Increasing Marginal Tendency to Tax Avoidance, Inequality and Economic Growth

Zixiang Qi (qzxok@vip.163.com)
Beijing Wuzi University

Bicong Wang
Beijing Wuzi University

Yaxin Wang
Beijing Wuzi University

Yongqiang Lv
Shandong Jianzhu University

Research Article

Keywords: Inequality, Economic Growth, Marginal Tendency to Tax Avoidance, Dynamic Theoretical Model

Posted Date: August 5th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1872827/v1

Increasing Marginal Tendency to Tax Avoidance, Inequality and Economic Growth

Zixiang Qi[1*], Bicong Wang[2], Yaxin Wang[3] and Yongqiang Lv[4]

[1*]School of Economics, Beijing Wuzi University, 1 Fuhe Street, Tongzhou District, Beijing, 101149, China.
[2]School of Economics, Beijing Wuzi University, 1 Fuhe Street, Tongzhou District, Beijing, 101149, China.
[3]School of Economics, Beijing Wuzi University, 1 Fuhe Street, Tongzhou District, Beijing, 101149, China.
[4]School of Surveying and Geo-Informatics, Shandong Jianzhu University, Jinan, 250101, China.

*Corresponding author(s). E-mail(s): qzxok@vip.163.com;

Abstract

According to increasing marginal tendency to tax avoidance, we establish a dynamic theoretical model and derive an optimal path of economic growth only using dimensionless parameters, which illustrates an inverted U-curve relationship between economic growth and income inequality in the long run. This finding stands in sharp contrast to the Kuznets curve—whereby inequality first increases and then decreases during economic process. Instead, the growth shows a trend of moving upward and then downward as the Gini coefficient increases. We present empirical evidence consistent with our model by controlling for endogeneity.

Keywords: Inequality, Economic Growth, Marginal Tendency to Tax Avoidance, Dynamic Theoretical Model

JEL Classification: O41 , O11 , E13

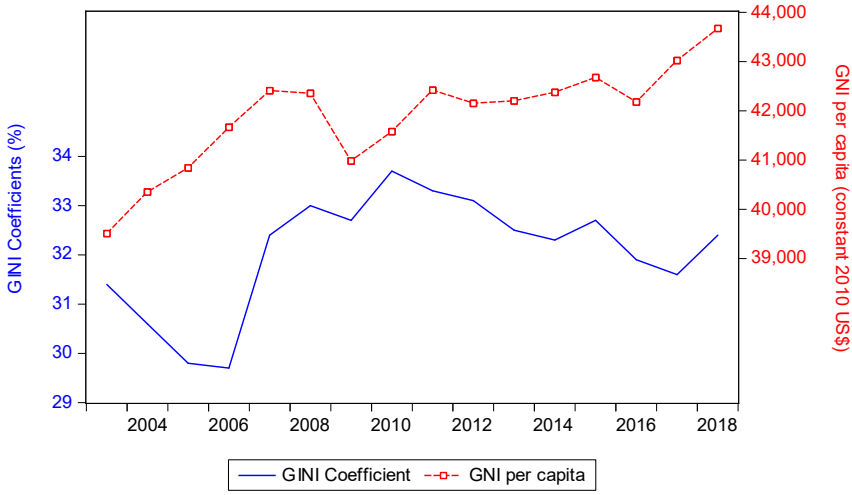
1 Introduction

Kuznets (1955, 1963) conjectured an inverted U-shaped relation between income inequality and economic growth. This result was interpreted as describing the evolution: income inequality should increase during the early stages of development and decrease later on. However, the explanatory effectiveness of this theory has faded since the 1980s (Aghion et al., 1999). The world economy as a whole has boomed over the past three decades, but equality goes bust all the time far from turning for the better. The "yellow vest" revolt erupted in Paris on Nov 17, 2018. High living costs and rising inequality led to the widespread rioting. Coincidentally, in the 10 months since the Novel Coronavirus crisis broke out in March 2020, the wealth of American billionaires has increased by 40%, or $1.1 trillion. As of January 18, 2021, the 660 billionaires in the United States had a combined wealth of $4.1 trillion, while the bottom 165 million Americans possessed a combined wealth of $2.36 trillion (IPS, 2021). Other evidence suggests that the top 0.1% wealth share has risen from 7% in 1978 to 22% in 2012 in the U.S. (Saez & Zucman, 2016).

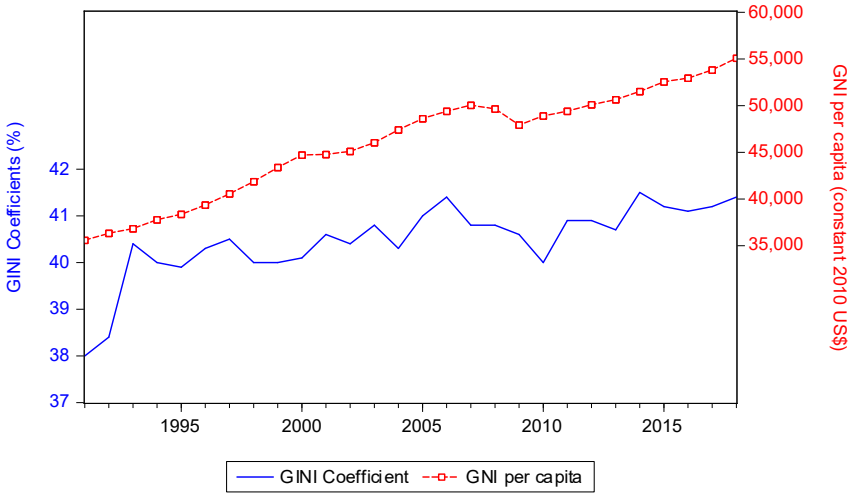
As shown in Fig. 1(A), gross national income (GNI) per capita of France has modestly increased from $39509.11 in 2003 to $43673.97 in 2018. Nevertheless, the Gini coefficient also grew from 31.4% to 32.4%. The Gini coefficient reflects the degree of gap between the rich and the poor. A higher value of the Gini coefficient means more inequality than lower.

In the United States, the steep upward trend in the per capita GNI beginning in the early 1990s was readily apparent from the graph, which has markedly increased from $35584.79 in 1991 to $55079.46 in 2018, rose by 54.78%, while the Gini coefficient has also risen from 38% in 1991 to 41.4% in 2018 (see Fig. 1(B)). This kind of situation is in line with China. Since the start of economic reform in the early 1980s, it experienced plenty of both: per capita income has driven a nearly 8% annual increase, while the Gini coefficient rose from 0.28 to 0.39 (see Ravallion & Chen, 2007).

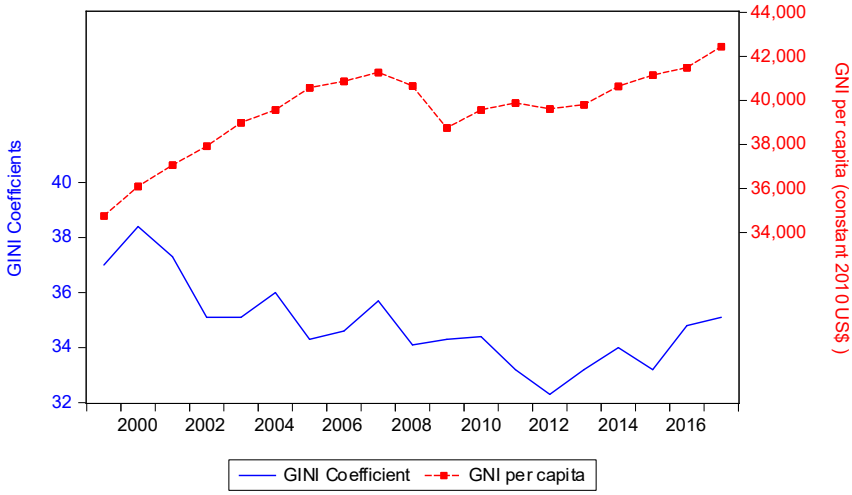
As shown in Fig. 1(C) and 1(D), the per capita GNI of the United Kingdom has gradually increased from $34754.81 in 1999 to $42441.17 in 2017. But in a sharp reversal of growth trends, the level of income inequality has fallen since 1999, to about 32.3% in 2012 and has continuously increased since then. In contrast, the per capita GNI of Italy peaked at $38301.21 in 2007, then dropped down to $35480.25 in 2009, and steadily declined, while its Gini coefficient has been slightly decreased by 5.7% since 2003, to around 32.9% in 2007, and has been progressively rising ever since then, to 35.9% in 2017. It is precisely why we doubt it seems that the Gini coefficient is not going to fall as the economy grows. Instead, income inequality has increasingly been deteriorating more rapidly than ever with industrialization. Analogous to the above countries, China's turning points for income and wealth inequality have nothing to do with the Kuznets Curve (Hvistendahl, 2014; Ravallion & Chen, 2021). In a word, this evidence cast considerable doubt on the inverted U-shaped relationship of Kuznetsian Hypothesis.



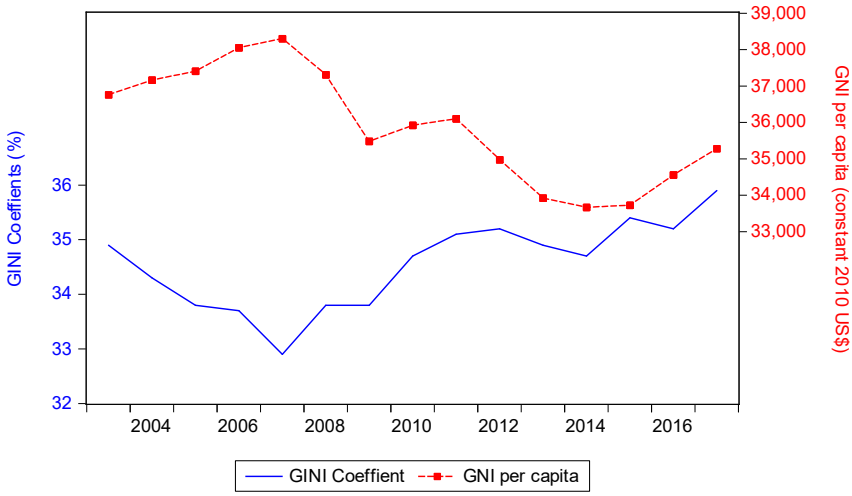
(A) France, 2003-2018



(B) The United States, 1991-2018



(C) The United Kingdom, 1999-2017



(D) Italy, 2003-2017

Fig. 1: The time trends of national income per capita and Gini coefficients across countries

[Source] The data come from the World Development Indicators 2021 of the World Bank.

We intend to build a bridge between economic growth and income inequality so that we can address the root cause of recession. The questions we examine are reminiscent of some perennial issues in the development literature (e.g., Kuznets, 1955). This body of work has traditionally been concerned with the distributional implications of economic growth. Here we reverse the question

and ask how income inequality affects economic growth. For this problem, the academic view is not uniform. Cross-national empirical research about the link between inequality and growth produces conflicting conclusions.[1]

Based on the macro perspective, some economists argue that inequality is negatively correlated with ensuing economic growth (Murphy et al., 1989; Bertola, 1993; Galor & Zeira, 1993; Alesina & Rodrik, 1994; Persson & Tabellini, 1994; Perotti, 1996; Benhabib & Rustichini, 1996; Aghion et al., 1999; Easterly, 2007; Halter et al., 2013; Braun et al., 2018). Even the Great Depression in 1929 and the financial crisis in 2008 were ultimately caused by both a large increase in the income share of high-income households and a large increase in debt leverage of low-and middle-income households (see Kumhof et al., 2015). In contrast, others claim that inequality is positively associated with subsequent growth (e.g., Kaldor, 1955; Partridge, 1997; Li & fu Zou, 1998; Forbes, 2000; Atkinson & Brandolini, 2001).

At the micro level, there are also wide discrepancy in the impact of inequality on growth. In China, the income of rural families is lower than that of urban families. Some scholars declare inequality did not have a reliable causal impact on growth in rural China (see Benjamin et al., 2011). By contrast, others document that reducing income inequality between low-and median-income households improves economic growth in the United States (Biswas et al., 2017).

These contradictory explanations show that the impact of inequality on economic growth is heterogeneous. There is an inverse relationship between growth and inequality in the sample of poor countries and a positive relationship in the sample of rich countries (see Barro, 2000), while Banerjee & Duflo (2003) take advantage of the same variables as used by Barro, yielding a non-linear relationship between economic growth and the magnitude of changes in lagged inequality. They argue that the relationship can take either sign (and in the case of Banerjee and Duflo that it is changes rather than levels of inequality that matter). Galor & Moav (2004) deem that in early stages of the Industrial Revolution, when physical capital accumulation was the prime source of growth, inequality stimulated development by channeling resources towards individuals with a higher propensity to save; whereas, in advance stages of development, as human capital emerged as a growth engine, equality alleviated adverse effects of credit constraints on human capital accumulation, stimulating the growth process.

