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Evaluating the role of income in national software piracy

Eric Kyper
Lynchburg College

Gerald Prante
Lynchburg College

Lee Schimmoeller
Lynchburg College

This study investigates the proper role of income in predicting national software piracy rates. We run regressions isolating various measures of income, including GDP per capita and median household income and variations thereof, to predict national software piracy rates. Then we also run multivariate regressions incorporating GDP and other non-income predictors such as corruption in a manner consistent with previous studies. This topic is of importance due to the multi-billion dollar losses incurred globally each year due to pirating. The results show that a square root version of median household income is the best measure of national income and consistent with what economic theory predicts.

Keywords: Software piracy; income; culture

Introduction

Software piracy is a well-studied topic with global losses in excess of $62 billion (BSA, 2014). However, the determinants of software piracy vary from study to study. One variable in common is some measure of national income, typically GDP per capita. Economic theory dictates that, ceteris paribus, higher income leads to more discretionary spending. Following that lead we conclude that wealthier nations should have lower national software piracy rates. Indeed this is generally true, but does not eliminate variation in software piracy rates among wealthy nations. The proper role of income is of importance because virtually every study regarding national piracy includes income, and only a nuanced understanding of income will flush out real differences between countries with similar incomes. Previous studies report conflicting results regarding income. For example, the statistical significance of GDP varies across studies and year of study. GDP is also sometimes used as a proxy for other data such as number of internet users. This study makes an important contribution to current literature by elucidating the role of GDP. We clarify that GDP is typically only significant in studies where more illuminating variables are not included. This amounts to GDP being used as a variable of convenience. While informative, if GDP is being used as a proxy for better variables, we should recognize this and work towards analyzing those variables. From this, we also ask the question whether or not a different income measure is superior to GDP per capita in predicting software piracy.

In addition, a number of variables beyond income have been found to influence piracy. These include culture and intellectual property protection. This study aims to determine the exact role GDP plays in determining national software piracy rates first in isolation, then in concert with non-income variables.

Literature Review

Software piracy is a huge and growing issue in the global economy. The BSA Software Alliance Survey in 2013 estimated the commercial value of unlicensed software totaled $62.4 billion globally. Furthermore, the global rate at which software was installed without proper licensing increased from 42% in 2011 to 43% in 2013 (BSA, 2014). This increase was attributed to the growth in emerging economies where unlicensed software is prevalent. There has been a large body of research concerning this topic. Some of the earlier studies of national software piracy rates included economic, cultural, and temporal variables. Table 1 below reviews a sample of studies from 1998 to 2014, summarizes the findings and identifies the variables included. Particular attention is given to GDP as an independent variable (IV).

This review of the literature indicates that some measure of economic performance is the most common determinant analyzed in the research of national software piracy rates. Often, this economic indicator is not at the country level (GDP) but as some type of proxy for individual wealth. Many such as Goel and Nelson (2012) use GDP per capita, while other such as Marron and Steel, (2000) use per capita income. A full list of variables used is illustrated in Table 1 above. Additionally, Harbi, Grolleau and Bekir (2012) believe there is a Kuznets curve in that as poor people acquire wealth and then technology, the piracy rates increase until the wealth is at a level where piracy rates begin to decrease. All of these nine studies used some type of economic indicator of either country or personal wealth, suggesting that income is a critical factor.

In addition to income, many of the previous studies incorporate cultural factors in their models. Hofstede's (1980) cultural model is the most frequently referenced framework for describing national cultural differences. These five dimensions attempt to quantify the key factors that determine a country's specific national culture and include power distance, individualism, masculinity, uncertainty avoidance, and long term orientation. Much of this research (4 of 9) focused on individualism versus collectivism and often found individualism to be a statistically significant predictor of national software piracy.

To clarify, Hofstede defines individualism as a preference for a loosely knit social framework in which individuals take care of themselves and their immediate families only; they are not much concerned with the greater society. Collectivism is a preference for a closely knit social framework in which individuals are emotionally integrated into an extended family, clan or other group which will protect them in exchange for loyalty. Analysis has shown that members of a collective, while extremely loyal to the collective, are less likely to be concerned about others outside the collective, this includes being more likely to copy software from others outside their collective. A collective is associated with a nation in this study. Collectivism data is included in the study.

