Technological Kuznets Curve? Technology, Income Inequality, and Government Policy

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Abstract
Existing research suggests the dual effects of technological advances on income inequality. This study proposes a "technological Kuznets Curve (TKC)," in which the technology-inequality relationship changes with the level of technological development. Two versions of TKC are developed, based on the role of technology as the engine of growth (leading to the inversely U-shaped relationship) and on the nature of Schumpeterian innovation (leading to the U-shaped relationship). The findings from the study's data analysis suggest the U-shaped version of TKC, with strong empirical support for government redistributive policy in reducing technology-induced inequality.

Keywords: technology, income inequality, Kuznets Curve, Schumpeterian innovation, redistribution, government policy

1. Introduction

Technology is hailed as a driver of "infinite progress (Sarewitz 1996, p.11)," a curer of many social ills, an engine of economic growth, and a source of competitive advantage in a global knowledge economy. Technology is at the same time blamed for deterioration of the environment, destruction of existing ways of life, inhumane engineering of scientific knowledge, or volatile economic changes.

One of the areas in which such dual effects of technology stand out is economic inequality. Scholars have long been interested in the causes and implications of economic inequality, as inequality closely correlates with various phenomena such as economic prosperity, political democracy, and social stability (Alesina & Perotti 1993, Bollen & Jackman 1985, Benabou 1996, Persson & Tabellini 1996).

Theoretically, technology may both improve and worsen the condition of economic equality. On one hand, it can contribute to greater equality by destroying old sources of wealth creation. On the other hand, technology can generate more inequality by enabling new methods of wealth accumulation. Such conflicting effects of technology imply that the relationship between technological development and income inequality is nonlinear.

In view of the potentially dual effect of technological advances on economic inequality, this paper undertakes an empirical test of two possibilities for what might be called the "technological Kuznets Curve (TKC)." One is the inverted U-shaped relationship, which mimics the original Kuznets curve capturing the inverse relation of development and income inequality

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(Kuznets 1955). In this relationship, technological innovations are expected to generate more inequality initially with only a few enjoying the high incomes of the technologically advanced sector. As technologies are diffused, however, more people can enjoy higher incomes and benefits thereof, which would lead to lower inequality (Barro 1999).

The other possibility of the TKC is a U-shaped relationship in which technology reduces inequality initially and raises inequality with its further advancement. The logic underlying this relationship hinges on two types of Schumpeterian innovation, namely Mark I and Mark II (Malerba & Orsenigo 1995). Schumpeterian innovation Mark I characterizes the early phase of technological development, where old products, skills, or occupations are eroded in the process of creative destruction. With low barriers to entry and erosion of monopoly rents from new products and processes, this phase finds technology as an equalizer. The later phase of technological development takes on the character of Schumpeterian innovation Mark II, in which technological innovation is notably dominated by heavy R&D efforts and huge profits from such investments. Technologies in this process of "creative accumulation" aggravate existing inequalities, as their benefits accrue mostly to those holding sizeable physical or human capital.

If technology leads to greater inequality, one might wonder whether and how the government can ameliorate technology-induced inequality. There seems to be a tension between two government policies pertaining to the technology-inequality relationship – R&D and redistributive policies. The former is intended to maximize the growth potentials of technological innovations, whereas the latter aims to enhance equality and fairness by redistributing aggregate welfare. With limited resources and competing demands from different constituencies, the government faces a dilemma between securing long-term development with its R&D policy and providing immediate assistance for the disadvantaged with its redistributive policy. In light of the significance of government roles in mediating the technology-inequality relationship, this paper also presents an additional empirical analysis of the effects of government policy on technology-induced inequality.

The paper is organized into the theoretical and empirical sections. The theoretical section explains various theoretical conjectures on the relationship of technology and inequality, introduces two forms of the TKC, and discusses the effects of government policies on the TKC. The empirical section presents the data, methods, and results of the empirical analysis. The last section concludes the paper with a discussion of the implications of the study's findings.

2. Theoretical Conjectures

Like in any hypothetical relationship between two phenomena, there are three theoretical possibilities for the relationship of technological development and economic inequality.[1)] First, technological development may produce more inequality; second, it may generate less inequality; and third, there may be no relationship between the two.

2.1 Technology Leads to More Inequality

There are several lines of arguments that technology is not a benevolent force as far as economic inequality is concerned. First, technological advances usually promote the development of products and services that are more likely to be consumed by the better-off segments of the population. For example, innovation in biomedical technologies in large part caters to the needs of the rich as exemplified by the rapidly growing field of anti-aging surgical procedures (Woodhouse & Sarewitz 2007).[2)] In contrast, technological advances have been slow for those diseases contracted by vast

1) Of course, the number of possibilities would increase if we account for reverse causality (i.e., inequality affecting technology development).

2) A well-known example of this skewed distribution of biomedical research priorities is the so-called "10-90" problem. This problem refers to the fact that less than 10% of global health research effort is devoted to problems suffered by more than 90% of the world population (Global Forum for Health Research 1999).

majorities of the population in the developing world. Even when technological development does not have explicit bias towards the rich, it may still harm the poor indirectly by its effects on the environment and health conditions, as the poor disproportionately bear the brunt of environmental hazards (Cozzens 2007).

Second, the so-called digital divide, both driven by and reinforcing existing socioeconomic inequalities, is anticipated to grow more with ever more sophisticated information technologies (Wyatt 2000). The literature on the digital divide has extensively documented inequalities in access to digital media and products enabled by information communication technologies (ICT), though some of such concerns have been mollified with diffusion of certain ICT products across a broader population.[3)]

Third, according to the well-known skill-biased technological change (SBTC) hypothesis, technological development offers premiums for skilled labor by raising the relative demand for skilled workers, thus generating a greater wage gap between skilled and unskilled labor. Underlined by the observation of a parallel rise in wage inequality and technological advances in the US economy during the 1980s and 1990s, the SBTC hypothesis has received much support from empirical studies linking technological changes, productivity, and wage dispersion,[4)] though there also exists controversial evidence against the hypothesis.[5)]

2.2 Tech Leads to Less Inequality

Somewhat ironically, technological advances may harm the rich more than the poor because the former use more frequently the products and services enabled by technologies. For example, potential side-effects of advanced cosmetic surgeries or costly new medical procedures would inflict the rich more than the poor. As Cozzens (2007) notes, however, this situation of reverse inequality (i.e., the rich having a greater chance to suffer from unintended side-effects) is often discussed in informal venues like conferences but has not actually been researched systematically.