It is three reasons why previous findings of the relationship between the level of inequality and growth are so different from one another. First, there is lack of a dynamic theoretical framework. Second, it is insufficient to analyze long-term impact of inequality on growth. For example, many economists insist that inequality affects economic growth through fertility (Galor & Zang, 1997; Kremer & Chen, 2002; de la Croix & Doepke, 2003; Berg et al., 2018). Unfortunately, we are afraid that simultaneous causality relationship between

[1] Unless otherwise noted, inequality highlights its gap in accordance with income and wealth distribution in our paper.

fertility and inequality in the short time causes inconsistent conclusions above. One may ask whether those are distorted by reverse causation leading to simultaneity bias. Fortunately, in the long period, fertility is legitimately regarded as a constant because the indispensable factors stimulating sustainable growth are human capital, technological changes and institutions rather than the size of the population(Romer, 1986, 1990; Acemoglu et al., 2001). Thus, fertility is ignored in our theoretical model. Third, some economists consider the impact of inequality on economic growth from political economy channels, and the main dimension of research concentrates on redistribution, whereas neglecting a more substantial perspective, namely tax avoidance (Alesina & Rodrik, 1994; Persson & Tabellini, 1994; Perotti, 1996; Bénabou, 1996, 2000; Galor et al., 2009; Berg et al., 2018). Compared to existing literature, we propose a unified dynamically theoretical model which is more inclined to discuss the effect of inequality on rate of growth over long periods of time.

2 Theoretical Model

2.1 Crucial Assumption

In this world nothing can be said to be certain, except death, taxes and tax avoidance (as verified by subsection 6.4 of Section 6). The old saying among tax professionals that "the poor evade and the rich avoid" means that the rich tend to reduce their taxes through legal avoidance measures such as tax shelters, while those with lower incomes attempt more outright evasion. For instance, ActionAid, an international non-governmental organization (NGO), published a report entitled "Addicted to Tax Havens: The Secret Life of the FTSE 100"(ActionAid, 2011). This highly-publicized report presented all the Financial Times Stock Exchange (FTSE) 100 firms, as of July 26, 2011, held over 30,000 subsidiaries, 8,492 of which were located in tax havens. For another example, total foreign portfolio investment in the Cayman Islands reported in the IMF's Coordinated Portfolio Investment Survey (CPIS) data in 2017 is $3.9 trillion, while the Cayman Islands' GDP is no more than $5 billion, a thousand-fold difference (Coppola et al., 2021). The higher taxes, the more evasion (Berger et al., 2016). The top of distribution have a greater incentive to evade or avoid payment of taxes than the bottom. The boundary line between tax evasion and avoidance is blurred sometimes. For a developing country, income tax evasion was concentrated in higher income classes in Jamaica (Alm et al., 1991). For a developed country, the proportion of misreported income relative to "true" income was significantly higher for higher income individuals in the United States (Johns & Slemrod, 2010). In Scandinavia, the 0.01% richest households evade almost 25% of their true tax liability through tax havens, a level of tax evasion that far exceeds the usual estimates (roughly 5% tax of taxes) generated from random tax audits and all of the wealth in offshore accounts belongs to the top 1% (Alstadsæter et al., 2019). Offshore tax evasion (avoidance) rises with wealth at the top and is highly concentrated among the very rich in the United Kingdom, Spain, France and the United

States (Alstadsæter et al., 2018; Johannesen et al., 2020). In Denmark, the long-run elasticity of wealth with respect to the net-of-tax return is sizeable at the top of distribution (Jakobsen et al., 2019). These materials provide a microscopic basis for our macroscopic theoretical model.

All theory is born in assumptions that are not quite true (Solow, 1956). Based on the evidence above, we assume there is an increasing marginal tendency to tax avoidance for every rational man, which can be perceived that the amounts of tax avoidance augment for each additional unit of income as one earns more and more of money.[2] This issue is of critical importance for economists and policymakers. We focus on the psychological pattern of human beings which have a profound influence on government tax revenue.

In a society where distributional conflict is severe, the higher is the Gini coefficient, the more are the top of distribution. The marginal tendency to tax avoidance among the rich are assumed to be become greater and greater. The higher the marginal tendency of tax avoidance, the less tax payments. The less impose levies, the smaller the amount of money that the government will spend on productive services. Consequently, the Gini coefficient is negatively related to subsequent government's productive purchase. More specifically, our theory relies on the assumption that can be essentially defended by some empirical evidence (see Fig. 2(A) and 2(B)).

The aggregate tax receipts are financed contemporaneously by total tax rate (τ), namely,

$$T = \tau Y \quad (Y > 0),$$

where T is the government tax revenue. The gross national income is represented by $Y = Y(t)$, at each moment of time. Let t denote the time. Especially, a distinguishing feature of our model is not the presence of an independent time variable, whereas the variable t can enter into the integrand via a discount factor. The aggregate government purchase expenditure, say G, is positively related to tax receipts (Barro, 1990) and inversely proportional to inequality (corresponding to the Fig. 2(A) and 2(B)), and consequently

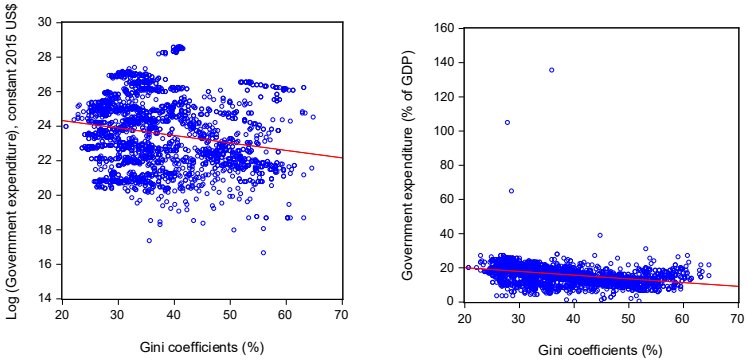
$$G = \frac{T}{g} = \frac{\tau Y}{g} \quad (0 < \tau, g < 1), \tag{1}$$

where g is the Gini coefficient.[3] The paper implicitly assumes that government has capacity for funding G with debt when τ is higher than g. [4] As an exogenous variable, the Gini coefficient is jointly determined by a country's economic institutions and political system as a whole. But that doesn't mean it's a constant, it's a parameter as well as the tax rate. Additionally, each endogenous

[2] Elon Musk, along with other prominent super-wealthy people, paid only small tax rates relative to the significant increase in his total wealth between 2014 and 2018 (Eisinger et al., 2021), with Musk paying a "real" rate of 3.27%. By estimate of Zucman (2013), rich individuals held unrecorded portfolios worth $4.5 trillion in tax havens at end 2008.

[3] We assume that setting the direct cash transfers to zero is an acceptable shortcut and there is not concerned with complete equality or absolute inequality with a range of the Gini coefficient from 0 to 1 (excluding 0's and 1's).

[4] The outliers in Fig.2(B) show that a government is capable of raising up money in an issue of debt.



(A) Scatters of G versus g (B) Scatters of $\frac{G}{Y}$ versus g

Fig. 2: Empirical Evidence of Negative Relationship between Government Expenditure and Gini Coefficient

[Source] The data come from the World Development Indicators 2021 of the World Bank across 161 countries or regions over the 1980-2018 period. Government expenditure (formerly general government final consumption expenditure) spans all government current expenditures for purchases of goods and services (including compensation of employees).

variable in the model used here is endowed with time t, but we omit the "(t)" part of the symbol, thereby underscoring the fact that it is the change in the position of the "entire Y" path—the variation in the $\frac{\tau}{g}Y$ path—as against the change in t, that results in a change in path value G.

2.2 Dynamic Theoretical Model

Let the social welfare of an economy at any time be measured by the total utility from sum of consumption. The overall utility function is given by

$$U = \frac{C^{1-\theta}}{1-\theta} \quad (0 < \theta < 1), \tag{2}$$

where C is total consumption ($C > 0$), and $1-\theta$ is termed a constant elasticity. Technological change is designated as A ($A > 0$). S is referred to as aggregate stock of human capital ($S > 0$). I accounts for gross levels of investment ($I > 0$). Total stock of physical capital is symbolized by K ($K > 0$). Aggregative supply of labor force is characterized by L ($L > 0$). To make the analysis simpler, we postulate international sectors do not exist. Hence, the national income is summarized by an aggregate demand function as follows:

$$Y = C + I + G. \tag{3}$$

As it is known, the whole capital accumulation is determined by the quantity of that to be set aside for investment which is, as usual, just not consumed by the private sector and the government. Thus, we have

$$\dot{K} = I = Y - C - G,^{5} \tag{4}$$

where the dotted symbol $\dot{K}$ denotes the time derivative (i.e., $\dot{K} \equiv \mathrm{d}K/\mathrm{d}t$). We substitute (1) into (4), and thereby $\dot{K}$ evolves according to the rule

$$\dot{K} = (1 - \frac{\tau}{g})Y - C. \tag{5}$$

In the conventionally neoclassical specification, competitive economy is implicitly defined as being the market equilibrium of demand and supply. For reflecting the people-oriented tenet in development, the aggregate supply function is the following extension of the Cobb-Douglas pattern where all technological changes are embodied in labor L, which is neutral in the Harrod definition,

$$Y = (AL)^{\alpha} S^{\beta} K^{\gamma} \quad with \quad \alpha,\ \beta,\ \gamma > 0. \tag{6}$$

Considering the way that A and L are combined, we may view technological progress and supply of labor force as perfect substitutes in the production process. Thus, the problem of ageing population is unlikely to have a long-term impact on economic growth.

Let us define

α = partial elasticity of national income with respect to A and L taken together,

β =partial elasticity of national income with regard to human capital, and

γ =partial elasticity of national income with respect to physical capital.

All of elasticity coefficients are parameters as well as τ and g mentioned above. It is assumed that Y is a linearly homogeneous function in AL, S and K, which shows constant returns to scale, that is, $\alpha+\beta+\gamma = 1$. Furthermore, the available labor supply identified with population and measured by head count remains constant.[6] Therefore, let us denote $L = L_0$. Value for L_0 is given and positive.

Replacing Y in equation (5) gives

$$\dot{K} = (1 - \frac{\tau}{g})A^{\alpha} {L_0}^{\alpha} S^{\beta} K^{\gamma} - C. \tag{7}$$

Technological change, on the other hand, can be created by engaging human capital stock S in research and applying the stock of technology A (Romer, 1990):

$$\dot{A} = \sigma S A \quad with \quad \dot{A} \equiv \mathrm{d}A/\mathrm{d}t, \tag{8}$$

[5] We assume away depreciation.

[6] Romer (1990) proposes that having a large population is not sufficient to generate growth. We share the same view that the total population will have remained stable in the long time.

where σ is the parameter of research productivity and $\dot{A}$ means the derivative of A with respect to time. S is determined by equation (30) and is not fixed. The social welfare with regard to sum of consumption is maximized among all feasible time paths resulting from the given initial capital stock, $K(0)$, and initial innovation stock, $A(0)$,

$$\max \int_0^\infty \frac{C^{1-\theta}}{1-\theta} e^{-\rho t} dt, \ for \ t \in [0, +\infty) \tag{9}$$

subject to the constraints below

$$\dot{A} = \sigma S A, \tag{10}$$

$$\dot{K} = (1 - \frac{\tau}{g}) A^\alpha {L_0}^\alpha S^\beta K^\gamma - C, \tag{11}$$

and initial conditions

$$A(0) = A_0, K(0) = K_0, \tag{12}$$

where $e^{-\rho t}$ is the discount factor of time in which the t argument appears explicitly only, and we term ρ a positive rate of discount in order to ensure the convergence of the objective functional. A and K are both interpreted to as the state variables. A_0 and K_0 imply initial state of A and K, respectively. S is visualized as a control variable of A and equation (10) is an equation of motion for A. Similarly, C is viewed as control variable of K and equation (11) is an equation of motion for K. The reason why S and C are devoted to control variables is that they act on human being, and the control variables generally stand in center stage in optimal control theory. S reflects human deepening, while C is on behalf of human widening. In an effort to keep the notation simple, we define symbol Δ as follow:

$$\Delta \equiv (1 - \frac{\tau}{g}) A^\alpha {L_0}^\alpha S^\beta K^\gamma = (1 - \frac{\tau}{g}) Y. \tag{13}$$

In this model, consumption C does not need to be expressed in per-capita terms because L_0 is time-invariant. By the same token, K rather than $\frac{K}{L}$ can appropriately serve as the variable for analysis. Using the current-valued Hamiltonian, H_c, such that we are capable of maintaining convergence in infinite time horizon and canceling the discount factor as follows:

$$H_c = \frac{C^{1-\theta}}{1-\theta} + \lambda_A \sigma S A + \lambda_K (\Delta - C), \tag{14}$$

where λ_A and λ_K stand for the shadow prices of A and K, respectively. The variable λ can take different values at different points of time. Thus, the symbol λ is really a short version of $\lambda(t)$. Since there is no explicit t argument in H_c, we presently have an autonomous system. The maximum of the current-valued Hamiltonian is determined by the first-order necessary condition that

follow by maximizing H_c with respect to the control variables C in terms of Pontryagin's Maximum Principle, and then we have

$$\frac{\partial H_c}{\partial C} = C^{-\theta} - \lambda_K = 0. \tag{15}$$

The first-order condition for maximizing H_c with respect to C gives the usual expression of shadow price of physical capital as follows:

$$\lambda_K = C^{-\theta}. \tag{16}$$

Similarly, H_c is partially differentiated with respect to S, and we therefore derive

$$\frac{\partial H_c}{\partial S} = \lambda_A \sigma A + \frac{\lambda_K \beta \Delta}{S} = 0. \tag{17}$$

After rearranging terms, that reshapes

$$\lambda_K = -\frac{\lambda_A \sigma A S}{\beta \Delta}. \tag{18}$$

Also, the second-order condition is a sufficient condition for the stationary value to be a maximum. Setting the second derivatives of the H_c with respect to C and S, separately, yield

$$\frac{\partial^2 H_c}{\partial^2 C} = -\theta C^{-\theta-1}, \tag{19}$$

and

$$\frac{\partial^2 H_c}{\partial^2 S} = -\frac{\lambda_K \beta^2 \Delta^2}{S^3}. \tag{20}$$