Theoretical framework of national software piracy rates: Cost-benefit analysis

From an economic theory perspective, software piracy is a simple cost-benefit decision for individuals and firms. On the benefit side, pirating software instead of paying for it simply increases an individual's disposable income. And economic theory would predict that higher individual incomes would reduce the need to engage in software piracy due to the concept of diminishing marginal utility of income. This concept states that the first dollar of income adds more to an individual's utility than the second dollar, which adds more to utility than the third dollar, and so forth. Put simply, a poor person making $7,000 who currently has a low utility level saving $100 dollar by pirating a piece of software is adding more to his/her utility than a rich person making $100,000 doing so, ceteris paribus.

Table 1. Summary of previous studies of Software Piracy Rates (SPR) where SPR is dependent variable (DV)

Authors	Sample size	IVs	Key Findings	Method
(Chavarria & Morrison, 2014)	42 countries	GDP per Capita, Hofstede 5 cultural values	Cultural values of collectivism and performance orientation positively related to SPR. Log of GDP per capital also positively related to SPR.	OLS Regression
(Hamister & Braunscheide, 2013)	105 countries	GDP per Capita, Hofstede 5 cultural values & Intellectual Property Rights Protection	GDP per capita and IPPR are negatively correlated with SPR. Also, high power distance is positively associated with SPR. Other cultural dimensions were not significant, including collectivism.	OLS Regression
(Goel & Nelson, 2012)	100 countries	GDP per capita shadow economy & internet diffusion	Underground economy has a positive relationship with SPR. Negative relationship with GDP per capita and internet diffusion.	OLS Regression
(Harbi, Grolleau, & Bekir, 2012)	100 countries	GDP per capita	Studied 100 countries over 15 years and showed piracy first increase with level of GDP per capita, reaches maximum, then decreases at higher income levels.	OLS Regression
(Yang, Sonmez, Bosworth, & Fryxell, 2009)	59 countries	GNI per capita, Individualism & technology development	All 3 IV's are negatively correlated with SPR.	OLS Regression
(Gopal & Sanders, Sep 2000)	65 countries	Per capita GNP	An inverse relationship between software piracy rates and per capita GNP with a break at $6,000 with those below the break being affected more.	OLS Regression
(Marron & Steel, April 2000)	77 countries,	Per capita income, individualism, R&D, Education, strength of economicinstitutions	The inverse relationships of individualism, per capita income and strength of economic institutions explain the greatest amount of variance in software piracy rates.	OLS Regression
(Husted, 2000)	39 countries,	Per capita GNP, individualism, income inequality, masculinity, power distance, uncertainty avoidance	Included cultural variables finding that GNP per capita, income inequality, and individualism are significantly related to software piracy (all relationships are inverse).	Correlation
(Gopal & Sanders, December 1998)	13 countries	GDP per capita, domestic software industry size	Provides support for the proposition that a government's incentive to enact and enforce copyright protection laws is closely related to the size of the domestic software industry. Also presents a model for ethical intentions based on ethical predisposition and demographics. This information can be used to create better prevention and deterrent controls for software piracy.	OLS Regression

Of course, utility is not directly observed or quantifiable. A standard form for writing a utility-income function is

Eq. 1: $U = cI^{\alpha}$

where c is a constant, I is income and α is the key parameter that determines the marginal effect of more income on utility. This form is derived from the standard Cobb-Douglas utility function. Mathematically, starting from the following Cobb-Douglas utility function, which expresses utility as a function of the quantities of goods X and Y consumed, where a and b are preference parameters:

Eq. 2: $U = X^a Y^b$
subject to the budget constraint (I = income, assuming all income is spent on X and Y):

Eq. 3: $I = P_X X + P_Y Y$
we can derive the following utility-income function:

Eq. 4: $U = \frac{I^{(a+b)}}{{P_X}^a \, (1+\frac{b}{a})^a \, {P_Y}^b \, (1+\frac{a}{b})^b}$

