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Automation and Inequality in China

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Yixiao Zhou
School of Economics and Finance, Curtin Business School, Curtin University

Rod Tyers
Business School, University of Western Australia
Research School of Economics, ANU and
Centre for Applied Macroeconomic Analysis, ANU

Abstract

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Keywords

Automation, income distribution, tax, transfers, general equilibrium, China

JEL Classification

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Address for correspondence:

(E) cama.admin@anu.edu.au

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Automation and Inequality in China**

Yixiao ZHOU

School of Economics and Finance
Curtin Business School
Curtin University

Rod TYERS

Business School
University of Western Australia,
Research School of Economics,
Centre for Applied Macroeconomic Analysis (CAMA)
Australian National University

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Author best contact details:
Rod Tyers
Winthrop Professor of Economics
UWA Business School
Crawley, WA 6009
Australia
rod.tyers@uwa.edu.au

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Abstract

In transitional economies like China, comparatively low real wages imply sub-OECD labor and skill shares of value added and comparatively high capital shares. Despite rapid real wage growth, however, rather than converge toward the OECD, China's low-skill labor share has been falling, due to structural and technical change. Here this dependence is quantified using an elemental national model with three households. Since 1994, a third of the total change in the Gini coefficient is estimated to be due to structural change and the rest to mainly skill-biased technical change. Widely anticipated further twists away from low-skill labor toward capital are then examined, assuming downward rigidity of low-skill wages and transfers that sustain low-skill welfare via taxes on capital income. The potential is identified for unemployment to rise extraordinarily, with negative effects mitigated if the population declines or if the share twists are accompanied by very strong total factor productivity growth.

1 Introduction

Economic growth and income inequality are both policy priorities in almost all countries, the former because it raises the average standard of living and the second because, apart from pure concerns about the welfare of the poor, it fosters dissention and the under-provision of essential public goods (Pickett and Wilkinson 2010, Stiglitz 2013, 2017). Since Deng Hsiao Ping's transformation of China's growth policy regime from its focus on class war to pragmatic accommodation of innovations that raise living standards, the record on growth performance has been unprecedented for so large an economy (Lin et al. 2016). Yet there has been a strong rise in its income inequality that appears to be larger and more sustained than the inequality curve of Kuznets (1955) would predict. Between 1978 and 2016, China's real GDP per capita grew at an average rate of 9.7%.[1] In 2016, nominal GDP per capita reached US$8,069, making China an upper-middle income country. The increased inequality, however, makes China one of the least equal 25 per cent of countries in the world, a group very few Asian countries belong to (Zhou and Song 2016). Its official Gini coefficient, at around 0.5, makes the degree of income inequality in China high both from the perspective of its past and in comparison with other countries at similar stages of economic development (Xie and Zhou 2014).

The evolution of economic policy and growth performance in China have broadly followed the "East Asian model" that had earlier been so successful for Japan, the Republic of Korea

[1] This is an estimate based on World Development Indicators, last updated by the World Bank in July 2017.

and the Southeast Asian economies and the Special Administrative Region of Hong Kong. Central to this model are the early specialization of production in light manufacturing, requiring high trade dependence to meet more diversified home consumption and investment demands, and foreign direct investment, which enables "catch-up" technical change. This comparative openness to both trade and financial flows yields strong exposure to trends in technology and economic policy in the rest of the world (Taylor and Tyers 2017).

Three prominent global trends are currently influential. First, rates of growth in economic activity in advanced economies have declined, most notably since the GFC (Lo and Rogoff 2015). Second, this has been combined with a declining trend in global bond yields at all maturities, weakening monetary policy (Summers 2014, 2016). And third, there has been a trend toward the direction of new income and wealth toward high-level professional and capital-owning households (Piketty 2014). It comes as no surprise that these three issues are related (Pichelmann 2015) and that they depend, at least in part, on changes in levels of investment and the associated alterations in the rate and composition of technical changes (Gordon 2014, 2015).[2]

In the early 2000s levels of real net investment in the advanced economies began to decline. Since investment embodies new and more productive technology slower rates of capital accumulation imply slower total factor productivity (TFP) growth. Indeed, TFP stopped growing quite suddenly across the OECD around this time and there has been little sign of resurgent growth since. Less suddenly, during the past three decades the advanced economies have shown a trend in factor bias, away from low-skill labor toward skill and physical capital, suggesting that technical change has roles in both stagnation and rising inequality. The open Chinese economy has therefore been increasingly subjected to external technical shocks that may explain, at least in part, its slowing growth rate and its extraordinary rise in inequality.

Yet there are techno-optimists who see immense potential for productivity and lifestyle improvements from the further expansion of modern ICT, artificial intelligence (AI) and robotics. Mokyr (2013) and Mokyr et al. (2015) are amongst those that argue, technology anxiety notwithstanding, that we are on the cusp of a new era of progress in innovation that

[2] Gordon's work leads the "technology pessimists", who highlight the "Solow paradox". Acemoglu et al. (2016) note Robert Solow's comment in his 1987 *New York Times Book Review* article: "... what everyone feels to have been a technological revolution, a drastic change in our productive lives, has been accompanied everywhere, including Japan, by a slowing-down of productivity growth, not by a step up. You can see the computer age everywhere but in the productivity statistics". See also Clark (2016), Crafts (2016) and Friedman (2016).

will provide an unprecedented boost to productivity. Nonetheless, even this optimistic literature foreshadows increased inequality.[3] Since human work has been the key mechanism for distributing income to the middle class for two centuries, accelerated automation threatens inequality. Further, the ownership of new technologies, software and know-how is now highly concentrated across regions. Repairs and local support tend to rely less on associated local industries and more on direct transactions with a few global centres of supply. As Ford (2016) suggests, the issue is not that we may no longer have "broad-based" innovation; it is that modern innovation may no longer procure broad-based prosperity. Households dependent for their incomes on work, once referred to as the "proletariat", are now being referred to as the "precariat", facing higher employment risk and stagnant prospects (Das 2016 a, b). Even if this process has had minor influence in China thus far, it is very much in prospect in China, where immense investments in automation are under way (The Economist 2017, State Council 2015), as it is elsewhere.

This distributionally pessimistic scenario has capital returns being raised by the new technology in well-connected places but not in others (Khanna 2016). Capital returns no longer depend on the availability of labour, to be combined with physical capital, but rather on technology property rights and skills (Acemoglu and Restrepo 2015), the holders of which will be increasingly attracted to connected cities and their hinterlands. Thus, not only is there the prospect of increased income stratification in the advanced economies but also a new geographic polarisation of the pattern of economic activity that favours regions with critical mass in AI and robotics research and development (R&D). This implies the localised concentration of property rights, including in China,

In this paper the focus is on the ways income stratification is affected by a range of determinants that, in China, combine transformative structural change on the one hand (Kanbur 2017) and automation on the other. The existing evidence on Chinese structural change, automation and inequality is first explored. Agriculture and manufacturing have receded as core employers in the economy while services have expanded. While, by itself, this would have shifted labor demand toward skill, technologies employed within industries also appear to have shifted toward skill and capital intensity. As the growth of low-skill labor supply has slowed and plateaued China-wide, and as rising incomes have demanded more

[3] Key contributors include Brynjolfsson and Andrew (2011), OECD (2012), Goos et al. (2014), Hemous and Olsen (2014) and Avent (2016).

skill-intensive services, governments and firms have looked to automation and robotics to maintain competitiveness.

To link these trends more formally to inequality, an elemental general equilibrium model is used in a decomposition of observed changes in the period 1994-2015. This model embodies a technology specification that allows changes in total factor productivity to be separated from factor bias. Three represented households supply raw labor, skill and capital in different proportions. The effects on their real incomes and the inequality between them are examined in response to changes in industry structure, factor abundance, total factor productivity and factor bias, along with changes in the relative cost of capital goods, labor force participation rates, the fiscal deficit and the unemployment rate.

Changes in factor bias that advantages skill and capital relative to low-skill labor emerge as the dominant explanator of the observed rise in inequality. The model is then applied to prospective automation, which differs from that observed in recent decades in that it favors capital rather than skill. Policy experiments are conducted on changes in tax and transfer rates that may be needed to avoid extreme labor displacement and inequality. It is shown that, even in China, unemployment could rise very substantially, that substantially higher tax rates on capital income will be required to compensate displaced workers and that, to offset these undesirable effects, new technologies will need to deliver very high rates of total factor productivity growth. Section 2 reviews the data and the literature on Chinese structural change, wage distribution and overall inequality, while Section 3 describes the general equilibrium framework used to conduct the analysis. Section 4 offers the decomposition analysis for the period 1994-2015 and Section 5 addresses prospective, capital-concentrating technical change. Section 6 then concludes.

2. Inequality, Technology, Factor Shares and Real Wages in China

Here we review developments in Chinese inequality and discuss proposed determinants. The roles of technical change and their implications for real wage and unemployment trends are then addressed in subsequent sections.

2.1 Income inequality

Two phases are identified in Chinese inequality trends since the beginning of the reform era in 1978 by Kanbur and Zhang (2005). After an initial short period of falling inequality as

rural income rose in the wake of the implementation of the personal responsibility system, overall inequality rose inexorably as China opened up to the world and explosive growth took place in its coastal regions. Using multiple data sources, Xie and Zhou (2014) reveal that China's income inequality rose after 2005 to extraordinary levels, as suggested by Gini coefficients in the range of 0.53-0.55[4]. Comparing survey data collected in 2010 in China and the United States, they seek to explain China's comparatively high income inequality, finding that a substantial part is due to regional disparities and the rural-urban gap. While these structural forces are strong in China they have negligible influence over income inequality in the United States. There, idiosyncratic personal risks, family structure and race or ethnicity, play much larger roles.

Recent trends in Chinese inequality are much debated. Xie and Zhou (2014) estimate the Gini coefficient for 2012 as close to that for 2009, and yet the estimate of 2010 is significantly higher (Figure 1). They draw a non-parametric local polynomial regression curve on the estimates of Gini coefficients since 1967 and identify an unabated upward trend that continues after 2010. Kanbur et al. (2017) reinterpret the after-2010 Gini estimates in Xie and Zhou (2014), however, as evidence for a plateauing of income inequality, with the Gini estimate for 2010 regarded as an outlier. They then use data from the Chinese Household Income Project (CHIP) and the China Family Panel Studies (CFPS) survey to re-estimate the coefficients, identifying a levelling-off of income inequality after 2010.

