ECONOMICS

Migration and Growth in China: A Sceptical Assessment of the Evidence

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DISCUSSION PAPER 17.03
Migration and Growth in China: A Sceptical Assessment of the Evidence

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Numerous studies report the growth effects from labor reallocation in China to be in the order of 1 to 2 percentage points per year, which would appear to be a significant fraction of China’s per capita income growth. We show that the total factor productivity gains are an order of magnitude smaller, at only 0.25 percentage points per year. There are two reasons for this difference. First, the majority of studies have used a decomposition method that effectively assumes linear production functions. This results in values that are much larger than the more appropriate Denison-Kuznets method. Second we also allow for sectoral differences in human capital. We conclude that the gains from labor reallocation may have been a far less important source of China’s growth than is conventionally thought.

JEL Codes: O4, O41, O1
Keywords: Economic Growth; Productivity; Dual Economy; Structural Change; China.

*The authors are grateful for comments and suggestions from anonymous referees and: Gordon Anderson; David Bulman; Hamming Fang; Doug Gollin; Bob Gregory; Aart Kraay; Debdulal Mallick; Xin Meng; John Piggott; Russell Smyth; Jon Temple; Xiaobing Wang; Annie Wei, and; our colleagues at UWA. We are also grateful to seminar participants at the 2nd Trade and Development Workshop, 2015, Deakin University, and the Centre of Excellence in Population Ageing Research (CEPAR) Workshop, 2015, UNSW. Robertson acknowledges the hospitality of St. Antony’s College Oxford and the Center for the Study of African Economies (CSAE) in the Department of Economics at the University of Oxford. Corresponding Author: Peter E. Robertson, Economics, The Business School, M251, University of Western Australia, 35 Stirling Highway, Crawley, Perth, W.A. 6009, Australia. Email: peter.robertson@uwa.edu.au, T: +61 8 6488 5633, F: +61 8 6488 1016.
1 Introduction

Two decades of 8% to 10% growth have propelled China from a poor to a middle-income country and removed half a billion people from poverty. Accompanying this growth has been the largest mass migration in history, with 150 to 200 million people relocating from China’s rural sector to the cities. A widely held view is that this mass internal migration has been a major source of China’s productivity growth, by facilitating the reallocation of labor from a low productivity agricultural sector to high productivity manufacturing and service sectors (Zhu, 2012, Krugman, 2013, The Economist, 2013).\(^1\)

This view is supported by an extensive macro-development literature based on two-sector growth models with factor market distortions. The literature includes a variety of studies such as growth accounting studies and calibrated growth models. Recent examples include Brandt et al. (2008), Bosworth and Collins (2008), Dekle and Vandenbroucke (2010, 2012), and Cao and Birchenall (2013). These studies typically report large labor reallocation effects, ranging from 1 to 2 percentage points per year.

Nevertheless the view that labor reallocation has been an important source of China’s growth is not ubiquitous. A few studies, such as Cao et al. (2009) and Bulman and Kraay (2011), suggest that labor reallocation effects have been a very small, if not insignificant, component of China’s growth.

We therefore reexamine this literature in order to gain a clearer view of the contribution of sectoral labor reallocation to China’s per capita GDP growth, and why some of these studies may differ so much. Specifically this paper has two parts. The first part focuses on the distinction between the more widely used “shift-share” method and the standard Denison-Kuznets multi-sector extension of Solow (1957) growth accounting (Kuznets, 1961, Denison, 1967). Both methods are used in the literature to describe “labor reallocation” effects, but there have been very few attempts to understand the differences between each method or to explore the quantitative implications of using one or the other.

We show that the numbers produced from the shift-share method are more than twice as large as those produced from the Denison-Kuznets method.\(^2\)

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\(^1\)The association between migration and growth has long been a subject of debate in development economics, particularly over the extent to which there is widespread factor misallocation. For example the Lewis (1954) model was extended by Ranis and Fei (1961), Sen (1967) and Harris and Todaro (1954). These models were criticized by Schultz (1964, 1967) and Jorgenson (1967), who question the assumption of sector gaps in the return to labor or surplus labor. Likewise the literature on dualistic models of development has also been criticized for a lack of empirical evidence and microeconomic foundations (Rosenzweig, 1988, Behrman, 1999). For a recent discussion of the evidence see Gollin et al. (2014).

\(^2\)The numbers produced from the shift-share method are more than twice as large as those produced from the Denison-Kuznets method.
large as the values obtained from the Denison-Kuznets growth accounting. In light of this we argue that the literature has failed to provide a clear sense of how labor reallocation has contributed to China’s GDP growth and, in the context of a standard competitive model, has perhaps overstated its quantitative importance.

The second part of our analysis builds on the observation that the existing growth accounting literature mostly abstracts from inter-sectoral differences in human capital. This is a potentially important omission since differences in human capital are a standard alternative explanation for the apparently large inter-sectoral productivity differences. As with Gollin et al. (2014) we find that human capital differences do not account for all of the observed average productivity gap. Nevertheless, allowing for these differences reduces the implied growth gains from labor reallocation by approximately one third.

We then show that the combined effect of these two adjustments is that the estimated gains from “labor reallocation” are reduced from a value of 1.76 percentage points per year to a value of just 0.25 percentage points per year for the period 1978-2011. This represents a very small fraction of China’s per capita income growth. Hence the gains from labor reallocation may have been a far less important source of China’s growth than conventionally thought.

Before proceeding some caveats are appropriate. First there are several recent studies that focus on capital allocation across firms. While this literature focuses on firms and misallocation within manufacturing, our focus is on the more conventional development process of labor reallocation across sectors, and hence structural change.

Second we focus on the shift of labor from agriculture to non-agriculture. While the change in sectoral employment overlaps with rural-urban migration, it is not exactly the same thing. Thus while we occasionally refer to rural-urban migration, the quantitative analysis of this study is specifically focused on the rising share of employment in non-agriculture.

Finally we are not trying to explain the cause of labor reallocation or develop models that explain this process. We are concerned only with the measurement of the impact of the changing non-agricultural labor share on allocative efficiency and per capita GDP growth in a neoclassical setting. Nevertheless the quantification of these gains is a necessary first step for quantifying more ambitious theoretical models.

These include studies that differentiate firms according to type of ownership, such as private versus state-owned, or the allocation of factors across monopolistically competitive firms that produce distinct varieties. See for example Hsieh and Klenow (2009) and also Brandt et al. (2013) for a recent discussion with respect to China.
2 Growth and Labor Reallocation in China

2.1 Existing Literature

The view that rural-urban labor migration and labor reallocation have been a key engine of growth in China is prominent in the literature. It features, for example, in discussions by: Meng and Bai (2007), Gong et al. (2009), Li et al. (2012), Gollet and Meng (2011), Cai and Du (2011), Ge and Yang (2011), Rodrik (2012), Meng (2012), Zhu (2012), and Yao (2011).

Likewise there is also a prominent view that the slowing of rural-urban migration implies a significant slowing of China’s growth. Examples include Brandt et al. (2008), Garnaut and Huang (2006), Cai and Wang (2010), Huang and Jiang (2010), Rodrik (2010), Cai and Du (2011), and The Economist (2013). In particular Krugman (2013) argues that China’s growth is about to “hit its Great Wall” because it is running out of “surplus peasants”.

The key proposition underlying this view is that reallocation generates efficiency gains through improvements in resource allocation, as emphasized first by Lewis (1954). In addition to the literature on China, this idea is supported by recent empirical studies that find large differences between agricultural and non-agricultural productivity across many countries (Gollin et al., 2014).

Similarly many recent studies have argued that factor misallocation is not only a ubiquitous feature of developing economies, but also a key part of the growth process (Young, 1995, 2003, Vollrath, 2009, McCaig and Pavcnik, 2013).

2.2 Data on Structural Change

A preliminary assessment of the data on sectoral labor misallocation and the productivity gap for China is given in Figures 1-4. Figures 1-2 show the changes in the employment and output (value-added) shares in China. The employment share of non-agriculture rises from 30% in 1978 to 65% in 2011. Similarly the output share of non-agriculture increases from 70% to 95%.

3 Also see Table 1 below for additional quantitative studies.

4 Gollin et al. (2014) observe these productivity gaps but deliberately refrain from drawing implications of these differences for growth which is the focus of this study.

5 In what follows we refer to sectoral value added, or output net of intermediate inputs, as simply “sectoral output”.
Figure 3 shows the average labor productivity (value added per worker) in China in the agricultural and non-agricultural sectors. Clearly output per worker is lower in agriculture. Moreover it can be seen that over most of this period, from the mid-1980s to about 2002, per worker income growth in agriculture was much slower than nonagriculture.

Figure 4 thus shows that the productivity gap was about 6-fold in the 1980s and, despite the large sectoral reallocation of labor, increased to 9-fold over three decades. In terms of the data presented by Gollin et al. (2014) this suggests that the sectoral productivity gap in China remains high relative to other countries.

3 Accounting for the Impact of Labor Reallocation

Given this large gap in average labor productivity, the proposition that labor reallocation has resulted in large efficiency gains, and hence significantly contributed to China’s growth, seems plausible. Table 1 summarizes the results from existing growth accounting literature on the contribution of labor reallocation to China’s growth. The reported “reallocation effects” range from approximately zero to over three percentage points per year, over any given period.

In interpreting these studies it is important to realize that two, quite distinct, decomposition methods have been used. In the first method the “reallocation effect” is calculated as the residual of the difference between aggregate GDP per capita growth and the sum of the growth rates of each sector weighted by their sectoral output shares. This method has been applied widely to quantify what are generally described as “reallocation effects from structural change”. Some prominent examples include Kuznets (1957), Nordhaus
(1972), Syrquin (1984), Maddison (1998), Broadberry and Crafts (2003), and McMillan and Rodrik (2011). For ease of reference we refer to this as the “shift-share” method.\footnote{Some studies, such as Fabricant (1942) and Timmer and Szirmai (2000), express the decomposition in terms of the absolute change in sectoral output weighed by the sectoral labor shares. Converting this expression into proportional changes is identical to (2).

Other related econometric approaches include Fan et al. (2003), Heytens and Zebregs (2003), and Li and Liu (2011). Another prominent growth accounting study on China is Young (2003), though this study focuses only on TFP growth in the non-agricultural sector and does not report estimates of reallocation effects.

