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The Impact of the Diffusion of Information and Communication Technology on Health: A Cross-Country Study

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Abstract This study employed aggregate data drawn from the World Bank database for 61 countries for the period 2000 to 2009 and quantitatively evaluated the impact of Information and Communication Technology (ICT) diffusion on health outcomes. The empirical methodology included a dynamic panel data (DPD) model and a fixed effect (FE) model. The results show that the diffusion of the Internet and fixed and mobile telephones was positively associated with life expectancy. The diffusion of fixed and mobile telephones was associated with a reduction in infant and under-five mortality rates. The diffusion of the Internet was associated with a higher prevalence of human immunodeficiency virus (HIV). The diffusion of mobile phones was associated with decreases in the incidence of tuberculosis. An important policy implication for governments worldwide is that investing in ICT infrastructures and educating the public the use of ICT can be an alternative policy to improve health.

Keywords Information and communication technology (ICT) · Diffusion · Health · Dynamic panel data model

JEL Classification I15 · I18 · H51

Introduction

Since the 1990s, rapid advancements in information and communication technology (ICT) have had a profound impact on many societies and economies. According to the

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World Bank, ICT is defined as the set of activities that facilitate the capture, storage, processing, transmission, and display of information by electronic means. The tools involved include telephone lines, wireless signals, and computers as well as enterprise software, middleware, storage, and audio-visual systems. In this study, we focus on the Internet, mobile phones, and fixed phones.

Motivated by the belief that ICT can play an important role in improving health and the quality of live (World Bank 2003), many development organizations and government agencies promote the use of ICT in the health field. For example, the World Health Organization (WHO) has proposed an "e-Health strategy" in 2004 and published *mHealth: New Horizons for Health through Mobile Technologies* (WHO 2004, 2011). The United Nation (UN) and the International Telecommunication Union (ITU) have also issued a variety of reports on promoting e-health strategies (UNESCAP/UNDP/ADB 2007). A number of studies have also documented how the application of ICT in the health field improves health outcomes. For example, Amoss (2002) recorded that the newly installed ICT equipment at the First Municipal Children's Hospital in St. Petersburg enabled physicians to overcome geographic barriers and provide long-distance medical consulting to pediatric patients. Micevska (2005) documented the cases in Peru, Bangladesh, and Laos and found that ICT tools enable real-time transmission of medical information and enhance the efficiency and outcomes of healthcare service.

However, while the existing studies documented the adoption of ICT in specific cases and evaluated the outcomes, less attention has been given to how the diffusion of ICT among the general public may change health outcomes. In this study, we define the diffusion of ICT as the proportion of population with access to ICT tools. Theoretically, ICT can facilitate the dissemination and communication of information and thus enhance the health knowledge of the general public. Members of the public with access to ICT tools can improve health literacy and develop healthier life styles (World Bank 2003; McNamara 2007; ECOSOC 2010; Ratzan 2011; Xie 2011). Furthermore, one major characteristic of the health field that often leads to problematic treatments and inefficient health outcomes is the asymmetry in information between physicians and patients (Lewis 2006). The improved accessibility of health-related information to patients (the general public) may reduce this problem. As a result, the diffusion of ICT may improve the health of the general public. In addition, many studies in other disciplines have found that ICT can be used to improve governance and reduce corruption (Lio et al. 2011; Lee and Lio 2014). The Internet provides the public with a channel to discuss public affairs and the supervision of public opinions forces governmental organizations to be more transparent (Walker and Akdeniz 1998; Ranerup 2000; Dean 2001; Shim and Eom 2008). The diffusion of ICT may thus lead to better utilization of health resources and better health outcomes. Furthermore, the flexibility and mobility of ICT tools may become critical in emergencies and render better health outcomes (Iannella et al. 2007; Vogt et al. 2011).

However, the diffusion of ICT may also create risks and lead to worse health outcomes. A large number of studies have discussed the negative health consequences of ICT use and ICT addiction. For example, Internet addiction may change dietary habits and reduce physical exercise, increasing the risks to health (Gustafsson 2009; Kim et al. 2010). ICT may also offer access to illegal, immoral or criminal material, with consequent threats to health and safety (Finkelhor 2011; Ramli 2011). In addition, the Internet offers the opportunity for easy, anonymous sexual contact, a major risk factor for sexually transmitted diseases (Bull and McFarlane 2000; Garofalo et al. 2007; Horvath et al. 2008; Sowell and Phillips 2010). Misinformation circulating in ICT platforms may also generate negative consequences to health outcomes (Scanfeld et al. 2010; Griffiths et al. 2012).

While ICT application in specific cases have been found to improve public health, it is not immediately obvious how the diffusion of ICT among the public affects health outcomes. To examine this question, this study employed international data drawn from the World Bank database on 61 countries for the period 2000–2009 and conducted empirical tests. A challenge that arises in econometric estimation lies in how to isolate the ICT-health relationship from other factors (both observed and unobserved) and measure this relationship without bias. As a result, we used a dynamic panel data (DPD) model with generalized method of moments (GMM) estimators to overcome the difficulties of empirical testing. The findings of this paper will increase our understanding of how ICT diffusion affects our health and can thus act as a reference for development organizations and policy makers.

Literature Review

ICT Adoption in the Health Field

A large number of studies have examined the impact of ICT adoption on health. Most are case studies that documented the application and outcomes of ICT in specific cases. We divided the literature into four categories based on the channel through which ICT improves health outcomes and reviewed the literature by category.

I. ICT application improves the Management and performance of health-information systems.

   Specifically, improvements arise from tracking and reminder functions used during treatment; logistical management of patient care; administrative management of medical institutions; and management of medical data, drug-stock databases, appointment systems, organ-transplant-matching systems, and billing systems. Thus, ICT application enhances the operational efficiency of medical institutions or care centers (Wireless Internet Institute 2003; World Bank 2003; Kahn 2004; Micevska 2005; Satellife 2005; McNamara 2007; Lucas 2008).