Drivers of income inequality

To gain more insight into the drivers of income inequality, Kanbur et al. (2017) decompose income by source, to include wage income, operational income, property income, transfer income and other income. From 1995 to 2002, the two greatest contributors to the proportionate increase of the Gini coefficient were wage income and transfer income. From 2002 to 2007, property income and operational income were the top two drivers. In the period from 2007 to 2010, wage income again became the most important contributor to the rise in income inequality. During 2010-2012, when inequality can be interpreted as turning downward, operational income played the most important role. From 2012 to 2014, the contributions to the proportionate change in the Gini coefficient from wage income, operational income, and property income were collectively strong. If the Theil's T index is

[4] Their data sources include the China Family Panel Studies (CFPS) 2010 and 2012, the Chinese General Social Surveys (CGSS) 2010 and 2012, the Mini-Census 2005, the China Labor Force Dynamic Survey (CLDS) 2012, and the Chinese Household Finance Survey (CHFS) 2011.

used as the measure of income inequality, wage income serves as the most important inequality-reducing component in this final period. The conclusion drawn is that it is the narrowing of the wage distribution and the role of transfers that appear to have reduced inequality in this period.

What are the mechanisms that drive the pattern of the above incomes and income inequality? The existing literature on China's inequality suggests the determining factors include within-rural and within-urban income gaps, the urban-rural income gap, regional differences in income, corruption and grey income, market-oriented economic reforms, the education gap, changes of factor demand associated with expanded trade, and technological change (Zhou and Song 2016; Fleisher et al. 2010). These factors are seen as interacting, though each clearly has independent implications for inequality.

Li (2013) points out that rural income inequality declined from 1979 to 1982 due to privatization and the assignment of property rights over land, and to the subsequent increase in farming production. From the mid-1970s to 1995, the development of the rural non-agricultural sector and township-village enterprises was unbalanced across regions and provinces, causing rural inequality to rise. It fell after 1996 as the rural terms of trade improved with growing urban demand for rural products. After 2000 this trend was further supported by the more equal spread of non-agricultural activities, more remittances from migrating urban workers, and government policies that included the abolition of agricultural taxes and the minimum living allowance program.

In urban areas, income inequality initially fell after the reforms in 1978 and then picked up rapidly after 1984. Contributing factors included 1) the enterprise reform that focused on the efficiency of enterprises by linking wage levels with performance in the late 1980s, and 2) the state-sector restructuring program launched after 1997 to shut down loss-making state owned enterprises, corporatize large state-owned enterprises, restructure small SOEs, and de-link the provision of social services from SOEs (Li 2013, Zhou and Song 2016). Later in the period, income inequality increases in association with the growing inequality of wealth (Krever and Zhang 2011, Sicular 2013, Ward 2013), which tended to be underestimated due to grey income and the under-representation of the wealthy in household surveys (Wang and Woo 2011). The urban-rural income gap had been on the rise between 1984 and 2009, peaking in 2009 and falling thereafter with the tightening of labor markets as China' reached the Lewis turning point (Zhang, Yang and Wang 2011).

High-skill wage premia and the associated education gap may also have contributed to income inequality. In 1998, compared to those with lower levels of education (junior high school and below), graduates from senior high school, technical school and college earned 4%, 7%, and 14% more, respectively; in 2009, these amounts had increased to 18%, 32%, and 61%, respectively (Li and Zhao 2011, Meng et al. 2013). The return to education in urban China has increased from only 3-4 per cent per year of schooling in the late 1980s to above 10 per cent in recent years (Yang 2005, Zhang et al. 2015). By contrast, Appleton et al. (2014), using data from the China Household Income Project (CHIP) for 1988, 1995, 2002, and 2008, find that the returns to education and experience fell in the period 2002-08 relative to those for 1988-95, suggesting that the growth surge pulled up low-skill wages relative to skilled. In the 1990s SOE restructuring led to excess demand for high-skill labor, widening the higher education wage premium. Golley and Kong (2013) apply survey data on rural to urban migrants to show that intergenerational education levels were less correlated for rural residents and migrants to urban areas than for urban residents. While education resources were then poorer in rural areas, and migration probably interrupted the educations of many migrants seeking higher paid urban work during the growth surge, persistent intergenerational transmission in urban areas is likely to have exacerbated rural–urban disparity in the early 1990s and in the period since the growth surge.

Trade openness and technological change are also key determinants of both growth and income inequality. The new openness supplied by China's accession to the WTO had two effects. First, it expanded trade which, alone, would have tended to raise low-skill wages and reduce income inequality by raising the relative price of goods intensive in low-skill labor (Tyers 2015). Second, it greatly increased the inflow of foreign direct investment, and therefore the introduction of new technologies. Coming from the comparatively skill-endowed advanced economies, these technologies tended to be skill-intensive, shifting Chinese labor demand away from low-skill toward high-skill labor.[5] That the second effect dominated the first during China's surge is suggested by Xu and Li (2008) and Wang (2017). Furthermore, Chinese firms have been observed to raise their in-house R&D activities substantially, initially to improve their adaptation of imported technologies but increasingly to generate primary innovation. This raises the skilled wage premium and income inequality

[5] This pattern was widely observed in transitional economies (Acemoglu 1998) and, particularly, in those following the East Asian growth model. The Indonesian case, for example, is highlighted by Suryahadi et al. (2001).

because the elasticity of wage levels to R&D intensity is considerably higher for high-skill that for low-skill workers (Mishra and Smyth, 2014; Ge and Yang, 2014).

2.2 Technology indicators: total factor productivity and factor shares

The literature on China's income inequality has been less strong on supply side or technical factors that impact on income distribution. Yet it is our hypothesis that these are fundamentally important. To explore them, we seek to divide aggregate technical change between growth in total factor productivity and shifts in factor shares, the latter suggesting bias, and then to separate out the contribution to factor share shifts as between structural and technical change.

Total factor productivity

The contribution to China's real GDP growth of total factor productivity is widely debated without consensus in sight. Divisions are sourced in both measurement and methodology. On the one hand, early work on East Asian growth suggested scepticism about the TFP contribution (Young 1992, 1994, 1995). This literature was popularised by Krugman (1992, 1994) as the "low TFP thesis". On the other hand, at about the same time Chow (1993) found strong contributions from TFP and Rodrik (1998) later suggested that the incorporation of institutional quality measures raised the possibility that TFP contribution could be higher than thus far measured. Yet Young (2003), returning to the issue with a focus on China, offered an analysis that transformed the measures of its growth experience in the 80s and 90s "from the extraordinary to the mundane".

The methodological elements of this controversy centred on the links between the primal approach (estimation of production functions) and the difficult question of time variation in factor shares and the implied values of inter-factor elasticities of substitution (Nelson and Pack 1999). As to measurement, the use of value rather than volume measures for the capital stock is readily shown to bias estimates of the Solow residuals, under some conditions rendering growth accounting to a mere restatement of production accounting identities.[6] By contrast with the TFP contribution, the majority of studies support a strong role for structural change in overall growth performance, implying the merits of relocating workers from low productivity employment in agriculture to higher productivity work on manufacturing or services, though even this is regarded with scepticism by Ye and Robertson (2017).

[6] Felipe and McCombie (2017) survey these methodological and measurement issues, concluding with skepticism about the merits of the entire exercise.

Beyond these controversies there are further measurement issues that affect the perceived role of TFP. Labor supply measures are naturally in volumes but, for China, the sectoral allocation of workers requires adjustment for the "floating population" – the workers, numbering in the hundreds of millions, who retain rural registration but are working in urban occupations (Tyers et al. 2008). More controversially, measures of China's capital stock vary enormously, depending on the sources of data and the choices of depreciation rate and capital goods price deflator. If the official measures of real GDP are accepted, the stronger the capital growth implied by these series, the smaller is the resulting contribution of TFP. To illustrate, the capital stock series adopted by the World Input Output Database (Timmer et al. 2015, 2016) shows an average growth rate of 4.7 per cent per year after 1994. That used in the Penn World Tables (Feenstra et al. 2015) implies a corresponding growth rate of 11.1 per cent per year. That derived by Wu (2016), based on provincial and industry level fixed capital formation data, grows at 12.9 per cent per year. Clearly these variations contribute to the correspondingly wide variations in estimated TFP contributions.

It is not our intention to attempt a resolution to these controversies of method and measurement, but rather to compile broad measures of the past effects of technical changes and to assess the potential future effects of their continuation. For this reason we adopt the relatively central and carefully compiled measures from the Penn World Tables database. Since 1994 they estimate the contribution of TFP to the average growth rate in this period to be about 2.7 per cent per year.[7] In looking back to 1994 we take this TFP performance as given. We then make the strong assumption that the contribution of TFP to the broad growth performance of agriculture, manufacturing and services has been roughly the same. The dictates of Balassa and Samuelson, who characterise services as "haircuts", lead us to expect the fastest TFP growth in manufacturing and the slowest in services. Yet Young (2003) confirms strong productivity performance in agriculture, the output from which has grown despite its labor force having declined substantially, and output volume from the services sector is so poorly measured that there is little strong empirical support for slower services productivity. Indeed, with the recent uptake of e-commerce, China's services sector would appear to be experiencing considerable productivity growth (Dai and Zhang 2015, Zhang and Zhu 2015).

[7] The Penn World Tables result is based on a capital stock series that includes intangible capital and is carefully deflated. We choose the period 1994 to 2015 because the major macroeconomic (both fiscal and monetary/exchange rate) reforms that triggered the acceleration in China's growth commenced in that year.

Figure 2 shows the resulting trends of TFP and real GDP in China after 1994. TFP grew from 1994 to 1997 at an average annual rate of 2.2 per cent. It fell significantly in 1998 as output fell relative to the labor force due the Asian Financial Crisis. It picked up quickly from 1999 and grew at an average annual rate of 3.4 per cent until the global financial crisis (GFC). It rose again after 2008 though its rate has since been much-attenuated, at 1.3 per cent per annum. This accompanied slower overall growth in real GDP, forming part of China's "new normal" growth regime. Across the two decades since 1994, however, the Penn World Tables analysis has Chinese TFP rising by a total of 57 per cent.

Factor shares

Factor bias in production technology can be reflected by changes in factor payment shares, though these can have other causes. When change is particularly rapid, for example, and there are lags in investment responses, oligopoly rents can temporarily inflate capital shares. In the longer run, these shares are affected by changes in the industry structure of the economy. Consistent with its transitional nature, the Chinese economy is continuing to experience such transformation in its industrial structure. The share of primary industry in national value added has declined by half, from around 20 per cent in 1995 to less than 10 per cent in 2015, while the share of services has increased by 50 per cent, from around 40 to nearly 60 per cent. At the same time, the share of manufacturing has changed by less, but it too has declined since the GFC with comparative growth in services, reaching a low of 35 per cent in 2015 (Figure 3).