We resort to the second-order test of a Hessian determinant, namely, $\mid D \mid$. More specifically, the first leading principal minor of $\mid D \mid$ is attained by

$$\left|D_1\right| = \left|-\theta C^{-\theta-1}\right| = -\theta C^{-\theta-1} < 0, \ for \ C, \ \theta > 0. \tag{21}$$

Then the second-order partial derivatives, properly arranged, give us the second leading principal minor of $\mid D \mid$as follows:

$$\left|D_2\right| = \begin{vmatrix} -\theta C^{-\theta-1} & 0 \\ 0 & -\frac{\lambda_K \beta^2 \Delta^2}{S^3} \end{vmatrix} = \frac{\theta \lambda_K \beta^2 \Delta^2}{S^3 C^{1+\theta}}. \tag{22}$$

Inserting (16) in (22) we shape

$$\left|D_2\right| = \frac{\theta \beta^2 \Delta^2}{S^3 C^{1+2\theta}} > 0, \quad subject \ to \ S, \ C, \ \theta > 0. \tag{23}$$

In the present case, there is only two leading principal minors available, and their signs will serve to ascertain whether the stationary value found there gives a maximum or a minimum of H_c. Because $\left|D_1\right|$ is negative while $\left|D_2\right|$ is positive, the second-order sufficient condition is satisfied for a concavity

function on the Hamiltonian. Therefore, the conditions of Mangasarian (1966) are satisfied, and we establish a maximum in the current-valued Hamiltonian. Applying Pontryagin's Maximum Principle, we have evolution of the multiplier with respect to time and get

$$\dot{\lambda}_A = -\frac{\partial H_c}{\partial A} + \rho\lambda_A = -\lambda_A \sigma S - \frac{\lambda_K \alpha \Delta}{A} + \rho\lambda_A. \tag{24}$$

In particular, we cast (18) into (24) and obtain

$$\dot{\lambda}_A = \left[\left(\frac{\alpha}{\beta} - 1\right)\sigma S + \rho\right]\lambda_A, \tag{25}$$

which allows us to rewrite equation (25) as follows:

$$\frac{\dot{\lambda}_A}{\lambda_A} = \left(\frac{\alpha}{\beta} - 1\right)\sigma S + \rho. \tag{26}$$

The maximum principle requires the following equations of motion for another costate variable:

$$\dot{\lambda}_K = -\frac{\partial H_c}{\partial K} + \rho\lambda_K = (\rho - \frac{\gamma\Delta}{K})\lambda_K. \tag{27}$$

The following is equivalent to

$$\frac{\dot{\lambda}_K}{\lambda_K} = \rho - \frac{\gamma\Delta}{K}. \tag{28}$$

Since standard transversality conditions are not necessarily applicable in infinite-horizon problems, we use plain economic reasoning to determine what the terminal state should be, as $t \to \infty$. Fortunately, it is an essential relation $\frac{\dot{\lambda}_A}{\lambda_A} = \frac{\dot{\lambda}_K}{\lambda_K}$ that characterizes the steady state as a substitute for the transversality condition (Romer, 1990), which can be simplified to yield

$$\frac{\dot{\lambda}_A}{\lambda_A} = \frac{\dot{\lambda}_K}{\lambda_K} \to \left(\frac{\alpha}{\beta} - 1\right)\sigma S + \rho = \rho - \frac{\gamma\Delta}{K}. \tag{29}$$

We rewrite equation (29) to

$$S = \frac{\gamma\Delta}{K\sigma(1 - \frac{\alpha}{\beta})}. \tag{30}$$

Equation (30) is the determination of the optimal time path for the control variable, S. Once the optimal control path, say, S, has been found, we can also ascertain the optimal economic growth path, $\frac{\dot{Y}}{Y}$, which corresponds to it. Because there exists a steady state of equilibrium (as proved in the subsection 6.4 of Section 6), the system will eventually develop toward a balanced growth path at the natural rate resulting from Harrod-neutral technological progress (Solow, 1956; Barro & Sala-i Martin, 2003).[7] According to equation (10), it

[7]The coefficients on initial logarithmic gross domestic product are negative and significant, implying conditional convergence in a steady state along the balanced growth path, as shown in Table 8 below.

must be the case that

$$\frac{\dot{Y}}{Y} = \frac{\dot{K}}{K} = \frac{\dot{A}}{A} = \sigma S \quad with \quad \dot{Y} \equiv \mathrm{d}Y/\mathrm{d}t. \tag{31}$$

Substituting (30) in (31) we formulate

$$\frac{\dot{Y}}{Y} = \frac{1-\frac{\tau}{g}}{1-\frac{\alpha}{\beta}} * \gamma * \frac{Y}{K} \tag{32}$$

where $\gamma * \frac{Y}{K}$ represents marginal returns to physical capital, namely,

$$MP_K \equiv \frac{\partial Y}{\partial K} = \gamma * \frac{Y}{K}. \tag{33}$$

Equation (33) combining with (32), the optimally long-term path of economic growth can be written as

$$\frac{\dot{Y}}{Y} = \frac{1-\frac{\tau}{g}}{1-\frac{\alpha}{\beta}} * MP_K. \tag{34}$$

Since γ, Y, $K > 0$, MP_K is positive (i.e., the production function is assumed to have positive marginal product throughout). Given constant L_0, $\frac{\dot{Y}}{Y}$ is just equivalent to rate of economic growth. It is $\frac{1-\frac{\tau}{g}}{1-\frac{\alpha}{\beta}}$ that is a vital adjusting coefficient of economic growth aside from MP_K, arising from law of diminishing marginal returns of physical capital.

More importantly, we proceed more in the spirit of the Romer's(1990) model. The expression of rate of economic growth in the Romer's model comprises not only the pure-number parameters, but also a parameter of the human capital at large which has a physical unit. The magnitude of the expression thus may become problematic. Alternatively, the equation (34) we develop is a purely numerical scaling factor regarding rate of economic growth without any physical units, explaining the bulk of variation in macroeconomic performance.

2.3 Implication of Equation (34)

We concern ourselves with comparison of the magnitude of between α and β. As mentioned previously, α is the partial elasticity of national income to innovation, and β is that to human capital. Generally speaking, be pupils before human beings become scientists (Arrow, 1962; Romer, 1986; Lucas, 1988; Elkan, 1996).[8]

In early stages of development, the partial elasticity of national income to human capital is higher than that to innovation. Crafts (1996) claims that productivity improvements through learning were far more important in the

[8] As argued by Elkan (1996) "A country will initially concentrate heavily on imitation, for which there exists a large catch-up opportunity. Subsequently, as it acquires more of the imitation spillover and its technical maturity increases, human-capital accumulation will increasingly be devoted to innovation..."

British economy than those obtained through investments in R&D from around the industrial revolution until World War I. Since World War I R&D investments have been of main importance. Before World War II almost no resources were devoted to R&D. The overall impression is that the importance of R&D activities has increased significantly in the second half of the twentieth century. This sort of pattern is found for the economy as a whole in France, Germany, Japan, the Netherlands, the United Kingdom, and the United States by Maddison (1991), in Germany, Britain, and the United States by Broadberry & Wagner (1994). Thus, α is less than β in early stages of economic development (Sørensen, 1999). [9]

In advance stages of development, innovation emerge as the prime engine of economic growth. (Solow, 1956, 1957; Romer, 1990; Aghion & Howitt, 1992). In turn, the partial elasticity of national income to innovation is greater than that to human capital (Sørensen, 1999). [10] Therefore, α is greater than β in advance stages of economic development.

In general, an economy always goes through pre-industrialization prior to post-industrialization in the long-term development process. As emphasized above, α will undergo a process of being less than β before greater than it over time. Recall that $MP_K > 0$, and τ, g, α, $\beta > 0$. Accordingly, equation (34) implies the positive effect of the Gini coefficient (g) on economic growth rate ($\frac{\dot{Y}}{Y}$) on condition that $\alpha < \beta$,[11] and negative effect otherwise.[12] Hence, the influence of inequality on economic growth reveals divergent paths in different development stages, where economic growth first increases and then decreases as Gini coefficient increases. In short, the fundamental idea of this paper is that the equation (34) releases an indispensable result, which points to an

[9] Sørensen (1999) argues it is not profitable to perform R&D in an economy at a low stage of development. The reason is that the rate of return to investments is higher when learning alone drives growth than in the presence of both growth-generating activities. Hence, education alone drives growth when the skill level is relatively low, whereas both learning and innovation are present after human capital has reached a threshold level.

[10] Sørensen (1999) provides a theory in support of our perception that the accumulation of human capital still contributes to economic growth in the transition from the regime shift until steady-state is reached. In the long-run equilibrium, however, economic growth is driven solely by R&D and education serves only to offset the depreciation of existing human capital. Solow (1957) discovers gross output per man hour of the U.S. doubled over 1909-1949, with 87.5% of the increase attributable to technical change and the remaining 12.5% to increased use of capital.

[11] For example, in 1984, China had a relatively low Gini coefficient of household income at 25.7 on a scale of 100. By 1992, China reached a relatively high Gini coefficient of income at 37.8. This rapid increase in inequality (12-point rise in 8 years) is associated with the spectacular performance of 9.8% average growth in real GDP (Li & fu Zou, 1998). Fan et al. (2021) document the real GDP per capita increased almost twentyfold from 1980 to 2016 in China. Over the same period, its Gini coefficient rose from 0.31 to 0.47. The following empirical data may explain these phenomena. Li et al. (2017)report a rise of human capital would typically be associated with a rise of 3.8 percent per year from 1980 to 2014, which is about 40 percent of China's actual growth rate. In deeply contrast, Nehru (1996) decompose the 10.2% GDP growth of China during the period of 1985-1994 into 6.6% from factor accumulation, 1.1 percentage points from labor reallocation effect and 2.5% from net TFP growth.

[12] For instance, the 10-point rise in the Gini coefficient of income inequality was associated with moderate (2–3%) or even negative episodes of economic growth from 1977 to 1991 for the UK (Goodman & Webb, 1994). The comparable data below might explain this phenomenon. Blundell et al. (1999) point out a one-percentage-point increase in the proportion of workers with higher qualifications raises annual output by between 0.42% and 0.63% from the UK covering the period 1971-1992. Bond et al. (2003) reveals the R&D output elasticity in the UK from 1987 to 1996 is approximate 6.5%.

inverted U-shaped effect of Gini coefficient on growth with industrialization. More specifically, our theory can be schematically summarized as Fig. 3.

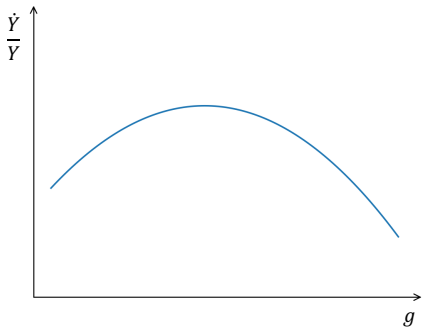


Fig. 3: The Inverted U-shaped Effect of Inequality on Growth

3 Empirical Evidence

3.1 Data Sources and Variables Explanation

We focus our examination directly on the relationship between growth and distribution of income. We derive a set of panel data (Panel A) from the World Development Indicators (WDIs) 2021 of the World Bank, limited to 161 countries or regions[13] over the 1980-2018 period,[14] where it is observations that are involved in at least one data on Gini coefficient compiled.

In compliance with the equation (34), the dependent variable in all our regressions is supposed to be growth rate of per capita GNI ($GROWTH$), and key explanatory variable is Gini coefficient ($GINI$). There is straightforward equivalence between the Gini coefficient and the Gini index. In addition to the Gini coefficient, we include three control variables: residents' patent applications ($PATENT$), adjusted savings: consumption of fixed capital ($CAPITAL$) and tertiary school enrollment ($EDUCATION$). For the independent variables, we attempt to find some variables that could match

[13]The panel A gets rid of British Virgin Islands, Cayman Islands, Channel Islands, Faroe Islands, French Polynesia, Gibraltar, Greenland, Guam, Isle of Man, New Caledonia, Northern Mariana Islands, Puerto Rico, Qatar, Saudi Arabia, Sint Maarten (Dutch part), Somalia, St. Martin (French part), St. Vincent and the Grenadines, Turks and Caicos Islands, Virgin Islands (U.S.), Trinidad and Tobago, St. Kitts and Nevis, Caribbean small states, Singapore, San Marino, Palau, Oman, New Zealand, Nauru, Monaco, Marshall Islands, Liechtenstein, Libya, Kuwait, Korea, Dem. People's Rep., Grenada, Eritrea, Equatorial Guinea, Dominica, Curacao, Cuba, Brunei Darussalam, Bermuda, Barbados, Bahrain, Bahamas, Aruba, Antigua and Barbuda, Andorra, American Samoa, Cambodia and Afghanistan due to lack of Gini coefficient data. West Bank is excluded because of a dispute over sovereignty. Note that although some countries are deleted, there is no selection bias here because the countries removed are either island countries or non-market economies. The question we are interested in is the effect of inequality on economic growth conditional on market economy country or region. As a result, the requirement of random sample is satisfied.

