Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Does ICT maturity catalyse economic development? Evidence from a panel data estimation approach in OECD countries

Mohammad Afshar Ali $^{1,2,3,*}$
Email: MohammadAfshar.Ali@usq.edu.au

Khorshed Alam$^{1,2}$
Email: Khorshed.Alam@usq.edu.au

Brad Taylor$^4$
Email: Brad.Taylor@usq.edu.au

Shuddhasattwa Rafiq$^5$
Email: srafiq@deakin.edu.au

$^1$School of Commerce, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Toowoomba, Australia.
$^2$Centre for Health Research, University of Southern Queensland, Toowoomba, Australia.
$^3$Department of Economics, Jagannath University, Dhaka, Bangladesh.
$^4$School of Commerce, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Springfield, Australia.
$^5$Faculty of Business and Law, BL Deakin Business School, Deakin University, Melbourne, Australia.
* Corresponding author
Does ICT maturity catalyse economic development? Evidence from a panel data estimation approach in OECD countries

Abstract
To date, definitions of information and communication technology (ICT) development used in quantitative studies on the relationship between economic development and ICT are incomplete and often based on single indicators. Thus, this study investigates the link between ICT maturity and economic development in the Organisation of Economic Cooperation and Development (OECD) countries. A novel composite index of ICT maturity that includes previously neglected dimensions of ICT maturity, such as affordability and quality of internet connectivity, is utilised. The baseline estimations using the feasible generalised least squares indicate that ICT maturity is associated with an increase in economic development by 1%–3.8% in OECD countries. These findings have been cross-validated by applying the generalised method of moments estimation. Results imply that the holistic development of ICT, including infrastructure, skills, and affordability, can augment economic development.

Keywords: Economic development, panel data, ICT maturity, information and communication technology, OECD
1. Introduction

Many empirical studies have confirmed that information and communication technology (ICT) can play a significant role in the socio-economic development of a nation (Asongu & Le Roux, 2017; Ferrigno-Stack et al., 2003; Obijiofor, 2009). Consequently, the governments of developed and developing countries have greatly invested in the development and diffusion of ICTs. Undoubtedly, ICT is a major catalyst for economic development. However, the nexus between ICT and economic development has been the subject of much debate. Some researchers are optimistic about the role of ICT in development (Palvia et al., 2018), whereas others suggest that ICT alone will not lead to economic development unless accompanied by social changes and other complementary factors (Morales-Gómez & Melesse, 1998). Thus, the literature is inconclusive on whether ICT is a significant driver of economic development. Importantly, some scholars have argued that the definitions used to measure ICT maturity in the literature are not comprehensive (Baller et al., 2016; Sridhar & Sridhar, 2008). Therefore, the assessment of ICT’s contribution to economic development might be flawed.

Most of the empirical studies considering the relationship between ICT and economic growth have concluded that a positive and significant relationship exists (Salahuddin & Alam, 2015; Salahuddin & Alam, 2016). However, the relationship between ICT and economic development is less clear. The concept of ‘economic development’ is broader than that of ‘economic growth’. The latter is concerned with the quantitative expansion of an economy’s output, whereas the former includes the qualitative aspects which tend to accompany growth in the narrower sense (Ranis, 2004). Economic development includes distributive issues of economic growth, that is, income inequality, the composition of social expenditure and measures of political well-being (Jingfeng & Zhao’an, 2018; Ranis, 2004; Srinivasan, 1994). Considering that ICT affects every area of life rather than simply the productive capacity of an economy, the relationship between ICT and economic development is an important area of study.
Existing studies explaining the nexus between economic development and ICT have used incomplete, partial or single indicator-based definitions of ICT development (Kundu & Sarangi, 2004; Lam & Shiu, 2010; Sridhar & Sridhar, 2008). Hence, this study aims to investigate the relationship between economic development and ICT maturity levels in the Organisation of Economic Cooperation and Development (OECD) countries using a holistic approach. Unlike the previous studies (Kundu & Sarangi, 2004; Lam & Shiu, 2010; Sridhar & Sridhar, 2008), the current study follows a comprehensive definition of the overall level of ICT maturity (Ali et al., 2020) to measure the effect of ICT on economic development. Ali et al. (2020) pointed out that the ICT maturity level is comprised of six dimensions of a country’s ICT development, namely, access, use, skills, affordability, efficiency and quality. Such dimensions significantly explain the socioeconomic outcomes of a nation. The weightings of these subcomponents are systematically determined through structural equation modelling rather than being arbitrarily defined (for details, see the technical note in Appendix A).

The primary research question of this study is whether any significant relationship exists between economic development and the level of overall development of the ICT sector. To the best of the authors’ knowledge, this study is the first attempt to explain the nexus between economic development and ICT maturity using a longitudinal dataset of OECD countries applying a standard panel data estimation framework. Therefore, this study provides several novel contributions to the existing literature. Firstly, this study employs a comprehensive composite index to measure the level of ICT maturity. Then, this index is used to capture the effects of ICT maturity on economic development by employing an advanced panel data estimation framework. In this regard, the study incorporates three new dimensions in measuring the overall ICT maturity level (viz. affordability, efficiency and quality). These dimensions are shown to significantly explain the overall maturity level of ICT alongside conventional considerations of ICT development including access, use and skills (Ali et al.,
2020). Single indicator- and other partial definition-based ICT development indices have several limitations including the following: subjective estimation; bias arising from the estimation of the weights of individual indicators and sub-indices; use of inappropriate quantitative models and faulty estimation arising from the exclusion of important dimensions including affordability, quality and efficiency aspects of ICT from the estimation models (Ali et al., 2020; Hair et al., 1995). Secondly, the panel data estimation techniques used in this study yield a reliable and accurate estimate than previous studies of the association between economic development, ICT maturity and other macro-economic and governance variables.

2. Review of literature
The nexus between economic performance and technological advancement is deeply rooted in established theories of economic growth and development. For example, Solow’s growth model postulates that economic growth can be generated in an economy by accelerating technological change (Solow, 1957). Subsequently, the endogenous growth theory developed by Romer (1990) and the capability theory of Sen (1985) indicated that technological progress can significantly affect the economic development process. On this view, the well-being of a nation is ultimately determined by its capabilities. ICTs, specifically internet access, enhance human capabilities by assisting in communication and information acquisition. Following this approach, an extensive body of empirical study has investigated the effect of ICT on economic development (Asongu & Le Roux, 2017; Bankole et al., 2013; Palvia et al., 2018). In these studies, proxy variables, such as human development (Ashraf et al., 2015; Asongu & Le Roux, 2017; Budd & Ziegler, 2017; Walsham, 2017), quality of life (Chiao & Chiu, 2018; Kadijevich et al., 2016) and well-being (Ganju et al., 2015; Palvia et al., 2018), have been used to define economic development.

Focusing on different target populations, some studies have reported a positive correlation between ICT use and quality of life (Chiao & Chiu, 2018; Kadijevich et al., 2016). Studies
have also shown that at the national level, the economic well-being of a nation is dependent on its ICT infrastructure (Czernich et al., 2011; James, 2014; Nouinou et al., 2015). At the micro level, studies have examined the impact of ICT use on the quality of work and personal lives (De Wet et al., 2016; Gopinathan & Raman, 2016). These studies indicate that ICT has played a significant role in enhancing the quality of life by maintaining a balance between working life and the personal one.

Other studies exploring the nexus between ICT and human development have shown that ICT diffusion promotes inclusive human development (Asongu & Le Roux, 2017; Brown & Brown, 2008). Moreover, empirical research has found that ICT positively contributes to the development of indigenous communities (Ashraf et al., 2015; Madden et al., 2012). Community-based studies also reported that ICT can act as a catalyst to promote development at the community level by mitigating social constraints (Ashraf et al., 2017). A few studies have claimed that ICT can augment human development by enhancing health-related outcomes (Bankole et al., 2013; UN, 2010). However, Samoilenko and Osei-Bryson (2016) counter-intuitively revealed that the annual revenue in the telecommunications sector had no significant influence on human development.