This structural change alters factor payment shares in an economy because the three sectors have very different production technologies and hence factor payment shares. Primary industries have the highest payment share to low-skilled labor, while capital takes up the highest proportion of value-added in both manufacturing and services. The share of payments to skilled labor is highest in services, significantly higher than in either the manufacturing or the primary industry. Structural change favoring services is therefore important because it shifts shares in the overall economy in favor of skill and, to a lesser extent, capital. To examine the independent effect of technical change these effects of structural change must be separated. Our approach to this decomposition is as follows.

Factor shares at the industry level are not available from official Chinese statistics. They are available, however, from the World Input Output Database (Timmer et al. 2015, 2016) but only up to 2009. At the national level, however, we have capital and aggregate labor (low-

skill labor and skill labor combined) shares from the national accounts in China Statistical Yearbooks through 2015. Our first step is to construct sectoral factor shares through 2015 by extrapolating the trends in factor shares exhibited in the World Input Output Database beyond 2009, constrained by consistency with the economy-wide aggregate labor and capital shares from the national accounts. This consistency is confirmed by the construction of nation-wide factor shares as the weighted sum of sectoral factor shares with sector shares as the weights, allowing the construction of counterfactual shares at the national level when structure is held constant. The exercise is summarized in the graphs in Figure 4.[8]

To determine the contribution to changes in the shares due to technical change alone we then re-calculate the national shares in this manner, assuming that no changes in industry structure occur in the period 1994-2015. The fourth plot in Figure 4 illustrates how the national shares might have differed had the structural change illustrated in Figure 3 not occurred. At least at this three-sector level of aggregation, the results show that the effects of structural change are not as large as those due to technical change. Indeed, despite the fact that the transition from manufacturing and agriculture to services appears to have accelerated in the past decade, over the entire two decades structural change, thus calculated, explains about a third of the period decline in the share of low-skill labor.

2.3 Real wages and Unemployment

Since employment has been the key mechanism for distributing income, it is important to examine the corresponding trends in real wages. For this purpose we draw on Yang et al. (2010), who document the general patterns of urban real wages by province, by ownership types and by industries for China for the period 1978-2007.

They observe that wage growth was moderate before 1985, at 4.9 per cent per annum. Despite the beginning of major urban reforms the growth rate remained modest at 3.9 per cent between 1986 and 1997, during which period employment in private and jointly-owned enterprises grew rapidly. In the period 1998-2007 wage growth picked up to an astounding 13.2 per cent per year. This period of wage explosion coincided with China's preparation for and accession to the WTO along with major SOE reforms. They then reveal that wage rates were clustered until the early 1990s, and by 2007, average wages in skill-intensive industries

[8] These graphs show a peak in the capital share arising at the end of the growth surge period, prior to the GFC. This is likely due to increased capital rents as demand outstripped the growth in production capacity during that period. While our subsequent analysis employs the constant returns to scale assumption, it compares 1994 with 2015 point to point rather than in time series.

(banking and insurance, scientific research and polytechnic services), began leading wage levels in the labor-intensive industries (manufacturing, construction, wholesale and retail services).

On the one hand, this wage trend shows a rise in return to skill or education during China's economic transition. On the other hand, this is due to the existence of a vast pool of surplus labor, a phenomenon specific to an economy transitioning from agrarian to industrial growth (Athukorala and Wei 2017). By 2007, however, manufacturing wages were moving in lockstep with wages in non-tradable services like construction and wholesale and retail sales, confirming the integration of low-skill labor markets at wage rates linked to the subsistence wage level in the rural sector. These patterns are evident from Figure 5, which presents hourly wage rates by skill level between 1995 and 2009.[9]

Despite the challenge from Ye and Robertson (2017), many studies find that the largest ever human movement from rural to the urban sector offered the major driving force behind China's transformation into the "global factory" (Meng 2012, Meng and Manning 2010). In more recent years, however, anecdotal evidence and empirical analysis suggests that the labor surplus may have been fully absorbed that the so-called "Lewisian Turning Point" has arrived (Lewis 1954, The Economist 2012, Cai and Du 2011, Cai and Wang 2010). And yet, precisely whether China has moved into an integrated national labour market without difference between rural and urban sector is still debated. Athukorala and Wei (2017), for example, claim that labour shortages and wage increases in booming provinces are a reflection of institutional constraints on labour mobility rather than the rapid depletion of the economy-wide surplus labor pool.

While prominent labor shortages help to motivate China's policy push toward automation, surplus labor continues in the urban economy in the form of underemployment, particularly amongst low-skill workers and in the the SOE sector. Moreover, the urban informal sector has been swelled by the SOE reforms (Athukorala and Wei 2017). Indeed, the automation-induced loss of job creation may yet aggravate unemployment as well as income inequality, retard the integration of labor markets and the final stages of the urbanization of the economy.

3. Modelling the Economy-Wide Consequences of Automation

[9] These data are from the World Input-Output Database (Timmer et al. 2015).

A closed economy, single product, real general equilibrium structure is used that has a complete financial market with government debt and three household groups. The regional rate of return on equity investment departs from the regional bond yield, the former reflecting expected rates of return on installed capital and the latter short run equilibrium in the financial market between savers, the indebted government and investors. On the supply side, there are three primary factors with "production" labor (L) a partially unemployed variable factor. In standard closures the stocks of physical capital (K) and skill (S) are fixed and fully employed.[10] Households have differing shares of the three primary factors and different consumption behavior, represented by reduced form relationships that depend on current and expected future disposable income and the interest rate.

3.1 The supply side

Since technology is exogenous and subject to shocks in this analysis, a "relative Cobb-Douglas" formulation allows us to capture changes in productivity and factor bias separably, via simple changes in readily observed parameters: a total factor productivity parameter, θ, and a set of factor shares, β.

$$(1) \qquad \frac{y}{y_0} = \theta \left(\frac{L}{L_0}\right)^{\beta^L} \left(\frac{S^K}{S_0^K}\right)^{\beta^S} \left(\frac{K}{K_0}\right)^{1-\beta^L-\beta^S},$$

where y_0, L_0, S_0^K, and K_0 are the initial levels of output and labor, skill and capital inputs. This formulation allows technology bias shocks, to β^L and β^S, to be neutral so far as the initial level of aggregate output is concerned.[11] Marginal products are then:

$$(2) \qquad MP^L = \beta^L \frac{y}{L}, \quad MP^S = \beta^S \frac{y}{S^K}, \quad MP^K = \left(1-\beta^L-\beta^S\right)\frac{y}{K}.$$

The real production wages of unskilled and skilled workers depend conventionally on the corresponding marginal products:

$$(3) \qquad w = \frac{W}{P^P} = \beta^L \frac{y}{L}, \quad w^S = \frac{W^S}{P^P} = \beta^S \frac{y}{S^K}.$$

Here the upper case wages are nominal (expressed relative to the numeraire, the GDP price)

[10] Alternative closures offer long run perspectives in which K and S are endogenous with financial flows and/or skilled migration preserving external rates of return and returns to skill.

[11] In effect, shocks to factor shares alone adjust the initial level of total factor productivity, so that the question becomes, how different would the economy have been had the factor shares been at their post-shock levels. Such shocks do not necessarily hold output constant, however, since this depends on whether real wage rigidities cause changes in unemployment.

and the lower case wages are real (expressed relative to the producer price, P^P).

Output, GDP and prices:

The real volume of output, y, is distinguished from nominal GDP, $Y = P^Y y$, where P^Y is the *GDP price* level (deflator).[12] Direct and indirect tax revenues, T^D and T^I, and transfers to households, T^R, play key roles in the formulation. GDP at factor cost (or producer prices), Y^{FC}, is the total of direct payments to the collective household in return for the use of its factors. Nominal GDP is then

(4) $$Y = Y^{FC} + T^I, \quad Y^{FC} = C + \left[T^D - T^R - \alpha W_0 \left(F - L\right)\right] + S^P.$$

This is the standard disposal identity for GDP, or the collective household budget, where C is the total value of final consumption expenditure, including indirect taxes paid, S^P is private saving and the term in square parentheses is direct taxation net of transfers to households (the latter including non-specific transfers, T^R, and unemployment benefits at fraction, α, of the initial low-skill wage). L is low-skill employment and F is the low-skill labor force. In this context the GDP price, P^Y, and the producer price, P^P, would be the same were it not for indirect taxes. In their presence we have:

(5) $$Y = P^Y y = P^P y + T^I, \text{ so that } P^Y = P^P + \frac{T^I}{y}.$$

Population and participation:

The three separate households, h, are defined based on factor ownership. The first has income dominated by production labor, the second by skill and the third by capital. Because few households depend on only one factor of production, the three are defined based on the stylised factor ownership shares, s_{hf}, offered in Table 2. The low-skill and skilled labor forces depend not only on these ownership shares but also on separate participation rates. All three households supply low-skill workers and skill but at different participation rates, λ_{Lh} and λ_{Sh}. The low-skill and skilled labor forces are then:

(6) $$F = \sum_{h=1}^{H} \lambda_{Lh} s_{hL} N_h, \quad S^K = \sum_{h=1}^{H} \lambda_{Sh} s_{hS} N_h,$$

where the participation rates are defined on household level populations, N_h. This level of

[12] In this real model, "nominal" refers to prices relative to the model numeraire, which is arbitrary but is chosen to be the GDP price P^Y. The producer price, P^P and the consumer price level, P^C, vary relative to this value in response to shocks.

detail in labor supply is required not only for labor market equilibrium but also for the eventual construction of Lorenz curves and for the analysis of changes in unemployment and participation rates, which have also had distributional implications.

3.2 The demand side

Central to the demand side in any economy-wide model is the financial market, which equates saving to investment. Here investment depends on the expected after-tax yield, or the rate of return on installed capital net of depreciation and capital tax, adjusted for sovereign risk, r^{ce}. This has a number of components. First, since only the after-depreciation component of capital income is taxed, after tax capital income is:

(7) $$Y_{KN} = \left(1 - t^K\right) K \left(P^P \, MP_K - P^K \, \delta\right) ,$$

where P^K is the price of capital goods,[13] t^K is the ad valorem capital income tax rate and δ is the depreciation rate. The rate of return net of both tax and depreciation is then:

(8) $$r^c = \frac{Y_{KN}}{P^K K} - \delta \ .$$

The expected form of this rate is then:

(9) $$r^{ce} = r^c \left(\frac{\varphi^0}{\varphi} \right) ,$$

where the interest premium factor, φ , permits consideration of the effects of changes in the fiscal balance on sovereign risk. A deteriorating fiscal balance causes investment to be less attractive.