[14]Because the World Bank did not start to count the data of Gini coefficient until 1980.

characteristics of our model as closely as possible. The Gini coefficient is entered to account for inequality. Technological change is measured by the residents' patent applications. The tertiary school enrollment and the adjusted savings: consumption of fixed capital clearly have to do with the representative indicators of human capital and physical capital, respectively. It is obviously possible to involve with a number of additional variables, yet this paper concentrates on the uniformity between the theoretical model and the empirical specification. So, we do not add too many covariates temporarily in baseline regression.[15] The units of all variables in our regressions are expressed as a percentage except $PATENT$. Summary and symbol for these variables appear in Appendix Table A.1.

3.2 Descriptive statistics and Scatters Plot

Table A2-A of the Appendix provides the main features of samples of the Panel A that is an unbalanced data set where common sample substantially shrink to 99 countries with a total of 961 observations for basic regression. Fig. 4 plots the per capita GNI growth against the Gini coefficients diagrammatically for Panel A. It depicts that the growth rate virtually looks like an inverted U curve—first rising, then falling as wealth gap between the rich and the poor is heavily widening.

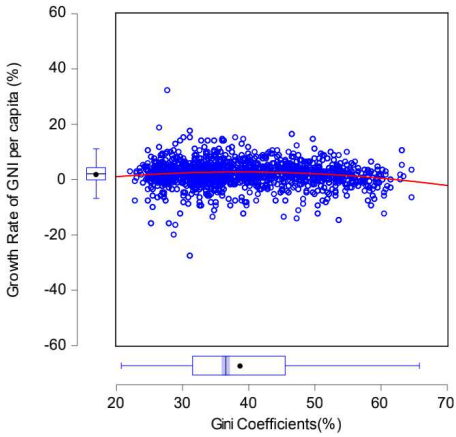


Fig. 4: Long-term Relationship between Growth and Inequality

[Source] The data come from the World Development Indicators 2021 of the World Bank.

[15] Biswas et al. (2017) analyzes that the reduction of income inequality through tax policy affects economic growth. Thus, the variation of marginal tax rate has embodied in the Gini coefficient.

3.3 Baseline Estimates

To formally examine the relationship between growth and inequality, we estimate baseline of the following specification:

$$\begin{aligned} GROWTH_{it} =& c + \beta_1 GINI_{it} + \beta_2 GINI_{it}^2 + \beta_3 Log\ PATENT_{it} \\ &+ \beta_4 CAPITAL_{it} + \beta_5 EDUCATION_{it} + \alpha_i + \gamma_t + \varepsilon_{it}, \end{aligned} \tag{35}$$

where the unobserved country fixed effect is represented by α_i, and year fixed effect by γ_t. Subscripts i and t index country and year, respectively. $GROWTH_{it}$ denotes GNI per capita growth for country i during period t. Constant is considered as c.[16] To substantiate for the aforementioned non-linearity, we add a squared term of Gini coefficient ($GINI_{it}^2$) as another key explanatory variable, and ε_{it} is a random error term. In order for all the coefficients to represent elasticity, we take the logarithm of $PATENT$. The coefficients of interest throughout this paper are β_1 and β_2—that is, the impact of inequality on growth.[17]

The results from a series of benchmark estimates are reported in Table 1. Column (1) is an Ordinary Least Squares (OLS) estimate. A two-way fixed effects (FE) estimate is applied to column (2) to control both individual and temporal heterogeneity to eliminate persistent non-observed discrepancies across different cross-sections and over periods. Table 1 displays that the coefficients on $GINI$ are significantly different from zero and positive in sign in both OLS estimate and FE estimate. Moreover, the coefficients for $GINI^2$ remain a statistical significance level of 5 percent at least in columns (1)-(2) and negative in sign with and without two-way fixed effects, indicating that economic growth rate implies a trend of moving upward and then downward with the level of inequality in accordance with our theoretical model.

Alternatively, the Least Absolute Deviations (LAD) estimate in Table 1 column (3), which corresponds to fitting the conditional median of the response variable, will be more robust if the sample data contains outliers. Overall, column (3) reports that the LAD estimate of the growth to inequality is commensurate with OLS regression in magnitude and statistically indistinguishable. We document our estimates of the effect of inequality on economic performance are not driven by outliers.[18]

[16] The constant term represents a given supply of labor force.

[17] Innovation is measured as the natural logarithm of $PATENT$ in order for all of β coefficients to stand for elasticity.

[18] We take explicitly into account the special role of transition (post-Soviet) countries and add a LAD estimation to address the problem of outliers.

Table 1: The Benchmark Results of Panel A

	Dependent variable: *GROWTH*		
	(1) OLS	(2) FE	(3) LAD
CONSTANT	-2.19	-6.48	-1.78
	(2.58)	(4.90)	(2.51)
GINI	0.39***	0.54**	0.35***
	(0.13)	(0.24)	(0.12)
$GINI^2$	-0.005***	-0.007**	-0.005***
	(0.002)	(0.003)	(0.002)
Log PATENT	0.01	0.73***	-0.08
	(0.06)	(0.27)	(0.05)
CAPITAL	-0.09**	-0.33***	-0.05
	(0.03)	(0.05)	(0.04)
EDUCATION	-0.01**	-0.009	-0.01**
	(0.007)	(0.02)	(0.006)
Country fixed effects	No	Yes	No
Year fixed effects	No	Yes	No
R^2	0.03	0.44	0.02
Adjusted R^2	0.02	0.34	0.01
Number of observations	961	961	961
Number of countries	99	99	

Note:*** indicates $p < 0.01$, ** indicates $p < 0.05$, * indicates $p<0.1$. Bidirectional fixed effects model employs estimator of Least Squares Dummy Variables. See Table A1 in Appendix for a description of *GROWTH*, *GINI*, *PATENT*, *CAPITAL*, and *EDUCATION*. Figures in parentheses are standard deviations of estimate coefficients of variables. In the median regression of column (3), we pursue Huber Sandwich Standard Errors. Sparsity method is Kernel (Epanechnikov) using residuals. Bandwidth method is Hall-Sheather and bw=0.099. This estimate successfully identifies unique optimal solution. Sparsity is 6.83 and probability of Quasi-LR statistic is 0.00003.

4 Endogeneity

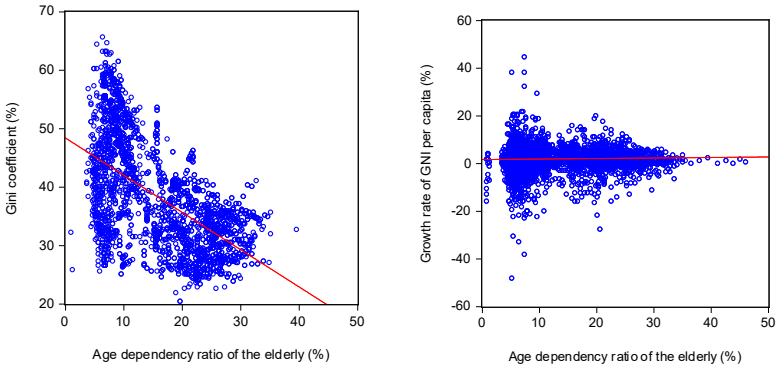
4.1 Identification Strategy of Instrumental Variable

Although country and year fixed effects attenuate potential endogeneity associated to time-invariant omitted variables, they are not capable of correcting for endogeneity biases involved with reverse causality. Lundberg & Squire (2003) demonstrate that the determinants of growth and inequality are not mutually exclusive. Variations in inequality are likely to be correlated with a range of unobservable factors related with growth (emphasized by Banerjee & Duflo, 2003). Thus, a systematic relation between inequality and growth, such as the Kuznets curve, would give rise to a simultaneous causality problem. To avoid reverse causation from growth to income distribution, we are mining for the instrumental variable of the Gini coefficient. To capture the causal

link more rigorously, we pursue an instrumental variable approach by employing age dependency ratio of the elderly (OLD), which is the ratio of older dependents—people older than 64—to the working—age population—those ages 15-64, as a plausible instrument. The data of OLD are drawn from the WDIs 2021 of the World Bank.

Initially, the increase in the age dependency ratio of the elderly means the arrival of the Lewis turning point. An ageing population incurs an expansion of the equilibrium wage which, in turn, causes a decline in the Gini coefficient (for example Japan). As a result, the Gini coefficient is negatively correlated with the age dependency ratio as shown in Fig. 5(A). Morley (1981) and Mosk & Nakata (1985) hold the similar views to us.

Then, our intuition behind this instrument is that China has still displayed exceptional growth records despite having thriving aging population while Japan's economy has been entering a period of secular stagnation for several decades because of aging. Globally, economy suffers modestly from the gradual disappearance of the demographic dividend in the long run. The recent literature predicts that aging process indeed induces the application of labor-saving technology or Artificial Intelligence (Acemoglu & Restrepo, 2018, 2021). Building upon this literature, AI is currently substituting for humans in a subset of tasks (Acemoglu et al., 2022). Hence the impact of aging on economic growth can be mitigated through productivity advance at least from the supply-side perspective. Moreover, firms are not inclined to hire young workers during recessions from the perspective of demand side (Forsythe, 2021). Acemoglu & Restrepo (2017) assert there is no negative relationship between aging and slower growth of GDP per capita. Futagami & Nakajima (2001) also show that aging is not necessarily a negative factor for growth. On the other side of the coin, there is no evidence that the large increase in life expectancy raised income per capita (Acemoglu & Johnson, 2007). Actually, that the fit line between $GROWTH$ and OLD seems to be level suggests the age dependency ratio of the elderly may be irrelevant to economic performance as illustrated in Fig. 5(B). It is the reason why the quantity of aggregative labour force is assumed to be a constant in our theoretical model. In other words, the age dependency ratio of old people is plausibly not directly correlated with most other contributors that affect contemporary economic growth.



(A) Scatters of $GINI$ versus OLD (B) Scatters of $GROWTH$ versus OLD

Fig. 5: Identification strategy for Instrumental Variable

[Source] The data are from the World Development Indicators 2021 of the World Bank.

4.2 Conditional Independence

The validity of the identification strategy rests on the assumption that the elderly dependency ratio is conditionally independent of economic growth. Anselin (1995) outlines a general class of local indicator of spatial association: Local Moran's I statistic[19] which serves a useful purpose in an exploratory analysis of spatial agglomeration of features with high or low values,[20] visualized in the form of significance and cluster maps. The maps depict the locations with significant Local Moran's I statistics and classify these locations by type of association. The cluster type field distinguishes between a statistically significant cluster of high values (High-High), cluster of low values (Low-Low), outlier in which a high value is primarily surrounded by low values (High-Low), and outlier in which a low value is mainly surrounded by high values (Low-High). The functionality for spatial autocorrelation analysis is rounded out by a range of operations to construct spatial weights. A type of spatial weights is to select the k-nearest neighbors, whose number can be specified as 7 conventionally. Statistical significance is set at the 95 percent confidence level. We attempt to account for the fact that the age dependency ratio does not correspond with economic growth via Local Moran's I statistic. We drop island countries owing to without neighbors, leaving 192 countries in our analysis.

Four cluster maps are shown in Fig.6, depicting the locations of significant Local Moran's I statistics, classified by type of spatial association. The red and

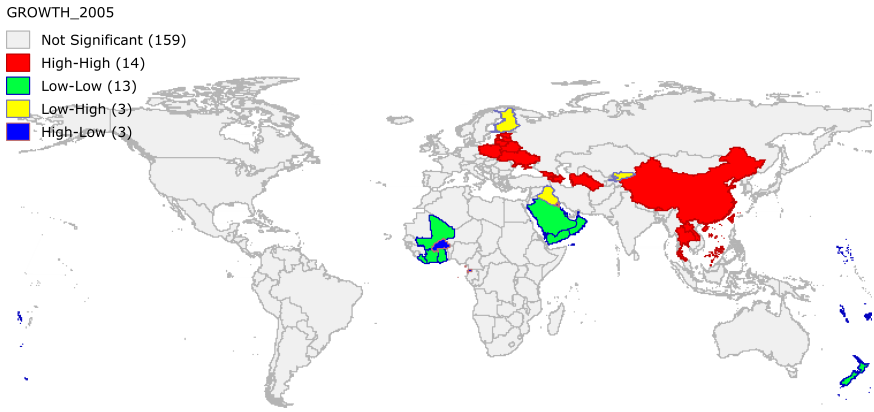
[19] This statistic is given in Appendix B.

[20] A positive value for this index indicates that a feature has neighboring features with similarly high or low attribute values; this feature is part of a cluster. A negative value for the index indicates that a feature has neighboring features with dissimilar values. In either instance, the p-value for the feature must be small enough for the cluster or outlier to be considered statistically significant.

green locations are indications of spatial clusters (respectively, high surrounded by high, and low surrounded by low). In contrast, the yellow and blue are indications of spatial outliers (respectively, high surrounded by low, and low surrounded by high).