The denominator of this fraction, which consists of the prices of goods X and Y and parameters, is a constant as it relates to income. If a+b < 1, then diminishing marginal utility of income holds because increasing income by a factor (a+b) would increase utility by less than that factor (a+b). The speed at which utility is increasing as income increases depends on the value of the factor (a+b). If a+b is close to 1, then utility is increasing as income increases at a rate that is relatively fast. If a+b is close to 0, then utility is increasing as income increases but at a relatively slow rate. For the purposes of this paper, we use a simple square root of income to approximate the utility-income function. Specifically, we assume that the denominator of the utility-income function above is 1 and a+b = 0.5. (Eq. 1: $\alpha = 0.5$ and c = 1) The hypothesis is that using the square root of income instead of the simple dollar value is likely to be a better proxy for the current utility level of a country's average (or median) citizen. This works because the square root captures the effect of diminishing marginal utility on income. A square root is adopted as a parsimonious choice in deriving diminishing marginal utility.

In addition to the question of whether or not to use simple income or a utility proxy that assumes diminishing marginal utility of income, there is also the question of which measure of central tendency for income in a country should be used to calculate the marginal utility from software piracy. Because income tends to be highly skewed, median income is often used to better gauge the economic position of a country's typical citizen than is mean income. That is the hypothesis in this paper. However, it should be noted that it is technically possible that using mean income could serve to better represent the economic position of software users (weighted by the amount of software they use) as compared to median income. That is because in many low-income countries a large fraction of the population does not use software in the first place. Therefore, as their inclusion at the low end of the distribution pushes down both the median and mean, it could lead to a situation where mean income for all citizens is actually closer to the median software user's income than is the median income of all citizens. Unfortunately, country-by-country data does not exist on the incomes of software users only, which would be the ideal income metric.

While the benefit of increasing disposable income (and thereby utility) from software piracy exists, engaging in software piracy is not costless, and the costs vary across countries. Like any crime, there is always the possibility of getting caught and facing civil or criminal consequences. Therefore, in those countries with greater enforcement of piracy laws and tougher penalties for piracy the expected cost of piracy is higher. In order to account for this, the study includes a measure of intellectual property protection across countries, as perceived by global business leaders.

Just like any type of theft, there are personal and social costs of piracy. Regardless of whether or not an individual believes he/she will get caught by the authorities, an individual may simply feel personally guilty for stealing software. Those who believe that piracy is the immoral stealing of another's work are likely to place a higher value on the individual contribution of that person or firm. In terms of an individualist-collectivist spectrum, these people would lean towards the individualist side. On the other hand, those who place little emphasis on the past contributions of the original piracy designer and instead place a greater emphasis on the usefulness of that software to overall society would lean towards the collectivist side (this is represented by Hofstede's indices). Even beyond the question of one's own personal viewpoint on the ethics of software piracy, that person may also be influenced by the views of his/her peers on whether or not it is acceptable to engage in software piracy. Therefore, he/she would be influenced by the overall country's attitude towards individualism-collectivism. The existence of these personal moral and social peer-pressure costs of piracy is the theoretical justification for using Hofstede's individualism-collectivism index in the analysis.

Similar to the individualist-collectivist question, a country's level of corruption may also influence a person's cost-benefit analysis for whether or not to engage in software piracy. If a country is perceived by its citizens as having a culture of corruption, there is likely to be lower peer-pressure costs from engaging in piracy. This is likely to be highly correlated with intellectual property protection (IPP), which is a legal issue, but it does add some information. Suppose two countries have similar degrees of IPP but one is rated as more corrupt than the other. The individual in the corrupt country may feel as though engaging in illegal activity generally comes with less social backlash than the individual in the less corrupt country even if the expected legal costs are the same.

Even though both income and cultural variables theoretically impact software piracy rates directly, there is obviously a high degree of correlation between income and the cultural variables themselves. The causation likely goes both ways in some cases, such as with corruption and income. This issue is discussed in the results section with a collinearity matrix of all the variables used.