(10) $$\varphi = \varphi^0 \left[\left(\frac{G}{T} \Big/ \frac{G_0}{T_0} \right) \right]^{\phi} ,$$

where ϕ is a positive elasticity indicating sensitivity to sovereign risk.

[13] In this single product model the product and capital goods prices are separated by a single parameter: $P^K = \gamma P^P$. This allows shocks to represent the relative cheapening of capital goods over time as their information technology content rises.

The demand for investment financing depends on the "Tobin's Q like" ratio of the expected rate of return on installed capital, r^{ce} and a domestic market clearing bond yield or financing rate, r .

(11) $$\frac{I^D}{I^0} = \left(\frac{r^{ce}}{r}\right)^{\varepsilon^I} ,$$

where ε^I is a positive elasticity. This investment demand is then matched by a supply of saving that incorporates the government's fiscal position:

(12) $$I^D = S^D = S^P + \left(T^D + T^I - G\right),$$

where T^D and T^I are, respectively, direct and indirect tax revenues, S^P is private saving and G is the total of all the government's expenditures, including those on goods and services, G^X, transfers to households, T^R, and unemployment benefits, which are paid at a fraction, α, of the initial nominal low-skill wage, W_0:

(13) $$G = G^X + T^R + \alpha W_0 \left(F - L\right), \quad T^R = \sum_h T_h^R, \quad T_h^R = t_h^R Y N_h ,$$

where F is defined in (5) as the total low-skill labor force, t_h^R is the proportion of GDP that is paid out to household h, per capita (the fundamental constant underlying transfers), and N_h is the household's population.

Calibration of the financial market is facilitated by the assumption that the initial database has the steady state property that the net rate of return is initially the same as the market bond yield: $r_0^{ce} = r$. Thus, the financial market clearing condition equates the value of domestic investment, I^D, which represents the sum total of all domestic long maturity asset issues, with demand for those assets in the form of net (private and government) savings.

Direct tax

Constant marginal direct tax rates, t^W, t^S and t^K, apply to all labor, skill and capital income, respectively. The corresponding "powers" of these rates are $\tau^L = \left(1 + t^L\right)$, $\tau^S = \left(1 + t^S\right)$ and $\tau^K = \left(1 + t^K\right)$ and so, bearing in mind taxation of capital income after depreciation (6), total direct tax revenue is:

(14) $$T^D = t^L WL + t^S W^S S^K + t^K K\left(P^P MP_K - P^K \delta\right).$$

Indirect tax revenue, T^I, depends on consumption and so it will emerge later.

Household disposable income and consumption

Disposable income, for each household, takes the form:

(15) $$\begin{aligned} Y_h^D &= s_{hL}\left[\left(1-t^L\right)WL + \alpha W_0\left(F-L\right)\right] + s_{hS}\left(1-t^S\right)W^S S^K \\ &\quad + s_{hK}\left(1-t^K\right)K\left(P^P MP_K - P^K \delta\right) + T_h^R, \quad \forall h \end{aligned},$$

Where $s_{hj}, j = (L,S,K)$ are the shares of household group claims over factors of production, as indicated in Table 1. $T_h^R = t_h^R N_h Y$ is a direct transfer to the household from government revenue, with t_h^R the transfer rate to household *h* per unit of group population, N_h, and per unit of nominal GDP.[14] Total disposable income is the sum of Y_h^D across households, which is also GDP at factor cost (household primary income) less total direct taxes, plus net transfers from the government to households and the unemployed:

$Y^D = \sum_h Y_h^D = Y^{FC} - T^D + T^R + \alpha W_0\left(F-L\right)$. Since, from (5), GDP at factor cost is full GDP less net indirect tax revenue, this can be written as

(16) $$Y^D = Y - T^I - T^D + T^R + \alpha W_0\left(F-L\right).$$

For each household, *h*, aggregate consumption expenditure, C_h, is a nominal sum but real consumption behavior is motivated by current and expected future real disposable incomes and the real interest rate. Real consumption, (lower case) c_h, depends negatively on the after-tax real return on savings (the home bond yield, *r*) and positively on both current and expected future real disposable income:

(17) $$c_h = \frac{C_h}{P^C} = A_h^C\left(\frac{r}{\tau^K}\right)^{-\varepsilon_h^{CR}}\left(\frac{Y_h^D}{P^C}\right)^{\varepsilon_h^{CY}}\left(\frac{Y_h^{De}}{P^C\left[1+\pi_h^{Ce}\right]}\right)^{\varepsilon_h^{CY}},$$

where the expected inflation rate of the consumer price level is π^{Ce}.[15] The different households have parameters reflecting different sensitivities to these determinants. The

[14] The expression (15) is more complex if the labor force participation rates, as defined in (6), of low skill workers, λ_{Lh}, are unequal across households and, similarly, if participation rates of skilled workers, λ_{Sh}, are unequal across households. The simpler expression is offered here, reflecting our simplifying assumptions. The participation rates within skill groups and across households are kept equal in the experiments conducted, although the rates differ *between* skill groups and may be differently shocked.

[15] There is no money-driven inflation in this model but expectations can be formed of a future increase in the consumption tax rate that would raise P^C relative to P^P and P^Y.

consumer price level is marked-up over the producer price level by the power of the consumption tax, $P^C = \tau_C P^P$. This yields consumption tax revenue:

(18) $$T^I = (\tau_C - 1) P^P \sum_h c_h .$$

Private saving

Households receive factor incomes amounting to GDP at factor cost, Y^{FC}. Their disposal of nominal income is this sum less direct tax, net of transfers to households and the unemployed (16). Private saving differs across households. It is what remains after consumption expenditure (gross of indirect taxes) is further deducted from disposable income.

(19) $$S^P = \sum_h \left[Y_h^D - C_h \right]$$

Since total consumption expenditure, inclusive of consumption tax, is

(20) $$C = \sum_h C_h = P^C \sum_h c_h = P^P \tau_C \sum_h c_h ,$$

And total disposable income is from (16), aggregate private saving can also be written as:

(21) $$S^P = Y^D - C = \left[Y - T^I - T^D + T^R + \alpha W_0 (F - L) \right] - C$$

Government and total domestic saving

This is government revenue less government expenditure, both measured net of direct transfers to households and the unemployed. Total domestic saving is then the sum of private and government savings in the home economy, in home currency, where government saving is $S^G = T^D + T^I - T^R - G^X - \alpha W_0 (F - L)$.

(22) $$S^D = S^P + S^G = Y - C - G^X .$$

The product balance

Product balance stems from a version of the expenditure identity in real volume terms:

(23) $$y = \frac{I + G^X}{P^P} + \sum_h c_h ,$$

where the final term is the sum of real consumption across the households. Neither investors nor the government pay indirect taxes on their expenditure and so the price they face for the home product is the producer price, P^P.

Welfare and inequality

For distributional analysis, the shares of disposable income and the population shares are then

(24) $$s_h^{YD} = Y_h^D / Y^D, \quad s_h^N = N_h / \sum_{i=1}^{H} N_i, \quad \forall\, h \in (1, H) \ .$$

Our measure of group welfare is real disposable income at consumer prices, $V_h = Y_h^D / P_C$ and a three-group Gini coefficient is calculated, first by calculating the area under the three-household Lorenz curve:

(25) $$A_L = 0.5\left[s_{Lh}^N s_{Lh}^{YD} + s_{Sh}^N \left(2 s_{Lh}^{YD} + s_{Sh}^{YD}\right) + s_{Kh}^N \left(1 + s_{Lh}^{YD} + s_{Sh}^{YD}\right)\right] \ ,$$

and the corresponding Gini coefficient is then

(26) $$G^C = 2\left(0.5 - A_L\right) \ .$$

Parameters, database and operation:

A complete list of the behavioral parameters used in the model is provided in the Appendix, Table A1. The model is structured to resemble the Chinese economy in 2011. The database is built on national accounts as well as international trade and financial data for that year. Trade and international financial flows are eliminated from the data, which is then rebalanced. Closures required to undertake the experiments for Sections 4 and 5, below, are detailed in Table A2. The model code and working software are available on request from the author.

4. Analysing Growth and Inequality Since 1994

Our first application of the model is to decompose the aggregate distributional changes in the Chinese economy into components due to structural change, technology and other shocks. Included are changes in factor use, TFP, factor bias, the capital relative to goods price, the fiscal deficit, labor force participation and the unemployment rate. Shocks to these elements follow from observation, as indicated in Table 2, and the labor market and fiscal closures adopted are listed in Appendix Table A2. The shocks are applied individually and collectively so that component contributions can be determined. Aggregate performance decompositions are summarized in Table 3. From these results the major contributors to the changes in GDP and real disposable income are seen to be, not surprisingly, factor use and total factor productivity. Inequality, as measured by the Gini coefficient, is improved by the considerable relative expansion in the stocks of physical capital and high-skill labor, but this

effect is outweighed by the twist in factor shares due to structural and technical change. This leaves the modelled Gini coefficient higher by 23 per cent (Table 3 and Figure 6).

The corresponding distributional decomposition is summarized in Table 4. These results show that even low-skill households have enjoyed large gains in real disposable income and consumption during the two decades of strong growth. Yet their real disposable incomes have lagged behind those of skilled and capital-owning households. Moreover, it is clear that the drag on the real disposable income of the low-income household is dominated by the change in factor bias. The structural and technical change shocks most favor skilled workers and hence professional households, yet the gain in real disposable income is almost the same in capital-owning households. Because the numbers in capital-owning households grow most, however, their growth in real disposable income per capita is more modest.[16]

5. Implications of Prospective Automation

It is a simple matter to use the model to calculate the distributional consequences of future changes in factor bias when labor markets clear and there are no changes in government policy. In that case the Cobb-Douglas technology necessitates that real compensation should change linearly with factor shares. Yet this is unlikely to be the form that future automation shocks take. If robotics and artificial intelligence do indeed displace labor at an accelerated rate it is most likely that displaced workers would be covered by a social safety net, and thus they would receive compensatory transfers. It is also unlikely that the low-skill wage will fall by very much, given that it is constrained by minimum wage laws. These conditions suggest the experiments reported in this section. We begin with an analysis of the implications for inequality and macroeconomic policy of further shifts in factor bias away from low-skill labor. In this context the implications of alternative Chinese population growth scenarios are then considered. Finally, the future roles of total factor productivity and capital accumulation are addressed.