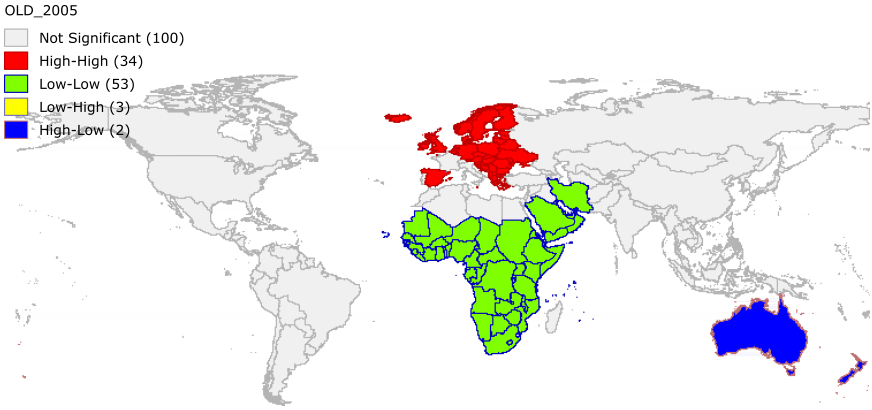
We observe that Fig. 6(A) portrays clusters map for the values of $GROWTH$[21] in the world. High-growth countries were located in China, Southeast Asia, and Eastern Europe, while low-growth countries are concentrated in the Arabian Peninsula and West Africa regions in 2005. In contrast, Fig. 6(B) provides an illustration of spatial correlation for the values of OLD around the world. Obviously, Europe were the agglomerative region with the highest level of OLD, while the spatial clusters of low values of OLD were converged on Sub-Saharan Africa in 2005.

The motivation for comparison is that Fig. 6(C) plots a cluster of high economic growth which appeared in Southeast Asia in 2015. Compared with Fig. 6(C), the high values of the age dependency of the elderly ratios were still remarkably illustrated in Europe at the same time in Fig. 6(D). There seems to be a spatial differentiation between $GROWTH$ and OLD once again graphically. These maps use the significance of 5-percent level.

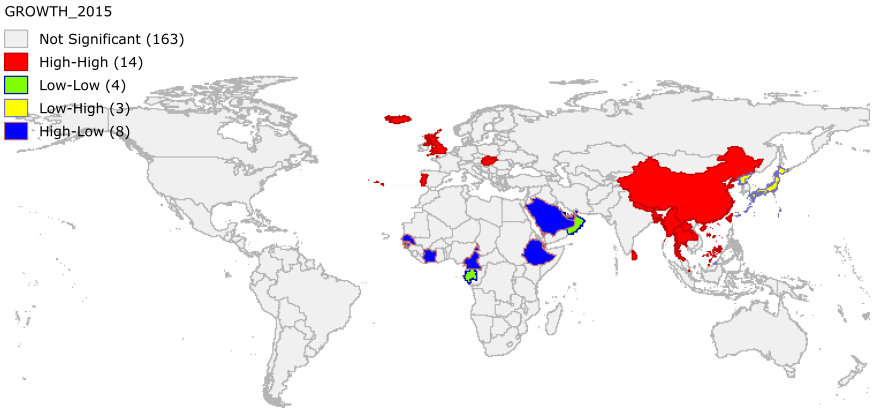


(A) Map for the Values of $GROWTH$ around the World in 2005

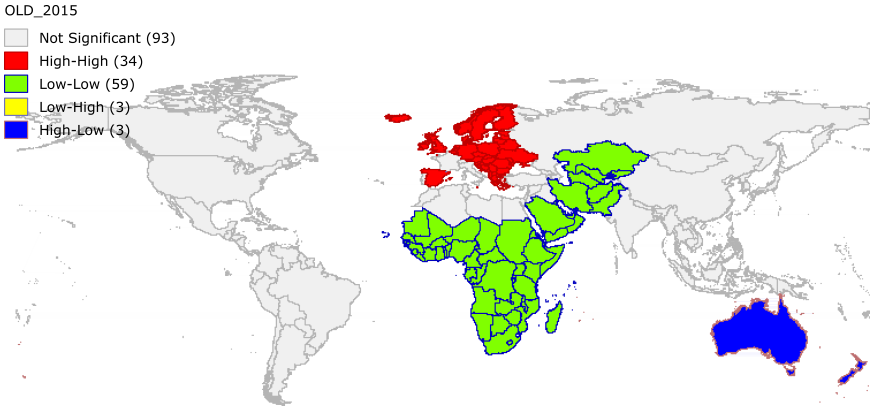
[21] We take advantage of GDP per capita growth rate instead in these spatial autocorrelation tests, because a number of data of growth rate of GNI per capita are not available.



(B) Map for the Values of OLD around the World in 2005



(C) Map for the Values of $GROWTH$ around the World in 2015



(D) Map for the Values of OLD around the World in 2015

Fig. 6: The Clusters Map of Local Moran's Index

[Source] Gray areas cease to be statistically significant at 5-percent level. The data originate from the World Development Indicators 2021of the World Bank.

Arguably, to the extent spatial correlation could reflect economic relation—that is, if OLD had been positively correlated with $GROWTH$, countries with high economic growth rate should have located in communities of OLD's high value; if OLD had been negatively related with $GROWTH$, high growth country should have gathered in the same area as agglomerations of low value of OLD. By comparing the regions of spatially clustering maps between $GROWTH$ and OLD, we come to the following conclusion that the age dependency ratio of the elderly is not directly relative to the per capita GNI growth across countries and over time.

4.3 Exclusive Restriction

Our identification strategy will be valid as long as OLD is uncorrelated with ε_{it}—that is, the age dependency ratio of the elderly has no direct effect on growth other than through its influence on inequality. A potential concern with this exclusion restriction is that OLD may be associated with other factors, such as technological progress, private investment, human capital, health status and consumption level, contributing to economic performance. To address these concerns, we conduct seven exercises to verify exclusion restriction. We adopt life expectancy at birth ($HEALTH$) as a potential indicator of overall health status and final consumption expenditure ($CONSUMPTION$) as a measure of aggregate consumption level respectively. These data are taken from the WDIs 2021 of the World Bank. It is particularly important to emphasize that the shock of investment has been embodied in $CAPITAL$.

Table 2 reveals the coefficients on OLD from a variety of latent relevant indicators analyses in which column (9) indicates the effect of aging on growth through the channel of health and column (10) implies the influence of aging on growth via consumption channel. We investigate whether OLD have a comparable effect on $GROWTH$ once we control for a number of variables potentially correlated with the age dependency ratio of the elderly. Column (4) of Table 2 initiatively reports that the coefficient of the reduced-form estimate of $GROWTH$ to OLD is insignificant at any standard level of significance. That would appear to be a pretty compelling evidence where $GROWTH$ is not directly relevant to OLD as analyzed by Acemoglu & Restrepo (2017).

According to Columns (5)-(10) of Table 2, we find that the estimates of $GROWTH$ to OLD change remarkably little when we control for $PATENT$, $EDUCATION$, $HEALTH$ and $CONSUMPTION$ respectively (i.e., OLD is still uncorrelated with $GROWTH$ in columns (6) and (8)-(10) respectively), indicating an older population can not affect economic growth through innovation, human capital, health status and consumption channels. The coefficients in front of OLD merely obtain significant after the addition of $GINI$ or $CAPITAL$ (i.e., OLD is related to $GROWTH$ in columns (5) and (7) respectively), suggesting the instrumental variable affects contemporary growth not only through inequality but also through private investment. More specifically, column (5) shows that aging hinders economic growth via inequality in income

distribution because the increase of equilibrium wage brings about the expansion of production cost of enterprise, while column (7) sheds light on the fact that OLD boosts economic growth through private investment since aging has constantly spurred investment in Artificial Intelligence and the Industrial Internet as predicted by Acemoglu & Restrepo (2018, 2021); Acemoglu et al. (2022). These two kinds of influences of aging on economic growth are approximately equal in magnitude but clearly opposite in sign. The two opposing forces cancel each other out. It is therefore a convincing result in column (4) that the coefficient of the reduced-form estimate of growth to aging is insignificant in spite of strongly negative correlation between aging and inequality, for aging population is not directly related to economic outcome. More specifically, the exclusive restriction can be schematically outlined in Fig.7.

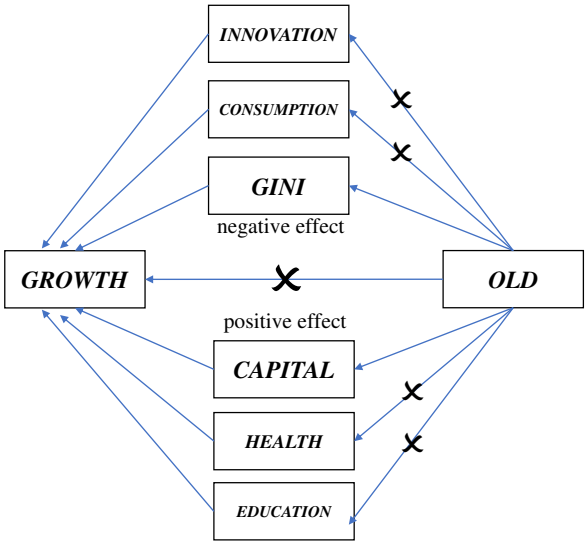


Fig. 7: The Results of Exclusive Restriction

After examining six channels of inequality, innovation, investment, human capital, health and consumption in turn, we find that aging interferes with economic growth only through inequality and investment. To relieve this endogenous bias, the exogenous instruments for the two-stage least-squares (TSLS) estimates proposed in subsection 4.5 are OLD and OLD^2. Meanwhile, the covariates are practically involved in $CAPITAL$ to control for another disturbance on which instrumental variables exert the dependent variable. In brief, OLD might be an essential factor in accounting for the Gini coefficient that we observe, but have no direct effects on contemporaneous economic growth.

Table 2: The Test of Exclusive Constraint

	Dependent variable: *GROWTH*						
	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS
CONSTANT	1.68***	5.93***	2.42***	2.36***	2.05***	-1.39	2.83***
	(0.30)	(1.18)	(0.36)	(0.37)	(0.31)	(1.46)	(0.78)
OLD	0.02	-0.07***	-0.02	0.05**	-0.01	-0.02	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
GINI		-0.06***					
		(0.02)					
Log PATENT			0.03				
			(0.04)				
CAPITAL				-0.09***			
				(0.03)			
EDUCATION					0.01		
					(0.01)		
HEALTH						0.05**	
						(0.02)	
CONSUMPTION							-0.01
							(0.009)
R^2	0.001	0.02	0.001	0.007	0.0008	0.006	0.003
Adjusted R^2	0.0008	0.01	0.0004	0.006	0.0001	0.006	0.002
Number of observations	4051	1468	2534	4049	2869	4049	4032
Number of countries	145	142	116	145	136	145	144

Note: Standard errors clustered at the year's level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Detailed sources and definitions for each of these variables are listed in Appendix Table A1.

4.4 Weak Instrumenting Test

We run several checks to assess the correlation between the instrumental variable and the endogenous explanatory variable. In column (11) of Table 3, we report the reduced-form estimate of *GINI* to *OLD*. Gini coefficient is supposed to be negatively correlated with *OLD*. As anticipated in subsection 4.1 , we find a highly significantly negative relationship between the age dependency ratio of the elderly and the Gini coefficient, that is, a one percent increase in the age dependency ratio leads to a 0.64% decrease in income inequality. The adjusted R^2 of the reduced-form regression in column (11) shows that differences in the age dependency ratio of the elderly alone explains over 30 percent of the variation in income distribution. Columns (12) and (13) are the first stage of TSLS estimates, respectively. According to the column (12) of Table 3, the first-stage F-statistic is 109.33, which is above the conventional threshold for weak instruments suggested by Stock & Yogo (2005). The regression

(13) replicates the specification from column (12) besides a combination of country and year fixed effects. The first-stage F-statistic of regression (13) is 91.95, which exceed 10 or even better. We formally reject the null hypothesis of weak instrumental variable. Instead, OLD is tied to $GINI$.

Table 3: Weak Instrumenting Test

	Dependent variable: $GINI$		
	(11) Reduced Form	(12) First Stage of TSLS	(13) First Stage of TSLS
$CONSTANT$	48.41***	48.82***	30.78***
	(0.67)	(0.83)	(1.67)
OLD	-0.64***	-0.45***	0.20***
	(0.03)	(0.05)	(0.05)
$Log\ PATENT$		0.12*	0.17
		(0.07)	(0.21)
$CAPITAL$		-0.34***	0.20***
		(0.07)	(0.04)
$EDUCATION$		-0.005	-0.04***
		(0.01)	(0.01)
$Country\ fixed\ effects$	No	No	Yes
$Year\ fixed\ effects$	No	No	Yes
R^2	0.32	0.29	0.94
Adjusted R^2	0.32	0.29	0.93
F-statistic	805.83	109.33	91.95
Prob(F-statistic)	0.00	0.00	0.00
Number of observations	1680	1058	1058
Number of countries	159	107	107

Note:*** indicates $p < 0.01$, ** indicates $p < 0.05$, * indicates $p < 0.1$. The timing is not continuous because of the lack of year data in many countries. When the fixed effects method is used to estimate unbalanced panel data, the sequential correlation problem is alleviated. Therefore, we pay more attention to the robustness to contemporaneous correlation on the standard error. We resort to White cross-section standard errors (i.e., standard errors clustered at the year's level). Standard deviations of estimate coefficients of variables are in parentheses. Detailed sources and definitions for each of these variables are listed in Appendix TableA1.

The above regressions are carried out under the assumption of homoscedasticity, which may make the results of F-statistics misleading. In the case of heteroscedasticity, we perform a feasible generalized least square approach (FGLS) in order to ensure that the values of the F-statistics are valid. Table A3 of Appendix demonstrates that our instrumental variable still uniformly satisfies the rule of thumb for weak instrumenting test by controlling for country-level or yearly heteroscedasticity.