Another group of studies attempt to relate ICT use with socio-economic and mental well-being. For example, Ganju et al. (2015) and Palvia et al. (2018) indicated that ICT use significantly improves a country’s economic well-being by alleviating poverty, whereas Sims et al. (2017) noted a positive association between ICT use and mental well-being. Moreover, some studies demonstrated that ICT-based programmes improved the mental well-being of young people by not only facilitating entertainment and socialising activities but also providing access to mental health information and support (Ellis et al., 2012; Stephens-Reicher et al., 2011). Studies have also suggested that social media can be used as a potential source of data on health to implement
policies to enhance well-being. Expressed differently, social media can be used to disseminate public messaging and model population sentiment (Yeung, 2018).

In contrast to the findings of the aforementioned studies, a few studies have highlighted ICT’s negative effects. For instance, Nimrod (2018) found that technostress has a negative influence on life satisfaction. In addition, Bekaroo et al. (2016) argued that the widespread adoption of ICT drained a substantial amount of energy and power, thereby leading to complex environmental problems with severe repercussions on people’s quality of life. Morawczynski and Ngwenyama (2007) noted that ICT maturity alone cannot promote economic development; other factors are also important. For example, income growth has an indirect effect on human development as it promotes literacy and health outcomes by mobilising private and public resources (Ranis, 2004). Moreover, social expenditure on health and education are significant predictors of economic development (Ranis et al., 2000). Research has shown that the quality of the environment is a significant predictor of economic development (Jingfeng & Zhao’an, 2018; Shahiduzzaman & Alam, 2014; Shahiduzzaman & Alam, 2017). Existing research has also shown that the ideological stance of a country’s ruling political party affects its overall economic development by inducing partisan cycles in society’s savings, investment and capital stocks (Aidt et al., 2018; Potrafke, 2017). More specifically, accelerated investment attributed to economic conservatism initiated by right-wing parties seems to drive developed countries to the path of economic development (Aidt et al., 2018; Potrafke, 2017). Nevertheless, Srinivasan (1994) pointed out that measures of political well-being and income inequality are the major determinants of human development, which have been ignored in the theorisation of UNDP’s Human Development Index (HDI). In this regard, income inequality addresses the distributional aspects of economic growth and also indicates whether economic development is inclusive. Moreover, several studies indicate that globalisation is positively correlated with economic development (Dreher, 2006; Pleninger & Sturm, 2020; Ulucak et al., 2020).
Although the existing literature convincingly demonstrates the association between particular dimensions of ICT maturity and economic development, there is a lack of empirical investigation of this relationship using a comprehensive measure of the ICT maturity level at a cross-country setting. In particular, these studies have used either access to ICT infrastructure or use of ICT devices at the expense of other factors that we consider important (Asongu & Le Roux, 2017; Ganju et al., 2015; Palvia et al., 2018). To this end, the current study employs the modified ICT maturity level index (MIMLI) to investigate the ICT-development nexus based on the novel and comprehensive ICT development measurement index computation method formulated by Ali et al. (2020). MIMLI incorporates new dimensions of ICT development including affordability, efficiency and quality alongside conventional considerations of access, use and skills. Recent empirical evidence has shown that the exiting ICT development indices including ICT development index (IDI) are not a comprehensive measurement of ICT maturity as IDI ignores significant factors, such as the quality, affordability and institutional efficiency of the telecommunication services (Baller et al., 2016; Raghupathi & Wu, 2011; Sridhar & Sridhar, 2008). This study fills the gap in the literature by applying a highly comprehensive composite index of ICT maturity to the question of whether ICT maturity promotes economic development. To do so, the study deploys a standard panel data estimation approach using a balanced longitudinal dataset of OECD countries.

3. Data, variables and estimation strategy
3.1. Data and variables
This study incorporated several control variables to explore the association between economic development and ICT maturity level. The selection of the variables was based on the existing literature (see Section 2 and Table 1 for details). The data were collected from several international databases, including Cornell University (2017); Döring and Manow (2019); Gygli et al. (2019); ITU (2016); UNDP (2017); UNU-WIDER (2017); World Bank (2017, 2018).
These datasets contain 35 cross-sectional units which represent 35 OECD countries. The datasets span throughout 2006–2015; thus, the panel data contain 10 years of data for 35 countries. The total number of observations is 350, and the panel dataset is strongly balanced.

Table 1 provides the definitions of the variables included in the models along with the corresponding summary statistics. In this study, the dependent variable is economic development, the explanatory variable is ICT maturity level and remaining variables are control variables (for details, see Section 3.2 on model specification). The main variable of interest—the MIMLI is computed following the study of Ali et al. (2020). This study uses the MIMLI score estimated through the formative measurement model for using the PLS-SEM for the period 2006–2015. The index building mechanism is thoroughly discussed in details in Appendix A as an Online Supplement to this article. This index is an extension of the IDI (ITU, 2009) and modified IDI (Gerpott & Ahmadi, 2015). The index consists of six sub-indices: access, use, skills, affordability, efficiency and quality (a detailed description of the variables used in constructing the index is in Appendix Tables A1 and A2).

Here, Scales are defined as follows: HDI, 0 to 1; Gini index, 0 to 1; MIMLI, 1 to 10; OverGovtIdeol, 1 to 10; and Globalisation, 1 to 100. Except the Gini index, a higher score indicates better performance in all indices. GDPG, PE, Forest and VoteShare are expressed in percentage form so as to exhibit less volatility. GovtEff is a multinominal categorical variable ranging from -2.5 to +2.5. Appendix Table B provides the summary statistics of the variables in the panel dimension. The descriptive statistics demonstrate that there are disparities in terms of the level of economic development and ICT maturity among OECD countries.

Table 2 reports the correlation matrix amongst the dependant, explanatory and control variables. Moreover, Table 2 shows that the correlation coefficient between economic
development and ICT maturity is very high (0.7747) and statistically significant. The correlation of economic development is positive and statistically significant with other explanatory variables including GDPG (0.0939), government expenditure (0.6686), government effectiveness (0.7855) and globalisation (0.6224). As expected, economic development is negatively correlated with income inequality (0.5561).

3.2. Model specification
This study deploys a set of panel data estimation models to investigate the association between economic development and the ICT maturity level. The selection of variables is determined by the following factors: (i) the theoretical foundations of the study rooted in endogenous growth theory (Romer, 1990) and capability theory (Sen, 1985); and (ii) the extensive body of literature outlined in Section 2. The estimation specification is as follows:

\[
HDI_{it} = \alpha + \gamma MIMLI_i + \lambda X_{it} + u_i + \eta_t + \varepsilon_{it} \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (1)
\]

where \( i \) stands for a given country and \( t \) represents the year. \( HDI_{it} \) represents the value of the HDI of country \( i \) in year \( t \). \( MIMLI_i \) is the main variable of interest—the ICT maturity level. The model also controls for observed time-varying covariates \( X_{it} \). GDPG, Gini, PE, Forest, GovtEff, VoteShare, OverGovtIdeol and Globalisation are the control variables. Three different equations are used to examine the influence of political well-being, policy stability and government ideology on the dependent variable. As outlined below, the first baseline estimation (Eq. 2.1) is conducted considering government effectiveness as political well-being. The second estimation (Eq. 2.2) is conducted using vote share of the government as a proxy for policy stability, whereas the third one (Eq. 2.3) uses the ideology of political parties as a proxy for overall government ideology (see Section 3.1 for details). \( u_i \) represents the individual fixed effect. \( \eta_t \) stands for the time effect, and \( \varepsilon_{it} \) is the error term. \( \alpha, \gamma \) and the vector \( \lambda \) are the
parameters to be estimated. The estimate $\gamma$ represents the average effect of the ICT maturity level on human development, which is the most important parameter in the estimation.

\[
\text{HDI}_{it} = \alpha + \gamma \text{MIMLI}_i + \text{GDPC}_{it} + \text{Gini}_{it} + \text{PE}_{it} + \text{Forest}_{it} + \text{GovtEff}_{it} + \text{Global}_{it} + u_i + \eta_i + \varepsilon_{it} \quad \ldots \quad (2.1)
\]

\[
\text{HDI}_{it} = \alpha + \gamma \text{MIMLI}_i + \text{GDPC}_{it} + \text{Gini}_{it} + \text{PE}_{it} + \text{VoteShare}_{it} + \text{Global}_{it} + u_i + \eta_i + \varepsilon_{it} \quad (2.2)
\]

\[
\text{HDI}_{it} = \alpha + \gamma \text{MIMLI}_i + \text{GDPC}_{it} + \text{Gini}_{it} + \text{PE}_{it} + \text{Forest}_{it} + \text{OverGovtIdeol}_{it} + \text{Global}_{it} + u_i + \eta_i + \varepsilon_{it} \quad \ldots \quad (2.3)
\]

### 3.3. Estimation methods

Two estimation techniques have been used to estimate the hypothesised models: (i) Panel feasible generalised least squares (FGLS) method is used to estimate the baseline model, and (ii) generalised method of moments (GMM) is applied to estimate the robustness of the baseline estimations.