5.1 Further Factor Bias

The central shocks are indicated in Table 5. They are, first, continued structural change, away from rural activities and manufacturing toward services, with implications for the value

[16] The growth in the population in capital-owning households is endogenous to participation rates and (mainly) skilled employment. The combined shocks show simulated average growth in the low-skill, professional and capital-owning households' populations at 0.6, 2.3 and 5.0 per cent per year, respectively, since 1994.

added shares changing in similar proportion to the changes over 1994-2015. This reflects our view that the structural change process in China is yet incomplete and that it will continue during the coming decades. Second, to represent further automation in the Chinese economy, albeit driven increasingly by AI and robotics, further technical change shocks see further declines in the low-skill labor share but, this time, favoring capital rather than skill. Two alternative tech scenarios are considered. Scenario 2 has the labor share declining by the same proportion observed to be due to tech change in 1994-2015. Scenario 3 has a decline by 50 per cent, reflecting our view that AI and robotics will have more dramatic impacts in the coming decade than they have had in the past.

Workers displaced by the decline in the low-skill share receive the standard unemployment benefit, to which can then be added a transfer sufficient to retain the real purchasing power of their incomes at consumer prices. When it is included, this transfer is financed by additional taxation. Two alternative sources of tax revenue might be considered: a rise in the capital income tax rate and a rise in the consumption tax rate. While the consumption tax alternative distorts investment incentives less it suffers from circularity since a higher consumption tax rate raises the consumer price level it also raises the scale of transfers in order that the real purchasing power of displaced workers is retained. As shown by Tyers and Zhou (2017), raising the capital income tax rate emerges as by far the most efficient choice, so the analysis presented here is restricted to this financing option.[17]

Consider first the case without additional transfers. The reductions in the low-skill share, combined with the assumed downward rigidity of low-skill wages, then see worker displacement and therefore reduced resources, so real GDP falls. With reduced output and collective income the real disposable income of capital-owning households is impaired as indicated in Figure 7, though the impairment declines as the tech twist is enlarged in favor of capital. Most striking is the scale of worker displacement. This drives the unemployment rate (the proportion of the combined low-skill and high-skill workforce that is unemployed)[18] to near 40 per cent in the case where the twist is of the same magnitude as during 1994-2015 and above 50 per cent when the twist is AI-augmented as in Scenario 3. This unemployment

[17] The one downside of this choice, which implies raising the top income tax rate and/or the company tax rate, is that capital is internationally mobile with high elasticity to net rates of return. The implications of this are the subject of further research by the authors.
[18] High-skill workers remain fully employed by assumption.

reduces average real incomes of low-skill households and raises inequality as measured by the Gini coefficient.

When the capital income tax rate is raised to finance transfers that hold low-skill household welfare constant the results are as summarized in the right-hand graph in the figure. The changes in real GDP and unemployment are unaltered from Scenario 2 but now the welfare of capital owning households declines by more and the gains to the skilled household diminish the larger is the share twist. In order to stabilize low-skill household welfare the rate of capital income taxation must increase to unsustainable levels.

5.2 The Implications of Labor Force Decline

Given the high levels of worker displacement that arise when the technology twists occur alone, it is not unreasonable to imagine that any economy subject to these shocks would be better off with a smaller population, and hence a smaller displaced worker burden. To examine this more formally, we consider the two alternative demographic projections for China that are offered by Golley et al. (2017). Taking the AI-augmented share twist scenario under which the low-skill share declines by half, we ask what the changes in economic performance would be under two alternative population and labor force projections. First, we have continuing low Chinese fertility and, on the other, a rising population and labor force associated with the success of 2016's "two child policy". The results are summarized in Table 6.

Most striking is the conflict between aggregate economic welfare (the real per capita purchasing power of disposable income at consumer prices) and real GDP. This conflict is widely recognized, including by Golley et al. (2017), as emerging from elemental growth models. Population growth increases GDP but decreases income per capita (Pitchford 1974). But this effect is here augmented by the welfare-sapping unemployment burden that emerges when workers are displaced. The strongest effects of population growth are seen in the structural change scenario, where there is skill augmentation but little share twist. The real GDP expansion is larger by 10 percentage points but the corresponding gain in welfare (real purchasing power of disposable income at consumer prices) is smaller by almost half.

The stronger tech twist of Scenario 3 causes worker displacement, reducing output at both levels of population growth. But the displacement is larger with greater population growth and so the real GDP expansion is then larger by only four percentage points and the welfare gain is smaller by two thirds. When transfers to low-skill households are financed by capital

income taxation sufficient to hold their welfare constant, there is not much change in the real GDP gain but aggregate welfare is smaller by three quarters. The AI-augmented tech twist causes 219 million workers to be added to unemployment with low fertility while the number rises to 312 million with high fertility. These numbers are still larger if transfers are financed by capital income taxation and the rates of this taxation are also higher with high fertility. The transfers nonetheless substantially reduce the loss of welfare in the low-skill household and so they reduce the Gini coefficient. Clearly, from a welfare standpoint, the dictum that slower population growth delivers faster development is borne out here, the more strongly because of the employment consequences of capital-biased technical change.

5.3 Factor Bias with Total Factor Productivity Growth

Clearly the outlook of the previous subsections is pessimistic. If the techno-optimists, like Mokyr et al. (2015), are to be believed the primary consequence of the anticipated automation will be gains to TFP. So, to explore the implications of this we take factor share Scenario 3 (the AI-augmented twist) and add successive increments to total factor productivity. The experiment is done under three different model closures, first assuming no minimum real wage of low-skill workers, then imposing the minimum wage, and finally introducing additional transfers that would hold constant the real purchasing power of the low-skill household over goods at consumer prices by raising the capital income tax rate. In all cases physical capital is allowed to accumulate so as to maintain a constant (expected) rate of return on capital.[19] The range of TFP gains simulated goes up to 40 per cent, in the context of which it is worth recalling that our preferred measure of the corresponding gain in the previous, and globally extraordinary, two decades was 57 per cent. Future gains in TFP will be more difficult to achieve because "catch-up" opportunities are now comparatively scarce. They will therefore rely heavily on the productivity advantages offered by AI and robotics.

In the absence of any downward wage rigidity and, therefore, holding the 2015 rate of unemployment constant, the simulated real consumption wage of low-skill workers falls by half without any TFP gain. This decline would be turned into an 11 per cent gain if TFP were to improve by 40 percent. The other key results are illustrated in Figure 8. As the first graph in the figure indicates, the holding by the low-skill household of some other assets, combined

[19] Capital accumulates to retain a constant level of r^{ce} (equation 9). If this implied a constant marginal product of capital and the shocks did not change the capital share, then the stock would rise in proportion with real GDP. In this case deviations occur because there are changes in the capital share. Even though the fiscal balance is held constant, there are also small changes in the risk premium associated with the relative scale of the government's initial imbalance.

with its receipt of some baseline unemployment benefits and transfers, means that effects on its welfare differ from the real low-skill wage changes. At low productivity gains the relative size of its welfare loss is reduced, but that loss remains considerable unless TFP improves by at least 25 per cent. The Cobb-Douglas assumption ensures that, while the tech twist by itself raises the Gini coefficient substantially, the successive additions of TFP do not change this distributional measure.

If the low-skill wage is downwardly rigid, the second graph in the figure shows the expected, and considerable, rise in the unemployment rate, with the welfare of the low-skill household moderated at any TFP change, relative to the first graph, by its better wage rate and its receipt of unemployment benefits. In this case the Gini coefficient rises with TFP advances, since the productivity change, combined with the tech twist, benefits capital and skill far more than the partially unemployed low-skill labor force. As the TFP gain passes 30 per cent, the unemployment rate approaches its initial, 2015, level from above. The low-skill wage is then allowed to rise to sustain the 2015 unemployment rate floor, and the welfare of the low-skill household rises. It is clear, however, that TFP growth would raise the marginal productivity of all factors, including low-skill labor, and this would raise low-skill labor demand. Nonetheless, the rise in TFP would need to be considerable to avoid the inequality effects of large scale worker displacement and, even then, further interventions would be needed to avoid continuously rising inequality.

One such further intervention is to provide additional transfers for the purpose of retaining as constant the real purchasing power of the low-skill household's income. As before, these are best financed by increments to the capital income tax rate. The results are as illustrated in the third graph. If the TFP rise is beyond 20 per cent, government revenue from other direct and consumption taxes rises so quickly that additional financing from a higher rate of capital income taxation is not required. Thereafter, even with budget balance, the transfers are readily financed by moderating the growth in government expenditure on goods and services. Of course, the trend of the unemployment rate is unaltered relative to the second graph and the Gini coefficient shows more initial growth as the effects of the transfers weaken with rising labor demand and the low-skill household is left behind by the TFP-driven expansion. For very high TFP growth performance levels, however, the low-skill labor market tightens to the level observed in the other two graphs and the path of the Gini coefficient returns to the levels in those graphs. This intervention, therefore, delivers reduced inequality and better

low-skill welfare at lower levels of TFP gain, but it does not address the rise in the Gini coefficient that is sustained at higher levels, when full employment is restored.

6. Conclusion

The trend in Chinese inequality since its major policy transitions in 1994 is reviewed and apportioned between the changes in sectoral and urban-rural structure that accompany development on the one hand and technical change on the other. While there is no doubting the long term trend toward more inequality, some controversy surrounds the pattern since the GFC which some believe suggests the beginning of a Kuznets turning point. To assess the relative roles of structural and technical change we first separate the components due to production technology alone, which has a Hicks-neutral component, measured as total factor productivity, and a biased component, measured by changes in factor shares. Our three-sector analysis suggests that structural change explains about a third of the observed decline in China's low-skill labor share in this period, with the rest due to technical change that has been biased in favor of skill and, to a lesser extent, physical capital.

An elemental three-household general equilibrium model is then used to quantify the links between real income inequality on the one hand and changes in factor abundance, total factor productivity, factor bias, the relative cost of capital goods, changes in labor force participation rates, the fiscal deficit and the unemployment rate on the other. Relative expansions in the stocks of skill and physical capital have, by themselves, mitigated inequality. Yet their effects have been dominated by the combination of structural change and biased technical change, with the latter having the dominant effect.