Research Questions and Accompanying Hypotheses

Do alternative income measures better predict national software piracy rates than standard GDP per capita? (Appendix B provides the regression models used to calculate R in the equations following H1-H3)

Ho1: Mean GDP per capita and square root of mean GDP per capita have the same predictive power of national software piracy rates

i.e. R (GDP per capita) – R (sq. root of mean GDP) = 0

Ho2: Mean GDP per capita and median household income have the same predictive power of national software piracy rates

i.e. R (GDP per capita) – R (median household income) = 0

Ho3: Mean GDP per capita and square root of median household income have the same predictive power of national software piracy rates

i.e. R (GDP per capita) – R (sq. root of median household income) = 0

How does the best alternative measure of income behave in the presence of standard software piracy predictors?

Ho4: Square root of income does not predict software piracy

Ho5: Corruption does not predict software piracy

Ho6: Collectivism does not predict software piracy

Ho7: Intellectual property protection does not predict software piracy

Hypotheses 4-7 are tested using the following regression model

Software Piracy $= B_0 + B_1$ *Corruption Index* $+ B_2$ *IPP Competitiveness Index* $+ B_3$ *Collectivism Index* $+ B_4$ *Square Root of Median Household Income* $+ \varepsilon$

Data Collection / Analysis

To examine the role of income in understanding national software piracy rates we collected data from 2006 to 2013 for the following variables: BSA's national software piracy rate (dependent variable), World Bank (GDP per capita by country PPP adjusted, Hoefstede's cultural indices (collectivism), Transparency International's corruption index, the World Economic Forum's Global Competitiveness Report (the intellectual property protection component), and median household income from Gallup by country (surveyed between 2006 and 2012).

There are 108 countries for which software piracy data from BSA exists for 2009, which is the year of reference. Of those 108 countries, 98 (91%) have data for both median income and GDP per capita (PPP basis). Complete data of all the explanatory variables exists for 61 countries (see Appendix A). The 37 country reduction in full country coverage is primarily due to a lack of coverage in Hoefstede's cultural indexes.

The dependent variable is national software piracy rate, collected from the BSA Global Software Survey. This variable represents the percentage of pirated software installed out of total software installed. Roughly this is calculated as the difference between total software installed (demand) and total legal software shipped (supply). The Software Alliance (BSA) is an advocacy group for software producers that seeks to promote the policy interests of software producers in governments throughout the world. One such area of public policy is their push to combat software piracy, which is why they commission this study on software piracy.

The independent variables used in the study fall into two categories: economic (income) and cultural/legal (collectivism, corruption, and intellectual property protection).

GDP per capita by country is derived using World Bank data on gross domestic product, which is then converted to international dollars using purchasing power parity (PPP) rates also provided by the World Bank. An international dollar has the same purchasing power over GDP as the U.S. dollar has in the United States; this controls for the difference of purchasing power among countries. GDP was the most commonly included economic variable in previous studies.

Median household income data comes from a Gallup report of country-by-country median household incomes, the results of which were released in 2013. Gallup surveyed the populations of 131 countries over a six-year period of 2006 through 2012. Like the study does with GDP, Gallup adjusted each country's income measure using the purchasing power parity rates provided by the World Bank. Because the Gallup figures are averages over a six year window from 2006 through 2012, we chose to use 2009 as the year of record in the analysis.

Our measure of intellectual property protection (IPP) comes from the World Economic Forum's *Global Competitiveness Report*, which it describes on its website as follows:

The Global Competitiveness Report 2014-2015 assesses the competitiveness landscape of 144 economies, providing insight into the drivers of their productivity and prosperity. The report remains the most comprehensive assessment of national competitiveness worldwide, providing a platform for dialogue between government, business and civil society about the actions required to improve economic prosperity. Competitiveness is defined as the set of institutions, policies and factors that determine the level of productivity of a country. The level of productivity, in turn, sets the level of prosperity that can be earned by an economy.

