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SOURCES OF INCOME DIFFERENCES ACROSS CHINESE PROVINCES DURING THE REFORM PERIOD: A DEVELOPMENT ACCOUNTING EXERCISE

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The present paper performs a development accounting analysis to investigate the sources of China's interprovincial income inequality over the period 1982–2005. We estimate a Cobb–Douglas aggregate production function with various specifications. Using the estimated parameters, we conduct a development accounting analysis as well as a variance decomposition. Our results suggest that differences in physical capital intensity and in total factor productivity are both important sources of cross-province income differences, each accounting for roughly half of the variation in income levels. Differences in human capital explain only a small amount of income differences across provinces. The results are robust to whether or not the assumption of constant returns to scale is imposed. The interaction between factor accumulation and total factor productivity is also discussed.

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I. INTRODUCTION

China has experienced rapid economic growth since the 1978 economic reform. However, economic performance has varied considerably among Chinese provinces and regions. As a result, over the period since the commencement of economic reform, provincial income inequality has risen substantially, particularly in the 1990s. Many studies have documented this issue, focusing in particular on the underlying sources of regional inequality. Various causes have been identified, such as policy biases, market reform, globalization, geography, and industrial concentration.[1]

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[1] Chan, Henderson, and Tsui (2008) provide a good explanation of the increasing trend of China's regional inequality.

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The vast literature can be classified into three broad strands according to their research methods: the decomposition approach, the convergence approach, and the accounting approach. In the studies applying the decomposition approach, income inequality is decomposed by subgroups and assessed in a broad composition, including within-group and between-group inequality. Different geographic scales have been used for subgrouping. For example, overall income inequality has been decomposed by the rural–urban or inland–coastal divide (Kanbur and Zhang 1999; Bhalla, Yao, and Zhang 2003), or at the intra-provincial level (Lee 2000; Herrmann-Pillath *et al.* 2006). However, studies using this approach implicitly assume that geographic location is the only determinant of differences in income. Therefore, other controls are not included to explain regional inequality.

Both the convergence approach and the accounting approach are derived from neoclassical growth theories integrated with some elements of endogenous growth theories (e.g., human capital) and new economic geography (e.g., agglomeration effects). Studies using the convergence approach attribute regional inequality to the determinants of different steady-state income levels, and even different long-run growth rates in the case of multiple equilibria, using cross-province growth regressions. Numerous studies show that convergence can be observed when variables such as physical and human capital (Chen and Fleisher 1996) and infrastructure (Démurger 2001) are controlled. Moreover, standard neoclassical growth theory suggests that convergence only occurs among closely integrated economies with perfect factor mobility and technological diffusion. Violation of these conditions causes the persistence of regional inequality. For example, imperfect labor mobility (Cai, Wang, and Du 2002), local protectionism (Poncet 2003), and limited spillover effects from growth centers in the coastal areas to interior regions (Fu 2004), all contribute to enlarging regional inequality. In addition, if the neoclassical assumption of perfect competition without externalities is not valid, industrial agglomeration will emerge. This will work against convergence and strengthen regional inequality (Fujita and Hu 2001; Catin, Luo, and Van Huffel 2005). However, the convergence literature is criticized for providing relatively little evidence of poor countries catching up with rich countries (Quah 1993). The statistical tests for convergence fail to address the notion of convergence in an economically interesting sense (Durlauf 2003).

Studies using the accounting approach quantify the relative importance of factor inputs and total factor productivity (TFP) in explaining regional disparities in growth rates or income levels. For example, Liu and Li (2006) implement growth accounting and find that inequalities in technology, physical and human capital stock are responsible for inequality of income growth between coastal and interior provinces. Lu (2008) determines that variances in capital intensity and factor elasticities are two main sources of China's provincial income inequality.

Several studies introduce a variety of variables other than factor inputs to account for the black box of TFP. For example, Zhang and Zhang (2003) use education, trade openness, and FDI as determinants of TFP, while Tsui (2007) explains TFP by estimating a production function augmented with industrial agglomeration and openness. Wan, Lu, and Chen (2007) take into account various TFP determinants, including privatization, education, location, globalization, and urbanization. These "augmented" accounting studies are appealing in that not only the respective contribution to inequality is quantified from factor inputs and TFP, but the unexplained TFP is also accounted for by various variables. However, an important fact has been ignored in all these studies. There might be complex causalities among the determinants of inequality. Some factors themselves are the results of other factors. For example, industrial agglomeration, used by Tsui (2007) to explain TFP, might affect the contribution of physical capital to income inequality because the concentration of industry certainly involves large accumulation of capital in a region but leaves other regions with relative scarcity of capital. Therefore, the estimated relative contribution of capital to the overall income inequality could be underestimated.

In the present paper, we opt to apply a simple accounting approach, specifically, development accounting, to investigate inequality in income levels across provinces in post-reform China. Development accounting, also known as level accounting, is similar to growth accounting except that it analyzes differences across sections rather than time (King and Levine 1994; Caselli 2005). Our results suggest that differences in both physical capital intensity and TFP account for approximately half of the variation in cross-province income disparities; whereas human capital, when involved simply as an input, only accounts for a small proportion of the variation. We also make an attempt to examine the implicit interactions between factor inputs and TFP. We find that human capital significantly affects the accumulation and flows of physical capital among provinces; and it contributes to provincial TFP only when interacting with openness.

The present paper is structured as follows. Section II details data issues. Section III reports production function estimations. In Section IV, using the estimated parameters, the Hall and Jones (1999) development accounting approach is applied, and a variance decomposition is conducted. Section V includes some further discussion on interactions between factor inputs and TFP, and Section VI concludes.

II. DATA ISSUES

The objective of development accounting is to decompose differences in income levels into contributions from differences in inputs levels and differences in TFP levels. Operationally, the key step lies in estimating a production function from which we derive the measures of TFP levels. This primarily depends on the proper measurement of income and factors. We use data on output, labor input, physical capital, and human capital for 28 Chinese provinces over the period 1982–2005.[2] The data come largely from the official data set in *Comprehensive Statistical Data and Materials on 55 Years of New China* (2005) and *China Statistical Yearbook* (various years) published by the National Bureau of Statistics of China (NBS). The output measure (Y) is real GDP computed using the nominal GDP and the implicit deflators. All current values are expressed in RMB in 1995 constant prices. The labor force (L) is measured by the number of employed workers. Data on the stock of physical and human capital are not directly found in the NBS data set. Such data need to be calculated from the related NBS statistics, and this indirect measurement has been the object of a long-lasting dispute. The remainder of this section thus describes their construction.

A. *Provincial Stock of Physical Capital*

Like previous studies, we generate estimates of the physical capital stock for each province over 1952–2005 using the perpetual inventory method. That is, with data on real investment ($I_{i,t}$), initial capital stock ($K_{i,0}$), and a common depreciation rate (δ), we construct a sequence of physical capital stock using the following equation:

$$K_{i,t} = (1 - \delta)K_{i,t-1} + I_{i,t}.$$

However, debates exist over the inclusion of each term of this equation in empirical work: the selection of the investment series and the corresponding investment deflators, the estimates of the initial physical capital stock as well as the depreciation rate. Early studies like Chow (1993) used accumulation data in official statistics to proxy for investment. In 1994, Chinese official national income statistics changed from the former "national income available" (consumption + accumulation) under the Material Product Balances System to the "GDP" (final consumption expenditure + gross capital formation + net export of goods and services) under the System of National Accounts. Since this change was made, the accumulation data has not been available. Researchers have also attempted to use gross capital formation to measure investment (Liu and Li 2006). However, gross capital formation is calculated as the sum of gross fixed capital formation (GFCF) and inventory changes. Whether or not the inventory changes should be included in the capital stock is controversial. Young (2000, p. 32) argues:

> . . . the "changes in stocks" figures reported in the national accounts of developing countries are frequently a residual, fabricated, item used to conceal large discrepancies between the production and expenditure sides of the accounts. In addition, the proper

[2] Mainland China includes 31 provinces. Hainan and Tibet are excluded from the analysis because of incomplete data on educational attainment. Data for Chongqing, which became a separate municipality in 1997, are included in the data for Sichuan.

measurement of inventory changes, including the adjustment for differences between current valuations and accounting conventions, is technically more challenging than the measurement of the flow value of investment in fixed capital. Finally, in the context of the People's Republic, considering the unsold inventories of state enterprises as a productive element of the capital stock would seem to be an egregious error.

Following Young (2000), we exclude inventories from the measure of the physical capital stock, and focus on GFCF alone. Data for some provinces in some years are missing from our data source. To maintain a complete sample, we estimate the GFCF series for these provinces on an important component of GFCF, namely, investment in capital construction (ICC), for the years where both series are available. With the estimated coefficients and the data on ICC we can thus obtain the GFCF using linear interpolation for these provinces for the years without data.

With a measure of nominal investment in hand, it is necessary to derive an appropriate fixed capital formation deflator. The price index of investment (PII) is an appropriate choice, but this index is not available until 1991. However, the *Gross Domestic Product of China 1952–1995*, published in 1997 by the NBS, provides the index of GFCF for all provinces over the period 1952–95, from which we can derive the implicit investment deflator. As a check, we compare the calculated implicit investment deflators for the period 1991–95 with the published PII for the same period, and find that they are extremely similar. Therefore, it is reasonable to believe that these two series are internally consistent. Hence, we use the calculated implicit investment deflators for 1952–95 and the PII for 1996–2005, both converted to 1995 constant prices, to deflate the GFCF to real value.

