Agricultural Productivity, Structural Change, and Economic Growth in Post-Reform China

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Abstract

We examine the role of agricultural productivity in China's post-reform economic growth and sectoral reallocations. Using microeconomic farm-level data, and treating labor as a highly differentiated input, we find that the labor input in agriculture decreased at 5% annually and agricultural TFP grew at 6.5%. Using a calibrated two-sector general equilibrium model, we find that agricultural TFP growth: (i) accounts for the majority of output and employment reallocations toward non-agriculture, (ii) contributes to aggregate and sectoral economic growth (at least) by as much as non-agricultural TFP growth, and (iii) influences economic growth mainly by reallocating workers to the non-agricultural sector, where rapid physical and human capital accumulation are taking place.

Keywords: China, agricultural productivity, structural change, economic growth

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1 Introduction

Market-oriented reforms have brought unprecedented growth to China. China's rapid economic growth has been accompanied by far-reaching changes in the structure of output and employment, and by a rapid spatial reallocation of labor toward urban areas. China's growth experience is among the most striking episodes in modern history. It is thus important to understand its sources of growth, if not least because China's experience may shed light on the growth potential of other developing countries. Our purpose in this paper is to study the role of agricultural productivity in China's economic growth and its structural changes during the reform period. The role of agriculture in China's growth is a particularly important. The theoretical literature and policy debate are both conflicted on the subject of agriculture. Is agricultural growth a necessary condition for overall economic growth? Or is agriculture pulled along by productivity growth in non-agricultural sectors?

Crucial for understanding China's transformation are the total factor productivities of agricultural and non-agricultural sectors. Alwyn Young (2003) has provided a careful growth accounting exercise for China's non-agricultural sector. So far, however, no similar exercises are available for the agricultural sector. The existing macroeconomic literature typically approaches Chinese agriculture by examining aggregate data only; see, e.g., Chow (1993), Fan and Zhang (2002), Fan et al. (2003), and Dekle and Vandenbroucke (2010, 2012). This approach fails to provide a proper measure of the growth of the labor input that accounts for differences in the human capital of the workforce. Since variations over time in the composition of the labor input are likely to explain agricultural growth in China, to measure effective labor units we need to control for the changing characteristics of agricultural workers.

Constructing a proper measure of the changes in the labor input, though, is a challenging exercise in agriculture. A fundamental difficulty is that in China, as well as in typical less developed economies, a large proportion of the income of an agricultural household comes from some sort of combined-factor rewards (land, labor, and capital), rather than from wage income. This implies that there is no explicit observable individual wage for other than a small and highly selective sample of agricultural workers. Without agricultural wages, it is not possible to quantify the relative productivities of different types of labor and hence their contribution to the aggregate labor input. In the absence of wage data, it is not possible to measure agricultural productivity using the standard approach, such as that in Young (2003, section II).[1]

The first contribution of this paper is that we estimate the total factor productivity (TFP) growth of China's agricultural sector between 1991 and 2009 accounting for the fact that labor is a highly differentiated input. Using the China Health and Nutrition Survey (CHNS) we obtain detailed measures of income for all the members of the household and from the households themselves. The CHNS also reports detailed time use data. A novelty in our strategy is the use of the average product of labor to measure the labor in efficiency units in agriculture. Our results show that between 1991 and 2009, China's agricultural labor input decreased at a rate of 4.5-5.5% annually, and that agricultural TFP grew by 6.5% on average. This growth rate is more than four times the level Alwyn Young estimated for the non-agricultural sector in China, 1.4%, and twice as large as the estimate of non-agricultural TFP in China based on official data, 3.0%; see Young (2003, Table 24).

China's rate of growth in agricultural TFP is not unprecedented; especially within the context of the rapidly growing economies of Southeast Asia. However, despite the broad scope of the reforms and the reduced State control over labor mobility, the Chinese economy remains distorted. Thus, any attempt to measure agricultural productivity in China has to deal with market distortions. To ensure that our measure of the effective

[1] One way to approach this problem is to assume that, on the margin, the return to agriculture workers is equal to the wage paid in the rural industry; see, e.g., Johnson and Chow (1997) and Dekle and Vandenbroucke (2010). However, such a wage rate is not a good proxy for the marginal productivity of the Chinese peasants. In order to absorb excess labor from agriculture, the Chinese central government encourages local rural officials to develop Township and Village enterprises (TVEs), which are owned by the local rural citizens and operated by the local government. Right now TVE employs about 138 million people. However, it is difficult to classify TVE as a market-oriented sector. Because of the fragmented labor market and official obstacles to both rural-urban and rural-rural migration, TVE contributes significantly to local employment. Due to the underdevelopment of financial institutions and the imperfect capital market, local governments use their political connections with the central banks to channel loans to TVEs; see Byrd and Gelb (1991) and Chang and Wang (1994) for more details. The strong political influence and the many other distortions mean that the rural industrial wage rate may be a poor proxy for agricultural wages in China.

labor of the various types of workers is robust, we perform a number of checks.[2] We examine the influence of State controlled prices on the estimated wage profiles, and we consider rural coastal and rural inland areas separately. State controlled prices, where available, provide a direct measure of the price distortions farmers face. Similarly, we employ the estimated differences in the effective labor units across regions as an indirect assessment of the significance of labor mobility restrictions. Our estimates of the labor input and TFP are remarkably stable across specifications.

The second contribution of this paper is to quantify the importance of agricultural and non-agricultural TFP in contributing to China's growth and its structural transformation during the reform period. These questions require an economy-wide representation of the Chinese economy. The economic growth literature describes structural change as occurring primarily through non-homothetic preferences or through differences in sectoral productivities.[3] In this paper, we rely on a dual-economy model that draws insights from both of these literatures. Using a calibrated version of the model, we first reproduce key patterns of the Chinese economy between 1978 and 2008. To examine the role of agriculture in China's transformation, we ask: if agricultural and non-agricultural TFP had not changed during the reform period, what would be the sectoral distribution of output and employment and the overall and sectoral growth rates of output?

The majority of the sectoral reallocation of output and employment toward non-agricultural sectors is due to China's rapid TFP growth in agriculture. Moreover, agricultural TFP is as important as non-agricultural TFP in accounting for China's overall

[2] We also estimate the labor input using a "shadow wage" approach; see, e.g., Jacoby (1993) and Skoufias (1994). The shadow-wage approach assumes the existence of a household production function that has different types of labor as distinct inputs, i.e., by sex, age, and education. The shadow wage of each farmer is just the marginal product of labor, estimated from the agricultural production function. Both methods yield similar results.

[3] Examples in the first class of models are Matsuyama (1992), Echevarria (1997), Laitner (2000), Kongsamut et al. (2001), and Caselli and Coleman (2001). In these models, an increase in income is associated with a smaller share of spending in agricultural goods (e.g., Engel's Law). The second class of models includes Ize and Roe (2005), Ngai and Pissarides (2007), Acemoglu and Guerrieri (2008). In these models, employment moves to the sector with the lowest productivity growth as a compensatory mechanism. The closest model to ours is Hayashi and Prescott (2008), which reviews patterns of Japanese economic development. They argue that the Japanese miracle did not take place before World War II because of cultural barriers that kept agricultural employment constant throughout the prewar period. Our emphasis is on the role of differences in productivity in China.

growth rate, and more important than non-agricultural TFP in accounting for the growth rate of the non-agricultural sector. Agricultural TFP contributes to aggregate and non-agricultural growth by reallocating workers to the non-agricultural sector, where capital accumulation takes place. This mechanism is well-known in the development literature, but it is especially important in China for two reasons. First, as much as 35% of the labor force is still in agriculture. Thus, there are still potential gains due to labor reallocations. Second, Chinese physical and human capital accumulation have proceeded at very rapid rates and with apparently little change in the rates of return to these investments; see, e.g., Bai et al. (2006), Li et al. (2009), Song et al. (2011), and Whalley and Zhao (2010). In these circumstances, due to the complementarity between capital and labor, a faster transfer of workers toward non-agriculture is fundamental for rapid economic growth.

Related literature. Sectoral reallocations out of agriculture have been a mayor component in the rapid growth of Taiwan and South Korea, and they characterize the modern growth experience of the majority of nations, including the U.S.; see Young (1995), Caselli and Coleman (2001), and Gollin et al. (2002). Sectoral reallocations and rapid productivity growth in agriculture are also typically seen as important factors in China's rapid growth. This view has been most prominently ascribed to Young (2003). According to Young (2003, p. 1260): "Despite the popular academic emphasis on industry and exports, a deeper understanding of the success of the world's most rapid growing economies may lie in that most fundamental of development topics: agriculture, land, and the peasant." Young (2003), however, did not go any further to investigate the agricultural sector. We directly confront agricultural changes.

A series of recent studies have focused on Chinese economic growth using a macroeconomic approach.[4] An emphasis in the literature has been in terms of reallocations

[4] There is a large literature that studies Chinese agricultural productivity. Lin (1992) and Huang and Rozelle (1996) emphasized the institutional reform as the main source of agricultural growth in the early 1980s. Some analysts, such as Wu (1993), argued that TFP growth would slow afterward. Many studies, have provided support for an optimistic view. Since the HRS was completed in 1984, technological changes have been the primary engines of agricultural growth. Studies that cover the 1990s include Fan (1997), Fan and Pardey (1997), Wu et al. (2001), Jin et al. (2002). Studies that consider the 2000s include Bosworth and Collins (2008), Nin-Pratt et al. (2010). Both Fan and Pardey (1997) and Jin et al. (2002) pointed out the importance of investment in agricultural R&D on TFP growth.

between private firms and state-owned enterprises (SOE), e.g., Song et al. (2011) and Dekle and Vandenbroucke (2011). The focus of Song et al. (2011) are capital markets and the interplay between high-productivity private firms, with limited access to credit markets, and SOEs, with much better access to credit. They show that this interplay is consistent with high savings rates and a trade surplus, such as those observed in China. Hsieh and Klenow (2009) have also examined the role of reallocation in China. They uncovered a large misallocation within manufacturing and a potential for a 50 percent increase in manufacturing TFP due to reallocations within the manufacturing sector. Separately, Bai et al. (2006) have measured the return to capital in China and have shown that while this return declined considerably between 1978 and 1998, it still remains at relatively high levels (about 20%) despite the high investment rates.

We do not consider a disaggregated analysis of the non-agricultural sector. We focus on agriculture to address the fact that there are large reallocations of labor within China; movements well into the tens of millions of people. In that metric, China's progress in agriculture has been remarkable. In fact, as noted by Lin (1998), China not only has feed itself but ex-post daily consumption of calories increased by 73 percent since the late 1970s, despite the near doubling of its population; see also Johnson (2000, p. 319) for related remarks about Chinese agriculture.

Dekle and Vandenbroucke (2010 and 2012) share many features with the present paper. However, we devote most of our attention to the measurement of agricultural productivity. In that regard, we have already pointed out an important difference in the measurement of agricultural productivity with respect to Dekle and Vandenbroucke (2010); see footnote 1. Further, in our model we abstract from changes in SOEs and mobility frictions, which are aspects emphasized by Dekle and Vandenbroucke (2012). Abstracting from these elements allows us to obtain highly transparent results and closed-form solutions for key variables in the model. We see both papers as complements.

Section 2 provides a brief background. Section 3 presents the theory. Section 4 measures agricultural TFP growth. Section 5 calibrates the model. Section 6 concludes.

2 Background

This section provides a brief background of China's reforms since 1978. Our discussion focuses on the reforms in agriculture and in labor mobility. The references herein, Chow (2007), Lin et al. (1997), Brandt and Rawsky (2008), and Xu (2011) provide detailed accounts of the reforms.

Before 1978, rural areas in China were severely affected by collective farming, the central planning system, and the orientation of the development strategy toward industrialization. The Chinese government had tight controls on commodity prices. Capital was mainly accumulated and concentrated in the infrastructure sector, while Chinese farmers bore most of the finance burden through the *unified purchase and sale system*, which maintained "price scissors" between agricultural and industrial prices. Farm products purchased at mandatory low prices by the State were sold to urban areas at a similarly low prices to minimize the production costs in heavy industry; see, e.g., Wu (1994). The national household registration system (*hukou*) also restricted rural-urban migration by limiting access to work opportunities and social benefits for unauthorized urban workers. The *hukou* system, instituted in the mid-1950s, require each person to register, reside, and work in their *hukou* location.[5]

Agricultural reforms in 1978 introduced a market mechanism for agricultural goods; see Lin et al. (1997). The reforms replaced the collective commune system with the household responsibility system (HRS).[6] Under HRS, state-owned land was assigned to households with contracts for up to 15 years; see Lin (1992). This meant that individuals became the primary units for decision making. A famous slogan stated the main principle of this reform as "once a peasant's state quota and collective contribution have been fulfilled, the rest is his to dispose of as he wishes." China also implemented a dual-track price system

[5] *Hukou* is either rural or urban and agricultural or non-agricultural. However, as noted by Fan (2008, p. 51) "in recent years, the distinction between agricultural *hukou* and non-agricultural *hukou* is no longer as compelling. Some provinces and large cities have, in fact, eliminated *hukou* classification."

[6] Under the commune system, people in rural areas were put together into a production team and by law all the land and machinery were owned collectively. Work in the field was assigned to each team member. Total income of a production team was either divided equally among the members or determined by the team leader subjectively. McMillan et al. (1989) estimated that an individual worker would be paid as little as 30 percent of his/her marginal product in the commune system.

to deregulate commodity prices. The weight of state-regulated prices declined steadily. In 1999, only 5% of commodity prices were still set by the government; see Lin and Yu (2008). The effect of the agricultural reforms on output has been large. According to Lin (1992), China's crop output increased by 42% during 1978-1984, with about half of that growth accounted for by the HRS.