We then turn to prospects in the coming decades, which are expected to bring a continuation in structural change and a further technical twist away from low-skill labor, this time toward physical capital, which is widely expected to stem from recent accelerations in the development of artificial intelligence and robotics. Assuming minimum wage laws make low-skill wages rigid downward and that the government protects the welfare of low-skill households via tax-funded transfers, the same model framework is used to evaluate aggregate performance and changes in the welfare of professional and capital-owning households. If the new technology delivers only a shift in bias then aggregate performance is impaired by worker displacement that could cause the unemployment rate to rise to anywhere between 20 and 50 per cent. The transfer burden makes capital-owners significant losers in this case.

Dual problems therefore arise: increased inequality and potentially very high levels of worker displacement. These effects are first shown to be mitigated by slower population growth, suggesting that the age when large low-skill populations can be advantageous to growth in developing countries may be numbered. More dramatically, however, the worker displacement, though not the inequality, is lessened the more the new technology also delivers increments to total TFP. The results suggest that there are, indeed, achievable levels of TFP growth at which aggregate demand would rise sufficiently to eliminate the pool of displaced workers, even with a further decline in the low-skill labor share by half. But the rates needed are high relative to what has been achieved by China in recent decades and the potential for continuing this pattern, constrained as it is by the exhaustion of opportunities for "catch-up" productivity advances, will rely on the pure productivity effects of AI and robotic advances.

Even then, it is possible that these results are too pessimistic. New technologies have, in the past, created new forms of skilled employment (Acemoglu and Restrepo 2015). Beyond the concerns of Ford (2016) about the concentrated structure of the new ICT industries there is the fact that the wealthy have always demanded personal services (Autor 2016). Unaesthetic though income inequality may be, and notwithstanding the associated issues with shared public good burdens (Stiglitz 2000), as income becomes more concentrated, personal service jobs are likely to expand and contribute to soaking up some of the unemployment.

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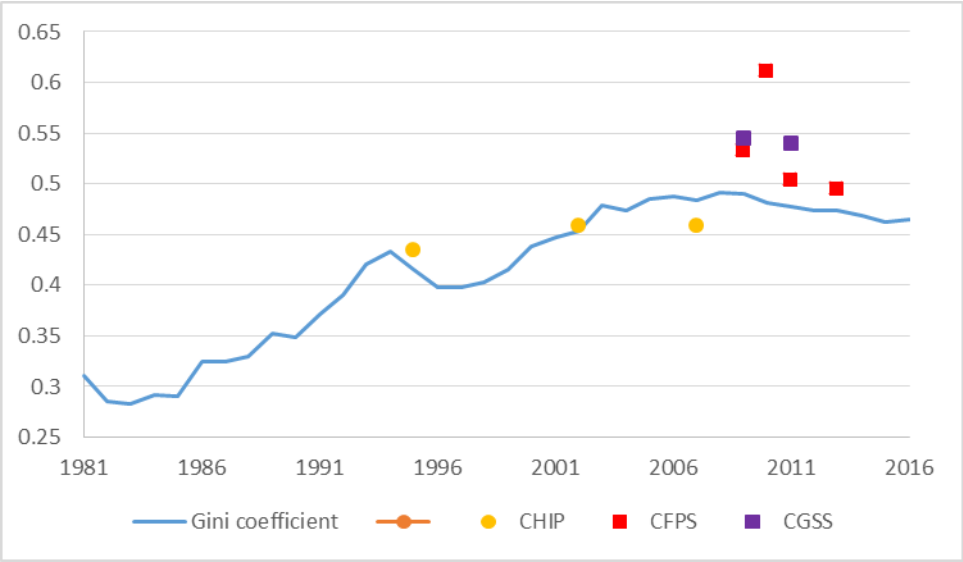
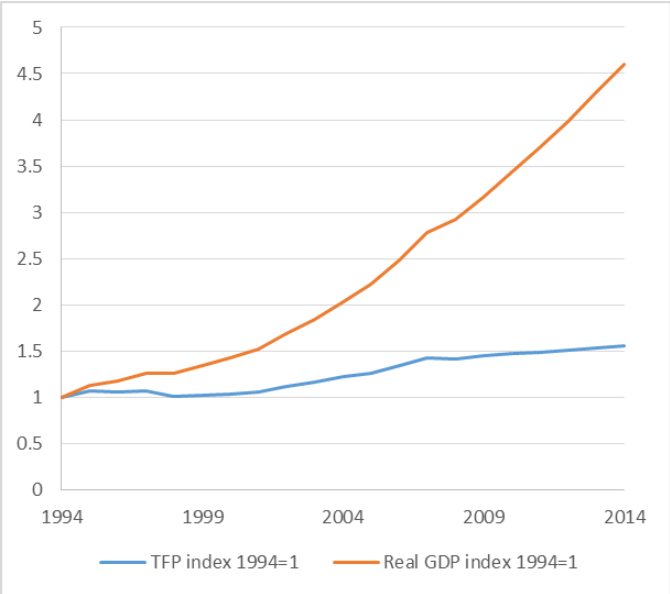
Figure 1: Gini Coefficient Estimates for China, 1981-2016



Source: The blue-line Gini coefficients for the years 1981-2001 are from Ravallion and Chen (2007), that for 2002 is from World Income Inequality Database and those for 2003-2016 are from the National Bureau of Statistics of China. Other plotted Gini coefficient values, indicated by scattered points, are from Kanbur et al. (2017) and Xie and Zhou (2014). CHIP is an abbreviation for the "China Household Income Project". CPFS abbreviates "China Family Panel Studies". CGSS refers to the "China General Social Survey".

Figure 2: China's total factor productivity (TFP[a]), 1994-2014

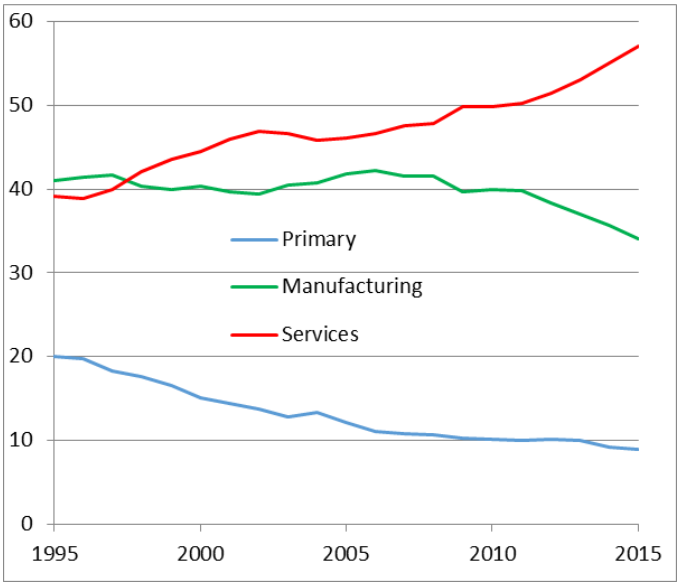


a TFP is the portion of output change not explained by the quantities of inputs used in production and is reported at constant national prices (2011=1). We normalize the data to set TFP in 1994 at unity.

Source: Penn World Tables, international comparisons of production, income and prices, version 9.0. See Feenstra et al. (2015).

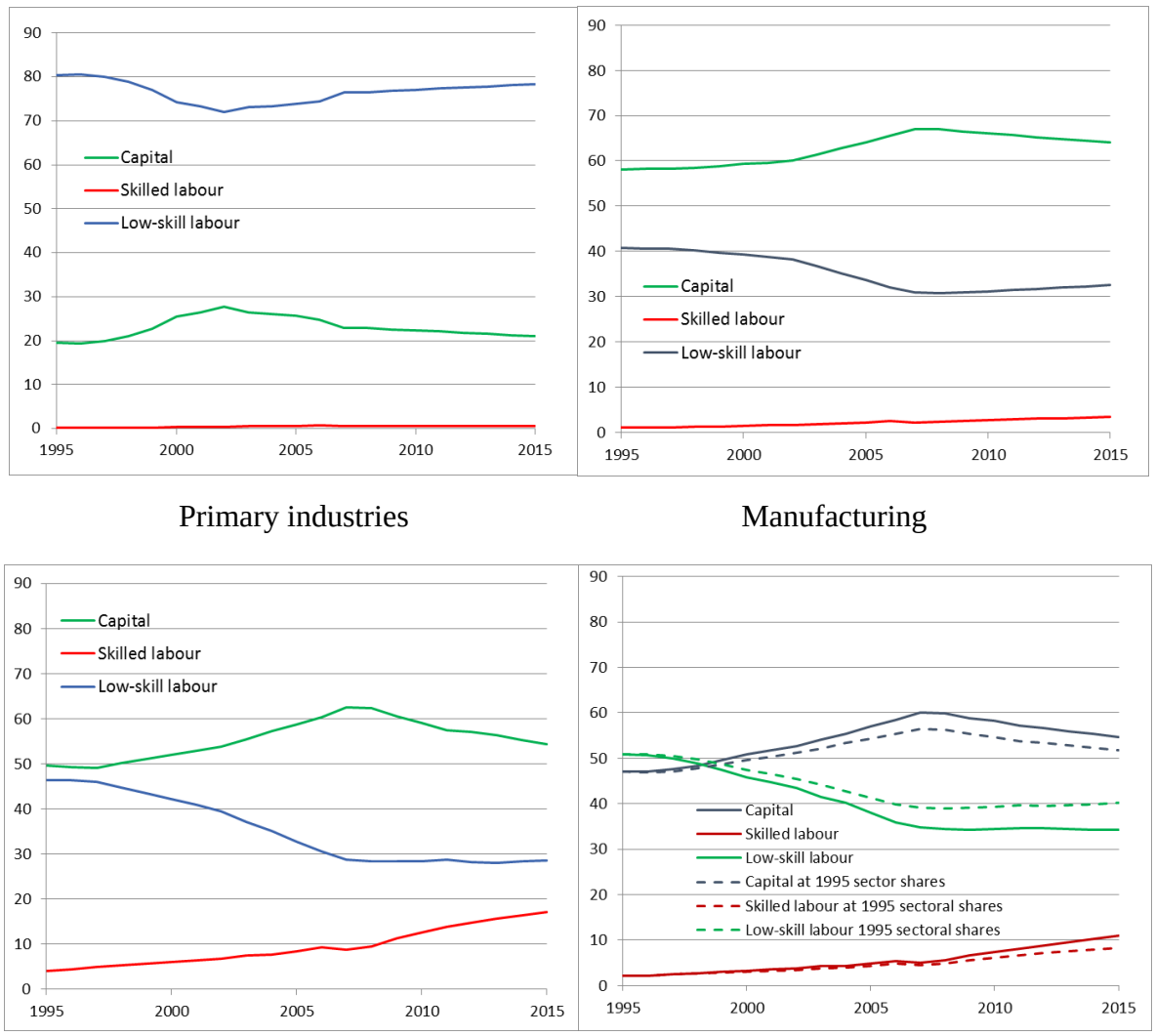
Figure 3: Broad Structural Change in China, 1995-2015

(Shares of national value added by industry group, %)



Source: National Bureau of Statistics of China, China Statistical Yearbook, 2014, 2015 and 2016. "Primary" is agriculture and mining, "Manufacturing" is industry less construction, and "Services" is tertiary plus construction.