#### 3.3.1. Panel FGLS method

Generalised least squares (GLS) is commonly used to estimate the unknown parameters in a linear regression model where a certain degree of potential correlation exists amongst the residuals. In these cases, ordinary least squares (OLS)-based estimations will be statistically inefficient, which can lead to flawed inferences (Wooldridge, 2010). The FGLS method is prescribed where heteroscedasticity problem can potentially arise (Wooldridge, 2010). The procedure to run FGLS to correct for heteroscedasticity is as follows:

(i) Run the regression of the dependent variable ($y$) on explanatory variables ($x_1, x_2, \ldots, x_k$) and obtain the regression residuals, $\hat{u}$.

(ii) Estimate $\log(\hat{u}^2)$ by firstly squaring the OLS regression residuals and then taking the natural log.

\[
\log(\hat{u}^2) = \alpha_0 + \delta_1 x_1 + \delta_2 x_2 + \ldots + \delta_k x_k + e \quad (3)
\]

(iii) Run the regression of $\log(\hat{u}^2)$ on $x_1, x_2, \ldots, x_k$ and obtain fitted values, $\hat{g}$.

(iv) Exponentiate the fitted values from the previous step and estimate the following:
\[ \hat{h} = \exp(\hat{g}) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (4) \]

(v) Finally, estimate the following equation

\[ y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + u \ldots \ldots \ldots (5) \]

3.3.2. GMM

GMM estimation is used to check the robustness of the baseline estimations. This method necessitates that a particular number of moment conditions are to be specified for the regression model (Wooldridge, 2010). These moment conditions are dependent upon the model parameters and the data, so their expected values are zero at the parameters’ true values. The GMM estimators are well established as consistent, asymptotically normal and efficient parameters (Wooldridge, 2010). A GMM estimation approach is appropriate here, because of the following: (i) the indicator of economic development is persistent as the correlation between the level of observations and the corresponding lagged values of 0.9977 is higher than the rule of thumb threshold of 0.800; (ii) the requirement that the number of countries \((N = 35)\) should be higher than the number of years \((T = 10)\) is met; (iii) the estimation technique takes endogeneity into account by controlling for time-invariant omitted variables and simultaneity; (iv) cross-country variations are automatically considered as the technique is consistent with the panel data analysis by definition and (v) small sample biases in the difference estimator are corrected by the system estimator (Bond et al., 2001). The specification used in this study is based on Roodman (2009a, 2009b) which is an extension of Arellano and Bover (1995). This extension checks for cross-sectional dependency and restricts instrument proliferation (Asongu & Nwachukwu, 2018; Tchamyou & Asongu, 2017; Tchamyou et al., 2019).
Identification, simultaneity and exclusion restrictions

The GMM specifications are validated with the following three fundamental issues which are considered to be vital: (i) identification, (ii) simultaneity and (iii) exclusion restrictions (Asongu & Acha-Anyi, 2019; Asongu & Nwachukwu, 2018; Tchamyou & Asongu, 2017; Tchamyou et al., 2019).

Asongu and Acha-Anyi (2019) defined identification as ‘the choice of the dependent, endogenous explaining, and strictly exogenous variables’ (p. 109). Following the findings of (Asongu & Nwachukwu, 2018; Tchamyou et al., 2019), all independent variables are considered potentially endogenous or predetermined indicators. Therefore, the gmmstyle is adopted for them. Moreover, only years are hypothesised as exogenous, and the procedure for considering ivstyle (years) is ‘iv(years, eq[diff])’ as the years becoming endogenous in first difference is not feasible (Roodman, 2009a).

Concerns over simultaneity are tackled by using the lagged value of regressors as instruments for the forward-differenced indicators. Hence, fixed effects (FE) that influence the measured relationships are eradicated utilising Helmet transformations that are performed following several scholarly studies (Love & Zicchino, 2006; Tchamyou et al., 2019). These kinds of transformations are composed of forwarding mean differencing of indicators—in contrast to subtracting preceding observations from present ones (Roodman, 2009a). This process permits orthogonal or parallel conditions between lagged regressors and forward-differenced indicators.

With regard to exclusion restrictions, in line with the identification procedure, the time-invariant variables affect economic development through the potential endogenous (or
endogenous) variables. Moreover, if and only if the null hypothesis corresponding to the difference-in-Hansen test (DHT) for instrument exogeneity is not rejected, then the underlying exclusion restriction assumption is regarded as valid. The results are reported in Section 4 (Table 4). The assumption with regard to exclusion restriction is not invalid as the null hypothesis of the DHT that is associated with instrumental variables (IV) (year, eq[diff]) is not rejected. The Sargan and Hansen overidentifying restrictions (OIRs) test suggests that the strictly exogenous variables affect economic development exclusively through the suspected endogenous variable channels (Asongu & Nwachukwu, 2018; Tchamyou et al., 2019).

4. Empirical findings

4.1. Main Results
The conventional OLS or panel data-based regression (e.g. fixed effect or random effect estimation) is not appropriate in this case as the regression coefficients would yield biased and inconsistent estimates due to heteroscedasticity and autocorrelation issues. To cope with this problem, FGLS is used to conduct baseline estimations (Romano & Wolf, 2017; Wooldridge, 2010).

Table 3 shows the estimation results based on the baseline models. The figures from columns 1 and 2, those in columns 3 and 4 and those in columns 5 and 6 indicate the regression coefficient estimates of Eqs. 2.1, 2.2 and 2.3, respectively. The ICT maturity variable is statistically significant and positive in all six cases. This result indicates that countries with high ICT maturity can demonstrate a high level of HDI. Specifically, the estimated parameters show that ICT development enhances economic development from 1% to 3.8%. As expected, the Gini index was found to have a significant negative effect on the HDI in most cases. The GDP growth, public expenditure on the social sector, environmental quality and globalisation are also found to have a positive effect on HDI in most cases. The governance indicators—
political well-being (GovtEff), political stability (VoteShare) and ideology of government are found to have a substantial positive effect on economic development.

[Table 3 about here]

4.2. Robustness checks
A series of further robustness checks was conducted to ascertain the stability of our results. Only the regression estimates using Eq. 2.3 have been reported in each case due to space constraints and to keep the paper simple.