4.5 Identification of Causality

After controlling for almost all other ways in which instrumental variable affects economic growth, we ascertain that OLD satisfies the exclusion restriction. We use exogenous variation in the age dependency ratio of the elderly as an instrumental variable for the Gini coefficient in order to estimate the impact of income inequality on economic growth. Columns (14)-(15) of Table 4 are both TSLS estimates of the growth to inequality by controlling for a range of potential confounders, such as innovation, physical and human capital. We treat $GINI$ and its quadratic term as endogenous and all other variables as exogenous. Column (14) shows that the coefficient on $GINI$ is 0.19 and remains statistically significant at 5 percent level. As predicted by equation (34), the sign for the squared term of $GINI$ is negative and remains statistically significant at 10 percent level. Column (15) copies the specification from column (14) besides two-way fixed effects used to control for the unobserved time-invariant country specific factors and the heterogeneity at year levels jointly. Column (15) uncovers that the coefficient on $GINI$ is 3.69 and remains statistically significant at 5 percent level. The coefficient of squared Gini coefficient is -0.04 and remains statistically significant at 10 percent level. We discover that the direct effect of Gini coefficient on the growth of GNI per capita is economically and statistically significant. All in all, these regression results described above give stronger evidence to our conclusion in equation (34), which turn out to be an inverted U-shaped effect of inequality on growth. Especially, even though our data only span a few decades, the empirical results still reflect the secular effect of inequality on economic growth. Because our cross-sections embrace four dimensions: countries in early stages of industrialization (such as Benin and Tajikistan), countries in middle stages of industrialization (for example Egypt and Philippines), countries in late stages of industrialization (for instance China and Belarus) and post-industrial countries (say, the UK and the US), respectively. Among the different development phases of country samples, we can succeed in capturing the impact of variation in inequality on economic growth from distinct periods.

Table 4: Results of TSLS Estimates

	Dependent variable: *GROWTH*	
	(14) TSLS	(15) TSLS
CONSTANT		-76.55**
		(34.85)
GINI	0.19**	3.69**
	(0.07)	(1.79)
$GINI^2$	-0.002*	-0.04*
	(0.001)	(0.02)
Log PATENT	0.01	0.65
	(0.06)	(0.48)
CAPITAL	-0.06	-0.56***
	(0.05)	(0.11)
EDUCATION	-0.01	0.01
	(0.01)	(0.02)
Country fixed effects	No	Yes
Year fixed effects	No	Yes
R^2	0.02	0.22
Adjusted R^2	0.01	0.09
Number of observations	961	961
Number of countries	99	99

Note:*** indicates p < 0.01, ** indicates p < 0.05, * indicates p < 0.1. White cross-section standard errors (i.e., year-level clustered) provide additional approach of the robustness to contemporaneous correlation and arbitrary heteroskedasticity in residuals in the both TSLS estimates. $GINI$ and $GINI^2$ are treated as endogenous and instrument variables include OLD, OLD^2, $CAPITAL$, $EDUCATION$, $log\ PATENT$ and $CONSTANT$. Detailed sources and definitions for each of these variables are listed in Appendix Table A1. We present descriptive statistics in Appendix Table A2-B and C.

5 Robustness and Dynamic Estimation

Mankiw et al. (1992) investigate that a neoclassical economic growth depended on the level of GDP per capita in the previous period. The recent literature establishes that a number of factors have potential influence on economic growth and possibly correlated with inequality, focusing on prevalence of infectious disease, military conflict, gender discrimination, health status and consumption level (inspired by Zhao, 2006; Weil, 2007; Barro, 2013; Curran & Mahutga, 2018; Miguel et al., 2004; Esteban & Ray, 2011; Easterly, 2019; Blau & Kahn, 2017; Butcher & Case, 1994; Macpherson & Hirsch, 1995; Akerlof & Kranton, 2000; Manning & Swaffield, 2008; Elson, 2009; Mitra et al., 2014; Berg et al., 2018). A related concern is that our results may also be partially driven by omitted factors. To mitigate this concern, we compare the estimates of interest with and without controlling for these variables. To further check the robustness of our results, we proceed with a dynamic growth regression specified in equation (36) which estimates growth as a function of growth

lagged one year, inequality, innovation, physical and human capital, contagion, politics, gender gap, health status and country-fixed effects.

$$\begin{aligned} GROWTH_{it} =& \beta_0 GROWTH_{i,t-1} + \beta_1 GINI_{it} + \beta_2 GINI_{it}^2 \\ &+ \beta_3 Log\ PATENT_{it} + \beta_4 CAPITAL_{it} + \beta_5 EDUCATION_{it} \\ &+ \beta_6 HIV_{it} + \beta_7 MILITARY_{it} + \beta_8 GPI_{it} + \beta_9 HEALTH_{it} \\ &+ \beta_{10} CONSUMPTION_{it} + \alpha_i + \varepsilon_{it}, \end{aligned} \tag{36}$$

where i represents each country and t is on behalf of each time period. HIV refers to the indicator of human immunodeficiency virus. $MILITARY$ is proxying for armed forces personnel. GPI denotes gender parity index of gross enrollment ratio in primary education—that is, the ratio of girls to boys enrolled at primary level in public and private schools. A brief description of these control variables and their sources are reported in Table A1 of the Appendix. We estimate equation (36), using a generalized method of moments (GMM) approach transformed by first differences (Arellano & Bond, 1991).

Table 5 shows the consolidated results from the robustness checks. Columns (16)-(21) in Table 5 resort to dynamic panel estimation of Arellano-Bond 2-step procedure with GMM weighting matrix by White period in which random errors have time series correlation structure that varies by cross-section. The regression equation of column (17) includes HIV which refers to the percentage of people ages 15-49 who are infected with human immunodeficiency virus, aiming to capture the impact of the pandemic on economic growth. Not only does the specification of column (18) repeat column (17) but also adds $MILITARY$, the measure of active duty military personnel. This measure has been utilized as a continuous proxy for the degree of impact of a potential war on economic shock and, more generally, of the extent to which military conflict is likely to break out. In column (19), the effect of gender inequality on economic performance has been governed by GPI. Additionally, column (20) is a dynamic GMM estimate with health determinant. In column (21), we control for the impact of consumption on economic growth.

The most striking result is the effect of inequality on growth. The coefficients on $GINI$ are positive and remains statistically significant at 1 percent level from column (16) to column (21). Importantly, the coefficients in front of $GINI^2$ are always negative and continue to be highly significant at any standard level of significance in columns (16)-(21). Furthermore, Hansen J-statistics and the corresponding p-values display a failure to reject the null hypothesis that supports all the instrumental variables are strictly exogenous for these cases of the dynamic GMM regressions.

Table 5: The Results of Dynamic GMM Estimates of Panel A

	Dependent variable: *GROWTH*					
	Difference GMM					
	(16)	(17)	(18)	(19)	(20)	(21)
GROWTH (−1)	0.19***	0.21***	0.20***	0.11***	0.11***	0.04
	(0.008)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)
GINI	2.66***	1.63***	1.61***	4.49***	4.29***	7.17***
	(0.20)	(0.17)	(0.26)	(0.36)	(0.44)	(1.17)
$GINI^2$	-0.03***	-0.02***	-0.02***	-0.05***	-0.05***	-0.08***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.01)
Log PATENT	1.45***	1.04***	1.11***	1.02***	1.02***	0.71
	(0.15)	(0.19)	(0.33)	(0.35)	(0.39)	(0.60)
CAPITAL	-0.99***	-0.60***	-0.58***	-0.66***	-0.65***	-0.75***
	(0.03)	(0.03)	(0.06)	(0.05)	(0.06)	(0.13)
EDUCATION	-0.02***	-0.05***	-0.06***	-0.01	-0.02	-0.05
	(0.006)	(0.01)	(0.02)	(0.02)	(0.02)	(0.07)
HIV		0.16	0.09	0.77	0.76	0.04
		(0.20)	(0.25)	(1.18)	(1.89)	(3.54)
MILITARY			-1.55***	-0.94	-1.00	0.09
			(0.39)	(0.80)	(0.63)	(1.37)
GPI				-0.08	-0.07	0.04
				(0.11)	(0.11)	(0.24)
HEALTH					-0.04	0.32
					(0.24)	(0.35)
CONSUMPTION						-0.35***
						(0.11)
GMM weighting matrix	White period	White period	White period	White period	White period	White period
Prob (Hansen J-statistics)	0.40	0.48	0.49	0.49	0.46	0.72
Number of observations	847	489	487	459	459	459
Number of countries	85	57	57	57	57	57

Note:*** indicates p < 0.01, ** indicates p < 0.05, * indicates p <0.1. Robust standard errors are clustered at the country level from final iteration. The instruments are specified as @*DYN* (*GROWTH*, −2, −3), *OLD*, OLD^2, *log PATENT*, *CAPITAL* and *EDUCATION* in column (16). The instrumental specification of column (17) is the same as that of the column (16) besides *HIV* surplus. The instrumental specification of column (18) is identical with that of the column (17) in addition to *MILITARY*. The instrumental specification of column (19) not only reproduces that of the column (18) but also adds *GPI*. The instrumental specification of column (20) is similar to that of the column (19), plus *HEALTH*. The instrumental specification of column (21) is set in the same way as in column (20) in addition to *CONSUMPTION*. @*DYN* (*GROWTH*, −2, −3) is equivalent to using lags of GROWTH from second order to third order as instruments for each period. The other instrumental variables that we wish to difference prior to use in estimating the transformed equation consist of *OLD*, OLD^2, *Log*(*PATENT*), *CAPITAL*, *EDUCATION*, *HIV*, *MILITARY*, *GPI* and *HEALTH*. Detailed sources and definitions for each of these variables are listed in Appendix Table A1. We present descriptive statistics in Appendix Table A2-B.

Table 6: The Results of Arellano-Bond Serial Correlation Test

	Column (16)	Column (17)	Column (18)	Column (19)	Column (20)	Column (21)
Statistics of the first-order test	-3.91***	-2.52**	-2.74***			-0.20
Statistics of the second-order test	-2.28**	-1.87*	-1.18	-0.47	-0.46	-0.18

Note: This test is only available for equation estimated by generalized method of moments (GMM) estimator using first difference so as to eliminate cross-section effects. *** is proxying for significant at the 1-percent level, ** is proxying for significant at the 5-percent level, and * is proxying for significant at the 10-percent level.

In Table 6, we pursue the Arellano-Bond serial correlation tests in order to confirm the consistency of the dynamic GMM estimates. The specification of regression model of Table 6 is the same as that of Table 5. In column (18) of Table 6, the test shows that the first order statistic is statistically significant, whereas the second order statistic is not, which is what we would expect. In Table 5 column (18), the coefficient on $GROWTH(-1)$ is positive and consistently significant at 99 percent confidence, which indicates that a one-percentage-point augment in lagged growth approximately increases the current growth by 0.2 percentage points per year. Therefore, it is reasonable to consider the time discounting method in our dynamic theoretical model.

The GMM estimates of the growth to inequality is close to the TSLS estimates after circumventing potential problems of omitted variables. To summarize, the inverted U-curve impact of inequality on growth is generally robust to a range of subnational controls for healthy characteristic, political confounder, gender and consumption contributors. We find the impact of inequality upon growth are barely affected by these controls. This empirical evidence just confirm the speculation about the equation (34). The robust tests described above are in favor of the implication about our theoretical model that a moderate Gini coefficient promotes economic growth, whereas considerable gap between rich and poor over wealth distribution would generally hinder development process. Nevertheless, heterogeneity in economic structure has not been taken into consideration so far.

6 Heterogeneity and Cointegration

6.1 Estimation Methodology

If the parameters of regressors differ significantly across countries for long time, M. Pesaran & Smith (1995) propose that the traditional procedures for estimation of pooled models, such as the fixed effects, instrumental variables,

and GMM estimators proposed, by among others, Anderson & Hsiao (1981), Arellano & Bond (1991), and Arellano & Bover (1995) can produce inconsistent, and potentially very misleading estimates of the average values of the parameters in dynamic panel data models unless the slope coefficients are virtually identical. Therefore, we utilize pooled mean group (PMG) estimator proposed by M. H. Pesaran et al. (1999) to estimate the dynamic heterogeneous panel data. This kind of estimator takes the cointegration form of the autoregressive distributed lag (ARDL) model and adapts it for a panel setting by allowing the intercepts, short-run coefficients and cointegrating terms to differ across countries but constraining long-run parameters to be identical in different cross-sections. Suppose that given data on time periods $t(t = 1 \cdots T)$, and countries $i(i = 1 \cdots N)$, we proceed to initially conduct an ARDL (p, q, q, q) model, allowing the beta coefficients of each country to vary:

$$\begin{aligned} GROWTH_{it} =& \alpha_i + \sum_{j=1}^{p} \delta_{ij} GROWTH_{i,t-j} + \sum_{j=0}^{q} \beta_{1ij} GINI_{i,t-j} \\ &+ \sum_{j=0}^{q} \beta_{2ij} {GINI^2}_{i,t-j} + \sum_{j=0}^{q} \beta_{3ij} Log\ GDP(-1)_{i,t-j} + \varepsilon_{it}, \end{aligned} \tag{37}$$

where j represents the order of the lag term, p and q reflect the maximum order of the lag dependent and independent variables respectively, and α_i is the fixed effects to control for time-invariant country-specific effects. Then, it is convenient to transform ARDL model into error correction model (ECM) for PMG estimator. Alternative measure of income distribution (i.e., the Gini coefficient of net income) stems from a set of panel data (Panel B) which composes of eighteen countries[22] taken from the Standardized World Income Inequality Database (SWIID provided by Solt (2019)) over the periods between 1971 and 2018, because PMG estimation demands the time series of Gini coefficient for sufficiently long. We just highlight the long-term effects of inequality on economic growth. Panel B meets this criterion, which is a set of balanced panel data. Also, it could be certain that the observed variations in the rate of economic growth to a large extent result from long term rise, as opposed to business cycles. Moreover, the SWIID used here is able to partially remedy measurement problem of data of the Gini coefficient from the WDIs 2021 of the World Bank.[23]

6.2 Variables Explanation of Panel B

Appendix Table A1 describes variables explanation and detailed sources of Panel B as well. $GROWTH$ still denotes per capita GNI growth, whose lags

[22] Panel B includes Australia, Brazil, Canada, Colombia, Costa Rica, Finland, Germany, Italy, Korea, Malaysia, Mexico, Panama, Philippines, Portugal, Sweden, Thailand, United Kingdom and United States across developing countries and developed countries.