The most comprehensive existing statement of this dichotomy is Syrquin (1984). Some discussion of the shift-share approach is also given in Syrquin (1998), Timmer and Szirmai (2000), van Ark and Timmer (2003), Timmer and de Vries (2009), and Temple (2001, 2005). The shift-share method has also been described as a “crude approximation” by Maddison (1998) and Brandt et al. (2008) express frustration in assigning a meaningful interpretation to their shift-share based labor reallocation estimates. Temple (2001) and Temple and Wößmann (2006) note that the shift-share approach and the Solow-Denison-Kuznets approach are different, though they don’t compare the methods formally. They suggest that the shift-share method may be intended to capture a broader notion of structural change.}

The second approach to quantifying the impact of factor reallocation and structural change is multi-sector growth accounting. This is a two-sector equivalent of standard growth accounting, due to Solow (1957), but developed to include multiple sectors by Kuznets (1961), Denison (1967), Robinson (1971), Chenery \textit{et al.} (1975), and Syrquin (1984, 1998). Recent expositions include Barro (1999) and Temple (2001).

As shown in Table 1 the shift-share method remains the most widely used approach in the growth literature on China. Eleven out of sixteen studies on China use the shift-share method and only five use standard growth accounting.\footnote{Most comprehensive existing statement of this dichotomy is Syrquin (1984). Some discussion of the shift-share approach is also given in Syrquin (1998), Timmer and Szirmai (2000), van Ark and Timmer (2003), Timmer and de Vries (2009), and Temple (2001, 2005). The shift-share method has also been described as a “crude approximation” by Maddison (1998) and Brandt \textit{et al.} (2008) express frustration in assigning a meaningful interpretation to their shift-share based labor reallocation estimates. Temple (2001) and Temple and Wößmann (2006) note that the shift-share approach and the Solow-Denison-Kuznets approach are different, though they don’t compare the methods formally. They suggest that the shift-share method may be intended to capture a broader notion of structural change.}

Although these alternative approaches to quantifying structural change have been discussed in the literature, there is relatively little discussion of the implications of each method in terms of how they relate to each other, or whether they are quantitatively different.\footnote{Most comprehensive existing statement of this dichotomy is Syrquin (1984). Some discussion of the shift-share approach is also given in Syrquin (1998), Timmer and Szirmai (2000), van Ark and Timmer (2003), Timmer and de Vries (2009), and Temple (2001, 2005). The shift-share method has also been described as a “crude approximation” by Maddison (1998) and Brandt \textit{et al.} (2008) express frustration in assigning a meaningful interpretation to their shift-share based labor reallocation estimates. Temple (2001) and Temple and Wößmann (2006) note that the shift-share approach and the Solow-Denison-Kuznets approach are different, though they don’t compare the methods formally. They suggest that the shift-share method may be intended to capture a broader notion of structural change.}

Moreover it is not obvious that the choice of method makes much difference. For example the study by Maddison (1998) finds an estimated “resource reallocation” effect of 1.4 percentage points over 1978-1993 whereas Nehru \textit{et al.} (1997) find a “labor reallocation effect” of 1.5 percentage points over the similar period 1978-1995.

Nevertheless it turns out that this supposition is incorrect. As we show below, analytically and quantitatively, the shift-share approach will typically give much larger “reallocation effects” than the Denison-Kuznets growth accounting method.
3.1 Alternative Measures of Reallocation Effects

In order to identify the analytical difference between the shift-share and Denison-Kuznets methods, consider an economy with two sectors, an agricultural sector \((A)\) and a non-agricultural sector \((M)\). Letting \(Y_M\) and \(Y_A\) be non-agricultural and agricultural output respectively, and choosing the price of agricultural output as the numeraire, GDP is \(Y = pY_M + Y_A\). Thus GDP per worker, \(y \equiv Y/L\) can be expressed as

\[
y = py_M l_M + y_A l_A
\]

where \(y_i \equiv Y_i / L_i, l_i \equiv L_i / L, i \in \{M, A\}\). As shown in Appendix 1, totally differentiating (1), and using a carat to denote a percentage change, \(\hat{x} = dx/x\), gives

\[
\hat{y} = s_M \hat{y}_M + s_A \hat{y}_A + ((p y_M - y_A)/y) l_M \hat{l}_M
\]

where \(s_A = y_A l_A / y\) and \(s_M = p y_M l_M / y\) are output shares of each sector.\(^9\)

This is the shift-share decomposition used by Maddison (1998), Bosworth and Collins (2008), and Bloom et al. (2010) among others listed in the first part of Table 1. In a non-China context this method has also been used to report reallocation effects by, for example, Timmer and Szirmai (2000), Ocampo et al. (2009), McMillan and Rodrik (2011), McCaig and Pavcnik (2013), and McMillan et al. (2014).

Typically the first two terms \(s_M \hat{y}_M + s_A \hat{y}_A\) are described as the \textit{“within sectoral contribution”} to aggregate growth, and the reallocation effect, \(R_{SS}\), is identified as the last term in (2).

\[
R_{SS} = ((p y_M - y_A)/y) l_M \hat{l}_M
\]

It can be seen that \(R_{SS}\) can be calculated directly from (3). Nevertheless it is more commonly calculated as a residual by subtracting the observed “within sectoral contribution” terms in (2) from observed values of \(\hat{y}\).

\(^9\)We follow the literature in treating the relative \(p\) as time invariant, hence \(\hat{p} = 0\).
The rationalization for identifying $R_{SS}$ as the “labor reallocation effect” follows from the fact that if there is no reallocation of labor then $\hat{t}_M = 0$ and $R_{SS} = 0$. Alternatively, if there is labor reallocation, but labor productivity is the same across sectors, then $p_y M - y_A = 0$ and again $R_{SS} = 0$. Moreover a positive value of $R_{SS}$ could also arise even when there is no misallocation in labor market, e.g. sectors can have different average product of labor but the same marginal product of labor.

But in what sense is $R_{SS}$ actually what we mean by “reallocation” effects? The usual concept of a labor reallocation effect is the effect of a change in the labor share on total output. Thus a reallocation effect can be defined as

$$ R \equiv (d \hat{y} / d\hat{t}_M) \hat{t}_M $$

It can be seen from inspection of (4) that the shift-share reallocation effect, $R_{SS}$ will be equal to this expression only if the values of output per worker $p y_M$, $y_A$ are independent of the allocation of labor, $t_M$. That is $R_{SS} = R$ only if $d \hat{y}_M / d\hat{t}_M = d \hat{y}_A / d\hat{t}_M = 0$.

Standard production theory, however, suggests that the reallocation of labor will affect the marginal product of each factor due to diminishing returns. Suppose, therefore, we specify a neoclassical production function in each sector, that exhibits constant returns to scale and diminishing marginal returns to each factor. Each sector consists of homogeneous price taking firms who choose capital and labor inputs to minimize costs and hence the return to each factor is equal to the value of its marginal product.

To keep the analysis as clear as possible we assume Cobb-Douglas production functions in each sector, $y_M = A_M k_M^\beta$ and $y_A = A_A k_A^\alpha$, where $y_i = Y_i / L_i$, $k_i = K_i / L_i$, $L = L_M + L_A$ and $K = K_M + K_A$, $0 \leq \alpha \leq 1$ and $0 \leq \beta \leq 1$.\(^{10}\) Cost minimization thus implies $w_M = (1 - \beta) p y_M$ and $w_A = (1 - \alpha) y_A$. Under these neoclassical assumptions (4) then gives a measure of $R$ which we label the Denison-Kuznets reallocation effect.

$$ R = ((w_M - w_A) / y) t_M \hat{t}_M \equiv R_{DK} $$

Comparing (5) with (3) we can see that $R_{SS}$ and $R_{DK}$ are similar. The difference is that $R_{SS}$ weights labor growth by the difference in average product of labor, $p y_M - y_A$.

\(^{10}\)We use a Cobb-Douglas production function only for analytical convenience. The derivation of $R_{DK}$ holds for neoclassical production functions in general. For an example see Temple (2001).
whereas for $R_{DK}$ the weights are the differences in the marginal product of labor or wages, $w_M - w_A$.

The two concepts are the same in the limiting case where the production function is a linear function of one factor – in which case the marginal and average products are the same. Thus the shift-share model can be thought of as the growth accounting reallocation effect based on linear production functions with one input, labor. In this sense it is a special case of the Denison-Kuznets method where $\alpha = \beta = 0$.

### 3.2 Interpreting the Reallocation Effects

Before proceeding it is useful to note other differences in the interpretation of $R_{DK}$ and $R_{SS}$. First consider the standard Solow-Residual concept, or total factor productivity growth, measured at the aggregate level. This is defined as $TFP \equiv \dot{y} - \gamma \dot{k}$ where $\gamma$ is the economy-wide capital share. It can also be shown, however, that $TFP = \dot{A} + R_{DK}$ where $\dot{A} \equiv s_M \dot{A}_M + s_A \dot{A}_A$ is the weighted sum of sectoral Hicks neutral productivity growth (see Appendix 4). Thus the sum of $R_{DK}$ and Hicks neutral productivity growth will exhaust total $TFP$.

Thus $R_{DK}$ satisfies this adding up condition and, in this sense, $R_{DK}$ is a component of $TFP$ whereas $R_{SS}$ is not. For example $R_{SS}$ may be positive even if $TFP$ is zero.\footnote{This is a simple extension of our earlier point that $R_{SS}$ may be positive even if there is no market distortion so that $w_M = w_A$ (see also Syrquin, 1984). In this case aggregate $TFP$ growth will be zero despite the fact that $R_{SS} > 0$. One can decompose aggregate $TFP$ into $R_{SS}$ and other possible factors, as for example Maddison (1987) and Bosworth and Collins (2008) do, but there is no adding up constraint that ensures that $R_{SS}$ and other productivity growth will exhaust total $TFP$ growth.