Alternatively, Young (2000) constructs an implicit deflator for GFCF as a residual between the GDP deflator and the deflators for other components of GDP, including private consumption, government consumption, inventories, and exports and imports. The overall GFCF deflators that we calculate are very similar to those in Young (2000, figure IV). However, as Wang and Yao (2003) point out, the inherent risk of Young's complex method is that a measurement error in any of these deflators could be passed onto the "residual" investment deflator.

Turning to the depreciation rate, a large number of studies assume a value equal to 6% and apply it to all countries for all years (McGrattan and Schmitz 1999; Hall and Jones 1999). Others either take a value of 3% (Klenow and Rodríguez-Clare 1997), 4% (Liu and Li 2006), 5% (Woo 1998; Wang and Yao 2003), or even 10% (Gong and Xie 2004). Theoretically, the effect of varying the depreciation rate in the perpetual inventory calculation is to change the relative weight of old and new investment. A higher rate of depreciation might increase the relative capital stock in countries that have experienced high investment rates towards the end of the sample period. In practice, however, such an effect is minimal and the accounting analysis is not sensitive to a higher or lower depreciation rate (Caselli 2005). In the present paper we adopt an overall depreciation rate of 9.6% advocated by Zhang, Wu, and Zhang (2004),[3] who conduct a detailed estimation of depreciation rates for Chinese provinces.

With regard to initial physical capital stock, standard practice in the literature is to initiate the capital stock K_0 as $I_0/(g + \delta)$, where I_0 is the value of the investment series in the first year with available data, and g is the geometric average growth rate of the investment between the first five or ten years. The underlying rationale is that $I/(g + \delta)$ is the expression for the capital stock in the steady state of the Solow model. For instance, Hall and Jones (1999) take 1960 as the first year and estimate the 1960 capital stock as $I_{60}/(g + \delta)$, where g is calculated as the geometric average growth rate of the real investment over 1960–70. Young (2000) initiates the capital stock of China in 1952 as real investment in 1952 divided by the depreciation rate of 6% plus the average annual growth of real investment between 1952 and 1957, which equals approximately 4%. This way of estimating initial capital stock, by assuming that the economy is roughly on a balanced growth path and that the real investment growth recorded in the first several years of the data extends to the infinite past, leads to a good approximation. Although one might suspect that most of the poorer economies certainly do not satisfy the steady-state condition that motivates the assumption $K_0 = I_0/(g + \delta)$, the importance of the estimate of the initial capital stock tends to diminish rapidly over time as a result of depreciation (Hall and Jones 1999; Caselli 2005). In particular, in the case of China, given that the period of interest is the reform period (i.e., after 1978), "with 26 years of data before the beginning of the analysis, the initial capital stock is fairly irrelevant, and any assumption will do equally well" (Young 2000, p. 37). Because of a lack of convictive alternatives, our estimations of the initial capital stocks in 1952 for each province are calculated using their respective real investment in 1952 divided by 10%, as in Young (2000).

B. *Provincial Stock of Human Capital*

We follow the standard practice of transforming educational attainment (i.e., years of schooling) into our measure of human capital stock (h) using estimates of private returns to education;[4] namely,

$$h = e^{\varphi(E)}, \tag{1}$$

[3] We tried other depreciation rate values, like 4% and 6%, and found that the main conclusions are not sensitive to the choice of rate.

[4] Many studies directly use educational attainment as a proxy for human capital stock (Mankiw, Romer, and Weil 1992; Barro and Lee 2001). The present paper, however, adopts the conventional approach in the development accounting literature of constructing human capital stock along the lines of Klenow and Rodríguez-Clare (1997), Hall and Jones (1999), and Bils and Klenow (2001), among others.

where E is the average years of schooling, and $\varphi(.)$ is a continuous, piecewise linear function constructed to match rates of return to education reported in Psacharopoulos (1994). Specifically, for schooling years between zero and four, the return to education $\varphi'(.)$ is assumed to be 13.4%, which is the average for sub-Saharan Africa. For schooling years between four and eight, the return to education is assumed to be 10.1%, which is the world average. With nine or more years, the return is assumed to be 6.8%, which is the average for the OECD countries. Despite the doubt about the applicability of these rates of return to schooling in the case of China, there is little alternative.[5]

Therefore, the challenge is to construct the educational attainment data (E). There have been several attempts to measure educational attainment for individual countries and across countries. For instance, Mankiw, Romer, and Weil (1992) use the proportion of the adult population enrolled in secondary school to capture educational attainment. However, secondary education does not adequately measure the aggregate stock of human capital available contemporaneously as an input for production process. In addition, it is problematic to use a flow variable, the enrolment rate, to represent the stock of human capital. Using various levels of enrolment ratios, Barro and Lee (2001) derive the percentage of population that has successfully completed a given level of schooling from a perpetual inventory approach and, hence, construct the average years of schooling.

In this paper, we also use a perpetual inventory procedure close in spirit to the work of Démurger (2001), Wang and Yao (2003), and Liu and Li (2006) to construct the educational attainment measure. The new school graduates are used as flows that are added to the human capital stock annually. The number of graduates is a more accurate measure of the addition to the existing educated human capital stock than the enrolment ratios used by Barro and Lee (2001). As in Démurger (2001), we take into account three schooling levels: primary, secondary (comprising junior secondary, senior secondary, and specialized secondary), and higher education, as follows:

$$H_{j,i,t} = (1 - \delta_{i,t})H_{j,i,t-1} + Grad_{j,i,t}, \tag{2}$$

where $H_{j,i,t}$ is the number of accumulated graduates who have completed at least j schooling level in province i, $Grad_{j,i,1}$ is the annual number of net graduates at j schooling level ($j = 1$ for primary, 2 for secondary, and 3 for higher education), and $\delta_{i,t}$ is the mortality rate of the population used as a proxy of the depreciation rate.

We derive initial educational attainment from the 1982 Chinese census, which provides the 1‰ sample population surveys by schooling levels for 28 provinces (without Hainan and Tibet). As such, the initial values for these three schooling levels ($H_{j,i,0}$) are given as follows:

[5] We address this concern by assuming a constant rate of return to schooling (e.g., 10% or 15%). The final results are robust to these changes.

$$H_{1,i,0} = Prim_{i,0} + Sec_{i,0} + High_{i,0},$$

$$H_{2,i,0} = Sec_{i,0} + High_{i,0},$$

$$H_{3,i,0} = High_{i,0},$$

where $Prim_{i,0}$, $Sec_{i,0}$, and $High_{i,0}$ denote the 1‰ sampling number of people in province i that have completed primary, secondary, and higher education, respectively, multiplied by the population of the province i in 1982, $Pop_{i,0}$.

Using these initial values for each level of schooling, combined with mortality rates and the annual number of net graduates, the three series $H_{j,i,t}$, which are the number of accumulated graduates at different schooling levels for province i at the end of the period t, can be obtained from the perpetual inventory procedure in equation (2). Assuming that the length of schooling cycles for primary, secondary, and higher education is 5, 10, and 14.5 years, respectively, the average years of schooling can be calculated as:

$$E_{i,t} = (5H_{1,i,t} + 10H_{2,i,t} + 14.5H_{3,i,t})/Pop_{i,t},$$

where $Pop_{i,t}$ is the total population of province i in year t.

Note, however, the educational attainment figures we calculate here are somewhat crude, as compared to some previous studies. For instance, Wang and Yao (2003) construct a time series of educational attainment in China at the national level from 1952 to 1999, while Liu and Li (2006) construct a panel data covering 30 provinces over 1985–2001, with both using the perpetual inventory method. Our construction of schooling differs from theirs in two ways. First, we assemble junior, senior, and specialized secondary in a global category for secondary education, whereas they deal with them separately and accord them respective weight (length of schooling cycles). The simplicity in our work is primarily due to the fact that there are no separate initial figures for the three secondary schooling levels in the 1982 census. Second, we use provincial data on the total population instead of population aged 15–64 years. The *China Population Statistical Yearbook*s provide only the 1% or 10% samplings from the population aged 15–64 years, and even this data is not available for all post-reform years. Although Liu and Li (2006) attempt to make some adjustments to these figures by using the national figures in the *World Development Indicators* and then decomposing these national figures using the respective provincial employment figures, we wonder if this complicated procedure could result in the incorporation of more measurement errors with each calculation.

In the final step, we apply the constructed educational attainment ($E_{i,t}$) to equation (1), and thus obtain the stock of human capital ($h_{i,t}$) for 28 provinces over 1982–2005. It may be argued that the human capital stock thus obtained is only the quantity-based measure of human capital which does not incorporate any adjustment for variations in the quality of education. Indeed, one year of education in province A

TABLE 1

Descriptive Statistics

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Real GDP Y (RMB100 million)	672	2,181.4	2,481.7	50.8	17,025.3
Physical capital stock K (RMB100 million)	672	3,872.8	4,619.8	163.8	31,561.3
Labor L (10,000 persons)	672	2,069.9	1,403.5	155.6	6,335.3
Educational attainment E (years)	672	6.8	1.6	3.4	11.1
Human capital stock h	672	2.3	0.3	1.6	3.2

may generate more human capital than in province B. One way of taking this possibility into account is to use some indicators to augment the quantity-based measure of human capital, such as the teacher–pupil ratio, the amount of teaching materials per student, or the human capital of teachers. Other extensions that augment quantity-based human capital involve allowing for differences across economies in experience levels (Bils and Klenow 2001), and in nutrition and health status (Shastry and Weil 2003), or considering social return to schooling instead of private return, which is used in this paper (Córdoba and Ripoll 2005). However, taking into account these issues is extremely difficult in our context. This is not only because relevant data are not available but also because these issues per se are the object of intense controversy when entering human capital measures. Hence, we regard our constructed data set as a reasonable measure of human capital stock given the available information. The descriptive statistics of the data are given in Table 1.