The IPP component of the *Global Competitiveness Report* is part of the institutions sub index of the GCR and is derived based on responses of business leaders to the following question in the *Executive Opinion Survey*:

How would you rate intellectual property protection, including anti-counterfeiting measures, in your country? [1 = very weak; 7 = very strong]

The two cultural variables used in this study were chosen based on the findings of previous researchers seeking to explain variation in piracy rates across countries. Many of these appear in the literature review. The measure for collectivism comes from Hofstede's seminal study on cultures across nations. As explained by Hofstede (1983):

"Individualism collectivism index: individualism, which stands for a preference for a loosely knit social framework in which individuals are supposed to take care of themselves and their immediate families only; as opposed to Collectivism, which stands for a preference for a tightly knit social framework in which individuals are emotionally integrated into an extended family, clan, or other in-group which will protect them in exchange for unquestioning loyalty. The word Collectivism in this sense carries no political connotations and does not assume any positions as to the role of the state; it operates at a much smaller scale of social integration (Hofstede, 1983)."

Merritt (2000) has shown that Hofstede's cultural indices are replicable across different time periods and subject groups. In particular collectivism showed to be durable across time and subjects. This provides the current study with the necessary empirical and theoretical foundations to continue using Hofstede's cultural indices.

Finally, the measure of corruption comes from Transparency International's *Corruption Perceptions Index*. The study rates countries on perception of public corruption on a scale of 0-10 where 0 is high corrupt countries and 10 is low corrupt countries. These ratings are based on surveys of surveys. That is, Transparency International uses multiple surveys that been conducted by organizations such as the World Bank, IHS Global Insight, Freedom House, and others in order to come up with a rating for each country. The respondents of these surveys are typically international experts and business persons.

We first address the question of what income measure best predicts software piracy by running bivariate OLS regressions for each income measure with the dependent variable for the 98 countries that have coverage of both income measures and software piracy. After running the four bivariate regressions, we then run four additional regressions, each containing a different income measure along with all of the non-income explanatory variables for the 61 countries that have full coverage. All hypotheses are tested at the 95% significance level ($\alpha = 0.05$).

Results

In understanding the relationship between software piracy and income we examined 98 countries using correlation tests. (See Table 2 below). We found that the difference between r for median income is statistically significant than r for mean income (alpha = 0.05), thus rejecting H2 (mean GDP vs. median household income). We find no statistically significant differences within means nor medians between standard values and square root values, thus NOT rejecting H1 (mean GDP vs. square root of mean GDP) and H3 (mean GDP vs. square root of median household income). However, model fit (R^2) improves consistently as we move from mean GDP to the square root of median income. This suggests that capturing the diminishing marginal utility of income is an important step in understanding software piracy.

Although H1 and H3 were not rejected using conventional hypothesis testing assuming a sample size of 98, recall there are only 108 countries with data on software piracy rates from BSA. Therefore, if one considers BSA countries to be the population of interest, we have near-population level coverage in this study. There are only 196 independent countries in the world. The 108 countries selected for inclusion in the BSA study is not a random sample from those 196. The BSA study focuses on the largest and richest countries given that BSA member companies would have the most at stake in those countries and given that those countries tend to have better data availability. Together, the 98 countries included in the bivariate analysis account for over 94% of the world's GDP.

Table 2. Pearson Correlation Coefficients and R^2 ( ) for different income measures with software piracy

Income Measure	All countries with data coverage of piracy and income (n = 98)	Countries with full data coverage of piracy, income, corruption, collectivism, and IPP (n = 61)
Mean GDP	0.674 (0.454)	0.825 (0.681)
Square Root of Mean GDP	0.764 (0.584)	0.851 (0.724)
Median Household Income	0.836 (0.699)	0.847 (0.717)
Square Root of Median Household Income	0.851 (0.724)	0.873 (0.762)

Table 3. Regression results for square root of median household income

Independent Variable	**Coefficient**	**P-value**	**Hypothesis Tested**
Constant	84.553	0.000*	N/A
Corruption Index	-0.954	0.453	H5
IPP (Competeveness Index)	-5.346	0.016*	H7
Collectivism Index	0.213	0.000*	H6
Square Root of Median HH income	-0.136	0.002*	H4
Sample Size	61		
Adj. R^2	0.856		
F Statistic	89.891		

Using the square root of median household income in Table 3 below highlights the multiple regression findings which allow us to further reject hypotheses H4 (square root of income), H6 (collectivism), and H7 (intellectual property protection). It shows that when we use the square root of median household income as the income metric along with all other non-income explanatory variables, the R^2 value is 0.856. Note that the universe of countries included is smaller because of the lack of coverage for certain non-income variables. All of the variables are significant except for corruption. Corruption (H5) is not significant largely because of collinearity with income as shown and discussed below in Table 4.

