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Digital Divide and Income Inequality: A Spatial Analysis

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Abstract: A spatial quantile regression model, which can fully describe the distribution characteristics and spillover effects, is applied to explore the effect of digital divide on the income inequality. Firstly, the estimation results based on the full data set reveal that income inequality is positively spatial dependent across regions, and the Internet has a significantly positive effect on income inequality. Secondly, the entire data set is divided into two groups based on income, i.e., high income countries and low income countries. The estimation results of two groups are quite different. The income inequality were positively spatially correlated among neighbouring countries in high-income countries but negatively in low-income countries. On the other hand, the Internet usage exacerbate income disparity in low-income countries but improve income inequality in high-income countries. The results also show that increasing school enrollment can alleviate income gap especially in low-income countries.

Keywords: Digital divide; Income inequality; Spatial econometrics; Quantile regression; Spillover effect

JEL Classifications: O33, D31, R12

1. Introduction

Anderson (2005) indicated that people care about not only their own incomes but also whether other people's incomes exceed their own incomes. People are typically not pleased when they discover that their incomes are less than those of other people's (Oishi *et al*., 2011). So when a country's income disparity problems deteriorate, it is no longer just economic problems, but will gradually evolve into social and political issues. Therefore, reducing income inequality has become the first priority in numerous countries when formulating social and economic policies.

Undoubtedly, the Internet has been one of the most influential inventions since the 20th century. The Internet is low-cost, real-time accessible, and highly efficient. Nevertheless, workers in regions without Internet connections have difficulty acquiring new technologies and using low-cost methods for marketing their products; therefore, they cannot benefit from the Internet. Accordingly, these workers are under disadvantageous conditions and income inequality rapidly rises. However, because using the Internet requires expenditures and established infrastructure, a difference in Internet usage among workers in various regions exists. This difference can be considered a digital divide. This study aimed to investigate whether digital divides cause income inequality and affect income distribution.

Since the Internet became prevalent in the 1990s, the prevalence and usage of the Internet in various countries have varied, resulting in a digital divide. According to the Organization for Economic Cooperation and Development (OECD, 2001), a digital divide is defined as follows:

"…, the term 'digital divide' refers to the gap between individuals, households, businesses and geographic areas at different socioeconomic levels with regard to both their opportunities to access information and communication technologies and to their use of the Internet for a wide variety of activities. The digital divide reflects various differences among and within countries."

In the modern world, countries frequently interact with one another, mainly through trading, education, and migration. Economic factors, such as personal income, not only depend on the conditions in the country but are also potentially affected by spillover effects created by trade with neighboring countries. Therefore, an econometric model that does not consider spatial dependence will produce biased results. It is necessary to consider spillover effect in the econometric model.

Koenker and Bassett (1978) proposed quantile regression model. According to this model, the information about the central and tail behavior contingent on conditional probability can be revealed (Tsai and Kuan, 2003); thus, the effects of explanatory variables on observable variables at various quantiles can be understood. The estimated results based on a quantile regression model are even more robust and suitable than those obtained using a least-squares regression model. Therefore, using a quantile regression model facilitates accurate data analysis. This study combined spatial and quantile regression models into a spatial quantile regression model to investigate the relationship between digital divide and income inequality.

2. Literature Review

Since the rise of the Internet in the 1990s, the Internet has substantially influenced our lives, especially in the economic aspect. The advantages of using Internet technology include convenient information exchange and reduced regional differences. Convenient information exchange can accelerate globalization and technological progress. Previous studies have shown that the adoption of communications equipment such as computers and the most current Internet technologies can increase the incomes of users, reduce costs, or both (e.g., Krueger, 1993; Choi and Hoon, 2009; Chang and Just, 2009; Bernanke, 2008; Lustig *et al*., 2013). However, not everyone has an equal opportunity to use a computer and the Internet. So that some people's income is relatively reduced, it may also cause the deterioration of income inequality. Zhang(2013) developed a theoretical framework for internet consumption and found the GDP per capita had positive relation with the slope of internet diffusion curve but Gini index had negative one. Vicente and López (2011) indicated the regional digital divide reflects to the social and economic inequality like income gap as ICT are getting more important for the competitiveness of individuals and firms. Acemoglu (2002) considered that the exacerbated income inequality in numerous developed countries resulted because the information industry enhanced the wage premium of information industry-related people. Lloyd-Ellis (1999) considered that the emergence of the information and communications industry enhanced productivity and reduced income inequality. Most of the previous articles discussed the impact of the ICT industry on income inequality or wage. However, there are few literatures that concern the impact of the digital divide on the income inequality and the effects are not similar in different countries. What is the real effect is the first issue we are concerned about.

In addition, Since Anselin (1988) proposed spatial econometrics, spatial econometric models have been widely applied in empirical analysis. Previous studies, such as that by Billón *et al*. (2008), have explored the spatial distribution of the Internet in Europe and showed that spatial correlations existed. Rey (2004), Tselios (2008), and Rodríguez-Pose and Tselios (2009) have adopted spatial econometric models to study income inequality and found that income inequality levels were positively spatially correlated among neighbouring countries or regions. Therefore, the spatial effect on income is crucial. If the spatial effect is ignored, then the endogeneity problems of explanatory variables can induce biased model estimations. This study is different from the previous literature. That is, using the spatial quantile regression model that can grasp the entire distribution feature and spatial dependency to describe this topic. In empirical study of spatial quantile model, Liao and Wang (2012) used spatial quantile model to explore the factors that affect house prices.