III. ESTIMATION OF THE PRODUCTION FUNCTION

A. *Specification*

The starting point of our analysis is an aggregate production function assumed to be the same across provinces. Specifically, consider the following Cobb–Douglas aggregate production function:

$$Y = AK^{\alpha}(hL)^{\beta} \quad 0 < \alpha < 1 \text{ and } 0 < \beta < 1, \tag{3}$$

where Y is real GDP, A is an index of technology, K is physical capital stock, h is per capita human capital stock, L is total employment, and hL is skill-adjusted labor input. α and β are output elasticities with respect to physical capital and skill-adjusted labor, respectively. Dividing equation (3) by the labor force, L, yields:

$$y = Ak^{\alpha}h^{\beta}L^{\alpha+\beta-1}, \tag{4}$$

where y is real GDP per worker (i.e., our provincial income indicator), and k is the stock of physical capital per worker $k = K/L$.[6]

Given the data on income and factor inputs, it is crucial to obtain plausible and robust estimates of parameters. Before estimation, several relevant issues deserve our attention. The first concerns the specification of the production function. Because of its simplicity, the Cobb–Douglas function has been the most widely used form of production function, although more general forms such as the translog or constant elasticity of substitution are potential candidates. The Cobb–Douglas production function has an additional advantage of sidestepping the arbitrage between Harrod-neutral and Hicks-neutral technical change. As Felipe and McCombie (2004) state, in the context of the Cobb–Douglas production function, there is no conceptual difference between Harrod-neutral and Hicks-neutral technical change.

How human capital enters the production function is controversial. In the published literature, there are generally two ways to deal with this issue. One way, proposed by Mankiw, Romer, and Weil (1992), is to incorporate human capital as another type of capital in the production function. Human capital is produced in the same way as physical capital. Therefore, it is better viewed as analogous to physical capital. The other method is to embody human capital in the labor force to produce effective labor input or augmented labor. This formulation, used by Hall and Jones (1999), is substantially more restrictive than that used by Mankiw, Romer, and Weil (1992). However, it generates the log-linear relation between wages and years of schooling. Because our construction of human capital is in line with Hall and Jones (1999), we adopt the labor-augmenting human capital formulation.

Should human capital be included as an input in the production function? Whereas Mankiw, Romer, and Weil (1992) obtain a better fit when including human capital in their regressions, Benhabib and Spiegel (1994) conclude that human capital should not enter the production function as an input, but that it instead affects growth through its effect on TFP. Therefore, in our estimations we consider both the case of excluding human capital and incorporating human capital in the production function so as to compare the resulting effect on capital and labor elasticities.

Another important issue concerns the assumption of constant returns to scale (CRS), represented by $\alpha + \beta = 1$. Many researchers argue that the CRS is a reasonable assumption in the context of China (Chow 1993; Liu and Li 2006). However, we believe that this is a rather strong hypothesis that needs to be treated cautiously. For

[6] Some studies work with the K/Y ratio instead of the K/L ratio. For example, Hall and Jones (1999) insist that the K/Y ratio is proportional to the investment rate along a balanced growth path. Moreover, writing y in terms of the K/L ratio tends to falsely raise the explanatory power of factor intensities. However, as argued by Caselli (2005), the K/Y is not invariant to differences in TFP and is less appropriate for answering the development accounting question, while the K/L ratio is more "intuitive and cleaner." We opt to use the K/L expression mainly because the assumption of a constant K/Y ratio seems unreasonable for Chinese provinces, most of which do not have steady-state conditions.

instance, Gong and Xie (2004) find that the parameter estimates are not sensitive to the specification of the production function but are sensitive to whether the assumption of CRS is imposed. Wang and Yao (2003), despite not exploring the possibility of variable returns to scale (VRS), admit that CRS might not be appropriate for a transition economy like China. However, allowing for the possibility of VRS does come at the cost of less tractability. We estimate the production function under CRS and then relax this assumption to check the robustness of our results.

In estimating the production function, the issue of whether to estimate it in levels or in first differences arises. We estimate the production function in levels because the first difference operator removes long-run information and emphasizes short-run fluctuations in the data, as documented in the cointegration literature. By differencing, we risk disregarding some of the most valuable pieces of information in the data, for example, the pure cross-section variation (Blundell and Bond 1998). Differencing might also decrease the signal-to-noise ratio, thereby exacerbating measurement error bias (Griliches and Hausman 1986). In addition, our data show that the growth rate of real GDP is not strongly linked with the growth rate of capital and labor inputs. This implies that level regressions should yield more accurate estimates of the parameters. Hence, taking logs on equation (4), we have:

$$\ln y = \ln A + \alpha \ln k + \beta \ln h + (\alpha + \beta - 1)\ln L. \tag{5}$$

B. *Endogeneity Bias*

As is well-known, when estimating an aggregate production function, the problem of endogeneity bias often arises. OLS estimates of parameters of production functions are biased and inconsistent if there is a contemporaneous correlation between the error term and factor inputs. The endogeneity problem usually occurs in the case of omitted variables, measurement errors, or simultaneity of explanatory variables (Wooldridge 2002). Classical cross-section regressions assume that omitted variables are independent of the included right-hand side variables and are independently, identically distributed. In the case of China, however, these omitted variables might contain some unobservable heterogeneity across provinces and/or across time. Unless heterogeneities are controlled for, the estimation will generate misleading results due to omitted variable bias. We use panel data estimation to address this problem (Villanueva, Knight, and Loayza 1992; Islam 1995). We restrict our regressions to fixed-effect estimators because the random-effect model assumes that individual effects are uncorrelated with other regressors, an assumption that is violated in the context of our model.[7] Hence, rewriting equation (5) in the two-way fixed-effect form yields the following:

[7] The Hausman specification tests also confirm that fixed-effect estimators are preferred to random-effect estimators.

CRS without human capital: $\ln y_{i,t} = \alpha \ln k_{i,t} + \mu_{i,t} + \eta_{i,t} + \varepsilon_{i,t}$, (6)

CRS with human capital: $\ln \tilde{y}_{i,t} = \alpha \ln \tilde{k}_{i,t} + \mu_{i,t} + \eta_{i,t} + \varepsilon_{i,t}$, (7)

VRS without human capital: $\ln y_{i,t} = \alpha \ln k_{i,t} + (\alpha + \beta - 1)\ln L_{i,t} + \mu_{i,t} + \eta_{i,t} + \varepsilon_{i,t}$, (8)

VRS with human capital: $\ln \tilde{y}_{i,t} = \alpha \ln \tilde{k}_{i,t} + (\alpha + \beta - 1)\ln(hL)_{i,t} + \mu_{i,t} + \eta_{i,t} + \varepsilon_{i,t}$, (9)

where $\ln \tilde{y} = \ln(Y/hL)$, $\ln \tilde{k} = \ln(K/hL)$, μ is the unobservable province-specific effect, η is the time-specific effect, ε is the error term, and i and t represent province and year, respectively. As argued above, we consider specifications that impose and relax the assumption of CRS, and specifications with and without human capital as an input. Obviously, equations (6)–(8) are special cases of equation (9). To verify the plausibility of CRS, we test whether the coefficient of $\ln L$ in equation (8) or $\ln(hL)$ in equation (9) equals zero.

Our panel data fixed-effect estimators involve a consistent treatment of the individual effect but still require a strong assumption of strict exogeneity of factor inputs. This is because measurement error and simultaneity problems may cause regressors and error terms to be correlated. We rely heavily on official Chinese data, although there is some dispute regarding their accuracy. Our physical capital and human capital are constructed with a few common assumptions, and their missing values are obtained using linear interpolations. Measurement errors are likely to occur in these series. Moreover, causality might be present between income and factor inputs in the case that both are simultaneously influenced by certain omitted factors. Therefore, simultaneity problems will emerge and bias the results. In such circumstances, the instrumental variables (IV) approach is called for, to alleviate the endogeneity bias and to achieve consistency of estimates.[8]

However, applying the IV estimation might give rise to much larger asymptotic variances than those of the OLS estimator, if regressors and errors are actually uncorrelated (Wooldridge 2002). The use of IV estimation for the sake of consistency must be balanced against the inevitable loss of efficiency vis-à-vis OLS, even if there are good reasons to suspect the non-orthogonality between regressors and errors (Baum, Schaffer, and Stillman 2003). Consequently, it is necessary to use the Wu–Hausman test to diagnose whether the regressors are endogenous variables. If they are, OLS is inconsistent and IV is required.