Technology can also lessen inequality as it destroys the existing sources of wealth. Simon Kuznets (1955) observed that technological development could be a strong mechanism deterring the effect of concentration of savings, which is one of the chief causes of income inequality. As he puts it in his own words, "the second group of forces (counteracting the concentration of savings) resides in the very nature of a dynamic economy with relative freedom of individual opportunity. In such a society technological change is rampant and property assets that originate in older industries almost inevitably have a diminishing proportional weight in the total because of the more rapid growth of younger industries (p.10)."

2.3 Tech Has Little Effect on Inequality

The last theoretical possibility for the technology-inequality relationship is that both are unrelated. In the utilitarian view of government policy, science and technology (S&T) as engines of growth are assumed to raise total welfare, and any unintended consequences of S&T should be dealt with by other government policies. Simply put, "S&T policies create wealth and other policies distribute them (Cozzens 2007, p. 89)." Bozeman & Sarewitz (2005) echo this observation when they notice that science policy in the US has been dominated by economic thinking and removed from meaningful political discussions of its consequences.

Also, since there exists a substantial lag between

3) Recent discussions of the digital divide have moved beyond the problem of physical access. Now scholars of the digital divide suggest a need to study barriers to effective utilization of ICT products and services (Van Dijk 2005; DiMaggio, et al. 2001).

4) For instance, the skill premium measured as the differential earnings of college and high-school graduates has increased twenty-fold between the 1960s and the 1990s (Card & DiNardo 2002). Various studies such as Galbraith & Hale (2006), Sanchez & Shady (2003), and Wang (2007) present case studies of wage polarization associated with the IT boom.

5) Card & DiNardo (2002) also document the evidence that goes against the SBTC hypothesis. For example, in the US economy, there is a significant lag between the timing of IT diffusion (which is considered to be a hallmark of technological development in the 1970s-1990s) and an increase in wage inequality.

technological innovations and actual deployment of the outcomes from inventive and innovative processes, it may be difficult to find evidence linking technological development directly to economic inequality.

2.4 Technological Kuznets Curve

The potentially dual effects of technology on inequality briefly reviewed above suggest that the technology-inequality relationship may not be linear. There are yet two possibilities for the nonlinearity in the technology-inequality relationship, however, as expounded below.

2.4.1 TKC Version I

First, the nonlinear technology-inequality relationship may take an inverted U-shape, which is a natural extension of the traditional Kuznets Curve. Since technology is a key component of economic growth, its impact on inequality would closely follow that of economic wealth. This logic of the "technological Kuznets Curve" is briefly indicated in Aghion & Howitt (1997), Barro (1999), and Helpman (1997), although these studies do not explicitly theorize it as the TKC. In the traditional Kuznets Curve, inequality increases as the economy shifts from the poor agricultural sector to the more prosperous industrial sector. This transition initially raises incomes of those moving to the new sector, widening the income gap with those remaining in the old sector. As the transition is completed, the effect of sectoral mobility on inequality diminishes. The whole transition process can also be thought of as the one from the technologically retarded sector to the technologically advanced sector. The introduction of new technologies would at first raise inequality as they benefit a small segment of the economy utilizing those technologies. As the new technologies are diffused, this initial advantage will disappear, hence reducing the income gap.[6]

Another mechanism that can potentially produce an inverted U-shape relationship between technology and inequality is the process of technological diffusion. In his book titled *The Third Industrial Revolution*, Jeremy Greenwood (1997) contemplates on a common trend characterizing revolutionary industrial transformations.[7] This trend works as follows. In the initial phase, production efficiency (measured by production equipment prices) increases with the adoption of new technologies but labor productivity (measured by output per hour of work) tend to decrease. This leads to a greater gap between the upper and lower segments of the labor force, which keeps wider until the new technologies are fully diffused. Once the new technologies get spread and mature, the skill premium decreases and correspondingly does inequality.

2.4.2 TKC Version II

We may conceive of an opposite (i.e., U-shaped) form of a nonlinear relationship between technology and inequality on the basis of the nature of innovation. In the innovation process known as Schumpeterian innovation Mark I, the early phase of technological development is characterized by "creative destruction." Numerous innovative initiatives by new entrepreneurs lead to the development of new products and new processes. As a consequence, monopoly rents from previous innovations are wiped out, technological barriers to the existing industries are lowered, competitive advantages of established firms are eroded, and old skills and occupations are destroyed. Technology in this process essentially plays the role of an equalizer.

In the later phase of technological development, however, innovation becomes more intensive requiring

6) Barro (1999) notes, however, that since technological innovation is not directly put into economic use, the curve would fit only "to the extent that a high level of per capita GDP signaled that a country had introduced advanced technologies or modern production techniques relatively recently (p. 9)."

7) In his terminology, the third industrial revolution refers to the modern era of rapid technological changes driven by the widespread use of computers. Like the two preceding industrial revolutions (one hallmarked by the invention of the steam engine in the late 1700s and the other associated with the discovery of electricity in the late 1800s), the third industrial revolution has seen a similar development in wage inequality associated with technological diffusion.

large-scale investments. This phase exhibits a strong tendency of "creative accumulation," where technological innovation is driven by large firms that can afford massive investment in R&D and therefore reap huge profits from R&D activities (Malerba & Orsenigo 1995). In contrast to the first phase where monopoly rents generated by technological innovation are constantly erased with continuous innovations, this phase of innovation called Schumpeterian innovation Mark II is characterized by high barriers to industrial entry and large amount of investments. Monopoly rents from new innovations are more sustainable in this phase. Technology here exacerbates existing inequality, as its benefits accrue mostly to those holding sizeable physical or human capital.[8)]

The U-shaped TKC can also be inferred from the work of Conceição and Galbraith (2000). Noting that the conventional Kuznets Curve is of limited utility in explaining the recent increase in income inequality in highly advanced countries such as the US, Conceição and Galbraith propose the "augmented Kuznets Curve." In this conjecture, inequality follows the traditional inverted U-shape pattern at lower levels of economic development. At very high levels of development, however, inequality increases again as a result of technological innovation which drives a wedge between the technologically intensive and more traditional sectors.