4.2.1. GMM estimation
A GMM estimation of the proposed regression model was conducted to examine the robustness checks one step further. GMM, developed by Arellano (1991) and Arellano and Bover (1995), is widely used to check for potential endogeneity in a dynamic panel model. Difference and system GMM have been applied to estimate the impact of ICT maturity on economic development as outlined in Eq. 6.

\[
HD_I_{it} = \alpha + \gamma MIMLI + GDPG_{it} + \text{Gini}_{i} + \text{PE}_{it} + \text{Forest}_{it} + \text{OverGovtIdeol}_{it} + \text{Globalisaton}_{it} + \partial HD_I_{i,t-1} + u_t + \eta_i + \varepsilon_{it} \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (6)
\]

In Eq. 6, GDPG, Gini index and PE are assumed to be endogenous. Based on existing literature, the instruments used in the model are government expenditure, total export earnings, total investment and per capita income (Amirkhalkhali & Atul, 2019; Andrašić et al., 2018; Ghosh, 2019; Konstantakopoulou, 2017; Machova & Kotlan, 2013). Columns 1 and 2 in Table 4 report the GMM estimations using difference and system GMM, respectively. In both cases, the coefficient of ICT maturity is positive and statistically significant. This finding implies that the baseline estimates are corroborated by the findings in the dynamic panel models. The serial correlation test statistics—AR(1), AR(2) and the Hansen test statistic—are also reported to demonstrate the validity and reliability of the instruments. The p-value of the AR tests indicates
the presence of serial correlation in the second order but not in the first order. Simultaneously, the Sargan and Hansen OIR shows that the null hypothesis of the overall endogeneity of the instruments used in the estimation cannot be rejected. In sum, these results suggest that the instruments used in the model are valid and reliable.

4.2.2. 2008 Global Financial Crisis (GFC)
Any findings of the treatment effect cannot be exclusively attributed only to the second phase of ICT maturity unless other significant events did not simultaneously occur. A global event that affected economic development was the GFC which began in 2008. This crisis undoubtedly had a negative effect on innovation and research and development (R&D) in all countries, but specifically in OECD countries (OECD, 2012). The GFC may affect the innovation of OECD countries through various transmission channels. Firstly, demand for innovation goods is reduced because the economic downturn may have induced firms to spend less on innovation. Moreover, the increased competition amongst multinational companies to gain a market share may have reduced R&D expenditure during the GFC. Moreover, the reduced flow of liquidity in the financial system coupled with uncertainties associated with demand and finance might have led to a substantial decrease in innovation expenditure (OECD, 2012). OECD (2012) identified that the GFC created havoc for innovation expenditure and patent filing in eight OECD countries—Canada, Germany, USA, Sweden, The Netherlands, Japan, Luxemburg and the UK. The innovation expenditure and patent filings of these countries went below pre-crisis levels in 2009 and took a long time to recover. Excluding those eight countries, the baseline estimation was estimated again to control for the effect of the GFC ICT maturity (Table 4). In this case, column 3 reports the FE estimation with robust standard errors, and column 4 indicates the estimates using FGLS. In both cases, the main indicator of interest—ICT maturity level—is found to have a statistically significant and positive effect on
economic development. These findings corroborate the earlier claim using the baseline estimations.

(Table 4 about here)

In addition to above-mentioned robustness estimations, baseline estimations have been supplemented by corresponding OLS-based estimations (Table 4) incorporating fixed period (column 5) and fixed country effects (column 6). As expected, the inferences remain the same compared with the baseline and other robust estimations.

4.3. Diagnostic tests
Whether the assumptions of the OLS are violated before conducting the baseline estimations following Eqs. 2.1, 2.2 and 2.3 needs further research. Thus, a series of diagnostic tests was conducted after running the OLS regression using the variables of those aforementioned equations. Table 5 shows a summary of the diagnostic tests. Moreover, Table 5 shows that all models suffer from the presence of group-wise heteroskedasticity and autocorrelation problems, but they are free from the problem of multicollinearity. The variance inflation factor for the explanatory variables of Eq. 2.1 ranges from 1.16 to 3.37; for Eq. 2.2, between 1.11 and 2.33; for Eq. 2.3, between 1.07 and 2.33.

(Table 5 about here)

5. Discussion
As mentioned in the literature review, a significant association between ICT maturity and economic development has been found. However, those studies relied on partial definitions (Asongu & Le Roux, 2017; Bankole et al., 2013; Ganju et al., 2015; Nouinou et al., 2015; Palvia et al., 2018; UNDP, 2017). The current study explains the relationship between ICT maturity and economic development using a composite index of ICT maturity consisting of access, use, skills, affordability, efficiency and the quality dimensions of ICT. Using cluster
analysis based on a novel index, this study demonstrates that ICT maturity significantly catalyses economic development. The current research also differs from previous empirical work in the methodological approaches undertaken. This study employs a panel data estimation framework to investigate the influence of ICT maturity on economic development at the country level during the post-treatment period coupled with innovation efficiency. Although evidence demonstrates a causal nexus between innovation and ICT maturity, evidence on how ICT leads to economic development is limited (Arendt & Grabowski, 2017; Billon et al., 2016; Pradhan et al., 2017). The result of the regression estimations shows that ICT maturity has a significant positive effect on economic development.

A detailed picture of the association between economic development and ICT maturity would, of course, require analysis of the concrete relationship between ICT and development in particular countries. Although a full analysis of this sort is beyond the scope of this study, some descriptive statistics for particular countries are instructive insofar as they suggest areas for further research. ITU (2015) reported that the top three countries that have dynamically improved their position in terms of ICT development in recent times are Denmark, Iceland and the Republic of Korea. Our findings also suggest that throughout 2006–2015, the MIMLI in these three countries surged from 7.05 to 9.32, 7.01 to 9.07 and 7.12 to 9.39, respectively (Appendix Table B). Following the trend of their respective advancement in the ICT maturity level, during that period, the economic development (measured by HDI) in those three economies also rose from 0.90 to 0.93, 0.89 to 0.92 and 0.87 to 0.90, respectively (Appendix Table B). The correlation between economic development and ICT maturity for Denmark is the highest (0.9254) followed by Iceland (0.9085) and Republic of Korea (0.8282). Country-level case studies demystifying the ICT development in those three countries corroborated the argument that respective governments improved competition in the telecommunications sector by liberalising the market (ITU, 2015). Those countries augment their level of overall economic
development by actively promoting the use of ICTs, particularly the Internet across the entire population (ITU, 2015). Particularly, the Republic of Korea’s remarkable ICT-led development in recent decades is viewed as an interesting success story. Relevant studies claimed that a major portion of the success can be explained by knowledge accumulation during its transformation into a network state (Larson & Park, 2014; Oh & Larson, 2011).

The current study has also shown that inequality is another factor that slows economic development by impeding the distributional efficiency. This finding is consistent with that of earlier empirical studies (Chiao & Chiu, 2018; Ganju et al., 2015; Ranis et al., 2000). In addition, the findings reported in earlier empirical investigations, government effectiveness, the vote share and ideology of the ruling political parties were also found to be significant predictors of economic development. This result implies that economically right-wing parties tend to promote economic development. In sum, these results imply that good governance and sound policy regulations arising from a strong government contribute positively towards economic development. These results must be treated with caution because they are primarily included in this study as control variables. However, they are broadly consistent with focussed works of political economists (Aidt et al., 2018; Karimi & Heshmati Daiari, 2018; Potrafke, 2017; Srinivasan, 1994). The current study also found that globalisation positively affects economic development. This finding is congruent with the findings of a couple of relevant studies which reported that globalisation has a positive relationship with human development in developed countries (Atif et al., 2012; Borjas & Ramey, 1994). As suggested by endogenous growth theory, this positive association between globalisation and economic development might be mediated through technological advancements. Theses advancements can be attributed to relaxation or removal of trade barriers as a part of pro-globalisation measures (Uluçak et al., 2020). However, several studies reported that globalisation has no significant positive effect on economic development (Haseeb et al., 2020; Uluçak et al., 2020). These
results can be explained by the low level of globalisation associated with trade barriers that prevail in developing economies. In line with these findings, several scholars argued that the direction of the association between economic development and globalisation varies between developed and emerging economies due to the differentiated economic condition (Atif et al., 2012; Haseeb et al., 2020).

6. Conclusion
This empirical study investigates whether economic development responds to ICT maturity in OECD countries. To do so, a series of baseline estimations is enumerated. The study reveals that ICT maturity enhances economic development by approximately 1%–3.8% in those countries. Among the control variables, GDP growth, government expenditure, environmental quality and governance and policy variables are found as significant predictors of economic development. These findings were supported by a series of robustness checks including GMM estimations.

