Telecommunications Policy 40 (2016) 102–115

Contents lists available at ScienceDirect

Telecommunications Policy

URL: www.elsevier.com/locate/telpol

The effects of ICT* on output per worker: A study of the Chinese economy

Ronald Ravinesh Kumar [a,b,*], Peter Josef Stauvermann [c], Aristeidis Samitas [d]

[a] FBE Green House, School of Accounting & Finance, Faculty of Business & Economics, Laucala Campus, The University of the South Pacific, Suva, Fiji
[b] School of Business, University of Bolton, Deane Road, Bolton BL3 5AB, UK
[c] School of Global Business & Economics, Changwon National University, Gyeongnam, 9, Sarim Dong, 641-773 Changwon, Republic of Korea
[d] Department of Business Administration, Business School, University of the Aegean, 8 Michalon street, Chios Island, Greece

ARTICLE INFO

Available online 7 July 2015

Keywords:
ICT* development
Fixed broadband
Mobile cellular
Internet
Telecommunication
Hi-tech exports
Economic growth
ARDL cointegration
Causality
China

ABSTRACT

In this paper, we explore the short-run and long-run contribution of five indicators of information and communication technology (ICT*) on economic growth of China over the sample period 1980–2013. We use the augmented Solow (1956) framework, the ARDL bounds (Pesaran, Shin, & Smith, 2001) approach to cointegration and the Toda and Yamamoto (1995) granger non-causality tests to examine the possible linkages. The results show evidence of long-run association among level variables for all the indicators of ICT*. From the results, we also note that all the indicators of ICT* have a positive and statistically significant elasticity coefficient ranging from 0.010 to 0.080. From the Granger causality results, we note bidirectional causality between mobile cellular, telecommunication and economic growth; and between mobile cellular, telecommunication and capital per worker, respectively. Other results indicate that fixed broadband cause capital accumulation; capital accumulation causes internet technology. We also note bidirectional causality between mobile cellular and telecommunication, and between fixed broadband and internet, respectively; and a unidirectional causality from internet and fixed broadband to hi-tech exports; and from mobile cellular and telecommunication to fixed broadband, respectively. From the overall results, within caveats, we highlight that while all the indicators of ICT* are imperative for long-run growth, besides capital per worker, the dominant technology drivers are mobile cellular and telecommunications technology.

1. Introduction

Since 1976, China has experienced an enormous increase of its gross domestic product (GDP) and an unprecedented growth in information and communications technology (ICT)*.[1] The average per capita income (constant 2005 prices)

* Corresponding author. Tel.: +679 3232638.
E-mail addresses: kumar_RN@usp.ac.fj, rrk1mpo@bolton.ac.uk, ronaldkmr15@gmail.com (R.R. Kumar), pstauvermann@t-online.de, pjsta@changwon.ac.kr (P.J. Stauvermann), a.samitas@ba.aegean.gr (A. Samitas).

[1] We associate an * to the information and communication technology (ICT) to indicate that ICT* is not only a broad term and comprises of a number of measures (Zhang & Liang, 2012), but a complex term to measure and can be “unpacked” by a number of proxies. In our case, ICT* is measured by the Internet users, mobile subscriptions, fixed broadband subscriptions, telecommunication lines and hi-tech exports.

http://dx.doi.org/10.1016/j.telpol.2015.06.004
0308-5961/

increased from US$175.36 (1970–1980) to US$3583.38 in 2013. In the same period, there was a marked increase in the ICT technologies. The first mobile phone was available in 1987 and in 1994 the internet age started in China (Loo, 2004). Until the middle of the 1990s the development of the telecommunication industry was led by the initiatives of the Ministry of Posts and Telecommunications. From this period onwards, China began to liberalize its telecommunication market slowly in line with reforms done to other sectors to effectively shift to market-oriented economy. The pace of the telecommunication market liberation increased as China sought to enter the World Trade Organization (WTO) and allowed domestic private companies to enter the telephone and internet services sector. However, it has remained from the past that only Chinese companies are allowed to participate in the market for telecommunication infrastructure internet service providers, and the market is protected by the state (Xia, 2010).

As part of the reform after accession to WTO, in 1998, the former Ministry of Posts and Telecommunications separated the postal operation from telecom operations, and telecom enterprises from government services resulting in the birth of real entities like China Telecom, China Netcom, China Mobile, China Unicom, China Railcom and China Satellite Communications with more than 4400 companies offering telecom value-added services and non-basic telecom services (Chen, Gao, & Tan, 2005). Furthermore, the drastic 2008 industry consolidation and government reform resulted in the reduction of the number of major industry players from six to three – that is, China Mobile, China Unicom, and China Telecom, and the merger of the former industry regulator, the Ministry of Information Industry, into Ministry of Industry and Information Technology (Xia, 2011).

Moreover, the inception of China's economic reforms over the last 30 years has shown promising results and the dynamism in the ICT* sector is notable (Meng & Li, 2002). Notably, China has become a computer production base for the rest of the world. The Chinese brand Lenovo which bought IBM's PC business in 2005 is the world biggest producer and supplier of personal computers (PC's). One of the biggest advantages of Chinese companies is the huge domestic market in which they can test the ICT products before offering them to the rest of the world. Moreover, the reforms initiated competition, attracted investment and technical innovation, reduced operational costs and improved the service quality in the telecom sector with a notable influence on the mobile communications (Chen et al., 2005). Further, the Open Policy since 1978 has resulted in a more than tenfold increase in fixed-line teledensity and the growth and popularity in mobile telecommunications and also superseded the fixed-line telephones. Similarly, the launch of the "Village Access Project" (VAP) in 2004 targeted the provision of basic telephone services and in the state's effort to "informatize" the rural areas (Loo & Ngan, 2012; Xia, 2007, 2010; Xia & Lu, 2008).

Similar developments are also noted in the entire consumer electronics world market because of the relatively low wages in China. Aggregating only the production quantity of consumer electronics and other electronic devices needed for telecommunication, China is the main production base of the world, because also the non-Chinese companies like Samsung, LG, Dell, Apple, Hewlett Packard among others manufacture all or a large proportion of their products in China. Besides the effects caused by the exports of ICT equipment, we also should expect in China that an increasing income leads to a rising domestic demand for ICT equipment like PCs, mobile phones, telecommunication services and so on, which in turn leads to more investments in the ICT equipment producing industry and therefore to a higher income.

In this paper we investigate the role of ICT* on the economic growth of China. We interpret investments in ICT as investments in a 'general purpose technology' or 'generic technology' in the sense of Breshnan and Trajtenberg (1995). Investments in this kind of technologies have mostly a much stronger impact on the economic performance of a country than traditional investments in capital, because very often general purpose technologies induce complementary innovations. Therefore, it can be expected that investments in generic technologies create positive externalities to some extent. At the microeconomic level, investments in ICT enable firms to increase its productivity and henceforth its production efficiency. If all firms in an industry adopt ICT technologies, the prices of the goods and services produced in this industry decline and the quantities produced increase (Oz, 2005). However, the effect of ICT on productivity of a firm can differ depending on how information intensive the firm is. Communication technologies imply in addition network externalities; the more firms and consumers are connected to a network, the higher will be the rate of return of investments in these communication technologies. However, if the generic technologies are sufficiently widespread the network externalities will probably vanish.

As a result, investments in ICT lead at the macroeconomic level to a rise of the total factor productivity, where the scale of the increase depends on the availability of skilled labor and experience. With respect to the question how to operationalize the effects of ICT investments, it seems to be reasonable to use indicators instead of taking the value of ICT investments into account. The reason is given by Yorukoglu (1998) who argued that ICT's pace of technological improvement is much higher than other capital goods and as a consequence, ICT capital and non-ICT capital are of poor compatibility. Additionally, by using other indicators for ICT investments than the value of ICT capital, the Solow-paradox[2] can be circumvented.

Subsequently, the main contributions of this paper are in terms of (a) methodology, where we show the application of augmented Solow (1956) framework to examine the ICT* impact; (b) examination of the short-run and long-run elasticity coefficients (magnitudes) of various indicators of ICT* and causality nexus using widely accepted tools in econometrics (ARDL bounds approach to cointegration) (Pesaran et al., 2001; Pesaran & Pesaran, 2009) and Toda and Yamamoto (1995) Granger non-causality tests. From the literature, there are no prior studies done on the Chinese economy that have looked at these aspects in particular. We intend to modestly contribute to the literature in this regard and highlight the momentous

[2] Solow (1987) remarked, "You can see the computer age everywhere, but in the productivity statistics."

impact of different technology indicators in the development process of China. The balance of the paper is organized as follows. In Section 2, we provide a short overview of the related literature. Section 3 is on materials and methods used. In Section 4, we present the results with discussion. Finally, in Section 5, we conclude with some policy deliberations.

2. Literature review

The discussion of the role of technology in propelling productivity and economic growth resonates at least as early as the neoclassical growth theory (Solow, 1956). Over the years, the apparent influence of ICT in driving economic activity and transforming knowledge-based economies has become relatively pronounced (Katz, 2009; Minghetti & Buhalis, 2010; Romer, 1990). However, in the early studies, the role of technology or technological progress was not precisely defined. The basic assumptions of the conventional models include constant returns to scale, diminishing marginal productivity of capital, exogenously determined technical progress, and substitutability between capital and labor thus emphasizing the role of savings or investment ratio as crucial driver of short-run economic growth. Technological progress is considered a long-run phenomenon and exogenously determined. However, in endogenous growth models (Lucas, 1988; Romer, 1986), the exogenously given technological progress is substituted by external factors such as increasing returns to scale resulting from knowledge spillovers (Grossman & Helpman, 1991; Romer, 1990), innovation (Aghion & Howitt, 1992), public infrastructure (Barro, 1990), among other things (Kumar, Stauvermann, Patel, & Kumar, 2014; Kumar, Kumar, & Patel, 2015; Rao, 2010), and are endogenously caused by efforts of economic agents. Notably, the effect of technology is magnified when the latter includes technology that supports communication, enhances productivity and improves the wellbeing of the society (Cronin, Colleran, Herbet, & Lewitzky, 1993; Datta & Agarwal, 2004; Lam & Shiu, 2010; Shahiduzzaman & Alam, 2014).