In explaining the augmented Kuznets curve, Conceição and Galbraith draw on the distinction between the K-sector and the C-sector. The K-sector refers to the industries that are knowledge-intensive capital producers dominated by Schumpeterian competition. This sector is made up of large firms with substantive market power, high capital-to-labor ratios, and higher-than-average wages (i.e., monopoly rents). The C-sector refers to the traditional sector, which produces consumer products with prices equal to marginal costs and no monopoly rents generated. As the economy moves beyond the industrial economy, the K-sector becomes dominant creating a wage and profit gap between the old sector and itself.

2.5 Effects of Government Policy

Given the effects of technological development on inequality, can the government help ameliorate them? The government may do so with its distributive policies that redistribute aggregate welfare among people or groups of different socioeconomic conditions. Many public policies involve a trade-off between conflicting goals, however (Stone 2001). As a prominent example, redistributive policies aimed to enhance equality may eliminate differential rewards needed to motivate people to work more efficiently.

As to policies pertaining to technology and inequality, the government faces a similar dilemma. On one hand, the government devises and implements R&D policies to ensure long-term growth facilitated by technological advances. On the other hand, the government is pressed to make sure that outcomes of aggregate growth are fairly shared with appropriate redistributive programs.

Government R&D and redistributive policies may well have opposite effects on the technology-inequality relationship, as each policy has different constituencies. R&D policies are promoted by individuals and sectors better endowed with resources. Since R&D is in essence a form of investment, government policies promoting R&D are likely to receive greater support from the "haves" rather than the "have-nots." As such, R&D policies would be more concerned with developing technologies that maximize the growth potentials of innovations rather than those designed to enhance social aggregate welfare. By contrast, redistributive policy helps the disadvantaged in the society and would thus receive greater support from the have-nots. Such a policy would be inherently "equality-enhancing." In short, government R&D policy is likely to amplify technology-induced inequality by promoting technological innovations for higher growth, whereas government redistributive policy is likely to

8) The analysis of thirty-three technology cases by Malerba & Orsenigo (1995) demonstrates the linkage between industrial structures and the pattern of innovation as predicted by those two types of innovation.

dampen the effects of technology on inequality.

Given such a trade-off between the long-term goal of growth and the short-term need of redistribution, it is of particular interest to check whether such a trade-off is really borne out in the empirical data.

3. Empirics

This section presents the empirical analysis for the TKC and the role of government policy in mediating the technology-inequality relationship. The section first introduces the measures of technological development, inequality, and government policies used in the current regression analyses. The estimation strategies are explained next, followed by the presentation of the major findings.

3.1 Measurement

Since technological development is inherently a multidimensional concept, it is crucial to use multiple indicators in order to enhance the validity of an empirical test. The measures of technological development can be classified into input/resource-based and output/performance-based indicators. For instance, resources devoted to R&D are of the former type, whereas patents and trade performance in high-tech industries are of the latter type. The current analysis employs ten indicators of technological development, most of which are output-based measures. This is because R&D data, a key input-based measure, also reflect government policy, which is an independent variable in the current design of the data analysis.

A main indicator of technological development in the current analysis is the number of patents from the NBER patent database (Hall, Jaffee & Trajtenberg 2001). While there is a lengthy debate as to the validity of the patent data, the patent is the most well-documented and widely used data item for technological innovation.[9] The NBER patent data contain the patents filed with the US Patent and Trademark Office (USPTO) between 1963 and 1999. This patent database covers 159 countries. I also use the patent data from the OECD's Main Science & Technology Indicators (OECD 2007), which include the number of triadic patent families and the number of patents granted in the ICT and biotechnology sectors. Note, however, that although the temporal data coverage for most variables of the MSTI database is 1981-2007, the foresaid indicators have data available only up to 2000. Other technological development indicators are listed in Appendix Table A1.

The measure of income inequality in this analysis is the estimated household income inequality (EHII) developed by the University of Texas Inequality (UTIP) Project. The UTIP team calculates Theil's T statistics based on the Deininger & Squire dataset[10] and the UN Industrial Development Organization's Industrial Statistics with the latter dataset providing pay data across industrial sectors. Somewhat fortuitously, the EHII data cover the same period (1963-1999) as that of the NBER patent data.

One of the controversial issues in comparing income inequality across countries is the use of population weights. It makes a large difference whether one weights populations or not, since countries like China and India with their huge populations can make global or worldwide income inequality much smaller if their populations are weighted (Firebaugh 2003). We are not concerned with this issue, however, as we are here comparing the within-country component of global income inequality.[11]

9) Technological innovation is one of the "hard-to-measure" concepts (Berndt & Hulten 2007). As such, questions have been raised about the validity of the patent data as an indicator of technological innovation. For a prominent example, it is noted that not all inventions are patentable, and therefore the patent data would systematically exclude certain types of innovative activities.

10) While the Gini index is a better-known indicator of income inequality and also available in the Deininger &Squire dataset, this analysis does not draw on it for the following reasons. First, the data sources are more heterogeneous for African and Asian countries, casting doubt on the quality of the inequality data from these regions. Second, the data points are too sparse to make a meaningful large-scale cross-national comparison of income inequality.

11) Global income inequality is the combination of within-country and between-country inequality. Sala-i-Martin (2002) shows that with appropriate population weighting and the use of purchasing-power-parity (PPP) data, the level of global income inequality becomes much lower than estimated otherwise.

Finally, government R&D and redistribution policies are captured mostly by the expenditure data. All of the R&D data come from the MSTI dataset, which include government expenditure on R&D, budget outlays for R&D, R&D financed by government, and R&D performed by the government. Government redistributive policies are approximated by both general indicators (total government expenditure and tax revenue) and specific indicators such as the highest marginal tax rates, taxes on income/profits/capital gains, and public health and education spending.

3.2 Estimation Strategy

One of the simplest ways to test the TKC and the effect of government policy would be to multiply the variables capturing technology and government policy as follows:

Income Inequality =

$$\alpha + \beta_{11}X_1 + \beta_{12}X_1^2 + \beta_2X_2 + \beta_3X_1X_2 + \varepsilon,$$

where X_1 is the indicator of the technological development and X_2 that of government policy. A problem with this specification is that the independent variables become highly collinear with those squared and multiplicative terms. Another problem is that since technological performance and economic development are closely intertwined, X_1's effect may in large part capture that of economic development rather than technology *per se*.

