REVISITING THE ROLE OF ICT IN CHINA'S GROWTH*

David Tao Liang
Institute of Developing Economies, JETRO
Tao_Liang@ide.go.jp

Harry X. Wu
National School of Development, Peking University
harrywu@nsd.pku.edu.cn

ABSTRACT

Based on the pioneering work on the estimation of China's information and communication technology (ICT) assets by industry in Liang, Wu, and Fukao (2022) and the substantial revisions of the China Industrial Productivity (CIP) capital and labor accounts, we revisit the role of ICT in the Chinese economy since the reform. Methodologically, we follow our earlier growth accounting work to quantify the role of China's ICT (Wu and Liang, 2017) *a la* Jorgenson (2001). However, the newly available data allows us to investigate ICT-specific industries, identified by the direct measure of ICT intensity, in a framework that is coherently integrated with the CIP capital accounts including the estimated stock of IT and CT assets. Our new results still support our earlier findings that Chinese ICT-producing and intensive-using industries in manufacturing were the key drivers to China's productivity growth. We show that over the 40 years investigated since 1978, while providing 34 percent of China's 8.3 percent annual value-added growth, these major ICT players contributed 132 percent of China's 1.1 percent annual total factor productivity (TFP) growth. We can therefore reiterate the proposition proposed in our 2017 paper that the rapid development of the ICT industries enabled the Chinese economy to compensate for its heavy productivity losses caused by other industries and the policy-induced misallocation of capital resources.

Keywords: ICT making and ICT intensive using; APPF (aggregate production possibility frontier) growth accounting; aggregation by Domar weights; resource reallocation; TFP (total factor productivity)

***JEL* Classification:** C82, E22, E24, O47

* We would like to thank participants at IDE discussion paper seminar for their comments and constructive suggestions, particularly from Kyoji Fukao, Tomohiko Inui, Bo Meng, and Wenyin Cheng. Intellectual and/or financial supports for the data work by NSD/Peking University, RIETI, and IDE-JETRO are gratefully acknowledged.

1. INTRODUCTION

China's rapid emergence as the world's largest manufacturing powerhouse cannot be properly assessed without a good understanding of the role of information and communication technology or ICT. Nevertheless, the lack of a direct measure of ICT assets in China's capital stock, especially at the industry level, was the main impediment to that assessment. Our earlier, yet the first ever, attempt to quantify the role of ICT in the Chinese economy (Wu and Liang, 2017) had no choice but adopted the US criteria in identifying, hence categorizing ICT-making and using industries as developed in Jorgenson's 2001 paper on the role of ICT in the US economy. We showed that over the period 1981–2012 the so-identified ICT-producing and using industries in manufacturing appeared to be the key drivers to China's productivity growth contributing 149 percent of China's 0.8 percent annual TFP growth while sharing only 29 percent of China's 9.4 percent annual GDP growth. We therefore suggested that the not only did ICT industries compensate for China's heavy productivity losses in other industries but also for policy-induced resource misallocation across industries.

However, either supporting or challenging this finding cannot easily bypass the potential problems of the use of the US ICT standards to identify "ICT-related industries" in China. This motivated us to explore proper approaches to a direct measure of China's ICT assets, which resulted in the preliminary, yet pioneering estimates as reported in Liang, Wu, and Fukao (2022), and hence making a revisiting of the role of ICT in China's growth possible.[1] In the present paper, to better account for the role of ICT in China's growth, considering the recent revisions of the CIP (China Industrial Productivity) or China KLEMS capital and labor accounts,[2] we have further improved China's ICT estimates following the same methodological principles in Liang, Wu, and Fukao (2022).

We first measure ICT intensity for each industry by the share of ICT capital services in total capital services, defined as changes in the user cost weighted capital assets, and then use it to categorize ICT or non-ICT industries together with their positions in the chains of production, i.e., ICT making or using. We however keep agriculture, mining, construction, and non-market services as independent groups. The so-grouped CIP data is analyzed in a growth accounting model *a la* Jorgenson (Jorgenson 2001; Jorgenson *et al.* 2005a) that specifies the role of individual industries in an aggregate production possibility frontier (APPF) framework and use a direct aggregation across industries approach by Domar weights to account for the interactions of individual industries within the system. It allows us to decompose the contribution of capital input into ICT and non-ICT capital and labor input by skill level, and to fragment China's productivity growth into the effect of ICT-specific industries and the effect of factor reallocation across industries.

What we have obtained based on this new data endeavor have lent a strong support to our earlier findings and conclusions (Wu and Liang, 2017). They show that despite for a much longer investigation period compared to our earlier work, ICT-producing industries and ICT-

[1] See Wu and Yu (2022) for an ICT policy-oriented analysis using part of the data provided by Liang, Wu, and Fukao (2022).

[2] See details of the data work revising the CIP capital and labor accounts in Wu and Liang (2023 forthcoming) and Wu and Zhang (2023 forthcoming).

using industries in manufacturing were still the key drivers to China's productivity growth, contributing 132 percent of China's 1.1 percent annual aggregate TFP growth while sharing only 34 percent of China's 8.3 percent annual value-added growth.

The rest of this paper will proceed as the followings. Section 2 describes our methodology for measuring rental prices and capital services and introduces a Jorgensonian growth accounting framework redesigned from an ICT/non-ICT perspective. Section 3 explains the updated and revised CIP data and ICT-specific industry groupings. Section 4 reports and interprets the growth accounting results. Section 5 concludes this study with caveats.

2. ACCOUNTING FOR THE ROLE OF ICT

Estimation of the Rental Prices and Capital Services

Liang, Wu, and Fukao (2022) were the first to attempt to estimate the ICT tangible investment series and construct the ICT capital stock by industry in China's assets over the past 40 years. A growth accounting framework at both the aggregate and industry levels is useful for investigating the role of ICT played in China's growth and productivity performance. However, the contribution of capital input to the economic growth under such a framework is defined in terms of capital services rather than capital stock. This is important to reflect the impact of shifting the composition of capital from non-ICT assets to ICT equipment on the growth.

The prices of capital services, also called rental prices, are crucial for transforming capital stock into capital services. To aggregate capital service flows across assets, rental prices should be used as the weights, as implied by the production theory, to reflect marginal products. Hence, assets with relatively high service prices and marginal products, such as ICT equipment, receive larger weights. As introduced by Jorgenson (1963) and Hall and Jorgenson (1967), rental prices can be estimated as follows:

$$(1)\ P_{k,j,t}^{K} = \left(i_{j,t} - \pi_{k,j,t}\right) P_{k,j,t-1}^{I} + \delta_k P_{k,j,t}^{I}$$

where $P_{k,j,t}^{K}$ is the rental price for asset type k in industry j at the year t, $i_{j,t}$ is the nominal rate of return, $P_{k,j}^{I}$ is the price of investment, the asset-specific capital gains term is $\pi_{k,j,t} = \left(P_{k,j,t}^{I} - P_{k,j,t-1}^{I}\right)/P_{k,j,t-1}^{I}$, δ_k is the rate of depreciation.

For ICT capital, we construct the harmonized deflators based on the US ICT capital goods prices to control for domestic inflation in Liang, Wu, and Fukao (2022). The depreciation rates for ICT capital from the Bureau of Economic Analysis (BEA)–31.5 percent for IT equipment and 11.5 percent for CT equipment–were adopted because of the lack of the survey data on the service lives of ICT assets in China. For non-ICT capital, we use investment prices and depreciation rates from Wu (2015).

The nominal rate of return can be derived from the ex-post approach that exhausts capital income and is consistent with constant returns to scale. The nominal rate of return is the same across assets within an industry but is allowed to differ across industries:

$$(2)\ i_{j,t} = \frac{P_{j,t}^{K} K_{j,t} + \sum_k \left(P_{k,j,t}^{I} - P_{k,j,t-1}^{I}\right) A_{k,j,t} - \sum_k P_{k,j,t}^{I} \delta_k A_{k,j,t}}{\sum_k P_{k,j,t-1}^{I} A_{k,j,t}}$$

where the first term $P_{j,t}^{K} K_{j,t}$ is the capital compensation in industry j, and $A_{k,j,t}$ is the real net capital stock.