   For example, Micevska (2005) found that in Peru, Bangladesh, and Laos, basic telephone services provide an opportunity for the real-time transmission of messages. Medical health personnel can track and monitor a patient's symptoms via fixed phones or mobile phones and input data into a central database. Using timely updated medical information, personnel at medical institutions can track the infection of communicable diseases in more remote areas and allocate limited medical supplies and drugs, enabling health care personnel to make better medical decisions.

   The World Bank (2003) has also noted that many diseases that cause child mortality, such as measles and diarrhea, can be treated with vaccines or antibiotic injections. With ICT, health workers can create a database to track vaccinations and coordinate stocks of antibiotics; they can also report on and inform health services organizations in the region to reduce child mortality.

II. ICT application enables digital long-distance medical consulting and clinics.

The use of computers, e-mail, personal digital assistants, servers, network cloud-space access, electronic microscopes, and photographic digital-imaging equipment allows medical staff to overcome geographical restrictions and conduct long-distance medical care (Musoke 2001; Wireless Internet Institute 2003; World Bank 2003; Lucas 2008).

For example, the Sustainable Access in Rural India (SARI) program implemented in the province of Tamil Nadu, India, provides wireless network connections to over 50 villages and approximately 8000 people. The online diagnosis, treatment, and counseling provided by Aravind Eye Care System represent part of the application of the plan. Personnel at the medical facilities take photos of the patient's eyes and send the photos to physicians at the medical institution via e-mail. Based on these photos, eye doctors can make a preliminary diagnosis and provide advice. (Wireless Internet Institute 2003)

III. ICT application strengthens the prevention and monitoring of public-health threats.

Infectious-disease surveillance systems, emergency epidemic reporting, and information-sharing platforms increase the efficiency of information exchange as well as the prevention and monitoring of infectious diseases (World Bank 2003; Kahn 2004; Micevska 2005; McNamara 2007).

The World Bank (2003) quoted the success stories of Voxiva in Peru and noted that the medical reports of the Peruvian Medical Center were entirely recorded on paper and that it took at least 3 weeks to report outbreaks of cholera, dengue fever, malaria, and poliomyelitis to the National Health Insurance Bureau. This low efficiency may have contributed to the diffusion of the epidemic. Currently, through voice communication and over the Internet, health care organizations have been able to learn of suspected cases of diseases within a few hours or days.

In addition, South Africa has one of the highest rates of tuberculosis infection. To effectively treat and control tuberculosis, patients must be in strict compliance with medical treatment, taking four tablets of medications five times per week for 6 months. It is very easy for this treatment to fail because patients forget to take their medications. In 2002, health programs in South Africa used ICT developments, such as mobile phones, SMS technology, and computer databases, to help patients. Every half hour, the database will automatically list the patients who are due to take their medications, and these patients are then notified by SMS. Among 138 patients treated using this method, all but one successfully completed the treatment program (Kahn 2004).

IV. ICT application enhances the education and training of health personnel.

Shared platforms for research and learning, online education programs, and training courses for medical and health personnel can strengthen knowledge sharing and technical cooperation among personnel and enhance research and performance (Amoss 2002; World Bank 2003; Satellife 2005; McNamara 2007).

For example, Satellife (2005) documented the use of personal digital assistants (PDAs) in Kenya and Uganda. These small handheld devices allow the local health care personnel to store and share important health information and data and to obtain information regarding the experiences of other colleagues, which improves their own skills and practical results. In Uganda, 95 % of clinicians reported that online reference data had made them more efficient in their clinical treatment of patients, including the improvement in medical diagnosis, drug selection, and overall treatment.

Nonetheless, several studies also noted the difficulties encountered in implementing ICT in the health field. For instance, hesitancy to learn to use and to accept new technologies and a lack of the resources needed to change behaviors hindered the application of ICT in the health-care system (Hanseth and Aanestad 2003). Problems involving the integration of the software platforms used in different medical institutes also present obstacles (Anderson et al. 2006). Anderson et al. (2006) further argued that the public's concern for privacy and confidentiality when digitalizing personal medical records and integrating networks and databases has become an obstacle. Panir (2011) noted that in areas with poor ICT-related infrastructure or inadequate usage, ICT is unlikely to have positive health effects on a large scale.

ICT Diffusion and Health Outcomes

While the literature above provides a wide range of evidence that ICT adoption in the health field improves health outcomes, less attention has been given to the question of how the diffusion of ICT among the general public affects health outcomes. We argue that ICT diffusion may lead to better health outcomes, but the contrary result is also possible.

ICT diffusion can promote the dissemination and communication of health-care knowledge via digital advocacy, which can be used to disseminate knowledge regarding health and preventive measures against infectious diseases, or via online disease and drug encyclopedias. Such communication renders it easier for the general public to obtain health knowledge and information on diseases and to develop healthier lifestyles, thereby enhancing public health (World Bank 2003; McNamara 2007; ECOSOC 2010). For example, in their survey that interviewed 1506 adults and 625 children in the United States, Brodie et al. (2000) found that 31 % of the respondents have already been using the Internet for health information. This percentage increased to 61 % in 2009 as indicated by the National Health Interview Survey (NHIS) of the United States. Kummervold et al. (2008) also reported that overall 42.3 % of the population in seven European countries (Denmark, Germany, Greece, Latvia, Norway, Poland, and Portugal) used the Internet for health purposes in 2005; this number had increased to 52.2 % in 2007. In addition, the World Bank (2003) noted that in West Africa, ICT plays a key role in the control of onchocerciasis. Onchocerciasis (known as river blindness) is spread by *Onchocerca volvulus*, an insect-borne parasite associated with rivers. Residents in local villages along rivers can use computers to obtain information about diseases and then take preventive measures to prevent the spread of disease and insect pests.

The literature on health literacy, which is defined as the ability to read, understand, and use healthcare information to make decisions and is considered the most promising area for disease prevention, has argued that improving health literacy can significantly improve health outcomes based on empirical evidence (Nutbeam 2000; Paasche-Orlow and Wolf 2007; DeWalt and Hink 2009; Berkman et al. 2011). Several studies have further proposed that the progress in ICT presents opportunities to develop health literacy (Ratzan 2011; Xie 2011). For example, with an increasing amount of high-quality health information available online from government agencies and nonprofit and for-profit organizations, the Internet is already an important source of health information (Bylund et al. 2007).

The improved accessibility of health knowledge may also decrease the problem of asymmetric information that is common in the health field. The asymmetry of information between physicians and patients places patients at a disadvantage, unable to monitor the quality and appropriateness of the decisions and treatments made by medical staff, and thus sometimes results in problematic or inefficient treatments (Lewis 2006; Savedoff and Hussmann 2006). As ICT diffuses more widely and makes information more accessible to the public, the enhancement of patients' health knowledge may reduce information asymmetry and improve health outcomes.

The communication and mobility provided by ICT tools may also offer critical assistance in emergent situations. For instance, the literature on emergency management has identified ICT as one of the most promising developments in the field (Iannella et al. 2007; Vogt et al. 2011). Technologies such as mobile phones, email, geographic information systems (GIS), and global-positioning systems (GPS) have the capability to assist involved parties and emergency management personnel before, during and after an accident/disaster.

In addition, several studies in other disciplines have found that ICT can be used for oversight and thus to improve governance and reduce corruption (Lee and Lio 2014). The convenience of ICT tools and their ability to transcend space and time could encourage individuals who were previously unable or unwilling to participate in public affairs to become more engaged (Grossman 1995; Shim and Eom 2008). The oversight of public opinion may reduce the potential for bad governance or official corruption (Ranerup 2000; Walker and Akdeniz 1998; Dean 2001; Shim and Eom 2008). In addition, ICT tools also make it easier to expose scandals and investigate corruption cases. Corruption has long been a serious problem in the health field, with serious consequences for health outcomes (Transparency International 2006; Dyer 2006). Improved governance or reduced corruption prompted by ICT diffusion may improve the utilization of health resources and health outcomes.

Conversely, ICT diffusion may also lead to worse health outcomes. A large number of studies have discussed the negative health consequences of ICT use and addiction. For example, Gustafsson (2009) argued that the use of ICT involves physical exposure that can have effects on health. Certain ICT tools, including computer mice, small keyboards and small mobile-phone screens, increase the prevalence of musculoskeletal symptoms/disorders of the neck, shoulder, wrist, and lower back. Eye problems and vision disturbances are also often reported. In addition, ICT addiction may change dietary habits and reduce physical exercise, increasing the risks to health. Kim et al. (2010) examined Korean adolescents and found that high-frequency internet users tend to have irregular diets due to the loss of appetite and a high frequency of skipping meals and snacking, causing nutritional imbalances. Booth et al. (2001) studied the determinants of physical activity and found that a computer connected to the Internet was associated with physical inactivity. Furthermore, addiction to ICT was also found to be associated with psychosocial problems, such as stress, sleep disturbances, symptoms of depression, drowsiness, mood changes and reduction of time devoted to other obligations (Rosell et al. 2007).

ICT may also have negative health effects through illegal, immoral or criminal material, with consequent threats to health and safety (Finkelhor 2011; Ramli 2011). For example, Finkelhor (2011) argued that the Internet promotes crime and hatred through exposure to extreme violence and hate materials that would not otherwise be accessible; the Internet also makes children more vulnerable to sexual abuse because predators can reach them easily and in secret. In addition, the Internet offers opportunities for online sex-seeking. Various Internet venues (e.g., chat rooms, bulletin boards, virtual communities) provide abundant opportunities for initiating sexual contact. This medium is emerging as an environment with the potential risk of acquiring or transmitting sexually transmitted disease, including HIV (Bull and McFarlane 2000; Garofalo et al. 2007; Horvath et al. 2008; Sowell and Phillips 2010). These risks have the potential to result in injury, disease or death.

Furthermore, misinformation or low-quality health information in ICT platforms can also lead to negative health effects. For example, Griffiths et al. (2012) argued that the propagation of misinformation can occur rapidly with social networking technology. Scanfeld et al. (2010) found that within 345 status updates on Twitter, misinformation regarding the need for antibiotics to treat the flue spread to a total of 172,571 followers.

As a result, it is not immediately obvious how the diffusion of ICT among the public affects health outcomes. Therefore, this study is dedicated to examine this question quantitatively. The findings of this paper complement the existing literature and offer a new perspective on how ICT affects health.

Data and Methodology

The data we used to conduct the empirical study were retrieved from the World Bank database for the period 2000 to 2009. The World Bank dataset contains data from 214 countries; however, several variables were available only for certain countries and limited years. We excluded countries with incomplete data from our sample. After the missing values were removed, 61 countries remained in our sample.[1] The list of sampled countries includes 20 high-income countries, 25 middle-income countries and 16 low-income countries[2] in Africa, America, Asia, and Europe. We believe the sample is globally representative and suitable for econometric analysis.

The major challenge when quantitatively evaluating the impact of ICT diffusion on health is how to isolate the ICT-health relationship from other factors, both observed

[1] The 61 countries include Austria, Bahamas, Barbados, Belgium, Bulgaria, Burkina Faso, Chad, Costa Rica, Czech Republic, Denmark, Djibouti, Dominican Republic, El Salvador, Estonia, Fiji, Finland, France, Germany, Ghana, Hungary, Iceland, Indonesia, Ireland, Israel, Japan, Kazakhstan, Korea Republic, Latvia, Lesotho, Lithuania, Malawi, Mauritania, Mauritius, Mexico, Moldova, Netherlands, Niger, Nigeria, Norway, Panama, Paraguay, Peru, Poland, Portugal, Qatar, Romania, Slovak Republic, Slovenia, South Africa, Spain, Sweden, Switzerland, Tajikistan, Tanzania, Turkey, Uganda, Ukraine, United Kingdom, United States, Uruguay, and Uzbekistan.

[2] We adopted the income classification of the World Bank in 2000. The classification was as follows: high-income countries: GNI per capita in US dollars >9265; middle-income countries: GNI per capita in US dollars >755, <9265; low-income countries: GNI per capita in US dollars <755.

and unobserved, and obtain unbiased estimates of this relationship. For example, the general development of a country, social or economic, may affect both health condition of people and ICT diffusion. Highly developed countries tend to realize better health conditions and higher ICT penetration. Consequently, a positive correlation between health variables and ICT variables obtained from econometric estimation may simply be driven by the progress of development among sample countries and say nothing about the impact of ICT diffusion on health.

Furthermore, some unobserved characteristics of the countries might also affect both health condition of people and ICT diffusion. One example of an unobserved characteristic is the ideologies or preferences of governments or political leaders. Countries experiencing political instability or with autocratic political systems may prioritize national defense over the construction of social and economic infrastructures, leading to poor health condition of people and low ICT penetration. In this case, a positive correlation between health variables and ICT variables obtained from econometric estimation is driven by the ideologies of political leaders and cannot be indicative of a causal relationship between ICT diffusion and health. Failure to address this problem of simultaneity would result in upward-biased estimation results.

To overcome the difficulties in estimation, we proposed the use of a dynamic panel data (DPD) model with generalized method of moments (GMM) estimators. The DPD model with system GMM estimators is able to cope with the endogeneity problem caused by unobserved variables by using the dynamic properties of the data to generate proper instrumental variables. More specifically, the system GMM estimator employs the lagged values of the endogenous regressors as instruments to solve the endogeneity problem (Lio et al. 2011). In addition, the World Bank dataset includes numerous social and economic indicators, which allow us to include indicators associated with the development of a country in the estimation as control variables. The inclusion of these control variables helps to control for the impact of the progress of development of a country and better isolate and capture the impact of ICT diffusion on health.

The Dynamic Panel Data (DPD) Model

We specified the following DPD model which includes the lagged dependent variable as an explanatory variable

$$Health_{it} = \beta_0 + \beta_1 \cdot Health_{i,t-1} + \beta_2 \cdot ICT_{it} + \delta Z_{it} + \vartheta_i + \varepsilon_{it} \tag{1}$$

where i represents the country and t represents the year; Z is a set of control variables; θ_i refers to the country fixed effects; and ε_{it} are disturbances assumed to be distributed across countries with a zero mean. *Health* is the dependent variable. The inclusion of the lagged dependent variable as an explanatory variable accounts for the possible persistence of the health condition in a country. Chronic factors such as chronic diseases and chronic environmental factors may cause slow changes in a country's health condition and, as a result, the health condition in time t may depend on the health condition in time t-1.

To measure health, we referenced the United Nations Millennium Development Goals (UN MDGs). Aiming to promote health, the United Nations proposed the Millennium Development Goals in 2000, with the hope of achieving these goals by

2015. Among the eight main goals, three are directly health-related, including reducing child mortality, improving maternal health, and combating HIV/AIDS, malaria, and other diseases such as tuberculosis. The World Bank dataset provides data on all of these variables; however, the figures for maternal mortality and the prevalence of malaria are available only for certain countries and very limited years. Therefore, we excluded maternal mortality and malaria prevalence from the set of health variables. The World Bank dataset provides data on life expectancy at birth, which was also included in the data set. In total, we used five variables to represent five aspects of health: life expectancy at birth (*life*), infant-mortality rate (*mr_infant*), under-five mortality rate (*mr_five*), prevalence of HIV (*hiv*), and incidence of tuberculosis (*tuberculosis*). The details of the variable definitions and descriptive statistics are presented in Table 1.

The main explanatory variable was *ICT*, which represents the diffusion of ICT in a country. We used three variables to measure ICT diffusion: the number of internet users per 100 persons (*internet*), the number of fixed telephone subscribers per 100 persons (*phone_fixed*), and the number of mobile-phone subscribers per 100 persons (*phone_mobile*).[3] We also derived an aggregate ICT variable from the three indices by calculating the common factor score of the three variables using factor analysis.[4] This new variable, denoted *ictfac*, was used to represent the overall diffusion of ICT. We estimated Eq. (1) using four different variables.

The parameter Z denotes the set of control variables. We include variables that reflect a country's state of development in the regression to control for the impact of a country's development and better isolate the impact of ICT diffusion on health. We also include factors that might be associated with a country's health condition. The variables include per capita GDP (*gdppc*), the net primary school enrollment rate (*edu*), health expenditures per capita (*hthexppc*), the percentage of the population with access to improved sanitation facilities (*sanitation*), the percentage of the population with access to an improved water source (*water*), and the age dependency ratio (*dependency*). In the regressions for life expectancy, infant mortality, and under-five mortality, we add variables regarding immunization: the percentage of children aged 12–23 months who received vaccinations against diphtheria, pertussis, and tetanus before 12 months (*immu_dpt*) and the percentage of children aged 12–23 months who received vaccinations against measles before 12 months (*immu_m*). In addition, because studies have found that children's health has a significant relationship with maternal education (Anand and Bärnighausen 2004), we replace the net primary school enrollment rate with the net female primary school enrollment rate (*edu_female*) in the regressions for infant mortality and under-five mortality. We also include the ratio of male to female population (*sexratio*) in the HIV regression. Other control variables that we would like to include in the regression but are forced to omit due to incomplete data include the number of healthcare facilities, such as the number of hospital beds or the number of physicians.

[3] Ideally, we would have used the number of ICT users utilizing ICT in health-related activities as the explanatory variables; however, we were unable to find such data on the international scale; hence, we used the number of ICT users as proxy variables.

[4] Specifically, we used principal-component analysis to estimate the components of these three variables. Then, we used the first principal component to generate fitted values and used the fitted values as a new variable, *ictfac*.

Table 1 Variable definitions and descriptive statistics

Variable	Definition	Mean	Std. Err.	Min.	Max.
Health variables					
life	Life expectancy at birth (years).	70.419	10.821	44.076	82.931
mr_infant	Infant mortality rate. The number of infants dying before reaching 1 year of age, per 1000 live births in a given year.	25.863	29.602	1.700	111.500
mr_five	Under-five mortality rate. The number of children dying before reaching 5 years of age, per 1000 children in a given year.	38.150	50.821	2.500	217.800
hiv	Prevalence of HIV. The percentage of people ages 15–49 who are infected with HIV.	1.639	4.093	0.100	24.500
tuberculosis	Incidences of tuberculosis, per 10,000 persons.	105.455	163.870	2.4	971
ICT variables					
internet	The number of persons who have access to the internet, per 100 persons.	29.478	27.694	0.036	92.181
phone_fixed	The number of fixed telephone subscribers, per 100 persons.	28.070	20.770	0.125	74.462
phone_mobile	The number of mobile phone users, per 100 persons.	59.653	41.615	0.019	175.241
ictfac	The common factor score of *internet*, *telephone*, and *mobile* with the factor analysis.	0	1	−1.401	1.837
Control variables					
gdppc	Per capita GDP, in constant 2000 U.S. dollars.	11,177	12,457	139	41,901
edu	Net primary school enrolment rate (%).	101.440	15.245	32.199	141.438
edu_female	Net female primary school enrolment rate (%).	100.109	16.631	26.451	139.191
hthexppc	Health expenditure per capita, in international dollars converted using 2005 purchasing power parity (PPP) rates.	1364.360	1437.947	16.781	7989.936
immu_dpt	The percentage of children ages 12–23 months who received vaccinations against diphtheria, pertussis, and tetanus before 12 months.	88.556	14.987	19	99
immu_m	The percentage of children ages 12–23 months who received vaccinations against measles before 12 months.	87.461	14.656	16	99
sanitation	The percentage of population with access to improved sanitation facilities.	79.895	28.874	7	100

Table 1 (continued)

Variable	Definition	Mean	Std. Err.	Min.	Max.
water	The percentage of population with access to an improved water source.	89.500	15.509	40	100
dependency	Age dependency ratio. The ratio of dependents–people younger than 15 or older than 64–to the working-age population–those ages 15–64.	58.285	17.967	18.669	109.537
sexratio	The ratio of male to female population.	0.986	0.166	0.842	2.980

Data source: The World Bank database. Available at: http://data.worldbank.org/

We choose the system GMM estimator which is proposed by Holtz-Eakin et al. (1988) and developed by Arellano and Bover (1995) and Blundell and Bond (1998) to estimate Eq. (1). The system GMM estimator employs the lagged values of the endogenous regressors (in our case ICT variables) as instruments to solve the problem of endogeneity. Follow the suggestions of Roodman (2009), we use their second lags as instruments for ICT variables; for other control variables, we use their first and second lags as instruments. In addition, the lagged dependent variable is instrumented with its past values to solve the problem of autocorrelation in the system GMM. Follow the suggestions of Roodman (2009), we use their second lags as instruments for health variables

Empirical Findings

Life Expectancy

Table 2 shows the impact of ICT diffusion on life expectancy. For each ICT variable, we report the results of the DPD model and the fixed effect model (FE) for comparison. Overall, the models generated similar results: the coefficients of all ICT variables, except for fixed telephones *phone_fixed* in model 5, are positive and significant, suggesting that the overall diffusion of ICT (models 1 and 2) and the diffusion of individual technologies such as the Internet (models 3 and 4), fixed telephones (model 6), and mobile phones (models 7 and 8) had a positive impact on life expectancy; however, the coefficients from the DPD model, which was designed to account for potential endogeneity, are much smaller than the coefficients from the FE model. This difference might indicate an upward bias in the FE model due to endogeneity; however, the coefficients of the ICT variables in the DPD model are positive and significant, indicating that the positive impact of ICT diffusion on life expectancy is robust to different models.

Our findings suggest that as the percentage of ICT users in a country increases, life expectancy at birth also increases, holding other factors constant. This result implies that the positive influences of ICT diffusion (such as enhancement of health knowledge

Table 2 Estimation Results: ICT and overall life expectancy

	Dependent variable: *life*							
	(1) FE	(2) DPD	(3) FE	(4) DPD	(5) FE	(6) DPD	(7) FE	(8) DPD
life (t-1)		0.995*** (0.007)		0.996*** (0.007)		0.995*** (0.007)		0.997*** (0.007)
ictfac	0.849*** (0.115)	0.142*** (0.049)						
internet			0.027*** (0.003)	0.003** (0.002)				
phone_fixed					0.011 (0.009)	0.006*** (0.002)		
phone_mobile							0.006*** (0.001)	0.002*** (0.001)
gdppc	0.0001*** (0.000)	0.004 (0.004)	0.0001*** (0.0000)	0.005 (0.003)	0.0002*** (0.0000)	0.003 (0.004)	0.0002*** (0.000)	0.007** (0.003)
edu	0.026*** (0.005)	−0.002 (0.003)	0.027*** (0.005)	−0.002 (0.003)	0.023*** (0.005)	−0.002 (0.003)	0.025*** (0.006)	−0.002 (0.003)
hthexppc	0.0004*** (0.0001)	−0.0001 (0.0002)	0.0003*** (0.0001)	−0.000 (0.000)	0.001*** (0.0001)	−0.000 (0.000)	0.001*** (0.0001)	−0.000 (0.000)
sanitation	0.083*** (0.018)	0.003 (0.003)	0.089*** (0.018)	0.002 (0.003)	0.077*** (0.019)	0.001 (0.003)	0.084*** (0.019)	0.002 (0.003)
water	0.208*** (0.020)	−0.008 (0.007)	0.218*** (0.019)	−0.007 (0.007)	0.219*** (0.021)	−0.009 (0.007)	0.206*** (0.021)	−0.007 (0.007)
dependency	−0.018 (0.012)	−0.009 (0.004)	−0.008 (0.012)	−0.009*** (0.003)	−0.019 (0.012)	−0.008** (0.004)	−0.006 (0.013)	−0.011*** (0.004)
immu_dpt	0.020*** (0.007)	0.012 (0.007)	0.017** (0.007)	0.013* (0.007)	0.019** (0.008)	0.013* (0.007)	0.021** (0.008)	0.012* (0.007)
immu_m	0.017** (0.008)	0.021 (0.007)	0.019** (0.008)	0.021*** (0.007)	0.019** (0.009)	0.023*** (0.008)	0.019** (0.009)	0.022*** (0.007)
R-squared	0.81		0.81		0.80		0.81	
Hansen test		chi2(240) = 41		chi2(240) = 41		chi2(240) = 44		chi2(240) = 47
AR(2) test		*z*=0.25		*z*=0.29		*z*=0.30		*z*=0.23
Obs	610	549	610	549	610	549	610	549

Numbers in parenthesis are standard errors. Significance level: *** 1 % ** 5 % * 10 %

and better utilization of health resources) may have outweighed the negative influences of ICT use/addiction.

Infant Mortality

Table 3 shows the impact of ICT diffusion on the infant-mortality rate. The results of FE model suggest that ICT diffusion was negatively and significantly associated with infant mortality: the coefficients of the aggregate ICT variable *ictfac* in model 9 and the individual technology *internet* in model 11 are both negative and significant; however, the coefficients in the DPD models are not significant (model 10 and 12), indicating no significant impact of overall ICT or the Internet on infant mortality. The inconsistent results could be the result of downward bias in the FE coefficients due to simultaneity.

The results of the DPD model further suggest that both fixed phones and mobile phones had significant negative impacts on the infant-mortality rate. The coefficient of *phone_fixed* in model 14 and the coefficient of *phone_mobile* in model 16 are both significant and negative. This finding shows that fixed phones and mobile phones had significant impacts on infant mortality, while the Internet did not. One possible interpretation of these results might be that conditions resulting in infant mortality are often time-sensitive and involve the need for immediate communication with medical personnel due to prematurity, asphyxia resulting from a lack of oxygen at birth, and infection (WHO 2012). Infants must reach competent medical staff quickly to survive, and phones may thus have a larger effect on infant mortality. Conversely, the Internet, which may enhance parents' knowledge of infant care, is not used for communication in the same way and thus may have limited impact on infant mortality. Another possible explanation is that members of the public with access to ICT tools may utilize one tool more often than others because of preference or costs, leading to differential impacts on health.

Under-Five Mortality

Table 4 shows the impact of ICT diffusion on under-five mortality. The result in Table 4 is similar to that found for the infant-mortality rate in Table 3. The results of the FE model suggest that overall ICT and the Internet were negatively and significantly associated with under-five mortality, while the DPD models show no significant impact of overall ICT or the Internet on under-five mortality. The inconsistent results might also result from downward bias in the FE coefficients due to endogeneity.

Of the individual ICT technologies, both models consistently show that diffusion of mobile phones helped to reduce under-five mortality rates. Similarly, we interpreted this finding to be a result of the urgency of the leading causes of death of children under five, such as severe re-occurrence after a minor illness due to inadequate immunity (WHO 2012). Such situations require emergency medical care; the use of mobile phones may thus have a significantly larger effect than other ICT technologies on the prevention of under-five mortality. In addition, many fatal diseases that cause child mortality, such as measles, poliomyelitis, diphtheria, tetanus, and pertussis, can be prevented by vaccination (Kahn 2004). Therefore, mobile phones and SMS (short message service) systems that can be used to issue reminders may have improved vaccination rates, reducing mortality. Conversely, the usefulness of the Internet is

Table 3 Estimation Results: ICT and infant mortality rate

	Dependent Variable: *mr_infant*							
	(9) FE	(10) DPD	(11) FE	(12) DPD	(13) FE	(14) DPD	(15) FE	(16) DPD
mr_infant (t-1)		0.970*** (0.008)		0.968*** (0.008)		0.972*** (0.007)		0.969*** (0.008)
ictfac	−2.318*** (0.461)	−0.099 (0.096)						
internet			−0.043*** (0.014)	−0.004 (0.003)				
phone_fixed					−0.052 (0.036)	−0.013** (0.007)		
phone_mobile							−0.034*** (0.005)	−0.003** (0.001)
gdppc	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000*** (0.000)	−0.000 (0.000)	−0.000 (0.000)
edu_female	−0.027 (0.023)	−0.028 (0.008)	−0.023*** (0.023)	−0.028*** (0.008)	−0.016 (0.023)	−0.027*** (0.007)	−0.025 (0.023)	−0.028*** (0.008)
hthexppc	0.000 (0.000)	0.000 (0.000)	0.0003 (0.0004)	0.000 (0.000)	−0.001** (0.0004)	0.000 (0.000)	0.0005 (0.0004)	0.000 (0.000)
sanitation	−0.356*** (0.058)	−0.012 (0.009)	−0.347 (0.059)	−0.014*** (0.009)	−0.295*** (0.061)	−0.016 (0.009)	−0.372*** (0.057)	−0.010 (0.008)
water	−0.783*** (0.077)	0.023 (0.022)	−0.813 (0.078)	0.023*** (0.022)	−0.809*** (0.078)	0.014 (0.023)	−0.744*** (0.077)	0.017 (0.022)
dependency	0.146*** (0.049)	0.012 (0.013)	0.203 (0.047)	0.013*** (0.013)	0.249*** (0.045)	0.018 (0.015)	0.114*** (0.049)	0.014 (0.014)
immu_dpt	−0.127*** (0.024)	−0.011 (0.010)	−0.122 (0.024)	−0.009*** (0.012)	−0.126*** (0.024)	−0.003 (0.013)	−0.136*** (0.024)	−0.010 (0.010)
R-squared	0.86		0.86		0.87		0.86	
Hansen test		chi2(216) = 47		chi2(216) = 42		chi2(216) = 47		chi2(216) = 49
AR(2) test		*z*=1.49		*z*=1.49		*z*=1.49		*z*=1.51
Obs	610	549	610	549	610	549	610	549

Numbers in parenthesis are standard errors. Significance level: *** 1 % ** 5 % * 10 %

Table 4 Estimation Results: ICT and mortality of children under five

	Dependent Variable: *mr_five*							
	(17) FE	(18) DPD	(19) FE	(20) DPD	(21) FE	(22) DPD	(23) FE	(24) DPD
mr_five (t-1)		0.967*** (0.012)		0.966*** (0.012)		0.967*** (0.011)		0.964*** (0.012)
ictfac	−3.107*** (0.840)	−0.089 (0.168)						
internet			−0.063*** (0.025)	−0.001 (0.004)				
phone_fixed					−0.014 (0.064)	0.011 (0.012)		
phone_mobile							−0.044*** (0.010)	−0.005** (0.002)
gdppc	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000*** (0.000)	−0.000 (0.000)	−0.000 (0.000)
edu_female	−0.106*** (0.042)	−0.028** (0.014)	−0.102*** (0.042)	−0.027** (0.013)	−0.092** (0.042)	−0.027** (0.012)	−0.102*** (0.041)	−0.028** (0.013)
hthexppc	0.001 (0.001)	−0.000 (0.000)	0.0008 (0.0009)	−0.000 (0.000)	−0.001 (0.001)	0.000 (0.000)	0.001 (0.001)	0.000 (0.000)
sanitation	−0.705*** (0.097)	−0.022 (0.018)	−0.691 (0.098)	−0.023*** (0.018)	−0.647*** (0.101)	−0.021 (0.017)	−0.728*** (0.097)	−0.021 (0.016)
water	−1.322*** (0.139)	0.045 (0.048)	−1.355 (0.139)	−0.045*** (0.048)	−1.349*** (0.140)	0.031 (0.046)	−1.276*** (0.139)	0.038 (0.047)
dependency	0.061 (0.089)	0.028 (0.019)	0.128 (0.085)	0.030 (0.019)	0.200*** (0.082)	0.033* (0.020)	0.024 (0.090)	0.031 (0.021)
immu_dpt	−0.140** (0.061)	0.037 (0.035)	−0.127** (0.061)	−0.039** (0.035)	−0.128** (0.061)	0.041 (0.034)	−0.152*** (0.060)	0.034 (0.034)
immu_m	−0.250*** (0.065)	−0.075** (0.038)	−0.258** (0.065)	−0.075*** (0.038)	−0.264*** (0.066)	−0.070** (0.037)	−0.247*** (0.065)	−0.073** (0.037)
R-squared	0.88		0.88		0.89		0.88	
Hansen test		chi2(240) = 48		chi2(240) = 39		chi2(240) = 46		chi2(240) = 47
AR(2) test		*z*=0.84		*z*=0.86		*z*=0.89		*z*=0.82
Obs	610	549	610	549	610	549	610	549

Numbers in parenthesis are standard errors. Significance level: *** 1 % ** 5 % * 10 %

relatively limited in emergent situations. Variation in the frequencies of utilizing different ICT tools in health-related activities may also have contributed to our findings.

Prevalence of HIV

Table 5 presents the impact of ICT diffusion on the prevalence of HIV. This variable trended in the opposite direction from those previously discussed. The results of the FE model show that the diffusion of overall ICT and all individual technologies was positively associated with the prevalence of HIV. In the DPD models, while other variables show no significant effect on HIV prevalence, the coefficient of *internet* is positive and significant. These findings suggest that when other variables are controlled for, greater ICT diffusion (especially greater Internet diffusion) was related to a higher prevalence of HIV. A possible explanation could be that the positive influences of ICT diffusion might have been outweighed by the negative influences. Specifically, while the Internet can promote sexual health (Keller et al. 2002), it also offers the opportunity to solicit multiple sex partners and seek unsafe sex, leading the spread of sexually transmitted diseases such as HIV.

Tuberculosis

Table 6 shows the impact of ICT diffusion on the incidence of tuberculosis. The coefficients of the aggregate ICT variable *ictfac* in FE model 33 and the individual technology *internet* in FE model 35 are both negative and significant; however, the coefficients of these two variables in the DPD models are not significant (models 34 and 36), indicating that overall ICT or the Internet had no significant impact on the incidence of tuberculosis. The result of the DPD model further suggests that mobile phones were the only ICT technology with a significant impact on the incidence of tuberculosis. As indicated in Literature Review, patients must strictly comply with medical treatment to effectively treat and control tuberculosis (four tablets of medication five times per week for 6 months). As a result, possession of mobile phones (and SMS technology) that can be used to issue reminders may facilitate treatment and thus decrease the prevalence of tuberculosis. Another possible explanation is that people with access to ICT tools other than mobile phones may utilize those tools in health-related activities only infrequently.

The results for the other control variables, as expected, indicate that the health status of a country was positively associated with its social and economic development. Per-capita GDP, the net primary-school enrollment rate, per-capita health expenditures, the rate of vaccination against DPT and measles, and access to an improved water source and sanitation facilities are positively associated with most of the health variables. These results are in line with those of Gupta et al. (2002, 2003). The age-dependency ratio is negatively associated with most of the health variables. In addition, the results for *sexratio* in the HIV regression correspond to the recent finding of a “feminizing” global HIV/AIDS pandemic: the prevalence of HIV is generally higher in women than in men (Dworkin and Ehrhardt 2007; Hertog 2008).

For each estimation of the DPD model, we performed the Hansen test and the AR(2) test to test for over-identification or autocorrelation in the estimates. The chi-squared statistics of the Hansen test and the z statistics of the AR(2) test are also reported in

Table 5 Estimation Results: ICT and prevalence of HIV

	Dependent variable: *hiv*							
	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)
	FE	DPD	FE	DPD	FE	DPD	FE	DPD
hiv (t-1)		0.999*** (0.005)		0.998*** (0.005)		0.998*** (0.006)		0.998*** (0.006)
ictfac	0.143*** (0.039)	−0.004 (0.015)						
internet			0.003** (0.001)	0.002* (0.001)				
phone_fixed					0.001 (0.003)	−0.0002 (0.0003)		
phone_mobile							0.002*** (0.001)	−0.0008 (0.0002)
gdppc	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000*** (0.000)	−0.000 (0.000)	−0.000 (0.000)
edu	0.0007 (0.002)	−0.001 (0.0001)	0.0005 (0.002)	−0.001 (0.001)	0.000 (0.002)	−0.001 (0.001)	0.0007 (0.002)	−0.001 (0.001)
hthexppc	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
sanitation	0.006 (0.007)	−0.001* (0.0006)	0.007 (0.007)	−0.001 (0.0006)	0.008 (0.007)	−0.001 (0.001)	0.005 (0.007)	−0.001* (0.0005)
water	−0.057*** (0.006)	−0.003 (0.002)	−0.057*** (0.006)	−0.003 (0.003)	−0.057*** (0.006)	−0.002 (0.003)	−0.058*** (0.006)	−0.003 (0.002)
dependency	0.010*** (0.004)	0.003* (0.001)	0.013*** (0.004)	0.003* (0.002)	0.015*** (0.004)	0.003 (0.002)	0.007* (0.004)	0.003* (0.002)
sexratio	−0.332** (0.167)	−0.059 (0.044)	−0.357*** (0.169)	−0.063 (0.041)	−0.307** (0.176)	−0.001 (0.051)	−0.313* (0.166)	−0.056 (0.036)
R-squared	0.25		0.23		0.23		0.26	
Hansen test		chi2(235) = 47		chi2(235) = 33		chi2(235) = 46		chi2(235) = 47
AR(2) test		*z*=1.34		*z*=1.33		*z*=1.33		*z*=1.35
Obs	610	549	610	549	610	549	610	549

Numbers in parenthesis are standard errors. Significance level: *** 1 % ** 5 % * 10 %

Table 6 Estimation Results: ICT and prevalence of tuberculosis

	Dependent variable: *tuberculosis*							
	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
	FE	DPD	FE	DPD	FE	DPD	FE	DPD
tuberculosis (t-1)		1.035*** (0.011)		1.036*** (0.011)		1.038*** (0.011)		1.034*** (0.011)
ictfac	−7.555* (4.346)	−1.454 (1.695)						
internet			−0.366*** (0.129)	−0.023 (0.042)				
phone_fixed					−0.439 (0.342)	0.041 (0.093)		
phone_mobile							0.036 (0.054)	−0.040* (0.020)
gdppc	−0.002* (0.001)	0.0005 (0.0001)	−0.002 (0.001)	0.000 (0.000)	−0.002** (0.001)	0.000 (0.000)	−0.002** (0.001)	−0.000 (0.0001)
edu	−0.475** (0.212)	−0.124 (0.141)	−0.453** (0.211)	−0.117 (0.138)	−0.523*** (0.211)	−0.118 (0.139)	−0.524*** (0.212)	−0.129 (0.139)
hthexppc	0.005 (0.004)	0.001 (0.001)	0.008 (0.005)	0.0008 (0.0008)	−0.001 (0.003)	0.001 (0.001)	−0.0002 (0.003)	0.001 (0.001)
sanitation	−0.285 (0.669)	−0.161*** (0.077)	−0.362 (0.672)	−0.176** (0.089)	−0.028 (0.686)	−0.177** (0.088)	−0.182 (0.672)	−0.135** (0.066)
water	−4.265*** (0.683)	−0.502*** (0.264)	−4.296*** (0.678)	−0.555** (0.283)	−4.349*** (0.682)	−0.579** (0.291)	−4.388*** (0.686)	−0.492** (0.233)
dependency	1.777*** (0.464)	0.376*** (0.181)	1.826*** (0.442)	0.352** (0.174)	1.468*** (0.424)	0.346** (0.167)	1.301*** (0.474)	0.430** (0.196)
R-squared	0.26		0.26		0.27		0.26	
Hansen test		chi2(211) = 54		chi2(211) = 51		chi2(211) = 51		chi2(211) = 51
AR(2) test		*z*=1.05		*z*=1.05		*z*=1.06		*z*=1.06
Obs	610	549	610	549	610	549	610	549

Numbers in parenthesis are standard errors. Significance level: *** 1 % ** 5 % * 10 %

Tables 2, 3, 4, 5 and 6. The statistics are all non-significant, indicating no over-identification or autocorrelation.

Conclusions

There is a large body of literature documenting the application and outcomes of ICT in the health field; however, less attention have been given to the impacts of the diffusion of ICT among the general public. This study is dedicated to empirically examine how ICT diffusion affects health outcomes.

Overall, our findings suggest that promoting the diffusion of ICT among the public can improve health outcomes. The estimation results show that the diffusion of ICT has had significant effects on health outcomes. Furthermore, the effect of individual ICT tools in improving health outcomes differed, which we infer was because of the different functionalities of the ICT tools and the features of the diseases (or health indicators).

An important policy implication embedded in our findings for governments worldwide is that, in addition to devoting resources to specific cases or regions to improve health, investments in ICT infrastructures and educating the public the use of ICT can be an alternative policy to improve public health. With proper guidance, education, and access to ICT tools, the public can become active agents, exploring and benefiting from the new technology to complement government-directed efforts to improve health and the quality of life.

A limitation of this study pertains to the interpretation of our findings. Because the methodology adopted in this study was secondary data analysis, the interpretation of most of the findings in our study is primarily based on inference.[5] As a result, future studies, especially small-scale case studies, will be necessary to corroborate and justify our interpretations. In addition, as smartphones with Internet access become more common, it will be difficult to distinguish between Internet users and mobile phone users. As a result, a newly defined variable will be needed for future research.

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[5] For example, the findings show that the use of mobile phones had a greater effect than other ICT technologies on the prevention of infant mortality, and we infer this result was because of the superior communication functionality of mobile phones, given that the major cause of infant mortality was often time-sensitive and involved the need for immediate communication.

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