In order to circumvent these problems, I have devised the following strategy. First, the EHII is regressed on GDP per capita and its squared term according to the traditional Kuznets Curve. The residuals obtained from this regression would then reflect the component of inequality remaining unexplained by the level of economic development. These residuals are then regressed on the technology indicator (e.g., patents) and its squared term, which would capture the technological Kuznets Curve. The predicted values from this regression can be interpreted as the levels of inequality generated by technological development. These predicted values are then regressed on the government policy indicator (e.g., government budget outlays for R&D), which would show whether and how government policy contributes to technology-induced inequality. Note that the regression of the Kuznets Curve is based on the random-effects model, as the data for per capita GDP are more regularly available for most countries forming a balanced panel of cross-sectional time-series. All the other regressions are based on cross-sectional ordinary-least-squares (OLS) estimation.[12)]

For more formal notation, the following model is estimated at Step 1:

$$Y_{1(i,t)} = \alpha_1 + \beta_{11}X_{1(i,t)} + \beta_{12}X1_{(i,t)}^2 + \varepsilon_{1(i,t)} \qquad (1\text{-}1)$$

The residual is obtained from this regression such that:

$$Y_{1(i,t)}^{res} \equiv Y_{1(i,t)} - y_{1(i,t)} \qquad (1\text{-}2)$$

$$where\ y_{1(i,t)} = a_1 + b_{11}X_1 + b_{12}X_1^2$$

Letting Y_{2j} be $Y_{1(i,\ t)}^{res}$, the following model is estimated at Step 2:

$$Y_{2,j} = \alpha_2 + \beta_{21}X_{2,j} + \beta_{22}X_{2,j}^2 + \varepsilon_{2,j} \qquad (2\text{-}1)$$

With the predicated value from this regression,

$$Y_{2,j}^{pred} = a_2 + b_{21}X_2 + b_{22}X_2^2 \qquad (2\text{-}2)$$

Step3 estimates the following model, with $Y_{3,k}$ being $Y_{2,j}^{pred}$

$$Y_{3,k} = \alpha_3 + \beta_3X_{3,k} + \varepsilon_{3,k} \qquad (3)$$

In the above models, Y_1 is EHII, X_1 is per capita GDP, X_2 is the technological development variable, X_3 is the government policy variable, and lowercase coefficients indicate the estimates. These steps are repeated for the alternative indicators of technological development and government policy.

3.3 Findings

Before presenting the regression results, let me first show a couple of figures graphing the trends of the patent and income inequality data. Figure 1 displays the NBER patent data and the UTIP EHII data in parallel, which are averaged for the whole sample of countries covered in both databases (first chart) as well

12) An inherent problem of the hard-to-measure data such as R&D efforts or technological inventions (see fn. 9) is that the trade-off between the quality and the availability of the data is much more serious. This is one of the major reasons for the use of conventional OLS for the second and third steps of the estimation.

as for the OECD countries only (second chart). For the whole sample of countries, the income inequality data show more fluctuations, with a steep rise in the early 1960s and the early 1990s. Interestingly, these are the two periods in which many of high- and middle-income countries went ahead transforming themselves into the industrial economy and the so-called knowledge economy. The first hump of the inequality trend therefore seems to match closely the traditional Kuznets Curve. The second hump seems to suggest the augmented Kuznets Curve proposed by Conceição and Galbraith (2000). In comparison, the inequality trend for the OECD countries is much more smooth, though it shows a substantial rise in the 1990s.

When juxtaposed with the patent data, the income inequality data do not appear to track the changes in the volume of patents. Note, however, that there is a lag between the two trends. For both the whole and OECD samples of countries, the number of patents per million people started to increase in the mid-1980s, which is just followed by a big jump of inequality levels in the early 1990s.

The inequality data for the OECD countries also follow the trends of the patent data in two sectors of highly intensive innovation activities – ICT and biotechnology (shown in Figure 2). These two patent series from the MSTI database cover the period of 1981-2000. If one looks at the same period of Figure 1, it turns out that the EHII of the OECD countries resembles the trends of the patents in these two sectors more closely than that of the overall number of patents.

Figure 3 gives a more direct illustration of the technology-inequality relationship. Using the same data from Figure 1, it plots each country's EHII against its number of patents (with and without division by one million people). Interestingly, the polynomial trend line through these data points shows a U-shaped pattern, suggesting the second version of the TKC described the previous section. This figure clearly shows a nonlinear pattern of the technology-inequality

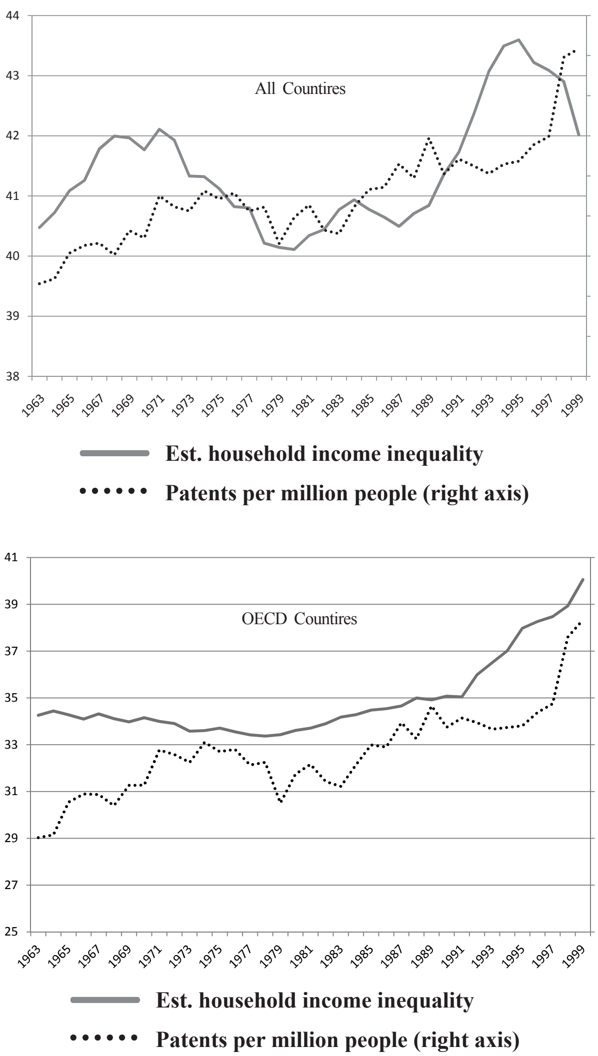

Figure 1 Trends of income inequality and patents (1963-1999)