A number of studies have focused on the technology-led growth (Tech-LG) hypothesis using cross-country regression techniques. Hardy (1980) considers 60 countries over the 1968–1976 periods and finds strong evidence that telephones contribute to the economic development. Madden and Savage (1998) examine a sample of 27 Central and Eastern European (CEE) countries over the period 1990–1995 and find a positive relationship between investment in telecommunication infrastructure and economic growth. Roller and Waverman (2001) consider 21 Organisation for Economic Co-operation and Development (OECD) countries over a 20-year period (1970–1990) and find a positive causal relationship between investment in telecommunication infrastructure and subsequent economic performance. Lee, Gholami, and Tong (2005) use Solow's Residual framework and Johansen's cointegration (Johansen & Juselius, 1990) and the VEC Granger causality tests to examine a total of 20 countries composed of developed, developing and newly industrialized economies (NIEs) and find evidence that ICT contributes to economic growth in many developed countries and newly industrialized economies (NIEs), however not in developing countries. Thompson and Garbacz (2007) look at a panel of 93 countries for the period 1995–2003 and find that penetration rates of telecommunication services improve the productive efficiency of the world as a whole and particularly in some subsets of low income countries. Seo et al. (2009) analyze a panel of 29 countries in the 1990s and conclude that ICT investment has a positive effect on GDP growth.

Moreover, Koutroumpis (2009) uses the model introduced by Roller and Waverman (2001) for 22 OECD countries over the period 2002–2007 and find broadband penetration (a proxy for ICT) has a positive causal link with economic growth in the presence of critical mass and infrastructure. Tseng (2009) examines the developments in ICT among six Asian countries, namely South Korea, Taiwan, Singapore, Hong Kong, China and India, and finds, *inter alia*, an enormous contribution from the use of ICT in economic growth; that innovation configurations of ICT differ significantly among these countries due to the relative innovation strengths within the sub-fields of ICT; and a high degree of inter-relationships among the six countries in ICT.

In addition, Gruber and Koutroumpis (2010) use the data from 192 countries for the period 1990–2007 and find a significant effect of mobile telecommunications diffusion on GDP and productivity growth. Vu (2011) investigates the effect of ICT on growth for a sample of 102 countries for the period 1996–2005 and finds *inter alia*: (1) a substantial improvement of growth in the sample period relative to previous years; (2) a statistically significant relationship between growth and ICT; and (3) that penetration of personal computers, mobile phones, and internet users have a significant causal effect on growth. Castellacci and Natera (2013) use a panel of 98 countries over the period 1980–2008 and present the idea that the dynamics of national innovation system is driven by the innovative capability which includes technological output, scientific output, and innovative output; and the absorptive capacity, which includes income per capita, infrastructures and international trade.

On the other hand, some studies find inconclusive outcomes. Dewan and Kraemer (2000) examine 36 countries over the 1985–1993 periods and find returns from capital investments in ICT is positive and significant for developed countries but not statistically significant for the developing countries. Pohjola (2002) considers a sample of 43 countries from 1985 to 1999 and finds no statistically significant correlation between ICT investment and economic growth.[3] At a country level, studies that support Tech-LG hypothesis include Jorgenson and Stiroh (2000), Jorgenson (2001), and Oliner and Sichel (2000) for the United States of America (US); Oulton (2002) for the United Kingdom (UK); Jalava and Pohjola (2002, 2008) for Finland; Daveri (2002) for European Union (EU) economies; Jorgenson and Motohashi (2005) for Japan; Jorgenson

[3] However, we argue that prior to 1993 many (developing) countries had poor accessibility and availability of communications technology and technology-based products. In light of this, post 1993 is a period of information age that has experienced a significant insurgence in technology as many countries slowly emulated the advanced production processes and adopted the superior communications technologies from the advanced and neighboring developed countries.

(2003) for the G-7 economies; Jorgenson and Vu (2007) for 110 countries; Kuppusamy, Raman, and Lee (2009) for Malaysia; Venturini (2009) for the US and 15 EU countries.

The Tech-LG hypothesis is also examined at firm-industry level. At a firm level, Lehr and Lichtenberg (1999) examine firms in service industries in Canada and find personal computers made a positive contribution to productivity growth. Stiroh (2002) investigates 57 major US industries and detects a strong link between ICT and productivity. Hu and Quan (2005) investigate the data of 8 US industries over a period of 30 years and confirm the Tech-LG hypothesis. Similarly, Brynjolfsson and Hitt (2003) find that firms that invested in computer technology were able to realize greater productivity (output per unit of input). O'Mahony and Vecchi (2005) use pooled data at the industry level for the US and the UK and find a positive effect of ICT on output growth and excess returns relative to the non-ICT assets. Atzeni and Carboni (2006) find a strong impact of ICT investments on productivity growth in Italian manufacturing firms. Fabiani, Schivardi, and Trento (2005) examined the data for 1500 Italian manufacturing firms that ICT investments have a stronger effect on productivity in information-intensive industries than in low-technology industries. Vu (2013) considers the role of ICT in determining the economic growth of Singapore over the periods 1990–2008, and finds a strong positive association between the intensity of ICT use and value-added and labor productivity growth at the sector level; ICT contributes about 1 percentage point to Singapore's GDP; and a notable contribution of the ICT manufacturing sector to Singapore's growth. Kumar et al. (2015) examined the impact of telecommunication on the economic growth of Small Pacific Island States (SPIS) over the period 1979–2012 and find that telecommunication contribute 0.33% in the long-run and a unidirectional causality running from telecommunication to output per worker.

3. Materials and method

3.1. Framework

We convene this section with the conventional Cobb–Douglas type production function expressed in the Solow (1956) framework (Kumar et al., 2014, 2015; Rao, 2007, 2010). The output per worker (y_t) equation is defined as

$$y_t = A_t k_t^{\alpha} \quad \alpha > 0 \tag{1}$$

where A_t is stock of technology and $k_t$is capital per worker at time t, and α is capital share. The Solow model assumes that the evolution of technology is given by

$$\Phi_t = A_0 e^{gt} \tag{2}$$

where g, and A_0 is the initial stock of knowledge at time t, g is the growth rate of technological progress, and Φ_t defines the aggregate technology, A_t. The effect of ICT* on total factor productivity (TFP) can be captured when ICT* is entered as a shift variable into the production function. One advantage of using augmented Solow framework is that it models the productivity determinants that may be consistent with an economy's (China's) growth experience (Zheng, Kjetil, & Fabrizio, 2011). Subsequently,

$$\psi_t = f(ICT_t^*) = ICT_t^{*\beta}, \tag{3}$$

Hence, ψ_t becomes an explicit part of the technology component in (1), and A_t is redefined as follows:

$$A_t = \Phi_t \, \psi_t = A_0 e^{gt} ICT_t^{*\beta} \tag{4}$$

In this case, e^{gt} includes the *catch-all* factors. Subsequently,

$$y_t = A_0 e^{gt} k_t^{\alpha} ICT_t^{*\beta} \tag{5}$$

Taking the natural log of (5) yields the desired general equation for estimation as

$$\ln y_t = \pi + \alpha \ln k_t + \beta_i \ln ICT_t^* + \gamma_i X\_T_{b \geq pi} + \varepsilon_t \tag{6}$$

where π is the constant term, α is the capital share, β_i is the elasticity coefficient of the individual indicator used to measure ICT* development, γ_i is the coefficient of the respective ith structural break dummy ,$X\_T_{b \geq p}$, where p is the single break period and X_T_b corresponds to the specific ICT* indicator for which the break period is examined in the sample; and ε is the error term.

3.2. Data

The data extracted are from *World Development Indicators and Global Development Finance* database (World Bank, 2014). The data for output is measured by the GDP at constant 2005 US dollars (1977–2013). The data for the capital stock is computed using the perpetual inventory method, $K_t = I_t + (1-\delta)K_{t-1}$, where I_t is proxied by the gross fixed capital formation (1978–2013), the initial capital, K_0 is set as 1.2 times the real GDP of 1977, and the parameter for depreciation is set as 0.15 which is arbitrarily selected. However, we examined other rates of depreciation and note that the rate of 0.15 provides a relatively more reliable outcome. The labor stock is computed by the average employment to population ratio (from the ILO estimate) times the annual population data which is available from 1960 to 2013. The indicators for ICT* are internet subscriptions per worker (%) (*INT*), fixed broadband connections per of worker (%) (*FBB*), mobile cellular subscriptions per worker (%) (*MBC*), high technology exports (% of manufactured exports) (*TCH*) and telephone lines per worker (%) (*TEL*). With the exception to the data on telecommunication lines (which is available from 1975 to 2013), all other

Table 1
Descriptive statistics and correlation matrix (1977–2013).
Source: Authors' calculation using Eviews 8.0.