$R_{DK}$ is the partial effect of labor reallocation for a given allocation of capital whereas the literature suggests that $R_{SS}$ is sometimes interpreted as a total, capital plus labor, factor reallocation effect. As

In addition there is considerable ambiguity in the literature as to whether $R_{SS}$ is a labor reallocation effect or a total factor reallocation effect. For example, Van Ark (1996), Broadberry (1997), Broadberry and Crafts (2003), and Bosworth and Collins (2008) refer to $R_{SS}$ as measuring the “shift of resources out of agriculture” or a “resource allocation” effect. Cao and Birchenall (2013) use the term “sectoral reallocation effect”. However Maddison (1998), Bloom \textit{et al.} (2010), Brandt \textit{et al.} (2008), Kujis and Wang (2006), Vries \textit{et al.} (2012), Dekle and Vandenbroucke (2010), and McMillan and Rodrik (2011) describe their shift-share value, $R_{SS}$, as capturing “labor reallocation effects”. Likewise recent studies by Roncolato and Kuca (2013), McCaig and Pavcnik (2013), and Ocampo \textit{et al.} (2009) also refer to $R_{SS}$ as measuring labor reallocation effects. This ambiguity highlights the difficulty of ascribing a clear economic interpretation to $R_{SS}$.
\footnote{\textit{The Shift-Share and Denison-Kuznets Methods of Growth Accounting.}\footnote{\textit{The Shift-Share and Denison-Kuznets Methods of Growth Accounting.}}}}
Thus while the Denison-Kuznets effect correctly measures the impact of allocative efficiency gains on the growth rate, it is less clear what $R_{SS}$ measures. In the standard neoclassical setting with competitive markets and constant returns to scale it can be viewed as an approximation to the actual impact of allocative efficiency improvements based on a linear production function. Similarly $R_{SS}$ can be seen as a special case of $R_{DK}$ when the production functions are linear in labor, with no other inputs. Hence, although the shift-share method is slightly more parsimonious, insofar as it does not require information or assumptions about the labor cost shares to compute $w_M$ and $w_A$, this parsimony also imposes limitations in terms of accuracy and creates ambiguity in its interpretation.\footnote{The shift-share method is nevertheless useful as a decomposition method in other applications where there is no particular theoretical guidance. For example decomposing inequality into “between” and “within” region effects.}

### 4 Quantitative Implications of the Shift-Share versus Denison-Kuznets Methods

#### 4.1 A Simple Rule

The preceding augments would be of little consequence if in fact $R_{SS}$ and $R_{DK}$ were typically similar, so that $R_{SS}$ was a good approximation for $R_{DK}$. We therefore now consider how $R_{SS}$ and $R_{DK}$ differ quantitatively.

Using (3) and (5) the ratio $R_{DK}/R_{SS}$ can be expressed as

\[
R_{DK}/R_{SS} = (1 - \beta) - (\beta - \alpha)/(p y_M/y_A - 1)
\]

Inspection of (6) shows that if the labor income shares are equal across both sectors, then $R_{DK}/R_{SS} = 1 - \beta < 1$. This particular case of equal factor shares is important since there is some evidence that factor shares across sectors are generally quite similar (Gollin, 2002).

More generally, however, from (6) it can also be seen that if: (i) the difference in shares noted above, however, $R_{SS}$ can be non-zero even when all factors are allocated efficiently. Hence it follows that $R_{SS}$ is not, in general, equal to the total factor reallocation effect. See Appendix 4 for a definition of the total factor reallocation effect.
\( \beta - \alpha \) is small, or; (ii) there is a large labor productivity gap, so that \( p_y M / y_A \) is large, then \( R_{DK} / R_{SS} \approx 1 - \beta \). We therefore have the following useful rule of thumb:

**Proposition:** If the labor cost shares are similar across sectors, or if there is a large labor productivity gap across sectors, then the shift-share reallocation value, \( R_{SS} \), will overstate the growth accounting labor reallocation value, \( R_{DK} \), by a factor of approximately \( 1 / (1 - \beta) \), where \( \beta \) is the non-agricultural labor share.

As noted above in Figure 4, for China the gap in average labor productivity, \( p_y M / y_A \), is large, varying between 6 and 9. Hence if, as the evidence suggests for China, \( 0.4 \leq 1 - \beta \leq 0.6 \) then \( R_{SS} \) will overestimate the TFP gains from labor reallocation by approximately \( 1 \frac{2}{3} \) to \( 2 \frac{1}{2} \) times.

### 4.2 Base Data

To obtain a more accurate estimate we proceed by computing both \( R_{SS} \) and \( R_{DK} \). We require Chinese data on sectoral outputs, sectoral factor inputs, factor shares and GDP.

Factor share data are taken from Bai and Qian (2010), which are based on provincial GDP data from Hsueh and Li (1999) and the National Bureau of Statistics China (2007). Bai and Qian (2010) find an average labor share of \( 1 - \beta = 0.47 \) for non-agriculture.\(^{14}\)

For agricultural labor shares Bai and Qian (2010) report a value of \( 1 - \alpha = 0.89 \) but acknowledge that this is overestimated since it includes land income. Cao and Birchenall (2013) therefore propose an adjustment which reduces this value from 0.89 to 0.38. In what follows we therefore choose a parsimonious value of \( 1 - \alpha = 2/3 \), as a base case and also experiment with \( 1 - \alpha = 0.89 \) and \( 1 - \alpha = 0.38 \). As implied by the preceding Proposition, however, the results are very insensitive to changes within this range.

These values are also similar to other values reported in the literature. For example, for agriculture and non-agriculture respectively, the labor shares are 0.5 and 0.6 over 1978-2004 in Bosworth and Collins (2008), 0.5 and 0.5 over 1978-2008 in Brandt et al. (2008), and 0.76 and 0.46 over 1978-2003 in Dekle and Vandenbergroucke (2010, 2012). An exception is Chow (1993) who obtains a much smaller value of 0.32 for agriculture over 1952-1988 using a production function estimation. Using alternative labor shares affects the results in predictable ways based on (6) and does not affect our conclusions significantly.\(^{15}\)

\(^{14}\)This is also very close to the value found by Young (2003) based on data from national accounts and input-output tables.

\(^{15}\)These alternative values are given in Appendix 6.
For output we use the sectoral value added data from Bosworth and Collins (2008) for 1978-2004. This is updated to 2011 using data from the China Statistics Yearbook (hereafter CSY).\textsuperscript{16} Hence, we use the official GDP deflator from the CSY for the agriculture and the ex-factory industry price index from the CSY as the deflator for the industry sector.

The capital stock estimates are calculated from the gross fixed capital formation drawn from various issues of the CSY. Following Young (2003) we use the official investment deflator taken from the World Development Indicators database. We use the capital-output ratio and assumed depreciation rate (6\%) from Young (2003). The resulting aggregate capital stock data are in line with existing estimates, such as Wang and Yao (2003) and Chow and Li (2002).

The sectoral capital shares for 1978-1995 are taken from Hsueh and Li (1999). For 1996-2011 we use investment in fixed asset shares by the three main sectors from the CSY.

Finally sectoral employment data are obtained from Bosworth and Collins (2008). Specifically for 1978-2002 we sum employment over sub-sectors from various issues of the CSY to obtain agricultural and nonagricultural employment, instead of relying on pre-summed totals. Sub-sector splits are not available after 2002, so we use the employment shares of the three main sectors from various issues of the CSY, and multiply by total employment to obtain employment in agriculture, industry, and services.\textsuperscript{17}

### 4.3 Alternative Data Sources

The base data described above are very standard. Nevertheless there are also many well known issues with Chinese data and there is a large literature on revised and corrected macroeconomic aggregates. To that end we have also conducted an extensive sensitivity analysis using some of these alternative data sets. These alternatives and additional results are detailed in Appendix 6. However we also briefly comment here on some of the sources and motives for data revisions.

\textsuperscript{16}Bosworth and Collins (2008) divide the economy into three sectors: agriculture, industry and services. For ease of comparison with other studies we aggregate industry and services, into the “non-agriculture” sector. Nevertheless we obtain the same reallocation as Bosworth and Collins (2008), to two decimal places, when using the same data and shift-share methodology.

\textsuperscript{17}Note that the pre-summed total employment or employment by the three main sectors from the CSY have been revised in accordance to the population censuses since 1997, they are not necessarily close to the sum of sub-sectoral employment data from administrative reporting system. Therefore, the magnitude of the 1997 downward revision was factored to obtain a new pre-summed employment figure for the years after 2002.
First it is often claimed that Chinese real GDP growth is overestimated due to firms’ incentives for upward reporting bias and the reporting system itself (Woo, 1998). This issue has been addressed by Bosworth and Collins (2008) and Young (2003) by using alternative price indices. A second way to overcome this bias is to develop a physical output index, as proposed by Wu (2012, 2011). Thus we also report the results using the real output series of Wu (2011) in Appendix 6.

With respect to capital, Holz (2006b) has constructed an index based on asset scrap rates instead of a depreciation rate. This series exhibits a lower growth rate in the mid 1990s. Similarly Wang and Szirmai (2012) report capital stocks based on the age-efficiency profiles instead of age-price profiles. These show a higher growth rate, since 1980, than the existing estimates. Again we report the results for these alternatives in Appendix 6.

Finally, Holz (2006a) and Brandt et al. (2008) have pointed to problems with Chinese employment data due to the treatment of laid-off workers, undocumented off-farm migration and non-farm rural self-employment. To address these concerns, we use data from these sources as well. In addition we also allow for floating migrants following Bulman and Kraay (2011). Lastly, we also consider the data set from Wu (2011) which adds military personnel to non-productive service employment. Again these results are given in Appendix 6.

4.4 Quantitative Results

4.4.1 Growth Accounting Results

Before discussing the actual reallocation effects it is useful to first consider the overall growth accounting results, in order to give some context and provide a point of comparison with other studies.

To that end Table 2 gives a summary of the standard growth accounting results for each sector and the aggregate economy. Notably, due to massive rural-urban migration, the annual growth rate of employment in the non-agriculture sector (4.03%) is much higher than the agricultural sector (-.59%). This is also reflected in a significant increase in the non-agricultural employment share from 0.29 to 0.65 over 1978-2011 (see also Figure 1). Accompanying this massive labor reallocation there is also rapid capital accumulation at

\[18\text{His estimates also address several other shortcomings associated with most previous estimates, particularly with respect to the choice of investment data.}\]
the sectoral and aggregate level.

The decomposition of per worker GDP reveals that the contribution of capital accumulation is 4.91 percentage points per year, out of 8.12 percentage points per year of GDP growth per worker. Thus, capital accumulation plays an important role in China’s labor productivity growth.