Numerous studies have investigated the factors that affect income inequality are reviewed below.

Most of the previous studies results show that education can effectively reduce the inequality of income (Park, 1996; Sylwester, 2002). Abdullah *et al*. (2015) found education reduces the income share of top earners and increase the income share of the bottom earners. Education can reduce the income inequality effectively especially in Africa. Some of the results indicated that secondary schooling has a stronger effect than others.

Stolper and Samuelson (1941) first used the Heckscher–Ohlin model to infer the effects of trade on income inequality. In the previous literatures can be found using different models and data, trade liberalization has different effects on income inequality of country. This study used trade volume to evaluate the degree of trading openness. Winters *et al*. (2004) indicated that no generalized conclusion can be made regarding the relationship between trade and income inequality. Dreher and Gaston(2008) found globalization has exacerbated income inequality and was particularly true in OECD countries. Jaumotte *et al*. (2013) mentioned that trade can reduce inequality. Lee and Vivarelli (2006) also refer to similar results with some exceptions. Meschi and Vivarelli (2009) suggest that trade with high-income countries, both import and export, will exacerbate income inequality in developing countries. Milanovic (2005) also suggested that in low-income countries, the greater the degree of trade liberalization, the greater the gap between rich and poor.

Kuznets (1955) indicated that a large rural population reflects a large population of farmers. Farmers typically earn comparatively low incomes. Therefore, the larger the rural population and the lower the income inequality. In addition, the rate of people living in cities can be considered as the degree of urbanization or industrialization in a country. A large rural population represents a low degree of industrialization.

3. Models and Data

Quantile regression analysis is used to explore the effects of explanatory variables on dependent variables at various quantiles. Least-squares regression analysis can estimate average values but cannot precisely analyze the distribution of a variable. The parameters of a quantile regression model are estimated by minimizing the sum of the absolute values of all error terms. A traditional quantile regression model can be expressed as follows (Koenker and Bassett, 1978).

$$\mathrm{Y} = \beta_\theta \mathrm{X} + \mu_\theta \quad \text{with} \quad \mathrm{Quant}_\theta(\mathrm{Y}) = \beta_\theta \mathrm{X} \tag{1}$$

where X denotes a vector of exogenous variables; θ denotes a quantile (0 < θ <1); β_θ denotes the parameter to be estimated at the θth quantile; $\mathrm{Quant}_\theta(\mathrm{Y})$ denotes the θth quintile of *Y* given *X*. The objective function can be expressed as

$$\min_{\beta \in R^k} \left\{ \sum_{Y \geq \beta X} \theta \left| Y - \beta_\theta X \right| + \sum_{Y < \beta X} (1-\theta) \left| Y - \beta_\theta X \right| \right\} \tag{2}$$

Differing from previous studies, this study also integrated various regional variables with neighboring effects so that the regional spillover effects of various regional variables can be functioned as an explanatory variable in the model. Anselin (1988) indicated that spatial dependence and spatial heterogeneity may exist among spatial observation values. If the spatial dependence and spatial heterogeneity exist in a regression model, then the model may be configured incorrectly and the Gauss-Markov assumption may be violated. Two commonly used spatial models are the spatial autoregressive model (SAR) and spatial error model (SEM). These spatial models were described in Anselin (1988, 2001) and LeSage and Pace (2009). But so far quantile regression has not yet applicable to estimation of spatial error model (Liao and Wang, 2012), so this study only estimates the SAR model.

If a spatial spillover effect can be explained by a single variable *WY*, then the SAR model can be expressed as

$$Y = \rho WY + \beta X + \varepsilon, \ \ \varepsilon \sim \mathrm{N}(0, \Sigma^2) \tag{3}$$

where *Y* is an $n \times 1$ vector of dependent variable, *X* is an $n \times k$ matrix consisting of the explanatory variables, *W* is the spatial weight matrix, an $n \times n$ non-negative matrix, ρ is the spatially autoregressive parameter that assesses spatial effect, β is the $k \times 1$ vector of parameters, ε is an $n \times 1$ vector of i.i.d. error terms, and *n* denotes sample size.

The matrix used to express the relationship between spatial units is expressed as

$$W = \left[w_{ij} \right]_{n \times n} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1j} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2j} & \cdots & w_{2n} \\ \vdots & & \ddots & & & \vdots \\ w_{i1} & & & w_{ij} & & w_{in} \\ \vdots & & & & \ddots & \\ w_{n1} & w_{n2} & \cdots & w_{nj} & \cdots & w_{nn} \end{bmatrix} . \tag{4}$$

The spatial weight matrix in the model is a distance-weighted inverse matrix. The symbol w_{ij} denotes elements in a spatial matrix ($\mathrm{w}_{\mathrm{ij}} = 1/\mathrm{distance}_{\mathrm{ij}}$, $\mathrm{i} \neq \mathrm{j}$; $\mathrm{w}_{\mathrm{ij}} = 0$ when i = j). In this study, the strengths of spatial relationships were considered to vary according to distance. In other words, a longer distance between two spatial units indicates a weaker relationship between the two spatial units and vice versa. Because of the endogeneity problem of the explanatory variable WY, using a traditional analysis method will yield biased estimations.