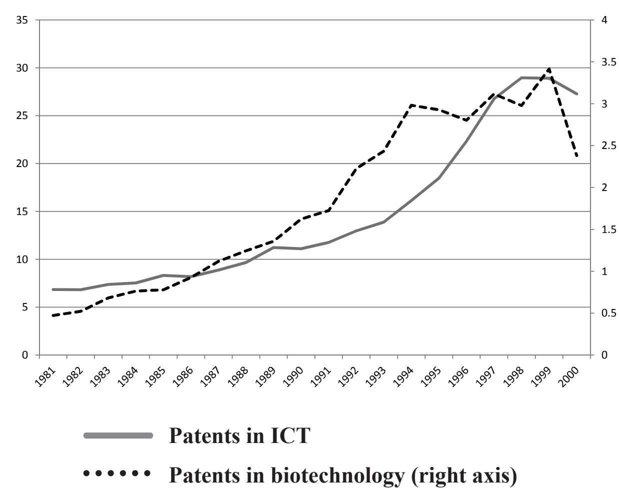

Figure 2 Patents (per million people) in the ICT and biotechnology sectors (1981-2000)

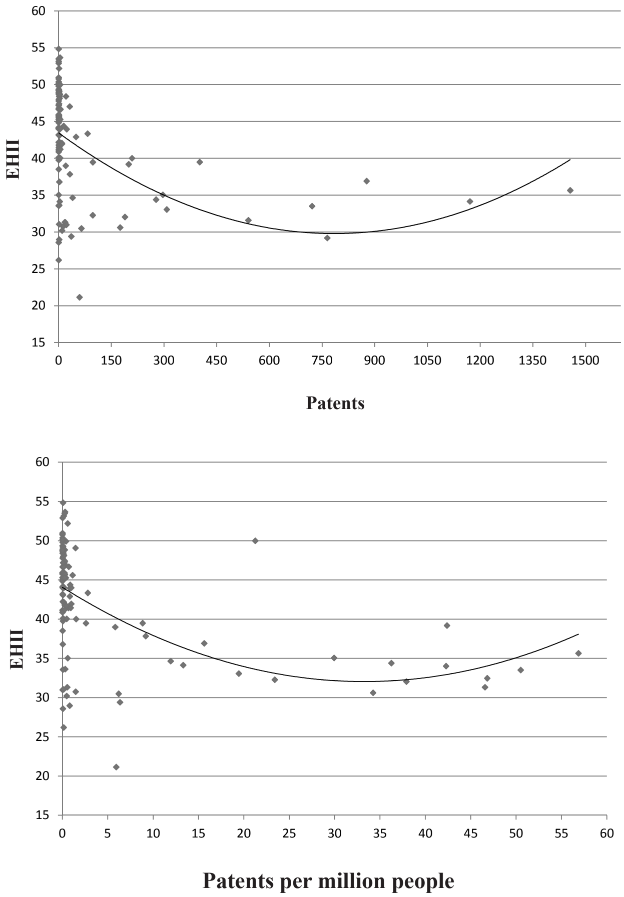

Figure 3 Cross-national comparison of income inequality and patent data

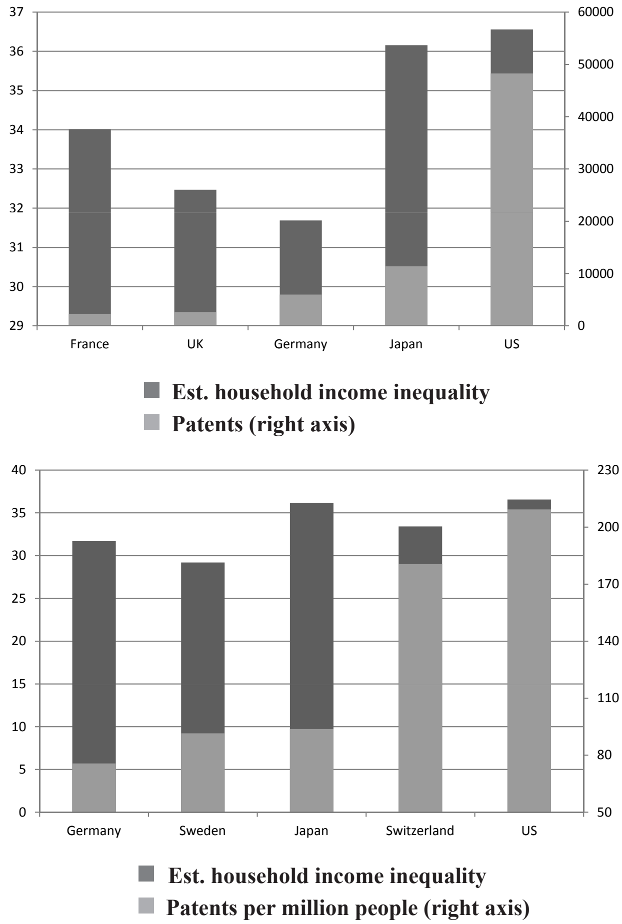

Figure 4 Income inequality and patent data for top five patent-data countries

relationship.

Figure 4 displays the inequality data for the top five patent-data countries separately. The patents from these countries are so huge in number that they all together dwarf the patents of the rest of the countries. Again, two charts are drawn for the total number of patents and the same number divided by a million (to take into account the size of a country). The light-colored bars represent the patent data and the dark-colored ones the EHII data. It makes a difference whether one compares the total number of patents or the number adjusted for population size. With the unadjusted total number of patents the technology-inequality relationship closely resembles a U-shape. The US and Japan with the largest numbers of patents show the highest levels of inequality, followed by France that has the smallest number of patents. Germany with its middle number of patents shows the lowest level of income inequality among the five countries. In contrast, if the adjusted number of patents is used, this U-shaped pattern disappears, as Japan takes the middle position along the axis of the patent data.

The graphical evidence introduced above hints at the curvilinear relationship between technological development and income inequality. Notably, the regression findings presented in Table 1 largely confirm such a relationship. This table contains the estimation results of the regression equation (2-1), where b_{21} and b_{22} capture the first-order and the second-order effect of technology on inequality.