Although nearly all (95%) of the capital is in non-agriculture, it can be seen that the annual growth rates of capital in each sector are relatively similar. Thus, although the agricultural sector has only 5% of the economy’s capital, agricultural capital has grown fast enough to maintain a constant share over time.\(^{19}\) Hence despite the importance of aggregate capital accumulation, the sectoral reallocation effects in China have been dominated by labor movements.

Finally we find that TFP growth is also important, accounting for 3.05 percentage points per year overall with a slightly higher growth rate in non-agriculture than agriculture.\(^{20}\)

### 4.4.2 Reallocation Effects

These growth accounting data give a picture of China’s growth that is very consistent with the existing literature, but our focus is on the reallocation effects. The results for the reallocation effects using the shift-share method, \(R_{SS}\), and the Dension Kuznets method, \(R_{DK}\), are given in Table 3. For reference Columns (1) - (3) report GDP per worker growth, the capital contribution, and the TFP contribution for the relevant sub-periods. By construction Column (1) is the sum of Columns (2) and (3).

The shift-share reallocation effect, \(R_{SS}\), from (3) is given in Column (4). It can be seen that for the period 1978-2011, \(R_{SS} = 1.76\) percentage points per year.\(^{21}\) Likewise \(R_{SS}\)

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\(^{19}\)Consequently the capital reallocation effects are very small. We find a value of 0.03 percentage points per year over 1978-2011. The capital reallocation effect is discussed further in Appendix 4.

\(^{20}\)This is a broad definition of TFP growth that includes the reallocation effects discussed below as well as any human capital accumulation and unmeasured inputs.

\(^{21}\)The reported value is the simple average of the values over the relevant period. Our values do not correspond exactly to those reported by Bosworth and Collins (2008) since for simplicity we aggregate the data to just two sectors whereas Bosworth and Collins use three sectors. However for the same time
varies from 1.17 percentage points per year in 1991-2001 to 2.46 percentage points per year in 2001-2011.

Thus these figures might be interpreted as implying that reallocation effects account for a relatively large fraction of growth. For example for 1978-2011 $R_{SS}$ is 1.76 percentage points per year compared to GDP per worker growth of 8.12 percentage points per year and a TFP growth rate value of 3.05 percentage points per year.

The Denison-Kuznets growth accounting results, $R_{DK}$ from (5), are shown in Column (5) of Table 3. It can be seen that the value of $R_{DK}$ for 1978-2011 is 0.77 percentage points per year, which is significantly less than $R_{SS} = 1.76$ percentage points per year. Likewise comparing Columns (4) and (5) over each sub-period the value of $R_{DK}$ is much smaller than $R_{SS}$, and it is easy to verify that $R_{SS}$ is around 2.3 times larger than $R_{DK}$ in each sub-period.22

These estimates therefore confirm the Proposition, that the shift-share method significantly overstates the impact of labor reallocation on growth in this neoclassical setting.

Thus we have shown that the vast majority of studies on growth and labor reallocation in China have used the shift-share method as opposed to the Denison-Kuznets method. Second we have shown that, with competitive markets and constant returns to scale, the Denison-Kuznets method is a preferred measure of the labor reallocation effect. Third we have now also shown, both analytically and numerically, that the shift-share method significantly overstates the growth effects of labor reallocation in China.

Consequently we reach a preliminary conclusion that most of the existing literature on China’s growth and labor reallocation has overstated the quantitative impact of labor reallocation on China’s TFP growth by a factor of around 2.3 times. Application of the Denison-Kuznets method, with a standard data set, suggests that labor reallocation has contributed 0.77 percentage points per year, to China’s growth. This compares with a TFP growth of 3.05 percentage points per year and a per worker GDP growth rate of 8.1 percentage points per year. Thus conventional growth accounting, with standard data and factor shares, indicates that labor reallocation effects have been quite small.

periods our results are very close to theirs. For example we find $R_{SS} = 1.8$ percentage points per year for 1978 to 1993 which corresponds to the value of 1.7 percentage points per year reported by Bosworth and Collins (2008).

22The results for $R_{DK}$ change very little when alternative labor shares in agriculture are used. If the labor share in agriculture is 0.89 or 0.38, then $R_{DK}$ becomes 0.71 and 0.85 percentage points per year, respectively, over 1978-2011. In terms of sensitivity in response to alternative data sources, $R_{DK}$ ranges from 0.59 (1978-2008) to 0.92 (1978-2011) percentage points per year (see Appendix 6). The ratio $R_{DK}/R_{SS}$ however remains fairly constant around 0.43 to 0.44.
5 Human Capital

The literature cited above implicitly assumes that differences in the marginal, or average, product of labor across sectors is evidence of inefficient factor allocation. Nevertheless there may be many reasons why the marginal product of labor may not be equated across sectors in equilibrium. This includes differences in living costs, transport, and migration costs. Similarly there may be unmeasured differences in human capital across sectors.

These factors are typically ignored because they are difficult to measure. Nevertheless Li (2014) have recently compiled data on human capital levels across sectors based on the standard Mincerian concept of human capital. It is therefore interesting to consider the extent to which differences in the average level of human capital might further adjust the gains from labor reallocation.

Figure 5 thus shows the ratio of the level of human capital across urban and rural sectors in China based on Li (2014). It can be seen that in the 1980s the urban sector had approximately twice as much human capital per worker than the rural sector and that this ratio rises gradually through time, to about 2.5 times. The growth in the ratio is a significant achievement given that there is also rapid rural-urban migration at this time.

While this rural-urban distinction is not identical to our agriculture and non-agriculture division, there is likely to be considerable overlap and we therefore proceed under the assumption that the rural-urban data on human capital will reflect human capital levels of labor employed in agriculture and non-agriculture. Then we can define the total supply of labor services to non-agriculture and agriculture to be $H_M = h_M L_M$ and $H_A = h_A L_A$, where $h_M$ and $h_A$ are the sectoral levels of human capital per worker taken from Li (2014).

Figure 6 then compares the labor productivity data, $py_M = p Y_M / L_M$ and $y_A = Y_A / L_A$, with productivity per effective unit of labor, $p Y_M / H_M = py_M / h_M$, and $Y_A / H_A = y_A / h_A$. As expected the gap in output per effective worker is much smaller than that of output per worker. Skill adjusted productivity, or output per effective worker, is around 3 to 4 times higher in non-agriculture. This is approximately half the gap in output per worker of 6 to 9 times. This magnitude of adjustment for human capital differences across sectors

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23Note however that Li (2014) distinguish between rural and urban sectors, instead of agriculture and non-agriculture. This represents a potential limitation of our data. Also, data on real human capital per worker by sector (rural and urban) are available for 1985-2010, thus data over 1978-1984 and 2011 are derived based on mean growth of real human capital per worker over 1985-1990 and 2005-2010, respectively.
is very similar to those reported by Gollin et al. (2014) across a number of countries. It suggests that the labor reallocation effects derived above overstate the actual gains since they overstate the actual difference in labor productivity between sectors.

[Figure 6 about here]

5.1 Growth Accounting with Human Capital

In order to see the implications of sectoral human capital differences for the measurement of the Denison-Kuznets reallocation effect, suppose workers all supply one unit of labor time inelastically and differ in only their skill level \( h_i \). The aggregate production functions in each sector are then \( y_M = A_M k_M^{\beta} h_M^{1-\beta} \) and \( y_A = A_A k_A^{\alpha} h_A^{1-\alpha} \). The value of the marginal product of a unit of labor in non-agriculture is \( w_e^M = (1 - \beta)(p y_M / h_M) \) and the wage per effective worker in agriculture is \( w_e^A = (1 - \alpha)(y_A / h_A) \). Hence the wage rates per unit of time for a worker providing a level of services \( h_i \) are respectively \( h_i w_e^M \) and \( h_i w_e^A \).

Labor market clearing requires that the wage rate is the same for workers with the same skill level, which therefore requires that the wage per efficiency unit is equated across both sectors, \( w_e^A = w_e^M \). Hence, even in an efficient market with no misallocation, there will exist an apparent wage gap of \( w_e^M - w_e^A = (h_M - h_A)w_e > 0 \) between sectors, which simply reflects the fact that skill levels differ across each sector.

Intuitively, the reallocation effect should depend on the gap \( w_e^M - w_e^A \) and the difference in human capital levels. Thus, as shown in Appendix 2, the Denison-Kuznets reallocation effect is now

\[
R^H_{DK} = \left( \frac{(w_e^M - w_e^A)}{y^e} \right) \left( \frac{h_i}{h_M} \right) l_M^e \hat{l}_M
\]

where \( l_M^e \equiv H_M / (H_M + H_A) \) and \( h_i \) is the skill level of the migrant. A similar human capital adjustment can also be applied to the shift-share methodology (see Appendix 3).

It can be seen that (7) differs from (5) in two main respects. First, as expected, the reallocation effect depends on the wage gap in terms of efficiency units. The higher level of human capital per worker in non-agriculture means that \( (w_e^M - w_e^A) / y^e < (w_M - w_A) / y \), so other things equal we expect \( R^H_{DK} < R_{DK} \).

Second, the reallocation effect contains the term \( h_i / h_M \) which reflects the impact of the
movement of skills on each sector’s average human capital level. For example suppose that migrants from agriculture have the same skill level as the agricultural average, so that \( h_i = h_A \) and so \( h_i/h_M < 1 \). In this case this term also reduces the size of \( R^H_{DK} \) and this can be thought of as the impact of migrants diluting average human capital per worker in non-agriculture. If \( h_i < h_A \) then this would further reduce \( R^H_{DK} \). Alternatively if migrants have the same level of human capital as modern sector workers, then \( h_i/h_M = 1 \). Even in this case, therefore, overall we still expect \( R^H_{DK} < R_{DK} \).

Li (2014) do not provide evidence on migrants’ human capital levels. Nevertheless evidence in Sicular et al. (2007) suggest that migrants’ human capital levels in China are significantly lower than the average in the urban sector, and very close to the rural average. Thus the human capital adjusted reallocation effects \( R^H_{SS} \) and \( R^H_{DK} \) are given in Columns (6) and (7) of Table 3 for the case \( h_i = h_A \). The implications of alternative assumptions, along with some evidence on the skill level of migrants in China, are given in Appendix 5.