[23] Solt (2020) documents wide-ranging revisions to the Standardized World Income Inequality Database (SWIID), which seeks to maximize the comparability of income inequality estimates for the broadest possible coverage of countries and years. The SWIID is comprised of data from both post-tax Gini coefficient and pre-tax Gini coefficient.

are applied to independent variables. The SWIID splits the data set of income distribution into two categories: post-tax Gini coefficient and pre-tax Gini coefficient. We divide the key explanatory variables into the post-tax Gini coefficient and the pre-tax Gini coefficient to estimate the impact of inequality on growth for a clear assessment of the shocks of tax avoidance. And, we add one order lag of logarithm of per capita GDP as right-hand-side variable proxied by $Log\ GDP(-1)$ which is used to control for national income convergence across countries in the growth regressions. Descriptive Statistics for each of these variables are listed in Table A2-C of Appendix.

6.3 Unit Root Test

The results for the panel unit root test are shown in Table 7. All the results nearly indicate that $GROWTH$ is stationary because both the LLC and the IPS tests reject the null of a unit root. Table 7 below also shows that $GINI$ are integrated process of order one, namely, I (1), regardless of whether the Gini coefficient is post-tax or pre-tax.

It is relatively straightforward to allow for the possible dependence of the post-tax Gini coefficient or pre-tax Gini coefficient on the stochastic error term when estimating the long-run coefficients, as long as these variables have finite-order autoregressive representations, as indicated by M. H. Pesaran et al. (1999). On the circumstance, they prove that the PMG estimator applying the principle of maximum likelihood (ML) is consistent under some regularity conditions (i.e., the regressors are stationary or I (1)), as time$\rightarrow \infty$ for a fixed number of cross-section.[24] The coefficients of $GINI$ and the country-specific error correction, namely φ_i, can be computed by ML method or calculated by a "back-substitution" algorithm. Given normality, these estimates are termed the pooled mean group (PMG) estimation to highlight both the pooling implied by the homogeneity restrictions on the long-run coefficients and the averaging across countries used to obtain means of the estimated error-correction coefficients, scilicet $\bar{\varphi}$. More importantly, the PMG estimation applying the principle of maximum likelihood could to a certain extent, be an alternative of the OLS estimate for easing the selection bias.

[24]The assumption that the disturbances are asymptotically independently distributed across time can be satisfied in most applications by increasing period lengths.

Table 7: Unit Root Test of Panel B

Methods	Fixed effects and trends	$GROWTH$	$GINI(Post-tax)$	$\Delta GINI(Post-tax)$	$GINI(Pre-tax)$	$\Delta GINI(Pre-tax)$
Levin, Lin and Chu (LLC)	Individual intercept and trend	-15.91***	-1.39*	-3.42***	-0.78	-1.41*
	Individual intercept	-15.83***	0.85	-3.65***	-1.44*	-2.23**
	None	-12.46***	-2.09**	-8.28***	-0.72	-7.31***
Im, Pesaran and Shin (IPS)	Individual intercept and trend	-13.36***	0.84	-3.37***	2.77	-3.33***
	Individual intercept	-14.18***	2.83	-5.16***	2.31	-4.63***
	None					

Note:*** indicates $p < 0.01$, ** indicates $p < 0.05$, * indicates $p < 0.1$. Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality. Lag length is specified as first order, which we choose the number of lag terms in the Dickey-Fuller equations to eliminate the effect of the correlation structure of the errors on the asymptotic distribution of the statistic. We implement Newey-West automatic bandwidth selection and Bartlett kernel.

6.4 Results of PMG Estimates

Table 8 reports the PMG estimated results of the long-run relationship between growth and income inequality using cointegration techniques for post-tax and pre-tax distribution. Column (22) in Table 8 implies that the long-term coefficient on post-tax Gini coefficient is 0.82 and remains statistically significant at 1 percent level. The long-run coefficient of the squared term in post-tax Gini coefficient is statistically significant at 5 percent level and has the expected negative sign. Column (23) in Table 8 indicates that the long-period coefficient on pre-tax Gini coefficient is still 0.82 and significant at 95 percent confidence while standing coefficient of its squared term continues to be of the expected negative sign and rejects the null hypothesis that its coefficient is zero at 10% level of significance. In particular the estimated coefficient on $GINI$ is remarkably stable: the coefficient of post-tax inequality in column (22) is equal to that of pre-tax Gini coefficient in column (23). We find a surprising similarity between column (22) and column (23), which account for the fact that, irrespective of whether the Gini coefficient is clearly distinguished between pre-tax and post-tax inequality, it is obviously consistent with the notion that points to an inverted U-curve relationship between growth and inequality in the long term, as predicted by equation (34). Regardless, the empirical evidence can also be interpreted that, as a matter of fact, this relationship is not influenced by tax burden in any way. It is probably attributed to tax avoidance, which testifies the crucial assumption we emphasize in subsection 2.1. In that case, the total tax rates are exogenous to serve either productive or re-distributive purpose taken by policymakers in our theoretical model.

In addition, the estimated elasticities of the rate of growth of GNI per capita with respect to $Log\ GDP\ (-1)$ are -3.19 and -2.25 in Table 8 columns (22) and (23), respectively. The statistical significances of those are attained. Also, both of the error-correction coefficients have negative signs. This empirical evidence of cross-country regressions is adequate to support that a growth rate of economy inversely varies with its level of development, thereby eventually converging to the state of the steady equilibrium.

Table 8: The Results of Pooled Mean Group Estimates of Panel B

	Dependent variable: *GROWTH*	
	(22) PMG (Post-tax)	(23) PMG (Pre-tax)
	Long run coefficients	
$GINI$	0.82***	0.82**
	(0.29)	(0.39)
$GINI^2$	-0.0088**	-0.0075*
	(0.004)	(0.004)
$Log\ GDP\ (-1)$	-3.19***	-2.25***
	(0.74)	(0.63)
	Short run coefficients	
$\overline{\varphi}$	-0.89***	-0.94***
	(0.19)	(0.20)
$\Delta GROWTH\ (-1)$		0.20**
		(0.03)
$\Delta GINI$	-87.09**	-47.59*
	(42.16)	(26.03)
$\Delta GINI^2$	1.13*	0.48*
	(0.58)	(0.27)
$\Delta log\ GDP\ (-1)$	16.40	7.76
	(20.65)	(22.13)
Log likelihood	-1923.64	-1909.79
Number of observations	828	828
Number of countries	18	18

Note:*** is significant at 1 percent level, ** is significant at 5 percent level, * is significant at 10 percent level. Akaike info criterion (AIC) is specified as the selection of lag order of model. ARDL (p=1, q=1, q=1, q=1) is finally selected in column (22) and ARDL (p=2, q=1, q=1, q=1) is eventually utilized in column (23). These results of selection are sketched in Fig. A1 of Appendix. Descriptive Statistics for each of these variables are listed in Table A2-C of Appendix.

7 Concluding Remarks

In this article, we thoroughly discuss the effects of income inequality on economic growth. Firstly, it could be supposed that law of increasing marginal tendency to tax avoidance prevails among social groups, which is characterized by the property that the tendency for tax avoidance is increasing with the level of income. Importantly, due to incremental marginal tendency to tax avoidance, potential government expenditures would be further declined as inequality increases. Based on this assumption, we construct a dynamic

growth model to capture the point of view that the rate of economic growth is an inverted U-shaped function of inequality. In other words, contrary to the Kuznets inverted U-curve (that is, inequality tends to rise and then fall as the economy grows), high or low Gini coefficient would impede long-term economic growth. If the Gini coefficient is too small, it will encourage laziness, discourage entrepreneurship and make an economy inefficient. Oppositely, provided that the Gini coefficient is too large, it is likely to urge exploitation, cause broadly-based popular unrest and induce a society unfair.

Secondly, we appeal to instrumental variable estimates for addressing the problem of the interplay between economic growth and inequality. The empirical evidence shows that there exits an inverted U-shaped impact of Gini coefficient on economic growth—that is, economic growth first increases and then decreases as the Gini coefficient increases.

Last but not least, output is driven by posing a trade-off between efficiency and equality rather than relying solely on competition. For developed economies, a higher level of Gini coefficient is harmful to the durable growth after all. Hopefully, any kind of sustained policies that crack down on tax avoidance are supposed to be sprayed to favor redistribution resources from rich to poor.

8 Declarations

8.1 Ethical Approval

Ethics approval and consent to participate are not applicable.

8.2 Competing Interests

The authors have no competing interests to declare that are relevant to the content of this article and potential conflicts of financial interests that are related to the research described in this paper.

8.3 Authors' contributions

Zixiang Qi wrote and reviewed the main manuscript text; Bicong Wang was responsible for material preparation, compiled this paper in Latex and prepared the appendix B; Data collection and analysis were performed by Yaxin Wang; Yongqiang Lv depicted figure 6; All authors approved the final manuscript.

8.4 Funding

No funding was received for conducting this study.

8.5 Acknowledgement

We appreciate Zhijuan Zhang and Ziyi Wang for excellent research assistance. Furthermore, we are extremely grateful to all anonymous referees for helpful comments and discussions.

8.6 Consent for Publication

We would like to submit the manuscript entitled "Increasing Marginal Tendency to Tax Avoidance, Inequality and Economic Growth", which we wish to be considered for publication in the Journal of Economic Inequality.

8.7 Availability of Data and Materials

All the research data and materials are publicly available.

Table 9: Data Availability Statements

Data set	Source
Panel A	The World Development Indicators (WDIs) 2021 of the World Bank
Panel B	Solt, Frederick, 2019, "The Standardized World Income Inequality Database, Versions 8-9", https://doi.org/10.7910/DVN/LM4OWF, Harvard Dataverse, V6.

References

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022, apr). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, *40*(S1), S293–S340. https://doi.org/10.1086/718327

Acemoglu, D., & Johnson, S. (2007, dec). Disease and development: The effect of life expectancy on economic growth. *Journal of Political Economy*, *115*(6), 925–985. https://doi.org/10.1086/529000

Acemoglu, D., Johnson, S., & Robinson, J. A. (2001, dec). The colonial origins of comparative development: An empirical investigation. *American Economic Review*, *91*(5), 1369-1401. https://doi.org/10.1257/aer.91.5.1369

Acemoglu, D., & Restrepo, P. (2017, may). Secular stagnation? the effect of aging on economic growth in the age of automation. *American Economic Review*, *107*(5), 174–179. https://doi.org/10.1257/aer.p20171101

Acemoglu, D., & Restrepo, P. (2018, jan). *Artificial intelligence, automation and work* (Tech. Rep.). https://doi.org/10.3386/w24196

Acemoglu, D., & Restrepo, P. (2021, jun). Demographics and automation. *The Review of Economic Studies*, *89*(1), 1–44. https://doi.org/10.1093/restud/rdab031

ActionAid. (2011, October). *Addicted to tax havens: The secret life of the ftse 100.* ActionAid, https://actionaid.org/sites/default/files/addicted_to_tax_havens.pdf. ActionAid London.

Aghion, P., Caroli, E., & García-Peñalosa, C. (1999, dec). Inequality and economic growth: The perspective of the new growth theories. *Journal of Economic Literature*, *37*(4), 1615-1660. https://doi.org/10.1257/jel.37.4.1615

Aghion, P., & Howitt, P. (1992, mar). A model of growth through creative destruction. *Econometrica*, *60*(2), 323-351. https://doi.org/10.2307/2951599

Akerlof, G. A., & Kranton, R. E. (2000, aug). Economics and identity. *Quarterly Journal of Economics*, *115*(3), 715–753. https://doi.org/10.1162/003355300554881

Alesina, A., & Rodrik, D. (1994, may). Distributive politics and economic growth. *The Quarterly Journal of Economics*, *109*(2), 465–490. https://doi.org/10.2307/2118470

Alm, J., Bahl, R., & Murray, M. N. (1991, jul). Tax base erosion in developing countries. *Economic Development and Cultural Change*, *39*(4), 849–872. https://doi.org/10.1086/451912

Alstadsæter, A., Johannesen, N., & Zucman, G. (2018, jun). Who owns the wealth in tax havens? macro evidence and implications for global inequality. *Journal of Public Economics*, *162*, 89–100. https://doi.org/10.1016/j.jpubeco.2018.01.008

Alstadsæter, A., Johannesen, N., & Zucman, G. (2019, jun). Tax evasion and inequality. *American Economic Review*, *109*(6), 2073–2103. https://doi.org/10.1257/aer.20172043

Anderson, T. W., & Hsiao, C. (1981). Estimation of dynamic models with error components. *Journal of the American statistical Association*, *76*(375), 598–606. https://doi.org/10.1080/01621459.1981.10477691

Anselin, L. (1995, April). Local indicators of spatial association-LISA. *Geographical Analysis*, *27*(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Arellano, M., & Bond, S. (1991, apr). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277. https://doi.org/10.2307/2297968

Arellano, M., & Bover, O. (1995, jul). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, *68*(1), 29–51. https://doi.org/10.1016/0304-4076(94)01642-d

Arrow, K. J. (1962, jun). The economic implications of learning by doing. *The Review of Economic Studies*, *29*(3), 155–173. https://doi.org/10.2307/2295952

Atkinson, A. B., & Brandolini, A. (2001, sep). Promise and pitfalls in the use of "secondary" data-sets: Income inequality in OECD countries as a case study. *Journal of Economic Literature*, *39*(3), 771–799. https://doi.org/10.1257/jel.39.3.771

Banerjee, A. V., & Duflo, E. (2003). Inequality and growth: What

can the data say? *Journal of Economic Growth*, *8*(3), 267–299. https://doi.org/10.1023/A:1026205114860

Barro, R. J. (1990, oct). Government spending in a simple model of endogenous growth. *Journal of Political Economy*, *98*(5, Part 2), S103–S125. https://doi.org/10.1086/261726

Barro, R. J. (2000). Inequality and growth in a panel of countries. *Journal of Economic Growth*, *5*(1), 5–32. https://doi.org/10.1023/A:1009850119329

Barro, R. J. (2013). Health and economic growth. *Annals of Economics and Finance*, *14*(2), 305–342. https://doi.org/10.1086/261726

Barro, R. J., & Sala-i Martin, X. I. (2003). *Economic growth*. MIT press.