The findings of this empirical work have practical implications. The results imply that the holistic development of ICT can augment economic development. In this regard, ICT laggards should seek to draw lessons from the successes of recent ICT success stories, such as Denmark, Iceland and the Republic of Korea. The success of these countries suggests that easing ICT use and enhancing ICT skills are crucial dimensions to ICT development. More generally, at the country level, policymakers should devise policies to enhance the affordability of ICT services. In this study, fiscal measures and regulatory reform are possible pathways to reduce barriers to entry and prevent anticompetitive behaviour.

On a cautionary note, the present investigation has some limitations. Firstly, the findings show a general association between ICT maturity and economic development in OECD countries. However, this finding does not provide the details of this relationship or the specific policies
which can be formulated to promote ICT maturity. A detailed country-level case study or qualitative comparative analysis designed to reveal the mechanisms through which ICT maturity promotes economic development would be helpful in this regard. Secondly, we have been unable to consider the effect of ICT diffusion on inclusive development in this study, although income inequality has been included as a control variable. This limitation is because the UNDP reports inequality-adjusted HDI only every 5 years rather than annually. The connection between ICT and socioeconomic disadvantage is of great importance. Further research at the micro level or targeted for particularly disadvantaged groups would be worthwhile insofar the effect of uneven ICT development and socioeconomic inequality could be revealed. Finally, this study was conducted before the COVID-19 pandemic and does not speak directly to the effects thereof. ICT maturity is unlikely to have a significant effect on the extent to which countries are able to withstand the severe disruptions to work practices and brick-and-mortar sales. Further study in this area will be valuable once post-outbreak economic data become available.

**Declaration of competing interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Acknowledgements**

The paper is a part of the PhD study of the first author. The PhD program was funded by the University of Southern Queensland, Australia [USQ International Stipend Research Scholarship & USQ International Fees Research Scholarship].
References

Aidt, T. S., Castro, V., & Martins, R. (2018). Shades of red and blue: government ideology and sustainable development. *Public Choice, 175*(3), 303-323.

Ali, M. A., Alam, K., & Taylor, B. (2020). Incorporating affordability, efficiency, and quality in the ICT development index: Implications for index building and ICT policymaking. *The Information Society, 36*(2), 71-96.

Amirkhalkali, S., & Atul, D. (2019). Trade Openness, Factor Productivity, And Economic Growth: Recent Evidence From Oecd Countries (2000-2015). *Applied Econometrics and International Development, 19*(1), 5-14.

Andrašić, J., Kalaš, B., Mirović, V., Milenković, N., & Pjanić, M. (2018). Econometric Modelling of Tax Impact on Economic Growth: Panel Evidence from OECD Countries. *Economic Computation & Economic Cybernetics Studies & Research, 52*(4).

Arellano, M. (1991). Some tests of specification for panel data: monte carlo evidence and an application to employment equations. *Review of Economic Studies, 58*(2), 277-297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics, 68*(1), 29-51.

Arendt, L., & Grabowski, W. (2017). Innovations, ICT and ICT-driven labour productivity in Poland: A firm level approach. *Economics of Transition, 25*(4), 723-758.

Ashraf, M., Grunfeld, H., Hoque, M., & Alam, K. (2017). An extended conceptual framework to understand information and communication technology-enabled socio-economic development at community level in Bangladesh. *Information Technology & People, 30*(4), 736-752.

Ashraf, M., Grunfeld, H., & Quazi, A. (2015). Impact of ICT usage on indigenous peoples’ quality of life: Evidence from an Asian developing country. *Australasian Journal of Information Systems, 19*, 1-16.

Asongu, S. A., & Acha-Anyi, P. N. (2019). The murder epidemic: A global comparative study. *International Criminal Justice Review, 29*(2), 105-120.

Asongu, S. A., & Le Roux, S. (2017). Enhancing ICT for inclusive human development in Sub-Saharan Africa. *Technological Forecasting and Social Change, 118*, 44-54.

Asongu, S. A., & Nwachukwu, J. C. (2018). Openness, ICT and entrepreneurship in sub-Saharan Africa. *Information Technology & People, 31*(1), 278-303.
Atif, S. M., Srivastav, M., Sauytbekova, M., & Arachchige, U. K. (2012). Globalization and income inequality: a panel data analysis of 68 countries.

Baller, S., Dutta, S., & Lanvin, B. (2016). Global information technology report 2016: Ouranos Geneva.

Bankole, F. O., Osei-Bryson, K. M., & Brown, I. (2013). The impact of ICT investments on human development: A regression splines analysis. *Journal of Global Information Technology Management, 16*(2), 59-85.

Bekaroo, G., Bokhoree, C., & Pattinson, C. (2016). Impacts of ICT on the natural ecosystem: A grassroots analysis for promoting socio-environmental sustainability. *Renewable and Sustainable Energy Reviews, 57*, 1580-1595.

Billon, M., Lera-Lopez, F., & Marco, R. (2016). ICT use by households and firms in the EU: links and determinants from a multivariate perspective. *Review of World Economics, 152*(4), 629-654.

Bond, S. R., Hoeffler, A., & Temple, J. R. (2001). *GMM estimation of empirical growth models*. Retrieved from Oxford:

Borjas, G. J., & Ramey, V. A. (1994). Time-series evidence on the sources of trends in wage inequality. *The American Economic Review, 84*(2), 10-16.

Brown, W., & Brown, I. (2008). *Next generation ICT policy in South Africa: Towards a human development-based ICT policy*. Paper presented at the IFIP International Conference on Human Choice and Computers.

Budd, C. H., & Ziegler, R. (2017). Social Innovation and the Capability Approach—Introduction to the Special Issue AU - Chiappero-Martinetti, Enrica. *Journal of Human Development and Capabilities, 18*(2), 141-147.

Chiao, C., & Chiu, C. H. (2018). The Mediating Effect of ICT Usage on the Relationship Between Students’ Socioeconomic Status and Achievement. *Asia-Pacific Education Researcher, 27*(2), 109-121.

Cornell University, I., and WIPO (2017). *Global Innovation Index 2017*. Retrieved from https://www.globalinnovationindex.org/about-gii#report

Czernich, N., Falek, O., Kretschmer, T., & Woessmann, L. (2011). Broadband infrastructure and economic growth. *The Economic Journal, 121*(552), 505-532.

De Wet, W., Koekemoer, E., & Nel, J. A. (2016). Exploring the impact of information and communication technology on employees’ work and personal lives. *SA Journal of Industrial Psychology, 42*(1), 1-11.
Döring, H., & Manow, P. (2019). Parliaments and governments database (ParlGov): Information on parties, elections and cabinets in modern democracies. Development version. Retrieved from: http://www.parlgov.org/#data

Dreher, A. (2006). Does globalization affect growth? Evidence from a new index of globalization. *Applied economics, 38*(10), 1091-1110.

Ellis, L. A., Collin, P., Davenport, T. A., Hurley, P. J., Burns, J. M., & Hickie, I. B. (2012). Young men, mental health, and technology: Implications for service design and delivery in the digital age. *Journal of Medical Internet Research, 14*(6), 417-430.

Ferrigno-Stack, J., Robinson, J. P., Kestnbbaum, M., Neustadtl, A., & Alvarez, A. (2003). Internet and society: A summary of research reported at WebShop 2001. *Social Science Computer Review, 21*(1), 73-117.

Ganju, K. K., Pavlou, P. A., & Banker, R. D. (2015). Does information and communication technology lead to the well-being of nations? A country-level empirical investigation. *MIS Quarterly, 40*(2), 417-430.

Gerpott, T. J., & Ahmadi, N. (2015). Composite indices for the evaluation of a country's information technology development level: Extensions of the IDI of the ITU. *Technological Forecasting and Social Change, 98*, 174-185.