The spatial quantile autoregressive model (SQARM) is expressed as

$$\mathrm{Y} = \rho_\theta \mathrm{WY} + \mathrm{X}\beta_\theta + \varepsilon_\theta \qquad (5)$$

where X and Y are as before; θ denotes a quantile; and ρ_θ and β_θ denote parameters to be estimated. The estimation process can be divided into two stages. At the first stage, the spatial-lag variable *WY* that represents a spillover effect may be endogenous; therefore, endogenous variables (including *WY*) are used to estimate all exogenous variables (i.e., *X*, *WX*, and *WWX*) in a quantile regression analysis and to obtain the estimated value of the endogenous variable ($\hat{\mathrm{WY}}$). At the second stage, the estimated value of the endogenous variable ($\hat{\mathrm{WY}}$) is used to replace the endogenous explanatory variables, after which a quantile estimation model is used to estimate parameters.

Table 1 presents the descriptive statistics for the data. The Gini coefficient (hereafter referred to as Gini) was used as the variable that assessed income inequality. The data source was the Standardizing the World Income Inequality Database. Except for the Ginis, all other data were obtained from the World Development Indicators (WDI) database. The Gini is expressed in percentage form.

Table 1. Descriptive statistics (year=2001/2005)

Variable	Definition	Obs. (2001/2005)	Mean (2001/2005)	Std. Dev (2001/2005)	Min (2001/2005)	Max (2001/2005)
Gini (Dependent Variable)	Gini coefficient(%)	114/115	39.10/38.26	9.27/8.92	22.56/23.21	64.80/66.64
inuse	Internet users (per 100 people)	114/115	11.99/23.88	16.92/25.47	0.04/0.20	64.00/87.00
rupop	Rural population (% of total population)	114/115	44.64/41.85	22.82/22.77	0.00/0.00	91.53/90.63
sero	School enrollment, secondary (% gross)	114/115	71.26/75.91	32.94/29.26	6.83/9.83	154.5/127.7
trade	Trade (% of GDP)	114/115	80.77/88.33	41.97/48.49	20.26/26.53	269.6/377.1

Note: "Sero" may exceed 100% due to the inclusion of over-aged and under-aged students because of early or late school entrance and grade repetition.

The prevalence of Internet use (represented by "inuse") was defined as the number of people using the Internet per 100 people in a country. The prevalence of Internet use was used to assess the degree of digital divide. The proportion of rural population (represented by "rupop") was used to indicate the degree of urbanization and industrialization in a country. Education level (represented by "sero") was defined as high school enrollment and was used to assess the overall education level and human resources of a country. Some countries included over-raged and under-raged students when calculating their high school enrollment rates; therefore, the high school enrollment rates in these countries exceeded 100%. Trade volume (represented by "trade") was defined as the proportion of the sum of import and export trade volumes in the GDP and was used to assess the trade openness of a country.

4. Results and Discussion

It can be seen from the above literature that the use of the Internet or other factors have a relative impact on the income. This relative impacts will likely result in improved or worsened income inequality. Besides, the income inequality has spatial spillover effect, and in the case of unknown distribution. So using the traditional regression analysis will prone to bias. The main purpose of this paper is to explore the effect of Internet use on the distribution of income by using a spatial quantile regression model that can grasp spatial dependence and sample characteristics better. Within the range we can find, no similar literature was published.

We performed the endogeneity test (results are reported in Table 2) for the data. Endogeneity, if present, would render inconsistent result. The endogeneity tests uses a two stage least square (2SLS) method which includes the instrumental variable (IV) technique. The IV approach is able to capture any exogenous shock to the parameters of interest. Both Durbin and Wu- Hausman test the endogeneity in the regressors used in the equation. Since we cannot reject the null hypothesis, the estimated coefficients of the models are unbiased and exogenous.

Table 2. Endogeneity tests of the data (year=2001/2005)

Test and Statistics	Coefficients (2001/2005)	*p*-value (2001/2005)	Indication (2001/2005)
Durbin Test (χ^2)	0.0488/0.2622	0.8252/0.6086	No endogeneity / No endogeneity
Wu-Hausman (*F*-statistics)	0.4581/0.2468	0.8309/0.6203	No endogeneity / No endogeneity

As aforementioned, a spatial weight matrix must be determined prior to model estimation. The spatial weight matrix consists of elements that are the reciprocals of distances between various countries. As in previous literature, not all countries are included in computations. Only a country's nearest neighboring countries are included in the calculation process of spatial weight matrix (Le Gallo and Ertur, 2003; Dall'Erba, 2005; Tselios, 2008; Rodríguez-Pose and Tselios, 2009). Typically, the distances between k-nearest countries and the distances between (k+2)-nearest countries are separately considered in computing spatial weight matrices. In this study, computations were performed by separately considering 8 and 10 nearest countries and then comparing the estimation results under the two conditions, as shown in Tables 3 and 4. If the estimation results under the two conditions are consistent, then the estimation results are considered robust. According to the estimation results, no significant difference existed between these two conditions. Therefore, the eight nearest countries were used for model estimation in this study.