Institutional reforms have also reduced the State control over labor mobility. Since the 1980s, local governments have been given autonomy to administer *temporary residential permits*, which allow rural migrants to move and work in cities. Additional reforms in the 1990s have further relaxed the criteria for granting urban hukou in large and medium-size cities; see Fan (2008, chapter 3). These reforms, however, have primarily benefited a selected group of people (e.g., investors, buyers of property, and professionals) who are allowed to purchase a blue-stamp *hukou*, a Chinese-style "green card." According to some analysts, the "*hukou* system has been weakened as a migration control tool during the reform period"; see, e.g., Liu (2005, p. 134). Easing mobility restrictions has had a large effect on internal migration. Between 1979 and 2009, China's urban population increased by about 440 million to 622 million, with over 75% of this increase attributable to net migration and urban reclassification; see Chan (forthcoming).

During the post-reform period, China has maintained rapid output growth and a rapid reallocation of labor. According to Young (2003), GDP per capita growth exceeded 6% between 1978 and 1998.[7] Further, the number of people engaged primarily in agricultural activities has declined from 70% of total employment in 1978 to less than 40% in 2008. The share of agricultural output has followed a similar path; this share has declined from 28% to 6%.[8] China's urbanization rate increased from 21% in 1982 to 43% in 2006; see Fan (2008, p. 1). In 2012, China passed the 50% urbanization point; see Chan (2012).

[7] There are measurement problems with official data. Young (2003) argues that the most serious problem is the implicit GDP deflator, which relies on enterprise-reported data and systematically underestimates inflation. Using independent price indices, the annual growth rate of output in the non-agriculture sector is reduced from 7.8% to 6.1%.

[8] China's pre-reform national accounts were compiled according to the Material Product System (MPS). The MPS, developed by the former Soviet Union, measured output in terms of physical production; therefore ignoring some services. Official data for the pre-1978 period shows a slight change in the employment and output shares; see Brandt and Rawski (2008, p. 482).

3 The model economy

We represent the Chinese economy using a two-sector neoclassical growth model with non-homothetic preferences, heterogeneous sectoral Cobb-Douglas production functions, and exogenous and heterogeneous productivity growth. To focus on the role of agricultural productivity, and for tractability, we assign a limited role to distortions in the output, labor, and capital markets. Using the baseline model, we briefly discuss ways to incorporate market distortions. In the measurement section, we examine the influence of controlled agricultural prices on productivity, and consider differences between inland and coastal agricultural labor markets. In the quantitative section, we also examine the significance of market distortions.[9]

Environment. Time is continuous, $t \geq 0$. There is an infinitely-lived representative household with time separable and non-homothetic preferences defined over the per capita consumption of agricultural goods, $c_a(t)$, and non-agricultural goods, $c_m(t)$,

$$\int_0^\infty e^{-\rho t} u(c_a(t), c_m(t)) dt, \tag{1}$$

where $u(c_a(t), c_m(t)) \equiv \omega \ln(c_a(t) - \gamma) + (1 - \omega) \ln(c_m(t))$, $\rho > 0$ is the rate of time preference, ω is the utility weight of the agricultural good, and $\gamma > 0$ is a "subsistence level" of agricultural consumption.

The agricultural sector produces consumption goods. Let $y_a(t)$ denote output per capita in the agricultural sector. Output from the non-agricultural sector can be either

[9] Analyses of how pre-reform distortions came to exist or changed, and of how new distortions emerged during the post-reform period are beyond the scope of this paper. Sah and Stiglitz (1992) studied "price scissors." Lin and Yu (2008) estimated Sah and Stiglitz's (1992) model using Chinese data. An analysis along the lines of Sah and Stiglitz (1992) requires, at a minimum, a framework that incorporates rural and urban markets, as well as markets for agricultural and non-agricultural goods. The measurement of market distortions is also beyond the scope of the paper. Brandt et al. (2008) infered distortions from Chinese sectoral data, and found little systematic change in the implied distortions between 1978 and 2000. Hsieh and Klenow (2009) measured the importance of output and labor market distortions in China but only within manufacturing. Young (2000) argued that during the reform period, local governments implemented a variety of interregional barriers to trade that lead to higher market fragmentation. Young (2000) provided supportive evidence of higher distortions using provincial and sectoral dispersion measures for price and output data. Holz (2009) questioned the results in Young (2000) and instead argued that dispersion in China is within the range of a relatively integrated large economy such as the US.

consumed or invested. Let $y_m(t)$ denote output per capita in the non-agricultural sector. Production takes place with constant return to scale Cobb-Douglas technologies. In terms of per capita quantities, these sectors are described by

$$c_a(t) = A_a(t)\,[k_a(t)]^{\alpha_a}\,n_a(t), \tag{2}$$

$$\dot{k}(t) = A_m(t)[k_m(t)]^{\alpha_m} n_m(t) - c_m(t) - (\delta + \nu)k(t), \tag{3}$$

where $\delta > 0$ is the depreciation rate, $\nu > 0$ is the growth rate of the labor force, α_i is the capital share in sector i, $k_i(t)$ is the capital-labor ratio in i, $n_i(t)$ is the employment share in i, and $n_a(t) + n_m(t) = 1$.

The aggregate capital-labor ratio, denoted by $k(t)$, satisfies

$$k(t) = n_a(t)k_a(t) + n_m(t)k_m(t). \tag{4}$$

Technological progress is exogenous and takes place at different rates across sectors

$$\frac{\dot{A}_i(t)}{A_i(t)} = \mu_i, \text{ for } i = a \text{ and } m.$$

Sectoral allocations. We study the solution to a social planning problem, although we describe some of the properties of the allocation using a market economy. The social planner chooses the sequences $\{c_a(t), c_m(t), k_a(t), k_m(t), n_a(t) : t \geq 0\}$ to maximize (1) subject to feasibility conditions, a transversality condition, and an initial value of capital, $k_0 > 0$. In this sub-section we study the static conditions that characterize the sectoral allocation of capital and consumption. The allocation of output into consumption and capital accumulation is discussed below.

The sectoral allocation of capital per capita is chosen to equalize the marginal rates of transformation across sectors so that

$$k_a(t) = Bk_m(t), \tag{5}$$

where $B \equiv \alpha_a(1-\alpha_m)/\alpha_m(1-\alpha_a)$. Since capital-labor ratios are proportional across sectors, (4) and (5) imply

$$k(t) = [(B-1)n_a(t) + 1]k_m(t). \tag{6}$$

The sectoral allocation of consumption equalizes the marginal rate of substitution to the marginal rate of transformation. In a competitive economy, this common value equals the relative price of agricultural goods, denoted by $p(t)$,

$$\frac{\omega}{1-\omega}\left(\frac{c_m(t)}{c_a(t)-\gamma}\right) = p(t) = D\left(\frac{A_m(t)}{A_a(t)}\right)[k_m(t)]^{\alpha_m-\alpha_a}, \tag{7}$$

where $D \equiv (\alpha_m/\alpha_a)^{\alpha_a}((1-\alpha_m)/(1-\alpha_a))^{1-\alpha_a}$.[10]

Sources of structural change. Using (7), we can discuss structural changes in the share of expenditures on agricultural goods relative to total expenditures. Let $c(t) \equiv p(t)c_a(t) + c_m(t)$ denote aggregate consumption expenditure, and let $\psi_a(t)$ denote the share of total expenditures on agricultural goods. Then,

$$\psi_a(t) \equiv \frac{p(t)c_a(t)}{c(t)} = \omega + (1-\omega)\frac{p(t)\gamma}{c(t)}. \tag{8}$$

The share $\psi_a(t)$ declines if $p(t)$ declines or if $c(t)$ increases. With $\gamma > 0$, the demand for agricultural goods is price-inelastic and has an income elasticity less than one. Thus, if the increase in the growth rate of agricultural productivity (relative not non-agriculture) is faster that the increased capital intensity in the non-agricultural sector (provided that $\alpha_m > \alpha_a$), agricultural prices would decline; see (7). With price-inelastic demands, the share $\psi_a(t)$ declines.[11] If the sectoral production functions are identical and the sectoral

[10] A competitive equilibrium is standard. Let (p, w, r) denote the price of agricultural goods, the market wage, and the rental price of capital with non-agricultural goods as the numeraire. In a *competitive market economy,* (i) the firms' profits are $\Pi_i \equiv \max_{k_i,n_i}\{p_iA_i[k_i]^{\alpha_i}n_i - rk_in_i - wn_i\}$ with $i = a$ and m, and $p_a \equiv p$, $p_m \equiv 1$, (ii) the representative household maximizes (1) subject to $\dot{k} + pc_a + c_m = (r-\delta-\nu)k + w$, and (iii) markets clear: $n_a + n_m = 1$ and (4) holds. In the absence of distortions, the competitive equilibrium and the social planner allocation coincide.

[11] Non-homothetic preferences are not necessary for the price effects just discussed. Ngai and Pissarides (2007) considered isoelastic preferences with an elasticity of substitution different from one. Under these general preferences, an asymptotic closed-form solution is possible only if $\alpha_a = \alpha_m$.

productivities are equal, agricultural prices satisfy $p(t) = D$ for $t \geq 0$; see (7). As $c(t)$ increases, however, the share (8) declines due to income effects.

We can also study changes in sectoral output. Let $y(t) \equiv p(t)y_a(t) + y_m(t)$ denote aggregate output, and let $\theta_a(t)$ denote the output share in agriculture. Then,

$$\theta_a(t) \equiv \frac{p(t)y_a(t)}{y(t)} = \frac{Fn_a(t)}{1 - n_a(t)}, \tag{9}$$

where $F \equiv DB^{\alpha_m}$. As expected, the output share $\theta_a(t)$ is increasing in $n_a(t)$.

Market distortions. In the above analysis, there are no distortions in the economy. In order to discuss the role of sector-specific distortions, let $(p(t), w(t), r(t))$ denote the *undistorted* price, the *undistorted* wage, and the *undistorted* rental price of capital with non-agricultural goods as the numeraire. Let τ_p^i and τ_n^i denote the price and labor market distortions for sector $i = a$ and m. Distortions in capital markets can be mapped into $\tau_{p,n}^i$. Due to the distortions $\tau_{p,n}^a$, the representative firm in the agricultural sector faces a *distorted* price and a *distorted* wage given by $p(t)(1 - \tau_p^a)$ and $w(t)(1 + \tau_n^a)$, respectively. The representative firm in the non-agricultural sector faces similar sector-specific prices.

Profit maximization implies that capital-labor ratios are still proportional across sectors, as in (5). The proportionality factor incorporates the labor market distortions,

$$B \equiv \frac{\alpha_a(1 - \alpha_m)}{(1 - \alpha_a)\alpha_m} \frac{1 + \tau_n^a}{1 + \tau_n^m}. \tag{10}$$

The sectoral allocation of consumption is as before. The right-hand side of (7) is

$$p(t) = D\left(\frac{A_m(t)}{A_a(t)}\right)\left(\frac{1 - \tau_p^m}{1 - \tau_p^a}\right)\left(\frac{1 + \tau_n^a}{1 + \tau_n^m}\right)^{1-\alpha_m} [k_m(t)]^{\alpha_m - \alpha_a}. \tag{11}$$

Changes in distortions, either across markets or across sectors, are an added source of structural changes in (8). Distortions are a reduced-form way to capture State intervention. For example, distortions that seek to favor the use of capital in non-agriculture and to depress the relative price of agricultural goods can be attained by setting $\tau_{p,n}^i$ appropriately. Brandt et al. (2008) contain several illustrations of how these distortions capture policy interventions in China.

It is possible to infer the distortions $\tau^i_{p,n}$ from the data. With that purpose, Brandt et al. (2008) studied changes in the relative price $p(t)$, the relative capital-labor ratio $k_m(t)/k_a(t)$, and the relative labor compensation across sectors in China. Overall, they found little evidence of long run trends in distortions between 1978 and 2000.[12] If the distortions are time-invariant, it is possible to treat $\tau^i_{p,n}$ as part of *measured sectoral productivities*, $A_i(t)$. For instance, let $A_i(t) \equiv \tilde{A}_i(t)(1-\tau^i_p)(1+\tau^i_n)^{\alpha_m-1}$. The price implications of an undistorted model with sectoral productivities $A_i(t)$ are the same as those of a distorted model with baseline productivity $\tilde{A}_i(t)$.

The dynamical system. In the context of an undistorted model, the allocation between consumption and capital accumulation for the non-agricultural good satisfies the standard Euler equation

$$\frac{\dot{c}_m(t)}{c_m(t)} = \alpha_m A_m(t)\left[k_m(t)\right]^{\alpha_m-1} - (\delta+\rho+\nu). \tag{12}$$

The solution to the social planner problem satisfies two differential equations, (3) and (12), and three static equations, (2), (6), and (7).