Statistics	*y*	*k*	*INT*	*FBB*	*MBS*	*TCH*	*TEL*
Mean	1560.933	3107.386	10.16090	2.886885	22.91399	13.99635	12.81426
Median	1055.352	1733.589	0.006882	8.11E−05	0.418331	10.43181	4.692324
Maximum	4976.911	12071.34	63.61111	19.32941	125.7644	30.84360	38.96309
Minimum	247.7104	297.2525	1.18E−08	3.86E−10	4.09E−07	2.240377	0.269842
Std. Dev.	1376.910	3243.390	18.60350	5.575358	36.84787	10.60163	14.45104
Skewness	1.095776	1.327610	1.808852	1.866365	1.516391	0.349719	0.632525
Kurtosis	3.041346	3.739607	4.866287	5.164498	4.044048	1.440919	1.719846
Jarque-Bera	7.407107	11.71237	25.54666	28.70325	15.86037	4.501586	4.993682
Probability	0.024636	0.002862	0.000003	0.000001	0.000360	0.105316	0.082345
y	1.000000	–	–	–	–	–	–
k	0.996275	1.000000	–	–	–	–	–
INT	0.945508	0.964652	1.000000	–	–	–	–
FBB	0.934676	0.956327	0.995475	1.000000	–	–	–
MBS	0.973805	0.985759	0.986657	0.982227	1.000000	–	–
TCH	0.876745	0.845443	0.691000	0.666721	0.784089	1.000000	–
TEL	0.865644	0.833411	0.700804	0.681879	0.799109	0.975778	1.000000

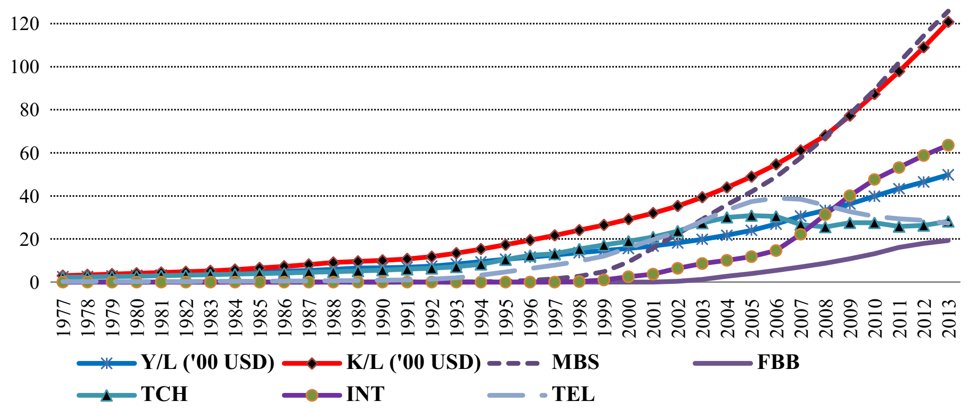

Fig. 1. Trend in ICT* (% of workers) and Y/L & K/L (in '00 USD).

indicators have shorter period of data points. Notably, the data for the internet subscriptions is available from 1993 to 2013; mobile cellular subscriptions are available from 1987 to 2013; fixed broadband connection is available from 2000 to 2013; and high-technology exports (% of manufactured exports) (*TCH*) from 1991 to 2013. Therefore, to overcome the problem of small data, we examined the trend of each indicator and used the exponential growth-rate formula to backward approximate the data for earlier periods. In other words, $X_{t-1} = \exp((\ln X_t) + \bar{g})$, where X_{t-1} refers to previous period data which is based on the current period data, X_t and the average growth rate, $\bar{g}$, of the actual data points in the series. As expected, the data points for all approximated periods are very close to zero which is due to the fact that the developments in information and communication technologies, particularly, the internet, mobile technologies, hi-tech equipments, and fixed broadband gained significance at least from the late 1980s. All data used in the analysis are transformed into log form before using them in the estimation. The descriptive statistics and correlation matrix of all variables in its original form over the sample periods 1977–2013 is provided in Table 1. As noted, the capital per worker (*k*) and the ICT* indicators (internet, fixed broadband, mobile cellular, hi-tech exports and telecommunication) are highly correlated with output per worker (*y*), and notably, *MBC* (mobile cellular subscriptions) has the largest correlation after capital per worker in comparison with other ICT* indicators. Moreover, we also note that *MBC* has the largest growth among all ICT* indicators with growth in output and capital per worker (expressed in hundreds of USD).[4]

[4] Noting the advice of an anonymous reviewer, we present the descriptive statistics in its original form and not in log-transformation, and also complement Table one with Fig. 1 where we present a trend in the ICT*, output and capital in per worker terms to capture the growth in these variables.

3.3. Modeling strategy

3.3.1. ARDL approach

Using (6), we specify the ARDL specification as (7) for the underlying relationship. The equation has a dummy variable ($X\_T_{b \geq pi}$) which represents a specific structural break in the series. The single period break is identified by applying the Zivot and Andrews (1992) unit root test. Notably, including $X\_T_{b \geq pi}$ provides a relatively more robust computation of bound statistics, the short-run and the long-run coefficients, and under certain conditions, the causality relationships.

$$\Delta \ln y_t = \beta_{10} + \beta_{11} \ln y_{t-1} + \beta_{12} \ln k_{t-1} + \beta_{13} \ln ICT^*_{t-1} + \beta^i_{14} X\_T_{b \geq p_i}$$
$$+ \sum_{i=1}^{p} \alpha_{11i} \Delta \ln y_{t-i} + \sum_{i=0}^{p} \alpha_{12i} \Delta \ln k_{t-i} + \sum_{i=0}^{p} \alpha_{13i} \Delta \ln ICT^*_{t-i} + \varepsilon_{1t} \tag{7}$$

The ICT* is defined by five different measures as mentioned above. Subsequently, for each equation, ICT* is replaced by the respective indicators (ln *INT*, ln *FBB*, ln *MBS*, ln *TCH* and ln *TEL*) in Eq. (7), thus giving a total of five separate equations.[5] The autoregressive distributed lag (ARDL) approach is used to examine the cointegration because it is relatively simple and recommended for small sample size (Ghatak & Siddiki, 2001; Pesaran et al., 2001). The requirement is that all variables should be at most $I(1)$, that is at most stationary in first difference. Moreover, examining the unit root provides information on the maximum lags which can be used in testing for Granger non-causality (Toda & Yamamoto, 1995). In what follows, we use the traditional unit root tests: augmented Dickey–Fuller (ADF), Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS), and the relatively advanced Zivot and Andrews (1992) tests to examine the time series properties of the variables. The latter test is used to examine the structural break in series.

Next, we examine the presence of cointegration (level effect). In essence, there are two steps involved. First, Eq. (7) is estimated by OLS technique. Given that we have five proxies for ICT*, we specify five cointegration equations with respect to each indicator and examine the cointegration relationship separately for each specification. We examine the *F*-statistics (or *W*-statistics) with the null hypothesis of no cointegration ($H_0: \beta_{i1} = \beta_{i2} = \beta_{i3} = 0$) against the alternative hypothesis of existence of long-run cointegration ($H_1: \beta_{i1} \neq 0; \beta_{i2} \neq 0; \beta_{i3} \neq 0$). If the computed *F*- or *W*-statistics falls above the respective upper critical bound, then the null hypothesis of no cointegration is rejected at the respective levels of significance. Alternatively, if the *F*- or *W*-statistics falls below the lower bounds, then the null hypothesis is accepted with the given level of significance. In case when the *F*- or *W*-statistics falls within the upper and lower bounds, the outcome is inconclusive. To examine the cointegration based on the computed bounds *F*-statistics, the critical bounds from Narayan (2005), which is specifically designed for small sample sizes ($n \leq 80$) is recommended since the initial critical bounds of Pesaran et al. (2001) are suitable for sample size of more than 80. This is useful when one is using software such as Microfit 4.1 (Pesaran & Pesaran, 1999) or some others that does not provide the corresponding critical bound values to compare the computed bounds statistics. However, with the updated version of Microfit 5.01 software (Pesaran & Pesaran, 2009) (and EViews 9.0), we can obtain the bound *F*- and *W*-statistics, and also the corresponding critical *F*- and *W*-statistics bounds at 90% and 95% levels by stochastic simulations using 2000 replications with the given sample size. Accordingly, we use Microfit 5.01 software to compute the bounds and the corresponding critical *F*- and *W*-statistics.