Tables 3-5 show the estimates for the parameters of the spatial quantile regression model. According to the estimation results, the estimates of the model coefficients (ρ) that represent spillover effects and spatial dependence at various quantiles were significant and positive values, indicating that income inequality levels in various countries were significantly influenced by their neighboring countries. These results accord with the results of the study by Rodríguez-Pose and Tselios (2009). They adopted the SAR and SEM models to study income inequality and found that the income inequality of a country was influenced by the economic factors of the country and that the spillover effects of neighboring countries existed. In other words, Rodríguez-Pose and Tselios (2009) found that the more even the income distribution in a country's neighboring countries, the more even the income distribution in the country, and vice versa; these are effects of the regional organizations for international economic cooperation that have emerged in recent years. In addition, the results showed that spatial spillover effects existed and that value of ρ tended to decrease (i.e., the absolute value decreased). The reason may be that previously, the interaction of various countries depended on geographical distances; however, currently, various countries mutually influence one another through the Internet and trading activities. As previously discussed, information can be rapidly circulated worldwide because of Internet use. Because of globalization, trading activities among various countries occur extremely frequently and the influence of distances has declined. Discussions like "death of distance" (Cairncross, 2001) and "the world is flat" (Freidman, 2005) were proposed to describe the declining effect of distances. The estimated values of ρ were all significant, indicating that Internet use reduced spatial dependence but did not replace it.

Table 3. Estimates of spatial quantile regression model (year=2001; nearest countries=8)

τ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Constant	19.62** (0.015)	16.78* (0.057)	19.76** (0.035)	20.07*** (0.007)	22.55*** (0.002)	10.86 (0.144)	17.63** (0.031)	27.75** (0.020)	31.74 (0.138)
ρ	0.673*** (0.000)	0.689*** (0.000)	0.705*** (0.000)	0.761*** (0.000)	0.660*** (0.000)	0.832*** (0.000)	0.753*** (0.000)	0.615*** (0.000)	0.650** (0.017)
inuse	-0.151*** (0.006)	-0.121*** (0.009)	-0.107** (0.035)	-0.149*** (0.000)	-0.156*** (0.000)	-0.188*** (0.000)	-0.175*** (0.000)	-0.221*** (0.000)	-0.190* (0.062)
rupop	-0.111** (0.019)	-0.071 (0.170)	-0.107* (0.064)	-0.142** (0.016)	-0.108** (0.030)	-0.069* (0.080)	-0.086* (0.068)	-0.135** (0.020)	-0.179* (0.086)
sero	-0.013 (0.749)	-0.026 (0.491)	-0.061 (0.127)	-0.065* (0.078)	-0.076** (0.031)	-0.022 (0.589)	-0.049 (0.287)	-0.061 (0.316)	-0.084 (0.398)
trade	-0.037* (0.051)	-0.019 (0.430)	0.000 (0.996)	0.018 (0.550)	0.038 (0.118)	0.039** (0.027)	0.029** (0.023)	0.026* (0.056)	0.016 (0.403)
Pseudo R^2	0.3874	0.3687	0.3468	0.3834	0.4079	0.4232	0.4168	0.4060	0.3616

Notes: *, **, and *** indicate statistical significance at the level of 10%, 5%, and 1%, respectively; In the parentheses under 2SQR estimates are *p*-values.

Table 4. Estimates of spatial quantile regression model (year=2001; nearest countries=10)

τ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Constant	18.30** (0.019)	19.56*** (0.005)	20.90*** (0.007)	20.36*** (0.009)	20.46*** (0.007)	16.89** (0.036)	24.87** (0.016)	23.26** (0.037)	24.70 (0.319)
ρ	0.710*** (0.000)	0.639*** (0.000)	0.703*** (0.000)	0.754*** (0.000)	0.748*** (0.000)	0.801*** (0.000)	0.687*** (0.000)	0.702*** (0.000)	0.688** (0.033)
inuse	-0.142** (0.015)	-0.115*** (0.008)	-0.113*** (0.006)	-0.129*** (0.002)	-0.164*** (0.000)	-0.165*** (0.000)	-0.202*** (0.000)	-0.208*** (0.000)	-0.204 (0.110)
rupop	-0.106** (0.036)	-0.066 (0.177)	-0.090* (0.069)	-0.125** (0.028)	-0.128** (0.018)	-0.101** (0.038)	-0.138** (0.020)	-0.138** (0.031)	-0.125 (0.301)
sero	-0.022 (0.530)	-0.030 (0.316)	-0.059 (0.126)	-0.077** (0.048)	-0.075* (0.076)	-0.059 (0.178)	-0.072 (0.219)	-0.047 (0.433)	-0.030 (0.753)
trade	-0.037* (0.070)	-0.029 (0.234)	-0.018 (0.512)	0.016 (0.601)	0.033 (0.164)	0.030* (0.079)	0.030** (0.029)	0.025* (0.068)	0.013 (0.528)
Pseudo R^2	0.3981	0.3832	0.3727	0.3904	0.4162	0.4337	0.4252	0.4132	0.3706

Notes: *, **, and *** indicate statistical significance at the level of 10%, 5%, and 1%, respectively; In the parentheses under 2SQR estimates are *p*-values.