To estimate capital services by industry, we assume that the flow of capital services for each asset is proportional to its stock and is independent of time. We use a Tornqvist quantity index to aggregate over assets. The quantity index of capital services in industry j is defined as follows:

(3) $\Delta \ln K_j = \sum_k \bar{w}_{k,j} \Delta \ln A_{k,j}$

where $\Delta \ln A_{k,j} = \ln A_{k,j,t} - \ln A_{k,j,t-1}$, K_j is an index of capital services in industry j, the time subscript is dropped for simplicity, and the value share of each type of capital services is:

(4) $w_{k,j} = \frac{P_{k,j}^{K} K_{k,j}}{\sum_k P_{k,j}^{K} K_{k,j}}$

and the two-period average value share weight is:

(5) $\bar{w}_{k,j} = \left(w_{k,j,t} + w_{k,j,t-1}\right)/2.$

Finally, we define the economy-wide index of capital services as the Tornqvist aggregate of the capital stock from all assets:

(6) $\Delta \ln K = \sum_k \bar{w}_k \Delta \ln A_k$

where the value share of each type of capital services is:

(7) $w_k = \frac{P_k^K K_k}{\sum_k P_k^K K_k}$

and the two-period average share weight is:

(8) $\bar{w}_k = \left(w_{k,t} + w_{k,t-1}\right)/2$

and the economy-wide capital stock for each type of asset is the simple sum across industries:

(9) $A_k = \sum_j A_{k,j}$.

Growth Accounting Framework

The role of ICT in China's economic growth and productivity performance can be examined through a growth accounting framework in which the contribution of ICT-specific industries and ICT capital can also be traced. We decompose the aggregate growth into contributions of ICT and non-ICT capital input, contributions of labor input from skilled workers, and TFP. The aggregate value-added production function is defined as:

(10) $V = f(K_{ICT}, K_{NON}, L_L, L_M, L_H, \Omega)$

where K_{ICT} is the ICT capital services, K_{NON} is the non-ICT capital services, L_L is the low-skilled labor services, L_M is the medium-skilled labor services, L_H is the high-skilled labor services, Ω is the aggregate TFP, and the time subscript is dropped for simplicity.

Under the assumption of perfect competitive factor markets where the marginal product of each input equals its price and constant returns to scale, the production function (10) can be transformed into the following growth accounting equations:

(11) $$\Delta \ln V = \bar{u}_K \Delta \ln K + \bar{u}_L \Delta \ln L + \Omega$$

(12) $$\Delta \ln V = \bar{u}_{K,ICT} \Delta \ln K_{ICT} + \bar{u}_{K,NON} \Delta \ln K_{NON} + \bar{u}_{L,L} \Delta \ln L_L + \bar{u}_{L,M} \Delta \ln L_M + \bar{u}_{L,H} \Delta \ln L_H + \Omega$$

where V is the aggregate real value-added, K is the aggregate capital services, L is the aggregate labor services, $\bar{u}$ denotes the two-period average shares of factor income in value-added, and the change in the logarithm of a variable denotes its growth rate. The assumption of constant returns to scale implies that $u_K + u_L = 1$, $u_{K,ICT} + u_{K,NON} = u_K$, and $u_{L,L} + u_{L,M} + u_{L,H} = u_L$.

This aggregate value-added growth may also be expressed in terms of the decompositions of stock and quality contributions of factor inputs as:

(13) $$\Delta \ln V = \bar{u}_K \Delta \ln A + \bar{u}_K \Delta \ln Q_K + \bar{u}_L \Delta \ln H + \bar{u}_L \Delta \ln Q_L + \Omega$$

where A is the aggregate capital stock, Q_K is the quality of capital, H is the aggregate hours worked, and Q_L is the quality of labor.

To trace the ICT-specific industry origins of growth, this study adopts APPF approach developed by Jorgenson (1966). This approach relaxes the strong assumption that all industries are subject to the same value-added production function, as imposed by the conventional aggregate production function (APF) approach. Given the heavy government interventions and institutional setups that cause market imperfections in China, the APF approach is undoubtedly inappropriate for the growth accounting exercise of the economy, especially when the performances of specified industries are compared across the economy. The aggregate value-added from the APPF approach is defined as a Tornqvist index of industry value-added as:

(14) $$\Delta \ln V = \sum_j \bar{w}_{V,j} \Delta \ln V_j$$

where $w_{V,j}$ is the share of industry value-added in aggregate value-added:

(15) $$w_{V,j} = \frac{P_j^V V_j}{\sum_j P_j^V V_j}$$

and P_j^V is the implicit price of industry value-added, V_j is the industry value-added, and the two-period average share $\bar{w}_{V,j} = \left(w_{V,j,t} + w_{V,j,t-1}\right)/2$.

We are particularly interested in the growth contributions of the industries that produce ICT goods (ICT-producing), those that intensively use ICT (ICT-intensive-using), those that do not intensively use ICT (non-ICT-intensive-using), and other industries (other) that are not grouped into ICT-related groups for convenience in analyzing their performance in the context of the Chinese economy, such as agriculture and non-market services. Note that, in empirical exercises, these broad groups may be further broken down. For example, both the ICT-intensive-using group and non-ICT-intensive-using group are divided into manufacturing and services sectors. Therefore, the equation (14) can be rewritten as the sum of the contribution of these ICT-specific groups:

$$(16) \qquad \Delta \ln V = \sum_{j \in ICT^P} \bar{w}_{V,j} \Delta \ln V_j + \sum_{j \in ICT^U} \bar{w}_{V,j} \Delta \ln V_j + \sum_{j \in NON} \bar{w}_{V,j} \Delta \ln V_j + \\ + \sum_{j \in OTH} \bar{w}_{V,j} \Delta \ln V_j$$

where subscript ICT^P denotes for ICT-producing group, ICT^U for ICT-intensive-using groups, NON for non-ICT-intensive-using groups, and OTH for other groups.

We also analyze the sources of aggregate labor productivity growth, defined as the aggregate value-added per economy-wide hour worked as:

$$(17) \qquad \Delta \ln v = \Delta \ln V - \Delta \ln H$$

$$(18) \qquad \Delta \ln v = \bar{u}_K \Delta \ln k + \bar{u}_L \Delta \ln Q_L + \Omega$$

where $v = V/H$ is aggregate value-added per hour worked, and $k = K/H$ is the capital per hour worked.

Finally, to investigate the contributions of industry to aggregate TFP growth, the “direct aggregation across industries” approach developed by Jorgenson, Gollop, and Fraumeni (1987) is preferred in this study. This approach has been used by Jorgenson and Stiroh (2000), Jorgenson (2001), and Jorgenson, Ho, and Stiroh (2005a, 2005b) to quantify the role of information technology (IT)-producing and IT-using industries in the US economy. No cross-industry restrictions on either value-added or inputs are imposed by this approach, which eliminates the assumptions of equal value-added functions, mobility of inputs across industries, and equal factor prices for all industries.

The aggregate value-added growth can be expressed as the weighted contribution of industry capital services, industry labor services, and industry TFP as follows:

$$(19) \qquad \Delta \ln V = \sum_j \left(\bar{w}_{V,j} \frac{\bar{v}_{K,j}}{\bar{v}_{V,j}} \Delta \ln K_j + \bar{w}_{V,j} \frac{\bar{v}_{L,j}}{\bar{v}_{V,j}} \Delta \ln L_j + \frac{\bar{w}_{V,j}}{\bar{v}_{V,j}} \Omega_j \right)$$

where L_j is industry labor services, Ω_j is industry TFP, $v_{K,j}$ is the share of industry capital income in industry gross output, $v_{L,j}$ is the share of industry labor income in industry gross output, and $v_{V,j}$ is the share of industry value-added in industry gross output. And the third term in the parentheses of the right side is the industry TFP growth weighted by Domar weight, $\frac{\bar{w}_{V,j}}{\bar{v}_{V,j}}$. All weights are two-period averages.