3.3.2. The Toda–Yamamoto approach to Granger non-causality

Furthermore, we examine the direction of causality using the Toda and Yamamoto (1995) non-Granger causality tests. It is important to highlight that when the economic series are of different orders, then relying on the error-correction model (ECM) for Granger causality assessment is not recommended, and the standard (pair-wise) Granger causality test may not give robust results since taking the first difference of the series in the effort to achieve stationarity of variables also results in loss of information. In this regards, the Toda and Yamamoto (1995) procedure is extremely useful as it enables one to test for the presence of non-causality irrespective of whether the variables are $I(0)$, $I(1)$ or $I(2)$, not cointegrated or cointegrated of an arbitrary order. Moreover, using this procedure, one can also examine the ‘combined’ or the conjoint effects of the parameters (excluded variables) on the target variable. At best, the statistical significance of the combined causality (that is, all the excluded variables in the set) indicate that as a set, the excluded variables cause the target variable and in most part, the causality is dominated by the statistically significant variables in the set. The variables which are not statistically significant in this case hence have a ‘weak causation’ on the target variable with evidence of the presence of interaction effect among variables causing the target variable. In the case where the combined causation is not statistically significant within the conventional 1–10 percent level, then the conclusion can be that only the statistically significant individual variables cause the target variable with absence of any interaction effect. In order to carry out the Granger non-causality test, the model is expressed as a vector autoregressive (VAR) system, which is as follows:

$$\ln y_t = \alpha_0 + \sum_{i=1}^{k} \alpha_{1i} \ln y_{t-i} + \sum_{j=k+1}^{d\max} \alpha_{2j} \ln y_{t-j} + \sum_{i=1}^{k} \eta_{1i} \ln k_{t-i} + \sum_{j=k+1}^{d\max} \eta_{2j} \ln k_{t-j} + \sum_{i=1}^{k} \varphi_{1i} \ln ICT^*_{t-i} + \sum_{j=k+1}^{d\max} \varphi_{2j} \ln ICT^*_{t-j} + \lambda_{1t} \tag{8}$$

[5] We did not write all the cointegration equations specification represented by each proxy for ICT* to save space.

$$\ln k_t = \beta_0 + \sum_{i=1}^{k} \beta_{1i} \ln k_{t-i} + \sum_{j=k+1}^{d\max} \beta_{2j} \ln k_{t-j} + \sum_{i=1}^{k} \theta_{1i} \ln y_{t-i} + \sum_{j=k+1}^{d\max} \theta_{2j} \ln y_{t-j} + \sum_{i=1}^{k} \vartheta_{1i} \ln ICT^*_{t-i} + \sum_{j=k+1}^{d\max} \vartheta_{2j} \ln ICT^*_{t-j} + \lambda_{2t} \tag{9}$$

$$\ln ICT^*_t = \gamma_0 + \sum_{i=1}^{k} \gamma_{1i} \ln ICT^*_{t-i} + \sum_{j=k+1}^{d\max} \gamma_{2j} \ln ICT^*_{t-j} + \sum_{i=1}^{k} \phi_{1i} \ln y_{t-i} + \sum_{j=k+1}^{d\max} \phi_{2j} \ln y_{t-j} + \sum_{i=1}^{k} \mu_{1i} \ln k_{t-i} + \sum_{j=k+1}^{d\max} \mu_{2j} \ln k_{t-j} + \lambda_{3t} \tag{10}$$

where the series are defined in Eqs. (8)–(10). The null hypothesis of no-causality is rejected when the p-values fall within the desired 1–10 percent level of significance. Hence, in (8), Granger causality from $\ln k$ to $\ln y$ and $\ln ICT^*$ to $\ln y$ implies $\eta_{1i} \neq 0 \forall i$ and $\varphi_{1i} \neq 0 \forall i$, respectively. Similarly, in (9), $\ln y$ and $\ln ICT^*$ causes $\ln k$ if $\theta_{1i} \neq 0 \forall i$ and $\vartheta_{1i} \neq 0 \forall i$, respectively; and from (10) $\ln y$ and $\ln k$ causes $\ln ICT^*$ if $\phi_{1i} \neq 0 \forall i$ and $\mu_{1i} \neq 0 \forall i$, respectively.

The Toda and Yamamoto (1995) non-Granger causality test requires that the maximum lags to be used should not exceed the sum of the maximum order of integration (d) and the lag-length (l) selected for the ARDL estimation, that is $d + l \leq 3$. Moreover, in conducting the causality tests, it is important to examine the properties of inverse roots of the auto-regressive (AR) characteristics polynomial diagram to ensure dynamic stability of the ARDL model. In order to obtain a robust causality result, the inverse roots, I_R, should lie within the positive and the negative unity, that is, $|I_R| \leq 1$. Where the I_R lies outside the unit circle, this needs to be corrected by using either (1) appropriate lags greater than the ones selected for endogenous variables, (2) trend variable, and/or (3) the structural break period dummies as exogenous (instruments) variables in the VAR equation. To ensure the AR inverse roots are within the positive/negative unit boundary, we included the structural break dummy for hi-tech exports ($TCH\_T_{b \geq 2007}$).

4. Results and discussion

In this section, we present the results of various stages of analysis. These include the unit root test for stationarity, cointegration, short-run and long-run estimations, [6] and Granger causality. The results using the traditional method of unit root are provided in Table 4.[7]

4.1. Unit root tests

Based on the conventional unit root tests (ADF, PP, and KPSS), the overall conclusion is that the variables are $I(1)$ stationary, that is, at least stationary in first difference (Table 2). This is further confirmed by the structural break test (Table 3) which also provides the possible break periods in the series. From the unit root results, it is also confirmed that the maximum order of integration is 1.

4.2. Cointegration test

The bounds results are reported in Table 4. As noted, all the indicators of ICT* have a long-run cointegration (association) with output per worker at least at 5% and 10% level of statistical significance.

4.3. Diagnostic tests from ARDL lag estimation

Once the existence of long-run association is confirmed, we estimate the long-run and the short-run coefficients for ICT*. The initial step is to examine the diagnostic test statistics from the lag-estimates which precedes the long-run estimation and the short-run dynamics. For the diagnostic test statistics, we examine the Lagrange multiplier test of residual serial correlation (χ^2_{sc}); Ramsey's RESET test using the square of the fitted values for correct functional form (χ^2_{ff}); normality test based on a test of skewness and kurtosis of residuals (χ^2_{n}); and heteroscedasticity test based on the regression of squared residuals on squared fitted values (χ^2_{hc}). In case where the respective diagnostic tests are statistically significant, this implies presence of the respective biasness in the model. Overall, we note from Table 5 that the results are promising in the sense that we cannot accept the presence of biasness in the model, at least at 5% level of significance and hence our model is also dynamically stable.

[6] The short-run period is defined as time extending over a few years. In the short-run, demand determines output, and any changes in the exogenous variables will have immediate impact on endogenous variables. In the long-run, periods extend over a number of decades and change in exogenous variables impact, usually after some transitional periods, results in a new equilibrium growth path. Short-run effects are time dependent and long-run effects are time-invariant changes in equilibrium values.

[7] The structural break indicates the periods of reforms and shifts from the previously planned economy to a market economy.

Table 2
Unit root tests results.

Variables	ADF T_{stat}		Phillips and Perron Adj. T_{stat}		KPSS LM_{stat}	
	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.
ln *y*	1.7858 [6]	−3.1685 [3]^{B}	0.8346 [3]	−2.8969 [9]^{C}	0.7290 [5]	0.1436 [1]^{A}
ln*k*	1.9894 [4]	−3.9190 [1]^{A}	1.3862 [1]	−2.9288 [2]^{C}	0.7319 [5]	0.2573 [1]^{A}
ln *INT*	−1.4080 [1]	−2.1088 [0]	−1.2986 [4]	−2.1979 [6]	0.7081 [5]	0.2610 [4]^{A}
ln *FBB*	−1.0631 [1]	−2.76701 [1]^{C}	−0.8517 [3]	−2.4968 [2]	0.7141 [5]	0.1394 [3]^{A}
ln*MBC*	−5.2845 [13]^{A}	−6.8442 [15]^{A}	−1.9646 [4]	−1.5922 [4]	0.6981 [5]	0.4379 [4]^{B}
ln *TCH*	−1.1784 [1]	−2.6187 [0]^{C}	−1.2650 [4]	−2.7201 [1]^{C}	0.6978 [5]	0.2404 [4]^{A}
ln *TEL*	−1.6313 [2]	−1.5147 [1]	−0.8193 [5]	−1.1150 [2]	0.6805 [5]	0.1944 [5]^{A}

Notes: The ADF critical values are based on MacKinnon (1996). The optimal lag length chosen on the basis of Akaike Information Criterion (AIC) is reported in the square brackets [ ]. The null hypotheses for ADF and Phillips–Perron tests are that a series has a unit root (non-stationary) and for KPSS, the series is stationary, respectively. A, B and C denotes 1%, 5% and 10% level of significance denotes the rejection (acceptance) of null in case of ADF and Phillips-Perron (KPSS) tests. *Source*: Authors' calculation using EViews 8.0.

Table 3
Unit root tests with structural break.

Variables	Level		1st Diff.	
	T_{stat}	T_b	T_{stat}	T_b
ln *y*	4.9077 [1]^{B}	1990	−5.4135 [4]^{A}	2005
ln *k*	−5.9454 [2]^{A}	1989	−5.2490 [3]^{B}	1989
ln *INT*	−4.9917 [4]^{B}	1994	−25.395 [15]^{A}	1997
ln *FBB*	−4.8131 [1]^{C}	2001	−13.9060 [15]^{A}	1999
ln *MBC*	−2.3768 [3]	1988	−5.3196 [2]^{B}	1988
ln *TCH*	−2.9207 [3]	2007	−4.6522 [0]^{A}	2005
ln *TEL*	−2.8241 [3]	1999	−5.2912 [14]^{B}	2006

Notes: The lag length chosen is reported in the square brackets [ ]. Critical values are obtained from Zivot and Andrews (1992). The null hypothesis is that a series a unit root with a structural break in both the intercept and trend. A, B denotes rejection of null hypothesis at 1% and 5% level of significance.

Table 4
Results of bounds test.