Once the IV estimator is judged to be the appropriate estimation technique, we need to find the relevant and valid instruments. In reality, it is very difficult to find

[8] It is argued that the approach of generalized method of moments (GMM) deals consistently and efficiently with both the correlated individual effects and endogenous explanatory variables problems. This procedure critically hinges on the assumption of no second-order serial correlation in errors of the level equations. However, the AR(2) tests suggest that none of the four specifications satisfies such a necessary condition in the context of our data.

instrumental variables that satisfy both conditions. The relevance of instruments can be assessed by examining the significance of the excluded instruments in the first stage IV regressions. To be valid, instruments should be independent from the error term. This condition is more difficult to achieve. Econometrically, the validity of instruments can be diagnosed via the Hansen J-test of overidentifying restrictions. However, this test can only be performed when the number of excluded instruments exceeds that of included endogenous variables. In this paper we follow Liu and Li (2006) and use twice-lagged endogenous regressors as instruments. We also do this because there are very few alternative plausible instruments. Thus, our IV models are exactly identified and the validity test of instruments cannot be applied. However, as Nakamura and Nakamura (1998) point out, if instruments are actually endogenous, the endogeneity problem will persist even after instrumentation. This could lead to far worse results than before. In this case, the OLS estimation is preferred despite the indication of endogeneity by the Hausman test. Given these caveats, both OLS and IV results are reported.

C. *Estimation Results*

Table 2 reports the estimates of equations (6) and (7). All the estimated coefficients are significant at the 1% level. Columns (1) and (2) provide the estimates of the specification without human capital. The Wu–Hausman test rejects that $\ln k$ is exogenous at the 1% level, suggesting that the OLS results might be inconsistent. The high value partial R^2 (0.880) found in Bound, Jaeger, and Baker (1995) indicates a strong relevance of the instrument we use; that is, the twice-lagged $\ln k$. However, the OLS and IV estimation yield extremely similar estimates for output elasticity of physical capital (α): 0.481 and 0.490 respectively. Moreover, the hypothesis that the elasticity α estimated using IV is not statistically different from that using OLS cannot be rejected with an F-statistic of only 0.12.

A similar pattern arises when human capital enters the production function, as shown in columns (3) and (4) of Table 2. The estimates of α increase slightly to 0.503 (OLS) and 0.519 (IV). The null hypothesis that the OLS estimator is consistent is rejected at the 5% level. Nevertheless, because we cannot provide statistical evidence for the orthogonality condition of the instrument, and the equality of coefficients between OLS and IV estimators is clearly not rejected, we focus on the OLS results only. To summarize, the estimates of α range from 0.481 to 0.503 under the assumption of CRS, implying a value for output elasticity with respect to the combination of raw labor and human capital (β) ranging from 0.519 to 0.497.

The estimates of the specifications with VRS, presented in equations (8) and (9), are reported in Table 3. Columns (1) and (2) display the estimates without human capital. The Wu–Hausman test rejects the overall exogeneity of $\ln k$ and $\ln L$, but only at the 10% level. The coefficients equality tests do not reject the hypothesis that there is no statistical difference between OLS and IV estimates for α, β, or α and β jointly.

TABLE 2

Production Function Estimates (Constant Returns to Scale)

	Dependent Variable: ln y		Dependent Variable: ln $\tilde{y}$	
	(1) OLS	(2) IV	(3) OLS	(4) IV
ln k	0.481***	0.490***		
	(21.21)	(17.92)		
ln $\tilde{k}$			0.503***	0.519***
			(22.65)	(19.62)
Implied β	0.519***	0.510***	0.497***	0.481***
	(22.85)	(18.63)	(22.42)	(18.19)
R^2	0.990		0.980	
Observations	672	616	672	616
Heteroskedasticity test	258.10	203.07	229.38	200.24
	[0.000]	[0.000]	[0.000]	[0.000]
Instrument used		L2.ln k		L2.ln $\tilde{k}$
Instrument relevance test				
Bound *et al*. partial $R^{2\dagger}$		0.880		0.885
Wu–Hausman test		3.22***		2.42**
		[0.001]		[0.016]
Coefficients equality test				
α		0.12		0.44
		[0.727]		[0.506]

Notes: 1. OLS is the ordinary least squares (fixed-effect) estimation.
2. IV is the two-stage least squares (fixed-effect) estimation with instruments being the related regressors lagged for two periods (denoted by "L2").
3. All regressions contain province-specific and year-specific fixed effects, which are statistically significant and not reported.
4. Figures in parentheses are robust *t*-statistics.
5. Figures of the heteroskedasticity test are White/Koenker statistics for OLS and Pagan–Hall statistics for IV.
6. Figures of the Wu–Hausman endogeneity test are *F*-statistics of the residuals, which are generated from the OLS estimation of the first-stage regression and then added in the regression of the original model.
7. Figures in square brackets are *p*-values.
8. y is real GDP per worker, $\tilde{y}$ is real GDP per effective worker, k is physical capital stock per worker, and $\tilde{k}$ is physical capital stock per effective worker. All the variables are in logarithms.

† Bound, Jaeger, and Baker (1995).
*** and ** represent statistical significance at the 1% and 5% level.

As before, we rely on the OLS results only. The OLS estimate of α equals 0.430, which is significant at the 1% level. The most striking result is that the coefficient of ln L equals –0.371, indicating the presence of decreasing returns to scale. The F-statistic

TABLE 3

Production Function Estimates (Variable Returns to Scale)

	Dependent Variable: ln y		Dependent Variable: ln $\tilde{y}$	
	(1) OLS	(2) IV	(3) OLS	(4) IV
ln k	0.430***	0.438***		
	(16.65)	(14.79)		
ln L	–0.371***	–0.406***		
	(–5.63)	(–5.20)		
ln $\tilde{k}$			0.433***	0.440***
			(17.73)	(15.48)
ln(hL)			–0.377***	–0.432***
			(–7.29)	(–6.88)
Implied β	0.200***	0.156**	0.190***	0.128***
	(3.60)	(2.32)	(4.14)	(2.28)
R^2	0.991		0.988	
Observations	672	616	672	616
F-test for constant returns to scale	31.67	27.04	53.10	47.37
	[0.000]	[0.000]	[0.000]	[0.000]
Heteroskedasticity test	304.82	216.56	297.70	207.83
	[0.000]	[0.000]	[0.000]	[0.000]
Instrument used		L2.ln k and L2.ln L		L2.ln $\tilde{k}$ and L2.ln(hL)
Instrument relevance test				
Bound *et al*. partial $R^{2\dagger}$		0.880 and 0.672		0.886 and 0.717
Shea partial R^2		0.900 and 0.687		0.897 and 0.727
Wu–Hausman test		2.79* [0.063]		1.90 [0.150]
Coefficients equality test				
α		0.10 [0.756]		0.08 [0.781]
β		0.29 [0.589]		0.91 [0.340]
α and β jointly		0.22 [0.804]		0.55 [0.579]

Notes: 1. OLS is the ordinary least squares (fixed-effect) estimation.
2. IV is the two-stage least squares (fixed-effect) estimation with instruments being the related regressors lagged for two periods (denoted by "L2").
3. All regressions contain province-specific and year-specific fixed effects, which are statistically significant and not reported.
4. Figures in parentheses are robust t-statistics.
5. Figures of the heteroskedasticity test are White/Koenker statistics for OLS and Pagan–Hall statistics for IV.
6. Figures of the Wu–Hausman endogeneity test are F-statistics of the residuals, which are generated from the OLS estimation of the first-stage regression and then added in the regression of the original model.
7. Figures in square brackets are p-values.
8. y is real GDP per worker, $\tilde{y}$ is real GDP per effective worker, k is physical capital stock per worker, $\tilde{k}$ is physical capital stock per effective worker, L is labor force, and hL is effective worker. All the variables are in logarithms.

† Bound, Jaeger, and Baker (1995).

***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

for testing CRS is 31.67, strongly rejecting that CRS is a reasonable assumption in the context of our data.

The main results, shown in columns (3) and (4) of Table 3, essentially do not alter when human capital is involved. The only exception is that the Wu–Hausman test fails to provide support for the endogeneity of regressors. Hence, OLS estimates are more appropriate. As shown in column (3), the estimated value for α is 0.433, slightly higher than that without human capital. The coefficient of $\ln(hL)$ declines further to −0.377, indicating even larger decreasing returns to scale. The implied value of output elasticity with respect to effective labor (β) falls in the range from 0.200 (without human capital) to 0.190 (with human capital), suggesting that the higher β of 0.519–0.497 in the specifications under CRS account for most of the influence of returns to scale.[9] Therefore, imposing the assumption of CRS could potentially bias the estimation. In contrast to the estimates of β, the estimates of α are relatively indifferent to the assumption of CRS and VRS. In the case of VRS, the estimated α range from 0.430 to 0.433, only slightly lower than those under CRS of 0.481–0.503. In particular, as shown in Table 4, our estimates of α are not only in line with the values reported in the literature on China but are even more plausible and precise.

IV. DEVELOPMENT ACCOUNTING

With the estimated parameters, we use development accounting to identify the "sources of development." In other words, we quantify by how much cross-province income inequality is attributable to differences in factor accumulation and by how much it is attributable to differences in TFP levels. Because we relax the assumption of CRS, the decomposition of equation (4) incorporates the scale efficiency term $L^{\alpha+\beta-1}$. It is not clear whether the contribution of the scale efficiency term should be assigned to TFP, or input factors, or as a separate component. In principle, the conventional notion of TFP, known as "a measure of our ignorance" (Abramovitz 1986), involves many factors, such as technology innovation, technology imitation, efficiency of resource allocation, institutional change, omitted variables, and measurement errors. If we broadly view the TFP as a mélange of factors other than inputs, then the scale efficiency can be combined with A to produce the TFP in the general sense;[10] that is, $TFP = AL^{\alpha+\beta-1}$.