Similarly, we can trace the contributions of ICT-specific groups to aggregate TFP growth by breaking down the Domar-weighted contributions from equation (19) as:

$$(20) \qquad \sum_j \frac{\bar{w}_{V,j}}{\bar{v}_{V,j}} \Omega_j = \sum_{j \in ICT^P} \frac{\bar{w}_{V,j}}{\bar{v}_{V,j}} \Omega_j + \sum_{j \in ICT^U} \frac{\bar{w}_{V,j}}{\bar{v}_{V,j}} \Omega_j + \sum_{j \in NON} \frac{\bar{w}_{V,j}}{\bar{v}_{V,j}} \Omega_j + \\ + \sum_{j \in OTH} \frac{\bar{w}_{V,j}}{\bar{v}_{V,j}} \Omega_j.$$

Resource Reallocation Effects

In practice, we can observe the different prices for each specific type of factor inputs across industries may be due to institutional obstacles which contradicts to the assumption imposed by the APPF approach that they must receive the same price in all industries. If factor inputs move from the industries with low factor prices to the industries with high factor prices, GDP can be raised. This reallocation effect will be reflected in the aggregate TFP growth measured using the APPF approach. However, this strong assumption is relaxed by "direct aggregation across industries" approach as discussed in the previous sub-section. The factor input growth is aggregated across industries using the factor income in each industry as aggregation weights. Therefore, if factor inputs are reallocated from the industries with low factor prices to those with high factor prices, the effect is treated as an increase in the aggregate input growth. Hence, the resource reallocation effects can be measured by the difference between these two growth accounting approaches. More precisely, we subtract equation (19) from equation (11) and rearrange it to obtain:

(21) $$\Omega = \Omega^D + \Psi^K + \Psi^L$$

where Ω^D is the Domar-weighted aggregate TFP growth, Ψ^K is the reallocation effect of capital, and Ψ^L is the reallocation effect of labor, which are defined as:

(22) $$\Omega^D = \sum_j \frac{\bar{w}_{V,j}}{\bar{v}_{V,j}} \Omega_j$$

(23) $$\Psi^K = \sum_j (\bar{w}_{V,j} \frac{\bar{v}_{K,j}}{\bar{v}_{V,j}} \Delta \ln K_j) - \bar{u}_K \Delta \ln K$$

(24) $$\Psi^L = \sum_j (\bar{w}_{V,j} \frac{\bar{v}_{L,j}}{\bar{v}_{V,j}} \Delta \ln L_j) - \bar{u}_L \Delta \ln L.$$

Equation (21) expresses the aggregate TFP growth in terms of three sources: Domar-weighted TFP growth (Ω^D), reallocation of capital (Ψ^K) and reallocation of labor (Ψ^L) across industries. This Domar weighting scheme ($\frac{\bar{w}_{V,j}}{\bar{v}_{V,j}}$), originated by Domar (1961), plays a key role in the direct aggregation across industries of the Jorgensonian growth accounting framework. A direct consequence of the Domar-aggregation is that the weights do not sum to unity, implying that aggregate productivity growth amounts to more than the weighted average of industry-level productivity growth (or less, if negative). This reflects the fact that productivity change in the production of *intermediate inputs* do not only have an "own" effect but in addition they lead to reduced or increased prices in downstream industries, and that effect accumulates through vertical links. As elaborated by Hulten (1978), the Domar aggregation method establishes a consistent link between the industry level productivity growth and the aggregate productivity growth. Productivity gains of the aggregate economy may exceed the average productivity gains across industries because flows of intermediate inputs between industries contribute to aggregate productivity by allowing productivity gains in successive industries to augment one another. The same logic can explain productivity losses.

The next two terms reflect the impact on aggregate TFP growth of the reallocation effect of capital (Ψ^K) and labor (Ψ^L) across industries, respectively. It should be noted that both theoretically and methodologically, when these terms are not negligible, it indicates that industries do not face the same factor costs, which suggests a violation of the assumption of the widely used aggregate approach. However, one should not expect a significant reallocation effect in an economy with a well-developed market system. However, this analytical tool is very useful for China, where strong government interventions in resource allocation may have caused severe market distortions (Hsieh and Klenow 2009; Wu 2016).

3. Data and ICT-Specific Industry Grouping

The CIP Data and its Revisions—A Brief Introduction

This study uses the revised and updated CIP (China Industrial Productivity) data (CIP 4.0, see Wu *et al*, 2023, forthcoming, for details). The construction of the CIP data adheres to the principle of KLEMS (an acronym for all inputs: Capital, Labor, Energy, Material, and Services; see O'Mahony and Timmer, 2009, for details). In the case of input and output data, the CIP industry accounts are made coherently consistent with the official annual GDP accounts as *control totals* and the official full input-output system published every five years as *control structures*, reconstructed and interpolated to obtain the time series of the national accounts (Wu and Ito, 2015). It should be noted that in constructing industry accounts we do not challenge the official statistics except for necessary consistency adjustments. Therefore, the widely reported and discussed data falsification problems should be born in mind when interpreting our results.[3]

The revision of the nominal input and output data in CIP 4.0 is based on the lately available Chinese 2012 and 2017 input-output tables and GDP accounts from 2010 onwards. Accordingly, the updated national accounts data for the period 2007–2017 are used to interpolate the input-output series between the 2007 and 2012 tables, and between the 2012 and 2017 tables replacing the extrapolated series from 2007 onwards in CIP 3.0 and an extension to 2018. The nominal accounts can then be double deflated by a producer price index (PPI) matrix, constructed based on official PPIs for the agricultural and industrial sectors, relevant components of consumer price index (CPI) for service industries and wage index for "non-market" services (i.e., education, healthcare, and government) (Wu and Li, 2021). However, the revised and updated CIP 4.0 PPI is still domestic transactions-based by nature, that is, due to the lack of official data it has not yet been able to consider the effect of the price changes of imported intermediate inputs. This may induce some biases to industries that have been heavily depending on imported materials, including ICT producers.

In the case of employment data, as explained in Wu, Yue, and Zhang (2015), the CIP 3.0 industry labor accounts are built on all available employment statistics and surveys, reconstructed to ensure consistency with population censuses as control totals. The numbers employed include both employees and self-employed people (farming households and self-employed retailers and transporters). They are converted to hours worked based on various census and survey data and made cross-classified by gender, age, and educational level. The cost or compensation accounts of the labor quantitative matrices are controlled by the national income accounts built in the input-output system. With a better use of the economic census data, the revision in CIP 4.0 has solved two major problems in CIP 3.0, that is, the cross-

[3] China's official estimates of GDP growth have long been challenged for upward bias (see Wu 2013 and 2014). Alternative estimates have indeed shown slower growth rates than the official accounts. The most affected sectors are manufacturing and so-called "non-material services" (including non-market services). Wu (2013) shows that the official industrial output index has substantially moderated the impact of external shocks. Besides, Wu (2014) also shows that the official 5-6 percent annual growth of labor productivity in "non-material services" appears to be too good to be true if considering the international norm of between -1 and +1 percent per annum in the literature (Griliches 1992; van Ark 1996).

industry distribution of "other employment" within the official employment statistical system, termed as Residual 1, and the cross-industry distribution of "other employment" within the census employment boundary, termed as Residual 2 (for details see Wu and Zhang, 2023 forthcoming).