In Table 4 we present results for four different regressions with each including a different income measure. The universe of countries included in these regressions is the 61 countries with full coverage of all the variables. These 61 countries make up 90% of world GDP. Regressions #1 and #2 use mean GDP per capita and its square root respectively. Regressions #3 and #4 use median household income and its square root respectively.

Regression #1 in the table shows that mean GDP per capita is not significant when the other explanatory variables are included. The other income variables are significant in their respective regressions. The relationship between mean GDP per capita and software piracy is simply not strong enough to overcome the effect of collinearity on statistical significance. That is not the case for the other income measures, which as we saw earlier have stronger relationships with software piracy than mean GDP per capita. We again find that in all regressions, corruption is not statistically significant. Although intellectual property protection (IPP) and collectivism are also correlated with the other explanatory variables, both of these variables were significant in each regression at a 95% confidence level.

Table 4. Coefficients and P-values ( ) from Regressions Predicting BSA Piracy Rates across Countries in 2009, by Income Metric Used

Independent Variable	**Regression #1** Mean GDP	**Regression #2** $\sqrt{MeanGDP}$	**Regression #3** Median Income	**Regression #4** $\sqrt{MedianIncome}$
Constant	76.928 (0.000)	85.421 (0.000)	76.465 (0.000)	84.553 (0.000)
Corruption Index	-1.962 (0.137)	-1.445 (0.255)	-1.512 (0.255)	-0.954 (0.453)
IPP (Competiveness Index)	-5.409 (0.025)*	-5.177 (0.024)*	-5.541 (0.018)*	-5.346 (0.016)*
Collectivism Index	0.2500 (0.000)*	0.231 (0.000)*	0.234 (0.000)*	0.213 (0.000)*
GDP per capita ($1,000)	-0.254 (0.087)			
Square Root of GDP per capita		-0.117 (0.006)*		
Median HH income ($1,000)			-0.351 (0.027)*	
Square Root of Median HH income				-0.136 (0.002)*
Sample Size	61	61	61	61
Adj. R^2	0.836	0.849	0.842	0.856
F Statistic	77.334	85.241	80.675	89.891

While there is strong collinearity between each of the non-income explanatory variables and the four income measures, collinearity is strongest between corruption and the income measures. The correlation coefficients shown in Table 5 explain why corruption is not a significant predictor of software piracy in the presence of an income variable. Table 5 also explains why the R^2 values only increase modestly when the non-income variables are included compared to the simple income-piracy regression.

One of the key takeaways from the analysis is that the high degree of statistical collinearity between the theoretical determinants of software piracy make it difficult to assess the individual magnitude of each determinant. For example, by itself, higher income leads to lower piracy. But the statistically strong relationship between income and piracy is, in part, masking the ability of corruption (and other variables) to explain piracy differentials across countries.

Table 5. Correlation coefficients between income and other explanatory variables

	Corruption	IPP	Collectivism
GDP per Capita	0.856	0.844	-0.627
Square Root of GDP per capita	0.850	0.830	-0.647
Median HH Income	0.866	0.839	-0.659
Square Root of Median HH income	0.866	0.835	-0.674
n = 61 (full coverage countries only) Note: All correlation coefficients are statistically significant at 95% confidence level.			

Sensitivity Analysis

Our findings are robust under various alternative specifications. Specifically, we ran regressions for years other than 2009 to verify that the research conclusions do not change based on the year chosen. In addition, we performed listwise regressions for year 2009 and concluded that are results do not change. The listwise regression included all 91 countries instead of just the 61 countries that have full coverage of all of the explanatory variables. Under listwise, for those countries that are missing one of the explanatory variables, the regression ignores that variable but includes the information from the variables for which data is present. We do not replace the missing data with the variable's mean value. We simply treated missing data as missing. Results under these alternative specifications are available to readers upon request from the authors.