The difference in estimation results between models with and without considering spatial dependence is also investigated here (Table 6). As shown in Tables 3 and 6, the absolute values of the coefficients for the spatial quantile regression model were mostly smaller than those for the traditional quantile regression model. The results suggested that the traditional quantile regression model that does not consider spatial dependence overestimated the effects of the variables. In addition, the spillover effects of neighbouring countries were underestimated because a spatial model was not used. The results suggested that Internet use reduced the effects of distances and the rising prevalence of Internet use reduced spatial correlation. According to the estimation results, spatial correlation still exists. The function of the Internet is to reduce the costs of disseminating ideas and information. For trading, distances still have a substantial influence on costs. Internet use can reduce but not eliminate the effects of distances. Therefore, spatial correlation still exists.

Table 5. Estimates of spatial quantile regression (year=2005; nearest countries=8)

τ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Constant	17.25 (0.106)	20.15** (0.033)	14.70 (0.162)	8.69 (0.390)	22.30** (0.030)	16.24 (0.144)	17.63 (0.169)	22.37* (0.097)	39.30 (0.164)
ρ	0.670*** (0.003)	0.608*** (0.000)	0.651*** (0.000)	0.765*** (0.000)	0.585*** (0.000)	0.670*** (0.000)	0.610*** (0.000)	0.619*** (0.000)	0.492 (0.204)
inuse	-0.097*** (0.004)	-0.114*** (0.000)	-0.111** (0.002)	-0.112*** (0.002)	-0.103** (0.023)	-0.121** (0.019)	-0.167*** (0.000)	-0.182*** (0.007)	-0.214* (0.060)
rupop	-0.097* (0.059)	-0.086 (0.107)	-0.037 (0.521)	-0.003 (0.954)	-0.071 (0.213)	-0.053 (0.333)	-0.069 (0.296)	-0.114 (0.185)	-0.146 (0.365)
sero	-0.027 (0.399)	-0.011 (0.767)	-0.002 (0.967)	0.020 (0.657)	-0.041 (0.387)	-0.013 (0.795)	0.034 (0.600)	0.019 (0.792)	-0.069 (0.478)
trade	0.001 (0.983)	-0.014 (0.519)	0.011 (0.653)	0.009 (0.741)	0.020 (0.350)	0.033* (0.081)	0.034** (0.031)	0.024 (0.124)	0.013 (0.533)
Pseudo R^2	0.3556	0.3624	0.3535	0.3455	0.3479	0.3617	0.3815	0.3889	0.3383

Notes: *, **, and *** indicate statistical significance at the level of 10%, 5%, and 1%, respectively; In the parentheses under 2SQR estimates are *p*-values.

Table 6. Estimates of quantile regression model (year=2001)

τ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Constant	44.07*** (0.000)	47.43*** (0.000)	54.41*** (0.000)	56.21*** (0.000)	55.77*** (0.000)	64.60*** (0.000)	65.19*** (0.000)	65.92*** (0.000)	69.70*** (0.000)
inuse	-0.057 (0.267)	-0.140** (0.013)	-0.156*** (0.001)	-0.145*** (0.005)	-0.164** (0.022)	-0.234*** (0.001)	-0.264*** (0.000)	-0.271*** (0.000)	-0.389*** (0.000)
rupop	-0.058 (0.315)	-0.081 (0.247)	-0.138* (0.057)	-0.136* (0.062)	-0.108 (0.219)	-0.202** (0.032)	-0.192*** (0.002)	-0.184*** (0.001)	-0.206*** (0.002)
sero	-0.127*** (0.000)	-0.099** (0.026)	-0.132*** (0.003)	-0.161*** (0.000)	-0.146*** (0.005)	-0.197*** (0.007)	-0.187*** (0.001)	-0.164** (0.017)	-0.101 (0.153)
trade	-0.013 (0.581)	-0.036 (0.284)	-0.032 (0.390)	-0.013 (0.741)	-0.008 (0.818)	0.029 (0.246)	0.028 (0.190)	0.030 (0.143)	0.005 (0.786)
Pseudo R^2	0.3212	0.2854	0.2567	0.2503	0.2461	0.2468	0.2319	0.2227	0.1946

Notes: *, **, and *** indicate statistical significance at the level of 10%, 5%, and 1%, respectively; In the parentheses under 2SQR estimates are *p*-values.

Tables 3 and 5 show the estimates for the parameters of the spatial quantile regression models based on the data for 2001 and 2005, respectively. The results based on the data for 2001 showed that in addition to spatial dependence, the estimates of the prevalence of Internet use (i.e., the digital divide) for most quantiles were significant. The estimates of school enrollment (%), rural population (%), and the proportion of trade volume in the GDP (%) were significant at several quantiles. The coefficients for the prevalence of Internet use at various quantiles were negative and their effects gradually increased with each quantile.