In the case of capital data, we have substantially revised the capital account in the CIP 3.0 database which was constructed based on the principles documented in Wu (2015). The revisions in CIP 4.0 are primarily designed for the reconciliations of the sum of industry investment series in the CIP, constructed mainly based on the investment statistics for officially defined "above-size" firms, with the national gross fixed capital formation or GFCF as reported in the Chinese input-output accounts. Considering the ownership breakdown by industry, an idea that uses more information than focusing on the industry level, the gap observed between the CIP investment total and the GFCF total is allocated to the below-size private firms, assuming that these below-size firms concentrate only in labor intensive industries and hence have constant labor productivity that allows us to distribute the investment gap by the labor employment structure of the concerned labor intensive industries (for details see Wu and Liang, 2023 forthcoming).

ICT-Specific Industry Grouping

Since we are interested in how ICT has affected the productivity performance in the Chinese economy, the entire economy can be divided into two large sectors: the ICT sector and the non-ICT sector. The impact of ICT is distributed through industries by means of using ICT assets with ICT-trained skilled workers. Therefore, to explore the role of ICT we may consider distinguishing industries making or intensively using ICT equipment from those not intensively doing so. We used the ICT intensity as our indicator to identify the "ICT-intensive-using industries". The ICT intensity in this study is defined as the share of ICT capital services within total capital services. Industries with ICT intensity above the median are identified as ICT-intensive-using industries.[4]

In addition, ICT producers should be distinguished from ICT users. As explained by Jorgenson (2001), on the one hand, as ICT-producing industries become more efficient, more ICT equipment and software can be produced using the same cost. This raises ICT producers' productivity and contributes to aggregate TFP growth through ICT users. On the other hand, investment in ICT equipment leads to the growth of productive capability in ICT-using industries because labor is working with more efficient equipment. Such an increase in ICT deployment affects TFP growth only if spillovers exist between ICT producers and users.

To better investigate the industry origins of the impact of ICT on the aggregate TFP performance, it is necessary to distinguish between manufacturing and services industries in ICT-intensive users and non-ICT-intensive users. Therefore, we categorize the 37 CIP industries into nine groups: ICT-producing, ICT-intensive-using manufacturing, ICT-intensive-using services, non-ICT-intensive-using manufacturing, non-ICT-intensive-using services and four others: agriculture, mining, construction, and non-market services (see Table

[4] To identify the ICT-intensive-using industries, considering the change of ICT intensity over time, we calculate the average of this indicator for three time points, i.e., 2005, 2010, and 2015.

A1 for details). This grouping is guided by our desire to study differences across industries that vary in ICT use intensity and also considers institutional settings in China.[5]

We conjecture that the productivity growth of ICT-producing and ICT-intensive-using manufacturing groups may generally outperform other groups. We may also expect the latter group to use ICT equipment most intensively and benefit from the spillover effect of the former, growing more rapidly than the former group; hence, it would be the most important contributor to aggregate TFP growth.

4. EMPIRICAL RESULTS

ICT-Specific Group Contributions to Aggregate Growth and Sources of Growth

We devote this sub-section to examine group contributions to China's aggregate value-added growth, in parallel with the scrutiny of factor contributions to aggregate value-added growth. For the latter, we further distinguish the contributions of various types of factor inputs and the contributions of the stock and quality of factor inputs to aggregate growth. The results are summarized in Table 1.

As shown in the first panel of Table 1, adopting double-deflation procedures and using the industry weights from our ICT-specific industry grouping, the Chinese economy achieved a real value-added growth of 8.31 percent per annum from 1978 to 2018. On average, the three ICT-related groups made up 56 percent of China's GDP growth (4.65 percentage points or ppts out of the 8.31 percent annual growth), or 34 percent if focusing only on ICT-producing and ICT-intensive-using manufacturing industries (2.83 ppts out of the 8.31 percent annual growth, of which 0.77 ppts was attributed to ICT-producing and 2.06 to ICT-using manufacturing). As expected, the latter group, as the one using ICT equipment most intensively and benefiting from the spillover effect of the former, indeed expanded more rapidly; hence, it was the most important contributor to aggregate GDP. The largest GDP contributor was nevertheless the non-ICT manufacturing group, which accounted for 28 percent (2.31 ppts) of GDP growth. This is not surprising, given the nature of China's catch-up through export-oriented manufacturing.

Factor contribution wise, of the economy-wide 8.31 percent annual value-added growth for the entire period, the contribution of capital input was 5.99 ppts, labor input 1.24 ppts, and TFP growth 1.08 ppts on average. This means that the Chinese economy relied 72.1 percent of its real value-added growth on capital input growth, 14.9 percent on labor input growth, and the remaining 13.0 percent on total factor productivity growth. Over time, the contribution of capital input increased from 56.8 percent in the initial 1980s to 65.7 percent post-WTO, then it even jumped to 98.2 percent post global financial crisis (GFC) (5.18 the contribution of capital input growth to 5.28 value-added growth in 2012–2018). The share of ICT capital input started at 0.4 percent of value-added growth and peaked at 9 percent on the eve of WTO entry and recently declined by 4.3 percent. Liang, Wu, and Fukao (2022) examined the decline in ICT investment within each industry rather than the substitution effect between industries. Moreover, ICT investment could be crowded out by huge investments in infrastructure during

[5] Compared with Wu and Liang (2017) in which the ICT-specific grouping is conducted using the US criteria from Jorgenson *et al*. (2005a) due to unavailability of ICT assets data for China, the change is minor in industry composition of the groups.

TABLE 1

SOURCES OF AGGREGATE VALUE-ADDED GROWTH IN CHINA, 1978–2018

(Contributions are share-weighted rate in percentage points)

	1978-1984	1984-1992	1992-1996	1996-2001	2001-2007	2007-2012	2012-2018	***1978-2018***
			Industry Contribution to Value-Added Growth					
Value-added growth due to (%)	9.92	7.66	9.40	7.48	10.73	8.14	5.28	***8.31***
-ICT-producing	*0.63*	*0.37*	*1.04*	*0.63*	*1.22*	*0.95*	*0.79*	***0.77***
-ICT-using manufacturing	*2.40*	*2.01*	*2.83*	*1.94*	*2.57*	*2.11*	*0.81*	***2.06***
-ICT-using services	*2.15*	*1.09*	*1.05*	*1.02*	*2.71*	*2.74*	*2.01*	***1.82***
-Non-ICT manufacturing	*3.13*	*1.52*	*3.26*	*2.20*	*3.01*	*2.36*	*1.29*	***2.31***
-Non-ICT services	*0.01*	*0.39*	*0.21*	*0.56*	*1.23*	*0.66*	*0.40*	***0.50***
-Agriculture	*1.80*	*1.12*	*0.76*	*0.51*	*0.38*	*0.35*	*0.25*	***0.77***
-Mining	*-0.75*	*0.09*	*-0.10*	*0.37*	*-0.01*	*0.14*	*0.10*	***-0.03***
-Construction	*0.28*	*0.70*	*0.26*	*0.17*	*0.60*	*0.08*	*0.21*	***0.36***
-Non-market services	*0.27*	*0.37*	*0.09*	*0.09*	*-0.98*	*-1.25*	*-0.57*	***-0.25***
			Factor Contribution to Value-Added Growth (by Type)					
Value-added growth due to (%)	9.92	7.66	9.40	7.48	10.73	8.14	5.28	***8.31***
- Capital input:	5.63	5.02	6.41	5.53	7.05	7.83	5.18	***5.99***
- Non-residential structure	*2.86*	*1.52*	*1.90*	*1.86*	*1.93*	*2.59*	*2.36*	***2.12***
- ICT equipment	*0.03*	*0.17*	*0.72*	*0.67*	*0.75*	*0.51*	*0.01*	***0.16***
- Non-ICT equipment	*2.71*	*3.25*	*3.50*	*2.75*	*4.14*	*4.56*	*0.21*	***0.25***
- Dwellings	*0.03*	*0.08*	*0.29*	*0.25*	*0.22*	*0.17*	*2.51*	***3.32***
- Labor input:	1.94	1.67	1.71	0.57	1.12	1.20	0.34	***1.24***
- Low-skilled labor	*0.50*	*0.09*	*-0.24*	*-0.41*	*-0.21*	*-0.54*	*-0.17*	***-0.11***
- Medium-skilled labor	*1.36*	*1.34*	*1.42*	*0.84*	*1.25*	*-0.47*	*-0.27*	***0.81***
- High-skilled labor	*0.08*	*0.25*	*0.54*	*0.14*	*0.07*	*2.21*	*0.78*	***0.54***
- Aggregate TFP	2.35	0.96	1.27	1.38	2.56	-0.89	-0.24	***1.08***
			Factor Contribution to Value-Added Growth (by Quantity and Quality)					
Value-added growth due to (%)	9.92	7.66	9.40	7.48	10.73	8.14	5.28	***8.31***
- Capital input:	5.63	5.02	6.41	5.53	7.05	7.83	5.18	***5.99***
- Stock	*5.62*	*4.78*	*6.46*	*5.71*	*6.95*	*7.25*	*4.94*	***5.85***
- Capital quality (composition)	*0.00*	*0.24*	*-0.05*	*-0.18*	*0.10*	*0.58*	*0.24*	***0.14***
- Labor input:	1.94	1.67	1.71	0.57	1.12	1.20	0.34	***1.24***
- Hours	*1.67*	*1.35*	*1.12*	*0.36*	*0.81*	*-0.84*	*-0.29*	***0.65***
- Labor quality (composition)	*0.27*	*0.32*	*0.60*	*0.22*	*0.31*	*2.04*	*0.63*	***0.59***
- Aggregate TFP	2.35	0.96	1.27	1.38	2.56	-0.89	-0.24	***1.08***