The dependent variable in the regressions presented in this table is the residual from the panel regression

Table 1 Technological Kuznets Curve? Impact of technological cevelopment on income inequality

Dependent Variable: residuals from the Kuznets Curve regression	b_{21}	s.e.	b_{22}	s.e.	adj-R^2	F	N
Patents (1963-99)	–0.202	0.007	0.801	0.037	0.264	447.4	2,490
Patents, triadic families (1981-2003)	–0.254	0.026	2.652	0.365	0.208	58.24	436
Patents in ICT (1981-2000)	–0.123	0.022	1.173	0.207	0.056	16.62	525
Patents in biotechnology (1981-2000)	–0.985	0.182	60.004	15.025	0.057	16.88	525
Scientific/technical journal articles (1981, 1985-2001)	–0.033	0.002	0.027	0.002	0.331	285.5	1,151
Researchers in R&D (1996-2002)	–0.005	0.001	0.001	0.000	0.561	74.96	117
Technicians in R&D (1996-2002)	–0.014	0.002	0.003	0.001	0.507	38.97	75
Hi-tech exports (1988-2003)	–0.429	0.050	0.663	0.101	0.125	44.98	619
Computer/communication BOP (1970-2003)	–0.041	0.009	0.118	0.024	0.016	16.24	1,940
Technology BOP (1981-2006)	0.747‡	1.240	14.848‡	48.776	-0.005‡	0.32	288

Notes: All coefficients are significant at the 95% level unless noted otherwise (‡: insignificant).
The Kuznets Curve regression refers to the panel regression of estimated household income inequality (EHII) on the logged GDP per capita and its squared term.
The coefficients, b_{21} and b_{22}, are the original and the squared term of the technological development indicators.
See Text for more information on the model specification and estimation methods.
Refer to Appendix Table A1 for the variable definitions and sources.

of the Kuznets Curve relationship (1-1). Note that virtually every indicator of technological development shows a U-shaped effect on income inequality with all b_{21}'s being negative and all b_{22}'s being positive. This result renders strong support for the second version of the TKC, which predicts greater inequality at low and high levels of technological development but smaller inequality at middle levels of technological development.

Table 2 presents the estimates for the effects of government R&D and redistributive policy based on the regression model (3). Here the dependent variable is the level of inequality predicted by the TKC regression on the patent data. The first panel contains the estimates for various indicators of government R&D efforts, and the second panel those for the different measures of government redistributive policy. The R&D indicators without bold-faced letters are included to give the sense of the relative size of the government R&D impact in comparison with the R&D efforts by other sectors.

The results for the redistributive policy are largely in line with the expectation. The three measures of taxes with redistributive implications are all negatively signed, though two of them do not reach the 95% significance level. More notably, all of the three redistributive expenditure variables (subsidies and other social benefits, public health spending, and public education spending) are negatively signed and highly significant, giving strong empirical support for the role of government redistributive policy in dampening the TKC.

In comparison, the results for government R&D policy do not seem to conform to the expectation, with apparently contradictory signs for the coefficient estimates for government R&D expenditure (GRD) and R&D financed by the government (RDG). Yet the opposite signs for these two terms are in fact the logical extension of their relationship. Note that RDG is the government R&D expenditure measured

Table 2 Impact of government policy on income inequality predicted by NBER patent data

Dependent Variable: predicted EHII values from the technological Kuznets Curve Regression	b_3	s.e.	adj-R^2	N
R&D Policy				
Gross domestic expenditure on R&D (GERD)	–4.380	0.170	0.629	392
Basic research expenditure	–22.615	1.909	0.424	190
Business expenditure on R&D	–5.380	0.235	0.579	381
Higher-education expenditure on R&D	–20.325	0.939	0.560	368
Government expenditure on R&D (GRD)	–12.219	1.723	0.118	369
Government budget outlays for R&D	–8.842	0.533	0.425	371
R&D financed by industry	–0.145	0.015	0.204	360
R&D financed by government (RDG)	0.168	0.015	0.255	360
R&D performed by business enterprises	–0.152	0.012	0.285	373
R&D performed by higher education	0.096	0.021	0.048	372
R&D performed by government	0.211	0.018	0.273	372
Redistributive Policy				
General government expenditure	–0.206	0.010	0.152	2,476
Tax revenue	–0.051†	0.027	0.007†	364
Highest marginal tax rates, corporate	–0.004‡	0.087	-0.014‡	74
Highest marginal tax rates, individual	–0.067‡	0.055	0.007‡	71
Taxes on income, profits and capital gains	–0.061	0.009	0.120	362
Subsidies and other social benefits	–0.082	0.009	0.237	274
Public spending on health	–0.921	0.258	0.128	81
Public spending on education	–1.314	0.372	0.152	65

Notes: All coefficients are significant at the 95% level unless noted otherwise (†: 90% signifcicant, ‡: insignificant).
The technological Kuznets Curve regression refers to the regression of estimated household income inequality (EHII) on the technological indicator (NBER patent in this table) and its squared term.
See Text for more information on the model specification and estimation methods.
Refer to Appendix Table A1 for the variable definitions and sources.

as a share of GERD, and GRD is the same measured as a share of GDP. Therefore, RDG is essentially GRD divided by GERD. Since the RDG and GERD coefficient estimates are oppositely signed, the GRD coefficient would be negatively signed. What we should note is the positive effects of RDG and R&D performed by the government sector, which fits the theoretical conjecture about the effect of government R&D.