Ghosh, S. (2019). Foreign Direct Investment, Female Education, Capital Formation, and Economic Growth in Japan and South Korea. *International Economic Journal, 33*(3), 509-536.

Gopinathan, S., & Raman, M. (2016). Information system quality in work-life balance. *Knowledge Management and E-Learning, 8*(2), 216-226.

Gygli, S., Haelg, F., Potrafke, N., & Sturm, J.-E. (2019). The KOF Globalisation Index – revisited. *The Review of International Organizations, 14*(3), 543-574.

Hair, J. F. J., Anderson, R. E., Tatham, R. L., & Black, W. C. (1995). *Multivariate Data Analysis* (3rd ed.). New York: Macmillan.

Haseeb, M., Suryanto, T., Hartani, N. H., & Jermsittiparsert, K. (2020). Nexus Between Globalization, Income Inequality and Human Development in Indonesian Economy: Evidence from Application of Partial and Multiple Wavelet Coherence. *Social Indicators Research, 147*(3), 723-745.

ITU. (2009). Measuring the information society-The ICT development index. Retrieved from https://www.itu.int/ITU-D/ict/publications/idi/material/2009/MIS2009_w5.pdf
ITU. (2015). *Measuring the Information Society Report 2015*. Retrieved from https://www.itu.int/en/ITU-D/Statistics/Documents/publications/misr2015/MISR2015-ES-E.pdf

ITU. (2016). *Yearbook of Statistics: Telecommunication/ICT Indicators 2006–2015*. Retrieved from http://handle.itu.int/11.1002/pub/80decce2-en

James, J. (2014). Internet Use, Welfare, and Well-Being: Evidence From Africa. *Social Science Computer Review, 32*(6), 715-727.

Jingfeng, Z., & Zhao’an, H. (2018). Research on coupling relationship between environmental quality and regional economic growth based on VAR model. *Cluster Computing*, 1-11.

Kadijevich, D. M., Odovic, G., & Maslikovic, D. (2016). *Using ICT and Quality of Life: Comparing Persons with and Without Disabilities*. Paper presented at the International Conference on Computers Helping People with Special Needs, Cham.

Karimi, M. S., & Heshmati Daiari, E. (2018). Does Institutions Matter for Economic Development? Evidence for ASEAN Selected Countries. *Iranian Economic Review, 22*(1), 1-20.

Konstantakopoulou, I. (2017). The aggregate exports-GDP relation under the prism of infrequent trend breaks and multi-horizon causality. *International Economics and Economic Policy, 14*(4), 661-689.

Kundu, A., & Sarangi, N. (2004). *ICT and Human Development: Towards Building a Composite Index for Asia: Realising the Millenium Development Goals*: Elsevier.

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.

Larson, J. F., & Park, J. (2014). From developmental to network state: Government restructuring and ICT-led innovation in Korea. *Telecommunications Policy, 38*(4), 344-359.

Love, I., & Zicchino, L. (2006). Financial development and dynamic investment behavior: Evidence from panel VAR. *The Quarterly Review of Economics and Finance, 46*(2), 190-210.

Machova, Z., & Kotlan, I. (2013). Interaction of Taxation, Government Expenditure and Economic Growth: Panel VAR Model for OECD Countries. *Politicka Ekonomie, 61*(5), 623-638.
Madden, D., Cadet-James, Y., Watkin-Lui, F., & Atkinson, I. (2012). Healing through ICT: enhancing wellbeing in an Aboriginal community. *Journal of Tropical Psychology, 2*, 1-19.

Morales–Gómez, D., & Melesse, M. (1998). Utilising information and communication technologies for development: The social dimensions. *Information Technology for Development, 8*(1), 3-13.

Morawczynski, O., & Ngwenyama, O. (2007). Unraveling the impact of investments in ICT, education and health on development: an analysis of archival data of five West African countries using regression splines. *The Electronic Journal of Information Systems in Developing Countries, 29*(1), 1-15.

Nimrod, G. (2018). Technostress: measuring a new threat to well-being in later life. *Aging & mental health, 22*(8), 1080-1087.

Nouinou, S., Razafimampianina, R. M., Regragui, B., & Doukkali, A. S. (2015, 14-16 December). *Big data: Measuring how information technology can improve the economic growth and better life*. Paper presented at the Information and Communication Technologies (WICT), 2015 5th World Congress on Information and Communication Technologies (WICT).

Obijiofor, L. (2009). Mapping theoretical and practical issues in the relationship between ICTs and Africa's socioeconomic development. *Telematics and Informatics, 26*(1), 32-43.

OECD. (2012). *OECD science, technology and industry outlook 2012*: OECD Publishing.

Oh, M., & Larson, J. (2011). *Digital development in Korea: Building an information society* (Vol. 22): Taylor & Francis.

Palvia, P., Baqir, N., & Nemati, H. (2018). ICT for socio-economic development: A citizens’ perspective. *Information and Management, 55*(2), 160-176.

Pleninger, R., & Sturm, J.-E. (2020). The effects of economic globalisation and ethnic fractionalisation on redistribution. *World Development, 130*, 104945.

Potrafke, N. (2017). Partisan politics: The empirical evidence from OECD panel studies. *Journal of Comparative Economics, 45*(4), 712-750.

Pradhan, R. P., Arvin, M. B., Bahmani, S., & Bennett, S. E. (2017). The innovation-growth link in OECD countries: Could other macroeconomic variables matter? *Technology in Society, 51*, 113-123.
Raghupathi, W., & Wu, S. J. (2011). The Relationship Between Information and Communication Technologies and Country Governance: An Exploratory Study. Communications of the Association for Information Systems, 28, 181-198.

Ranis, G. (2004). Human development and economic growth. Yale University Economic Growth Center Discussion Paper No. 887. Retrieved from https://ssrn.com/abstract=551662

Ranis, G., Stewart, F., & Ramirez, A. (2000). Economic growth and human development. World Development, 28(2), 197-219.

Romano, J. P., & Wolf, M. (2017). Resurrecting weighted least squares. Journal of Econometrics, 197(1), 1-19.

Romer, P. M. (1990). Endogenous technological change. Journal of Political Economy, 98(5), 71-102.

Roodman, D. (2009a). How to do xtabond2: An introduction to difference and system GMM in Stata. The Stata Journal, 9(1), 86-136.

Roodman, D. (2009b). A note on the theme of too many instruments. Oxford Bulletin of Economics and Statistics, 71(1), 135-158.

Salahuddin, M., & Alam, K. (2015). Internet usage, electricity consumption and economic growth in Australia: A time series evidence. Telematics and Informatics, 32(4), 862-878.

Salahuddin, M., & Alam, K. (2016). Information and Communication Technology, electricity consumption and economic growth in OECD countries: A panel data analysis. International Journal of Electrical Power & Energy Systems, 76, 185-193.

Samoilenko, S. V., & Osei-Bryson, K. M. (2016). Human Development and Macroeconomic Returns within the Context of Investments in Telecoms: An Exploration of Transition Economies. Information Technology for Development, 22(4), 550-561.

Sen, A. (1985). Well-being, agency and freedom: The Dewey lectures 1984. The Journal of Philosophy, 82(4), 169-221.

Shahiduzzaman, M., & Alam, K. (2014). A reassessment of energy and GDP relationship: The case of Australia. Environment, Development and Sustainability, 16(2), 323-344.

Shahiduzzaman, M., & Alam, K. (2017). Trade-off between CO2 emissions and income: is there any evidence of an Environmental Kuznets Curve in Australia? Applied Economics Quarterly, 63(2), 211-231.
Sims, T., Reed, A. E., & Carr, D. C. (2017). Information and communication technology use is related to higher well-being among the oldest-old. *Journals of Gerontology - Series B Psychological Sciences and Social Sciences, 72*(5), 761-770.

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics, 39*(3), 312-320.

Sridhar, K., & Sridhar, V. (2008). Telecommunications infrastructure and economic growth: Evidence from developing countries. *Applied Econometrics and International Development, 7*(2), 37-61.