Source: Authors' estimates.

the GFC decade, considering the government's fiscal stimulus packages and heavy interventions in structural adjustments.

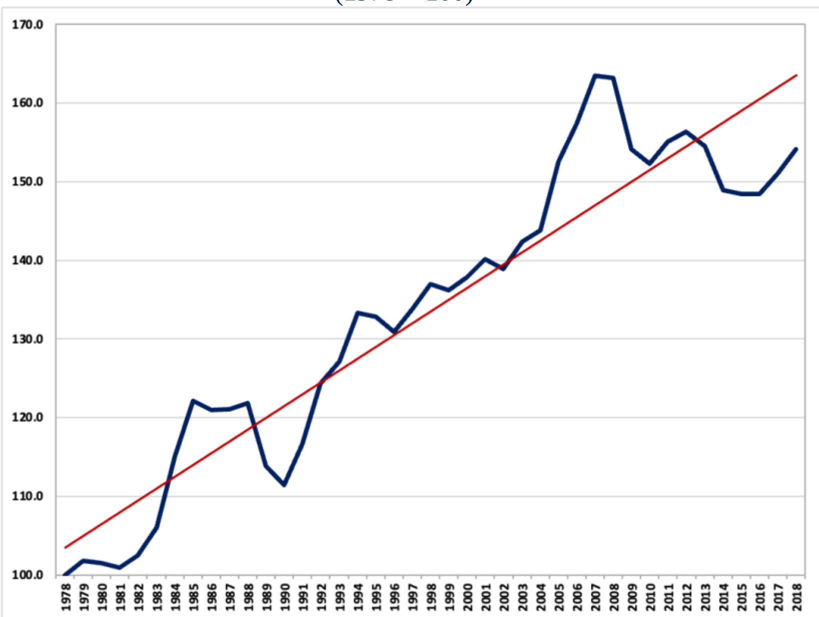
On the other hand, the contribution of labor input declined from 19.6 percent in the initial 1980s to 10.4 percent post-WTO, then dropped to only 6.4 percent over the last sub-period of 2012–2018. In fact, the decline in hours worked was substantial, 0.84 ppt per annum, between 2007 and 2012. Nonetheless, the decline effect was cancelled out by a labor quality improvement of 2.04 ppts, which reflects the relatively fast growth of high-skilled workers with higher wages. In sharp contrast, the contribution of capital quality is very small, indicating less substitution for assets with relatively higher rates of return.

The estimated TFP performance was highly unstable over time with the highest TFP growth achieved in the post-WTO stage during the period of 2001–2007 and the worst in the wake of the GFC. If the estimated annual aggregate TFP growth rates are translated into an index benchmarked in 1978, as shown in Figure 1, we observe a very volatile TFP performance around its underlying trend (level, not rate). Using the trend line as a yardstick to identify major shocks, we find that they are largely institutional.

FIGURE 1

AN INDEX OF CHINA'S AGGREGATE TOTAL FACTOR PRODUCTIVITY

(1978 = 100)



Source: Based on the results reported in Table 1.

The first TFP drive was observed through the early to the late 1980s benefitted by China's agricultural reforms and early industrial reforms. The move of TFP collapsed in the wake of the 1989 political crisis but recovered in the early 1990s in response to Deng's call for bolder reforms and hence the SOE reforms in the mid-1990s. A strong TFP acceleration was seen following China's WTO entry till it peaked on the eve of the global financial crisis. Unsurprisingly, the TFP index dropped sharply and lost all it had gained in the wake of the GFC. The TFP dive was temporarily saved by the unprecedented monetary and fiscal expansionary policies. Since the 2010s, when there was little room for further expansionary policy, it dropped again, negatively and substantially deviated from the underlying trend. It is perhaps too early to make a clear remark on the TFP recovery during the period of 2016–2018.

In our preliminary view, increasingly market-based consolidation and restructuring might have played a role as government interventions had to decrease because of the rising fiscal pressure.

Table 2 presents the results of the decomposition of China's aggregate value-added per hour worked into changes in capital deepening, labor quality, and TFP. This enables us to separate the contribution of hours worked from the contribution of genuine labor productivity improvement and its sources. The Chinese economy once benefited significantly from the increase in hours worked or the so-called "demographic dividend." However, this declined overtime, as shown in Table 2, from 3.74 percent per annum in 1978–1984 to 1.67 after China joined the WTO. In the post-GFC period (2007–2012), the growth of hours worked started to fall and dropped substantially by 1.83 percent per annum. This figure continued to drop by 0.57 percent per annum over the last sub-period of 2012–2018, clearly indicating the complete loss of the "demographic dividend." Although the growth of value-added per hour worked increased from 6.18 to 9.96 percent per annum, it appeared to rely increasingly on the growth in capital deepening ranging from 3.57 to 8.82 percent per annum. In fact, Table 2 shows that TFP growth was not necessarily in line with, or even completely contradictory to, the pace of capital deepening, which suggests a serious misallocation of resources as shown in Table 3.

The ICT-Specific Industry Origins of Aggregate TFP Growth

In order to explicitly account for productivity differences across ICT-specific groups and their impact on China's aggregate TFP performance, we now introduce the "direct aggregation across industries" approach as given in equation (19) following the ICT studies on the US economy by Jorgenson, Ho, and Stiroh (2005a and 2005b). It accounts for the genuine TFP improvement within industries and factor reallocation effects across industries. The results presented in the first row of Table 3 are estimated with the stringent assumption that the marginal productivity of capital and labor are the same across all industries, which are the same as those presented in Table 1 and Table 2 above. As expressed in equation (19), if Domar weights are used, such an aggregate TFP growth rate can be decomposed into three additive components: 1) the change in aggregate TFP originating in industries summed up by Domar weights, 2) the change in capital reallocation across industries, and 3) the change in labor reallocation across industries.