Conclusion

The role of income in predicting national phenomena such as software piracy has been frequently studied. Average per capita GDP is an understandably common measure of individual income. However, failure to recognize the diminishing marginal utility of income can be an egregious error when comparing countries with dramatically different income levels. This creates the potential for the misinterpretation of the role of income. Furthermore, because income is highly skewed within countries, using median in place of the average has significant advantages. The findings show applying the square root of median income captures the diminishing role of income and provides the best income measure to use in software piracy studies.

Whatever income measure is chosen, the study shows that collinearity between income and other variables is a major issue in trying to assess the predictive power of non-income variables on software piracy rates. The problem stems from two competing realities: (1) Income should theoretically be part of any software piracy model, and (2) Income is highly correlated with other variables – such as intellectual property protection, corruption, and collectivism – that should theoretically be part of any software piracy model. Ideally these findings will inform future studies using income to predict national phenomena.

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Eric Kyper, Gerald Prante, and Lee Schimmoeller work at Lynchburg College.

Appendix A

List of countries included in multiple regression analyses

Australia	Guatemala	Peru
Austria	Hong Kong	Poland
Bangladesh	Hungary	Portugal
Belgium	India	Romania
Brazil	Indonesia	Russia
Bulgaria	Ireland	Serbia
Canada	Israel	Singapore
Chile	Italy	Slovakia
China	Japan	Slovenia
Colombia	Latvia	South Africa
Costa Rica	Lithuania	South Korea
Croatia	Malaysia	Spain
Czech Republic	Malta	Sweden
Denmark	Mexico	Thailand
El Salvador	Morocco	Turkey
Estonia	Netherlands	United Kingdom
Finland	New Zealand	United States
France	Norway	Uruguay
Germany	Pakistan	Venezuela
Greece	Panama	Vietnam

Additional countries included in the bivariate regressions of income and software piracy

Albania	Egypt	Nicaragua
Algeria	Georgia	Nigeria
Armenia	Honduras	Paraguay
Azerbaijan	Iraq	Qatar
Bahrain	Jordan	Saudi Arabia
Belarus	Kazakhstan	Senegal
Bolivia	Kenya	Sri Lanka
Bosnia and Herzegovina	Kuwait	Tunisia
Botswana	Lebanon	Ukraine
Cameroon	Libya	Yemen
Cyprus	Luxembourg	Zambia
Dominican Republic	Moldova	
Ecuador	Montenegro	

The following 10 countries have BSA piracy rates but are lacking data for either GDP per capita or median household income:

Argentina	Mauritius	Taiwan
Brunei	Oman	UAE
Iceland	Puerto Rico	
Ivory Coast	Switzerland	

Appendix B

Do alternative income measures better predict national software piracy rates than standard GDP per capita?

Ho1: Mean GDP per capita and square root of mean GDP per capita have the same predictive power of national software piracy rates

(Regression #1): *Software Piracy* = B_0 + B_1 *Corruption Index* + B_2 *IPP Competitiveness Index* + B_3 *Collectivism Index* + B_4 *GDP per capita* + ε

vs.

(Regression #2): *Software Piracy* = B_0 + B_1 *Corruption Index* + B_2 *IPP Competitiveness Index* + B_3 *Collectivism Index* + B_4 *Square Root of GDP per capita* + ε

Ho2: Mean GDP per capita and median household income have the same predictive power of national software piracy rates

(Regression #1): *Software Piracy* = B_0 + B_1 *Corruption Index* + B_2 *IPP Competitiveness Index* + B_3 *Collectivism Index* + B_4 *GDP per capita* + ε

vs.

(Regression #3): *Software Piracy* = B_0 + B_1 *Corruption Index* + B_2 *IPP Competitiveness Index* + B_3 *Collectivism Index* + B_4 *Median Household Income* + ε

Ho3: Mean GDP per capita and square root of median household income have the same predictive power of national software piracy rates

(Regression #1): *Software Piracy* = B_0 + B_1 *Corruption Index* + B_2 *IPP Competitiveness Index* + B_3 *Collectivism Index* + B_4 *GDP per capita* + ε

vs.

(Regression #4): *Software Piracy* = B_0 + B_1 *Corruption Index* + B_2 *IPP Competitiveness Index* + B_3 *Collectivism Index* + B_4 *Square Root of Median Household Income* + ε