We are interested in the transitional phase. When $c_a(t)$ and $c_m(t)$ grow over time, however, γ becomes unimportant for the allocation as preferences are homothetic asymptotically. With homothetic preferences the model can be fully characterized without a direct role for agricultural productivity. As $\gamma \to 0$, (2) and (7) yield

$$c_m(t) = EA_m(t)\left[k_m(t)\right]^{a_m} n_a(t), \tag{13}$$

where $E \equiv (1-\omega)(1-\alpha_m)/\omega(1-\alpha_a)$, which is a decreasing function of the utility weight of the agricultural good, ω. Omit the time index for simplicity. Normalize the consumption of non-agricultural goods and capital goods in terms of non-agricultural

[12] Brandt et al. (2008) found a slight decline in the relative price $p(t)$, little evidence of long run trends in the relative capital-labor ratios in the two sectors, and a fall in labor market distortions in the non-agricultural sector but only during the initial years of the reform. They interpreted these findings as indicative of improvements in non-agricultural TFP relative to agricultural TFP. One of our quantitative exercises examines the role of improvements in non-agricultural TFP.

productivity: $\widehat{k} \equiv kA_m^{-1/(1-\alpha_m)}$, $\widehat{k}_m \equiv k_m A_m^{-1/(1-\alpha_m)}$, and $\widehat{c}_m \equiv c_m A_m^{-1/(1-\alpha_m)}$. Also, let $g_m \equiv \mu_m/(1-\alpha_m)$. The state of the economy evolves according to

$$\frac{\dot{\widehat{c}}_m}{\widehat{c}_m} = \alpha_m[\widehat{k}_m]^{\alpha_m - 1} - (\delta + \rho + \nu + g_m), \tag{14}$$

$$\dot{\widehat{k}} = [\widehat{k}_m]^{\alpha_m}(1-n_a) - \widehat{c}_m - (\delta + \nu + g_m)\widehat{k}. \tag{15}$$

Steady state. Let $(^*)$ indicate steady state values. From (14) we obtain $\widehat{k}_m^*$:

$$\alpha_m[\widehat{k}_m^*]^{\alpha_m - 1} = \delta + \rho + \nu + g_m. \tag{16}$$

In the steady state, the *employment share in agriculture* is constant. Substituting (6) and (13) into (15) yields

$$n_a^* = \frac{[\widehat{k}_m^*]^{\alpha_m - 1} - (\delta + \nu + g_m)}{[\widehat{k}_m^*]^{\alpha_m - 1}(1+E) + (\delta + \nu + g_m)(B-1)}. \tag{17}$$

The values of $\widehat{c}_m^*$ and $\widehat{k}^*$ follow from static conditions. Given n_a^*, and $k_m^*(t) \equiv \widehat{k}_m^* A_m(t)^{1/(1-\alpha_m)}$, (5) determines $k_a^*(t)$. Both capitals growth at a constant rate determined by μ_m. These values and $A_a(t)$ determine the consumption of the agricultural good, $c_a^*(t)$, and its relative price, $p^*(t)$. The *share of expenditures on agricultural goods* ψ_a^* is constant and determined by ω; see (8), and the *output share in agriculture* θ_a^* is constant and determined by n_a^*; see (9).

Notice that growth is non-balanced because outputs in the two sectors grow at different rates. Notice also that $\gamma > 0$ is only important during the transitional phase. In the transition, sectoral capital and output depend on agricultural productivity. We solve for the transitional phase numerically to investigate this interdependence.

4 Productivity growth in Chinese agriculture

We need two important inputs to simulate the model: agricultural and non-agricultural productivity growth; μ_i for $i = a$ and m. We rely on Young (2003) for estimates of μ_m and we provide our own estimates of μ_a.

In order to estimate agricultural TFP, we pay considerable attention to the analysis of the labor input. The methodology is standard; see, e.g., Jorgenson et al. (1987) and Young (2003). We assume that the labor input can be viewed as a constant return to scale function H with N "types" of labor: $L = H(L_{1,}L_2, ..., L_N)$. Each labor type is different by age, gender, or educational background, so each one has its specific marginal productivity. An index for the aggregate labor input is computed as a weighted sum of the number of each types of labor. The most common weights are the marginal products or the share of earnings on total compensation. The change in the labor input is:

$$\frac{dL}{L} = \sum_{i=1}^{N} s_i \left(\frac{dL_i}{L_i} \right), \text{ where } s_i \equiv \frac{dH}{dL_i} \frac{L_i}{H}. \tag{18}$$

Under the assumption of competitive markets, we can equate dH/dL_i to w_i, which is the wage for labor type i. By construction, the index L places greater weight on the growth of groups with higher relative wages.

Data. We use longitudinal data from the China Health and Nutrition Survey (CHNS), conducted by the Carolina Population Center at the University of North Carolina at Chapel Hill. This survey includes eight waves (1989, 1991, 1993, 1997, 2000, 2004, 2006, and 2009), and covers nine provinces in the coast, northeast, middle, and west of China.[13] The analysis here is restricted to data from the samples of rural areas from 1991 to 2009. The questions asked in the 1989 survey are different from the rest of the sequence and it is difficult to compare the data in 1989 to the others consistently. Our final sample size

[13] Initiated in 1989, the CHNS was designed as a time-cohort survey and covers: Heilongjiang, Liaoning, Shandong, Jiangsu, Henan, Hubei, Hunan, Guangxi, and Guizhou. A multistage, random cluster-sampling scheme is used to draw a sample from each province. In particular, counties in the nine provinces were stratified by income and then four counties from each province are selected by a weighted method. Villages and townships within the counties as well as urban and suburban neighborhoods within the cities were selected randomly.

is 3,689 households and 29,413 individual observations.

Table 1. Distribution of the agricultural working population by sex and education.

	1991	1993	1997	2000	2004	2006	2009
				A. Sex			
Male	0.46	0.46	0.48	0.47	0.48	0.45	0.46
Female	0.54	0.54	0.52	0.53	0.52	0.55	0.53
				B. Educational attainment			
None	0.26	0.24	0.20	0.17	0.17	0.17	0.15
Primary	0.39	0.38	0.39	0.38	0.42	0.40	0.41
Secondary	0.27	0.28	0.29	0.30	0.35	0.34	0.37
Tertiary	0.08	0.10	0.11	0.15	0.09	0.10	0.07
				C. Age group			
< 20	0.09	0.07	0.05	0.04	0.04	0.04	0.03
20-24	0.11	0.09	0.08	0.05	0.03	0.01	0.02
25-29	0.13	0.10	0.10	0.08	0.05	0.03	0.03
30-34	0.10	0.11	0.12	0.11	0.08	0.07	0.05
35-39	0.14	0.13	0.09	0.13	0.11	0.11	0.10
40-44	0.12	0.14	0.14	0.11	0.12	0.15	0.13
45-49	0.09	0.11	0.14	0.15	0.13	0.10	0.13
50-54	0.07	0.07	0.10	0.12	0.15	0.16	0.13
55-59	0.06	0.06	0.06	0.08	0.12	0.13	0.14
60-64	0.04	0.05	0.05	0.06	0.07	0.09	0.12
≥ 65	0.05	0.06	0.06	0.07	0.10	0.12	0.14
Sample Size	5,389	4,616	4,656	4,409	3,672	3,226	3,445

Notes.– Source: China Health and Nutrition Survey (CHNS). None: no formal education. Primary: 1-6 years of education. Secondary: 6-9 years of education. Tertiary: >9 years of education.

The CHNS allows us to determine the individual income and the time allocation in agriculture. Individual income is defined as the sum of net revenue in a given year from all agricultural production activities.[14] Individual income adds each person's income source and does *not* use a simple division of household income evenly among household

[14]Individual income is derived from farming, fishing, gardening, and raising livestock. The calculation for income is similar in all activities. For example, for farming income, the head of the household would provide: value of sale of farming product, value of consumed farming product, and expense to such farming product. Net household farming income is calculated as the value of sales from farming plus the value of consumed farming product minus farming expense. Each member of the household reports the total hours spent farming. Thus, individual farming income is the individual proportion of net household farming income, where the proportion is determined by the share of time spent farming.

members.[15] To measure the number of hours worked, participating individuals were asked three questions related to their labor input in each agricultural activity: on ex-post how many hours of work per day, how many days of work per week, and how many months of work per year. Using these questions, we compute an individual's working hours per survey year. Our measure of individual wages in agriculture divides total annual income by the total number of hours worked. That is, our benchmark measure of individual wages is the average product of labor. Later in this section we discuss estimates of the marginal product of labor based on a "shadow wage" approach. Both approaches yield virtually the same implications for agricultural productivity.

We cross-classify the labor input into three factors: sex (s), age (a) and education (e). We distinguish the labor input according to 88 ($= 2 \times 11 \times 4$) categories. Table 1 contains the distribution of the working population across sex, age, and education. As the table shows, there has been an improvement in the measures of human capital in China. The fraction of rural working populations without any formal education, for example, has declined from 26% in 1991 to 15% in 2009. This evidence suggests an increase in the quality of the labor in agriculture. People aged 50 or above account for 22% of the working population in 1991. In 2009 this number goes up to above 50%. This shows a trend of migration from rural to urban areas in the younger generation.[16]

Log-wage profiles. We regress log(income/hours) for each individual on sex, education, and age indicator variables. We control for marital status and include and indicator if the value of individual income is imputed. We report OLS estimates and estimates that control for individual fixed effects. In all specifications we include a time control. There is a small number of instances with negative wages in the survey; we exclude these

[15] Imputation for missing individual data is sometimes made if a filter variable indicated certain agricultural activity for an individual. Income imputation is based on the mean of the household, the mean of individuals in the community, or the mean in the city, by the order of availability. We control for income imputation in all our estimates.

[16] In order to verify the validity of the CHNS, we examined the distribution of the rural population in the 2000 Census. The composition of the population is similar in the CHNS and the Census. The fraction of males in the Census is 0.51 while in the CHNS in 2000 is 0.49. The distribution of education in the Census according to the categories of Table 1 is 0.14, 0.38 , 0.40, and 0.07. The main difference with the CHNS in 2000 is in the tertiary level of education. The values in the 2000 Census are very similar to those of later CHNS waves.

individuals.[17]

Table 2 displays the resulting wage estimates of age, sex, and education in China's agricultural sector from 1991 to 2009. Column (1) presents pooled OLS estimates. In (2), we investigate whether our wage profile changes with individual fixed effects controls. In (3) and (4), we separate our sample by coastal and inland provinces to examine regional differences in the returns to age, education, and gender. Finally, in column (5), we reproduce the log-wage profile of non-agricultural workers in 1986 from Young (2003, Table 17). We use Young (2003) as an indirect way to examine the validity of our estimates.

The age profiles are consistent across specifications. In rural China, wages rise with educational attainment but at a slower rate than in the non-agricultural sector. Similarly, the age-income profile follows an inverted U-shape pattern. In specification (1), which is closer conceptually to specification (5), wages peak at ages 35-39 for agricultural populations. In specification (2), wages peak at ages 60-65. In the non-agricultural sector (column (5)), the peak is in the age group 50-54. Finally, specification (1) suggests no difference between the wages of men and women in the agricultural sector. Young (2003), however, suggests that women earn lower non-agricultural wages than men.

[17] Dropping individuals with negative incomes reduces our sample size to 28,062 individual observations. In some instances, individuals report negative income and this leads to negative wages. Due to the cyclical nature of agriculture (e.g., unavoidable fluctuations in prices and the weather), individuals report expenses at the beginning of the year that exceed sales at the end of the year. Slightly less than 5% of our sample has negative wages. About 16% of households reported more expenses than sales of livestock in our sample. We implemented various methods to impute positive wages. For example, we replaced the negative wages by the lowest positive wage in the community. These results are virtually identical to those in Table 2, and are available upon request.

Table 2. Estimated log-wage profiles by worker characteristics (relative to base group).

Dependent variable: log(income/hours)	Data: CHNS				Estimates in Young (2003)
	OLS	Fixed effects	OLS: Coast	OLS: Inland	
	(1)	(2)	(3)	(4)	(5)
	A. Educational attainment				
None	−0.170	−0.116	−0.143	−0.220	−0.32
	(0.045)	(0.071)	(0.070)	(0.059)	(0.022)
Primary	base	base	base	base	base
Secondary	0.085	0.122	0.059	0.109	0.16
	(0.039)	(0.069)	(0.060)	(0.053)	(0.008)
Tertiary	0.227	0.157	0.175	0.266	0.25
	(0.059)	(0.103)	(0.092)	(0.077)	(0.010)
	B. Age group				
< 20	0.072	0.286	−0.114	0.172	−0.25
	(0.080)	(0.149)	(0.135)	(0.100)	(0.014)
20-24	base	base	base	base	base
25-29	0.326	0.282	0.393	0.289	0.30
	(0.076)	(0.122)	(0.125)	(0.095)	(0.010)
30-34	0.445	0.233	0.330	0.556	0.49
	(0.076)	(0.140)	(0.123)	(0.099)	(0.009)
35-39	0.625	0.454	0.586	0.659	0.54
	(0.073)	(0.156)	(0.119)	(0.093)	(0.009)
40-44	0.621	0.515	0.437	0.771	0.58
	(0.073)	(0.173)	(0.120)	(0.093)	(0.009)
45-49	0.501	0.586	0.434	0.568	0.66
	(0.076)	(0.191)	(0.124)	(0.098)	(0.010)
50-54	0.423	0.651	0.168	0.621	0.71
	(0.082)	(0.211)	(0.133)	(0.104)	(0.011)
55-59	0.248	0.650	0.132	0.363	0.67
	(0.087)	(0.231)	(0.142)	(0.111)	(0.014)
60-64	0.346	1.034	0.0630	0.584	0.60
	(0.094)	(0.249)	(0.150)	(0.121)	(0.023)
≥ 65	0.098	0.338	−0.118	0.276	0.55
	(0.090)	(0.261)	(0.143)	(0.119)	(0.033)
	C. Sex				
Male	base	-	base	base	base
Female	0.041	-	−0.101	0.156	−0.12
	(0.032)	-	(0.051)	(0.043)	(0.005)
N. Obs.	28,062	28,062	11,466	16,596	222,281
R^2	0.21	0.19	0.22	0.21	0.83

Note.– Standard errors in parentheses. See Table 1 for the definition of the educational groups. Young (2003) indicates the log-wage estimates for non-agricultural workers in 1986. Specifications (1)-(4) include time controls. The coastal provinces are Liaoning, Jiangsu, Shandong, and Guangxi. The inland provinces are Heilongjiang, Henan, Hubei, Hunan, and Guizhou.