On average, for the entire period of 1978 to 2018, China's Domar-weighted TFP growth is estimated at 1.00 percent per annum, compared to the aggregate TFP growth of 1.08 percent per annum. This result implies a net factor reallocation effect of 0.08 ppts. Table 3 also shows the contribution of each industrial group to the Domar-weighted annual TFP growth (see Table A2 for the results for individual industries). The biggest contributor to the Domar-weighted aggregate TFP growth was the ICT-intensive-using manufacturing group, contributing 1.04 ppts. The ICT-producing group contributed 0.38 ppts. The non-market services group was the worst performer, dragging down the Domar weighted TFP growth by 0.66 ppts (Table 3). Such a sharp contrast across industry groups in TFP performance can also be observed over different sub-periods, reflecting significant shifts of policy regimes, which clearly suggests that treating individual industries as homogenous in growth accounting can substantially distort our view of the productivity performance of the Chinese economy and provide no vision of the industry origins of the aggregate TFP performance.

TABLE 2

DECOMPOSITION OF AGGREGATE LABOR PRODUCTIVITY GROWTH IN CHINA

(Contributions are weighted growth in percentage points)

	1978-1984	1984-1992	1992-1996	1996-2001	2001-2007	2007-2012	2012-2018	***1978-2018***
Value-Added Growth (APPF) (% p.a.)	9.92	7.66	9.40	7.48	10.73	8.14	5.28	***8.31***
				Decomposition of Value-Added Growth				
-Value added per hour worked	*6.18*	*4.89*	*7.17*	*6.69*	*9.06*	*9.96*	*5.85*	***6.94***
- Hours[1]	*3.74*	*2.78*	*2.23*	*0.80*	*1.67*	*-1.83*	*-0.57*	***1.37***
				Contributions to Labor Productivity Growth				
Value-Added per hour worked	6.18	4.89	7.17	6.69	9.06	9.96	5.85	***6.94***
- Capital deepening	*3.57*	*3.60*	*5.30*	*5.09*	*6.19*	*8.82*	*5.46*	***5.27***
- Labor quality	*0.27*	*0.32*	*0.60*	*0.22*	*0.31*	*2.04*	*0.63*	***0.59***
- TFP growth	*2.35*	*0.96*	*1.27*	*1.38*	*2.56*	*-0.89*	*-0.24*	***1.08***

Source: Authors' estimates.

Note: 1) The growth rate of hours worked, which is different from the contribution of hours in Table 1.

TABLE 3

DECOMPOSITION OF CHINA'S AGGREGATE TOTAL FACTOR PRODUCTIVITY GROWTH: DOMAR-AGGREGATION VIS-À-VIS FACTOR REALLOCATION EFFECTS

(Decomposed TFP growth in percentage points)

	1978-1984	1984-1992	1992-1996	1996-2001	2001-2007	2007-2012	2012-2018	***1978-2018***
Aggregate TFP growth (% p.a.)	2.35	0.96	1.27	1.38	2.56	-0.89	-0.24	***1.08***
1. Domar-weighted TFP growth	1.55	0.01	0.75	1.88	2.95	-0.30	0.31	***1.00***
-ICT-producing	*0.58*	*0.17*	*0.42*	*-0.05*	*0.60*	*0.58*	*0.42*	***0.38***
-ICT-using manufacturing	*1.37*	*0.78*	*1.48*	*1.91*	*1.00*	*0.53*	*0.52*	***1.04***
-ICT-using services	*0.79*	*-0.89*	*-1.23*	*-0.98*	*1.19*	*0.12*	*-0.32*	***-0.16***
-Non-ICT manufacturing	*0.94*	*-0.34*	*1.10*	*1.31*	*1.28*	*0.63*	*0.76*	***0.73***
-Non-ICT services	*-0.50*	*0.08*	*-0.21*	*-0.30*	*0.30*	*-0.32*	*-0.58*	***-0.20***
-Agriculture	*-0.30*	*0.15*	*0.40*	*0.24*	*0.45*	*0.69*	*0.49*	***0.28***
-Mining	*-1.20*	*-0.31*	*-0.40*	*0.30*	*-0.54*	*-0.25*	*0.11*	***-0.34***
-Construction	*-0.20*	*0.30*	*-0.42*	*-0.35*	*0.34*	*-0.49*	*-0.08*	***-0.08***
-Non-market services	*0.07*	*0.07*	*-0.38*	*-0.19*	*-1.68*	*-1.79*	*-0.99*	***-0.66***
2. Reallocation of capital	0.38	0.60	-0.16	-0.39	-1.09	-0.44	-0.67	***-0.21***
3. Reallocation of labor	0.42	0.35	0.69	-0.12	0.70	-0.16	0.11	***0.29***

Source: Authors' estimates following equation (19) and (21).

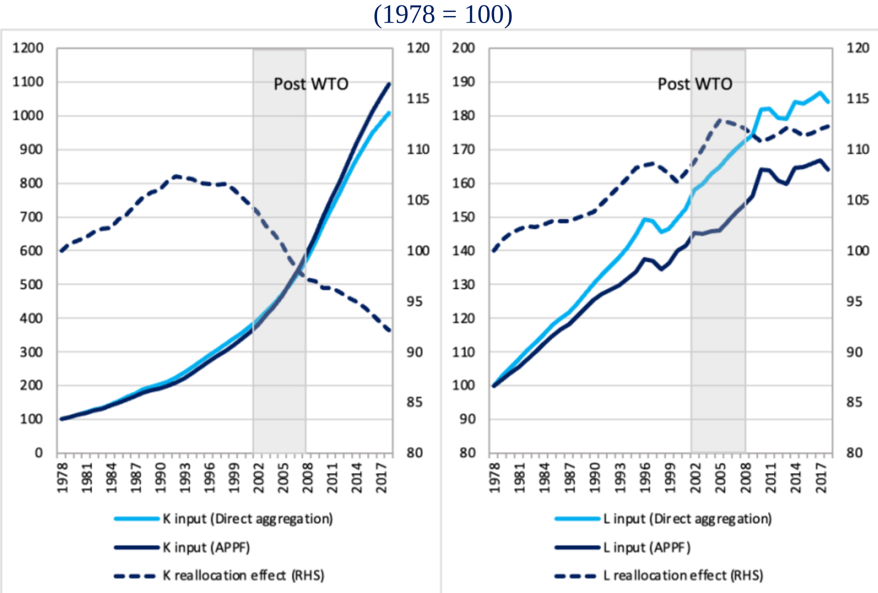
In terms of Domar-weighted TFP growth, the period of post-WTO was appraised with a very impressive 2.95 percent annual growth. The non-ICT-intensive-using manufacturing group was the key TFP contributor during this period, which could be due to the rise in labor-intensive manufacturing after China's WTO entry and the low labor cost. This is followed by ICT-intensive-using services and manufacturing. However, the post-GFC period (2007–2012) saw a considerable TFP decline of 0.3 percent per annum, the worst throughout the entire period in question. However, all three ICT-related groups, together with the non-ICT manufacturing group (0.63), still registered a positive TFP growth of 1.86 percent per annum (Table 3). See our above discussion of the TFP index for the TFP performance during the second half of the GFC decade in which the Domar-weighted TFP growth turned positive.

The Effect of Factor Reallocation

The slower Domar-weighted TFP growth (1.00) compared to the aggregate TFP growth (1.08) implies that the net reallocation of capital and labor is positive. Following equation (21), in Table 3 we show that this effect consists of a positive labor reallocation effect (Ψ^L) of 0.29 ppts, yet a negative capital reallocation effect (Ψ^K) of -0.21 ppts. Figure 2 depicts the two reallocation effects as indices benchmarked at the initial point in 1978.