It can be seen that the adjustment for sectoral differences in human capital also results in a significant downward adjustment in the size of the labor reallocation effect. Over 1978-2011, the Denison-Kuznets measure is reduced from 0.77 percentage points per year to 0.25 percentage points.\(^{24}\) In each sub-period the adjustments to \( R^H_{SS} \) and \( R^H_{DK} \) are of similar magnitude. Likewise allowing for human capital differences across sectors reduces the shift-share measure from 1.76 percentage points per year to just 0.66 percentage points per year.

### 5.2 Combined Impact

We now summarize the total impact of all adjustments by comparing the values obtained from the shift-share analysis, \( R_{SS} \) in Column (4) of Table 3, with our preferred measure, \( R^H_{DK} \) in Column (5).

It can be seen that the total effect is substantial. Over the entire period 1978-2011, moving from the shift-share method to the more appropriate Denison-Kuznets method, and allowing for human capital differences across sectors, the value of the “reallocation effect” falls from 1.76 percentage points per year to just 0.25 percentage points per year.

Thus on the one hand we have the conventional figure of around 1.76 percentage points per year as a measure of the gains from labor reallocation in China. But using the more

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\(^{24}\) \( R^H_{DK} \) using alternative data sources varies from 0.13 percentage points per year to 0.25 percentage points per year, for the period 1978-2011.
appropriate Denison-Kuznets method, and allowing for the difference in labor quality across sectors, reduces the contribution of labor reallocation to 0.25 percentage points per year, making it a relatively minor component of growth. The pattern is similar across each period where we find that the human capital adjusted Denison-Kuznets labor reallocation effects are always quite small relative to per worker GDP growth.

6 Discussion

Our results thus suggest that the conventional view – that labor reallocation has made a major contribution to China’s growth – is not readily justified by standard growth accounting analysis. A reallocation effect of 0.25 percentage points per year is very small relative to China’s overall growth and is much smaller than the conventional view in the literature of 1 to 2 percentage points per year.\textsuperscript{25}

This conclusion may seem surprising given the historical importance of structural change in development theory, and the extensive literature on labor reallocation and growth in China. Hence it is important to note some caveats.

First there are clearly a number of reliability or quality issues with Chinese data. In particular the human capital data should be viewed as indicative only. But more broadly there is significant room for improvement for most of the macroeconomic data. We have tried to minimize this uncertainty by showing that the results are not very sensitive to the use of alternative data on employment, capital, output and labor shares.

In addition our results are clearly conditional upon the framework in which they are derived – the neoclassical production model with competitive markets and constant returns to scale. Under these assumptions the Denison-Kuznets reallocation effect is the correct measure of the gains from labor reallocation and the shift-share method can be seen as an approximation based on a linear production function.

This gives a clear basis for preferring the Denison-Kuznets measure of reallocation effects. Nevertheless it is possible that the neoclassical model doesn’t capture all of the relevant links between labor reallocation and growth.

\textsuperscript{25}Moreover it is also possible that our estimates, though very small, overstate the gains from labor reallocation, since we have not taken into account differences in prices across urban and rural regions. Some estimates of these differences are given by Sicular et al. (2007).
6.1 Externalities, Economies of Scale, and Surplus Labor

Many models of structural change are based on explicit assumptions about economies of scale in the modern sector, or externalities associated with public goods. Both imply additional direct links between labor reallocation and productivity that are not considered in the standard growth accounting framework.

Likewise the standard Denison-Kuznets growth accounting approach assumes that all factors are fully employed and valued at their marginal products. Hence it excludes a class of “surplus labor” arguments that are sometimes used to motivate a sectoral gap in the marginal product of labor. Denison-Kuznets growth accounting does incorporate surplus labor to the extent that agricultural labor can be earning a wage less than the value of its marginal product in the non-agricultural sector. Nevertheless some surplus labor arguments imply additional consequences of labor reallocation on growth by reducing underemployment.\footnote{Surplus labor theories build on traditional models of Lewis (1954), Ranis and Fei (1961) and Harris and Todaro (1970). As noted above, however, the evidence for surplus labor is very mixed and in the case of China, the gap can be seen purely as a consequence of the Hukou system.}

Thus inter-sectoral labor reallocation may affect growth in other ways, beyond the standard allocative efficiency gains, which are not captured by the Denison-Kuznets reallocation effect. Nevertheless, in this case, neither the shift-share method or the Denison-Kuznets method is necessarily the most appropriate method.\footnote{For examples of modified “shift-share” analyses that take into account increasing returns to scale and surplus labor see Timmer and Szirmai (2000) and van Ark and Timmer (2003).}

6.2 Capital Accumulation

Another consideration relates to the interaction between reallocation effects and capital accumulation. Specifically in a neoclassical growth model, where capital accumulation is endogenous, an improvement in allocative efficiency will induce capital accumulation.\footnote{Specifically in a standard Ramsey model an improvement in output per effective input, will generate an increase in capital equal to the inverse of the aggregate labor share of output. See for example Klenow and Rodriguez-Clare (1997) and Robertson (2000) on the impact of productivity on capital accumulation, and Robertson (1999) and Landon-Lane and Robertson (2009) on the impact of reallocation on capital accumulation.}

It is also useful to know how much extra growth is generated by these induced capital accumulation effects from labor reallocation. Nevertheless this requires an explicit theory of capital accumulation. Because of this the induced capital accumulation effects can only be decomposed using calibrated growth models that specify an explicit mechanism for
Thus, although we find that the effect of labor reallocation on China’s growth, due to improvements in allocative efficiency, is small, this doesn’t mean that structural change is unimportant in China’s growth. But the results do suggest that this particular link between agricultural labor reallocation, allocative efficiency and growth, has been far less significant in China than much of the literature suggests.

Specifically, as noted above, many studies view the slowing of rural-urban migration as a significant cause of China’s growth slowdown (Gong et al., 2009, Zhu, 2012) and this is also a widely held view in the policy literature (The Economist, 2013, Krugman, 2013). Likewise there is a significant literature that emphasizes internal migration and factor accumulation, as opposed to productivity growth, as the main sources of growth in the successful Asian economies including China (Young, 1995, Krugman, 1994, Young, 2003). Since we find that China’s high growth has not relied on large gains from allocative efficiency, our results cast some doubt on the relevance of this perspective for China, and possibly for other countries as well.

7 Conclusion

Seemingly small differences in per capita income growth rates have very large consequences for living standards. Thus it is important to be as accurate as possible when investigating the sources of growth. To that end the standard framework for decomposing growth, dating back to Solow (1957), Denison (1967), and Kuznets (1961), divides growth into factor accumulation and TFP, including reallocation effects. If markets are competitive and there are constant returns to scale, then this Denison-Kuznets method is the correct measure of the impact of labor reallocation on growth. In particular it satisfies an adding up condition such that the value share weighted growth of factor inputs, reallocation effects, and technological progress exhaust total output growth.

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29 For an example with respect to China see Ye (2015). Since we have found that the reallocation effects are a minor component of per worker GDP growth, in a neoclassical growth model they would also be a relatively minor contributor to capital accumulation. As a rule of thumb if, as in China, the capital share is approximately 0.5 then any given improvement in allocative efficiency will have double impact on the level of per worker GDP from one steady state to the next, due to induced capital accumulation.

30 In this context it is interesting to note that our more modest estimates of labor reallocation effects in China are not dissimilar from estimates used in assessing the historical sources of growth in Europe, using the Denison-Kuznets method. Specifically labor reallocation in Europe appears to have accounted for only 1/20 - 1/7th of annual growth in GDP per worker (Temple, 2001). This is similar to our estimates of 0.77 percentage points per year, which represents just under 1/10th of GDP per worker growth in China, before any adjustment for human capital.
Most of the literature on reallocation effects in China (11 out of 16 studies) has, however, used an alternative “shift-share” method, which doesn’t satisfy these adding up properties, but can be interpreted as an approximation to the Denison-Kuznets labor reallocation effect based on linear production functions.

We compare the two approaches and show that the shift-share method produces reallocation effects that are larger than the Denison-Kuznets measure by a factor of, approximately, \(1/(1 - \beta)\), where \(1 - \beta\) is the labor share in non-agriculture. We then show further that, for a range of Chinese data sets, the shift-share reallocation effects are more than twice as large as the Denison-Kuznets labor reallocation effects.

Second, we use recent data on rural-urban human capital differences to improve the measurement of misallocation effects. Specifically, since the measured wage differences across sectors are affected by differences in the average level of human capital, we use the sectoral human capital levels to infer the efficiency wage gap across sectors. Since human capital per worker is much higher in non-agriculture this also leads to a significant downward adjustment in the size of the estimated gains from labor reallocation.

Together these two adjustments lead to a very substantial revision of the role of sectoral labor reallocation in China’s growth from 1.76 percentage points per year over the period 1978-2011 to just 0.25 percentage points per year. This represents a small fraction of China’s growth. As such our results cast doubt on the importance of allocative efficiency gains from labor reallocation in China’s economic miracle. This observation also has implications for contemporary policy – particularly for understanding China’s growth prospects as rural-urban migration slows, and for understanding how other countries might replicate China’s growth miracle.
Appendix 1: Labor Reallocation Effects $R_{SS}$ and $R_{DK}$

(1) The shift-share method and Derivation of $R_{SS}$

Consider an economy with two sectors, an agricultural sector ($A$) and a non-agricultural sector ($M$). Letting $Y_M$ and $Y_A$ be non-agricultural and agricultural output respectively, and choosing the price of the agricultural output as the numeraire, GDP is $Y = pY_M + Y_A$. Thus GDP per worker, $y \equiv Y/L$ can be expressed as

\[(A.1) \quad y = p y_M l_M + y_A l_A\]

where $y_i \equiv Y_i/L_i$, $l_i \equiv L_i/L$, $i \in \{M, A\}$. Totally differentiating (A.1), and using a carat to denote a percentage change, $\hat{x} = dx/x$, gives

\[(A.2) \quad \hat{y} = s_M \hat{y}_M + s_A \hat{y}_A + s_M \hat{l}_M + s_A \hat{l}_A\]

where $s_A = y_A l_A / y$, $s_M = p y_M l_M / y$.\(^{31}\) Finally, noting that $l_A = 1 - l_M$ implies $\hat{l}_A = -l_M / (1 - l_M) \hat{l}_M$, we obtain

\[(A.3) \quad \hat{y} = s_M \hat{y}_M + s_A \hat{y}_A + ((p y_M - y_A)/y) l_M \hat{l}_M\]