[9] Liu and Li (2006) find that estimates of the elasticity of labor range from 0.027 for interior provinces to 0.159 for coastal provinces. The share of labor is often found to be lower in developing countries than in industrial countries (Elias 1993). A possible reason involves the distortion of the labor market in developing countries, which causes a divergence between the actual price per unit of employed labor and the marginal product of labor. This might also be the case for China's labor market during economic transition.

[10] In the published literature on production frontier analysis, the change in TFP is often decomposed into technological progress, technical efficiency change, and scale efficiency (Färe *et al.* 1994).

TABLE 4

Summary of Output Elasticities of Capital Used in the Studies on China

Study	Period of Study	Output Elasticity to Capital	Method
Perkins (1988)	1953–85	0.4	Assumption
Li, Gong, and Zheng (1995)	1953–90	0.4–0.5	Assumption
Chow (1993)	1952–85	0.6	Estimation
Borensztein and Ostry (1996)	1953–78	0.47	Estimation
	1978–94	0.63	
Hu and Khan (1997)	1953–94	0.411	Estimation
	1952–78	0.386	
	1979–94	0.453	
World Bank (1996)	1985–94	0.5	Assumption
World Bank (1997)	1978–95	0.4	Assumption
Woo (1998)	1979–93	0.4–0.6	Assumption
Démurger (1999)	1978–96	0.548–0.590	Estimation
Chow and Li (2002)	1952–98	0.558–0.628	Estimation
Wang and Yao (2003)	1953–99	0.33–0.67	Assumption
Liu and Li (2006)	1986–98	0.612 (Coastal) 0.582 (Interior)	Estimation
Our study	1982–2005	0.481–0.503 (CRS) 0.430–0.433 (VRS)	Estimation

Note: CRS = constant returns to scale; VRS = variable returns to scale.

A. *Hall and Jones (1999) Level Accounting*

Following Hall and Jones (1999), we carry out level accounting on equation (4) for the year 2000,[11] when cross-province dispersion of GDP per worker reached its peak. The parameters (α and β) used in the level accounting for each of the four specifications are obtained from the OLS estimates of the corresponding specification. The accounting results for the four specifications, given in Tables 5 and 6, tell a consistent story. Variations of physical capital intensity and those of TFP both explain a large amount of the disparity in income levels across provinces, whereas differences in human capital accounts for a very small fraction of the disparity. Look at, for example, the results obtained from the specification under VRS with human capital (the right section of Table 6). All numbers are levels relative to Shanghai in 2000. The first observation is the smaller variation in human capital, with a standard deviation of only 0.021. Most provinces have about the same human capital as Shanghai. In contrast, both physical capital and TFP (comprising scale efficiency and residual A) are important for the rich provinces and for the poor provinces as well. For example,

[11] We also carry out level accounting using the traditional Denison (1967) approach. The results are similar and are available upon request.

TABLE 5

Hall and Jones' Level Accounting (Specifications under Constant Returns to Scale), in the Year 2000

Province	Without Human Capital			With Human Capital		
	y	k^{α}	TFP $(= A)$	k^{α}	h^{β}	TFP $(= A)$
Shanghai	1.000	1.000	1.000	1.000	1.000	1.000
Tianjin	0.615	0.782	0.786	0.774	1.008	0.789
Beijing	0.575	0.811	0.710	0.803	1.017	0.704
Jiangsu	0.393	0.545	0.721	0.531	0.938	0.789
Guangdong	0.388	0.525	0.740	0.510	0.876	0.869
Liaoning	0.372	0.526	0.706	0.512	1.014	0.716
Fujian	0.365	0.502	0.728	0.487	0.897	0.837
Zhejiang	0.351	0.529	0.663	0.515	0.937	0.728
Heilongjiang	0.301	0.471	0.639	0.456	1.010	0.654
Shandong	0.288	0.455	0.634	0.439	0.956	0.687
Xinjiang	0.288	0.569	0.506	0.555	0.927	0.559
Jilin	0.267	0.437	0.611	0.421	0.993	0.638
Hubei	0.254	0.434	0.586	0.418	0.938	0.648
Hebei	0.223	0.428	0.521	0.413	0.942	0.575
Inner Mongolia	0.210	0.390	0.538	0.374	0.958	0.585
Shanxi	0.186	0.384	0.485	0.368	0.973	0.520
Qinghai	0.168	0.447	0.376	0.432	0.871	0.448
Jiangxi	0.164	0.321	0.509	0.306	0.926	0.578
Hunan	0.163	0.322	0.506	0.306	0.953	0.558
Anhui	0.155	0.327	0.476	0.311	0.903	0.554
Ningxia	0.152	0.421	0.361	0.405	0.902	0.416
Sichuan	0.143	0.335	0.426	0.319	0.903	0.495
Guangxi	0.139	0.323	0.431	0.307	0.923	0.491
Henan	0.139	0.320	0.435	0.304	0.939	0.487
Shaanxi	0.135	0.367	0.369	0.351	0.956	0.404
Yunnan	0.126	0.332	0.379	0.316	0.822	0.484
Gansu	0.116	0.299	0.389	0.283	0.854	0.480
Guizhou	0.075	0.272	0.274	0.257	0.845	0.343
Mean 27 provinces	0.219	0.423	0.519	0.407	0.931	0.579
Standard deviation	0.136	0.133	0.141	0.135	0.052	0.138
Mean 3 poorest provinces	0.103	0.300	0.343	0.285	0.840	0.431
Variance decomposition (%)		51.7	48.3	54.0	6.2	39.8

Notes: 1. All numbers are measured as ratios to the Shanghai values.
2. y is real GDP per worker, k is physical capital stock per worker, h is human capital stock per capita, TFP is total factor productivity, and A is an index of technology.

GDP per worker in Jiangsu is approximately 39% of that in Shanghai. This income gap is attributable to Jiangsu's lower physical capital intensity (58% of Shanghai's physical capital) as well as its lower TFP level (69% of Shanghai's TFP level). Nonetheless, Jiangsu has nearly the same amount of human capital (98%) as Shanghai.

TABLE 6

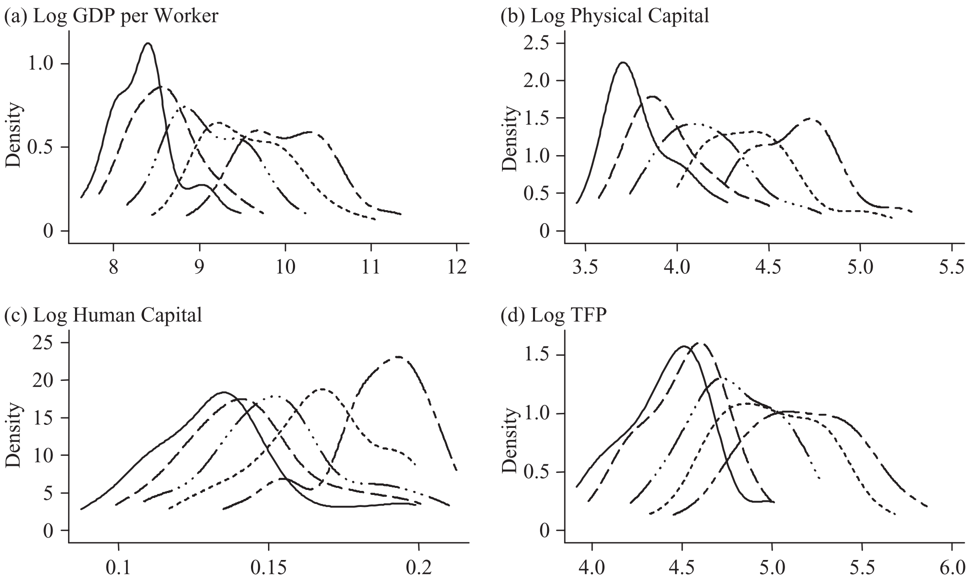
Hall and Jones' Level Accounting (Specifications under Variable Returns to Scale), in the Year 2000