It should be noted that such a magnitude of reallocation effect is typically not observed in market economies. Based on their empirical work on the US economy from 1977 to 2000, Jorgenson, Ho, and Stiroh (2005a) showed that, first, the reallocation effect was generally negligible; second, if it was non-negligible for some subperiods, the capital and labor reallocation effects generally moved in opposite directions. Jorgenson, Gollop, and Fraumeni (1987) also reported the reallocation of capital, which was typically positive, and the reallocation of labor, which was typically negative for the US economy for the period 1948–1979. This is because capital grew more rapidly in industries with high capital service prices and, hence, high returns on capital, whereas labor grew relatively slowly in industries with high marginal compensation.

FIGURE 2
REALLOCATION EFFECTS OF CAPITAL AND LABOR INPUT
(1978 = 100)



Source: Based on the results reported in Table 3.

In the case of China, such a large magnitude and unexpected sign of capital and labor reallocation effects have two important implications. First, individual industries indeed face significantly different marginal factor productivity, suggesting that there are barriers to factor mobility that cause the misallocation of resources in the economy. The flip side of this finding is that corrections to distortions can potentially enhance productivity, which is good news in terms of much-talked-about and long-awaited structural reforms.

We found that the effect of labor reallocation is generally positive over time, which suggests that labor market was much less distorted than the capital market, benefitting from increasing labor mobility along with reforms. Notably, the post-WTO period experienced the most significant productivity gain attributable to labor reallocation (0.7 in 2001–2007), which could be driven by the rapid expansion of export-oriented, labor-intensive industries, in line with China's comparative advantage. In the wake of the GFC, the reallocation effect of labor turned negative immediately, which reflected the misallocation of labor caused by the shock of China's export market, but it turned positive again in the later post-GFC period in 2012–2018 mainly because of the rise of the market-based restructuring when the government interventions reduced.

However, the capital reallocation differs in this case. In the early 1980s, the positive reallocation effect of capital was caused by the partial removal of the distortions inherited from the central planning period and the emergence of township and village enterprises (TVEs) that helped China to gain from its comparative advantage. However, it turned negative since the early 1990s largely caused by the government's "freeing the small while maintaining the big" policy in the SOE reform, with its worst performance in the post-WTO period when China's export expansion substantially improved the government fiscal position. This may also reflect local governments' increasing engagement in GDP race by promoting local urbanization and a new round of extensive heavy industrialization that has been criticized as repetitious and redundant (J. Wu 2008). The capital misallocation continued since the GFC with the government's four trillion rescue package that apparently took a heavy toll on the productivity growth regardless of the implementation of the "supply-side reform" in 2015.

5. Concluding Remarks

In this study, following the Jorgensonian APPF growth accounting framework and his approach of "direct aggregation across industries" through the Domar weights, extended to handle ICT-specific industry groups, and using the pioneering industry-level ICT capital stock estimates in Liang, Wu, and Fukao (2022), further revised based on the new CIP 4.0 capital and labor accounts, we revisit the role of ICT in the post-reform Chinese economy from 1978 to 2018. The results in general not only confirm but also enhance our earlier findings that the Chinese ICT-producing and ICT-intensive-using manufacturing industries are the key drivers to China's productivity growth. Specifically, while sharing about 34 percent of China's 8.3 percent annual value-added growth, these industries contributed 132 percent to China's 1.1 percent annual aggregate TFP growth.

We therefore maintain our proposition in the Wu-Liang 2017 paper that the rapid development in ICT has enabled the Chinese economy to fully compensate for its heavy productivity losses in other industries, especially in mining, construction and some services, and the policy-induced misallocation of capital resources albeit very costly. The findings are alarming enough for the Chinese policy makers to seriously reconsider the China model of growth so that to give more room for the market to enhance the ICT dynamism through more competitions and freer mobility of resources.

We interpret the new findings with two caveats. Firstly, the rising role of ICT in today's world could never be comprehensively assessed without considering the investment in software, but it is missing in our data. For example, we cannot be sure that if the observed significant decline in the input of ICT equipment since 2012 is true without a proper measure of the investment in software. Secondly, missing price changes of imported materials may have to some extent affected our results. Solving this problem is not only to make the price matrix more realistic and reflect the true intermediate costs facing Chinese producers, but more importantly to improve our measure of the real value-added growth for industries that heavily rely on imported parts and materials, among which ICT-related industries should be unquestionably on the top of the list.

APPENDIX

TABLE A1
CIP/CHINA KLEMS INDUSTRIAL CLASSIFICATION AND ICT-SPECIFIC GROUPING

CIP	EU-KLEMS	Grouping	Industry	
01	AtB	Agriculture	Agriculture, Forestry, Animal Husbandry and Fishery	AGR
02	10	Mining	Coal mining	CLM
03	11	Mining	Oil and gas extraction	PTM
04	13	Mining	Metal mining	MEM
05	14	Mining	Non-metallic minerals mining	NMM
06	15	Non-ICT-M	Food and kindred products	F&B
07	16	Non-ICT-M	Tobacco products	TBC
08	17	ICT-M	Textile mill products	TEX
09	18	Non-ICT-M	Apparel and other textile products	WEA
10	19	Non-ICT-M	Leather and leather products	LEA
11	20	Non-ICT-M	Saw mill products, furniture, fixtures	W&F
12	21t22	ICT-M	Paper products, printing & publishing	P&P
13	23	Non-ICT-M	Petroleum and coal products	PET
14	24	Non-ICT-M	Chemicals and allied products	CHE
15	25	Non-ICT-M	Rubber and plastics products	R&P
16	26	Non-ICT-M	Stone, clay, and glass products	BUI
17	27t28	ICT-M	Primary & fabricated metal industries	MET
18	27t28	Non-ICT-M	Metal products (excl. rolling products)	MEP
19	29	ICT-M	Industrial machinery and equipment	MCH
20	31	ICT-M	Electric equipment	ELE
21	32	ICT-P	Electronic and telecommunication equipment	ICT
22	30t33	ICT-P	Instruments and office equipment	INS
23	34t35	ICT-M	Motor vehicles & other transportation equipment	TRS
24	36t37	ICT-M	Miscellaneous manufacturing industries	OTH
25	E	Non-ICT-M	Power, steam, gas and tap water supply	UTL
26	F	Construction	Construction	CON
27	G	ICT-S	Wholesale and Retail Trades	SAL
28	H	Non-ICT-S	Hotels and Restaurants	HOT
29	I	ICT-S	Transport and Storage	T&S
30	64	ICT-P	Information Services	P&T
31	J	ICT-S	Financial Intermediation	FIN
32	K	Non-ICT-S	Real Estate Activities	REA
33	71t74	ICT-S	Leasing, Technical, Science & Business Services	BUS
34	L	Non-market	Public Administration and Defense	ADM
35	M	Non-market	Education	EDU
36	N	Non-market	Health and Social Security	HEA
37	O&P	Non-ICT-S	Other Services	SER

Source: See Wu and Ito (2015) for CIP classification.
Notes: ICT-P: producing; ICT-M: using in manufacturing; ICT-S: using in services; non-ICT-M: manufacturing; non-ICT-S: services; non-market: services.