Figure 4: Factor Shares of Value Added, By Industry Group and Nationally[a]
(%)



Primary industries

Manufacturing

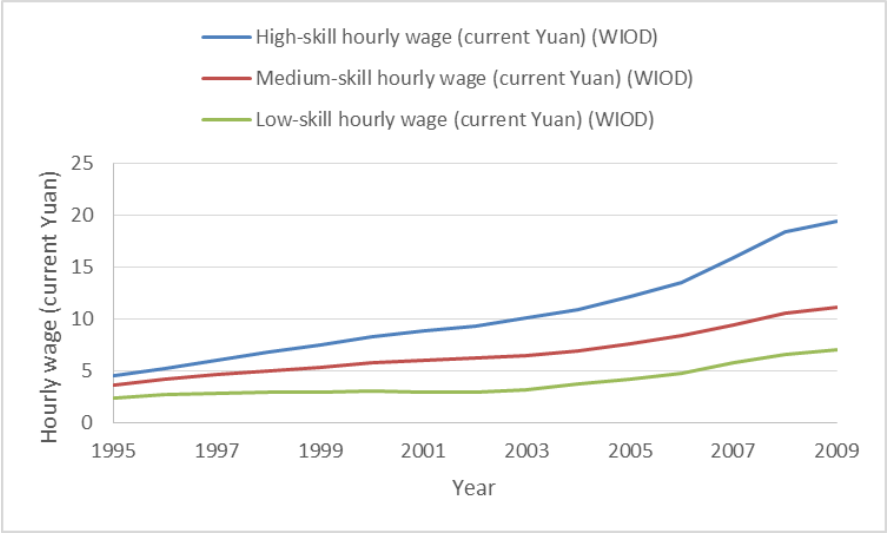
Services

Whole economy
(with and without structural change)

a Factor shares at the industry level are not available from official Chinese statistics. They are available, however, from the World Input Output Database (WIOD, 2013) but only up to 2009. Nation-wide factor shares for capital and aggregate labour are available from the national accounts through 2015. To arrive at these estimates, sectoral factor shares are first constructed through 2015 to meet the following criteria. First, the implied nation-wide shares of industry groups should be consistent with the sector shares in the national accounts, as per Figure 3. Second, the results should also be consistent with the nation-wide shares of aggregate labour (low-skill labour and skill) and capital emerging from the national accounts. And third, beyond these constraints the simple extrapolation of share trends is used from 2010. The fourth figure illustrates how the national shares might have differed had the structural change illustrated in Figure 3 not occurred.

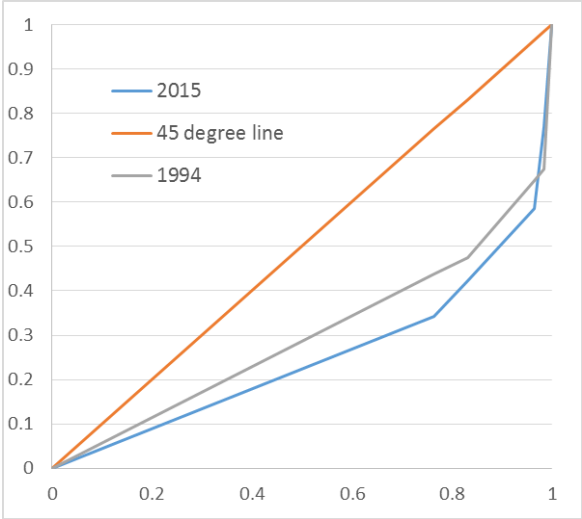
Source: WIOD–World Input Output Database (Timmer et al. 2015, 2016) and NBS–National Bureau of Statistics of China, as drawn from the *China Statistical Yearbook*, 2014, 2015 and 2016.

Figure 5: Hourly wage rate by skill-level in China, 1995-2009



Source: Authors' calculation based on data from the World Input Output Database (Timmer 2015, 2016).

Figure 6: Simulated Three-Household Lorenz Curves, 1994 and 2015[a]

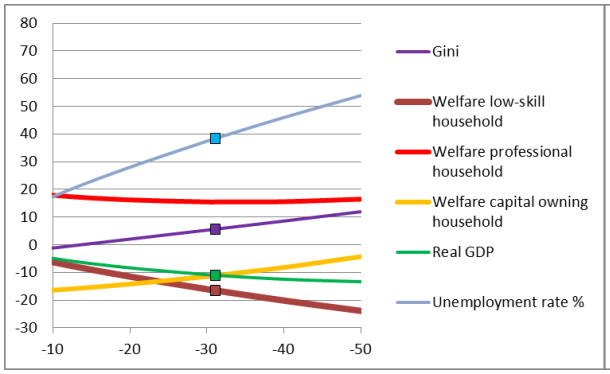


a This summarises the results of a comparative static response to reductions in the low-skill labour share, associated with a complementary rise in the capital share. There is no change in total factor productivity and the low-skill wage is downwardly rigid to reflect minimum wage laws. "Welfare" is an abbreviation for the real purchasing power of disposable income at consumer prices. This measure for the low-skill household is here held constant by tax-financed transfers.

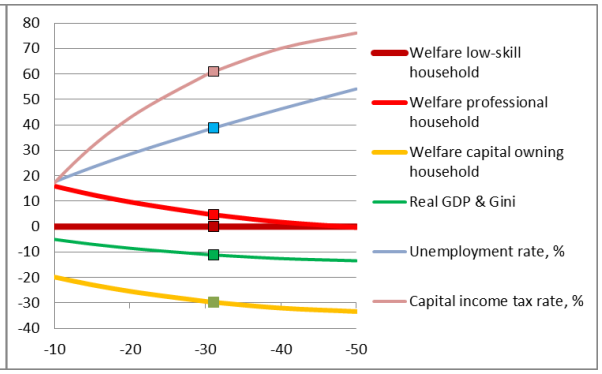
Source: Solutions to the model described in the text.

Figure 7: Prospective Effects of Low-Skill Labour Share Decline[a]

Share twists only



Share twists with capital income financed transfers to the low-skill household

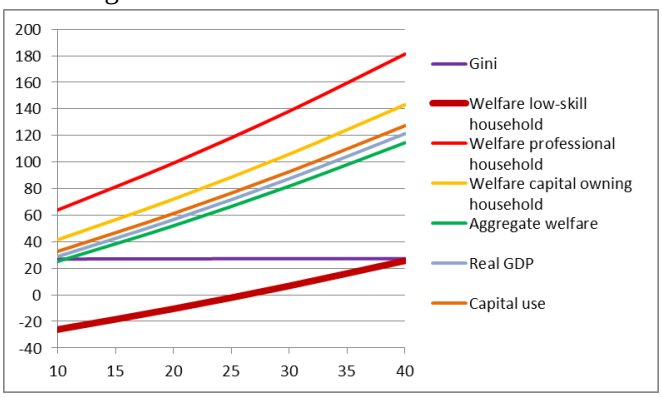


a Here the low-skill share declines as indicated on the horizontal axis, with the three factor share scenarios earmarked at declines of 11%, 31% and 50%. The low skill wage is rigid downward in both cases. Shown in the graphs are the percentage changes in the levels of each variable, except the unemployment rate and the capital income tax rate. In those cases the actual levels of the rates are given (in percentage terms).

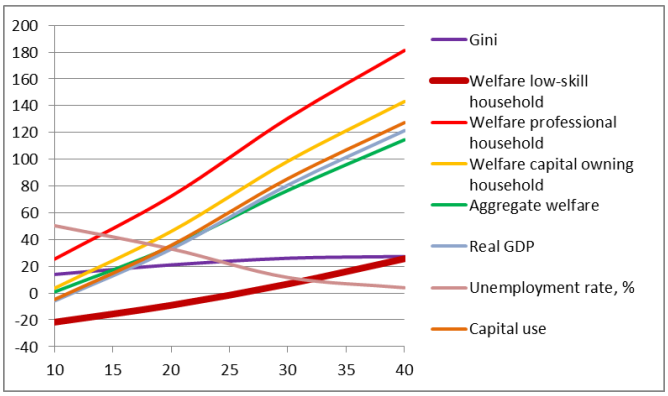
Source: Solutions to the model described in the text.

Figure 8: Prospective Effects of TFP Growth with the AI-Augmented Tech Shock[a]

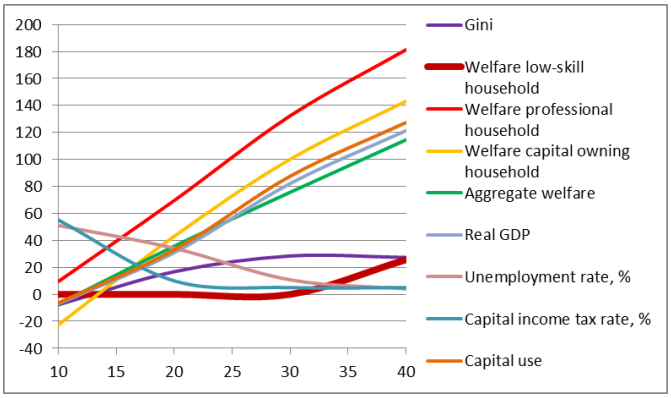
Clearing labour markets



Downwardly rigid low-skill wage and unemployment



Rigid low-skill wage with low-skill household compensation financed by capital income tax[b]



a In each case the shocks of the combined restructuring and AI-augmented tech scenario 3 are implemented at every level of productivity, with capital use endogenous to retain constant rates of return on capital. The per cent changes are shown for all variables except the rate of unemployment and the rate of capital income taxation. In those cases the actual levels of the rates are given (in percentage terms).

b The capital income tax rate is floored at 5%, upon reaching which continued transfers are financed by adjusting endogenous government spending on goods and services.