The results based on the data for 2001 and 2005 were consistent and showed that the effects of the prevalence of Internet use on income inequality were significant and that the coefficients were negative. By considering spatial dependence and heterogeneity, the prevalence of Internet use alleviated income inequality at each quantile; in addition, the alleviating effect of the prevalence of Internet use was large when the degree of income inequality was high.

In this study, the proportion of import and export trade volumes in the GDP was used to assess the trade openness of a country. Previous studies cannot prove that trade openness and income inequality have a consistent relationship (Dollar and Kraay, 2004; Winters *et al*., 2004; Meschi and Vivarelli, 2009; Babones and Vonada, 2009; Furusawa and Konishi, 2012; Jaumotte *et al*., 2013). Milanovic (2005) found strong evidence that at low average income level, it is the rich who benefit from openness. According this study model estimation, the effects of trade volume on income distribution at high quantiles was the opposite of those at low quantiles. Income inequality is affected not only by trade volume but also by the income inequality of various countries. This is why the quantile regression model should be adopted. For countries with high income inequality, increased trade volumes will worsen the income inequality. The results of this study can be used to resolve disagreements among numerous researchers about the effects of trade on income inequality because previous studies rarely adopted a quantile regression model.

Therefore, the degree of income inequality reduced as education level improved (Park, 1996; Sylwester, 2002; Abdullah *et al*., 2015). According to the estimation results that were negative at various quantiles but significant only at central quantiles. This may explain why the results in the past researches were not consistent, like Rodr ǵuez-Pose and Tselios (2009) showed that education level was not significantly correlated with income inequality. The articles described before most of them used the OLS method, and the results obtained are average effects, that is, the position of the middle quantiles in our results. In our results, we can see that the previous results are not applicable in all types of countries. Our results also demonstrate the adaptability of the spatial quantile model again.

The World Bank divided all countries of the world into four categories: High income, Upper middle income, Lower middle income and Low income. We classify High income and Upper middle income as high-income countries, the remaining two categories of countries are classified as low-income countries. The data used in this study in 2001 based on the above criteria are divided into two categories. There are 69 high-income countries and 45 low-income countries. The results of the model estimation are shown in Table 7 and Table 8, respectively. The results of the high-income countries show that the effect of the explanatory variables on the income inequality is similar to the estimation result for the whole sample. However, we can find that in the low-income countries, the higher the internet usage, the greater the income inequality. This means that there are only a few who can really use internet to get the benefits resulting in increased income inequality in low-income countries. The reason for this is that if you want to earn extra revenue from the internet, you may have to have some special technology or equipment, so you can access to the internet, but that does not mean you can increase your revenue. According to the results of the estimation, this impact is more significant in the high quantile.

Table 7. Estimates of spatial quantile regression model (year=2001; High-income countries)

τ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Constant	19.799* (0.087)	25.664 (0.012)	29.999*** (0.008)	28.208*** (0.010)	31.589*** (0.000)	30.837*** (0.007)	23.856** (0.040)	23.381 (0.150)	2.951 (0.874)
ρ	0.714*** (0.000)	0.629*** (0.000)	0.647*** (0.000)	0.717*** (0.000)	0.704*** (0.000)	0.706*** (0.000)	0.818*** (0.000)	0.790*** (0.000)	0.960*** (0.000)
inuse	-0.078 (0.317)	-0.104* (0.078)	-0.070 (0.238)	-0.088* (0.097)	-0.101* (0.098)	-0.175*** (0.002)	-0.104* (0.069)	-0.118** (0.035)	-0.057 (0.568)
rupop	-0.035 (0.448)	-0.055 (0.227)	-0.104* (0.067)	-0.136** (0.040)	-0.137** (0.031)	-0.156* (0.064)	-0.105 (0.263)	-0.106 (0.414)	0.081 (0.569)
sero	-0.112 (0.285)	-0.115 (0.115)	-0.165** (0.044)	-0.153** (0.044)	-0.167** (0.018)	-0.126** (0.048)	-0.130** (0.025)	-0.111 (0.116)	-0.003 (0.972)
trade	0.002 (0.927)	-0.005 (0.819)	0.022 (0.420)	0.024 (0.292)	0.016 (0.483)	0.016 (0.322)	0.017 (0.330)	0.022 (0.247)	0.008 (0.758)
Pseudo R^2	0.483	0.513	0.526	0.546	0.562	0.581	0.592	0.578	0.540

Notes: *, **, and *** indicate statistical significance at the level of 10%, 5%, and 1%, respectively; In the parentheses under 2SQR estimates are *p*-values.