What is then puzzling is the negative effect of R&D efforts in general (such as GERD or basic R&D expenditure as a share of GDP) on technology-induced inequality. In particular, R&D performed or financed by the government aggravates technology-induced inequality to a greater degree than that performed or financed by other sectors. These results need to be checked further in future research, though we may ponder that government-funded R&D typically support larger-scale research than those in private sectors and could thus be more skewed towards aggravating

Table 3 Impact of government R&D policy on income inequality predicted by other tech indicators

Dependent Variable: predicted values from the TKC regression of [the following variable]	b_3	adj-R^2	N
[Patents, triadic families]			
Government expenditure on R&D	–7.550	0.131	524
Government budget outlays for R&D	–5.275	0.334	487
R&D financed by government	0.078	0.176	486
R&D performed by government	0.109	0.208	519
[Patents in ICT]			
Government expenditure on R&D	–2.170	0.043	488
Government budget outlays for R&D	–1.834	0.193	470
R&D financed by government	0.028	0.082	459
R&D performed by government	0.040	0.112	485
[Patents in biotechnology]			
Government expenditure on R&D	–1.236	0.013	488
Government budget outlays for R&D	–1.576	0.135	470
R&D financed by government	0.049	0.262	459
R&D performed by government	0.059	0.258	485
[Hi-tech exports]			
Government expenditure on R&D	–3.630	0.052	443
Government budget outlays for R&D	–2.973	0.199	411
R&D financed by government	0.086	0.342	412
R&D performed by government	0.075	0.155	432
[Computer/communication BOP]			
Government expenditure on R&D	–1.037	0.045	573
Government budget outlays for R&D	–0.825	0.173	546
R&D financed by government	0.006	0.006	539
R&D performed by government	0.010	0.033	567

Notes: All coefficients are significant at the 95% level.
The technological Kuznets Curve regression refers to the regression of EHII on each technological indicator (in the bracket) and its squared term.
See Text for more information on the model specification and estimation methods.
Refer to Appendix Table A1 for the variable definitions and sources.

inequality.

The regressions presented in the final two tables are intended to check the robustness of the above findings against alternative indicators of technological development. For convenience of presentation, the results for R&D policy are shown in Table 3 and those for redistributive policy in Table 4. All of the coefficient estimates for the government R&D policy variables are statistically significant, with the same pattern of the signs as in Table 2. The coefficient

Table 4 Impact of government redistributive policy on income inequality predicted by other tech indicators

Dependent Variable: predicted values from the TKC regression of [the following variable]	b_3	adj-R^2	N
[Patents, triadic families]			
Highest marginal tax rates, corporate	–0.043‡	0.002‡	178
Taxes on income, profits and capital gains	–0.061	0.133	245
Subsidies and other social benefits	–0.028	0.025	212
Public spending on health	–0.609	0.131	190
Public spending on education	–1.045	0.283	121
[Patents in ICT]			
Highest marginal tax rates, corporate	0.043‡	0.002‡	106
Taxes on income, profits and capital gains	–0.013†	0.017†	172
Subsidies and other social benefits	–0.019	0.060	140
Public spending on health	–0.165‡	0.010‡	114
Public spending on education	–0.504	0.120	92
[Patents in biotechnology]			
Highest marginal tax rates, corporate	–0.037‡	0.009‡	106
Taxes on income, profits and capital gains	–0.025	0.052	172
Subsidies and other social benefits	–0.040	0.166	140
Public spending on health	–0.347	0.115	114
Public spending on education	–0.575	0.321	92
[Hi-tech exports]			
Highest marginal tax rates, corporate	–0.017‡	0.001‡	447
Taxes on income, profits and capital gains	–0.031	0.056	740
Subsidies and other social benefits	–0.044	0.175	631
Public spending on health	–0.532	0.178	662
Public spending on education	–0.218	0.025	405
[Computer/communication BOP]			
Highest marginal tax rates, corporate	–0.007‡	0.000‡	448
Taxes on income, profits and capital gains	0.006	0.008	946
Subsidies and other social benefits	–0.004	0.004	769
Public spending on health	–0.068	0.010	718
Public spending on education	–0.044‡	0.002‡	452

Notes: All coefficients are significant at the 95% level unless noted otherwise (†: 90% signifcicant, ‡: insignificant).
The technological Kuznets Curve regression refers to the regression of EHII on each technological indicator (in the bracket) and its squared term.
See Text for more information on the model specification and estimation methods.
Refer to Appendix Table A1 for the variable definitions and sources.

estimates for the government redistributive policy variables in Table 4 are all negatively signed, except for some of those in the regressions of the predicted values inequality from the TKC regression of balance of payments in computer and communication.

4. Discussion

With the potentials and promises of technological advances for human welfare enhancement, national economic growth, and global competitiveness, scholars, policymakers and the public have been preoccupied with understanding and measuring the effects of technology on various public goods. While technology is viewed as key to achieving prosperity and enhancing quality of human life, concerns about the potential side-effects of technological development are also growing.

One of such concerns involves the implications of technological progress for socioeconomic equality. With the stories of the IT boom-generated billionaires, increasing gaps of profits and wages between the high-tech and low-tech sectors, and the concerns about the growing digital divide, technological advances in the recent decades seem to have been accompanied by rising inequality. In a sense, technology is inherently distributive, as the process of technological development creates winners and losers by generating opportunities for certain groups in the society better positioned to take advantage of. On the other hand, technological progress is inherently emancipator, as it destroys existing resources and methods of wealth accumulation opening a new window for reducing inherited unequal distribution of wealth.

In view of these potentially conflicting effects of technology on inequality, this paper has presented and tested a curvilinear relationship between the two and further explored how government policies affect such a relationship. Its empirical findings support the U-shaped version of the technological Kuznets Curve, where inequality initially goes down with technological progress (presumably of Schumpeterian Mark I type) and then rises at more advanced stages of technological progress (accompanied by innovations of Schumpeterian Mark II type). The empirical results also confirm the effect of government redistributive policy in dampening technologically induced inequality.

There are many fruitful ways to refine or expand the current research. One interesting venue for further research is to look at the effects of scope or character of technology on inequality. Some of the economic research on technological innovations has studied the nature of technology in relation to wage inequality. For instance, a distinction between extensive and intensive technological change is made. The former raises the marginal productivity of skilled labor without necessarily lowering that of unskilled labor, whereas the latter (for example, use of robotics in manufacturing) raises the marginal productivity of skilled labor and lowers that of unskilled labor. Hence the effect of technology on inequality would vary by the scope of technological change (Card & DiNardo 2002).

One might also compare the effects of different types of technology on inequality. For example, ICTs as a general-purpose technology (GPT) are more likely to take an inverted U-shaped trajectory with their diffusion processes (Helpman 1998). In contrast, biotechnologies may show a U-shaped TKC given the huge scale investments required to make break-through innovations at early phases.

Finally, the current empirical analysis may be further improved by introducing control variables at each step of the regressions, trying a different method of analysis (such as survival analysis to account for a large number of zero observations for the patent data), and securing more high-quality cross-national data on such hard-to-measure variables as technological progress and economic inequality.