Dependent Var.| Independent Var.	ARDL	*F*-stat.	*W*-stat	
ln *y*| ln *k*, ln *INT*		2,2,0	12.7744	38.3233
ln *y*| ln *k*, ln *FBB*		2,2,2	14.9986	44.9957
ln *y*| ln *k*, ln *MBC*		2,2,2	17.8938	53.6813
ln *y*| ln *k*, ln *TCH*		2,2,2	18.2599	54.7796
ln *y*| ln *k*, ln *TEL*		2,2,0	17.9287	53.7860
Critical bounds	95% Lower bound	95% Upper bound	90% Lower bound	90% Upper bound
F-statistics	6.9394	7.8017	5.7437	6.5298
W-statistics	20.8183	23.4051	17.2311	19.5894

Notes: Critical Bounds are computed using Microfit 5.01 Software (Pesaran & Pesaran, 2009).

4.4. Long-run and short-run results

In the long-run (Table 5), we note that the contribution of ICT* is positive and statistically significant. Specifically, the elasticity coefficient of internet (ln $INT = 0.010$), fixed broadband (ln $FBB = 0.011$), and mobile cellular (ln $MBC = 0.011$) are between 0.010 and 0.011. In other words, a 10% increase in these technologies is expected to increase output per worker by 0.10–0.11 percent. Moreover, the elasticity coefficient of hi-tech exports (ln $TCH = 0.076$) and telecommunication (ln $TEL = 0.035$) is 0.08% and 0.04%, respectively. Given the different measures of ICT* used in the analysis, we note that the long-run average capital share is around 0.74. While all the indicators for ICT* have positive elasticity coefficients in the long-run, in short-run (Table 6), we note that only internet ($\Delta \ln INT_t = 0.007$) and telecommunication technology ($\Delta \ln TEL_t = 0.024$) are positive and statistically significant at 1% level. Fixed broadband is not statistically significant and mobile technology and hi-tech exports have a lagged marginal negative coefficient in the short-run.

Table 5
Long-run: dependent variable (ln *y*).

Regressor	Coefficient	Standard error	*t*-Ratio
Panel 5a: internet			
ln *k*	0.7440	0.02565	29.0070^{A}
ln *INT*	0.0100	0.00397	2.5255^{B}
Constant	1.2976	0.20111	6.4522^{A}
$k\_T_{b \geq 1989}$	0.0687	0.01250	5.4988^{A}
$INT\_T_{b \geq 1994}$	−0.0659	0.02543	-2.5910^{B}
$TCH\_T_{b \geq 2007}$	0.0537	0.01465	3.6699^{A}
ARDL(2,2,0); χ^2_{sc}: $\chi^2(1)=5.5465^{B}$, $F(1, 24)=4.5195^{B}$; χ^2_{ff}: $\chi^2(1)=0.10077$, $F(1, 24)=0.069301$; χ^2_{n}: $\chi^2(2)=8.8088^{B}$; χ^2_{hc}: $\chi^2(1)=0.84003$, $F(1, 33)=0.81150$; $SER = 0.0105$; $SSR = 0.0028$; $\bar{x}_y = 7.0436$; $\hat{\sigma}_y = 0.8776$; $AIC = 105.7626$; $SBC = 97.9859$; $LL = 115.7626$; $F-Stat.(9, 25) = 26484.3$; $DW-stat. = 1.4167$.			
Panel 5b: fixed broadband			
ln *k*	0.7165	0.03344	21.4268^{A}
ln *FBB*	0.0111	0.00404	2.7477^{B}
Constant	1.5365	0.26461	5.8064^{A}
$k\_T_{b \geq 1989}$	0.0774	0.01523	5.0864^{A}
$INT\_T_{b \geq 1994}$	−0.0287	0.01885	−1.5235
$TCH\_T_{b \geq 2007}$	0.0365	0.01476	2.4713^{B}
ARDL(2,2,2); χ^2_{sc}: $\chi^2(1)=1.7892$, $F(1, 22)=1.1853$; χ^2_{ff}: $\chi^2(1)=7.8983^{A}$, $F(1, 22)=6.4115^{B}$; χ^2_{n}: $\chi^2(2)=0.23040$; χ^2_{hc}: $\chi^2(1)=0.0287$, $F(1, 33)=0.0271$; $SER = 0.0150$; $SSR = 0.0099$; $\bar{x}_y = 7.0436$; $\hat{\sigma}_y = 0.8776$; $AIC = 107.1151$; $SBC = 97.7831$; $LL = 119.1151$; $F-Stat.(11, 23) = 24145.3$; $DW-stat. = 1.6125$.			
Panel 5c: mobile cellular			
ln *k*	0.7354	0.02279	32.2671^{A}
ln *MBC*	0.0114	0.00481	2.3680^{B}
Constant	1.3810	0.19219	7.1854^{A}
$k\_T_{b \geq 1989}$	0.0704	0.01966	3.5813^{A}
$INT\_T_{b \geq 1994}$	−0.0593	0.02196	-2.6991^{B}
$TCH\_T_{b \geq 2007}$	0.0571	0.01191	4.7961^{A}
ARDL(2,2,2); χ^2_{sc}: $\chi^2(1)=0.1792$, $F(1, 22)=0.1132$; χ^2_{ff}: $\chi^2(1)=0.5110$, $F(1, 22)=0.3260$; χ^2_{n}: $\chi^2(2)=5.5076$; χ^2_{hc}: $\chi^2(1)=0.5663$, $F(1, 33)=0.5427$; $SER = 0.0127$; $SSR = 0.0094$; $\bar{x}_y = 7.0436$; $\hat{\sigma}_y = 0.8776$; $AIC = 109.1452$; $SBC = 99.8131$; $LL = 121.1452$; $F-Stat.(11, 23) = 27115.5$; $DW-stat. = 1.8486$.			
Panel 5d: hi-technology export			
ln *k*	0.7345	0.02214	33.1770^{A}
ln *TCH*	0.0762	0.02604	2.9248^{A}
Constant	1.1129	0.09880	11.2642^{A}
$k\_T_{b \geq 1989}$	0.0887	0.01269	6.9884^{A}
$INT\_T_{b \geq 1994}$	−0.0481	0.01949	-2.4681^{B}
$TCH\_T_{b \geq 2007}$	0.0453	0.01783	2.5396^{B}
ARDL(2,2,2); χ^2_{sc}: $\chi^2(1)=0.0096$, $F(1, 22)=0.0060$; χ^2_{ff}: $\chi^2(1)=3.6281$, $F(1, 22)=2.5442$; χ^2_{n}: $\chi^2(2)=0.8662$; χ^2_{hc}: $\chi^2(1)=0.6181$, $F(1, 33)=0.5933$; $SER = 0.0080$; $SSR = 0.0015$; $\bar{x}_y = 7.0436$; $\hat{\sigma}_y = 0.8776$; $AIC = 114.8011$; $SBC = 105.4690$; $LL = 126.8011$; $F-Stat.(11, 23) = 37461.6$; $DW-stat. = 2.0135$			
Panel 5e: telecommunication			
ln *k*	0.7594	0.01588	47.8358^{A}
ln *TEL*	0.0346	0.01059	3.2683^{A}
Constant	1.0987	0.10123	10.8540^{A}
$k\_T_{b \geq 1989}$	0.0664	0.01132	5.8685^{A}
$INT\_T_{b \geq 1994}$	−0.0755	0.02433	-3.1014^{A}
$TCH\_T_{b \geq 2007}$	0.0518	0.01235	4.1970^{A}
ARDL(2,2,0); χ^2_{sc}: $\chi^2(1)=1.5399$, $F(1, 24)=1.1045$; χ^2_{ff}: $\chi^2(1)=4.3834$, $F(1, 24)=3.4361$; χ^2_{n}: $\chi^2(2)=0.2897$; χ^2_{hc}: $\chi^2(1)=0.0933$, $F(1, 33)=0.0882$; $SER = 0.0095$; $SSR = 0.0022$; $\bar{x}_y = 7.0436$; $\hat{\sigma}_y = 0.8776$; $AIC = 109.3805$; $SBC = 101.6038$; $LL = 119.3805$; $F-Stat.(9, 25) = 32567.3$; $DW-stat. = 1.6745$.			

Notes: A and B indicates 1% and 5% level of statistical significance, respectively. *Source*: Authors' calculation using Microfit 5.01.

Moreover, in case of both the short-run and the long-run, the structural break in capital stock ($k\_T_{b \geq 1989}$) in 1989[8] and hi-tech exports ($TCH\_T_{b \geq 2007}$) in 2007[9] is positive and statistically significant, implying that 1989 and onwards which marked the period

[8] On March, 1988, China successfully launches the DFH-2A fully operational communication satellite into earth's orbit. Within the periods 1988–1999, China experienced Chinese government implemented drastic austerity measures to limit foreign investments and restrict monetary flows subsequent to Deng Xiaoping's economic reforms and the increasing liberalization which lead to widespread corruption and high inflation of more than 18% in the late 1980s.

[9] In 2007, China in its effort to meet energy-electricity demand finalized an agreement with France to build two nuclear power plants by 2013. During this period, French companies secured trade agreements with China amounting to almost 20 billion Euros. Moreover, the number of internet users in China reaches 210 million, and in late 2007, China launched its first lunar orbiter, Chang'e 1 into space, and developed China's first Xiang Feng, or the "Flying Phoenix", domestically passenger jet.

Table 6
Short-run: dependent variable ($\Delta \ln y$).