Table 8. Estimates of spatial quantile regression model (year=2001; Low-income countries)

τ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Constant	36.041*** (0.000)	40.339*** (0.001)	49.718*** (0.000)	43.179*** (0.000)	42.165*** (0.000)	41.603*** (0.000)	41.512*** (0.000)	48.829*** (0.000)	49.110*** (0.000)
ρ	0.035 (0.618)	-0.002 (0.982)	-0.110 (0.253)	-0.088 (0.250)	-0.107* (0.091)	-0.095* (0.084)	-0.056 (0.291)	-0.047 (0.428)	-0.071 (0.247)
inuse	1.280 (0.501)	0.577 (0.801)	0.873 (0.706)	1.116 (0.638)	3.561 (0.213)	3.830 (0.244)	7.006** (0.035)	7.692** (0.017)	10.656** (0.013)
rupop	-0.011 (0.900)	-0.026 (0.819)	-0.074 (0.383)	0.041 (0.650)	0.074 (0.485)	0.084 (0.360)	0.110 (0.250)	0.042 (0.648)	0.015 (0.906)
sero	-0.119** (0.038)	-0.123* (0.082)	-0.189*** (0.009)	-0.154** (0.030)	-0.180*** (0.001)	-0.163*** (0.010)	-0.183** (0.013)	-0.213** (0.017)	-0.258** (0.024)
trade	0.033 (0.483)	0.020 (0.722)	0.039 (0.458)	0.022 (0.663)	0.027 (0.555)	0.020 (0.677)	-0.008 (0.867)	-0.017 (0.703)	0.044 (0.302)
Pseudo R^2	0.210	0.176	0.161	0.171	0.190	0.173	0.168	0.205	0.222

Notes: *, **, and *** indicate statistical significance at the level of 10%, 5%, and 1%, respectively; In the parentheses under 2SQR estimates are *p*-values.

In addition, the results of the spatial correlation estimation can be found from the positive correlation in global analysis to negative correlation. The positive impact of the educational level on the resulting income inequality will be better than that of the high-income country classification. This result is similar to Abdullah *et al*. (2015) that education can reduce the income inequality effectively especially in Africa. The results can be used as the policy recommendations of the countries of the low-income countries. In low-income countries, efforts to improve the educational environment remain the most important. This result is significant and positive in any national classifications. The increase in internet usage in high-income countries will be an effective tool to improve income inequality. On the contrary, it does not in low-income countries. The policy makers need to pay special attention in this issue to avoid the resulting income inequality becomes worse.

5. Conclusion

The spatial quantile regression model is adopted to investigate the influences of social and economic factors (e.g., the digital divide) on income inequality by considering spatial dependence and heterogeneity. The estimation results indicated that Internet use had a significant effect on income inequality. Internet use can accelerate technological progress and enhance production efficiency. Accordingly, Internet use will effectively improve income structure and alleviate income inequality. Technological progress can enhance productivity and Internet use can rapidly propagate new technologies in a low-cost manner, thereby effectively increasing income. Therefore, as shown in this study, improvement in digital divide is an effective method for reducing income inequality. This result can be applied to most countries in the world except low income countries.

This study shows that education, trade, and rural population also significantly influence income inequality. We adopted the spatial quantile regression model and analyzed the situations of multiple countries under various economic conditions. For example, the effects of trade volume on income inequality at high and low quantiles were completely opposite. This is why previous studies did not obtain consistent results regarding the effects of trade on income inequality. Similarly, regarding the effects of internet usage on income inequality, the government must consider their own conditions when implementing policies to reduce income inequality because similar policies adopted by various countries do not necessarily yield the same results.

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References

[1] Abdullah, A., Doucouliagos, H., and Manning, E. (2015). “Does education reduce income inequality? A meta-regression analysis”, *Journal of Economic Surveys*, 29 (2): 301-316.

[2] Acemoglu, D. (2002). “Technical change, inequality, and the labor market”, *Journal of Economic Literature*, 40 (1): 7-72.

[3] Anderson, E. (2005). “Openness and inequality in developing countries: A review of theory and recent evidence”, *World Development*, 33 (7): 1045-1063.

[4] Anselin, L. (1988). *Spatial Econometrics: Methods and Models*. Boston: Kluwer Academic Publishers.

[5] Anselin, L. (2001). *Spatial Econometrics- A companion to Theoretical Econometrics*. Oxford: Blackwell Publishing Ltd.

[6] Babones, S. J., and Vonada, D. C. (2009). “Trade globalization and national income inequality—are they related?”, *Journal of Sociology*, 45 (1): 5-30.

[7] Bernanke, B.S.(2008). “*Remarks on class day 2008*”, [Online] Available at: http://www. federalreserve.gov/newsevents/speech/bernanke20080604a.htm (Accessed on April 5th, 2017).

[8] Billón, M., Ezcurra, R., and Lera-López, F. (2008). “The spatial distribution of the internet in the European Union: Does geographical proximity matter?”, *European Planning Studies*,16 (1): 119-142.

[9] Cairncross, F. (2001). *The Death of Distance: How the Communications Revolution Will Change Our Lives.* Boston: Harvard Business Publishing.

[10] Chang, H. H., and Just, D. R. (2009). "Internet access and farm household income–empirical evidence using a semi-parametric assessment in Taiwan", *Journal of Agricultural Economics*, 60 (2): 348-366.

[11] Choi, C., and Yi, M. H. (2009). "The effect of the internet on economic growth: Evidence from cross-country panel data", *Economics Letters*, 105 (1): 39-41.

[12] Dall'Erba, S. (2005). "Distribution of regional income and regional funds in Europe 1989–1999: an exploratory spatial data analysis", *The Annals of Regional Science*, 39 (1): 121-148.