$R_{SS}$ is defined as the last term in (A.3)

\[(A.4) \quad R_{SS} \equiv ((p y_M - y_A)/y) l_M \hat{l}_M\]

(2) The Denison-Kuznets Method and Derivation of $R_{DK}$

We assume Cobb-Douglas production functions in each sector

\[(A.5) \quad y_M = A_M k_M^\beta\]

\(^{31}\)We follow the literature in treating the relative $p$ as time invariant, hence $\hat{p} = 0$.\]
\[ y_A = A_A k_A^\alpha \]

where \( y_i = Y_i / L_i \), \( k_i = K_i / L_i \), \( L = L_M + L_A \) and \( K = K_M + K_A \)\(^{32}\). Differentiating (A.1) and using (A.5) and (A.6) then gives

\[ \dot{y} = \dot{A} + s_M \beta \dot{k}_M + s_A \alpha \dot{k}_A + s_M \dot{i}_M + s_A \dot{i}_A \]

where \( \dot{A} = s_M \dot{A}_M + s_A \dot{A}_A \) is sector weighted average productivity growth. It is straightforward to show that

\[ \frac{d \dot{y}}{d \hat{l}_M} = s_M (1 - \beta) - s_A (1 - \alpha) (l_M / l_A) \]

Further assuming that each factor receives the value of its marginal product \( w_M = p (1 - \beta) y_M \) and \( w_A = (1 - \alpha) y_A \), we can define the Denison-Kuznets reallocation effect, from (4) in the main text, as

\[ R_{DK} = ((w_M - w_A) / y) l_M \hat{i}_M \]

\(^{32}\)We use a Cobb-Douglas production function for analytical convenience. The derivation of \( R_{DK} \) holds for neoclassical production functions in general. For an example see Temple (2001).
Appendix 2: Denison-Kuznets Labor Reallocation Effects with Human Capital

Suppose we define a stock of labor in effective units as $H = hL$, and $H = H_M + H_A$. In each sector therefore

\[(A.10)\quad H_M = h_M L_M\]

\[(A.11)\quad H_A = h_A L_A\]

Similarly we define $y_e \equiv Y/H$, $y^e_M \equiv Y_M/H_M$, $y^e_A \equiv Y_A/H_A$, $l^e_M \equiv H_M/H$, $l^e_A \equiv H_A/H$ and the sectoral production functions are given by

\[(A.12)\quad y^e_M = A_M(k^e_M)^\beta, \quad y^e_A = A_A(k^e_A)^\alpha\]

where $k^e_i = K_i/H_i$.

The impact of labor reallocation on aggregate labor productivity growth rate can now be redefined as an adjusted “reallocation effect”

\[(A.13)\quad R^H_{DK} \equiv (d\hat{y}/d\hat{l}^e_M)\hat{l}^e_M\]

Using the chain rule $d\hat{y}/d\hat{l}^e_M$ can usefully be expressed as the product

\[(A.14)\quad d\hat{y}/d\hat{l}^e_M = (d\hat{y}/d\hat{y}^e)(d\hat{y}^e/d\hat{l}^e_M)\]

Note that the second term in this expression is similar to the term derived in Appendix 1, for example in (A.8), without efficiency units. Hence we have

Result A1. Analogous to the model without human capital in the text, the derivative
\( d \hat{y}^e / d \hat{l}_M^e \) can be expressed

\[
(A.15) \quad d \hat{y}^e / d \hat{l}_M^e = (w_M^e - w_A^e) \hat{l}_M^e / y^e
\]

**Proof:** Using (A.10), (A.11), and (A.12) output per effective worker \( \hat{y}^e \) can be expressed as

\[
(A.16) \quad \hat{y}^e = \hat{A} + s_M \beta \hat{k}_M^e + s_A \alpha \hat{k}_A^e + s_M \hat{l}_M^e + s_A \hat{l}_A^e
\]

where \( \hat{l}_M^e = \hat{H}_M \) and \( \hat{l}_A^e = \hat{H}_A \), and we define \( \hat{A} \equiv s_M \hat{A}_M + s_A \hat{A}_A \). Holding total capital stock \( K \) constant to focus on labor reallocation gives

\[
(A.17) \quad d \hat{y}^e / d \hat{l}_M^e = s_M (1 - \beta) - s_A (1 - \alpha) (\hat{l}_M^e / \hat{l}_A^e)
\]

which can be seen to be analogous to (A.8) in Appendix 1. Given that \( py_M^e (1 - \beta) = w_M^e \) and \( y_A^e (1 - \alpha) = w_A^e \) this gives

\[
(A.18) \quad d \hat{y}^e / d \hat{l}_M^e = (w_M^e - w_A^e) \hat{l}_M^e / y^e
\]

This concludes the Proof of Result A1.

To complete the description of reallocation effects with human capital, \( R_{DK}^{\hat{H}} \), from (A.4), we need an expression for \( \hat{l}_M^e \), which expresses how the share of effective workers in each sector changes with reallocation, and an expression for \( d \hat{y} / d \hat{y}^e \).

First note that \( y = y^e \hat{h} \) so that \( \hat{y} = \hat{y}^e + \hat{h} \). Although human capital is reallocated, the total stock of human capital does not change so that \( \hat{h} = 0 \), hence

\[
(A.19) \quad d \hat{y} / d \hat{y}^e = 1
\]

26
Next we need to consider an expression for $\hat{L}_M$ where $\hat{L}_M = \hat{H}_M - \hat{H}$. If the total stock of $H$ and $L$ are constant so that $\hat{H} = \hat{L} = 0$, then

\begin{equation}
(A.20) \quad \hat{L}_M = \hat{H}_M - \hat{H} = \hat{H}_M = d(H - H_A)/H_M = -dH_A/H_M
\end{equation}

We have two cases to consider. First if migrants’ level of human capital is the average level in the agricultural sector, $h_A$, then $dH_A = h_A \, dL_A = -h_A \, dL_M$. Substituting, and noting $H_M = h_M \, L_M$, then (A.20) becomes

\begin{equation}
(A.21) \quad \hat{L}_M = h_A \, dL_M/H_M = (h_A/h_M) \hat{L}_M
\end{equation}

Combining (A.18), (A.19) and (A.21) gives

\begin{equation}
(A.22) \quad R^H_{DK} \equiv \left( (w^e_M - w^e_A)l^e_M/y^e \right) (h_A/h_M) \hat{L}_M
\end{equation}

More generally if migrants’ human capital differs from the average level in the agricultural sector, $h_i \neq h_A$, then $dH_A = h_i \, dL_A = -h_i \, dL_M$, so that

\begin{equation}
(A.23) \quad \hat{L}_M = h_i dL_M/H_M = (h_i/h_M) \hat{L}_M
\end{equation}

Likewise combining (A.18), (A.19) and (A.23) gives

\begin{equation}
(A.24) \quad R^H_{DK} \equiv \left( (w^e_M - w^e_A)l^e_M/y^e \right) (h_i/h_M) \hat{L}_M
\end{equation}

which is equation (7) in the main text.
Appendix 3: Shift-Share Labor Reallocation Effects with Human Capital

Using the definition from Appendix 2, note that we can express output per effective worker $y^e \equiv Y/H$ as

\[
(A.25) \quad y^e = p y^e_M l^e_M + y^e_A l^e_A
\]

Total differentiation gives

\[
(A.26) \quad \dot{y}^e = s_M \dot{y}^e_M + s_A \dot{y}^e_A + s_M \dot{l}^e_M + s_A \dot{l}^e_A
\]

where $s_M = p y^e_M l^e_M / y^e$, and $s_A = y^e_A l^e_A / y^e_A$.

Using $\dot{l}^e_A = -l^e_M / (1 - l^e_M) \dot{l}^e_M$ gives

\[
(A.27) \quad \dot{y}^e = s_M \dot{y}^e_M + s_A \dot{y}^e_A + ((y^e_M - y^e_A) l^e_M \dot{l}^e_M
\]

The reallocation effect by shift-share method can be redefined as the final term in this expression.

\[
(A.28) \quad R_{SS} = ((y^e_M - y^e_A) / y^e) l^e_M \dot{l}^e_M
\]

This can also be thought as $R_{SS} \equiv (d \dot{y}/d \dot{l}^e_M) \dot{l}^e_M$, assuming that $\dot{y}^e_A$ and $\dot{y}^e_M$ are independent from $\dot{l}^e_M$ since, as shown in Appendix 2, $d \dot{y}/d \dot{y}^e = 1$.

Finally we obtain

\[
(A.29) \quad R_{SS}^H \equiv ((y^e_M - y^e_A) / y^e) l^e_M (h_i / h_M) \dot{l}^e_M
\]
Appendix 4: The Growth Accounting Approach to Total Reallocation Effects

The purpose of this section is to prove the claim in the text that the labor reallocation effect in standard structural growth accounting is equivalent to \( R_{DK} \) in (5) in the main text. Thus for example Syrquin (1984) defines the total reallocation effect, \( R_T \), as the increase in efficiency that results from resources (labor and capital) reallocation.

(A.30) \[ R_T = \hat{A} - s_A \hat{A}_A - s_M \hat{A}_M \]

where \( s_A = Y_A/Y \), \( s_A = pY_M/Y \), \( \hat{A} = \hat{Y} - \gamma \hat{K} - (1 - \gamma) \hat{L} \), \( \hat{A}_A = \hat{Y}_A - \alpha \hat{K}_A - (1 - \alpha) \hat{L}_A \), \( \hat{A}_M = \hat{Y}_M - \beta \hat{K}_M - (1 - \beta) \hat{L}_M \). \(^{33}\)

\( R_T \) can be further written as:

(A.31) \[ R_T = (s_A(1 - \alpha) \hat{L}_A + s_M(1 - \beta) \hat{L}_M - (1 - \gamma) \hat{L}) + (s_A \alpha \hat{K}_A + s_M \beta \hat{K}_M - \gamma \hat{K}) \]

The expression \( R_T \) consists of a labor reallocation effect, \( s_A(1 - \alpha) \hat{L}_A + s_M(1 - \beta) \hat{L}_M - (1 - \gamma) \hat{L} \), and a capital reallocation effect, \( s_A \alpha \hat{K}_A + s_M \beta \hat{K}_M - \gamma \hat{K} \).

