84 and the latter ranging from 0.42 to 0.50. Based on evidence from eight industrialised countries in the last three decades of the twentieth century, García-Peñalosa and Orgiazzi (2013) find that the distribution of CI, including interest, rent, dividends annuities, private individual pensions and royalties, is much more unequal than labour earnings. More specifically, using the squared coefficient of variation as the inequality measure, the magnitude of CI inequality is at least eight times larger than that of earnings inequality (García-Peñalosa & Orgiazzi, 2013). These findings are consistent with Piketty (2014), who shows that wealth inequality is much higher than income inequality in many countries. For example, in the United Kingdom and the United States, the top 10% of the population held 45–50% of national income and around 70% of national wealth. While in France, Germany and Sweden, the top 10% of population possessed 30% of national income and 60% of national wealth.

Based on the discussions above, the impact of technical change on the overall inequality can be gauged by modelling the labour share of income using (2):

$$S_\iota = f(Tech, X) = \alpha_0 + \beta_1 Tech + \theta' X + u. \tag{2}$$

The sign of β_1 informs if technical change increases or decreases the labour share of income and thus makes income distribution better or worse.

There is a literature focusing on the relationship between the labour share of income and technical change. For instance, Acemoglu (2003) treats technical change as an endogenous variable in his growth model and establishes the linkage between the direction of technical change and labour share of income. According to the European Commission (2007), technological progress made the largest contribution to the fall in the aggregate labour share of income. This finding is consistent with Guscina (2006) who found that in OECD countries, capital-biased technical change caused declines in the labour share of income. Similarly, Zhang, Li, and Xu (2012) employ 1980–2007 data from 75 developed and developing countries and find that capital-augmenting technical change has a negative impact on the share of labour income. However, Jaumotte and Tytell (2007) showed that technical change, especially in the information and communications sectors, appears to have a non-linear effect on the labour share of income.

The impact of technical change on the factor income share essentially depends on the property or direction of technical change, which is not always neutral. As defined by Hicks (1932), when technical change increases the marginal output of labour/capital, it is labour/capital-augmenting. Capital-augmenting or capital-biased technical change will induce more capital investment, replacing labour by capital and causing declines in the labour share of income (see Acemoglu, 2002, 2003). The contrary holds when labour-biased technology change prevails. For developing countries, technical change is more likely to be capital-biased as they receive net capital inflows from affluent economies (Acemoglu & Zilibotti, 2001; Gancia & Zilibotti, 2009).

2.2 | Measuring technical change

The key variable, *Tech* in (2), is usually not directly observable. As its proxy, time trend is often used, see Ellis and Smith (2010) and Guscina (2006). Others use the capital–labour ratio or the share of ICT capital in total capital stock (Bentolila & Saint-Paul, 2003; European Commission 2007; Jaumotte & Tytell, 2007). A more formal approach is to use the growth accounting framework to estimate technical change (see Haskel & Slaughter, 2001). However, it is not clear how these proxies or estimates can capture the direction of technical change (Stockhammer, 2009).

In this paper, we follow Acemoglu (2002, 2007) by directly estimating technical change *Tech*. Using Y to denote output, a production function with factor-augmenting technologies can be written as:

$$Y_t = F(A_t, N_t, B_t, K_t), \tag{3}$$

where t indexes time, and A_t and B_t denote labour-augmenting and capital-augmenting technologies, respectively. K_t represents capital, and N_t represents labour. Based on (3), an indicator of capital-biased technical change can be defined as (Acemoglu, 2003, 2007):

$$TD = \frac{\partial\left(\frac{F_K}{F_N}\right)}{\partial\left(\frac{B}{A}\right)}. \tag{4}$$

The production function F can be specified as:

$$Y_t = [(1-\alpha)(A_t N_t)^{\frac{\sigma-1}{\sigma}} + \alpha(B_t K_t)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}}, \tag{5}$$

where α denotes capital intensity, and σ represents the substitution elasticity of capital for labour. Thus, capital-biased technical change can be expressed as:

$$TD_t = \frac{\alpha}{1-\alpha}\left(\frac{K_t}{N_t}\right)^{-\frac{1}{\sigma}}\frac{\sigma-1}{\sigma}\left(\frac{B_t}{A_t}\right)^{-\frac{1}{\sigma}}. \tag{6}$$

Clearly when σ is larger than 1, *TD* is positive, vice versa. It is also noted that when σ is equal to 1, technical change is neutral.

However, *TD* only measures the curvature of biased technical change. The extent or magnitude of technical change can be gauged using the following measure proposed by Dai and Xu (2010):

$$Tech_t \triangleq \frac{TD_t}{\varepsilon_t}\Delta(B_t/A_t) = \frac{\sigma-1}{\sigma}\frac{A_t}{B_t}\Delta(B_t/A_t), \tag{7}$$

where:

$$\varepsilon_t = \frac{\partial Y/\partial K}{\partial Y/\partial N} = \frac{\alpha}{1-\alpha}\left(\frac{B_t}{A_t}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{N_t}{K_t}\right)^{\frac{1}{\sigma}}, \tag{8}$$

$$A_t = \frac{Y_t}{N_t}\left[\frac{w_t N_t}{(1-\alpha)(w_t N_t + r_t K_t)}\right]^{\frac{\sigma}{\sigma-1}}, \tag{9}$$

$$B_t = \frac{Y_t}{K_t}\left[\frac{r_t K_t}{\alpha(w_t N_t + r_t K_t)}\right]^{\frac{\sigma}{\sigma-1}}. \tag{10}$$

Here, ε_t represents the ratio of marginal productivities of labour to capital, and w and r represent wage rate and returns to capital. By multiplying *TD* with the change in relative technology

$\Delta(B_t/A_t)$, both the direction and magnitude of biased technical change can be captured. When *Tech* is positive, technical change is capital-biased; otherwise, it is labour-biased.