[13] Dollar, D., and Kraay, A. (2004). "Trade, growth, and poverty", *The Economic Journal*, 114 (493): F22-F49.

[14] Dreher, A., and Gaston, N. (2008). "Has globalization increased inequality?", *Review of International Economics*, 16 (3): 1-21.

[15] Freidman, T. (2005). *The World Is Flat : A Brief History of the Twenty-first Century*. New York: Farrar, Straus and Giroux.

[16] Furusawa, T., and Konishi, H. (2012). "International trade and income inequality", Mimeo, [Online] Available at http://www.econ.hit-u.ac.jp/~furusawa/paper/income.pdf .

[17] Jaumotte, F., Lall, S., and Papageorgiou, C. (2013). "Rising income inequality: technology, or trade and financial globalization", *IMF Economic Review*, 61 (2): 271-309.

[18] Koenker, R. and Bassett Jr, G. (1978). "Regression quantiles", *Econometrica*, 46 (1): 33-50.

[19] Krueger, A. B. (1993). "How computers have changed the wage structure: evidence from microdata, 1984–1989", *The Quarterly Journal of Economics*, 108 (1): 33-60.

[20] Kuznets, S. (1955). "Economic growth and income inequality", *The American Economic Review*, 45 (1): 1-28.

[21] Lee, E. and Vivarelli, M. (2006). "The social impact of globalization in the developing countries", *International Labour Review*, 145 (3): 167-184.

[22] Le Gallo, J. and Ertur, C. (2003). "Exploratory spatial data analysis of the distribution of regional per capita GDP in Europe, 1980− 1995", *Papers in Regional Science*, 82 (2): 175-201.

[23] LeSage, J. and Pace, R. K. (2009). *Introduction to Spatial Econometrics*, Boca Raton, FL: CRC Press.

[24] Liao, W. C., and Wang, X. (2012). "Hedonic house prices and spatial quantile regression", *Journal of Housing Economics*, 21 (1): 16-27.

[25] Lloyd-Ellis, H. (1999). "Endogenous technological change and wage inequality", *American Economic Review*, 89 (1): 47-77.

[26] Lustig, N., Lopez-Calva, L. F., and Ortiz-Juarez, E. (2013). "Declining inequality in Latin America in the 2000s: the cases of Argentina, Brazil, and Mexico", *World Development*, 44 (C): 129-141.

[27] Meschi, E. and Vivarelli, M. (2009). "Trade and income inequality in developing countries", *World Development*, 37 (2): 287-302.

[28] Milanovic, B. (2005). "Can we discern the effect of globalization on income distribution? Evidence from household surveys", *The World Bank Economic Review*, 19 (1): 21-44.

[29] OECD (2001). "*Understanding the Digital Divide*", OECD Digital Economy Papers, No. 49, OECD Publishing, Paris. [Online] Available at http://dx.doi.org/10.1787/236405667766 .

[30] Oishi, S., Kesebir, S., and Diener, E. (2011). "Income inequality and happiness", *Psychological Science*, 22 (9): 1095-1100.

[31] Park, K. H. (1996). "Educational expansion and educational inequality on income distribution", *Economics of Education Review*, 15 (1): 51-58.

[32] Rey, S. J. (2004). "Spatial analysis of regional income inequality", *Spatially Integrated Social Science: Examples in Best Practice*, 280-299.

[33] Rodríguez-Pose, A., and Tselios, V. (2009). "Education and income inequality in the regions of the European Union", *Journal of Regional Science*, 49 (3): 411-437.

[34] Solt, F. (2009). "Standardizing the world income inequality database", *Social Science Quarterly*, 90 (2): 231-242. (SWIID Version 3.1, December 2011).

[35] Stolper, W., and Samuelson, P. A. (1941). "Protection and real wages", *Review of Economic Studies*, 9 (1): 58-73.

[36] Sylwester, K. (2002). "Can education expenditures reduce income inequality?", *Economics of Education Review*, 21(1): 43-52.

[37] Tsai, S. L., and Kuan, C. M. (2003). "Assortative Mating and Income Inequality in Taiwan: a Quantile Regression Approach", In presentation at the conference "Social Inequality, Family, and Intergenerational Transfer" of the Research Committee on Social stratification and Social Mobility of the International Sociological Association (ISA-RC28), held at the University of Tokyo, Japan, on March, 2003 (pp. 1-3).

[38] Tselios, V. (2008). "Income and educational inequalities in the regions of the European Union: Geographical spillovers under welfare state restrictions", *Papers in Regional Science*, 87 (3): 403-430.

[39] Vicente, M. R., and López, A. J. (2011). "Assessing the regional digital divide across the European Union-27", *Telecommunications Policy*, 35 (3): 220-237.

[40] Winters, L. A., McCulloch, N. and McKay, A. (2004). "Trade liberalization and poverty: the evidence so far", *Journal of Economic Literature*, 42 (1): 72-115.

[41] Zhang, X. (2013). "Income disparity and digital divide: The Internet Consumption Model and cross-country empirical research", *Telecommunications Policy*, 37 (6): 515-529.