Srinivasan, T. N. (1994). Human development: a new paradigm or reinvention of the wheel? *The American Economic Review, 84*(2), 238-243.

Stephens-Reicher, J., Metcalf, A., Blanchard, M., Mangan, C., & Burns, J. (2011). Reaching the hard-to-reach: How information communication technologies can reach young people at greater risk of mental health difficulties. *Australasian Psychiatry, 19*(1), 58-61.

Tchamyou, V. S., & Asongu, S. A. (2017). Information sharing and financial sector development in Africa. *Journal of African Business, 18*(1), 24-49.

Tchamyou, V. S., Erreygers, G., & Cassimon, D. (2019). Inequality, ICT and financial access in Africa. *Technological Forecasting and Social Change, 139*, 169-184.

Ulucak, R., Danish, & Li, N. (2020). The nexus between economic globalization and human development in Asian countries: an empirical investigation. *Environmental Science and Pollution Research, 27*(3), 2622-2629.

UN. (2010). *Financing Mechanisms for Information and Communication Technology for Development*. Retrieved from [http://unctad.org/en/Docs/dtlstict20095_en.pdf](http://unctad.org/en/Docs/dtlstict20095_en.pdf)

UNDP. (2017). *Human Development Data (1990-2015)*. Retrieved from: [http://hdr.undp.org/en/data](http://hdr.undp.org/en/data)

UNU-WIDER. (2017). *World Income Inequality Database - WIID3.4*. Retrieved from: [https://www.wider.unu.edu/database/world-income-inequality-database-wiid34](https://www.wider.unu.edu/database/world-income-inequality-database-wiid34)

Walsham, G. (2017). Information Technology, Innovation and Human Development: Hospital Information Systems in an Indian State AU - Sahay, Sundeep. *Journal of Human Development and Capabilities, 18*(2), 275-292.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*: MIT press.
World Bank. (2017). *World Development Indicators*. Retrieved from:

http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators

World Bank. (2018). *World Governance Indicators*. Retrieved from:

http://info.worldbank.org/governance/wgi/index.aspx#reports

Yeung, D. (2018). Social media as a catalyst for policy action and social change for health and well-being: Viewpoint. *Journal of Medical Internet Research, 20*(3).
| Variable   | Mean  | Med   | Min   | Max   | Std  |
|------------|-------|-------|-------|-------|------|
| HDI        | 0.87  | 0.88  | 0.70  | 0.95  | 0.05 |
| GDPG       | 1.80  | 1.98  | -14.72| 25.56 | 3.66 |
| Gini       | 31.39 | 30.95 | 22.50 | 52.40 | 6.14 |
| PE         | 11.76 | 11.58 | 5.54  | 18.27 | 2.42 |
| MIMLI      | 7.10  | 7.12  | 3.55  | 9.50  | 1.17 |
| GNIPC      | 37688.5 | 38760.0 | 7350.0 | 104860.0 | 20530.2 |
| Forest     | 33.91 | 33.14 | 0.38  | 73.11 | 18.16 |
| GovtEff    | 1.31  | 1.46  | 0.09  | 2.35  | 0.53 |
| VoteShare  | 34.95 | 35.30 | 15.36 | 67.84 | 9.47 |
| OverGovtIdeol | 5.79 | 6.44 | 2.50  | 8.66  | 1.81 |
| Globalisation | 82.13 | 82.54 | 63.04 | 91.31 | 5.81 |
| GFCE       | 19.33 | 19.50 | 9.93  | 27.94 | 3.78 |
| Exp        | 50.20 | 41.23 | 10.65 | 222.70| 32.39 |
| Inv        | 23.00 | 22.69 | 9.82  | 41.54 | 4.53 |

**Table 1: Description of the variables in the regression models (N=350).**

| Description                                                                 | Reference |
|-----------------------------------------------------------------------------|-----------|
| The Human Development Index is a composite measure of three key dimensions of human development, namely healthy and long life, knowledge and a decent standard of living. | Asongu and Le Roux (2017), Aitd et al. (2018); Ranis (2004); Shahiduzzaman and Alam (2017) |
| Annual gross domestic product growth (%)                                   | Ranis (2004) |
| Gini index on income inequality                                             | Srinivasan (1994) |
| Public expenditure in education and health (as % of GDP)                   | Ranis et al. (2000) |
| The Modified ICT Maturity Level Index score                                 | Asongu and Le Roux (2017); Brown and Brown (2008); Nouinou et al. (2015) |
| Annual gross national income per capita                                     | Srinivasan (1994) |
| Forest area (% of total land area)                                          | Shahiduzzaman and Alam (2014); Shahiduzzaman and Alam (2017) |
| The perceptions of the quality of public and civil services, the degree of its independence from political pressures, the quality of policy formulation and implementation | Srinivasan (1994) |
| Share of votes received by the political parties which formed the government | Srinivasan (1994) |
| Overall ideological stance of ruling political parties in a particular country for a particular period. Each party’s overall ideology on a scale ranges between 0 (extreme left) and 10 (extreme right) | Aitd et al. (2018); Potrafke (2017) |
| KOF globalization index is a composite indicator consists of economic, social and political globalisation of a country. The index score ranges from 1 to 100. The higher the score higher the degree of globalisation | Pleninger and Sturm (2020); Uluçak et al. (2020) |
| Government final consumption expenditure (as % of GDP)                     | Andrašić et al. (2018); Machova and Kotlan (2013) |
| Total export earnings (as % of GDP)                                         | Amirkhalkhali and Atul (2019); Konstantakopoulou (2017) |
| Total public and private investment (as % of GDP)                          | Andrašić et al. (2018); Ghosh (2019) |
Data sources: UNDP (2017), UNU-WIDER (2017), World Bank (2017; 2018), ITU (2016), Cornell University et al. (2018), Döring and Manow (2019), and Gygli et al. (2019).

Note: GDPG= GDP growth, Gini= Gini index, PE= Public expenditure on the social sector, Forest= Forest area, GovtEff = government effectiveness, Vote= Vote share of the elected government, and OverGovtIdeol= Overall ideology of the government. Med: Median; Max: Maximum; Min: Minimum; Std.: Standard Deviation.
Table 2: Correlation matrix.

| Variable   | HDI     | GDPG    | Gini    | PE      | FMIMLI  | GNIPC   | Forest   | GovtEff  | VoteShare | OverGovtIdeol | Globalisation | GFCE    | Exp    | Inv    |
|------------|---------|---------|---------|---------|---------|---------|----------|----------|-----------|----------------|---------------|---------|--------|--------|
| HDI        | 1.0000  |         |         |         |         |         |          |          |           |                |               |         |        |        |
| GDPG       | 0.9539***| 1.0000  |         |         |         |         |          |          |           |                |               |         |        |        |
| Gini       | -0.5561***| 0.1197*| 1.0000  |         |         |         |          |          |           |                |               |         |        |        |
| PE         | 0.6686* | -0.2641*| -0.5420 | 1.0000  |         |         |          |          |           |                |               |         |        |        |
| FMIMLI     | 0.7747* | -0.1012***| -0.4635*| 0.5710* | 1.0000  |         |          |          |           |                |               |         |        |        |
| GNIPC      | 0.7808* | -0.0730 | -0.4576*| 0.6440* | 0.5877**| 1.0000  |          |          |           |                |               |         |        |        |
| Forest     | 0.0369 | -0.0844 | -0.0627 | 0.0825  | -0.0966***| 1.0000  |          |          |           |                |               |         |        |        |
| GovtEff    | 0.7855* | -0.0333 | -0.4397*| 0.6877* | 0.6004* | 0.7670**| 0.0395   | 1.0000   |           |                |               |         |        |        |
| VoteShare  | -0.2020*| 0.0426  | 0.4578* | -0.2536*| -0.2194*| -0.2652*| -0.0811  | -0.2215* | 1.0000    |                |               |         |        |        |
| OverGovtIdeol | 0.0505 | 0.0496  | 0.1818* | -0.0418 | 0.0284* | -0.0092 | -0.0813  | 0.0134   | -0.0381  | 1.0000         |               |         |        |        |
| Globalisation | 0.6224* | -0.1347***| -0.6303*| 0.5765* | 0.5039* | 0.5838* | -0.0240  | 0.6026** | -0.2804* | -0.1549***     | 1.0000       |         |        |        |
| GFCE       | 0.3981* | -0.3048*| -0.6090*| 0.7081* | 0.3966* | 0.2708* | -0.0584  | 0.3624*  | -0.4315* | -0.0876       | 0.4510*      | 1.0000  |         |        |
| Exp        | 0.0959  | 0.1166***| -0.3914*| -0.0769 | 0.1451**| -0.2000*| -0.0435  | -0.2341* | -0.0137  | 0.3458**       | -0.0075      | 1.0000  |         |        |
| Inv        | -0.1823*| 0.4060* | 0.0134  | -0.3144*| -0.2653*| -0.1505*| 0.2595*  | -0.0796  | -0.0372  | 0.0348         | -0.2298*      | -0.2788*| -0.0790| 1.0000 |