Regional differences.– Columns (3) and (4) show important differences in the return to education between coastal and inland rural provinces. Wages rise with educational attainment at faster rates in the rural inland provinces. The higher returns to education in the inland areas imply that human capital investments in these relatively poorer areas can reduce regional inequalities.[18] For the age-income profiles, both coastal and inland areas show an inverse U-shape, but the peak is higher in the inland provinces. Interestingly, the agricultural wage for women is lower than men's wages in the coastal areas. The differences between coastal and inland rural provinces explain the lack of wage differences between men and women in the full sample; column (1).

We will use the estimates in columns (3) and (4) as an indirect way to examine the importance of labor market distortions. The idea is that with perfect labor mobility, the rates of return to age, education, and gender in the different rural regions would tend to be equalized. Instead, in our sample agricultural wages in rural coastal provinces are about 20% higher than in rural inland provinces. These differences are partly due to a favorable policy to the coastal provinces during the early stage of the reform and to better access to global markets. As we have discussed in the background section, the restriction on labor mobility and factor allocation imposed by the *hukou* system also contributes to regional inequalities; especially to rural-urban differences; see, e.g., Liu (2005).[19] Our objective is not to identify the impact of labor mobility restrictions on China's structural changes. However, since rural coastal areas are likely to be better integrated, it is possible to measure the agricultural labor input using the coefficients from the coastal and inland provinces separately. The difference between the estimates of the labor input will be due in part to factor market distortions.

Price distortions.– We also measure the influence of price distortions directly. CHNS

[18] Fleisher et al. (2010) have indeed showed that human capital has reduced regional inequalities in China. Whalley and Zhao (2010) draw a similar conclusion from 1978 to 2008. In their study, human capital contributes in 38% to the economic growth in China. Finally, Li et al. (2009) estimate that human capital in China has increased by almost 4 times from 1985 to 2007. The growth rate of human capital accumulation has accelerated to 7.5% per year since 1995. They suggest that this high growth rate is primarily due to an increase in educational attainment.

[19] Liu (2005) examined paired urban and rural communities in Beijing and showed that an urban *hukou* raises a person's income by about 26%. In our quantitative section, we will examine numerically the role of labor barriers to mobility.

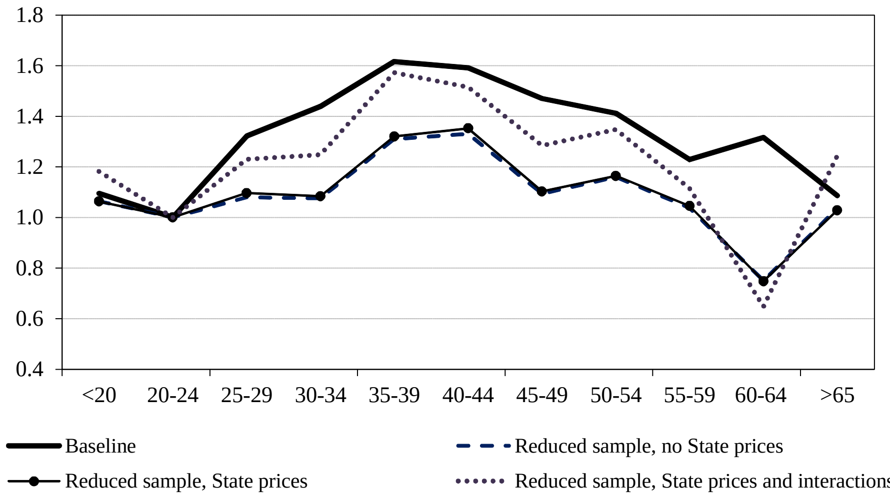

Figure 1: Agricultural log-wage by age groups with and without State controlled prices.

collects information about ration coupon prices and free market prices for agricultural goods from 1991 to 1997 in the community-level survey. To examine the importance of price distortions, we augment the log-wage profiles to include State ration coupon prices for rice and the difference between the State ration price and the free market price.[20]

We focus on the influence of price distortions on the log-wage profiles. In China, as argued by Young (2003, p. 1260), "agriculture remains distorted in many respects (e.g., with local procurement and price controls)." Moreover, as noted by Young (2000, p. 1114), prices across China's provinces "have gone through bouts of falling and rising dispersion." Young (2000) interpreted this lack of convergence as evidence of higher interregional distortions. Holz (2009, p. 604), however, argues that "the observed patterns in price dispersion are perfectly well explained by institutional changes." Although it is virtually impossible to examine the effects of all existing distortions, including the controlled price or its difference with respect to the market price, provides a direct measure of the local (dis)incentives farmers face.

[20]The analyses in this sub-section are based on confidential data. We focus on price distortions for rice due to its importance in China. Our results, however, are consistent if we include other commodities whose prices are also controlled by the State. The sample sizes for additional commodities are reduced because price controls were less prevalent. These results are available upon request. We use pre-2000 data because after 2000, most commodity prices are determined by market forces.

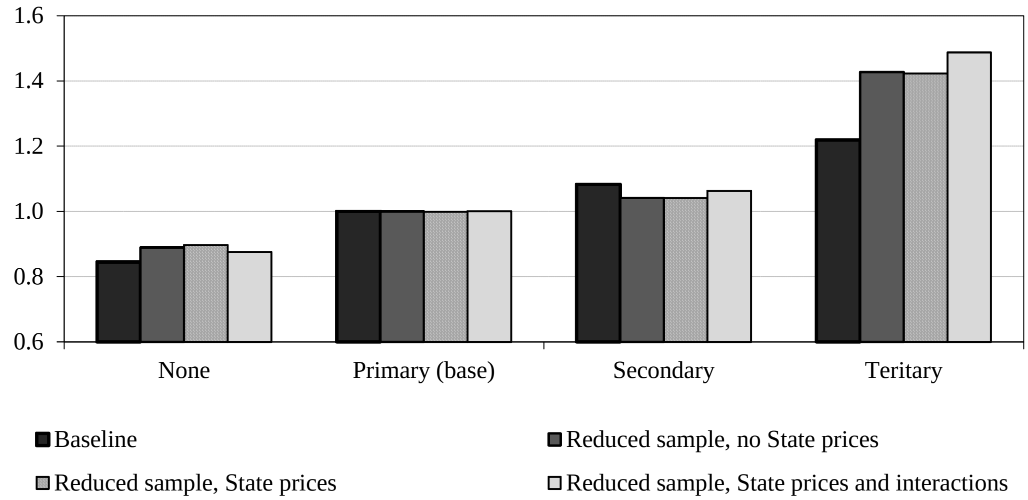

Figure 2: Agricultural log-wage by education groups with and without State controlled prices.

The econometric estimates are available upon request. Due to data limitations, the data we use to examine price distortions only include the 1991, 1993, and 1997 waves. The sample size is 5,592 observations. We find that price distortions influence the level of log-wages. For example, a 1 *Yuan* increase in the ration coupon price of rice in the community increases individual wages by about 9.64%; the implied elasticity is 0.083. Log-wages also increase as the gap between State prices and free market prices widens. There are, however, no significant differences in the sex-age-education *wage profiles* if we include state prices or the price differential as control variables.

To provide further evidence of the impact of price distortions, we interacted the ration coupon price of rice with the sex-age-education indicators. Interaction terms capture the effect of price controls on the slope of the wage profiles. We display the results graphically. Figures 1 and 2 plot the log-wage profiles by age and education categories for four specifications: (i) our baseline estimates obtained from the entire sample; Table 2, column (1), (ii) the log-wage profile in our reduced sample without the State price as control (to show that the our subsample is representative), (iii) the log-wage profile when State prices are included as controls, and (iv) the log-wage profile when interactions between State prices and the sex-age-education indicators are added as controls.

Figures 1 and 2 show that the age and education profiles are similar across specifications. The main differences in the figures are due to a small number of observations at ages 60 and above, and for individuals with tertiary education. In general, since the log-wage profiles are virtually unchanged, the first-order effect of price distortions appears to be a uniform shift in the level of log-wages. This overall change in wages is consistent with a distortions having a "level effect" on measured productivity.

"Shadow wages."– The previous estimates rely on the average product of labor. We also estimated the marginal product of agricultural labor using a "shadow wage" approach; see, e.g., Jacoby (1993) and Skoufias (1994). We present these results in an Appendix since they are not central to the paper. We estimate a Cobb-Douglas production function and use the resulting marginal product estimates as the wage for each labor type. Under a Cobb-Douglas, the marginal and the average product of labor are proportional. The implications of this approach for the labor input and productivity are presented below.

Labor input. Given the previous log-wage estimates, we next derive our estimate of the labor input in agriculture. Equation (18) defines the growth rate of a Divisia index of labor input (Hulten, 1993). The discrete approximation of equation (18) is given by:

$$\Delta \ln L = \sum_{i=1}^{N} \overline{s}_i \Delta \ln H_i, \tag{19}$$

where there are $N = 88$ types of labor, H_i is the hours worked for type i, $\overline{s}_i \equiv \frac{1}{2}(s_{i,t}+s_{i,t-1})$ where $s_{i,t}$ is the labor i's share in total wage compensations at time t, and the Δ denotes the first time differences, $\Delta \ln L_t \equiv \ln L_t - \ln L_{t-1}$. The unweighted sum of total hours worked is $H_t = \sum_i H_{i,t}$, and the quality of labor, Q_t, is given by $L_t = Q_t H_t$. Expression (19) implies that $\Delta \ln Q = \Delta \ln L - \Delta \ln H$, with

$$\Delta \ln Q = \sum_{i=1}^{N} \overline{s}_i \Delta \ln d_i,$$

where $d_{i,t} = H_{i,t}/H_t$, is the proportion of hours worked by the i-th type of labor. $\Delta \ln Q$ measures the changes in the composition of hours worked by sex, age and education.

To compute the growth rates defined above, we need to compile the data on hours worked and labor compensation. The latter is based on the estimated log-wage profiles. To obtain average hours worked for each type of labor we rely on the CHNS data. Finally, the employment for each category is calculated by multiplying the categorical distribution of the labor force from the CHNS (summarized in Table 1) and aggregate agricultural employment data from the *China Statistical Yearbook* (CSY).

Table 3. Average annual growth rate of Chinese agricultural labor input and labor quality.

	Estimates based on Table 2								"Shadow wage" estimates	
	(1)		(2)		(3)		(4)			
	$\Delta \ln L$	$\Delta \ln Q$	$\Delta \ln L$	$\Delta \ln Q$	$\Delta \ln L$	$\Delta \ln Q$	$\Delta \ln L$	$\Delta \ln Q$	$\Delta \ln L$	$\Delta \ln Q$
1991-1993	−2.73	1.92	−5.88	−1.22	−3.68	1.02	−2.10	2.55		
1993-1997	−4.40	0.64	−5.31	−0.26	−4.50	0.51	−3.79	1.24	−5.94	−1.75
1997-2000	−2.05	0.36	−2.98	−0.55	−1.74	1.26	−1.90	0.25	−4.27	−3.45
2000-2004	−4.76	−0.76	−4.85	−0.85	−5.45	1.61	−4.52	−0.44	−4.76	−1.73
2004-2006	−7.69	0.69	−7.82	−0.05	−8.31	0.01	−7.86	−0.37	−7.87	−1.50
2006-2009	−7.73	−0.08	−7.83	−0.17	−8.03	0.26	−7.62	−0.03	−7.01	−0.51
1991-2009	−4.82	0.24	−5.58	−0.51	−5.17	0.03	−4.54	0.46	−5.13	−1.60

Note.– Estimates of changes in the labor input based on a divisia index of labor input. The "shadow wage" approach is discussed in the Appendix.

Table 3 presents the main results of this analysis. We present estimates based on specifications (1)-(4) from Table 2. We also include the resulting change in the labor input from our "shadow wage" approach.

Overall, Table 3 suggests that *the labor input in agriculture decreased at an average annual rate of 4.5-5.5%*. In comparison, Young (2003) finds that the growth rate of the labor input in non-agriculture between 1978 and 1998 is about 2.6% per year. Moreover, the quality of labor is, on average, increasing at a lower rates than Young's (2003) estimate for the quality of non-agricultural workers during 1978 to 1998 (1.1% per year). The difference in the quality of labor between agriculture and non-agriculture shows that there are important compositional changes in employment and hours of work for the workers leaving and staying in agriculture. Table 3 and the previous estimates suggest that workers leaving agriculture tend to be the most educated ones or those with higher wages. The estimated changes in Table 3 highlight the importance of treating labor as a differentiated input.

Table 3 shows important temporal differences in the rate of change of the labor input. In particular, the labor input's rate of decline is accelerating in recent years. In terms of regional differences, specifications (3) and (4) in Table 3 apply the set of coefficients from coastal and inland provinces to the national distribution of labor, and compute the growth rates of the labor input and labor quality. With the coastal coefficients, the agricultural labor input decreased at 5.17% per year. With the inland coefficients, this number is 4.54%. As we argued before, the difference between these estimates of the labor input may be in part due to geographic or legal barriers to labor mobility.

There are three important observations regarding specifications (3) and (4) in Table 3. First, the labor input has declined at faster rates according to the coastal coefficients; the difference between both estimates is 0.63%. This positive difference is consistent with the idea that coastal areas face less mobility barriers than inland areas. Second, labor quality has increased at smaller rates in coastal areas, perhaps due to the selective migration of agricultural workers in these areas. In the rural inland areas, the quality of the labor input shows the fastest increase in our sample. Third, even if one considers the coefficients from inland areas, the labor input has declined at rates that exceed 4.5% per year. As we will see below, the difference between the labor input measured according to coastal and inland coefficients leads to small differences in agricultural TFP.

Finally, notice that estimates of the labor input that rely on the estimation of an agricultural production function, the "shadow wage" approach, suggest a decline in the labor input in agriculture of about 5%. This estimate lies between our estimates based on the other specifications in Table 3.

Total Factor Productivity Growth. Besides the labor input, to estimate TFP growth we need aggregate measures of agricultural output, capital, and land. The data is mostly taken from the China Statistical Yearbook (CSY) with necessary adjustments. First, according to Young (2003), the official GDP deflator underestimates inflation.

Young (2003) suggests using alternative official price indices to construct real GDP series. We follow Young's approach and deflate the nominal GDP in the agriculture, industry, and service sectors by the purchasing price index for farm products, the ex-factory price index of industrial products, and the consumer price index (services), respectively. This data shows that agricultural output grew at 5.6% on average from 1978 to 2009.

Second, because the CSY only contains one measure of national capital stock and does not break down the capital into different categories by sectors, our measurement of agricultural capital stock relies on the estimates by Dekle and Vandenbroucke (2010, 2012). They aggregate the provincial data, which does decompose the capital into three sectors, into a national measure. In their data, the growth rate of capital in agriculture is 3.1% annually. Third, labor is measured by the number of persons who engaged in working activities and received some income in each calendar year. The employment data from the CSY shows that after 1978 the number of people engaged in agriculture increased about 1.1% annually, which is much less than Young's (2003) estimates for the whole country (2.2%) and for the industrial sector (4.5%). Last, the input of land in the agricultural sector is measured by the total crops sown area. This figure does not vary much over time; its annual growth rate is 0.3%.

Factor Shares.– The share of labor income is typically obtained either from the national accounts or from input-output tables. Using the data from Chinese input-output tables in 1992, 1995, 1997, and 2000, the ratios of compensation for laborers in the agricultural value added are 0.84, 0.84, 0.88, and 0.88, respectively. Not only are those numbers substantially higher than the estimates for the non-agriculture sector by Young (2003), they are much higher than the shares in other East Asian countries.[21] This abnormally high share of the labor input appears to be due to the fact that the compensation of labor in the agricultural sector is calculated by adding the "net incomes" of various activities associated with production in the rural area; see OECD (2000).[22] In other words, the

[21]Hayami et al. (1979) report that agricultural labor shares in Japan, Taiwan, Korea, and the Philippines range from 0.31 to 0.53 during the period from the beginning of the twentieth century to the sixties. Data from input-output tables in China fall outside of this range by a large margin. Our estimated labor share in agriculture for China is 0.38, which falls within the previous range.

[22]In particular, the compensation of employees in the agricultural sector is calculated as the net incomes

measure from the input-output tables appears to contain not only the "labor income," but a combination of many incomes. Since there is no market for land, we must find ways to obtain a separate valuation of land relative to capital and labor.

We first estimate factor shares using an aggregate Cobb-Douglas production function. This approach is similar to Chow (1993), who argued that the capital, labor, and land shares are 0.25, 0.40 and 0.35 respectively for Chinese agriculture from 1952 to 1980. We next extend Chow's (1993) study to 2003 for comparability. The aggregate agricultural production function is specified by:

$$\ln Y = \alpha_0 + \alpha_K \ln K + \alpha_T \ln T + \alpha_L \ln L + \alpha_t t, \tag{20}$$

or with the constant returns to scale assumption:

$$\ln(Y/L) = \alpha_0 + \alpha_K \ln(K/L) + \alpha_T \ln(T/L) + \alpha_t t,$$

where Y is the output, K is capital, T is area of land, and L is labor. We exclude the years 1958-69. As Chow (1993) suggests, these years are irregular due to political movements such as the Great Leap Forward and the Cultural Revolution. The CSY contains data for output, labor, and land before 1978. For capital, the CSY does not break down the capital into different sectors, so we rely on the investment data estimated by Chow (1993). We set the initial capital in 1952 such that our constructed capital series matches the data in 1978.

The coefficients of the variable inputs represent the factor shares in production. The variable t has a value of zero from 1952 to 1977 and increases by one thereafter. Thus, the coefficient of t can be read as a crude estimate of total factor productivity growth in the Chinese agricultural sector after 1978. Table 4 shows the regression results. The coefficients of labor and capital from both regressions are almost identical. The estimates

per capita in the rural area times the population in the rural areas, while for all others industry, the compensation of employees equals the average wages times the number of workers. Fan and Zhang (2002) measure the share of labor cost in total agricultural production in China to be about $\alpha_L = 30\%$ in 1997. The labor cost is based on survey data on daily wage and the number of working days. Their estimate is consistent with ours, although the estimation methods differ considerably.

indicate that the factor share of land and capital are about 37% and 25%, respectively. Labor shares are 38%. These values are consistent with Chow's (1993) estimate. The sum of land and labor shares is 75%, which is close to the "labor income" reported by input-output tables. This suggests that input-output tables appear to report a composite of labor and land returns. The two regressions also suggest that there is a 4% increase in productivity for the Chinese agricultural sector in 1978-2003. This number is lower than our TFP estimate from microdata reported immediately below. The reason is that the estimates of Table 4 do not disaggregate the labor input to take into account quality differences.

Table 4. Estimates of the agricultural production function.

Dependent variable: $\ln Y$			Dependent variable: $\ln(Y/L)$		Time trend	
$\ln K$	$\ln L$	$\ln T$	$\ln(K/L)$	$\ln(T/L)$	after 1978	R^2
Period: 1952-1980. Based on Chow (1993)						
0.25	0.32	1.034				0.98
(0.044)	(0.095)	(0.024)				
Period: 1952-2003						
0.26	0.39	0.68			0.039	0.99
(0.082)	(0.15)	(0.46)			(0.003)	
			0.25	0.37	0.041	0.97
			(0.081)	(0.081)	(0.003)	

Note.– Standard errors in parentheses. The period from 1958 to 1969 is excluded from the estimations. For the period between 1952-2003 we rely on an extension based on the investment data of Chow (1993).

An alternate way to obtain factor shares is to use our micro-estimates of the agricultural production function. In the Appendix we use these estimates to determine the labor and land shares, as well as to estimate TFP growth rates based on a time trend, as in Table 4. The estimates are not directly comparable because we do not include capital in these estimates (capital is not available in the survey data). We also use household data and hours of work (not the number of workers) to measure the labor input. Nonetheless, the estimated land share, 34%, is virtually the same as in Table 4. The estimated labor share is 23%. We can also estimate TFP growth using a time trend in the production function. Our time trend estimate for the years 1991-2009 is 6.5%. This estimate is virtually the same as our estimate of TFP growth presented immediately below, and larger than the trends in Table 4, which as we just mentioned, do not take into account quality differences in the labor input.

Overview.– The TFP growth can be estimated as follows:

$$\text{TFP growth} = \frac{d \ln Y}{dt} - \alpha_K \frac{d \ln K}{dt} - \alpha_L \frac{d \ln L}{dt} - \alpha_T \frac{d \ln T}{dt}, \tag{21}$$

where $\alpha_K = 25\%$ is the capital share, $\alpha_L = 38\%$ is the labor share, and $\alpha_T = 37\%$ is the land share. These factor shares are suggested by the aggregate agricultural production function from Table 4, and by our estimates of the aggregate production function based on microdata. Official data (CSY) for the Chinese economy from 1978 to 2009 shows that agricultural output grew at 5.6% annually, capital grew at 3.1%, and land barely changed and only increased by 0.3% each year. We also showed that the labor input decreased at an average annual rate of 4.5-5.5%. Therefore, *agricultural TFP growth in China between 1991 and 2009 in (21) increased at an annual rate of 6.5%.*[23] Since there is no data for the early part of the reform period, we use this estimate for the entire period.

5 Quantitative results

In this section, we use our theoretical model and our previous measurement results to examine the contribution of agricultural productivity to China's post-reform growth and sectoral reallocation.

Baseline calibration. The baseline calibration relies on our measurement results for

[23] Based on a range of 4.5 to 5.5% decline in the labor input, the range of TFP growth is 6.4% to 6.8%. The labor share from input-output data, 0.84, suggests a much higher TFP growth rate. If we use $\alpha_L = 84\%$, $\alpha_T = 0\%$, and $\alpha_K = 25\%$, the estimate of TFP would exceed 8% per year. Brandt et al. (2008, p. 723) suggested a labor share of $\alpha_L = 50\%$. If we use that value in (21), TFP would be 7.1%. Fan and Zhang (2002) argue that official data overstated the TFP growth by about 2%. Their estimate of agricultural TFP growth from 1979 to 1997 was about 3.3% per year. Their measures of labor input, however, are homogenous and ignore the changes in the composition of the Chinese agricultural labor. This implies that part of the improvements in labor quality and the reduction in agricultural labor input may be allocated to TFP growth.

agriculture, and on Young's (2003) results for non-agriculture. Since technological change is labor-augmenting, productivity growth in each sector is $\mu_a = 6.5\% \times (1 - \alpha_a)$, and $\mu_m = 1.4\% \times (1 - \alpha_m)$. We use our estimate of the capital share in agriculture, $\alpha_a = 25\%$. In our baseline calibration we use the non-agricultural capital share from Young (2003, p. 1255), $\alpha_m = 54\%$. The parameter α_m plays a central role for the transition and we present alternate values of α_m later on.

A period is defined as one year. The initial period is 1978 and we consider a transition of 30 years. Population growth is $\nu = 1\%$, the depreciation rate is $\delta = 5\%$, and the discount rate is $\rho = 3\%$. The steady state expenditure share of agricultural goods is set to $\omega = 0.15$. We normalize $A_a(0) = 1$. We calibrate γ to match the level of the employment share in agriculture in the Chinese economy in 1978; that is, $n_a(0) = 70\%$. We calibrate $\hat{k}_m^*/\hat{k}_m(0)$ to match an average growth rate of income per worker of 5.5%.[24] Aggregate output growth per worker between 1978 and 1998 in China was 5.2% according to Young (2003, p. 1258). Dekle and Vandenbroucke's (2010) estimates suggest a 5.5% growth rate between 1978 and 2008. Table 5 summarizes the values of the parameters.

Figures 3 and 4 provide information about the employment and output shares in the data and the simulations. Figure 3 displays the employment share based on official data and the estimate from Brandt et al. (2008).[25] Table 6 provides additional information about the average growth rate in the aggregate and the non-agricultural sector, growth in the output-capital ratio, the rate of return to capital, and the relative price of agricultural goods. We take the rate of return to capital from Bai et al. (2006). They measure r as the ratio of the capital share in output to the capital-output ratio (net of depreciation). From 1978 to 2005, their rate of return to capital in China is about 23%, which is driven by a relatively low capital-output ratio (1.5), and by a relatively high capital share (49%).

[24] In the baseline calibration, the steady-state value of normalized capital in (16) is $\hat{k}_m^* = 35.9$, and the fraction of labor allocated to agriculture in (17) is $n_a^* = 14.6\%$. In order to obtain a high transitional growth rate of output, the initial capital is $\hat{k}_m(0) = 5.3$.

[25] Brandt et al. (2008) conclude that the official Chinese data may underestimate the agricultural employment due to the exclusion of private employment prior to 1984, incomplete tabulation of self-employed individuals who receive income outside of agriculture, and erroneous inclusion of migrants. Their alternative series of agricultural employment in Figure 3 is based on information from Chinese Census and rural household surveys.

The price data are based on general price index of farm products and ex-factory price indices of industrial products from various issues of CSY. We report the change in relative prices during the 30 years of our simulations, but we must acknowledge that price data is subject to a number of caveats that make a definite interpretation difficult.[26]

Table 5. Parameter values.

	Parameter description	Baseline Value	Alternate Value
	A. Preferences		
ω	Expenditure share of agricultural consumption	0.15	-
γ	"Subsistence level" of agricultural consumption	0.65	1.73
ρ	Time discount rate	0.03	-
ν	Population growth rate	0.01	-
	B. Technology		
α_a	Capital share in agriculture	0.25	-
α_m	Capital share in non-agriculture	0.54	0.75
δ	Depreciation rate	0.05	-
	C. Productivity and initial conditions		
$\mu_a/(1-\alpha_a)$	Productivity growth in agriculture	0.065	-
$\mu_m/(1-\alpha_m)$	Productivity growth in non-agriculture	0.014	-
$A_a(0)$	Initial productivity in agriculture	1	-
$\hat{k}_m^*/\hat{k}_m(0)$	Initial normalized capital in non-agriculture	6.70	4.26

Note.– Parameters are described in the text.

The baseline model reproduces well structural changes. Figure 3 shows that the share of agricultural employment in the model starts at about 70% and gradually decreases to 22% in 30 years, matching the historical data. The baseline calibration yields employment shares that are closer to those estimated by Brandt et al. (2008), especially at the beginning of the reform period. The baseline model also yields a decline in the output share in agriculture. The model, however, does not fit the initial level of the output share.

[26]Before 1984, prices of important materials were set by the government and held unchanged for a long time. During the initial part of the reform period, the artificially low food prices, along with other consumer goods prices, began to increase; see Lin and Yu (2009). This initial increase in prices is likely to simply reflect the fact that prices were below their equilibrium value. How distorted were relative prices initially? Lardy (1983, Chapter 3) shows that in 1976 the price of fertilizers relative to rice in China was more than twice as high as the same relative price in other Asian countries. He also shows that in 1980 the quota price for rice, wheat, and corn were about half the average price in rural markets. Both these figures suggests that before the reform, the Chinese government artificially suppressed the agricultural price level by about 50%.

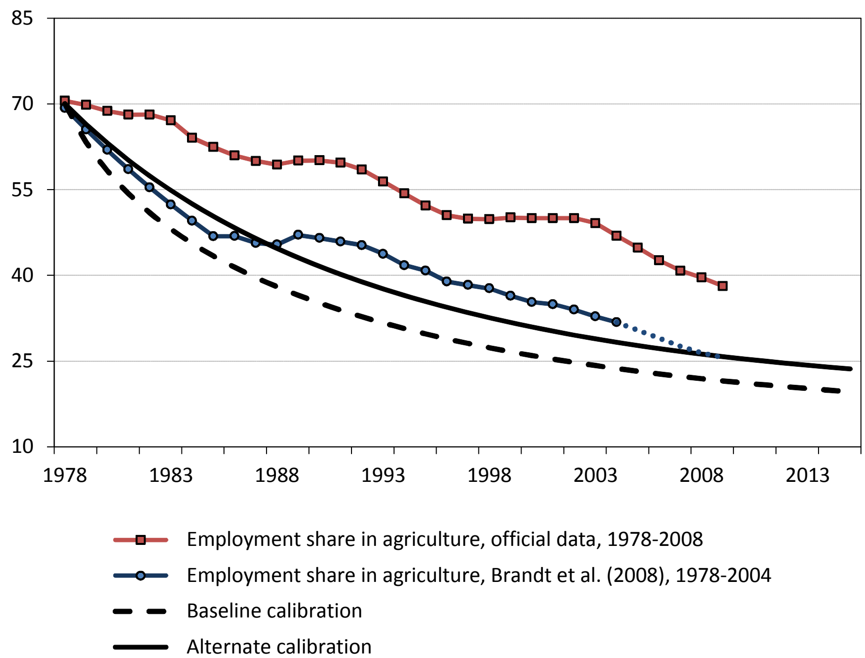

Figure 3: Employment share in agriculture: Data and model, 1978-2008.

The model's output share of agriculture starts from around 58%. In the data, agriculture accounts for about 30% of GDP in 1978 and for 15% of GDP in 2008; see Figure 4. The baseline calibration also predicts rapid convergence, capital-deepening, rapid growth in non-agriculture, and a rapid decline in relative prices and the rate of return to capital. In the data, output per worker in non-agriculture grew at slower rates than in the aggregate, the output-capital ratio remained virtually unchanged between 1978 and 1998; see, e.g., Young (2003, p. 1259), and the rate of return to capital has been stable; see, e.g., Bai et al. (2006) and Song et al. (2011).

Alternate calibration. The baseline calibration yields the previous counterfactual implications because the capital share in manufacturing is relatively low. A low value of α_m implies rapid convergence; see, e.g., Barro and Sala-i-Martin (1995). In King and Rebelo (1993, p. 921), for example, protracted transitions that maintain high rates of return to capital require a capital share of the order of 0.9.

There are several ways to motivate a higher capital share. Alternative interpretations that lead to the same value of the capital share will have the same implications for reallocations between agriculture and non-agriculture, which is the focus of our paper. The model considers a single form of capital. Using a broader concept of capital, such as human capital in Barro and Sala-i-Martin (1995) or intangible capital in Parente and Prescott (2000, chapter 5), increases the capital share. For instance, let z_m denote the additional capital per worker, and let the augmented production function in the non-agricultural sector be $A_m[k_m]^{\alpha_m} z_m^{\theta} n_m$. (In our benchmark model $\theta = 0$.) The equality between the marginal products of capital implies $\alpha_m z_m = \theta k_m$. The production function becomes $A_m[k_m]^{\alpha_m} z_m^{\theta} n_m = A'_m[k_m]^{\alpha_m+\theta} n_m$, where $A'_m = A_m\theta/\alpha_m$, and the relevant capital share is $\alpha_m + \theta$, which exceeds α_m.[27]

The model also abstracts from reallocations within manufacturing. Song et al. (2011) constructed a microfounded model of the Chinese economy with an emphasis on resource reallocations within manufacturing. In their model, "during the transition, the dynamic equilibrium has AK features: within each type of firm, the rate of return to capital is constant"; see Song et al. (2011, p. 204). With an asymptotic AK technology, the marginal product of capital would not decline over time, and the capital share would tend to one; $\alpha_m \to 1$.

For the alternate calibration, we consider $\alpha_m = 0.75$. All other parameter values remain as in Table 5, but we calibrate γ and $\hat{k}_m^*/\hat{k}_m(0)$ to obtain $n_a(0) = 70\%$ and a 5.5% growth rate of GDP per worker during the transition. The alternate value of α_m fits better the transitional path of the employment and output shares, and it yields slower convergence and more stable rates of return to capital and output-capital ratios. The alternate parameterization still predicts a high growth rate of output in the non-agricultural sector and capital-deepening. Later on we discuss an even higher capital share $\alpha_m = 0.85$; this value makes the dynamics in non-agriculture close to an AK model.

Counterfactual experiments. The transitional path of the model economy depends on the productivity growth in agriculture and non-agriculture. We measure the contribution of agricultural TFP to China's structural change and post-reform growth by

[27] Barro and Sala-i-Martin (1995, figure 2.5) showed that the transitional properties of the neoclassical model improve considerably with higher values of α_m. Using relatively higher capital shares, Parente and Prescott (2000, p. 80) showed that the neoclassical growth model "with intangible capital [...] matches the development miracle of Japan."

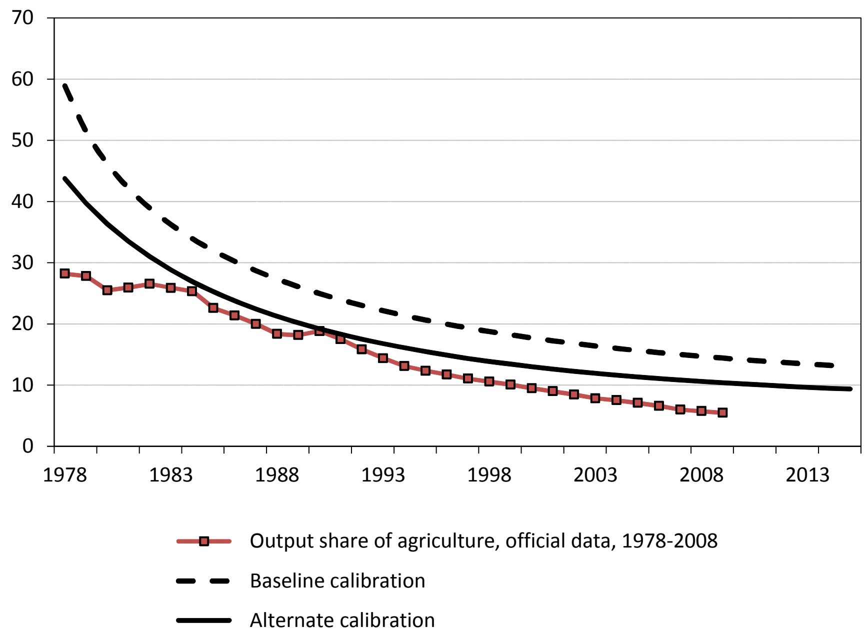

Figure 4: Output share in agriculture: Data and model, 1978-2008.

solving the model when each of these TFP growth rates equals zero. We perform these experiments for both calibrations.

Table 6 presents the results. Consider first Panel A. The model attributes the majority of the sectoral reallocation of employment, output, and consumption to agricultural TFP. For example, if $\mu_a = 0$, the employment share only declines by one-third of the total predicted decline. In contrast, the reallocation of employment, output, and consumption remain virtually unchanged if $\mu_m = 0$. Consider next Panel B. The baseline calibration predicts modest growth effects. If $\mu_a = 0$, the average growth rate declines to 5.0%. If $\mu_m = 0$, the average growth rate declines to 4.5%. In the alternate calibration, setting $\mu_a = 0$ lowers aggregate growth to 4.7%. Thus, *the growth effects of agricultural TFP are as large as the growth effects of non-agricultural TFP.*

The growth effects of TFP are modest because a high fraction of aggregate growth is catch up growth. In the alternate calibration, initial capital is higher than in the baseline case and the growth effects of agricultural TFP are higher. (Large capital shares, e.g., $\alpha_m = 0.85$, yield even larger growth effects of agricultural TFP; see Table 7.) Agricultural

TFP, however, has larger effects on the growth rate of the non-agricultural sector. In the baseline case, setting $\mu_a = 0$ lowers average growth $\bar{g}_m$ from 8.3% to 6.7%. Under $\mu_m = 0$, $\bar{g}_m$ declines to 7.3%. In the alternate calibration, the contribution of μ_a to $\bar{g}_m$ is also larger than that of μ_m. That is, *agricultural TFP is more important for non-agricultural growth than non-agricultural TFP.*

Table 6. Simulation results and counterfactuals.

	Data	Baseline Calibration	Counterfactuals $\mu_a = 0$	Counterfactuals $\mu_m = 0$	Alternate Calibration	Counterfactuals $\mu_a = 0$	Counterfactuals $\mu_m = 0$
	A. Sectoral allocations of labor, output, and consumption						
$n_a(0)$	0.70	0.70	0.70	0.70	0.70	0.70	0.70
$n_a(30)$	0.25-0.35	0.22	0.48	0.22	0.24	0.54	0.25
$\theta_a(0)$	0.30	0.58	0.58	0.58	0.50	0.50	0.50
$\theta_a(30)$	0.15	0.15	0.36	0.15	0.12	0.34	0.12
$\psi_a(0)$	-	0.53	0.53	0.52	0.53	0.53	0.57
$\psi_a(30)$	0.32	0.22	0.38	0.22	0.22	0.38	0.22
	B. Average growth rates						
$\bar{g}$	0.055	0.055	0.050	0.045	0.055	0.047	0.048
$\bar{g}_m$	0.036	0.083	0.067	0.073	0.077	0.057	0.069
$\bar{g}_{y/k}$	0.004	−0.035	−0.031	−0.039	−0.023	−0.013	−0.026
	C. Rate of return to capital and relative prices						
$r(0)$	0.23	0.25	0.25	0.25	0.17	0.17	0.17
$r(30)$	0.21	0.11	0.11	0.10	0.11	0.11	0.10
$p(30)/p(0)$	1.07	0.54	2.22	0.42	0.54	2.26	0.46

Note.– Data in Panel A are from CSY and Brandt et al. (2008). Data in Panel B are from Young (2003, Table 24), after the adjustments, and Dekle and Vandenbroucke (2010). The rates of return in panel C are taken from Bai et al. (2006). Price data are from CSY.

The model predicts a decline in the output-capital ratio due to capital deepening. The data, as pointed out by Young (2003, p. 1258), suggests no capital deepening in non-agriculture. If $\mu_a = 0$, the model predicts a slower capital accumulation an a smaller increase in capital relative to output.

Consider finally Panel C. The model predicts a decline in the rate of return to capital and a decline in the relative price of agricultural goods. The changes in $r(t)$ are more or less independent of agricultural and non-agricultural TFP. These changes are driven almost exclusively by capital accumulation. The rates of return in the baseline calibration are higher than in the alternate calibration because initial capital is lower. Prices $p(t)$ are driven primarily by agricultural TFP. If $\mu_a = 0$, the model predicts an increase rather than a decline in relative prices. This finding highlights the importance of price changes for the sectoral reallocations described in Panel A.

Agricultural TFP plays a central role in the sectoral reallocations. One channel for these reallocations is a decline in relative prices. Evidence in support of this channel is difficult to assemble due to the initial price distortions in China (footnote 26). Relative agricultural prices have declined steadly since the mid-1980s when agricultural reforms accelerated; see, e.g., Brandt et al. (2008, Figure 17B4) and Dekle and Vandenbroucke (2010, 2012). Finally, notice that the growth effects of agricultural TFP are larger than the growth effects of non-agricultural TFP in the alternate calibration. Agricultural TFP is especially important for growth in non-agriculture. Capital accumulation, even under the alternate parameter values, still yields high catch up growth, capital-deepening, and a decline in the rates of return to capital.

Alternative experiments. In this subsection we measure the importance of labor mobility, and consider scenarios with higher productivity growth in non-agriculture and market distortions.[28] We also consider an even higher capital share in non-agriculture.

No labor mobility.– Table 7 measures the effect of labor mobility on aggregate and non-agricultural growth. By assumption, there are no reallocations in employment and output; $n_a(t) = n_a(0) = 70\%$. In the absence of labor mobility, aggregate growth is 4.6%, which also equals the growth rate in non-agriculture. The growth effect of labor mobility is large, particularly in non-agriculture whose baseline growth is $\bar{g}_m = 8.3\%$. Using the alternate parameter values, yields even stronger effects (we do not display these results to save space). The growth rates become $\bar{g} = \bar{g}_m = 3.9\%$. Overall, *labor reallocations account for about one-third of the aggregate growth and for about half of the non-agricultural growth during the transition.*

Higher TFP in non-agriculture.– So far we have used a moderate TFP growth rate

[28] In our theory discussion we noted that the importance of γ declines over time. We solved the model under $\gamma = 0$ to verify that this allocation coincides with our asymptotic results under $\gamma > 0$. These results are available upon request.

in non-agriculture. Using official data, growth in TFP in non-agriculture between 1978 and 1998 was 3%; see Young (2003, Table 24).[29] Table 7 replaces our benchmark value of $\mu_m/(1-\alpha_m) = 1.4\%$ by 3.0%. There are only minor differences in terms of sectoral reallocations. The higher TFP in non-agriculture, however, increases aggregate growth to 9.5% and growth in non-agriculture to 12.4%. As Brandt et al. (2008) argued, the main effects of a higher growth rate of TFP in non-agriculture are the slower decline in the rate of return to capital and the increase in agricultural prices. When $\mu_m/(1-\alpha_m) = 3.0\%$, $p(t)$ actually increase during the transition.