Province	Without Human Capital			With Human Capital		
	y	k^{α}	TFP $(= AL^{\alpha+\beta-1})$	k^{α}	h^{β}	TFP $(= AL^{\alpha+\beta-1})$
Shanghai	1.000	1.000	1.000	1.000	1.000	1.000
Tianjin	0.615	0.803	0.765	0.802	1.003	0.764
Beijing	0.575	0.829	0.694	0.828	1.007	0.690
Jiangsu	0.393	0.582	0.675	0.580	0.976	0.695
Guangdong	0.388	0.563	0.690	0.560	0.950	0.730
Liaoning	0.372	0.564	0.659	0.562	1.005	0.658
Fujian	0.365	0.540	0.677	0.538	0.959	0.707
Zhejiang	0.351	0.567	0.619	0.564	0.975	0.637
Heilongjiang	0.301	0.511	0.590	0.509	1.004	0.590
Shandong	0.288	0.495	0.583	0.492	0.983	0.596
Xinjiang	0.288	0.604	0.476	0.602	0.972	0.492
Jilin	0.267	0.478	0.559	0.475	0.997	0.563
Hubei	0.254	0.475	0.536	0.472	0.976	0.552
Hebei	0.223	0.469	0.476	0.467	0.977	0.489
Inner Mongolia	0.210	0.431	0.486	0.429	0.984	0.497
Shanxi	0.186	0.426	0.437	0.423	0.990	0.445
Qinghai	0.168	0.488	0.345	0.485	0.948	0.365
Jiangxi	0.164	0.363	0.451	0.361	0.971	0.468
Hunan	0.163	0.363	0.448	0.361	0.982	0.459
Anhui	0.155	0.368	0.422	0.366	0.962	0.442
Ningxia	0.152	0.462	0.329	0.459	0.961	0.344
Sichuan	0.143	0.377	0.378	0.374	0.962	0.396
Guangxi	0.139	0.365	0.382	0.362	0.970	0.396
Henan	0.139	0.361	0.385	0.359	0.976	0.397
Shaanxi	0.135	0.408	0.332	0.406	0.983	0.339
Yunnan	0.126	0.374	0.337	0.371	0.928	0.365
Gansu	0.116	0.340	0.342	0.338	0.941	0.366
Guizhou	0.075	0.313	0.238	0.310	0.937	0.256
Mean 27 provinces	0.219	0.464	0.511	0.462	0.973	0.525
Standard deviation	0.136	0.128	0.169	0.128	0.021	0.166
Mean 3 poorest provinces	0.103	0.341	0.306	0.339	0.935	0.329
Variance decomposition (%)		46.2	53.8	46.5	2.4	51.1

Notes: 1. All numbers are measured as ratios to the Shanghai values.
2. y is real GDP per worker, k is physical capital stock per worker, h is human capital stock per capita, TFP is total factor productivity, A is an index of technology, and L is labor force.

The poorest province, Guizhou, although its human capital is 94% of that in Shanghai, has only 31% of Shanghai's physical capital intensity and 26% of Shanghai's TFP level. Shortages in both physical capital and TFP are the reasons for the relative poverty in Guizhou. On average, GDP per worker in Shanghai is approximately 9.72

Fig. 1. Distribution of Income, Factor Inputs, and Total Factor Productivity (TFP): Specification under Variable Returns to Scale with Human Capital



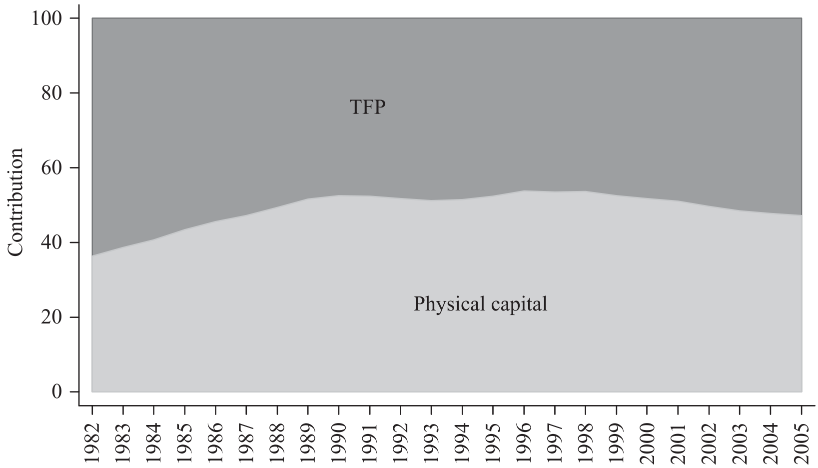
Note: Kernel (Gaussian) density estimate in 1985, 1990, 1995, 2000, and 2005.

times higher than that in the three poorest provinces. This 9.72-fold income difference can be decomposed as the multiplication of a 2.95-fold difference in physical capital, a 1.07-fold difference in human capital, and a 3.08-fold difference in TFP level. Obviously, disparities in physical capital and TFP play large and almost equally important roles in explaining cross-province income differences.

B. *Variance Decomposition over Time*

The above analysis of proximate causes of regional inequality is derived from development accounting for the year 2000 only. This is the source of some concern regarding the time consistency of the results. Do the contributions of factor inputs and TFP to cross-province income differences change greatly over time? A simple way to answer this question is to examine the cross-province distribution dynamics across time. Figure 1 plots kernel density estimates of y, k^{α}, h^{β}, and TFP (in logs) for 1985, 1990, 1995, 2000, and 2005. It is observed that the cross-province distribution of incomes becomes increasingly twin-peaked. Both physical capital and TFP display similar movements to income distribution, whereas human capital tends to converge to a high level. Considering that human capital exhibits fairly small variations

Fig. 2. Relative Contributions of Inputs and Total Factor Productivity (TFP) to Income Inequality: Specification under Constant Returns to Scale without Human Capital



across regions, if our estimate of human capital is accurate enough, we can conclude that human capital accumulation does not account for much of the long-term cross-province income differences. The long-run bimodal income distribution apparently mirrors bimodal distributions of physical capital and TFP.

In addition to intuitive comparisons using plots, we can also use variance decomposition to verify the above accounting analysis results. We rewrite equation (4) in logarithms:

$$\ln y = \ln k^{\alpha} + \ln h^{\beta} + \ln TFP, \qquad (10)$$

where $TFP = AL^{\alpha+\beta-1}$. Following Shorrocks (1982), we decompose the variance of $\ln y$ in equation (10) as:

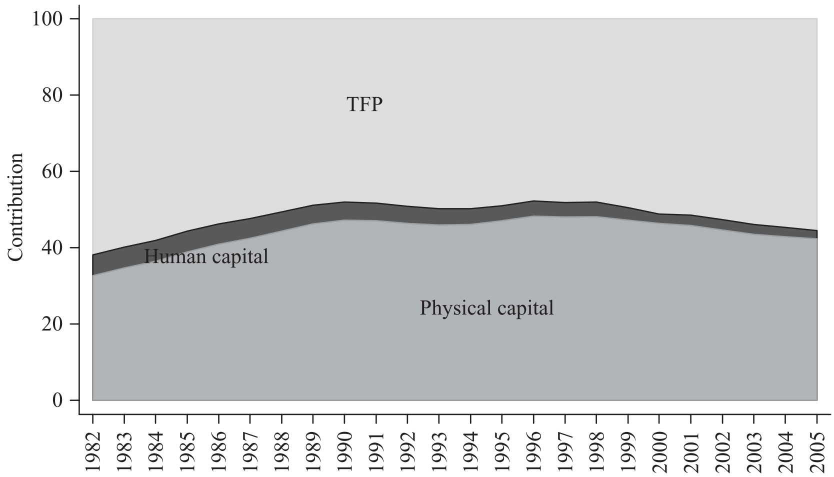
$$\mathrm{var}(\ln y) = \mathrm{cov}(\ln y, \ln k^{\alpha}) + \mathrm{cov}(\ln y, \ln h^{\beta}) + \mathrm{cov}(\ln y, \ln TFP), \qquad (11)$$

where var($\ln y$) is the variance of the log of GDP per worker, and cov($\ln y$) is the covariance of $\ln y$ with other variables. Note that var($\ln y$) is a standard index of inequality; namely, *logarithmic variance*. The covariance terms on the right side of equation (11) can be regarded as the contributions of factor inputs and TFP to total inequality.[12]

Figure 2 plots the relative contributions of factor inputs and TFP to income inequality throughout the period 1982–2005. The figure is based on the results for the most restricted specification; that is, the production function with CRS but without human

[12] Equation (11) is the "natural" decomposition of the variance in that each component of y (i.e., k^{α}, h^{β}, TFP) is assigned half of the value of all interaction terms involving the component (Shorrocks 1982, p. 194).

Fig. 3. Relative Contributions of Inputs and Total Factor Productivity (TFP) to Income Inequality: Specification under Variable Returns to Scale with Human Capital



capital. It is clear that differences in TFP and in physical capital intensity are both important sources of cross-province income differences, with each accounting for roughly half of the variation in income levels. Overall, the relative importance of physical capital rose from 1982 to the end of the 1990s and then declined slightly. This conclusion remains even when we include human capital and relax the assumption of CRS in the production function, as shown in Figure 3. The relative contribution of human capital is consistently small and even declines over time.

V. INTERACTION BETWEEN FACTORS AND TOTAL FACTOR PRODUCTIVITY

The above analysis is based on the essential assumption of exogenous TFP. If we relax this assumption and allow TFP to interact with factor inputs, an analysis that relies monocausally on factors and/or TFP to explain cross-province income differences might be inadequate. For example, provinces with higher physical capital intensity tend to exhibit higher TFP. Table 7 displays the correlation matrix under the general specification.[13] It is found that physical capital intensity is strongly correlated with TFP (0.842). Despite the lack of variation across provinces, human capital is also positively correlated with TFP (0.604) and physical capital (0.576).

How should these rather positive correlations between factor inputs and TFP be interpreted? A possible explanation is that there may be common driving forces

[13] Correlations under the other three specifications are similar.