Using \( \gamma = (r_A K_A + r_M K_M)/Y \), \( 1 - \gamma = (w_A L_A + w_M L_M)/Y \), \( \alpha = r_A K_A/Y_A \), \( 1 - \alpha = w_A L_A/Y_A \), \( \beta = r_M K_M/pY_M \), \( 1 - \beta = w_M L_M/pY_M \), the labor reallocation term, \( s_A(1 - \alpha) \hat{L}_A + s_M(1 - \beta) \hat{L}_M - (1 - \gamma) \hat{L} \), can be simplified to

(A.32) \[ R_{DK} = (w_A L_A/Y) \hat{l}_A + (w_M L_M/Y) \hat{l}_M \]

Using \( \hat{l}_A = -l_M/(1 - l_M) \hat{l}_M \) gives

(A.33) \[ R_{DK} = (w_M - w_A)L_M(\hat{L}_M - \hat{L})/Y \]

or

\(^{33}\) \( \hat{p} = 0 \) is assumed.
Hence the standard growth accounting approach based on (A.30) is identical to our more intuitive approach in the text.\textsuperscript{34}

The advantage of the approach derived in this appendix and followed by Syrquin (1998) and also Barro (1999), is that it highlights the relationship between the reallocation effects and total factor productivity. Specifically (A.30) shows that the reallocation effect in this methodology is a component of TFP growth. Importantly there is no such equivalence with the shift-share methodology unless, as previously noted, the production function is linear in labor input.

\textsuperscript{34}Likewise, the capital reallocation effect \( s_a \alpha \dot{K}_A + s_M \beta \dot{K}_M - \gamma \dot{K} \) can be simplified to \( (r_M - r_A)K_M(\dot{K}_M - \dot{K})/Y \).
Appendix 5: Labor Heterogeneity

In this appendix we briefly consider relaxing the assumption that rural, or agricultural, labor is homogeneous. Specifically suppose labor is indexed by skill level such that effective labor supply per unit of labor \( L_i \) is given by \( H_i = h_i L_i \), where \( h_i \) differs across workers. Suppose further that some migrant, \( i \), has human capital level that differs from the average rural level, \( h_A \leq h_i \leq h_M \).

Differences in the schooling level between migrants and non-migrants in China are given by Sicular et al. (2007). They find that the average years of schooling for migrants, from the rural sector in China, is 7.91 years compared to the rural average of 7.11 years, and 10.85 years in the urban sector. Similar gaps between the average years of schooling of migrants and the rural average are reported by Zhao (1999) and Zhu (2002). Likewise Meng (2012) and Qu and Zhao (2014) also report similar gaps between the average years of schooling of migrants and the urban average. Thus there appears to be a small difference in the average skills of migrants compared to non-migrants in the rural sector, though both appear to be significantly lower than the urban schooling levels.

Based on the evidence above suppose that for a migrant \( i \), \( h_A < h_i < h_M \). Then the expression for \( R_H^{DK} \) now becomes

\[
(A.35) \quad R_H^{DK} = \left( \frac{w^e_M - w^e_A}{y^e} \right) \left( \frac{h_i}{h_M} \right) l^e_M \hat{l}_M
\]

It is straightforward to see that if \( h_i/h_M > h_A/h_M \), then \( R_H^{DK} \) will be larger.

A difficulty is that while Li (2014) report a Mincerian human capital index for each sector, we do not have the equivalent metric for migrants. Thus we need to convert years of schooling data \( s \) into a Mincerian human capital concept \( h \). To do this we follow Klenow and Rodriguez-Clare (1997) and assume \( h = e^{(\phi/(1-\varphi))} s \), where \( \phi \) is the Mincerian return to schooling, and \( \varphi \) is the capital income share in a Cobb-Douglas production function.

Based on Sicular et al. (2007)’s data we have \( s_A = 7.11, s_i = 7.90, s_M = 10.85 \). These values and the human capital ratio \( h_A/h_M \) from Li (2014) implies a return rate to schooling \( (\phi) \) of 6% per year. This is in the middle of the range reported, for example, by Zhang et al. (2005). Using \( \phi = 6\% \) we can infer \( h_i/h_M = 0.51 \), which is compared to the value of \( h_A/h_M = 0.47 \) from Li (2014).

This is clearly a small difference and it only increases the value of \( R_H^{DK} \), over the whole
sample period, from 0.25 percentage points per year to just 0.28 percentage points per year. The adjusted values for other sub-periods are shown in Table A1, and are similarly close to the values we reported in Table 3.

Furthermore, in order to gain a sense of the sensitivity of the results to estimates of the skill level of migrants, Table A1 also reports the results for the extreme case where $h_i/h_M = 1$. It can be seen that this increases the size of the reallocation effect, $R_{DK}^H$, but the value is still significantly smaller than $R_{DK}$.

The main lesson from this exercise, therefore, is that heterogeneity of agricultural labor appears to be a second order effect in terms of our results. This is partly because the observed differences in the schooling of migrants and the rural average is very small. But also the key reason that $R_{DK}^H$ is smaller than $R_{DK}$ is the large gap between the average rural and urban human capital levels, which reduces the size of the wage gap such that $w_M^e - w_A^e < w_M - w_A$. 

[Table A1 about here]
Appendix 6: Robustness Check with Alternative Data Sources

As discussed in the main text there are many well known problems with Chinese data and considerable work has been undertaken in a range of studies to improve accuracy. In this appendix we therefore discuss how the main quantitative results change when we use some of these alternative data sources. These robustness checks are summarized in Table A2.

As expected the choice of data source affects the growth accounting results, including per worker GDP growth, TFP growth, and the size of labor reallocation effects. For example, $R_{DK}$ ranges from 0.59 to 0.92 percentage points per year for any given period, and $R_{DK}^H$ varies from 0.13 to 0.25 percentage points per year. These compare with our benchmark values of $R_{DK} = 0.77$ and $R_{DK}^H = 0.25$ percentage points per year. Nevertheless, regardless of sample periods and data sources, the ratio $R_{DK}/R_{SS}$ is fairly stable (0.41 to 0.44) and close to the labor share in non-agriculture (0.47), as implied by the Proposition in the main text.

We now discuss these alternative estimates in more detail.

(1) Output

In addition to constructing alternative price indices, another way to overcome the upward bias of real output is to develop a physical output index, as proposed by Wu (2002, 2011). They use physical output of major industrial products or product groups weighted by output weights taken from China’s 1987 input-output table. Estimates based on physical output index suggest an average GDP growth of 7.5 percentage point per year over 1978-2007, lower than 9.78 percentage points per year in our data, implying a lower per worker GDP growth and TFP growth.

In terms of the agricultural output share, Wu (2011) suggests a smaller change from 0.30 to 0.18 over 1978-2008, compared to a decline from 0.28 to 0.07 over the same period in our data. Thus Wu’s (2011) data suggest a smaller productivity gap, hence a smaller labor reallocation effect. For example, $R_{DK}$ based on Wu (2011) is 0.59 percentage points per year over 1978-2008, compared with 0.75 percentage points per year using our data for the same period. Nevertheless, the ratio $R_{DK}/R_{SS}$ using Wu (2011) is 0.41, close to 0.44 in our data.

(2) Capital
Our estimates of the aggregate capital stock are in line with existing estimates, such as Wang and Yao (2003) and Chow and Li (2002). These estimates are based on the standard perpetual inventory method. Alternatively, estimates of productive capital stocks are available. For example, the series from Holz (2006b) are based on scrap rates instead of a depreciation rate, and they exhibit a lower growth rate in the mid 1990s.\(^{35}\) The series from Wang and Szirmai (2012), derived from the age-efficiency profiles instead of the age-price profiles, show a higher growth rate since 1980 than the existing estimates, implying a lower TFP growth.

Thus, we experiment with two series from Wang and Yao (2003) and Chow and Li (2002) based on wealth capital stock and another two series from Holz (2006b) and Wang and Szirmai (2012) based on productive capital stock. All else equal, the choice of aggregate capital data only affects the estimates of growth contribution from capital accumulation and TFP, but it has no influence on labor reallocation effects (both \(R_{DK}\) and \(R_{SS}\)). As evidenced in Table A2, \(R_{SS}\) and \(R_{DK}\) are identical across data sources for the same period. Furthermore, the ratio \(R_{DK}/R_{SS}\) is either 0.43 or 0.44, close to our benchmark value of 0.44.

(3) Employment

One concern with our employment data based on administrative reporting system is that they include workers who are effectively laid off (Holz, 2006a) for the years prior to 1998. An alternative source of employment data is the population census, which has also been incorporated into the CSY. The official data from the CSY provide total employment and a breakdown by the three main sectors: primary, secondary and tertiary. A major issue with this source is the break in 1990, due to the CSY’s scale-up revision in accordance with population censuses of 1990 and 2000. Thus we consider alternative data from Holz (2006a) which extend upward revision for the years prior to 1990.

Another concern with our employment data is an overestimation of agricultural employment as a result of undocumented off-farm migration and non-farm rural self-employment (Brandt et al. 2008). To address this concern, we use data from Brandt et al. (2008) based on detailed labor supply for rural households from annual rural household surveys. Alternatively, as in Bulman and Kraay (2011), we subtract the floating population from the agricultural employment drawn from Holz (2006a) and add them into the non-agricultural employment. The estimates of floating population are from Liang and Ma (2004) and Cai and Wang (2010). Lastly, we also consider the data from Wu (2011)

\(^{35}\)This is because previous studies use the full investment expenditures instead of effective investment for the 1990s data, and they do not take into account the fact that at times of high investment growths the transfer rate falls drastically.
which add military personnel to non-productive service employment.

We find that the annual growth rates of total employment are similar across data sources, therefore per worker GDP growth and TFP growth are similar across sources. In terms of sectoral employment shares, the agricultural employment share in Brandt et al. (2008) shows a larger decline from 0.69 to 0.32 over 1978-2004, in contrast with a change from 0.71 to 0.47 in our data over the same period.\footnote{The floating population adjusted data show a decline in the agricultural employment share from 0.71 to 0.34 over 1978-2004, similar to Brandt et al., (2008).}

As shown in Table A2, other things equal, the choice of employment data has an impact on per worker GDP growth and TFP growth but little impact on the contribution of capital accumulation. A larger change in the agricultural employment share implies a smaller labor productivity gap as well as a faster rate of reallocation, which have opposite impacts on the size of labor reallocation effects. We find that, using the sectoral employment shares from Brandt et al. (2008) and floating population revised employment data, both $R_{SS}$ and $R_{DK}$ are slightly larger than the benchmark values. However, the ratio $R_{DK}/R_{SS}$ across data sources and sample periods remains stable, varying from 0.41 to 0.44.