Table 7. Alternative experiments.

	Baseline Calibration			$\alpha_m = 0.85$	
	$n_a = 70\%$	$\mu_m/(1-\alpha_m) = 3.0\%$	$1+\tau_n^a = 50\%$	$\mu_a/(1-\alpha_a) = 6.5\%$	$\mu_a = 0$
	A. Sectoral allocations of labor, output, and consumption				
$n_a(0)$	0.70	0.70	0.70	0.70	0.70
$n_a(30)$	0.70	0.20	0.25	0.28	0.65
$\theta_a(0)$	0.58	0.58	0.46	0.31	0.31
$\theta_a(30)$	0.58	0.13	0.11	0.07	0.27
$\psi_a(0)$	0.53	0.53	0.40	0.69	0.69
$\psi_a(30)$	0.47	0.21	0.16	0.23	0.40
	B. Average growth rates				
$\bar{g}$	0.046	0.095	0.056	0.055	0.037
$\bar{g}_m$	0.046	0.124	0.075	0.066	0.039
$\bar{g}_{y/k}$	−0.025	−0.024	−0.030	−0.010	−0.004
	C. Rate of return to capital and relative prices				
$r(0)$	0.24	0.24	0.22	0.13	0.13
$r(30)$	0.11	0.15	0.11	0.11	0.11
$p(30)/p(0)$	0.54	1.33	0.50	0.50	2.07

Labor market distortions.– Table 7 examines the role of labor distortions τ_n^i. We consider $1+\tau_n^m = 50\%$ and $\tau_n^a = 0$; these values bias capital toward non-agriculture; see, e.g., (10). An important effect of τ_n^m is to lower the output share in agriculture. In our baseline specification in Table 6, $\theta_a(0) = 58\%$, whereas now $\theta_a(0) = 46\%$. Thus, the

[29] Our alternate measure of non-agricultural TFP is more conservative than some existing estimates. Brandt et al. (2012), for example, present a firm-level study of Chinese manufacturing TFP. In their estimates, manufacturing TFP grew by 8% annually during 1998 to 2006. They found that net entry contributes by about half of this growth. They also found that the reallocations toward more productive firms have small effects.

relatively low value of the output share in agriculture in China in 1978 may be partly due to the distortions in the pre-reform period. Biasing capital toward non-agriculture in the way specified here increases aggregate growth only marginally to 5.6%. This increase contrasts with a reduction in the growth rate of the non-agricultural sector. In our baseline parameterization, $\bar{g}_m = 8.6\%$, while under the labor distortions $\bar{g}_m = 7.5\%$. Non-agricultural growth declines because the diminishing returns to capital become more important for this sector.[30]

Higher capital share.– Some capital implications of the model are problematic even with $\alpha_m = 0.75$. Here we consider $\alpha_m = 0.85$, and recalibrate γ and $\hat{k}_m^*/\hat{k}_m(0)$ to obtain $n_a(0) = 70\%$ and $\bar{g} = 5.5\%$. In terms of sectoral allocations, the model performs as the baseline case in Table 6. The initial output share $\theta_a(0)$, however, is lower. The growth rate in non-agriculture is the lowest of all exercises, there is virtually no capital deepening, and the rate of return to capital is constant. These aspects of the Chinese economy are not matched by the other parameterizations. Table 7 also examines $\mu_a = 0$. The growth effects are considerably larger. The aggregate growth rate declines to 3.7%. Growth in non-agriculture also declines to 3.9%. S*ince capital is very productive, a limited transfer of workers toward non-agriculture becomes the main limitation for rapid economic growth.*

6 Conclusion

The first contribution of this paper has been to use microeconomic farm data to measure the rate of growth of agricultural TFP in China, while recognizing the differentiation in the human capital of the labor force. We found that the labor input declined at a 4.5-5.5% annual rate, and that this decline was fairly robust across a number of specification checks. We also found that between 1991 and 2009, agricultural TFP grew at an average annual rate of 6.5%. This number is many times higher than the rate of growth of TFP in the non-agricultural sector estimated by Young (2003), even without correcting for measurement problems typical in official Chinese data. Our findings support the common

[30] We also examined price distortions, τ_p^i. Their main effect is to lower the output share $\theta_a(0)$. Their growth implications are similar to those of labor distortions.

belief that the agricultural sector contains a large fraction of the efficiency gains of the Chinese economic reform.

What role did agriculture play in China's overall economic growth and its structural changes during the reform period? To quantitatively examine agriculture's role, we developed a two-sector neoclassical growth model with non-homothetic preferences, heterogeneous sectoral Cobb-Douglas production functions, and exogenous and heterogeneous productivity growth. The model takes into account many of the possible linkages between the agricultural and the non-agricultural sectors. The model also reproduced well the path of the Chinese economy since 1978.

Within the context of the model, we performed a series of counterfactual exercises to measure the contribution of agricultural and non-agricultural TFP to sectoral and overall economic growth, and to structural changes. Agricultural productivity was the main factor in the reallocation of output and employment toward non-agriculture. Agriculture also contributed to overall growth in similar amounts as non-agricultural TFP. The model also shows that agriculture's main contribution lies in reallocating workers to the non-agricultural sector, where capital accumulation takes place. The reallocation of labor is especially important in China because a considerable fraction of the labor force is still in agriculture, and because physical and human capital accumulation has proceeded at very rapid rates. These are precisely the kind of circumstances under which agriculture is fundamental for economic development.

7 Appendix: TFP based on "shadow wages"

In this Appendix, we estimate the labor input using a "shadow wage" approach. The shadow-wage approach assumes the existence of a household production function that has different types of labor as distinct inputs, i.e., by sex, age, and education; see, e.g., Jacoby (1993) and Skoufias (1994). The shadow wage of each farmer is just the marginal product of labor, estimated from the agricultural production function.

The main goal of our additional specification is to control for endogeneity biases. For instance, the allocation of labor within a family is endogenously decided and is affected by unobservable factors (e.g., management skills, preference toward leisure, weather conditions, and so on).[31] In the absence of appropriate econometric controls, however, estimates of marginal productivities are generally not very precise. We follow Levinsohn and Petrin (2003) and use the level of intermediate inputs as a *control* for this endogeneity problem. This approach yields consistent estimates of the marginal productivity of differentiated labor types that we use to measure productivity.

Assume a Cobb-Douglas production function:

$$\ln Y = \sum_i \beta_i \ln L_i + \varepsilon, \tag{22}$$

where Y is the total value of output, L_i is the various types of labor, and ε is an error term. Based on the estimation result of (22), the shadow wage of labor type i is:

$$w_i = \hat{\beta}_i \frac{\hat{Y}}{L_i}, \tag{23}$$

where $\hat{\beta}_i$ is the estimated coefficient on $\ln L_i$. Under the Cobb-Douglas assumption, the marginal product of labor is proportional to the average product of labor, which we used in our benchmark calculations.

An OLS estimation of equation (22) suffers from an *endogeneity problem*. At least a part of the productivity is observed by the farmers only at a point in time early enough that it allows the farmer to change the labor input decision. If so, the error term in equation (22) is expected to influence the choice of inputs. That means that the regressors and the error term are correlated, which biases OLS estimates for (22).[32]

[31] To sign the bias, one needs to know how the labor input relates to unobservables. For example, suppose women work in the farm only in good harvests, which implies that the share of female labor input increases within a season as the size of the output increases. In this case, female labor is positively correlated to the unobserved productivity shock, and OLS estimates of women's marginal productivity would tend to be biased upward (i.e., suggesting that they caused a high level of output), given that all other factors remain constant.

[32] This endogeneity problem in estimating a production function has a long history in economics. One approach is to use fixed-effects. But this fixed-effects estimator needs a strict exogeneity assumption of the inputs (Wooldrige, 2002), which implies inputs cannot respond to productivity shocks. Instrumental variables estimation requires a proxy that correlates with the dependent variable, but uncorrelates with

We follow Levinsohn and Petrin (2003) and use intermediate inputs to control for the endogeneity problem in the estimation of production function. They build upon Olley and Pakes (1996) who address the endogeneity problem by using investment as a proxy for unobserved productivity. Under certain assumptions, investment will be a monotone function of unobserved productivity and so inverting this function would yield consistent estimates of unobserved influences. Levinsohn and Petrin (2003) modify this approach by suggesting the intermediate input as a proxy instead of investment. Their motivation is that many firms report zero investment, but almost every firm uses a positive amount of intermediate inputs. For the same reason, we follow Levinsohn and Petrin (2003) by using land and intermediate inputs to proxy for the household-specific unobservable terms.

Following Olley and Pakes (1996) and Petrin et al. (2004), we use a third order polynomial function of land and intermediate inputs in the Cobb-Douglas production function (22). This method identifies the output elasticities of various types of labor which are our parameters of interest. Identifying the output elasticity of other factors is possible, but this requires further assumptions and procedures. These other elasticities, however, are not the main focus of our study.[33]

We cross-classify the labor input into three factors: sex (s), age (a) and education (e). For age and education, we only consider three categories within each group. To obtain

the error term. One candidate for such an instrument is the input price along with the assumption that there exists a competitive input market. However, input prices often have not enough variation across households, and are not observed. Characteristics of a household, such as number of children, generally are not good for an instrument, since household composition reflects the life-long decision on how to allocate time and resources for a family.

[33] Their method can be seen as a *control-function* approach. Consider, as an illustration, the following production function with only one type of labor input and only an intermediate input, M_t:

$$\ln Y_t = \beta_0 + \beta_l \ln L_t + \beta_m \ln M_t + \epsilon_t + \zeta_t, \tag{24}$$

where the term ϵ_t represents productivity shocks that are not observable by researchers, but which can be realized by the household when they are making input-time allocation decisions. Separately, assume the demand for M_t varies with ϵ_t such that f: $M_t = f_t(\epsilon_t)$. Under the assumption that the intermediate input is monotonic in ϵ_t, inverting f_t gives: $\epsilon_t = f_t^{-1}(M_t)$. This function allows us to identify the coefficient in the labor input. To see this, rewrite (24) as: $\ln Y_t = \beta_l \ln L_t + \Phi_t(M_t) + \varepsilon_t$, where $\Phi_t(M_t) = \beta_0 + \beta_c \ln M_t + f_t^{-1}(M_t)$. We treat Φ_t nonparametrically as a polynomial function of M_t and T_t. Petrin et al. (2004) present a through discussion regarding the estimation procedure as well as the implementation in Stata. We follow their implementation strategy.

the marginal product of each type, we estimate the following production function:

$$\ln Y_t = \beta_0 + \sum_{l=1}^{18} \beta_l \ln L_{lt} + \sum_{i=0}^{3} \sum_{j=0}^{3-i} \delta_{ij} \ln M_t^i \ln T_t^j + \varepsilon_t$$

where Y_t is a household's total output at time t, L_{lt} is the number of hours of work at time t for labor type l, M_t is the total expenditure of intermediate inputs, and T_t is the land input. Based on the estimates on the labor input, $\hat{\beta}_l$, the marginal productivity (or shadow wage) of each individual from the sample was derived using equation (23). Table A1 reports estimates of β_l , and Table A2 reports the change in the agricultural labor input based the shadow wage estimates. These changes were reported in Table 3.

Table A1. Estimates of agricultural production function.

	0 yrs Education		$1-6$ yrs Education		>6 yrs Education	
	Male	Female	Male	Female	Male	Female
<25 yrs old	0.068	0.002	0.005	0.019	0.023	0.024
	(0.028)	(0.019)	(0.012)	(0.011)	(0.008)	(0.009)
25-45 yrs old	0.036	0.030	0.029	0.013	0.034	0.016
	(0.012)	(0.007)	(0.007)	(0.006)	(0.005)	(0.006)
>45 yrs old	0.016	0.014	0.018	0.028	0.012	0.015
	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.008)

Note.– Standard errors in parentheses. Point estimates for β_l for differentiated labor types.

The estimates in Table A2 are consistent with a rapid decline in the labor input in agriculture. The decline in the labor input is also very similar to the one we obtained using the log-wage profiles in Table 2. The main difference is that labor quality declines more according to our direct estimates of the production function. Overall, the estimates of TFP growth based on this shadow-wage approach are about 6.7% per year, which are very similar to results from the main text.

The shadow-wage approach relies on a household production function that allows us to examine the productivity growth similar to (20). In particular, we have estimated the following regression

$$\ln Y_{it} = \alpha_0 + \alpha_T \ln T_{it} + \alpha_L L_{it} + \alpha_t t + \varepsilon_{it},$$

where Y_{it} is the total output for household i at time t, T_{it} is the amount of land used, L_{it} is the total working hours of a household, and t indicates time. The sample size is 11,961 and the R^2 of the regression is 0.27. Our results show $\alpha_T = 0.23$ (s.e. 0.0078); $\alpha_L = 0.34$ (s.e. 0.010); and $\alpha_t = 0.065$ (s.e. 0.0018). We use these values in the text to validate our estimates of factor shares and agricultural TFP.

Table A2. Average annual growth rate of Chinese agricultural labor input and labor quality.