Note: *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively.
| Variables     | Eq. 1          | Eq. 2          | Eq. 3          |
|--------------|---------------|---------------|---------------|
|              | (1)           | (2)           | (3)           |
| GDPG         | 0.0002*       | 0.0007***     | -0.0001       |
|              | (0.0001)      | (0.0004)      | (0.0001)      |
| Gini         | -0.0008*      | -0.0005**     | -0.0008**     |
|              | (0.0003)      | (0.0003)      | (0.0003)      |
| PE           | 0.0009        | 0.0004        | 0.0009        |
|              | (0.0005)      | (0.0007)      | (0.0005)      |
| MIMLI        | 0.0088*       | 0.0300*       | 0.0088*       |
|              | (0.0006)      | (0.0022)      | (0.0006)      |
| Forest       | -0.0030**     | 0.0001*       | 0.0032**      |
|              | (0.0012)      | (0.0003)      | (0.0012)      |
| GovtEff      | 0.0013        | 0.0234*       |                |
|              | (0.0032)      | (0.0039)      |               |
| VoteShare    | 0.0001        | 0.0002***     |                |
|              | (0.0001)      | (0.0001)      |               |
| OverGovtIdeol|               |               | 0.0008*       |
|              |               |               | (0.0002)      |
| Globalisation| 0.0016*       | 0.0004        | 0.0016*       |
|              | (0.0004)      | (0.0003)      | (0.0003)      |
| Constant     | 0.6979*       | 0.6371        | 0.6935*       |
|              | (0.0337)      | (0.0312)      | (0.0340)      |
| Country FE   | Yes           | No            | Yes           |
| Time FE      | No            | Yes           | No            |
| Wald chi-    | 23825.76*     | 1654.22*      | 23882.43*     |
| squared      |               |               | 1481.66*      |
|              | 24617.28*     |               | 1491.74*      |
| Number of    | 35            | 35            | 35            |
| groups       |               |               |               |
| Time periods | 10            | 10            | 10            |
| Number of    | 350           | 350           | 350           |
| observations |               |               |               |

Note: Figures in the parentheses represent standard error. *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively.
| Variables          | GMM      | Excluding GFC affected countries | OLS      |
|-------------------|----------|----------------------------------|----------|
|                   | (1)      | (2)                              | (3)      | (4)      | (5)      | (6)      |
| GDPG              | 0.0005*  | 0.0004*                          | 0.0003***| 0.0008** | 0.0001   | 0.0003*  |
|                   | (0.0001) | (0.0001)                         | (0.0002) | (0.0004) | (0.0001) | (0.0001) |
| Gini              | -0.0004* | <0.0001                          | -0.0009***| -0.0009* | -0.0010* | -0.0008** |
|                   | (0.0001) | (<0.0001)                        | (0.0005) | (0.0003) | (0.0003) | (0.0003) |
| PE                | 0.0005   | 0.0001                           | 0.0012   | 0.0040*  | 0.0011** | 0.0008   |
|                   | (0.0005) | (0.0001)                         | (0.0011) | (0.0009) | (0.0006) | (0.0006) |
| MIMLI             | 0.0016** | 0.0001***                        | 0.0091*  | 0.0224*  | 0.0036*  | 0.0086*  |
|                   | (0.0007) | (<0.0001)                        | (0.0029) | (0.0001) | (0.0002) | (0.0012) |
| Forest            | 0.0011   | <0.0001                          | 0.0031   | -0.0003* | -0.0001  | 0.0034** |
|                   | (0.0007) | (<0.0001)                        | (0.0029) | (0.0001) | (0.0002) | (0.0003) |
| OverGovtIdeol     | 0.0001   | -0.0001                          | 0.0011** | -0.0018**| 0.0008*  | 0.0008*  |
|                   | (0.0002) | (0.0001)                         | (0.0004) | (0.0009) | (0.0002) | (0.0003) |
| Globalisation     | -0.0002  | <0.0001                          | 0.0018** | 0.0016*  | 0.0015*  | 0.0017*  |
|                   | (0.0002) | (<0.0001)                        | (0.0009) | (0.0004) | (0.0003) | (0.0004) |
| Lagged HDI        | 0.8046*  | 0.9808*                          |          |          |          |          |
|                   | (0.0375) | (0.0061)                         |          |          |          |          |
| Constant          | 0.0224*  | 0.0220*                          | 0.5603   | 0.5814   | 0.7296*  | 0.6792*  |
|                   | (0.0059) | (0.0057*)                        | (0.1393) | (0.0370) | (0.0299) | (0.0358) |
| Time FE           | Yes      | Yes                              | Yes      | Yes      | Yes      | No       |
| Country FE        | No       | No                               | No       | No       | No       | Yes      |
| R-squared         |          |                                  | 0.7188   | 0.5746   | 0.9860   |
| AR(1)             | 0.0010   | 0.0010                           |          |          |          |          |
| AR(2)             | 0.8900   | 0.5370                           |          |          |          |          |
| Sargan OIR        | 0.1240   | 0.1260                           |          |          |          |          |
| Hansen OIR        | 1.0000   | 1.0000                           |          |          |          |          |
| DHT for instruments |         |                                  |          |          |          |          |
| (a) Instruments in levels H excluding group | 1.0000 | 1.0000 |
| Dif (null, H ¼ exogenous) | 1.0000 | 1.0000 |
| (b) IV (years, eq [diff]) H excluding group | 1.0000 | 1.0000 |
| Dif(null, H ¼ exogenous) | 0.6470 | 0.9460 |
| Fisher            | 6101.62* | 9319.41*                         |          |          |          |          |
| Wald chi-squared  |          |                                  | 1054.67* | 21663.21*|
| Number of instruments | 28      | 28                               |          |          |          |          |
| No. of groups     | 35       | 35                               | 27       | 27       | 35       | 35       |
| Number of observations | 350    | 350                             | 270      | 270      | 350      | 350      |

Note: Figures in the parentheses represent standard error. *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively. DHT: difference-in-Hansen test for exogeneity of instruments’ subsets; Dif: difference; OIR: over-identifying restrictions test.
Table 5: Summary of the test for multicollinearity, heteroscedasticity and autocorrelation.

| Equation | Mean variance inflation factor | Test for group wise heteroscedasticity$^a$ | Test for autocorrelation$^b$ |
|----------|-------------------------------|-------------------------------------------|-------------------------------|
|          |                               | Test statistics | p-value | Test statistics | p-value |
| 2.1      | 2.10                          | 2516.05*        | 0.0000  | 120.15*        | 0.0000  |
| 2.2      | 1.76                          | 1916.21*        | 0.0000  | 118.94*        | 0.0000  |
| 2.3      | 1.72                          | 3835.75*        | 0.0000  | 118.48*        | 0.0000  |

Note: $^a$ Modified Wald test for group wise heteroscedasticity; $^b$ Wooldridge test for autocorrelation in panel data. *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively.