

Feng, Xiaodong; Jayakar, Krishna; Zhang, Huiping; Tang, Zhiwei

## Conference Paper

Does the adoption of Information and Communication Technologies improve the subjective well-being of citizens? A micro-level and city-level empirical investigation

22nd Biennial Conference of the International Telecommunications Society (ITS): "Beyond the Boundaries: Challenges for Business, Policy and Society", Seoul, Korea, 24th-27th June, 2018

## Provided in Cooperation with:

International Telecommunications Society (ITS)

*Suggested Citation:* Feng, Xiaodong; Jayakar, Krishna; Zhang, Huiping; Tang, Zhiwei (2018) : Does the adoption of Information and Communication Technologies improve the subjective well-being of citizens? A micro-level and city-level empirical investigation, 22nd Biennial Conference of the International Telecommunications Society (ITS): "Beyond the Boundaries: Challenges for Business, Policy and Society", Seoul, Korea, 24th-27th June, 2018, International Telecommunications Society (ITS), Calgary

This Version is available at:

<https://hdl.handle.net/10419/190381>

### Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

### Terms of use:

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*

# **Does the adoption of Information and Communication Technologies improve the subjective well-being of citizens?**

## **A micro-level and city-level empirical investigation**

Xiaodong Feng, University of Electronic Science and Technology of China  
Krishna Jayakar, Penn State University<sup>1</sup>  
Huiping Zhang, University of Electronic Science and Technology of China  
Zhiwei Tang, University of Electronic Science and Technology of China

Paper presented at the International Telecommunications Society  
Annual Convention, 2018  
Seoul, South Korea

### **Abstract**

*This paper investigates the role of information and communication technologies (ICT) adoption and usage in enhancing the subjective well-being (SWB) of citizens, using the latest available China General Social Survey (CGSS) database. The impact is assessed using a two-level hierarchical linear model (HLM) accounting for both individual- and city-level characteristics. The findings suggest that government policies to increase the adoption of broadband and ICTs have implications beyond economic growth and opportunity, extending to the “happiness” of citizens.*

### **Introduction**

Traditionally, economic analyses have focused on economic growth (specifically of gross domestic product, GDP) as the primary measure of development. Research has found a strong correlation between GDP per capita and a number of measures of social welfare including adult literacy (Reder, 2010), life expectancy (Hansen & Lonstrup, 2015) and infant mortality (Hales, Howdenchapman, Salmond, Woodward, & Mackenbach, 1999; Osawe, 2014). Though the direction of causation is debatable, the correlation between economic growth as represented by GDP per capita and measures of social welfare are so strong that GDP per capita is often used as a proxy for social development and individual wellbeing.

However, over the last two decades, a concern has emerged that economic growth alone is not improving subjective measures of well-being. This observation, commonly called the Easterlin paradox, is based on the observation that indices of self-reported “happiness” have not improved in the Western economies, despite a doubling or tripling of GDP in the post-World War II period (Easterlin, 1995). Despite improvements in objective measures such as longer life expectancy, better education and generally

---

<sup>1</sup> Corresponding Author, email [kpj1@psu.edu](mailto:kpj1@psu.edu)

improving living standards, people are not reporting that they are happier or more fulfilled in their everyday life.

Researchers initially responded to this paradox by attempting to identify a broader set of variables that addressed different dimensions of quality of life. As early as the 1970s, Nordhaus and Tobin (1973) proposed an alternative to GDP based on the premise that GDP is a measure of production whereas social wellbeing is a function of consumption. They proposed a metric titled Measure of Economic Welfare (MEW) that included household and public consumption, allowances for negative externalities such as environmental damage, and “disamenities” (reductions) for social ill such as urbanization and industrialization. A similar composite index was proposed by Cobb and Daly (1989), called the Index of Sustainable Economic Welfare (ISEW). The United Nations Development Program (UNDP) implemented the widely used Human Development Index (HDI) and its opposite, the Human Poverty Index (HPI), that included variables such as life expectancy at birth, school enrollment rates, adult literacy rates, etc. (Kula, Panday, & Mantia, 2010). An even broader composite metric, titled the Human Enabling (HENX) Index, was proposed by Kula, Panday and Parrish (2008), which included quality of government, freedom of information and association, living standards, and opportunities to participate in economic life. Other broad indices include the Cato Institute’s Human Freedom Index (Vasquez & Porcnik, 2016) and the Heritage Foundation’s Index of Economic Freedom (Miller, Kim, & Roberts, 2018).

A common element of these indices proposed as alternatives of GDP is that they are based on objective metrics that are often available from national statistical organizations. But a substantial literature has also emerged on “subjective well-being” (SWB) as an alternative measure of social welfare. Researchers were initially ambivalent about using subjective measures. They questioned whether happiness was a true indicator of human progress; whether it can be compared across cultures; whether it was a Western construct irrelevant in the rest of the world, etc. (Diener, 2009). Eventual acceptance of SWB as a field of academic study required not just a theoretical emphasis away from objective (observable) metrics to include self-reported measures of well-being, as well as new methodological tools for enabling interpersonal comparisons of subjective measures. Through the work of scholars such as Diener (2009), Kahneman (1994), and others, the investigation of SWB (“happiness studies”) has become a respectable social scientific discipline. A number of indices have been proposed aiming to measure SWB: the Gross National Happiness (GNH) Index (Center for Bhutan Studies and GNH, 2016), the World Happiness Report (Helliwell, Layard, & Sachs, 2017) and the Happy Planet Index (Jeffrey, Wheatley, & Abdallah, 2016).

Research has identified many factors that contribute to SWB, as reviewed below. Of these, the contributions of information and communication technologies (ICTs) to SWB have been less thoroughly studied. The impact of computers, broadband and ICTs in general on economic growth, household incomes and employment have been well-documented elsewhere. The consensus in the literature is that ICTs improve the

economic well-being of citizens. Research has also shown that ICT use increases social and political engagement and empowerment. For example, ICT use provides networking opportunities and accessibility for participating in society (Baker, Hanson, & Myhill, 2009); improves educational opportunity through online education (Ellis, 2011) and enables workforce participation through telecommuting and telework (Fuhr & Pociask, 2011). These factors are often mentioned as correlated with SWB.

Nonetheless, the impact of ICT use on SWB has been studied only by a few (Cotten, Goldner, Hale, & Drentea, 2011; Ganju, Pavlov & Banker, 2016; Leung, 2009). Ganju, Pavlou and Banker (2016) found that ICT use contributed to increases in SWB. However, due to limitations of data, their research was conducted using data aggregated at the country level. Leung (2009) investigated the relationship between Internet connectedness, information literacy and quality of life using a random survey of 756 individuals. He found that internet connectedness and information literacy were significantly correlated, and in turn information literacy was strongly associated with quality of life. Taking the opposite route, Cotten et al (2011) studied the relationship between online health information access and psychological distress (a negative indicator of SWB). They found that online health information reduced psychological distress, but comparing among Internet users alone, heavy use was correlated with greater distress. Both Leung (2009) and Cotten et al (2011) used a number of demographic variables as controls, such as gender, age, education, family income, and hours spent at work, but did not account for other predictors commonly correlated with SWB such as religiosity or social connections (see below in section on Predictors of SWB). To fill this gap in the literature, this paper will use individual level data from the latest available China General Social Survey (CGSS), to study the connection between ICTs and SWB.

The rest of the paper proceeds as follows. In the next section, we discuss predictors of SWB from the research literature with the goal of identifying other variables to be included in the model to control for alternative explanations of SWB. This section also discusses previous studies of ICTs and SWB, specifically Ganju, Pavlou and Banker (2016), that comes closest to our goals in this paper. The next section presents our data, followed by a section on method. The results are then presented, and finally the discussion and conclusions.

### **SWB and its predictors**

Though it is one of the primary drivers of human life (“the pursuit of happiness”), the concept of “happiness” is hard to define. Diener (2009) presents a thorough review of the literature, cataloging the three broad ways happiness has been defined since the ancient Greeks to modern times. For the Greeks, happiness was defined as *eudaemonia*, an objective characteristic based on the observable virtue or holiness of an individual. Modern social scientists define happiness subjectively as “life satisfaction,” relying on the “standards of the respondent to determine what is the good life” (Diener, 2009, p.

13). A third definition comes closer to what we think of as happiness in everyday language: pleasant emotional experience. “(T)he person is experiencing mostly pleasant emotions during this period of life or that the person is predisposed to such emotions, whether or not he or she is currently experiencing them” (p. 13).

According to Diener (2009), modern definitions of SWB share three characteristics: first, they are subjective, based on the self-reports of respondents; second, they include positive measures and not just the absence of negative factors such as pain or alienation; and third, they are based on an overall assessment of a person’s life, and not just on feelings within a domain (e.g. career or family life). SWB may however be measured within narrower time frames like a week. The expectation is that though people undergo fluctuations in SWB subject to everyday occurrences, most individuals have a baseline SWB to which they return.

Numerous scales have been proposed to operationalize SWB, from single-item measures to multi-item scales (see Table 1, Diener, 2009, p. 16 for a sampling of these scales). Multi-item scales typically measure cognitive judgmental evaluations of “life satisfaction,” as well as affective components: the frequency, duration, and intensity of positive and negative affective states. However, Diener (2009) finds that single-item measures, while having lower reliability than multi-item scales, have satisfactory convergent, construct and criterion validities. In their work on investigating SWB in the workplace, Williams and Smith (2016) found single-item measures to be a valid approach. For the purposes of this article, it was therefore considered sufficient to operationalize SWB with a single-item measure querying respondents about their “life as a whole” (see Data section below for more on this measure).

Turning to predictors of SWB, researchers have extensively examined the factors contributing to SWB scores. One of the primary drivers is material well-being, as represented by personal or household income (Diener, Tay, & Oishi, 2013; Pouwels, Siegers, & Vlasblom, 2008; van Hoorn, 2008). But this effect is not simple and linear. First, as demonstrated in the Easterlin paradox, the effect of rising prosperity on SWB diminishes after societies have achieved a certain living standard (Easterlin, 1995). Later research has challenged the Easterlin paradox: for example, Weimann, Knabe and Schob (2015) review the evidence from multiple studies and argue that rising incomes do affect SWB scores. However, it is not the absolute income that matters but changes in income, and the same percentage change has a stronger effect at lower income levels than at higher incomes. Using a time series of data from multiple countries, Stevenson and Wolfers (2008) also found evidence for the income effects on SWB.

An added complexity in the relationship between income and SWB is that individuals are not just concerned about their own material wealth, but how their income and living standards compare to those of their neighbors and associates. According to this argument, income inequality is associated with lower SWB scores (Verme, 2011). But some countries view inequality more negatively: for example, Europeans have a greater

preference for equal income distributions than Americans do (Alesina, Tella, & Macculloch, 2004). Based on this evidence, we include income as a predictor of SWB in our analysis. We suitably modify the variable to accommodate the research findings that (1) there is a diminishing effect of income on SWB, and (2) the individual's income relative to that of the community predicts SWB.

An explanation for the complicated relationship between income and SWB might be that the effort to earn income may impose significant disutility on the individual (Knabe & Ratzel, 2010). Conversely, leisure is a significant predictor of SWB (Pouwels, Siegers, & Vlasblom, 2008; van Hoorn, 2008). Not just the amount of leisure time, but also what you do with leisure, i.e., leisure activities have been found to be positively associated with life satisfaction (Brajša-Zganec, Merkas, & Sverko, 2010). Regular meetings with others in the community build relationships, generate positive emotions, help acquire knowledge and skills, and thus help individuals increase their overall life satisfaction. To accommodate these effects, we include two additional variables as predictors of SWB: leisure hours, and social activities.

The main predictor of interest in this analysis is ICT use. Following previous research (Cotten, Goldner, Hale, & Drentea, 2011; Ganju, Pavlov & Banker, 2016; Leung, 2009), we include a measure of ICT as a predictor in our model. To justify the inclusion of ICT use as a predictor of SWB, Ganju, Pavlov and Banker (2016) point to the impact of ICTs on social capital and social equality, health, education, and economic opportunity. In other words, individuals with better access to ICTs are able to realize many of the antecedents of life satisfaction, such as a wider social network, access to better health information, education and employment opportunities. By allowing individuals to access political information and to petition government officials, ICT connectivity also increases social empowerment and political participation. Cotton et al.'s (2011) analysis of secondary data from the National Cancer Institute's Health Information National Trends Survey used the type, amount and timing of Internet use as predictors of psychological distress.

If the researchers cited in the introduction and in the paragraph above show significant positive impacts of ICTs (Baker, Hanson, & Myhill, 2009; Cotten, et al., 2011; Ellis, 2011; Fuhr & Pociask, 2011; Ganju, Pavlov & Banker, 2016; Leung, 2009), other researchers have been more ambivalent. ICTs can be dis-empowering for some individuals: a phenomenon that has been labeled "technostress" (Ayyagiri, Grover, & Purvis, 2011; Raghunathan, Tarafdar, Raghunathan, & Tu, 2003). These include the feelings of helplessness and incompetence accompanying engagement with a new technology, device or service, the constant demands of time and attention from people on the network, and fears of cyber-intrusions, attacks and loss of privacy and security. Social media, often considered tools of friendly networking, can also lead to feelings of anxiety, inadequacy, and depression, in sum, "Facebook envy" (Tandoc, Ferrucci & Duffy, 2015). Intensive social media engagement can even be so stressful as to induce actual physiological illnesses in college students (Campisi, Bynog, Mcgehee, Oakland,

Quirk, Taga & Taylor, 2012). We therefore include ICT access as a predictor in our model, without hypothesizing a specific direction of effect.

A number of demographic variables have been used as controls in previous research on SWB. Cotten et al (2011) used gender, age, race, marital status, education and family income as controls. Ganju, Pavlov and Banker (2016), in their analysis of country level data, used primary school enrollment, level of health, religious belief, average volunteer time, quality of air and water as controls. There is strong justification to include religion as a predictor of SWB from other research as well (Doane, 2013; Lim, 2015).

In addition to the individual-level variables identified as predictors in the literature, research also shows that community characteristics also affect an individual's sense of well-being. It has already been discussed that individuals compare their income to that of their community in assessing their life satisfaction. In addition, research has also found that the presence of social networks and safety-net welfare programs in communities can affect the level of wellbeing of its residents (Requena, 2010). In their comparison of a multinational sample of respondents, di Tella, McCulloch and Oswald (2003) found individual-level and country-specific variables as significant predictors of wellbeing. Helliwell (2003) too used individual-level and societal-level data to assess SWB. Following this research, we include a number of community level variables as predictors of SWB in our study.

More information on the operationalization and measurement of these variables, as well as sources of data are discussed in the next section.

## **Data**

Previous research on ICTs and SWB by Ganju, Pavlou and Banker (2016) and others were based on aggregated measures of SWB (subjective well-being) at the country level, due to limitations of data. In this paper, to measure the SWB and the micro-level factors we use individual-level data from one of the earliest nationally representative surveys aimed at systematically monitoring the changing relationship between social structure and quality of life. Launched in 2003, the China General Social Survey (CGSS)<sup>2</sup> database covers all 28 provinces, municipalities and autonomous regions in China including both urban and rural areas. The CGSS has been accepted as representative of mainland China in the International Social Survey Program. For our analysis, we use the last available year of data (2013), which included approximately 10,000 individual-level observations. It uses face-to-face interviews and has a set of strict quality control procedures. This paper uses the whole set of observations after necessary data cleaning and processing. For city-level characteristics, data were compiled from the China City Statistical Yearbook for cities that appears in the CGSS (2013) survey as the individual's place of residence.

---

<sup>2</sup> CGSS official website: <http://www.chinagss.org/index.php?r=index/index>

Dependent Variable: The dependent variable in this analysis is SWB, a self-reported measure of satisfaction with life. As argued by Diener (2009), a single-question instrument for SWB may provide a valid metric of the concept, though it is not as reliable as multi-item metrics and admittedly it does not capture all elements of an individual's well-being. The variable is measured from Question No. A36 in the CGSS: "How happy do you feel about your life as a whole these days?" The answers were scored on a 5-point Likert scale (1 = *very unhappy*, 2 = *unhappy*, 3 = *neither happy nor unhappy*, 4 = *happy*, 5 = *very happy*). The respondents who felt somewhat happy or very happy comprise about 72% of respondents.

Independent variables (individual level): According to the proposed hypotheses, the individual-level independent variables include *ICT\_Usage*, *Work\_Time*, *Income*, *Social\_Activities* and demographics. The definitions are as follows.

*ICT\_Usage:* In the CGSS, respondents were asked to evaluate their usage of different media in Question No. A28: "How often do you use Newspapers/Magazines/Radio/TV/Internet (including mobile phone)/Mobile Phone Messaging?" We measured individual-level ICT usage based on how often they use Internet. It is a categorical variable (1 = *never*, 2 = *seldom*, 3 = *sometimes*, 4 = *often*, 5 = *very frequently*) with 56.7%, 7.8%, 8.1%, 12.9% and 14.3% respectively in those categories. (Note that the sum is less than 100% since not all respondents answered the question. Responses with missing variables are omitted from the sample before analysis.)

*Work\_Time:* Question No. A53 asked respondents: "How many hours did you work (including serving in the army) in the last week for pay?" The continuous variable had a mean of 48.77 after deleting non-responses.

*Income:* In question No. A8a, respondents were asked about their annual occupational/labor income. The original variable is numeric and the mean is Yuan 23,450 or 2.345 in ten thousand after deleting unknown samples. Based on the finding from the literature that the effect of income is non-linear and diminishing (Weimann, Knabe & Schob, 2015), we apply a '*ln*' function to income; also, since research has found that SWB is sensitive to relative income (Verme, 2011), we divide the log-transformed individual income by the average income (in "*ln*") of respondents in the same district or county to get the relative income.

*Social\_Activities:* This variable addresses respondents' time spent in social entertainments and activities with neighbors and friends (question Nos. A31a and A31b). This is categorical variable (1 = *every day*, 2 = *several times a week*, 3 = *several times a month*, 4 = *one time a month*, 5 = *several times a year*; 6 = *one time a year*; 7 = *never*). We sum the answers of these two questions and reverse it as *Social\_Activities* = 14 – (sum of scores on A31a and A31b); the mean value is 6.41 and the standard deviation is 3.08.



*Demographic Variables:*

Also, we select some demographic variables as control variables, as in Table 1. Gender and Education were used as controls in Ganju, Pavlov and Banker (2016) and Cotten et al (2011). Religion too has strong support to be included as a control (Doane, 2013; Lim, 2015). Only about 11 percent of the sample claimed religious belief. We include two additional variables that indicate an individual's connection to social networks: Communist party membership, and rural-to-urban migrant status. Approximately 11 percent of the sample were party members, and a quarter (25.1%) were rural migrants.

Table 1. The definition of demographic variables from CGSS

Variable	Question	Definition	Frequency
<i>Gender</i>	A2	male=1, female=0	1(50.3%), 0(49.7%)
<i>Education</i>	A7a	elementary school and below=1, middle school =2, high school or similar=3, undergraduate=4, graduate or above =5	1(35.5%), 2(29.1%), 3(19.0%), 4(15.5%), 5(8.0%)
<i>Religion</i>	A6	believe in religion = 1 no religion = 0	1(11.1%) 0(88.9%)
<i>Party</i>	A10	Communist Party member=1, non-member=0	1(10.7%), 0(89.3%)
<i>Rural migrant</i>	A25	migrant =1 native =0	1(25.1%) 0(74.9%)

Independent variables (city level): Research by Requena (2010), di Tella, McCulloch and Oswald (2003), and Helliwell (2003) has shown that SWB is dependent on the characteristics of the community or place of residence of individuals. Accordingly, we also included several city-level variables for each individual in the sample, collected from the China City Statistical Yearbook (2012). See Table 2 for a listing of city-level variables and their definitions. *Capital City* is included as a dummy since provincial capitals are more likely to have greater financial resources and more senior leadership, which will contribute to the greater availability of financial resources. The city's *Gross Regional Product* and the *Public Finance Expenditures* (budget) of the city are included as alternative measures of the city's affluence. *Telephone penetration* was included as proxy for the degree of informatization of the city. Though data on the number of broadband connections and mobile phones are available in the China City Statistical Yearbook (2016), preliminary examination revealed that this data were highly unreliable. Calculations of per capita broadband density (no. of broadband subscriptions / population) showed numbers > 3.4 for Beijing, for example and similarly unrealistic numbers for smaller cities. Accordingly we decided not to use the

Yearbook data for broadband connections and mobile subscriptions. Instead, we used telephone subscriptions data as a reasonable (but imperfect) proxy for degree of informatization of the city. The percentage of *Students* in the city was included as a proxy for opportunities for advancement available in the city. Finally, the percentage of *Social Workers* in the city was included as an indicator of the size and resources of the social safety net.

Table 2. The definition of city-level variables

Variable	Definition	Mean	SD
<i>Capital_City</i>	dummy variable for the Capital City = 1, others = 0	0.19	0.40
<i>GRP</i>	Gross regional product; final products at market prices (million yuan) for city	56.27	43.10
<i>PFE</i>	Public finance expenditures for local government (million yuan) for city	8.75	7.19
<i>Telephone_pen</i>	Number of telephone subscriptions in the city (mill.) divided by the population.	0.17	0.12
<i>Students</i>	Number of students in college, high school, secondary, and primary schools divided by the population.	0.28	0.42
<i>Social_Workers</i>	Number of employed staff and workers in public management and social organization divided by the population.	0.01	0.01

## Methods

Our hypotheses and data include both micro level features of each individual and macro level characteristics of their place of residence. To appropriately estimate the independent effects of individual and macro level ICT adoption on individual happiness, we use a fixed effects two-level hierarchical linear model (HLM) following the literature on multi-level modeling (Raudenbush & Bryk 2002). HLM can appropriately model the interdependence of individual and city-level data, nesting individuals within cities. HLM allows for the appropriate estimation of city-level effects on individual-level outcomes, controlling for the included variables at both the individual and city levels. In general, the equations can be expressed as:

*Individual-Level 1:*

$$Happiness_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \varepsilon_{ij}$$

*City-Level 2:*

$$\begin{aligned}\beta_{0j} &= \gamma_{00} + \gamma_{01} W_j + \mu_{0j} \\ \beta_{1j} &= \gamma_{10} + \mu_{1j}\end{aligned}$$

Where,  $i$  stands for the individual;  $j$  stands for city;  $X$  are the individual layer variables;  $\beta_{0j}$  and  $\beta_{1j}$  are the intercept and slope, respectively, of unit  $j$  (second layer unit) in the first layer;  $\gamma_{00}$  is the average values for  $\beta_{0j}$ , its fixed components meaning that they are constant among the city variables;  $\gamma_{01}$  is regression coefficients for city level variables;  $W$  is predictor variable at the city level;  $\mu_{0j}$  and  $\mu_{1j}$  are random elements of  $\beta_{0j}$  and  $\beta_{1j}$  respectively, representing the difference between city units.

## Results

After filtering out responses with missing or unknown data, a dataset of 5463 individuals living in 78 different cities was available. To assess the direct effects of city-level facility and individual level ICT usage on individual happiness, we then estimated a two-level hierarchical linear model (Table 3). Again, the dependent variable is SWB. Table 3 lists the coefficients, standard errors and p-values for each variable.

Table 3. Two-Level Hierarchical Linear Model Estimating Happiness

Variables	Model1		
	Coefficient	SE	P-Values
<b>Individual-Level</b>			
<i>ICT_Usage</i>	0.015	0.005	0.004**
<i>Work_Time</i>	-0.003	0.001	0.000***
<i>Income</i>	0.329	0.069	0.000***
<i>Social_Activities</i>	0.022	0.004	0.000***
<i>Gender</i>	-0.036	0.023	0.110
<i>Education</i>	0.041	0.021	0.049*
<i>Religion</i>	0.088	0.042	0.021*
<i>Party</i>	0.123	0.038	0.002**
<i>Immigrant</i>	0.017	0.028	0.417
<b>City-Level</b>			
<i>Capital_City</i>	-0.061	0.033	0.062
<i>GRP</i>	0.001	0.001	0.423
<i>PFE</i>	0.964	0.479	0.044*
<i>Telephone_pen</i>	0.234	0.224	0.002**
<i>Students</i>	0.042	0.033	0.202
<i>Social_Workers</i>	-4.970	3.005	0.098
<i>Intercept</i>	3.758373	0.011358	0.000
% of Variance Explained at			
<i>Individual-Level</i>	0.61718	$\chi^2$	
<i>City-Level</i>	0.02876	300.13038	0

\*p<0.05, \*\*p<0.01, \*\*\*p<0.001

Results in Table 3 show that the coefficient on *ICT\_usage* is significant and positive. As previously discussed, there is precedent in the literature to hypothesize either a positive or a negative effect of ICT usage on SWB. The results indicate that the positive impacts outweighed the potential negatives. Of the other variables, the effects were in

the expected directions. Work time was a significant negative predictor whereas income and social activities were positive predictors, as expected from the literature. Education too was a positive predictor. Religious belief and party affiliation, both indicating engagement with wider social networks, were positive predictors of SWB.

At the city level, only two variables were significant, both positively: public finance expenditures, and telephone penetration that was included as a proxy for the informatization of the city. Surprisingly, the percentage of social workers in the city was negatively correlated with SWB, though it was not significant. This may perhaps be because not all employees included in the “social worker” category in the China City Statistical Yearbook (2016) were actually active in the delivery of social services: it also includes employees in public management. This is an aspect that needs further investigation.

## **Discussion and Conclusions**

This paper investigated the impact of ICT use on SWB, after controlling for other demographic and economic factors (specifically household incomes) at the individual and city levels. Previous research on similar lines by Ganju, Pavlou and Banker (2016) and others was based on aggregated measures of SWB at the country level, due to limitations of data. By using large scale survey data from CGSS database, this paper was able to examine how individual-level attributes affected SWB. A two-level hierarchical linear model (HLM) with a self-reported measure of happiness as the dependent variable was run, utilizing a number of predictors including our main variable of interest (ICT use), as well as gender, household income, education level, social activity, religious engagement, and several city-level variables.

Preliminary results indicate that ICT usage significantly increases SWB, though the size of the effect is very small. The positive impacts of ICTs in enabling social networking, access to information, and promoting educational opportunity outweigh the potential negatives of exposure to the steep costs of learning new technology, constant demands of time and attention, fears of cyber-intrusions, loss of privacy and security, and the stress of social media. It may be pointed out that the latest available data from the CGSS was collected in 2013, before the wide diffusion of smartphones and social media in the Chinese population. It may be argued that some of the worst effects of ICT access on SWB were yet to manifest at the time the data were collected. Nevertheless, the results of this study make a plausible case for the deployment of ICTs in society, not only for economic growth (which has been well-established in the literature), but also for the subjective well-being of citizens.

There are several limitations to this study primarily deriving from the use of secondary data. Overall the use of secondary data was an advantage for this study, since it enabled us to use a much larger sample of respondents as well as to have access to individual level information (unlike previous studies that had used country level data). But it also

holds a significant disadvantage that some information that would have been helpful for this analysis was unavailable, and the measurement of some other variables was unsatisfactory. For example, additional information on the type of Internet connectivity (wired vs. wireless), duration and intensity of Internet use, etc. would have been useful for the analysis.

## Reference

Alesina, A., Tella, R. D., & Macculloch, R. (2004). Inequality and Happiness: Are Europeans and Americans Different?. *Journal of Public Economics*, 88(0), 2009-2042.

Ayyagari, R., Grover, V., & Purvis, R. L. (2011). Technostress: Technological antecedents and implications. *Management Information Systems Quarterly*, 35(4), 831-858.

Baker, P. M. A., Hanson, J., & Myhill, W. N. (2009). The promise of municipal WiFi and failed policies of inclusion: The disability divide. *Information Polity*, 14, 47-49.

Brajsa-Zganec, A., Merkas, M., & Sverko, I. (2010). Quality of Life and Leisure Activities: How do Leisure Activities Contribute to Subjective Well-Being? *Social Indicators Research*, 102(1), 81-91.

Campisi, J., Bynog, P., Mcgehee, H., Oakland, J. C., Quirk, S. K., Taga, C., & Taylor, M. (2012). Facebook, stress, and incidence of upper respiratory infection in undergraduate college students. *Cyberpsychology, Behavior, and Social Networking*, 15(12), 675-681.

Centre for Bhutan Studies and GNH Research (2016). A compass towards a just and harmonious society: 2015 GNH survey report. Thimphu, Bhutan: Centre for Bhutan Studies. Accessed May 9, 2018, at <http://www.grossnationalhappiness.com/>

China City Statistical Yearbook (2016). Beijing, China: China Statistical Press.

Cobb, J. B., & Daly, H. E. (1989). For the common good: redirecting the economy towards community, the environment, and a sustainable future. Beacon Press, Boston.

Diener, E. (2009). The science of well-being: The collected works of Ed Deiner. New York: Springer.

Diener, E., Tay, L., & Oishi, S. (2013). Rising income and the subjective well-being of nations. *Journal of Personality and Social Psychology*, 104(2), 267-276.

Doane, M. J. (2013). The association between religiosity and subjective well-being:

The unique contribution of religious service attendance and the mediating role of perceived religious social support. *Irish Journal of Psychology*, 34(1), 49-66.

Easterlin, R. A. (1995). Will raising the income of all increase the happiness of all? *Journal of Economic Behavior and Organization*, 27, 35-48.

Ellis, K. (2011). Embracing learners with disability: Web 2.0, access and insight. *Telecommunications Journal of Australia*, 61(2), 30.1-30.11.

Fuhr, J. P., & Pociask, S. (2011). Broadband and telecommuting: Helping the U.S. environment and the economy. *Low Carbon Economy*, 2, 41-47.

Ganju, K. K., Pavlou, P. A., & Banker, R. D. (2016). Does information and communication technology lead to the well-being of nations? A country-level empirical investigation. *MIS Quarterly*, 40(2), 417-430.

Hales, S., Howdenchappman, P., Salmond, C., Woodward, A., & Mackenbach, J. P. (1999). National infant mortality rates in relation to gross national product and distribution of income. *The Lancet*, 354(9195).

Hansen, C. W., & Lonstrup, L. (2015). The Rise in Life Expectancy and Economic Growth in the 20th Century. *The Economic Journal*, 125(584), 838-852.

Helliwell, J. F. (2003). How's Life? Combining Individual and National Variables to Explain Subjective Well-Being. *Economic Modelling*, 20(2), 331-360.

Helliwell, J., Layard, R., & Sachs, J. (2017). *World Happiness Report 2017*, New York: Sustainable Development Solutions Network. Accessed May 9, 2018, at <http://worldhappiness.report/ed/2017/>

Jeffrey, K., Wheatley, H., & Abdallah, S. (2016). *The Happy Planet Index*. London, UK: New Economics Foundation. Accessed May 9, 2018, at <http://happyplanetindex.org/>

Kahneman, D. (1994). New challenges in the rationality assumption. *Journal of institutional and theoretical economics*, 150, 18-36.

Knabe, A., & Ratzel, S. (2010). Income, happiness and the disutility of labour. *Economics Letters*, 107(1), 77-79.

Kula, M., Panday, P., & Mantia, K. (2010). Real GDP, well-being and happiness. *International Journal of Arts and Sciences*, 3(7), 431-433.

Lee, H., Park, N., & Hwang, Y. (2015). A new dimension of the digital divide: Exploring

the relationship between broadband connection, smartphone use and communication competence. *Telematics and Informatics*, 32(1), 45-56.

Lim, C. (2015). Religion and Subjective Well-Being Across Religious Traditions: Evidence from 1.3 Million Americans. *Journal for the Scientific Study of Religion*, 54(4), 684-701.

Miller, T., Kim, A. B., & Roberts, J. M. (2018). 2018 Index of Economic Freedom. Washington, DC: Heritage Foundation. Accessed May 9, 2018, at <https://www.heritage.org/index/download>

Nordhaus, W. D., & Tobin, J. (1972). Is growth obsolete? In W. Nordhaus & J. Tobin (Eds.), *Economic Research: Retrospect and Prospect, Volume 5, Economic Growth*. Washington, DC: NBER.

Osawe, O. W. (2014). Determinant of Infant Mortality Rate: A Panel Data Analysis of African Countries. *Developing Country Studies*, 4(18), 111-115.

Pouwels, B., Siegers, J., & Vlasblom, J. D. (2008). Income, working hours and happiness. *Economic Letters*, 99(1), 72-74.

Ragunathan, T. S., Tarafdar, M., Ragunathan, B. S., & Tu, Q. (2008). The consequences of technostress for end users in organizations: Conceptual development and empirical validation. *Information Systems Research*, 19(04), 417-433.

Raudenbush, S. W., & Anthony S. Bryk. 2002. *Hierarchical linear models: Applications and data analysis methods*, 2nd ed. Thousand Oaks, CA: Sage.

Reder, S. (2010). Adult literacy development and economic growth. Washington, DC: National Institute for Literacy, *Adult Literacy Development and Economic Growth*. Accessed May 8, 2018, at <http://www.lsal.pdx.edu/docs/pdf/LitEconGrowth2010.pdf>

Requena, F. (2010). Welfare Systems, Support Networks and Subjective Well-Being Among Retired Persons. *Social Indicators Research*, 99(3), 511-529.

Stevenson, B., & Wolfers, J. (2008). Economic growth and subjective well-being: Reassessing the Easterlin paradox. *Brookings Papers on Economic Activity*, 39, 1-102.

Tandoc, E. C., Ferrucci, P., & Duffy, M. (2015). Facebook use, envy, and depression among college students: Is Facebooking depressing? *Computers in Human Behavior*, 43, 139-146.

Van Hoorn, A. A. (2008). Income, leisure, and happiness. NiCE Working Paper No.

08-116, System Dynamics Review. Accessed May 12, 2018, at <http://repository.uhn.ru.nl/bitstream/handle/2066/74904/74904.pdf?sequence=1>

Vasquez, I., & Porcnik, T. (2016). The Human Freedom Index – 2016. Washington, DC: Cato.

Verme, P. (2011). Life Satisfaction and Income Inequality. *Review of Income and Wealth*, 57(1), 1-30.

Weimann, J., Knabe, A., & Schob, R. (2015). *Measuring happiness: The economics of well-being*. Cambridge, MA: MIT Press.

Williams, G., & Smith, A. P. (2016). Using single-item measures to examine the relationships between work, personality, and well-being in the workplace. *Psychology*, 7(6), 753-767.