To estimate σ and α, we use the normalised supply side system of Klump, McAdam, and Willman (2007):

$$\ln\left(\frac{Y_t}{\overline{Y}}\right)=\ln(\xi)+\frac{\sigma}{\sigma-1}\ln\left\{(1-\alpha)\left[\frac{N_t}{\overline{N}}\exp\left[\left(\bar{t}\frac{\gamma_N}{\lambda_N}\right)\left(\frac{t}{\bar{t}}\right)^{\lambda_N}-1\right]\right]^{\frac{\sigma-1}{\sigma}}+\alpha\left[\frac{K_t}{\overline{K}}\exp\left[\left(\bar{t}\frac{\gamma_N}{\lambda_N}\right)\left(\frac{t}{\bar{t}}\right)^{\lambda_N}-1\right]\right]^{\frac{\sigma-1}{\sigma}}\right\}, \tag{11}$$

$$\ln(w_t)=\ln(1-\alpha)+\ln\left(\frac{\overline{Y}}{\overline{N}}\right)+\frac{\sigma-1}{\sigma}\ln(\xi)-\frac{\sigma-1}{\sigma}\ln\left(\frac{Y_t/\overline{Y}}{N_t/\overline{N}}\right)+\frac{\sigma-1}{\sigma}\left[\left(\bar{t}\frac{\gamma_N}{\lambda_N}\right)\left(\frac{t}{\bar{t}}\right)^{\lambda_N}-1\right], \tag{12}$$

$$\ln(r_t)=\ln\alpha+\ln\left(\frac{\overline{Y}}{\overline{K}}\right)+\frac{\sigma-1}{\sigma}\ln(\xi)-\frac{\sigma-1}{\sigma}\ln\left(\frac{Y_t/\overline{Y}}{K_t/\overline{K}}\right)+\frac{\sigma-1}{\sigma}\left[\left(\bar{t}\frac{\gamma_K}{\lambda_K}\right)\left(\frac{t}{\bar{t}}\right)^{\lambda_K}-1\right], \tag{13}$$

where ξ denotes an adjustment coefficient so that $\xi\overline{Y}=Y_0, \overline{N}=N_0, \overline{K}=K_0, \bar{t}=t_0$. γ_K and γ_N denote the growth rate of capital and labour productivity, and λ_K and λ_N represent the curvature of capital and labour productivity, respectively. In this system, the growth rate of factor productivity takes the Box-Cox form. This approach is shown to be robust by León-Ledesma, McAdam, and Willman (2010).

2.3 | Empirical model specification

To estimate the impact of technical change on the labour share of income, we follow the modelling strategy of Decreuse and Maarek (2015), who focus on the effect of globalisation on the labour share of income. We simply extend their model by adding the index of technical change as the key variable:

$$S_{it}=\alpha_0+\beta_1 Tech_{i,t-1}+\theta' X_{i,t-1}+\eta_t+\mu_i+u_{it}, \tag{14}$$

where i indexes province and t indexes year. S_{it} denotes the labour share of income, and X contains control variables. η and μ represent year and provincial fixed effects, respectively. u is the usual white noise term. In (14), all independent variables are lagged to alleviate possible reverse causality. β_1 measures the effect of technical change on the labour share of income.

Following the literature on the modelling of labour share of income, variables of economic growth, structural transformation and globalisation are considered. We use the logarithm of GDP per capita to represent economic growth. To capture the effect of structural transformation, the manufacturing share in GDP is included. Regarding globalisation, indicators of trade (% of GDP) and foreign direct investment or FDI (% of GDP) are added. FDI may induce higher labour share of income via increased competition. It may also help lower the labour share of income due to improvement in the labour productivity induced by FDI-related technical changes (Decreuse & Maarek, 2015). Intuitively, importing labour-intensive goods erodes the labour share of income while exporting labour-intensive goods can increase the labour share of income (Jaumotte & 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 labour share of income.

To allow for possible neutral technical change, we add the time trend variable too. Other variables such as government expenditure, human capital, physical capital and state-owned enterprises (SOEs) will be considered after baseline estimations. All nominal variables are appropriately deflated.

3 | DATA AND ESTIMATION OF TECHNICAL CHANGE

Estimating technical change requires data on output, capital stock, labour input, labour income and CI, which are all available from the National Bureau of Statistics. Our panel data cover 28 provinces of China for the period of 1978–2012, excluding Tibet, Hainan and Chongqing (included in Sichuan Province).

3.1 | Capital stock

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

$$K_0 = I_1/(g+\delta), \tag{15}$$

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 (DE).

We use provincial fixed capital formation to measure capital investment which is available from 1952 onwards. Following Hall and Jones (1999), we average the growth rate of real fixed capital formation in the first 10 years (1953–63) and use this average value as the growth rate of capital investment. The DE rate is set to be 5%. Note that our empirical modelling results are robust to different DE rates.

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

$$K_{t+1} = I_{t+1} + (1-\delta)K_t. \tag{16}$$

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.

3.2 | Labour input

We use the number of employees as the proxy of labour input.

3.3 | Labour and capital income

National Bureau of Statistics (various years) publishes provincial GDP and its components: labour income (NI), CI, net taxes on production (NT) or indirect tax, and DE. DE can be viewed as part of CI. The indirect tax, following Lu et al. (2008), is proportionally shared between labour and CI. Thus, we have the following estimates of labour income and CI:

$$wN = NI + \frac{NI}{NI + CI + DE} NT, \tag{17}$$

$$rK = DE + \frac{CI + DE}{NI + CI + DE} NT. \tag{18}$$

The above data are used to estimate (11)–(13) as seemingly unrelated regressions (SUR). As Klump et al. (2007) pointed out, the results are only sensitive to different starting values of σ. For various starting values of $\sigma < 1$, the estimation always converges to the same point. For starting values that are >1, the estimation converges to a different point. However, the sum of squared residuals is found to be always smaller in the earlier case.

Table 1 presents the estimation results of the elasticities of substitution. These elasticities are then used to compute the provincial indicator of capital-biased technical change, which is plotted in Figure 1. The majority of the estimates of technical change are positive, suggesting that technical change in China is mostly capital-biased.[2]

Table 2 presents the summary statistics of variables for estimating the model of labour share of income, including the summary statistics for estimated technical change.

4 | EMPIRICAL RESULTS

4.1 | Baseline results

Table 3 presents estimation results for the baseline model (14). As have been mentioned, all independent variables are lagged to alleviate possible reverse causality. Robust standard errors are clustered at the provincial level to alleviate possible serial correlation.

In columns (1)–(3) of Table 3, we only include the variable of technical change. Province fixed effect and year fixed effect are added one by one. It is shown that technical change is negatively correlated with the labour share of income and the relationship is significant once both fixed effects are controlled. In subsequent columns, variables of economic growth, structural transformation, globalisation and time trend are added one by one. The coefficient of capital-biased technical change remains negative and significant in every model in Table 3, suggesting that in general, technical change in China helps reduce the labour share of income. This finding is in line with Guscina (2006) and Zhang et al. (2012), among others. More specifically, a one percentage point increase in the indicator *Tech* leads to approximately 0.108 percentage point decrease in the labour share of income.

Turning to control variables, economic growth is found to be negatively correlated with the labour share of income, which is consistent with Piketty (2014). The manufacturing share in GDP is also negatively correlated with the labour share of income. This is reasonable as the manufacturing sector is more capital-intensive than the agricultural and service sectors. The effect of globalisation is mostly insignificant, a result of different offsetting impacts as previously discussed.

The estimation results of Table 3 are obtained using the whole sample of data. However, structural break may have happened, given the dynamics of the Chinese economy. In particular, the year of 1992 is important as it marks the start of the second wave of opening up and reforms following the famous Tour of Southern China by Deng Xiaoping. Also, the food rationing system

[2] One may notice that the indicator for Hebei Province is always 0. This is because the estimated $\sigma = 1$ or Hebei.

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)
InnerMon	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; $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

was abolished in late 1992, providing the sufficient condition for large-scale migration. Furthermore, as Song, Storesletten, and Zilibotti (2011) argued, 1992 marks the beginning of SOE reforms in China. As a consequence, the total amount of FDI inflow into China tripled in 1992 and further doubled in 1993. Trade volume also rose significantly.

It is thus appropriate to estimate technical change and also the model of labour share of income, separately using data for two subperiods: 1978–92 and 1993–2012 (referred to as split samples hereafter).

As shown in Figure 2, the estimates of technical change using the whole sample and split samples are similar. In Table 4, we replicate the baseline estimations using estimates of technical

FIGURE 1 Indicator of technical change (whole sample) [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 2 Summary statistics

Variable	Obs	Mean	*SD*	Min	Max
Labour share of income	945	0.581	0.099	0.273	0.797
Technical change (whole sample)	918	0.022	0.107	−0.435	0.474
Technical change (split samples)	918	0.016	0.106	−0.503	0.351
ln (GDP per capita)	945	7.370	1.081	5.156	10.30
Manufacturing sector GDP ratio	945	0.456	0.087	0.190	0.812
FDI/GDP	794	0.029	0.040	0.000	0.322
Trade/GDP	939	0.251	0.466	0.000	3.824
Government expenditure/GDP	945	0.154	0.074	0.049	0.612
Human capital	944	0.007	0.007	0.000	0.035
Physical capital	945	−0.287	1.129	−2.461	2.511
SOE proportion	810	0.531	0.190	0.119	0.967
MPK	945	0.189	0.076	0.071	0.859
ln (Wage)	890	7.354	0.727	6.240	9.420

TABLE 3 Baseline results

Labour share of income$_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Technical change$_{i,t-1}$	−0.114***	−0.0496	−0.104***	−0.107***	−0.0997***	−0.107***	−0.108***	−0.132***	−0.108***
	(0.0318)	(0.0350)	(0.0205)	(0.0197)	(0.0165)	(0.0174)	(0.0175)	(0.0175)	(0.0175)
ln (GDP per capita$_{i,t-1}$)				−0.138***	−0.0466***	−0.0799***	−0.0807***	−0.0492***	−0.0807***
				(0.0131)	(0.0107)	(0.0157)	(0.0156)	(0.00471)	(0.0156)
Manufacturing sector GDP ratio$_{i,t-1}$					−0.553***	−0.484***	−0.487***	−0.532***	−0.487***
					(0.0439)	(0.0563)	(0.0566)	(0.0412)	(0.0566)
(FDI/GDP)$_{i,t-1}$						0.0621	0.111	0.245***	0.111
						(0.0979)	(0.0918)	(0.0534)	(0.0918)
(Trade/GDP)$_{i,t-1}$							−0.00907	−0.0400***	−0.00907
							(0.00698)	(0.00392)	(0.00698)
Time trend								0.00208***	0.00517***
								(0.000468)	(0.00153)
Province FE	N	N	Y	Y	Y	Y	Y	N	Y
Year FE	N	Y	Y	Y	Y	Y	Y	Y	Y
N	891	891	891	891	891	767	767	767	767
R^2	0.016	0.179	0.693	0.726	0.807	0.791	0.792	0.647	0.792

Note: Standard errors in parentheses; *p < .1, **p < .05, ***p < .01.

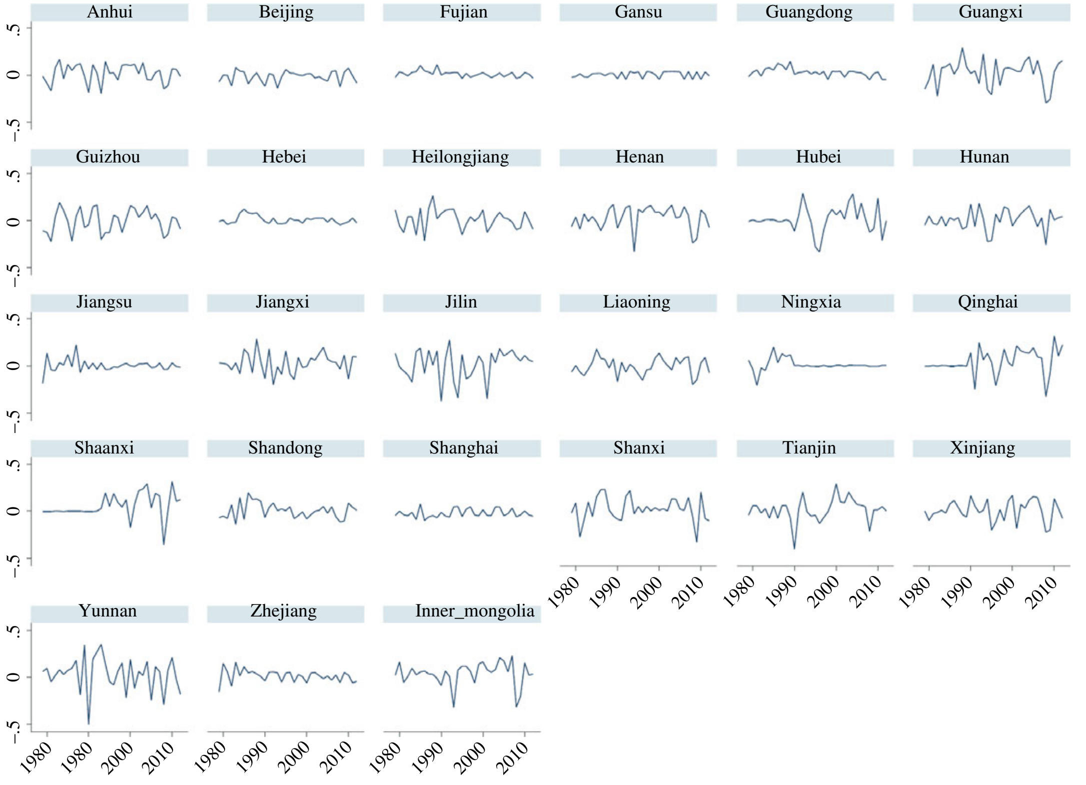

FIGURE 2 Indicator of technical change (split sample) [Colour figure can be viewed at wileyonlinelibrary.com]

change based on the split samples. The results do not change much, although the estimated effect of technical change on the labour share of income became larger.

To examine whether the impact of technical change on the labour share of income differs in different periods, we consider the following model:

$$S_{it} = \alpha_0 + \beta_1 T_{i,t-1} * I_{[1978,1992]} + \beta_2 T_{i,t-1} * I_{[1993,2002]} + \theta' X_{i,t-1} + \varphi_{it}, \tag{19}$$

where $I_{[1978,1992]}$ is a dummy variable for the period 1978–92, $I_{[1993,2002]}$ is a dummy variable for the period of 1993–2002, and φ_{it} denotes two-way fixed effects as well as the random error term.

The estimation results of (19) are reported in Table 5. Consistent with a priori expectation, the impact of technical change on the labour share of income is found to be significant for the post-1993 period only. This is because the Chinese economy was dominated by central plan before 1992, and the government rather than markets played a major role in determining functional income distribution. After 1992, the impact of technical change on the labour share of income began to take effect.

4.2 | Endogeneity

Next, we address possible endogeneity, which may be caused by either common third factors or omitted variables.

TABLE 4 Split samples

Labour share of income$_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Technical change$_{i,t-1}$	−0.0862***	−0.0387	−0.0975***	−0.110***	−0.102***	−0.110***	−0.111***	−0.146***	−0.111***
	(0.0283)	(0.0304)	(0.0193)	(0.0186)	(0.0165)	(0.0175)	(0.0175)	(0.0191)	(0.0175)
ln (GDP per capita$_{i,t-1}$)				−0.142***	−0.0501***	−0.0815***	−0.0823***	−0.0522***	−0.0823***
				(0.0132)	(0.0108)	(0.0157)	(0.0156)	(0.00468)	(0.0156)
Manufacturing sector GDP Ratio$_{i,t-1}$					−0.552***	−0.490***	−0.493***	−0.526***	−0.493***
					(0.0437)	(0.0560)	(0.0564)	(0.0412)	(0.0564)
(FDI/GDP)$_{i,t-1}$						0.0553	0.101	0.225***	0.101
						(0.0993)	(0.0931)	(0.0529)	(0.0931)
(Trade/GDP)$_{i,t-1}$							−0.00842	−0.0373***	−0.00842
							(0.00706)	(0.00396)	(0.00706)
Time trend								0.00219***	0.00529***
								(0.000467)	(0.00153)
Province FE	N	N	Y	Y	Y	Y	Y	N	Y
Year FE	N	Y	Y	Y	Y	Y	Y	Y	Y
N	891	891	891	891	891	767	767	767	767
R^2	0.009	0.178	0.692	0.726	0.807	0.791	0.792	0.651	0.792

Note: Standard errors in parentheses; $*p < .1$, $**p < .05$, $***p < .01$.

TABLE 5 Structural break of technical change indicator

Labour share of income$_{i,t}$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Technical change (1978–92)$_{i,t-1}$	0.0759	0.0693	−0.00251	−0.0201	−0.0327	−0.0341	−0.0348	−0.0370	−0.0348
	(0.0481)	(0.0511)	(0.0265)	(0.0267)	(0.0230)	(0.0301)	(0.0300)	(0.0295)	(0.0300)
Technical change (1993–2012)$_{i,t-1}$	−0.193***	−0.116***	−0.167***	−0.175***	−0.153***	−0.151***	−0.152***	−0.200***	−0.152***
	(0.0327)	(0.0352)	(0.0264)	(0.0253)	(0.0219)	(0.0213)	(0.0213)	(0.0223)	(0.0213)
ln (GDP per capita$_{i,t-1}$)				−0.141***	−0.0501***	−0.0822***	−0.0830***	−0.0519***	−0.0830***
				(0.0131)	(0.0107)	(0.0157)	(0.0156)	(0.00463)	(0.0156)
Manufacturing sector GDP Ratio$_{i,t-1}$					−0.546***	−0.479***	−0.482***	−0.523***	−0.482***
					(0.0437)	(0.0562)	(0.0565)	(0.0407)	(0.0565)
(FDI/GDP)$_{i,t-1}$						0.0576	0.104	0.228***	0.104
						(0.0983)	(0.0921)	(0.0522)	(0.0921)
(Trade/GDP)$_{i,t-1}$							−0.00852	−0.0378***	−0.00852
							(0.00694)	(0.00390)	(0.00694)
Time trend								0.00237***	0.00529***
								(0.000464)	(0.00153)
Province FE	N	N	Y	Y	Y	Y	Y	N	Y
Year FE	N	Y	Y	Y	Y	Y	Y	Y	Y
N	891	891	891	891	891	767	767	767	767
R^2	0.030	0.186	0.698	0.732	0.810	0.795	0.795	0.659	0.795

Note: Standard errors in parentheses; $^*p < .1$, $^{**}p < .05$, $^{***}p < .01$.

4.2.1 | Common third factors

Common third factors simultaneously affect technical change and labour share of income, resulting in a spurious correlation between them. One possible common third factor is government interference. Generally speaking, more affluent governments are in a better position to intervene in the local economy including technology adoption and re-distribution. To address this problem, the ratio of government expenditure to GDP is added to the regressions (see Table 6). As the results indicate, the estimated effects of biased technical change on the labour share of income remain negative and significant.

4.2.2 | Omitted variables

Two possible omitted variables are human capital and physical capital, as they can directly affect labour and CI, and thus factor income shares. The omission of physical capital in the model may lead to overestimation of the impact of technical change on the labour share of income. In Table 7, we control for both human capital (measured by number of university students over total population) and physical capital (measured by the logarithm of capital per worker). The estimated results of technical change on the labour share of income still remain negative and significant.

Another possibly overlooked determinant of labour share of income is the presence of SOEs. As is known, SOEs in China are partly responsible for providing jobs to help maintain social stability. Also, compared with non-SOEs, the trade union of SOEs is larger and better organised, which helps protect labour income. Therefore, it is expected that in those regions with more SOEs, the effect of technical change on job replacement, and thus on the labour share of income, might be weaker. Omitting the SOE variable could lead to underestimation of the impact of technical change on the labour share of income.

To rectify this problem, the SOE share in total asset investment and its interaction with technical change can be considered. We expect the coefficient of the interactive term to be positive, indicating the role of SOEs in weakening the impact of technical change. This is confirmed by the results in columns (1)–(6) of Table 8.

It is worth noting that once the interactive term is controlled, the absolute value of the coefficient estimate for technical change becomes much larger. This suggests that if there are no SOEs, a 1% increase in the indicator of technical change will lead to an approximately 0.23–0.26 percentage point decrease in the labour share of income. Evaluated at the sample mean of SOE, the SOEs offset the negative effect of technical change on the labour share of income by roughly 0.11–0.13%, which is quite significant.

When the split samples are combined with the use of the SOE variable and the interactive term, the coefficients of the interactive term are no longer significant any more. This is understandable because SOE reforms took place in the post-1992 period when technical changes also sped up. Thus, there are sufficient variations across the two samples for estimating the impact of the interactive term on the labour share of income, as reported in Table 7. However, within sample variations are insufficient for estimating this impact (see Table 8).

4.3 | Transmission mechanisms

In this subsection, we explore the mechanisms underlying the nexus between technical change and the labour share of income. Given that the latter is a function of labour input, wage, capital stock and capital return, it is useful to examine the impacts of technical change on these four variables, respectively.

TABLE 6 Effect of government expenditure

	Whole sample			**Split samples**			**Structural break**		
Labour share of income$_{i,t}$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Technical change$_{i,t-1}$	−0.105***	−0.0987***	−0.107***	−0.0995***	−0.101***	−0.107***			
	(0.0206)	(0.0165)	(0.0174)	(0.0194)	(0.0166)	(0.0177)			
Technical change (1978–92)$_{i,t-1}$							−0.00509	−0.0307	−0.0299
							(0.0266)	(0.0231)	(0.0304)
Technical change (1993–2012)$_{i,t-1}$							−0.168***	−0.152***	−0.149***
							(0.0266)	(0.0219)	(0.0214)
(Government expenditure/GDP)$_{i,t-1}$	0.0926	−0.102**	−0.210***	0.103	−0.0931**	−0.192***	0.0963	−0.0963**	−0.198***
	(0.0751)	(0.0468)	(0.0553)	(0.0740)	(0.0459)	(0.0548)	(0.0725)	(0.0457)	(0.0556)
Economic growth	N	Y	Y	N	Y	Y	N	Y	Y
Structural transformation	N	Y	Y	N	Y	Y	N	Y	Y
Globalisation	N	N	Y	N	N	Y	N	N	Y
Time trend	N	N	Y	N	N	Y	N	N	Y
Province and year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	891	891	767	891	891	767	891	891	767
R^2	0.694	0.807	0.794	0.693	0.808	0.794	0.699	0.811	0.798

Note: Standard errors in parentheses; $*p < .1$, $**p < .05$, $***p < .01$.

TABLE 7 Effect of human and physical capital

	Whole sample			Split samples			Structural break		
Labour share of income$_{i,t}$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Technical change$_{i,t-1}$	−0.110***	−0.101***	−0.108***	−0.109***	−0.102***	−0.108***			
	(0.0198)	(0.0165)	(0.0173)	(0.0201)	(0.0167)	(0.0177)			
Technical change (1978–92)$_{i,t-1}$							−0.0198	−0.0338	−0.0327
							(0.0257)	(0.0229)	(0.0303)
Technical change (1993–2012)$_{i,t-1}$							−0.174***	−0.152***	−0.149***
							(0.0282)	(0.0225)	(0.0217)
Human capital$_{i,t-1}$	6.685***	0.543	−0.376	6.846***	0.743	−0.0953	6.756***	0.744	−0.0935
	(1.164)	(0.917)	(0.977)	(1.157)	(0.908)	(0.969)	(1.148)	(0.910)	(0.968)
Physical capital$_{i,t-1}$	−0.0169*	0.0527***	0.0465***	−0.0192**	0.0518***	0.0459***	−0.0193**	0.0512***	0.0448***
	(0.00955)	(0.0105)	(0.0128)	(0.00968)	(0.0107)	(0.0128)	(0.00961)	(0.0106)	(0.0127)
Economic growth	N	Y	Y	N	Y	Y	N	Y	Y
Structural transformation	N	Y	Y	N	Y	Y	N	Y	Y
Globalisation	N	N	Y	N	N	Y	N	N	Y
Time trend	N	N	Y	N	N	Y	N	N	Y
Government expenditure	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province and year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	890	890	767	890	890	767	890	890	767
R^2	0.713	0.813	0.798	0.713	0.814	0.798	0.718	0.817	0.801

Note: Standard errors in parentheses; $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

TABLE 8 Effect of state-owned enterprises (SOEs)

	Whole sample			Split samples			Structural break		
Labour share of income$_{i,t}$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Technical change$_{i,t-1}$	−0.299***	−0.248***	−0.255***	−0.243***	−0.222***	−0.234***			
	(0.0738)	(0.0620)	(0.0635)	(0.0819)	(0.0658)	(0.0677)			
Technical change (1978–92)$_{i,t-1}$							0.141	0.0101	−0.0325
							(0.139)	(0.131)	(0.145)
Technical change (1993–2012)$_{i,t-1}$							−0.228**	−0.201***	−0.205***
							(0.100)	(0.0770)	(0.0773)
Technical change$_{i,t-1}$ × SOE proportion$_{i,t-1}$	0.319***	0.243**	0.251**	0.231*	0.198*	0.216**			
	(0.118)	(0.0977)	(0.101)	(0.130)	(0.105)	(0.109)			
Technical change (1978–92) $_{i,t-1}$ × SOE proportion $_{i,t-1}$							−0.210	−0.0585	0.00562
							(0.210)	(0.192)	(0.213)
Technical change (1993–2012)$_{i,t-1}$ × SOE proportion$_{i,t-1}$							0.112	0.0965	0.106
							(0.172)	(0.132)	(0.132)
Economic growth	N	Y	Y	N	Y	Y	N	Y	Y
Structural transformation	N	Y	Y	N	Y	Y	N	Y	Y
Globalisation	N	N	Y	N	N	Y	N	N	Y
Time trend	N	N	Y	N	N	Y	N	N	Y
Government expenditure and Capitals	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province and year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	783	783	748	783	783	748	783	783	748
R^2	0.710	0.791	0.790	0.706	0.789	0.789	0.712	0.792	0.791

Notes: Standard errors in parentheses; $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.
The Variable of "SOE Proportion" is also controlled.

To estimate the impact of technical change on labour input, we use the logarithm of employment as the dependent variable. Table 9 shows that technical change in China is negatively correlated with labour input. This is consistent with earlier results, showing that technical change in China is mostly capital-biased. Holding everything else constant, this means lower labour share of income or higher inequality.

Next, we investigate the impact of technical change on the average wage. Table 10 reports estimation results where the logarithm of real wage per worker is regressed on technical change and other variables. The impact is found to be significant and negative. Thus, technical change in China reduces both the average wage and the labour input and contributes to the declines in the labour share of income.

Turning to CI, we take the logarithm of capital stock as the dependent variable and replicate the estimations of Tables 9 and 10. As Table 11 shows, the impact of technical change on capital stock is insignificant. However, Table 12 shows that the impact on capital return (as measured by the marginal productivity of capital, or MPK) is positive and significant. Taking together, technical change in China is found to lead to rises in the CI by improving returns to capital. Holding everything else constant, this means lower labour share of income or higher inequality.

Finally, to further verify that technical change reduces labour share of income through its effects on capital and labour incomes, we follow Cutler and Lleras-Muney (2010) and James and Brett (1984) by estimating a mediation model. That is, we replicate the technical change–labour share of income regressions in Table 8 but add the variables of current-period labour input, average wage, capital stock and capital return as additional independent variables. Under the mediation framework, if the coefficients of technical change become less significant than those in Table 8, we can confirm the transmission mechanisms discussed above.

Table 13 presents the estimation results of the mediation model. The parameter estimates for technical change decrease significantly while the coefficients for labour input, average wage, capital stock and capital return remain significant. Thus, it can be confirmed that the inequality-increasing effect of technical change does come from its negative impacts on the labour income and positive impacts on the CI.

5 | SUMMARY AND CONCLUDING REMARKS

Rising inequality has been ranked among the top socioeconomic issues for decades in China. Despite a large literature on this topic (Wan, 2007, 2008; Wang, Wan, & Yang, 2014), much more research efforts are called for to explore what drive the rising inequality. One major driver is technical change (Acemoglu, 1998, 2003).

This paper represents an early attempt to gauge the impact of technical change on inequality in China. Based on provincial data for the period of 1978–2012, we first estimate the direction and magnitude of technical change using the framework of Acemoglu (2002, 2007) and Dai and Xu (2010). These estimates are then used as an independent variable in modelling the labour share of income. Robust estimation results indicate that technical changes in China, mostly capital-biased, are negatively correlated with the labour share of income. As Piketty (2014) among others established, a declining labour share of income implies increases in inequality.

Technical advances, including capital-biased technical change, are inevitable, as most developing economies such as China rely on the import and imitation of technology from developed economies, which is relatively more capital-intensive. Accordingly, three policy options can be suggested to alleviate the negative effect of technical change on the labour share of income and income inequality.

TABLE 9 Technical change and employment

	Whole sample			Split samples			Structural break		
ln(Employment$_{i,t}$)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Technical change$_{i,t-1}$	−0.208***	−0.211***	−0.218***	−0.166**	−0.155**	−0.157**			
	(0.0679)	(0.0678)	(0.0665)	(0.0758)	(0.0769)	(0.0774)			
Technical change (1978–92)$_{i,t-1}$							−0.482***	−0.393**	−0.478***
							(0.168)	(0.159)	(0.165)
Technical change (1993–2012)$_{i,t-1}$							−0.104	−0.105	−0.0984
							(0.0926)	(0.0953)	(0.0959)
Economic growth	N	Y	Y	N	Y	Y	N	Y	Y
Structural transformation	N	Y	Y	N	Y	Y	N	Y	Y
Globalisation	N	N	Y	N	N	Y	N	N	Y
Time trend	N	N	Y	N	N	Y	N	N	Y
Government expenditure	Y	Y	Y	Y	Y	Y	Y	Y	Y
Capitals	Y	Y	Y	Y	Y	Y	Y	Y	Y
SOE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province and year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	783	783	748	783	783	748	783	783	748
R^2	0.995	0.995	0.995	0.995	0.995	0.995	0.995	0.995	0.995

Note: Standard errors in parentheses; *$p < .1$, **$p < .05$, ***$p < .01$.

TABLE 10 Technical change and real wage

	Whole sample			Split samples			Structural break		
ln(Wage$_{i,t}$)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Technical change$_{i,t-1}$	−0.315***	−0.281***	−0.299***	−0.301***	−0.273***	−0.286***			
	(0.0897)	(0.0876)	(0.0866)	(0.105)	(0.103)	(0.103)			
Technical change (1978–92)$_{i,t-1}$							−0.194	−0.145	−0.135
							(0.200)	(0.196)	(0.210)
Technical change (1993–2012)$_{i,t-1}$							−0.315**	−0.312**	−0.298**
							(0.129)	(0.125)	(0.121)
Economic growth	N	Y	Y	N	Y	Y	N	Y	Y
Structural transformation	N	Y	Y	N	Y	Y	N	Y	Y
Globalisation	N	N	Y	N	N	Y	N	N	Y
Time trend	N	N	Y	N	N	Y	N	N	Y
Government expenditure	Y	Y	Y	Y	Y	Y	Y	Y	Y
Capitals	Y	Y	Y	Y	Y	Y	Y	Y	Y
SOE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province and year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	729	729	694	729	729	694	729	729	694
R^2	0.990	0.991	0.991	0.990	0.991	0.991	0.990	0.991	0.991

Note: Standard errors in parentheses; $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

TABLE 11 Technical change and capital stock

	Whole sample			Split samples			Structural break		
ln(Capital stock$_{i,t}$)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Technical change$_{i,t-1}$	−0.0474	−0.0687	−0.0775	−0.0849	−0.0756	−0.0755			
	(0.0615)	(0.0577)	(0.0565)	(0.0674)	(0.0657)	(0.0655)			
Technical change (1978–92)$_{i,t-1}$							−0.459***	−0.280**	−0.261**
							(0.145)	(0.123)	(0.126)
Technical change (1993–2012)$_{i,t-1}$							−0.0280	−0.0398	−0.0419
							(0.0811)	(0.0807)	(0.0806)
Economic growth	N	Y	Y	N	Y	Y	N	Y	Y
Structural transformation	N	Y	Y	N	Y	Y	N	Y	Y
Globalisation	N	N	Y	N	N	Y	N	N	Y
Time trend	N	N	Y	N	N	Y	N	N	Y
Government expenditure	Y	Y	Y	Y	Y	Y	Y	Y	Y
Capitals	Y	Y	Y	Y	Y	Y	Y	Y	Y
SOE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province and year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	783	783	748	783	783	748	783	783	748
R^2	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999

Note: Standard errors in parentheses; *p < .1, **p < .05, ***p < .01.

TABLE 12 Technical change and marginal productivity of capital (MPK)

	Whole sample			Split samples			Structural break		
$MPK_{i,t}$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Technical $change_{i,t-1}$	0.122***	0.0965***	0.0992***	0.102**	0.0971***	0.102***			
	(0.0385)	(0.0310)	(0.0313)	(0.0437)	(0.0342)	(0.0351)			
Technical change $(1978–92)_{i,t-1}$							−0.0817	0.0275	0.0545
							(0.0838)	(0.0742)	(0.0834)
Technical change $(1993–2012)_{i,t-1}$							0.0928*	0.0790**	0.0801**
							(0.0531)	(0.0399)	(0.0399)
Economic growth	N	Y	Y	N	Y	Y	N	Y	Y
Structural transformation	N	Y	Y	N	Y	Y	N	Y	Y
Globalisation	N	N	Y	N	N	Y	N	N	Y
Time trend	N	N	Y	N	N	Y	N	N	Y
Government expenditure	Y	Y	Y	Y	Y	Y	Y	Y	Y
Capitals	Y	Y	Y	Y	Y	Y	Y	Y	Y
SOE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province and year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	783	783	748	783	783	748	783	783	748
R^2	0.700	0.782	0.779	0.698	0.782	0.779	0.702	0.783	0.780

Note: Standard errors in parentheses; $*p < .1$, $**p < .05$, $***p < .01$.

TABLE 13 Mediation: technical change and labour share of income

	Whole sample			Split samples			Structural break		
Labour share of income$_{i,t}$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Technical change$_{i,t-1}$	−0.255***	−0.267***	−0.0772*	−0.234***	−0.278***	−0.0831*			
	(0.0635)	(0.0704)	(0.0432)	(0.0677)	(0.0716)	(0.0434)			
Technical change (1978–92)$_{i,t-1}$							−0.0325	−0.0225	0.0666
							(0.145)	(0.145)	(0.0856)
Technical change (1993–2012)$_{i,t-1}$							−0.205***	−0.277***	−0.0913*
							(0.0773)	(0.0857)	(0.0518)
ln(Employment$_{i,t}$)		−0.0178	0.126***		−0.0112	0.133***		−0.00707	0.135***
		(0.0323)	(0.0363)		(0.0322)	(0.0362)		(0.0322)	(0.0362)
ln(Wage$_{i,t}$)		0.0601**	0.1000***		0.0597**	0.0996***		0.0569**	0.0980***
		(0.0285)	(0.0199)		(0.0285)	(0.0199)		(0.0287)	(0.0200)
ln(Capital stock$_{i,t}$)			−0.168***			−0.175***			−0.176***
			(0.0442)			(0.0442)			(0.0441)
MPK$_{i,t}$			−1.259***			−1.258***			−1.252***
			(0.0907)			(0.0907)			(0.0908)
All controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province and year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	748	694	694	748	694	694	748	694	694
R^2	0.790	0.803	0.922	0.789	0.803	0.922	0.791	0.805	0.923

Note: Standard errors in parentheses; *p < .1, **p < .05, ***p < .01.

Firstly, the government shall institute a well-functioning child care system with subsidies to promote population growth. This can help increase labour force participation and fertility in both the short and the long run (Del Boca, 2002). Secondly, capital-saving (labour-biased) technical change should be encouraged, which can lead to increases in the demand for labour. Finally, healthy development of SOEs can play a role in reducing the inequality-rising effect of technical change, but their operating efficiency must be improved.

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