Appendix A1. Variable definitions, sources, and descriptive statistics

Variable	Source	Coverage	Obs	Mean	Std. Dev.	Min	Max
Kuznets Curve elements							
Estimated Household Income Inequality (EHII)	UTIP	1963-1999	3179	41.41	7.53	19.70	64.75
GDP Per Capita (constant 2000 US$)	WDI	1960-2004	6271	4996.13	7518.30	0.00	61505.89
Patent indicators (per million people)							
Patents	NBER	1963-1999	5243	9.03	29.39	0.00	300.74
Patents, triadic families	MSTI	1981-2000	722	20.78	27.02	0.00	126.97
Patents in ICT	MSTI	1981-2000	697	14.68	24.51	0.00	145.33
Patents in biotechnology	MSTI	1981-2000	697	1.71	2.70	0.00	21.66
Other technological indicators							
S&T journal articles (per million people)	WDI	1981, 1985-2001	2688	176.73	1605.75	0.00	39837.84
Researchers in R&D (per million people)	WDI	1996-2002	432	1497.74	1431.44	14.39	7430.73
Technicians in R&D (per million people)	WDI	1996-2002	334	509.69	645.39	1.37	3819.63
Hi-tech exports (% manufactured exports)	WDI	1988-2003	1633	9.94	12.68	0.00	74.96
Computer/communication BOP (% commercial service trade)	WDI	1970-2003	3996	0.62	19.14	-75.47	88.92
Technology BOP (% GDP)	MSTI	1981-2006	498	-0.03	0.54	-3.01	6.30
R&D policy indicators							
Gross domestic expenditure on R&D (GERD) (% GDP)	MSTI	1981-2006	711	1.58	0.87	0.13	4.77
Basic research expenditure (% GDP)	MSTI	1981-2006	380	0.26	0.16	0.03	0.83
Business expenditure on R&D (% GDP)	MSTI	1981-2006	701	0.97	0.69	0.01	3.64
Higher-education expenditure on R&D (% GDP)	MSTI	1981-2006	686	0.32	0.18	0.00	0.87
Government expenditure on R&D (% GDP)	MSTI	1981-2006	694	0.25	0.13	0.02	0.75
Government budget outlays for R&D (% GDP)	MSTI	1981-2006	659	0.66	0.29	0.10	1.85
R&D financed by industry (% GERD)	MSTI	1981-2006	635	49.33	14.15	5.70	90.70
R&D financed by government (% GERD)	MSTI	1981-2006	635	42.48	13.45	7.70	85.60
R&D performed by the business enterprises sector (% GERD)	MSTI	1981-2006	687	55.85	15.58	9.60	92.60
R&D performed by the higher education sector (% GERD)	MSTI	1981-2006	684	22.45	10.75	0.30	71.10
R&D performed by the government sector (% GERD)	MSTI	1981-2006	686	19.88	10.65	1.10	63.10
Redistributive policy indicators							
General government expenditure (% GDP)	WDI	1960-2003	5809	15.95	7.25	2.15	94.24
Tax revenue	WDI	1990-2003	1057	16.09	7.02	0.09	42.79
Highest marginal tax rates, corporate	WDI	1998-00, 2002-04	658	28.18	9.52	0.00	54.00
Highest marginal tax rates, individual	WDI	1998-00, 2002-04	647	32.36	14.36	0.00	60.00
Taxes on income, profits and capital gains	WDI	1998-00, 2002-04	1032	33.08	16.77	2.41	91.11
Subsidies and other social benefits	WDI	1990-2003	839	34.53	21.20	0.45	90.65
Public spending on health	WDI	1998-2002	937	3.53	1.91	0.17	9.73
Public spending on education	WDI	1998-2002	531	4.67	2.13	0.57	16.46

Appendix A2. Sample of countries by region

Sub-Saharan Africa	Middle East/ North Africa	Southeast Asia	Latin America	Western Europe/ North America
Angola	Algeria	Afghanistan	Argentina	Australia
Benin	Bahrain	Bangladesh	Bahamas	Austria
Botswana	Egypt	Bhutan	Barbados	Belgium
Burkina Faso	Iran	India	Belize	Canada
Burundi	Iraq	Indonesia	Bolivia	Cyprus
Cameroon	Israel	Myanmar	Brazil	Denmark
Cape Verde	Jordan	Nepal	Chile	Finland
Central Africa	Kuwait	Pakistan	Colombia	France
Congo, Republic	Libya	Philippines	Costa Rica	Germany
Cote d'Ivoire	Malta	Sri Lanka	Cuba	Greece
Equatorial Guinea	Morocco	Thailand	Dominican Republic	Iceland
Eritrea	Oman		Ecuador	Ireland
Ethiopia	Qatar	East/Central Europe	El Salvador	Italy
Gabon	Senegal	Albania	Guatemala	Luxembourg
Gambia	Syria	Armenia	Haiti	Netherlands
Ghana	Tunisia	Azerbaijan	Honduras	New Zealand
Kenya	UAE	Bosnia & Herzegovina	Jamaica	Norway
Lesotho	Yemen	Bulgaria	Mexico	Portugal
Liberia		Croatia	Netherlands Antilles	Spain
Madagascar	East/Central Asia	Czech	Nicaragua	Sweden
Malawi	China	Germany East	Panama	Turkey
Mauritania	Hong Kong	Hungary	Paraguay	UK
Mauritius	Japan	Latvia	Peru	US
Mozambique	Korea, South	Lithuania	Puerto Rico	
Namibia	Kyrgyz R	Macedonia	St. Vincent & the Grenadines	Pacific
Nigeria	Macao	Moldova	Suriname	Fiji
Samoa	Malaysia	Poland	Trinidad and Tobago	Papua New Guinea
Saudi Arabia	Mongolia	Romania	Uruguay	Tonga
Seychelles	Singapore	Russia	Venezuela	
Sierra Leone	Taiwan	Rwanda	Suriname	
Somalia		Slovakia	Trinidad and Tobago	
South Africa		Slovenia	Uruguay	
Sudan		Ukraine	Venezuela	
Swaziland		Yugoslavia	Virgin Islands (U.S.)	
Tanzania				
Togo				
Uganda				
Zambia				
Zimbabwe				

This country list contains the countries that have observations for the UTIP's estimated housholed income inequality (EHII) for any year of the 1963-1999 period.

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