TABLE 7

Correlation Matrix (Specification under Variable Returns to Scale with Human Capital)

	y	k^{α}	h^{β}
k^{α}	0.955		
h^{β}	0.639	0.576	
TFP ($= AL^{\alpha+\beta-1}$)	0.963	0.842	0.604

Note: y is real GDP per worker, k is physical capital stock per worker, h is human capital stock per capita, *TFP* is total factor productivity, A is an index of technology, and L is labor force.

beneath factors and TFP, such as institutions, geography, language, and climate. For instance, Hall and Jones (1999) argue that differences in "social infrastructure" lead to cross-country variations in both factor accumulation and TFP and, therefore, are regarded as fundamental determinants of income differences across countries.[14]

However, these driving forces are themselves highly persistent and tend to change slowly over time. It is more likely that TFP changes in most provinces involve the process of adopting advanced technologies developed at the technological frontier. In this way, the high correlation between capital intensities and TFP reflects the possibility of positive externalities, suggesting that TFP is not exogenous, as invoked by the Solow model. The level of TFP could be affected by the abundance of factors. Recent studies (Aghion, Howitt, and Mayer-Foulkes 2005) suggest that if technology transfer is costly, receiving countries cannot keep up with improvements in the technological frontier by simply imitating advanced technologies developed in leading countries. They must make technology investments of their own to acquire foreign technologies and adapt them to the local environment because technological knowledge is often circumstantially sensitive. There might also be linkages between human capital accumulation and TFP. A high level of human capital also facilitates technology adoption. In fact, in many early endogenous growth models, productive externalities are generated by human capital accumulation. Therefore, provinces with more factor endowments, including physical and human capital, can adopt more advanced technologies, accumulate a larger stock of knowledge, and produce more efficiently. In particular, although human capital only makes a very limited contribution to cross-province income differences, it might still play an important role through reinforcing the externalities of human capital and TFP.

[14] The social infrastructure involves institutions and government policies that provide the incentives for individuals and firms: either positive incentives that can encourage productive activities, such as skills accumulation and new production techniques, or negative incentives that can encourage predatory behavior, such as rent-seeking and corruption (Hall and Jones 1999, p. 95).

We attempt to test the aforementioned theoretical underpinnings by separately regressing physical capital and TFP on a few explanatory variables, including human capital. The sample consists of 28 Chinese provinces over 1982–2005. TFP levels are derived from the development accounting results under the general specification (VRS with human capital). Five-year lagged values of all regressors are used to mitigate the possible endogeneity bias. We apply the fixed-effects model with province-specific and year-specific fixed effects for all regressions in Table 8.

Columns (1)–(3) in Table 8 report the results when TFP is the dependent variable. In column (1), we do not include physical capital as an explanatory variable. The estimates of human capital and infrastructure are insignificant albeit positive, although both market reform and openness have a positive and significant impact on TFP. Furthermore, the highly significant coefficient of FDI highlights its role in improving the level of local technology through technological diffusion (Berthélemy and Démurger 2000). These results do not alter when physical capital is included in the regression, as shown in column (2). In addition, physical capital appears to positively affect TFP, but this relationship is not significant. This finding indicates that, in the Chinese context, local physical capital intensity might not be closely related to the innovation and adoption of technology.

Some authors argue that human capital cannot achieve a positive effect unless a certain openness threshold is passed (Miller and Upadhyay 2000). To verify this argument, we introduce an interaction term between the FDI/GDP ratio and human capital in the regression, shown in column (3). The estimate of the interaction term is positive and significant at the 5% level, while that of human capital remains insignificant. This indicates that human capital may contribute to TFP improvement only in an economic environment with a high degree of openness. A possible explanation for this is that open provinces might have better access to advanced technology adopted from overseas and, therefore, can utilize the stock of human capital efficiently.

Column (4) in Table 8 reports the results when physical capital is the dependent variable. We find that human capital exerts a positive and highly significant influence on physical capital accumulation. This finding is consistent with Chi (2008). During the transition towards becoming a market economy, China's government-budgetary fixed-assets investment has reduced considerably, whereas foreign investment and private fund-raising have increased dramatically. When selecting investment locations, firms also take into account the local stock of human capital available for achieving high efficiency in production. Therefore, provinces with a large stock of human capital are more likely to attract physical capital investment.

VI. CONCLUSION

This paper uses the development accounting approach to investigate the sources of income differences across Chinese provinces over the reform period. We first

TABLE 8

Determinants of Physical Capital Investment and Total Factor Productivity

	Dependent Variable: ln *TFP*			Dependent Variable: ln *k*
	(1)	(2)	(3)	(4)
ln *k*		0.009 (0.37)	0.010 (0.41)	
ln *h*	0.028 (1.48)	0.026 (1.32)	0.056 (1.44)	0.229*** (4.75)
Infrastructure	0.002 (0.01)	–0.012 (–0.10)	–0.004 (–0.04)	0.479*** (3.21)
Market reform	0.097** (2.01)	–0.099** (2.01)	0.092* (1.91)	0.124 (1.21)
Openness	1.566*** (8.40)	1.550*** (8.19)	2.521*** (5.27)	2.012*** (5.59)
ln $h \times$ Openness			1.357** (2.38)	
Observations	479	479	479	479
R^2	0.947	0.947	0.948	0.953
F-test for fixed effects	199.47 [0.000]	114.46 [0.000]	115.61 [0.000]	207.70 [0.000]

Notes: 1. Five-year lags of all explanatory variables are used in regressions.
2. All regressions contain province-specific and year-specific fixed effects.
3. Figures in parentheses are robust t-statistics.
4. Figures in square brackets are p-values.
5. "Infrastructure" is measured by the mileage of highways per 1,000 km^2.
6. "Market reform" is measured by the share of the production of the non-state sector in the total production.
7. "Openness" is measured by the ratio of FDI to GDP.
8. *TFP* is total factor productivity, which is derived from the development accounting results with specification under variable returns to scale with human capital, k is physical capital stock per worker, and h is human capital stock per capita. All the variables are in logarithms.

***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

estimate a production function with various specifications and find that output elasticity to physical capital is relatively stable, in a range of 0.4–0.5, consistent with the usual values used in the existing literature. Decreasing returns to scale is observed in the estimated production function. Our results using the development accounting approach suggest that differences in physical capital intensity and TFP are both important sources of cross-province income differences, each accounting for roughly half of the variation in income levels. The relative contributions of physical capital and TFP are rather stable over time, although the former tends to slightly increase in the 1980s and 1990s. Differences in human capital explain only a small fraction of cross-province income differences when human capital is simply considered as an input. A closer examination, however, reveals that human capital significantly affects the accumulation and flow of physical capital among provinces. It also has a significant influence on provincial TFP once it interacts with openness. Moreover, our study on the interaction between factor accumulation and TFP reveals some implicit complex causalities, which have often been ignored in the existing literature on inequality. The effects of factor accumulation and TFP on regional inequality should be treated carefully in economic and econometric analyses. More research should be devoted to this issue.

REFERENCES

Abramovitz, Moses. 1986. "Catching Up, Forging Ahead and Falling Behind." *Journal of Economic History* 46, no. 2: 385–406.

Aghion, Philippe; Peter Howitt; and David Mayer-Foulkes. 2005. "The Effect of Financial Development on Convergence: Theory and Evidence." *Quarterly Journal of Economics* 120, no. 1: 173–222.

Barro, Robert J., and Jong-Wha Lee. 2001. "International Data on Educational Attainment: Updates and Implications." *Oxford Economic Papers* 53, no. 3: 541–63.

Baum, Christopher F.; Mark E. Schaffer; and Steven Stillman. 2003. "Instrumental Variables and GMM: Estimation and Testing." Boston College Working Paper no. 545. Chestnut Hill, Mass.: Department of Economics, Boston College.

Benhabib, Jess, and Mark M. Spiegel. 1994. "The Role of Human Capital in Economic Development: Evidence from Aggregate Cross-Country Data." *Journal of Monetary Economics* 34, no. 2: 143–73.

Berthélemy, Jean-Claude, and Sylvie Démurger. 2000. "Foreign Direct Investment and Economic Growth: Theory and Application to China." *Review of Development Economics* 4, no. 2: 140–55.

Bhalla, Ajit; Shujie Yao; and Zongyi Zhang. 2003. "Causes of Inequalities in China, 1952 to 1999." *Journal of International Development* 15, no. 8: 939–55.

Bils, Mark, and Peter J. Klenow. 2001. "Quantifying Quality Growth." *American Economic Review* 91, no. 4: 1006–30.

Blundell, Richard, and Stephen Bond. 1998. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics* 87, no. 1: 115–43.

Borensztein, Eduardo, and Jonathan D. Ostry. 1996. "Accounting for China's Growth Performance." *American Economic Review* 86, no. 2: 224–28.

Bound, John; David A. Jaeger; and Regina M. Baker. 1995. "Problems with Instrumental Variables Estimation When the Correlation between the Instruments and the Endogenous Explanatory Variable Is Weak." *Journal of the American Statistical Association* 90, no. 430: 443–50.

Cai, Fang; Dewen Wang; and Yang Du. 2002. "Regional Disparity and Economic Growth in China: The Impact of Labor Market Distortions." *China Economic Review* 13, nos. 2–3: 197–212.

Caselli, Francesco. 2005. "Accounting for Cross-Country Income Differences." In *Handbook of Economic Growth* 1A, ed. Philippe Aghion and Steven N. Durlauf. Amsterdam: Elsevier.

Catin, Maurice; Xubei Luo; and Christophe Van Huffel. 2005. "Openness, Industrialization and Geographic Concentration of Activities in China." World Bank Policy Research Working Paper no. 3706. Washington, D.C.: World Bank.