TABLE A2

INDUSTRY CONTRIBUTIONS TO VALUE-ADDED AND TOTAL FACTOR PRODUCTIVITY GROWTH 1978–2018

	Value-Added			Total Factor Productivity		
	VA weight	VA growth	Contribution to aggregate VA growth	Domar weight	TFP growth	Contribution to aggregate TFP growth
AGR	0.184	3.76	0.77	0.294	1.50	0.28
CLM	0.016	3.82	0.06	0.030	0.06	-0.01
PTM	0.017	-8.52	-0.17	0.025	-12.91	-0.35
MEM	0.006	6.12	0.03	0.014	0.04	0.00
NMM	0.006	7.95	0.05	0.013	1.65	0.02
F&B	0.028	15.61	0.45	0.131	1.66	0.22
TBC	0.012	6.58	0.06	0.018	-4.84	-0.13
TEX	0.025	10.19	0.29	0.104	1.09	0.11
WEA	0.009	13.10	0.11	0.034	1.37	0.04
LEA	0.004	13.37	0.05	0.018	1.12	0.02
W&F	0.007	14.11	0.10	0.025	2.18	0.06
P&P	0.010	14.58	0.14	0.035	2.08	0.07
PET	0.012	3.88	0.01	0.048	-3.00	-0.11
CHE	0.035	16.38	0.56	0.130	2.27	0.27
R&P	0.012	18.42	0.23	0.048	2.59	0.12
BUI	0.024	10.49	0.25	0.073	1.36	0.13
MET	0.034	6.25	0.16	0.137	-0.71	-0.09
MEP	0.012	21.48	0.23	0.048	3.80	0.14
MCH	0.033	17.42	0.58	0.115	4.33	0.42
ELE	0.014	25.07	0.31	0.062	4.57	0.18
ICT	0.015	39.29	0.50	0.075	7.69	0.32
INS	0.003	16.71	0.05	0.011	3.77	0.03
TRS	0.019	18.73	0.34	0.076	2.93	0.19
OTH	0.013	18.59	0.23	0.035	4.03	0.16
UTL	0.025	9.16	0.24	0.063	-0.74	-0.04
CON	0.056	6.99	0.36	0.214	-0.31	-0.08
SAL	0.079	10.89	0.77	0.139	0.90	0.08
HOT	0.017	6.55	0.12	0.046	-1.14	-0.05
T&S	0.048	7.77	0.38	0.095	-0.88	-0.07
P&T	0.016	15.18	0.22	0.029	0.31	0.03
FIN	0.045	11.03	0.44	0.070	-0.66	-0.06
REA	0.035	11.49	0.30	0.047	1.21	-0.06
BUS	0.025	8.90	0.24	0.060	-1.86	-0.11
ADM	0.033	3.06	0.05	0.061	-1.32	-0.12
EDU	0.026	-6.18	-0.16	0.043	-7.18	-0.30
HEA	0.013	-9.84	-0.15	0.034	-6.37	-0.24
SER	0.032	3.16	0.08	0.064	-1.21	-0.09
Sum	***1.000***		***8.31***	***2.563***		***1.00***

Source: See Tables 1 and 3.

Notes: See Table A1 for industry abbreviation. Value added and TFP growth rates are annualized raw growth rates in percent. Industry contribution to VA and TFP growth is weighted growth rate in percentage points. See equation (22) for Domar aggregation.

REFERENCES

Domar, Evsey. 1961. "On the Measurement of Technological Change," *Economic Journal* 71.

Griliches, Zvi. 1992. Introduction in Griliches (ed.) *Output Measurement in the Service Sectors*, University of Chicago Press.

Hall, Robert E. and Dale W. Jorgenson. 1963. "Tax Policy and Investment Behavior," *American Economic Review* 57 (3): 391–414.

Hsieh, C. and Klenow, P.J. 2009. "Misallocations and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, Vol. CXXIV, No.4: 1403–1448.

Hulten, Charles. 1978. "Growth Accounting with Intermediate Inputs," *Review of Economic Studies* 45.

Jorgenson, Dale W. 1963. "Capital Theory and Investment Behavior," *American Economic Review* 53 (2): 247–259.

Jorgenson, Dale W. 1966. "The Embodiment Hypothesis," *Journal of Political Economy* 74 (1): 1-17.

Jorgenson, Dale W. 2001. "Information Technology and the U.S. Economy," *The American Economic Review,* Vol. 91 (1), pp. 1–32.

Jorgenson, Dale W. and Griliches, Z., 1967. "The Explanation of Productivity Change," *Review of Economic Studies*, vol. 34 (3), pp. 249–83.

Jorgenson, Dale W., Frank Gollop and Barbara Fraumeni. 1987. *Productivity and U.S. Economic Growth,* Harvard University Press, Cambridge, MA.

Jorgenson, Dale W., Mun S. Ho and Kevin J. Stiroh. 2005a. *Information Technology and the American Growth Resurgence, Productivity Volume 3*. Cambridge, MA: MIT Press.

Jorgenson, Dale W., Mun S. Ho and Kevin J. Stiroh. 2005b. "Growth of the US Industries and Investments in Information Technology and Higher Education." In Carol Corrado, John Haltiwanger and Daniel Sichel (eds.), *Measuring Capital in a New Economy*. University of Chicago Press.

Jorgenson, Dale W. and Kevin J. Stiroh. 2000. "Raising the Speed Limit: US Economic Growth in the Information Age," *Brookings Papers on Economic Activity* 1: 125–211.

Liang, David T., Harry X. Wu, and Kyoji Fukao. 2022. "Estimation of China's Investment in ICT Assets and Accumulated ICT Capital Stock," *IDE Discussion Paper* No. 833.

O'Mahony, Mary and Marcel P. Timmer. 2009. "Output, Input and Productivity Measures at the Industry Level: The EU KLEMS Database," *The Economic Journal*, 119 (June), F374–F403.

van Ark, Bart. 1996. "Sectoral Growth Accounting and Structural Change in Postwar Europe," pp. 84-164 in B. van Ark & N. Crafts, *Quantitative Aspects of post-war European Economic Growth,* Cambridge University Press.

Wu, Harry X. 2013. "How Fast Has Chinese Industry Grown? – The Upward Bias Hypothesis Revisited," *China Economic Journal*, Vol. 6 (2-3): 80-102.

Wu, Harry X. 2014. "The Growth of 'Non-Material Services' in China – Maddison's 'Zero-Labor-Productivity-Growth' Hypothesis Revisited," *The Economic Review*, Institute of Economic Research, Hitotsubashi University, Vol. 65 (3).

Wu, Harry X. 2015. "Constructing China's Net Capital Stock and Measuring Capital Service in China," *RIETI Discussion Papers*, 15-E-006.

Wu, Harry X. 2016. "On China's Strategic Move for a New Stage of Development – a Productivity Perspective," in Jorgenson, D.W., Fukao, K., and Timmer, M.P. (eds.) *The World Economy: Growth or Stagnation?* Cambridge: Cambridge University Press, pp. 153–198.

Wu, Harry X. and Keiko Ito. 2015. "Reconstruction of China's National Output and Income Accounts and Supply-Use and Input-Output Accounts in Time Series," *RIETI Discussion Papers*, 15-E-004.

Wu, Harry X. and Zhan Li. 2021. "Reassessing China's GDP Growth Performance: An Exploration of the Underestimated Price Effect," *RIETI Discussion Papers*, 21-E-018.

Wu, Harry X., Zhan Li, David T. Liang, and George G. Zhang. 2023. "The Industry Origin of China's Growth and Productivity Performance in 1992–2017: An Introduction to the China Industrial Productivity (CIP) Database 4.0," *RIETI Discussion Papers*, forthcoming.

Wu, Harry X. and David T. Liang. 2017. "Accounting for the Role of Information and Communication Technology in China's Productivity Growth," *RIETI Discussion Papers*, 17-E-111.

Wu, Harry X. and David T. Liang. 2023. "Measuring Capital Input in the Post-Reform Chinese Economy 1978–2018," NSD, *Peking University mimeo*, forthcoming.

Wu, Harry X. and Changhua Yu. 2022. "The Impact of the Digital Economy on China's Economic Growth and Productivity Performance." *China Economic Journal*, 15(2), pp.153-170.

Wu, Harry X., Ximing Yue and George G. Zhang. 2015. Constructing Employment and Compensation Matrices and Measuring Labor Input in China, *RIETI Discussion Papers*, 15-E-005.

Wu, Harry X. and George G. Zhang. 2023. "Measuring Labor Input in the Post-Reform Chinese Economy 1978–2018," NSD, *Peking University mimeo*, forthcoming.

Wu, Jinglian. 2008. *The Choice of China's Growth Model* [Zhongguo zengzhang moshi jueze). Shanghai: Yuandong Book Press.