Source: Solutions to the model described in the text.

Table 1: Stylised Household Factor Ownership Shares Used in Modelling, %

	Primary factors		
Households	**Low-skill labour**	**Skill**	**Physical capital**
Low-income	84	1	2
Professional	15	70	25
Capital-owning	1	29	73
All households	100	100	100

Source: These are highly stylized but representative of data on wealth shares from Ward (2013) and Golley and Kong (2017)

Table 2: Historical Decomposition Shocks Expressed as Forward 1994 to 2015[a]

Variable shocked, 1994 to 2015			**Shock, % change**
Factor use:	Low-skill labour		24.1
	Skill		422
	Capital		790
Total factor productivity			57.0
Factor shares:	Structural change	Low-skill labour	-11.3
		Skill	145
		Capital	6.4
	Technical change	Low-skill labour	-22.4
		Skill	334
		Capital	11.4
Fiscal deficit			900.0
Price of capital relative to consumption goods			-27.0
Participation rate of low-skill labour			8.7
Unemployment rate			44.6

a The decomposition is achieved by shocking these variables individually and collectively.

Sources: Factor use shocks are constructed from the Penn World Tables Database (Version 9, Feenstra et al. 2015), as is the shock to TFP. Factor share shocks are drawn from the analysis behind Figures 3 and 4 as described in the text. The fiscal deficit shock is based on government accounts data from the NBS as are the shocks to the unemployment and participation rates. The relative capital goods price shock is based on a comparison of period changes in China's GDP deflator with those in the corresponding fixed asset investment price index, sourced also from the NBS. The changes in the employment and participation rates are linked to household population levels and hence to the per capita measures in the modelling.

Table 3: Decomposition of Simulated Aggregate Performance Changes in China – 1994 to 2015[a]

Per cent change in↓ due to shock to→	Factor use	TFP	Factor share twist		Cheaper capital	Govt deficit	Low skill partn rate	Unempl rate	Total effects	Av growth rate, %/yr
			Struct change	Tech change						
Real total consumption	250	180	-5.6	-9.5	-6.8	-1.31	0.0	5.36	413	8.1
Real government spending	225	171	-2.0	-3.1	2.3	135	0.0	-36.75	492	8.8
Real gross investment	193	190	5.7	13.3	4.4	-34.4	0.0	-1.15	371	7.7
Real net investment	60.0	165	11.0	30.7	4.4	-33.3	0.0	-1.43	236	5.9
Net real rate of return	-113	23.4	12.3	29.3	32.5	0.05	0.0	-1.49	-16.8	-0.9
Real financing interest rate	-107	1.3	5.5	10.9	1.9	0.45	0.0	-0.17	-87.1	-9.3
Total domestic saving	-50.0	-12.2	-6.1	-11.7	-0.2	1.44	0.0	0.09	-78.7	-7.1
Government saving	0.0	0.0	0.0	0.0	0.0	900	0.0	0.00	900	11.6
Real consn low-skill wage[b]	106	98.4	-14.5	-19.1	0.0	0.00	0.0	2.27	173	4.9
Real consn high-skill wage[b]	-222	203	33.3	446	0.0	0.00	0.0	-2.62	458	8.5
Real disposable income	216	175	0.2	0.3	-0.5	0.15	0.0	1.04	393	7.9
Real GDP	222	183	0.0	0.0	0.0	0.00	0.0	-2.69	403	8.0
Real per capita disp income	142	132	-0.5	-1.1	-1.0	-0.01	26.7	1.72	299	6.8
Gini coefficient	-12.8	1.0	10.5	27.9	-0.4	0.00	-2.5	-1.15	22.6	1.0

a All but the final column show forward % changes on the 1994 base. Changes in real government spending are constrained so that the fiscal deficit remains the same as a proportion of GDP, except in column six, where the deficit is shocked up forward (down backward).
b Real consumption wages are relative to the consumer price, P^C.
Source: Back-casting using the model described in the text.

Table 4: Decomposition of Simulated Household Performance Changes in China – 1994 to 2015[a]

Per cent change in↓ due to shock to→		Factor use	TFP	Factor share twist		Cheaper capital	Govt deficit	Low-skill partn rate	Unempl rate	Total effects	Av growth rate, %/yr
				Struct change	Tech change						
Real consn	Low income	179	139	-13.8	-19.1	-2.0	-0.41	0.0	6.0	289	6.7
	Professional	377	254	4.67	12.9	-15.4	-2.82	0.0	4.0	634	10.0
	Capital-owning	445	252	4.22	9.26	-30.5	-5.71	0.0	-0.05	675	10.2
	Total	250	180	-5.56	-9.53	-6.8	-1.31	0.0	5.4	413	8.1
Real disposable income	Low income	152	121	-11.8	-16.5	0.5	0.1	0.0	3.1	248	6.1
	Professional	272	221	6.9	18.3	-1.0	0.2	0.0	0.5	518	9.1
	Capital-owning	272	224	7.5	16.9	-2.4	0.2	0.0	-2.6	515	9.0
	Total	216	175	0.21	0.30	-0.49	0.15	0.0	1.04	393	7.9
Real disposable income per capita	Low income	111	97.5	-12.5	-17.4	-0.08	-0.01	24.2	3.65	206	5.5
	Professional	124	136	6.11	16.4	-1.23	0.00	0.00	0.78	282	6.6
	Capital-owning	20.0	79.5	6.73	14.9	-1.21	0.00	0.00	-0.87	119	3.8
	Total	142	132	-0.52	-1.14	-0.96	-0.01	26.7	1.72	299	6.8

a All but the final column show forward % changes on the 1994 base.
Source: Back-casting using the model described in the text.

Table 5: Prospective Scenarios for Factor Value Added Shares[a]

Scenario	Primary factor		
	Low-skill labour	Skill	Physical capital
Base, 2015	34.3	11.0	54.7
Prospective scenarios			
1. Continued restructuring only, low skill share drops 11%	30.4	26.9	42.6
2. Continued restructuring with 94-2015 low-skill share decline by 31%	23.6	26.9	49.4
3. Continued restructuring with AI low-skill share decline by 50%	17.2	26.9	55.9

a In all prospective scenarios the skill share is considered only to be affected by restructuring, rising by 145% from its base 2015 value. These scenarios differ according to the associated declines in the low-skill share, which are matched by rises in the capital share.

Table 6: Population and Labour Force Growth under AI-Augmented Tech Change

	Population and labour force projection[a]	
	Success of 2-child policy	Continued low fertility
Changes in labour force by type		
Low-skill labour	-0.14	-14.1
Skill	110.6	88.5
Scenario 1: Structural change with labour supply shocks		
% changes in		
Aggregate welfare[b]	10.0	17.3
Real GDP	24.2	15.1
Scenario 3: AI augmented tech and labour supply shocks		
% changes in		
Aggregate welfare[b]	6.0	15.5
Real GDP	11.0	7.1
Final levels (%) of		
Gini coefficient	0.56	0.57
Unemployment rate	39.0	33.0
Capital income tax rate	5.0	5.0
Above shocks with transfers to low-skill households		
% changes in		
Aggregate welfare[b]	3.2	13.9
Real GDP	10.9	7.0
Final levels (%) of		
Gini coefficient	0.50	0.53
Unemployment rate	39.3	33.3
Capital income tax rate	27.3	20.2

a These two sets of results depend on population and labour force projections by Golley et al. (2017) over the two decades 2015-2035. Although results are available for all three factor share scenarios of Table 5, here we display only results for output and welfare for the first and third and further details for the third, AI-augmented, share twist scenario.
b "Aggregate welfare" is the real purchasing power of total disposable income at the consumer price level, per capita.
Source: Demographic projections by Golley et al. (2017) and solutions to the model described in the text.

Appendix: Model Parameters and Operation

Table A1: Key Parameters

	US
Depreciation rate	0.04
Production factor shares[a]	
Labour, β^L	0.18
Skill, β^S	0.47
Capital, β^K	0.35
Initial household consumption volume shares, %[b]	
Low income	30.0
Prof income	40.0
Capital owning	30.0
Initial household saving rates, %[c]	
Low income	3.6
Prof income	17.6
Capital owning	38.5
Income tax rates[d]	
Labour income, t^L	0.18
Professional income, t^S	0.20
Capital income, t^K	0.15
Indirect (consumption) tax rate[e]	
t^C	0.14
Unemployment benefit ratio	
α	0.60
Transfer rates (initial shares of GDP)	
$t_h^R = T_h^R / Y$, %	
Low income	6.0
Prof income	2.0
Capital owning	0.0
Elasticities	
Consumption, c to r, ε^{CR}	
Low income	0.02
Prof income	0.10
Capital owning	0.20
Consumption, c to Y^D, ε^{CY}	
Low income	1.05
Prof income	0.98
Capital owning	0.90
Investment, I_i to $r^C{}_i/r_i$, $\varepsilon^I{}_i$	1.00
Premium to G/T, ϕ_i	0.20

a Production shares are based on estimates of factor incomes and capital stocks from the GTAP Database.
b Initial consumption shares are used to calibrate consumption structure of the model database.
c Initial household saving rates are from disposable income. These emerge from the calibration and are indicative of embodied behaviour but do not remain constant in response to shocks.
d These income tax rates are lower than observed because direct transfers and sovereign debt service are deducted from income tax revenue so that observed fiscal balances are consistent with *T-G*, where *G* includes only expenditure on goods and services.
e Consumption elasticities are consistent with a variety of estimates in use in other models, both of marginal propensities and elasticities (including McKibbin and Wilcoxen 1995 and Jin 2011).

Table A2: Closures: Choices of Exogenous Variables[a]

Long run equilibrium analysis

Labour market

Back-casting to 1994

Endogenous: low-skill wage, W

Exogenous: employment of low-skill workers, L

Prospective shocks:

Exogenous: nominal production wage, W

Endogenous: Employment of low-skill workers, L

Fiscal policy

Back-casting to 1994

Constant net government saving after transfers

Endogenous government expenditure, G

Exogenous: net government saving after transfers, S^G

Tax rates exogenous

Prospective shocks

Constant net government saving after transfers

Exogenous: net government saving after transfers, S^G

Endogenous: either

Government expenditure on goods, G or

capital income tax rate, τ_K.

Note that in the back-casting shocks, S^G is set at a constant proportion of GDP to reflect observation.