Chan, Kam Wing; J. Vernon Henderson; and Kai Yuen Tsui. 2008. "Spatial Dimensions of Chinese Economic Development." In *China's Great Economic Transformation*, ed. Loren Brandt and Thomas G. Rawski. Cambridge: Cambridge University Press.

Chen, Jian, and Belton M. Fleisher. 1996. "Regional Income Inequality and Economic Growth in China." *Journal of Comparative Economics* 22, no. 2: 141–64.

Chi, Wei. 2008. "The Role of Human Capital in China's Economic Development: Review and New Evidence." *China Economic Review* 19, no. 3: 421–36.

Chow, Gregory C. 1993. "Capital Formation and Economic Growth in China." *Quarterly Journal of Economics* 108, no. 3: 809–42.

Chow, Gregory C., and Kui-Wai Li. 2002. "China's Economic Growth: 1952–2010." *Economic Development and Cultural Change* 51, no. 1: 247–56.

Córdoba, Juan Carlos, and Marla Ripoll. 2005. "Endogenous TFP and Cross-Country Income Differences." Working Paper no. 247. Pittsburgh, Pa.: Department of Economics, University of Pittsburgh.

Démurger, Sylvie. 1999. "Elément de comptabilité de la croissance chinoise." CERDI Working Paper no. 13. Clermont-Ferrand: Centre d'Etudes et de Recherches sur le Développement International.

———. 2001. "Infrastructure Development and Economic Growth: An Explanation for Regional Disparities in China?" *Journal of Comparative Economics* 29, no. 1: 95–117.

Denison, Edward F. 1967. *Why Growth Rates Differ: Postwar Experience in Nine Western Countries*. Washington, D.C.: Brookings Institution.

Durlauf, Steven N. 2003. "The Convergence Hypothesis after 10 Years." Working Paper no. 6. Madison, Wis.: University of Wisconsin.

Elias, Victor J. 1993. "Sources of Growth: A Study of Seven Latin American Economies." *Journal of Latin American Studies* 25, no. 3: 675–77.

Färe, Rolf; Shawna Grosskopf; Mary Norris; and Zhongyang Zhang. 1994. "Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries." *American Economic Review* 84, no. 1: 66–83.

Felipe, Jesus, and John S. L. McCombie. 2004. "Is A Theory of Total Factor Productivity Really Needed?" CAMA Working Paper no. 12. Canberra: Centre for Applied Macroeconomic Analysis, Australian National University.

Fu, Xiaolan. 2004. "Limited Linkages from Growth Engines and Regional Disparities in China." *Journal of Comparative Economics* 32, no. 1: 148–64.

Fujita, Masahisa, and Dapeng Hu. 2001. "Regional Disparity in China 1985–1994: The Effects of Globalization and Economic Liberalization." *Annals of Regional Science* 35, no. 1: 3–37.

Gong, Liutong, and Danyang Xie. 2004. "Factor Mobility and Dispersion in Marginal Products: A Case on China." *Economic Research Journal* 39, no. 1: 45–53.

Griliches, Zvi, and Jerry A. Hausman. 1986. "Errors in Variables in Panel Data." *Journal of Econometrics* 31, no. 1: 93–118.

Hall, Robert E., and Charles I. Jones. 1999. "Why Do Some Countries Produce So Much More Output per Worker than Others?" *Quarterly Journal of Economics* 114, no. 1: 83–116.

Herrmann-Pillath, Carsten; Sheng Zhaohan; Jiangu Du; Tiaojun Xiao; Kai Li; and Jiangcheng Pan. 2006. "The Evolution of Regional Disparities in China, 1993–2003: A Multi-Level Decomposition Analysis." SSRN Working Paper. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=949072#.

Hu, Zuliu, and Mohsin S. Khan. 1997. *Why Is China Growing So Fast?* Economic Issues no. 8. Washington, D.C.: International Monetary Fund.

Islam, Nazrul. 1995. "Growth Empirics: A Panel Data Approach." *Quarterly Journal of Economics* 110, no. 4: 1127–70.

Kanbur, Ravi, and Xiaobo Zhang. 1999. "Which Regional Inequality? The Evolution of Rural-Urban and Inland-Coastal Inequality in China from 1983 to 1995." *Journal of Comparative Economics* 27, no. 4: 686–701.

King, Robert G., and Ross Levine. 1994. "Capital Fundamentalism, Economic Development, and Economic Growth." *Carnegie-Rochester Conference Series on Public Policy* 40: 259–92.

Klenow, Peter J., and Andrés Rodríguez-Clare. 1997. "The Neoclassical Revival in Growth Economics: Has It Gone Too Far?" In *NBER Macroeconomics Annual* Vol. 12, ed. Ben S. Bernanke and Julio J. Rotemberg. Cambridge, Mass.: MIT Press.

Lee, Jongchul. 2000. "Changes in the Source of China's Regional Inequality." *China Economic Review* 11, no. 3: 232–45.

Li, Jingwen; Feihong Gong; and Yisheng Zheng. 1995. "Productivity and China's Economic Growth, 1953–1990." In *Productivity, Efficiency and Reform in China's Economy*, ed. Kai-yuen Tsui, Tien-tung Hsueh, and Thomas G. Rawski. Hong Kong: Hong Kong Institutes of Asia-Pacific Studies, Chinese University of Hong Kong.

Liu, Tung, and Kui-Wai Li. 2006. "Disparity in Factor Contributions between Coastal and Inner Provinces in Post-Reform China." *China Economic Review* 17, no. 4: 449–70.

Lu, Ding. 2008. "China's Regional Income Disparity: An Alternative Way to Think of the Sources and Causes." *Economics of Transition* 16, no. 1: 31–58.

Mankiw, N. Gregory; David Romer; and David N. Weil. 1992. "A Contribution to the Empirics of Economic Growth." *Quarterly Journal of Economics* 107, no. 2: 407–37.

McGrattan, Ellen R., and James Schmitz Jr. 1999. "Explaining Cross-Country Income Differences." In *Handbook of Macroeconomics* 1A, ed. John. B. Taylor and Michael Woodford. Amsterdam: Elsevier.

Miller, Stephen M., and Mukti P. Upadhyay. 2000. "The Effects of Openness, Trade Orientation, and Human Capital on Total Factor Productivity." *Journal of Development Economics* 63, no. 2: 399–423.

Nakamura, Alice, and Masao Nakamura. 1998. "Model Specification and Endogeneity." *Journal of Econometrics* 83, nos. 1–2: 213–37.

Perkins, Dwight Heald. 1988. "Reforming China's Economic System." *Journal of Economic Literature* 26, no. 2: 601–45.
Poncet, Sandra. 2003. "Measuring Chinese Domestic and International Integration." *China Economic Review* 14, no. 1: 1–21.
Psacharopoulos, George. 1994. "Returns to Investment in Education: A Global Update." *World Development* 22, no. 9: 1325–43.
Quah, Danny. 1993. "Galton's Fallacy and Tests of the Convergence Hypothesis." *Scandinavian Journal of Economics* 95, no. 4: 427–43.
Shastry, Gauri Kartini, and David N. Weil. 2003. "How Much of Cross-Country Income Variation Is Explained by Health?" *Journal of the European Economic Association* 1, nos. 2–3: 387–96.
Shorrocks, A. F. 1982. "Inequality Decomposition by Factor Components." *Econometrica* 50, no. 1: 193–211.
Tsui, Kai-yuen. 2007. "Forces Shaping China's Interprovincial Inequality." *Review of Income and Wealth* 53, no. 1: 60–92.
Villanueva, Delano; Malcolm D. Knight; and Norman Loayza. 1992. "Testing the Neoclassical Theory of Economic Growth: A Panel Data Approach." IMF Working Paper no. 92/106. Washington, D.C.: International Monetary Fund.
Wan, Guanghua; Ming Lu; and Zhao Chen. 2007. "Globalization and Regional Income Inequality: Empirical Evidence from Within China." *Review of Income and Wealth* 53, no. 1: 35–59.
Wang, Yan, and Yudong Yao. 2003. "Sources of China's Economic Growth 1952–1999: Incorporating Human Capital Accumulation." *China Economic Review* 14, no. 1: 32–52.
Woo, Wing Thye. 1998. "Chinese Economic Growth: Sources and Prospects." In *The Chinese Economy: Highlights and Opportunities*, ed. Michel Fouquin and Francoise Lemoine. London: Economica.
Wooldridge, Jeffrey M. 2002. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, Mass.: MIT Press.
World Bank. 1996. *The Chinese Economy: Fighting Inflation, Deepening Reforms*. Washington, D.C.: World Bank.
———. 1997. *Sharing Rising Incomes: Disparities in China*. Washington, D.C.: World Bank.
Young, Alwyn. 2000. "Gold into Base Metals: Productivity Growth in the People's Republic of China during the Reform Period." NBER Working Paper no. 7856. Cambridge, Mass.: National Bureau of Economic Research.
Zhang, Jun; Wu Guiying; and Zhang Jipeng. 2004. "The Estimation of China's Provincial Capital Stock: 1952–2000." *Economic Research Journal* 39, no. 10: 35–44.
Zhang, Xiaobo, and Kevin H. Zhang. 2003. "How Does Globalization Affect Regional Inequality within A Developing Country? Evidence from China." *Journal of Development Studies* 39, no. 4: 47–67.