Regressor	Coefficient	Standard error	*t*-Ratio
Panel 6a: internet			
$\Delta \ln y_{t-1}$	0.2547	0.11002	2.3153[B]
$\Delta \ln k_t$	0.6581	0.13612	4.8346[A]
$\Delta \ln k_{t-1}$	0.7642	0.20062	3.8091[A]
$\Delta \ln INT_t$	0.0070	0.00252	2.7744[A]
$\Delta k\_T_{b \geq 1989}$	0.0480	0.00933	5.1418[A]
$\Delta INT\_T_{b \geq 1994}$	−0.0460	0.01440	−3.1962[A]
$\Delta TCH\_T_{b \geq 2007}$	0.0375	0.01243	3.0206[A]
ECM_{t-1}	−0.6985	0.12718	−5.4919[A]
$R^2 = 0.874$; $\overline{R}^2 = 0.829$; $\bar{x}_{\Delta y} = 0.0840$; $\hat{\sigma}_{\Delta y} = 0.0253$; $F-Stat.(8,26) = 21.724$			
Panel 6b: fixed broadband			
$\Delta \ln y_{t-1}$	0.1441	0.11105	1.2972
$\Delta \ln k_t$	0.6112	0.13100	4.6659[A]
$\Delta \ln k_{t-1}$	0.7637	0.19003	4.0190[A]
$\Delta \ln FBB_t$	0.0061	0.00524	1.1605
$\Delta \ln FBB_{t-1}$	−0.0093	0.00560	−1.6531
$\Delta k\_T_{b \geq 1989}$	0.0482	0.00883	5.4543[A]
$\Delta INT\_T_{b \geq 1994}$	−0.0179	0.01006	−1.7772[C]
$\Delta TCH\_T_{b \geq 2007}$	0.0227	0.01057	2.1476[B]
ECM_{t-1}	−0.6221	0.12572	−4.9484[A]
$R^2 = 0.896$; $\overline{R}^2 = 0.847$; $\bar{x}_{\Delta y} = 0.0840$; $\hat{\sigma}_{\Delta y} = 0.0253$; $F-Stat.(9,25) = 22.057$			
Panel 6c: mobile cellular			
$\Delta \ln y_{t-1}$	0.3778	0.12763	2.9598[A]
$\Delta \ln k_t$	0.4057	0.15381	2.6375[B]
$\Delta \ln k_{t-1}$	0.9447	0.21580	4.3777[A]
$\Delta \ln MBC_t$	0.0100	0.01055	0.9510
$\Delta \ln MBC_{t-1}$	−0.0413	0.01567	−2.6373[B]
$\Delta k\_T_{b \geq 1989}$	0.0622	0.02034	3.0563[A]
$\Delta INT\_T_{b \geq 1994}$	−0.0523	0.01624	−3.2222[A]
$\Delta TCH\_T_{b \geq 2007}$	0.0504	0.01258	4.0093[A]
ECM_{t-1}	−0.8829	0.13329	−6.6240[A]
$R^2 = 0.908$; $\overline{R}^2 = 0.863$; $\bar{x}_{\Delta y} = 0.0840$; $\hat{\sigma}_{\Delta y} = 0.0253$ $F-Stat.(9,25) = 25.084$			
Panel 6d: hi-technology export			
$\Delta \ln y_{t-1}$	0.1165	0.08899	1.3093
$\Delta \ln k_t$	0.7094	0.10822	6.5550[A]
$\Delta \ln k_{t-1}$	0.8906	0.15900	5.6012[A]
$\Delta \ln TCH_t$	−0.0342	0.04198	−0.8154
$\Delta \ln TCH_{t-1}$	−0.0653	0.03607	−1.8104[C]
$\Delta k\_T_{b \geq 1989}$	0.0570	0.00738	7.7166[A]
$\Delta INT\_T_{b \geq 1994}$	−0.0309	0.01081	−2.8571[A]
$\Delta TCH\_T_{b \geq 2007}$	0.0291	0.01261	2.3065[B]
ECM_{t-1}	−0.6420	0.09706	−6.6150[A]
$R^2 = 0.933$; $\overline{R}^2 = 0.901$; $\bar{x}_{\Delta y} = 0.0840$; $\hat{\sigma}_{\Delta y} = 0.0253$; $F-Stat.(9,25) = 35.6294$			
Panel 6e: telecommunication			
$\Delta \ln y_{t-1}$	0.2468	0.09927	2.4863[B]
$\Delta \ln k_t$	0.5901	0.12538	4.7064[A]
$\Delta \ln k_{t-1}$	0.7766	0.17640	4.4026[A]
$\Delta \ln TEL_t$	0.0236	0.00606	3.8995[A]
$\Delta k\_T_{b \geq 1989}$	0.0454	0.00835	5.4336[A]
$\Delta INT\_T_{b \geq 1994}$	−0.0515	0.01260	−4.0887[A]
$\Delta TCH\_T_{b \geq 2007}$	0.0354	0.01042	3.3985[A]
ECM_{t-1}	−0.6830	0.11456	−5.9619[A]
$R^2 = 0.898$; $\overline{R}^2 = 0.861$; $\bar{x}_{\Delta y} = 0.0840$; $\hat{\sigma}_{\Delta y} = 0.0253$; $F-Stat.(8, 26) = 27.4314$			

Notes: A, B and C indicates 1%, 5% and 10% level of statistical significance, respectively. *Source*: Authors' calculation using Microfit 5.01.

of structural changes in investment (capital accumulation) policies, and 2007 and onwards, which influenced the policies pertaining to hi-tech exports, supported the short-run and long-run economic growth. On the other hand, we note that break period in internet ($INT\_T_{b \geq 1994}$) in 1994 has a negative coefficient, implying that structural changes pertaining to internet (technology use) from 1994 onwards has some adverse effect on growth.[10]

[10] In late 1994, Premier Li Peng officially announces the launching of the Three Gorges Dam project (most dangerous hydroelectric dam), which is expected to have adversely affect 13 cities and resulting in resettling of more than 1.4 million people.

Similarly, the short-run capital per worker is statistically significant at 1% level, and on average, the capital per worker contributes 50% to the output per worker. Finally, the coefficient of the error-correction term is statistically significant, negative, and as expected, $-1 < ECM_{t-1} < 0$, for all short-run dynamic equations. The magnitude of the coefficient implies that on average, 71% of any disequilibrium between the output per worker, capital per worker and ICT* is corrected within one year, hence indicating a relatively speedy convergence to the long-run equilibrium.

4.5. Granger causality results

From the unit root results (Tables 2 and 3) we note that the maximum order of integration (d) is 1, and that the optimal lag length chosen from the ARDL VAR estimation using the Akaike information and Schwarz Bayesian criteria is 2 ($l = 2$). This means the maximum lags used for causality tests need to be at most 3, that is, $d + l \leq 3$. For our purpose, we used the lag ($d + l = 2$). From Table 7, we note a bidirectional causation between: output per worker and capital per worker ($\ln y \leftrightarrow \ln k$), output per worker and mobile cellular ($\ln y \leftrightarrow \ln MBS$), and output per worker and telecommunication ($\ln y \leftrightarrow \ln TEL$); mobile cellular and telecommunication ($\ln MBS \leftrightarrow \ln TEL$); capital per worker and mobile cellular ($\ln k \leftrightarrow \ln MBS$); capital per worker and telecommunication ($\ln k \leftrightarrow \ln TEL$); and internet and fixed broadband ($\ln INT \leftrightarrow \ln FBB$). A unidirectional causation runs from: capital per worker to internet ($\ln k \rightarrow \ln INT$); internet to hi-tech exports ($\ln INT \rightarrow \ln TCH$); fixed broadband to capital per worker ($\ln kFBB \rightarrow \ln k$) and hi-tech exports ($\ln FBB \rightarrow \ln TCH$); mobile cellular to capital per worker ($\ln MBC \rightarrow \ln k$) and fixed broadband ($\ln MBC \rightarrow \ln FBB$); hi-tech exports to capital per worker ($\ln TCH \rightarrow \ln k$) and mobile cellular ($\ln TCH \rightarrow \ln MBS$); and telecommunication to fixed broadband ($\ln TEL \rightarrow \ln FBB$) and hi-tech exports ($\ln TEL \rightarrow \ln TCH$). Using the combined causality effect statistics and the primary model (Eq. (6)) as guide, we note from column (1) that the dominant drivers causing of output per worker are capital per worker (k), mobile cellular (MBC), and telecommunications (TEL) technology.

5. Conclusion and policy implications

In this paper, we set out to explore the contribution of ICT* on the economic growth of China over the period 1977–2013. We used five different measures of ICT*, namely internet, fixed broadband and mobile cellular subscriptions, hi-tech exports, and telecommunication lines. We used the augmented Solow (1956) framework and the ARDL procedure (Pesaran et al., 2001) to examine the cointegration and the long-run and short-run results. Finally, we explored the causality nexus using the Toda and Yamamoto (1995) procedure.

The results show that all indicators used to measure ICT* are co-integrated with economic growth duly supporting the presence of a long-run association. Moreover, all indicators of ICT* have a positive and statistically significant elasticity coefficient in the long-run. In regards to the short-run model, we note that internet and telecommunication have positive coefficients, mobile cellular and high-tech exports have marginal lagged negative coefficients, and fixed broadband, although positive, is not statistically significant in the short-run. We note that the long-run elasticity coefficients for ICT* is between 0.01 and 0.08, which implies that a 1% change in ICT* will result in changes in output per worker between 0.01 and 0.08 percent, *ceteris paribus*. From the Granger causality results, we note bidirectional causality between mobile cellular, telecommunication and economic growth; and between mobile cellular, telecommunication and capital per worker, respectively. Other results indicate that fixed broadband cause capital per worker; capital per worker causes internet technology. We also note bidirectional causality between mobile cellular and telecommunication, and between fixed broadband and internet, respectively; and a unidirectional causality from internet and fixed broadband to hi-tech exports; and from mobile cellular and telecommunication to fixed broadband, respectively.