	1993-1997	1997-2000	2000-2004	2004-2006	2004-2006	1993-2009
Labor Input	−5.94	−4.27	−4.76	−7.87	−7.01	−5.13
Labor Quality	−1.75	−3.45	−1.73	−1.50	−0.51	−1.60

Note.– Estimates based on a divisia index of labor input.

References

[1] Acemoglu, Daron and Veronica Guerrieri. "Capital Deepening and Nonbalanced Economic Growth," *Journal of Political Economy*, Vol. 116, No. 3, (2008): 467-498.

[2] Bai, Chong-En, Chang-Tai Hsieh, and Yingyi Qian. "The Return to Capital in China," *Brookings Papers on Economic Activity, Economic Studies Program*, Vol. 37, No. 2, (2006): 61-102.

[3] Bosworth, Barry, and Susan M. Collins. "Accounting for Growth: Comparing China and India," *Journal of Economic Perspectives*, Vol. 22, No. 1, (2008): 45-66.

[4] Brandt, Loren, Johannes Van Biesebroeck, and Yifan Zhang. "Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing," *Journal of Development Economics*, Vol. 97, No. 2, (2012): 339-351.

[5] Brandt, Loren, Chang-Tai Hsieh, and Xiaodong Zhu. "Growth and Structural Transformation in China," in Loren Brandt and Thomas Rawski ed. *China's Great Economic Transformation*, Cambridge University Press, (2008): 569-632.

[6] Brandt, Loren and Thomas Rawski. *China's Great Economic Transformation*, Cambridge University Press, (2008).

[7] Byrd, William and Alan Gelb. "Township, Village, and Private Industry in China's Economic Reform," in de Melo and Sapir (eds.), *Trade Theory and Economic Reform: North, South, and East: Essays in Honor of Bela Balassa*, Blackwell, Oxford and Cambridge, Mass, (1991): 327-349.

[8] Caselli, Francesco and John Coleman. "The U. S. Structural Transformation and Regional Convergence: a Reinterpretation," *Journal of Political Economy,* Vol. 109, No. 3, (2001): 584-616.

[9] Chan, Kam Wing. "Crossing the 50 Percent Population Rubicon: Can China Urbanize to Prosperity?" *Eurasian Geography and Economics*, Vo1.53, No.1, (2012): 63-86.

[10] Chan, Kam Wing, "China, Internal Migration," in Immanuel Ness and Peter Bellwood (eds.) *The Encyclopedia of Global Migration*, Blackwell Publishing (forthcoming).

[11] Chang, Chun and Yijiang Wang. "The Nature of the Township-Village Enterprise," *Journal of Comparative Economics*, Vol. 19, No. 3, (1994): 434-452.

[12] Chow, Gregory. "Capital Formation and Economic Growth in China," *Quarterly Journal of Economics*, Vol. 108, No. 3, (1993): 809-842.

[13] Chow, Gregory. *China's Economic Transformation.* Oxford: Blackwell Publishing, Ltd., (2007).

[14] Dekle, Robert and Guillaume Vandenbroucke."Whither Chinese Growth? A Sectoral Growth Accounting Approach," *Review of Development Economics*, Vol. 14, No. 3, (2010): 487-498.

[15] Dekle, Robert and Guillaume Vandenbroucke. "A Quantitative Analysis of China's Structural Transformation," *Journal of Economic Dynamics & Control*, Vol. 36, No. 1, (2012): 119-135.

[16] Echevarria, Cristina. "Changes in Sectoral Composition Associated with Economic Growth," *International Economic Review,* Vol. 38, No. 2, (1997): 431-452.

[17] Fan, C. Cindy. *China on the Move: Migration, the State, and the Household*. New York, NY: Routledge, (2008).

[18] Fan, Shenggen. "Production and Productivity Growth in Chinese Agriculture: New Measurement and Evidence," *Food Policy,* Vol.22, No.3, (1997): 213-228.

[19] Fan, Shenggen and Philip G. Pardey. "Research Productivity and Output Growth in Chinese Agriculture," *Journal of Development Economics,* Vol. 53, No. 1, (1997): 115-137.

[20] Fan, Shenggen, and Xiaobo Zhang. "Production and Productivity Growth in Chinese Agriculture: New National and Regional Measures," *Economic Development and Cultural Change*, Vol. 50, No. 4, (2002): 819-838

[21] Fan, Shenggen, Xiaobo Zhang, and Sherman Robinson. "Structural Change and Economic Growth in China," *Review of Development Economics*, Vol. 7, No. 3. (2003): 360-377.

[22] Fleisher, Belton, Haizheng Li, and Minqiang Zhao. "Human Capital, Economic Growth, and Regional Inequality in China," *Journal of Development Economics*, Vol. 92, No. 2, (2010): 215-231.

[23] Gollin, Douglas, Steve Parente, and Richard Rogerson. "The Role of Agriculture in Development," *American Economic Review: P&P*, Vol. 92, No. 2 (2002): 160-164.

[24] Hayami, Yujiro, Vernon W. Ruttan, and Herman M. Southworth. *Agricultural Growth in Japan, Taiwan, Korea, and the Philippines*. Honolulu: The University Press of Hawaii, (1979).

[25] Hayashi, Fumio and Edward Prescott. "The Depressing Effect of Agricultural Institutions on the Prewar Japanese Economy," *Journal of Political Economy,* Vol. 116, No. 4, (2008): 573-632.

[26] Holz, Carsten A. "No Razor's Edge: Reexamining Alwyn Young's Evidence for Increasing Interprovincial Trade Barriers in China," *Review of Economics and Statistics*, Vol. 91, No. 3, (2009): 599-616.

[27] Hsieh, Chang-Tai and Peter Klenow. "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, Vol. 124, No. 4, (2009): 1403-1448.

[28] Huang, Jikun and Scott Rozelle. "Technological Change: The Re-discovery of the Engine of Productivity Growth in China's Rural Economy," *Journal of Development Economics*, Vol. 49, No. 2, (1996): 337-369.

[29] Hulten, Charles R. "Divisia Index Numbers," *Econometrica,* Vol. 41, No. 6, (1973): 1017-1025.

[30] Imamura, Hajime. "Compositional Change of Heterogeneous Labor Input and Economic Growth in Japan," in C. Hulten (eds.) *Productivity Growth in Japan and the United States.* Chicago: The University of Chicago Press, (1990), 349-384.

[31] Irz, Xavier and Terry Roe. "Seeds of Growth? Agricultural Productivity and the Transitional Dynamics of the Ramsey Model," *European Review of Agricultural Economics*, Vol. 32, No. 2, (2005): 143-165.

[32] Jacoby, Hanan G. "Shadow Wages and Peasant Family Labour Supply: An Econometric Application to the Peruvian Sierra," *Review of Economic Studies*, Vol. 60, No. 4, (1993): 903-921.

[33] Jin, Songqing, Jikun Huang, Ruifa Hu and Scott Rozelle. "The Creation and Spread of Technology and Total Factor Productivity in China's Agriculture," *American Journal of Agricultural Economics,* Vol. 84, No. 4, (2002): 916-930.

[34] Johnson, D. Gale. "Agriculture Adjustment in China: Problems and Prospects," *Population and Development Review*, Vol. 26, No. 2, (2000): 319-334.

[35] Johnson, Emily and Gregory Chow. "Rates of Return to Schooling in China," *Pacific Economic Review,* Vol. 2, No. 2, (1997): 101-113.

[36] Jorgenson, Dale W., Frank M. Gollop, and Barbara M. Fraumeni. *Productivity and U.S. Economic Growth*. Cambridge: Harvard University Press, (1987).

[37] King, Robert G and Sergio T. Rebelo. "Transitional Dynamics and Economic Growth in the Neoclassical Model," *American Economic Review*, Vol. 83, No. 4, (1993): 908-931.

[38] Kongsamut, Piyabha, Sergio Rebelo, and Danyang Xie. "Beyond Balanced Growth," *Review of Economic Studies*, Vol. 68, No. 4, (2001): 869-882.

[39] Laitner, John. "Structural Change and Economic Growth," *Review of Economic Studies*, Vol. 67, No. 3, (2000): 545-561.

[40] Lardy, Nicholas. *Agriculture in China.s Modern Economic Development*, New York: Cambridge University Press, (1983).

[41] Levinsohn, James and Amil Petrin. "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies*, Vol. 70. No. 2, (2003): 317-342.

[42] Li, Haizheng, Barbara M. Fraumeni, Zhiqiang Liu, and Xiaojun Wang, "Human Capital in China," *NBER Working Paper 15500*, (2009).

[43] Lin, Justin Yifu. "Rural Reform and Agricultural Growth in China," *American Economic Review*, Vol. 82, No. 1, (1992): 34-51.

[44] Lin, Justin Yifu. "How did China Feed Itself in the past? How Will China Feed Itself in the Future?" Second Distinguished Economist Lecture presented, Centro

Internacional de Mejoramiento de Maiz y Trigo, Mexico, D.F., Mexico, 9 January 1998.

[45] Lin, Justin Yifu , Fang Cai, and Zhou Li. *The China Miracle: Development Strategy and Economic Reform*. Hong Kong: Chinese University Press, (1996).

[46] Lin, Justin and Miaojie Yu. "The Economics of Price Scissors: An Empirical Investigation for China," *Jingji Yanjiu* (Economic Research), Vol. 44, No. 1, (2009): 42-56.

[47] Liu, Zhiqiang, "Institution and Inequality: The *Hukou* System in China", *Journal of Comparative Economics*, Vol. 33, No. 1, (2005): 133-157.

[48] Matsuyama, Kiminori. "Agricultural Productivity, Comparative Advantage, and Economic Growth," *Journal of Economic Theory*, Vol. 58, No. 2, (1992): 317-334.

[49] McMillan, John, John Whalley, and Lijing Zhu. "The Impact of China's Economic Reforms on Agricultural Productivity Growth," *Journal of Political Economy,* Vol. 97, No. 4, (1989): 781-807.

[50] Ngai, L. Rachel and Christopher A Pissarides. "Structural Change in a Multisector Model of Growth," *American Economic Review*, Vol. 97, No. 1, (2007): 429-443.

[51] Nin-Pratt, Alejandro, Bingxin Yu, and Shenggen Fan. "Comparisons of Agricultural Productivity Growth in China and India," *Journal of Productivity Analysis*, Vol. 33, No. 3, (2010): 209-223.

[52] OECD. *National Accounts for China: Sources and Methods,* Organisation for Economic Co-operation and Development, (2000).

[53] Olley, Steven and Ariel Pakes. "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, Vol. 64, No. 6, (1996): 1263-1297.

[54] People's Republic of China, National Bureau of Statistics of China, *China Statistical Yearbook (Zhongguo tongji nianjian).* Beijing: China Statistical Publishing House, various issues.

[55] Petrin, Amil, Brain Poi, and James Levinsohn. "Production Function Estimation in Stata Using Inputs to Control for Unobservables,"*Stata Journal*, Vol. 4, No. 2, (2004): 113-123.

[56] Singh, Inderjit, Lyn Squire, and John Strauss. "An Overview of Agricultural Household Models –The Basic Model: Theory, Empirical Results, and Policy Conclusions," in I. Singh, L. Squire and J. Strauss (eds.), *Agricultural Household Models, Extensions, Applications and Policy.* Baltimore: The Word Bank and the Johns Hopkins University Press, (1986): 17-47.

[57] Skoufias, Emmanuel. "Using Shadow Wages to Estimate Labor Supply of Agricultural Households," *American Journal of Agricultural Economics*, Vol. 76, No. 2, (1994): 215-227.

[58] Song, Zheng, Kjetil Storesletten, and Fabrizio Zilibotti. "Growing Like China," *American Economic Review*, Vol. 101, No. 1, (2011): 201-241.

[59] Whalley, John, and Xiliang Zhao, "The Contribution of Human Capital to China's Economic Growth", *NBER Working Paper 16592*, (2010).

[60] Wen, Guanzhong James. "Total Factor Productivity Change in China's Farming Sector: 1952-1989," *Economic Development and Cultural Change,* Vol. 42, No. 1, (1993): 1-41.

[61] Wooldridge, Jeffrey. *Econometric Analysis of Cross Section and Panel Data*, MIT Press: Massachusetts Institute of Technology, (2002).

[62] Wu, Shunxiang, David Walker, Stephen Devadoss, and Yao-chi Lu. "Productivity Growth and its Components in Chinese Agriculture after Reforms," *Review of Development Economics,* Vol.5 , No. 3, (2001): 375-391.

[63] Wu, Xiang. "Why did China's Reforms Start in the Countryside?," in C. Howe, Y.Y. Kueh and R. Ash (eds.), *China's Economic Reform: A Study with Documents.* Routledge Curzon, (2003): 232-241.

[64] Xu, Chenggang. "The Fundamental Institutions of China's Reforms and Development," *Journal of Economic Literature*, Vol. 49, No. 4, (2011): 1076-1151.

[65] Yearbook, Annual. *Zhongguo Tongji Nianjian* [China Statistical Yearbook]. Beijing: China Statistics Press.

[66] Young, Alwyn. "The Tyranny of Numbers: Confronting the Statistical Realities of the East Asian Growth Experience," *Quarterly Journal of Economics,* Vol. 110, No. 3, (1995): 641-680.

[67] Young, Alwyn. "The Razor's Edge: Distortions and Incremental Reform in the People's Republic of China," *Quarterly Journal of Economics,* Vol. 115, No. 4, (2000): 1091-1135.

[68] Young, Alwyn. "Gold into Base Metals: Productivity Growth in the People's Republic of China during the Reform Period," *Journal of Political Economy,* Vol. 111, No. 1, (2003): 1220-1261.