(4) Labor Income Shares

Finally we also consider the impact of alternative labor income shares from Bai and Qian (2010) and Bulman and Kraay (2011) that are yearly varying. These studies report a larger mean share for agriculture and a slightly smaller mean share for non-agriculture. The results show a smaller $R^H_{DK} = 0.19$ percentage points per year using Bai and Qian (2010)’s labor shares, and $R^H_{DK} = 0.11$ percentage points per year using data from Bulman and Kraay (2011) for the same sample period.

Our Proposition in the main text implies that a smaller labor share in non-agriculture yields a smaller ratio $R_{DK}/R_{SS}$, other things equal. Indeed, the ratios $R_{DK}/R_{SS}$ using data from Bai and Qian (2010) and Bulman and Kraay (2011) are 0.40 and 0.31 respectively, lower than our benchmark value 0.44, for the period 1978-2011. Thus these alternative shares amplify our conclusions in the main text.
References


Vollrath, D., “How Important are Dual Economy Effects for Aggregate Productivity?"


Table 1: Reallocation Effects in China (% per Year)

<table>
<thead>
<tr>
<th>Studies Using Shift-Share Method, $R_{SS}$</th>
<th>Period</th>
<th>Labor Reallocation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1993-2004</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>1993-2005</td>
<td>1.1</td>
</tr>
<tr>
<td>Brandt et al. (2008)</td>
<td>1978-2004</td>
<td>1.7</td>
</tr>
<tr>
<td></td>
<td>1978-1988</td>
<td>3.4</td>
</tr>
<tr>
<td></td>
<td>1988-2004</td>
<td>0.8</td>
</tr>
<tr>
<td>Bosworth and Collins (2008)</td>
<td>1978-2004</td>
<td>1.6</td>
</tr>
<tr>
<td></td>
<td>1978-1993</td>
<td>1.7</td>
</tr>
<tr>
<td></td>
<td>1993-2004</td>
<td>1.2</td>
</tr>
<tr>
<td>McMillan and Rodrick (2011)</td>
<td>1990-2005</td>
<td>1.0</td>
</tr>
<tr>
<td>Vries et al. (2012)</td>
<td>1997-2008</td>
<td>1.2</td>
</tr>
<tr>
<td></td>
<td>1987-1997</td>
<td>1.0</td>
</tr>
<tr>
<td>Cao and Birchenall (2013)</td>
<td>1978-2008</td>
<td>1.8</td>
</tr>
<tr>
<td>McMillan et al. (2014)</td>
<td>1990-2005</td>
<td>1.0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Studies Using Denison-Kuznets Method, $R_{DK}$</th>
<th>Period</th>
<th>Labor Reallocation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nehru et al. (1997)</td>
<td>1978-1995</td>
<td>1.5</td>
</tr>
<tr>
<td>Woo (1998)</td>
<td>1979-1993</td>
<td>1.1</td>
</tr>
<tr>
<td></td>
<td>1985-1993</td>
<td>1.3</td>
</tr>
<tr>
<td>Cao et al. (2009)$^{bc}$</td>
<td>1982-2000</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>1994-2000</td>
<td>0.0</td>
</tr>
<tr>
<td>Bulman and Kraay (2011)</td>
<td>1979-2008</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>1979-1995</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>1996-2008</td>
<td>0.7</td>
</tr>
<tr>
<td>Ercolani and Wei (2011)</td>
<td>1966-2009</td>
<td>1.37</td>
</tr>
</tbody>
</table>

*Source:* Authors’ compilation.

*Note:* “a” – The number is reported as total resource reallocation effect;

“b” – Study based on gross output rather than value added, but conceptually similar to the Denison-Kuznets approach.

“c” – This study also includes adjustments for labor quality.
### Table 2: Growth Accounting Results (% per Year)

<table>
<thead>
<tr>
<th></th>
<th>Total Economy</th>
<th>Agriculture</th>
<th>Non-agriculture</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Annual Growth (1978-2011):</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP, $Y$</td>
<td>9.81</td>
<td>4.56</td>
<td>10.72</td>
</tr>
<tr>
<td>Capital, $K$</td>
<td>11.37</td>
<td>9.64</td>
<td>11.45</td>
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<tr>
<td>Employment, $L$</td>
<td>1.56</td>
<td>-0.59</td>
<td>4.03</td>
</tr>
<tr>
<td>Per worker capital, $k$</td>
<td>9.67</td>
<td>10.30</td>
<td>7.13</td>
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<tr>
<td>Per worker GDP, $y$</td>
<td>8.12</td>
<td>5.19</td>
<td>6.43</td>
</tr>
<tr>
<td><strong>Contribution to per worker GDP Growth from:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Per worker capital, $k$</td>
<td>4.91</td>
<td>3.32</td>
<td>3.72</td>
</tr>
<tr>
<td>TFP</td>
<td>3.05</td>
<td>1.82</td>
<td>2.60</td>
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<tr>
<td><strong>Shares/Ratios:</strong></td>
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<tr>
<td>Employment in non-agriculture, $L_m/L$</td>
<td>0.29</td>
<td>0.65</td>
<td></td>
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<tr>
<td>Capital in non-agriculture, $K_m/K$</td>
<td>0.95</td>
<td>0.97</td>
<td></td>
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<tr>
<td>GDP in non-agriculture, $p Y_m/Y$</td>
<td>0.72</td>
<td>0.94</td>
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<tr>
<td>Capital intensity ratio, $k_m/k_a$</td>
<td>44</td>
<td>17</td>
<td></td>
</tr>
<tr>
<td>Labor productivity ratio, $p y_m/y_a$</td>
<td>6</td>
<td>9</td>
<td></td>
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</tbody>
</table>

*Note:* Following Solow (1957), the TFP growth is defined as a residual from $\hat{y}$ and the contribution of per worker capital, hence it is a broad definition of TFP growth that includes the reallocation effects as well as any human capital accumulation and unmeasured inputs. The size of aggregate TFP growth, however, is not the focus of this paper.
### Table 3: Growth and Reallocation Effects (% per Year)

<table>
<thead>
<tr>
<th></th>
<th>(1) GDP per Worker</th>
<th>(2) Contribution of Human Capital $\gamma k$</th>
<th>(3) TFP Growth $\hat{y} - \gamma k$</th>
<th>(4) Shift–Share $R_{SS}$</th>
<th>(5) Denison-Kuznets with Denison-Kuznets $R_{DK}$</th>
<th>(6) Shift–Share with Human Capital $R_{SS}^H$</th>
<th>(7) Denison-Kuznets with Human Capital $R_{DK}^H$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1978-2011</td>
<td>8.12</td>
<td>4.91</td>
<td>3.05</td>
<td>1.76</td>
<td>0.77</td>
<td>0.66</td>
<td>0.25</td>
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<tr>
<td>1978-1991</td>
<td>5.24</td>
<td>2.96</td>
<td>2.20</td>
<td>1.51</td>
<td>0.65</td>
<td>0.56</td>
<td>0.20</td>
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<tr>
<td>1991-2001</td>
<td>9.27</td>
<td>5.51</td>
<td>3.54</td>
<td>1.17</td>
<td>0.51</td>
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<tr>
<td>2001-2011</td>
<td>10.81</td>
<td>6.87</td>
<td>3.76</td>
<td>2.46</td>
<td>1.09</td>
<td>0.92</td>
<td>0.37</td>
</tr>
</tbody>
</table>

*Note:* Following Solow (1957), the TFP growth is defined as a residual from $\hat{y}$ and the contribution of per worker capita $\gamma k$ (where $\gamma$ is the capital income share at the aggregate level), thus it is a broad definition of TFP growth that includes the reallocation effects as well as any human capital accumulation and unmeasured inputs. With data on per worker human capital from Li (2014), the contribution of human capital accumulation, $(1 - \gamma)\hat{h}$, is estimated at a value of 2.46 percentage points per year for period 1978-2011, and 1.21, 1.40, and 5.21 percentage points for each sub-period. If we define the TFP growth as a concept net of the contribution from human capital accumulation and denote it as $TFP^H$, then the comparable ratio $R_{DK}^H/TFP^H$ over 1978-2011 is 0.42.
Table A1: Alternative Values of $R^{H}_{DK}$ With Heterogeneity of Agricultural Labor (% per Year)

<table>
<thead>
<tr>
<th>Period</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$h_i/h_M = 0.47$</td>
<td>$h_i/h_M = 0.51$</td>
<td>$h_i/h_M = 1.00$</td>
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*Note: $h_M$ and $h_i$ refer to the per worker human capital index from Li (2014), for urban workers and migrants respectively. Column (1) denotes the scenario where the rural workers are homogenous, and $h_i/h_M = 0.47$ is drawn from the data on per worker human capital index for rural and urban workers in Li (2014); Column (2) denotes the scenario where the migrants are more skillful than non-migrants in rural sector, and $h_i/h_M = 0.51$ is inferred from schooling years in Siculic et al. (2007) (see Appendix 5); Column (3) denotes the scenario where the migrants have the same skill level as urban workers.*
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*Note: Alternative data sources and labor shares are discussed in detail in Appendix 6.*
Figure 1. Employment Share of Non-agriculture in China (1978-2011)

Note: For data sources see section 4.2 Base Data in the main text.
Figure 2. Value Added Share of Non-agriculture in China (1978-2011)

Note: For data sources see section 4.2 Base Data in the main text.
Figure 3. GDP per Worker in China, RMB in 1978 Price (1978-2011)

Note: For data sources see section 4.2 Base Data in the main text.
Figure 4. Productivity Gap in China (1978-2011)

Note: For data sources see section 4.2 Base Data in the main text.
Figure 5. Real Human Capital per Worker Index by Sector in China (1978-2011)

Note: For data sources see section 4.2 Base Data in the main text.
Figure 6. Productivity Gap in China, Human Capital Adjusted (1978-2011)

Note: For data sources see section 4.2 Base Data in the main text.
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