While in general, the results points to the momentous role of ICT* in China, we would like to highlight some caveats. First, the estimated capital share in the study is higher than the stylized value of one-third (0.40 of Bosworth and Collins (2008) and 0.50 of Bai, Hsieh, and Qian (2006).[11] This is plausible due to a couple of reasons: when (a) the capital and labor inputs tend to grow at relatively similar rates; (b) an economy is predominantly developing and hence a large number of self-employed persons earn income from both capital and their own labor (Gollin, 2002) thus making it difficult to obtain meaningful measures of income shares; and (c) the quality and availability of data is weak and therefore making it difficult to compute or estimate the capital stock per worker (Bosworth & Collins, 2008) that can perfectly exhibit decreasing returns to scale and conform to a desirable steady-state convergence process. We concur to all these reasons in case of this study. Second, we have used a specific set of ICT* measures which are more relevant to communications technology. Nevertheless, exploring further measures and the availability of consistent data on newer version of technology is likely to improve the results, particularly in examining the magnitude effects of ICT* on the long-run growth. Third, while ICT* technologies as a subset of Internet of Things (IoT) have the positive contributory power *viz.* growth, intuitively if all important economic institutions are well equipped with the ICT* technologies (and IoT) and mostly all network benefits are exploited, then we can expect any further investments in ICT* to contribute only marginally to the economic growth.[12] Fourth, we note that all

[11] We further examined the capital share by using higher depreciation rates and find that the share remains high, even with different depreciation rates.

[12] The flipside of this argument is the resulting near zero marginal cost society that will be welfare optimizing.

Table 7
Granger non-causality test based on χ^2

	Dependent variable ($\boldsymbol{Y}$)							
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\boldsymbol{X}$	ln y	ln k	ln *INT*	ln *FBB*	ln *MBC*	ln *TCH*	ln *TEL*
	ln y	–	10.3606^A	1.5968	0.5561	21.5142^A	0.5240	7.4314^B
	ln k	68.0384^A	–	6.6770^B	2.3182	14.7193^A	0.2129	7.4476^B
$\underbrace{\boldsymbol{X} \to \boldsymbol{Y}}_{causes}$	ln *INT*	0.6506	3.8970	–	25.508^A	1.6535	12.0679^A	0.4900
	ln *FBB*	3.2204	8.6536^B	7.9836^B	–	0.9689	9.7987^A	1.9815
	ln *MBC*	9.2892^A	29.6890^A	15.0214^A	6.7015^B		−0.6262	16.0875^A
	ln *TCH*	2.6548	10.9350^A	3.7989	3.5512	9.4444^A	–	1.7064
	ln *TEL*	5.4765^C	6.1356^B	4.2274	13.8757^A	19.1557^A	5.0656^A	–
	Combined	102.3091^A	47.7813^A	45.1251^A	66.2268^A	39.8240^A	83.0869^A	40.9547^A

Notes: A, B and C indicates presence of causality at 1%, 5% and 10% level of significance, respectively; degree of freedom (df)=2. *Source*: Authors' calculation using Eviews 8.0.

the ICT* variables exhibit long-run association with output per worker, have positive long-run elasticity coefficients, and the causality result indicates a number of directional causality between variables, thus making it relatively difficult to suss out the dominant driver of economic growth. To overcome this problem, we restrict our conclusion on the primary model we intended to estimate (Eq. (6)) and examine the variables which support output per worker based on the statistical significance of (a) coefficients of long-run variables (elasticity), (b) causality between individual variables and output per worker, and (c) combined effect and the output per worker. Fifth, admittedly, we only examine the single period structural break. From an econometrics point of view, there is also a likelihood of more than one structural break in each series which can be captured using relatively advanced techniques such as the two-period break test of Lee and Strazicich (2003), and/or the recently developed technique by Narayan and Popp (2013).

From a policy front, it is important to highlight that all the indicators of ICT* are important determinants and drivers of growth. Nevertheless, for more targeted development policies, we conclude (within caveats) that capital per worker, mobile cellular and telecommunication technology are the dominant drivers of output per worker and hence have relatively high contributory power to support the long-run economic growth of China. Therefore, further investment in and advancement of ICT* with specific focus to mobile technology and telecommunications will boost productivity and support long-run growth. Focusing on the effective use of recent generation mobile technologies, such as 3G and 4G need to be harnessed and made accessible to less developed areas of China to further narrow the digital divide (Loo & Ngan, 2012). As much as there is optimism to expand its mobile communication technologies and move to the next-generation-networks (NGNs), 3G and higher, China's ICT* sector is also confronted with challenges relating to technology, economic and institutional factors and the current market landscape (Xia, 2012). In terms of technology adoption, the challenge is the transition between early adopters and early majority ("chasm"), as the latter is necessary for the industry to reach maturity. Other aspects that can support China to become a highly technology-driven economy will be firm-level reconsolidation, which will require physical, organizational and cultural integration between merged parties; convergence of technology and market to boost the level of competition; and resolving regulatory uncertainty resulting from market convergence between telecommunication, internet, and cable. Therefore, technology (IoT) will be the key growth driver of productivity and growth of the Chinese economy. It is also important that the spill-over gains resulting from investing in one technology to another is recognized and realized to ensure a sustainable and supportive environment for ICT* development in the economy.

China is also shifting from growth maximizing to a growth optimizing economy where the focus is now on balanced growth, social harmony and environmental sustainability. Subsequently, the role of green ICT is pivotal for restructuring, transforming and upgrading traditional industries in the economy, improving energy efficiency, and supporting environmental monitoring, natural resource management, and emission assessment (Zhang & Liang, 2012). In this regard, policymakers will have to juggle with multiple competing objectives in a coherent and efficient manner, *inter alia*: developing and/or adopt advanced ICT* (smart) technologies, building the necessary third industrial revolution (technology) infrastructure to support and enhance productivity, leveraging from IoT to improve the welfare of people across all the facets of the economy – education, health, tourism, trade and manufacturing are just to name a few, and identifying the 'right' technology products and proactively responding to the investor and customer requirements to ensure competition among firms. As noted, the recent initial public offering of the Chinese firm Alibaba.com, which is an online marketplace, shows that institutional investors expect that online commerce will become an important business in China in the future which implicitly means a stable and an increasing demand for ICT* products and in particular, the mobile and wireless communication devices.

Acknowledgment

The authors sincerely thank the two anonymous reviewers and the editors of *Telecommunications Policy*, Professor Erik Bohlin and Professor Jun Xia for their helpful comments and suggestions. Peter J. Stauvermann sincerely acknowledges and thanks the Faculty of Business & Economics of the Changwon National University for the financial support in conducting the research. All remaining errors are ours.

References

Aghion, P., & Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, *60*(2), 323–351.
Atzeni, G. E., & Carboni, O. A. (2006). ICT productivity and firm propensity to innovative investment: evidence from Italian microdata. *Information Economics and Policy*, *18*, 139–156.
Bai, C.-E., Hsieh, C.-T., & Qian, Y. (2006). *The Return to Capital in China. NBER Working paper 12755*. Cambridge, MA: NBER.
Barro, R. (1990). Government spending in a simple model of endogenous growth. *Journal of Political Economy*, *98*(5), S103–S125.
Bosworth, B., & Collins, S. M. (2008). Accounting for growth: Comparing China and India. *Journal of Economic Perspectives*, *22*(1), 45–66.
Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies: Engines of growth? *Journal of Econometrics*, *65*(1), 83–108.
Brynjolfsson, E., & Hitt, L. M. (2003). Computing productivity: Firm-level evidence. *Review of Economics and Statistics*, *85*(4), 793–808.
Castellacci, F., & Natera, J. M. (2013). The dynamics of national innovation systems: A panel cointegration analysis of the coevolution between innovative capability and absorptive capacity. *Research Policy*, *42*(3), 579–594.
Chen, X., Gao, J., & Tan, W. (2005). ICT in China: A strong force to boost economic and social development. In J. Berleur, & C. Avegrou (Eds.), *Perspectives and Policies on ICT in Society, IFIP International Federation for Information Processing*, Vol. 179.
Cronin, F. J., Colleran, E. K., Herbet, P., & Lewitzky, S. (1993). Telecommunications and growth: The contribution of telecommunications infrastructure investment to aggregate and sectoral productivity. *Telecommunications Policy*, *17*(9), 677–690.
Datta, A., & Agarwal, S. (2004). Telecommunications and economic growth: a panel data approach. *Applied Economics*, *36*(15), 1649–1654.
Daveri, F. (2002). The new economy in Europe, 1992-2001. *Oxford Review of Economic Policy*, *18*(3), 345–362.
Dewan, S., & Kraemer, K. (2000). Information technology and productivity: Evidence from country-level data. *Management Science*, *46*(1), 548–562.
Fabiani, S., Schivardi, F., & Trento, S. (2005). ICT adoption in Italian manufacturing: Firm-level evidence. *Industrial and Corporate Change*, *14*(2), 225–249.
Ghatak, S., & Siddiki, J. (2001). The use of ARDL approach in estimating virtual exchange rates in India. *Journal of Applied Statistics*, *28*(5), 573–583.
Gollin, D. (2002). Getting income shares right. *Journal of Political Economy*, *110*(2), 458–474.
Grossman, G. M., & Helpman, R. (1991). *Innovation and Growth in the Global Economy*. Cambridge, MA: MIT Press.
Gruber, H., & Koutroumpis, P. (2010). Mobile communications: Diffusion facts and prospects. *Communications and Strategies*, *77*(1), 133–145.
Hardy, A. P. (1980). The role of the telephone in economic development. *Telecommunications Policy*, *4*(4), 278–286.
Hu, Q., & Quan, J. (2005). Evaluating the impact of IT investments on productivity: A causal analysis at industry level. *International Journal of Information Management*, *25*, 39–53.
Jalava, J., & Pohjola, M. (2008). The roles of electricity and ICT in economic growth: Case Finland. *Explorations in Economic History*, *45*(3), 270–287.
Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration - with applications to the demand for money. *Oxford Bulletin of Economics & Statistics*, *52*(2), 169–210.
Jorgenson, D. (2001). Information technology and the US economy. *American Economic Review*, *91*(1), 1–32.
Jorgenson, D. (2003). Information technology and the G7 economies. *World Economics*, *4*(4), 139–169.
Jorgenson, D., & Motohashi, K. (2005). Information technology and the Japanese economy. *Journal of the Japanese and International Economies*, *19*(4), 460–481.
Jorgenson, D., & Vu, K. (2007). Information technology and the world growth resurgence. *German Economic Review*, *8*(2), 125–145.
Jorgenson, D. W., & Stiroh, K. J. (2000). Raising the speed limit: U.S. economic growth in the information age. *Brookings Papers on Economic Activity*, *31*(1), 125–236.
Katz, R. L. (2009). The economic and social impact of telecommunications output a theoretical framework and empirical evidence for Spain. *Intereconomics*, *44*(1), 41–48.
Koutroumpis, P. (2009). The economic impact of broadband on growth: A simultaneous approach. *Telecommunications Policy*, *33*(9), 471–485.
Kumar, R. R., Kumar, R. D., & Patel, A. (2015). Accounting for telecommunications contribution to economic growth: A study of Small Pacific Island State. *Telecommunications Policy*, *39*(3–4), 284–295.
Kumar, R. R., Stauvermann, P. J., Patel., A., & Kumar, R. R. (2014). Exploring the effects of energy consumption on output per worker: A study of Albania, Bulgaria, Hungary and Romania. *Energy Policy*, *69*, 575–585.
Kuppusamy, M., Raman, M., & Lee, G. (2009). Whose ICT investment matters to economic growth: private or public? The Malaysian perspective. *The Electronic Journal on Information Systems in Developing Countries*, *37*(7), 1–19.
Lam, P.-L., & Shiu, A. (2010). Economic growth, telecommunications development and productivity growth of the telecommunications sector: Evidence around the world. *Telecommunications Policy*, *34*(4), 185–199.
Lee, T. S.-Y., Gholami, R., & Tong, T. Y. (2005). Time series analysis in the assessment of ICT impact at the aggregate level – lessons and implications for the new economy. *Information and Management*, *42*(7), 1009–1022.
Lee, J., & Strazicich, M. C. (2003). Minimum Lagrange Multiplier Unit Root Test with Two Structural Breaks. *The Review of Economics and Statistics*, *85*(4), 1082–1089.
Lehr, B., & Lichtenberg, F. (1999). Information technology and its impact on firm-level productivity: Evidence from government and private data sources, 1977–1993. *The Canadian Journal of Economics*, *32*(2), 335–362.
Loo, B. P. Y., & Ngan, Y. L. (2012). Developing mobile telecommunications to narrow digital divide in developing countries? Some lessons from China. *Telecommunications Policy*, *36*, 888–900.
Loo, B. P. Y. (2004). Telecommunications reforms in China: Towards an analytical framework. *Telecommunications Policy*, *28*(9–10), 697–714.
Lucas, R. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, *22*(1), 3–42.
MacKinnon, J. G. (1996). Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Econometrics*, *11*(6), 601–618.
Madden, G., & Savage, S. J. (1998). CEE telecommunications investment and economic growth. *Information Economics and Policy*, *10*(2), 173–195.
Meng, Q., & Li, M. (2002). New economy and ICT development in China. *Information Economics and Policy*, *14*(2), 275–295.
Minghetti, V., & Buhalis, D. (2010). Digital divide in tourism. *Journal of Travel Research*, *49*(3), 267–281.
Narayan, P. K. (2005). The saving and investment nexus for China: evidence from cointegration tests. *Applied Economics*, *37*(17), 1979–1990.
Narayan, P. K., & Popp, S. (2013). Size and power properties of structural break unit root tests. *Applied Economics*, *46*, 721–728.
O'Mahony, M., & Vecchi, M. (2005). Quantifying the impact of ICT capital on output growth: A heterogeneous dynamic panel approach. *Economica*, *72*(288), 615–633.
Oliner, S., & Sichel, D. (2000). The resurgence of growth in the late 1990s: Is information technology the story? *Journal of Economic Perspectives*, *14*(4), 3–22.
Oulton, N. (2002). ICT and productivity growth in the UK. *Oxford Review of Economic Policy*, *18*(3), 363–379.
Oz, E. (2005). Information technology productivity: In search of a definite observation. *Information & Management*, *42*, 789–798.
Pesaran, B., & Pesaran, H. M. (1999). *Microfit 4.1 InteractiveEconometric Analysis*. Oxford: Oxford University Press.
Pesaran, B., & Pesaran, H. M. (2009). *Time Series Econometrics using Microfit 5.01*. Oxford: Oxford University Press.
Pesaran, M. H., Shin, Y., & Smith, R. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, *16*(3), 289–326.
Pohjola, M. (2002). The new economy in growth and development. *Oxford Review of Economic Policy*, *18*(3), 380–396.
Rao, B. B. (2007). Estimating short and long-run relationships: A guide for the applied economist. *Applied Economics*, *39*(13), 1613–1625.
Rao, B. B. (2010). Estimates of the steady state growth rates for selected Asian countries with an extended Solow Model. *Economic Modelling*, *27*(1), 46–53.

Roller, L. H., & Waverman, L. (2001). Telecommunications infrastructure and economic development, a simultaneous equations approach. *American Economic Review*, *91*(4), 909–923.
Romer, P. (1986). Increasing returns and long run growth. *Journal of Political Economy*, *94*(2), 1002–1037.
Romer, P. (1990). Endogenous technological change. *Journal of Political Economy*, *98*(5), S71–S102.
Seo, H. J., Lee, Y. S., & Oh, J. H. (2009). Does ICT investment widen the growth gap? *Telecommunications Policy*, *33*(8), 422–431.
Shahiduzzaman, M., & Alam, K. (2014). Information technology and its changing roles to economic growth and productivity in Australia. *Telecommunications Policy*, *38*(2), 125–135.
Solow, R. M. (1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*, *70*(1), 65–94.
Solow, R. M. (1987). *We'd Better Watch Out*. 12. New York: Times Book Review36 July.
Stiroh, K. J. (2002). Are spillovers driving the new economy? *Review of Income and Wealth*, *48*(1), 33–57.
Thompson, H. G., Jr., & Garbacz, C. (2007). Mobile, fixed line and Internet service effects on global productive efficiency. *Information Economics and Policy*, *19*(2), 189–214.
Toda, H. Y., & Yamamoto, T. (1995). Statistical inferences in vector autoregressions with possibly integrated process. *Journal of Econometrics*, *66*(1–2), 225–250.
Tseng, C.-Y. (2009). Technological innovation and knowledge network in Asia: Evidence from comparison of information and communication technologies among six countries. *Technological Forecasting and Social Change*, *76*(5), 654–663.
Venturini, F. (2009). The long-run impact of ICT. *Empirical Economics*, *37*(3), 497–515.
Vu, K. M. (2011). ICT as a source of economic growth in the information age: empirical evidence from the 1996–2005 period. *Telecommunications Policy*, *35*(4), 357–372.
Vu, K. M. (2013). Information and Communication Technology (ICT) and Singapore's economic growth. *Information Economics and Policy*, *25*, 284–300.
World Bank. (2014). *World Development Indicators and Global Development Finance*. Washington, DC: World Bank.
Xia, J., & Lu, T.-J. (2008). Bridging the digital divide for rural communities: The case of China. *Telecommunications Policy*, *32*, 686–696.
Xia, J. (2007) Towards a sustainable institutional arrangement for USOs in China: Current status, support mechanisms, and regulatory governance. A Journal of Law and Policy for the Information Society. 3(1): 147-181. moritzlaw.osu.edu/students/groups/is/files/2012/02/Xia-formatted.pdf (accessed 25.08.14).
Xia, J. (2010). Linking ICTs to rural development: China's rural information policy. *Government Information Quarterly*, *27*(2), 187–195.
Xia, J. (2011). The third-generation-mobile (3G) policy and deployment in China: Current status, challenges, and prospects. *Telecommunications Policy*, *35*, 51–63.
Xia, J. (2012). Reprint of: Competition and regulation in China's 3G/4G mobile communications industry—Institutions, governance, and telecom SOEs. *Telecommunications Policy*, *36*(10–11), 798–816.
Yorukoglu, M. (1998). The information technology productivity paradox. *Review of Economics Dynamics*, *1*, 551–592.
Zheng, S., Kjetil, S., & Fabrizio, Z. (2011). Growing Like China. *American Economic Review*, *101*(1), 196–233.
Zhang, J., & Liang, X. (2012). Promoting green ICT in China: A framework based on innovation system approaches. *Telecommunications Policy*, *36*, 997–1013.
Zivot, E., & Andrews, D. W. K. (1992). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business and Economic Statistics*, *10*(3), 251–270.