Bénabou, R. (1996, jan). Inequality and growth. *NBER Macroeconomics Annual*, *11*, 11–74. https://doi.org/10.1086/654291

Bénabou, R. (2000, mar). Unequal societies: Income distribution and the social contract. *American Economic Review*, *90*(1), 96–129. https://doi.org/10.1257/aer.90.1.96

Benhabib, J., & Rustichini, A. (1996, mar). Social conflict and growth. *Journal of Economic Growth*, *1*(1), 125–142. https://doi.org/10.1007/bf00163345

Benjamin, D., Brandt, L., & Giles, J. (2011, jun). Did higher inequality impede growth in rural china? *The Economic Journal*, *121*(557), 1281–1309. https://doi.org/10.1111/j.1468-0297.2011.02452.x

Berg, A., Ostry, J. D., Tsangarides, C. G., & Yakhshilikov, Y. (2018, jun). Redistribution, inequality, and growth: new evidence. *Journal of Economic Growth*, *23*(3), 259–305. https://doi.org/10.1007/s10887-017-9150-2

Berger, M., Fellner-Röhling, G., Sausgruber, R., & Traxler, C. (2016, mar). Higher taxes, more evasion? evidence from border differentials in TV license fees. *Journal of Public Economics*, *135*, 74–86. https://doi.org/10.1016/j.jpubeco.2016.01.007

Bertola, G. (1993). Factor shares and savings in endogenous growth. *The American Economic Review*, *83*(5), 1184–1198. Retrieved from http://www.jstor.org/stable/2117555

Biswas, S., Chakraborty, I., & Hai, R. (2017, may). Income inequality, tax policy, and economic growth. *The Economic Journal*, *127*(601), 688–727. https://doi.org/10.1111/ecoj.12485

Blau, F. D., & Kahn, L. M. (2017, sep). The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*, *55*(3), 789–865. https://doi.org/10.1257/jel.20160995

Blundell, R., Dearden, L., Meghir, C., & Sianesi, B. (1999, March). Human capital investment: The returns from education and training to the individual, the firm and the economy. *Fiscal Studies*, *20*(1), 1–23. https://doi.org/10.1111/j.1475-5890.1999.tb00001.x

Bond, S., Harhoff, D., & Van Reenen, J. (2003, Dec). *Corporate r&d and productivity in germany and the united kingdom* (Tech. Rep.).

Braun, M., Parro, F., & Valenzuela, P. (2018, apr). Does finance alter the relation between inequality and growth? *Economic Inquiry*, *57*(1), 410–428. https://doi.org/10.1111/ecin.12581

Broadberry, S. N., & Wagner, K. (1994, October). *Human Capital and Productivity in Manufacturing during the Twentieth Century: Britain, Germany and the United States* (CEPR Discussion Papers No. 1036). C.E.P.R. Discussion Papers. Retrieved from https://ideas.repec.org/p/cpr/ceprdp/1036.html

Butcher, K. F., & Case, A. (1994, aug). The effect of sibling sex composition on women's education and earnings. *The Quarterly Journal of Economics*, *109*(3), 531–563. https://doi.org/10.2307/2118413

Coppola, A., Maggiori, M., Neiman, B., & Schreger, J. (2021, may). Redrawing the map of global capital flows: The role of cross-border financing and tax havens. *The Quarterly Journal of Economics*, *136*(3), 1499–1556. https://doi.org/10.1093/qje/qjab014

Crafts, N. (1996, January). *Endogenous Growth: Lessons for and from Economic History* (CEPR Discussion Papers No. 1333). C.E.P.R. Discussion Papers. Retrieved from https://ideas.repec.org/p/cpr/ceprdp/1333.html

Curran, M., & Mahutga, M. C. (2018, nov). Income inequality and population health: A global gradient? *Journal of Health and Social Behavior*, *59*(4), 536–553. https://doi.org/10.1177/0022146518808028

de la Croix, D., & Doepke, M. (2003, aug). Inequality and growth: Why differential fertility matters. *American Economic Review*, *93*(4), 1091–1113. https://doi.org/10.1257/000282803769206214

Easterly, W. (2007). Inequality does cause underdevelopment: Insightsfrom a new instrument. *Journal of Development Economics*, *84*, 755–776.

Easterly, W. (2019, dec). Review of walter scheidel's the great leveler: Violence and the history of inequality from the stone age to the twenty-first century. *Journal of Economic Literature*, *57*(4), 955–971. https://doi.org/10.1257/jel.20191477

Eisinger, J., Ernsthausen, J., & Kiel, P. (2021). The secret irs files: Trove of never-before-seen records reveal how the wealthiest avoid income tax. *ProPublica*, *8*.

Elkan, R. V. (1996, aug). Catching up and slowing down: Learning and growth patterns in an open economy. *Journal of International Economics*, *41*(1-2), 95–111. https://doi.org/10.1016/s0022-1996(96)01433-x

Elson, D. (2009, jul). Gender equality and economic growth in the world bank world development report 2006. *Feminist Economics*, *15*(3), 35–59. https://doi.org/10.1080/13545700902964303

Esteban, J., & Ray, D. (2011, jun). Linking conflict to inequality and polarization. *American Economic Review*, *101*(4), 1345–1374. https://doi.org/10.1257/aer.101.4.1345

Fan, Y., Yi, J., & Zhang, J. (2021, feb). Rising intergenerational income persistence in china. *American Economic Journal: Economic Policy*, *13*(1), 202–230. https://doi.org/10.1257/pol.20170097

Forbes, K. J. (2000, sep). A reassessment of the relationship between inequality and growth. *American Economic Review*, *90*(4), 869–887. https://doi.org/10.1257/aer.90.4.869

Forsythe, E. (2021, dec). Why don't firms hire young workers during recessions? *The Economic Journal*, *132*(645), 1765–1789. https://doi.org/10.1093/ej/ueab096

Futagami, K., & Nakajima, T. (2001). Population aging and economic growth. *Journal of Macroeconomics*, *23*(1), 31–44. https://doi.org/10.1016/S0164-0704(01)00153-7

Galor, O., & Moav, O. (2004, dec). From physical to human capital accumulation: Inequality and the process of development. *Review of Economic Studies*, *71*(4), 1001–1026. https://doi.org/10.1111/0034-6527.00312

Galor, O., Moav, O., & Vollrath, D. (2009, jan). Inequality in landownership, the emergence of human-capital promoting institutions, and the great divergence. *Review of Economic Studies*, *76*(1), 143–179. https://doi.org/10.1111/j.1467-937x.2008.00506.x

Galor, O., & Zang, H. (1997, may). Fertility, income distribution, and economic growth: Theory and cross-country evidence. *Japan and the World Economy*, *9*(2), 197–229. https://doi.org/10.1016/s0922-1425(96)00245-9

Galor, O., & Zeira, J. (1993, jan). Income distribution and macroeconomics. *The Review of Economic Studies*, *60*(1), 35–52. https://doi.org/10.2307/2297811

Goodman, A., & Webb, S. (1994, nov). For richer, for poorer: The changing distribution of income in the UK, 1961-91. *Fiscal Studies*, *15*(4), 29–62. https://doi.org/10.1111/j.1475-5890.1994.tb00209.x

Halter, D., Oechslin, M., & Zweimüller, J. (2013, dec). Inequality and growth: the neglected time dimension. *Journal of Economic Growth*, *19*(1), 81–104. https://doi.org/10.1007/s10887-013-9099-8

Hvistendahl, M. (2014, may). While emerging economies boom, equality goes bust. *Science*, *344*(6186), 832–835. https://doi.org/10.1126/science.344.6186.832

IPS. (2021, Jan). *10 months into crisis, u.s. billionaires' wealth continues to climb, up $ 1.1 trillion, nearly 40 percents.* Institute for Policy Studies, https://americansfortaxfairness.org/10-months-crisis-u-s-billionaires-wealth-continues-climb-1-1-trillion-nearly-40/. Institute for Policy Studies and Americans for Tax Fairness.

Jakobsen, K., Jakobsen, K., Kleven, H., & Zucman, G. (2019, oct). Wealth taxation and wealth accumulation: Theory and evidence from denmark. *The Quarterly Journal of Economics*, *135*(1), 329–388. https://doi.org/10.1093/qje/qjz032

Johannesen, N., Langetieg, P., Reck, D., Risch, M., & Slemrod, J. (2020, aug). Taxing hidden wealth: The consequences of US enforcement initiatives on evasive foreign accounts. *American Economic Journal: Economic Policy*, *12*(3), 312–346. https://doi.org/10.1257/pol.20180410

Johns, A., & Slemrod, J. (2010, sep). The distribution of income tax noncompliance. *National Tax Journal*, *63*(3), 397–418. https://doi.org/10.17310/ntj.2010.3.01

Kaldor, N. (1955). Alternative theories of distribution. *The Review of*

Economic Studies, *23*(2), 83. https://doi.org/10.2307/2296292

Kremer, M., & Chen, D. L. (2002). *Journal of Economic Growth*, *7*(3), 227–258. https://doi.org/10.1023/a:1020154031908

Kumhof, M., Rancière, R., & Winant, P. (2015, mar). Inequality, leverage, and crises. *American Economic Review*, *105*(3), 1217–1245. https://doi.org/10.1257/aer.20110683

Kuznets, S. (1955). Economic growth and income inequality. *The American Economic Review*, *45*(1), 1–28. Retrieved from http://www.jstor.org/stable/1811581

Kuznets, S. (1963, jan). Quantitative aspects of the economic growth of nations: VIII. distribution of income by size. *Economic Development and Cultural Change*, *11*(2, Part 2), 1–80. https://doi.org/10.1086/450006

Li, H., & fu Zou, H. (1998, oct). Income inequality is not harmful for growth: Theory and evidence. *Review of Development Economics*, *2*(3), 318–334. https://doi.org/10.1111/1467-9361.00045

Li, H., Loyalka, P., Rozelle, S., & Wu, B. (2017, feb). Human capital and china's future growth. *Journal of Economic Perspectives*, *31*(1), 25–48. https://doi.org/10.1257/jep.31.1.25

Lucas, R. E. (1988, jul). On the mechanics of economic development. *Journal of Monetary Economics*, *22*(1), 3–42. https://doi.org/10.1016/0304-3932(88)90168-7

Lundberg, M., & Squire, L. (2003, apr). The simultaneous evolution of growth and inequality. *The Economic Journal*, *113*(487), 326–344. https://doi.org/10.1111/1468-0297.00127

Macpherson, D. A., & Hirsch, B. T. (1995, jul). Wages and gender composition: Why do women's jobs pay less? *Journal of Labor Economics*, *13*(3), 426–471. https://doi.org/10.1086/298381

Maddison, A. (1991). *Dynamic forces in capitalist development: A long-run comparative view*. Oxford University Press, USA.

Mangasarian, O. L. (1966, feb). Sufficient conditions for the optimal control of nonlinear systems. *SIAM Journal on Control*, *4*(1), 139-152. https://doi.org/10.1137/0304013

Mankiw, N. G., Romer, D., & Weil, D. N. (1992, may). A contribution to the empirics of economic growth. *The Quarterly Journal of Economics*, *107*(2), 407–437. https://doi.org/10.2307/2118477

Manning, A., & Swaffield, J. (2008, jun). The gender gap in early-career wage growth. *The Economic Journal*, *118*(530), 983–1024. https://doi.org/10.1111/j.1468-0297.2008.02158.x

Miguel, E., Satyanath, S., & Sergenti, E. (2004, aug). Economic shocks and civil conflict: An instrumental variables approach. *Journal of Political Economy*, *112*(4), 725–753. https://doi.org/10.1086/421174

Mitra, A., Bang, J. T., & Biswas, A. (2014, jul). Gender equality and economic growth: Is it equality of opportunity or equality of outcomes? *Feminist Economics*, *21*(1), 110–135. https://doi.org/10.1080/13545701.2014.930163

Morley, S. A. (1981). The effect of changes in the population on several measures of income distribution. *The American Economic Review*, *71*(3), 285–294. Retrieved from http://www.jstor.org/stable/1802779

Mosk, C., & Nakata, Y.-F. (1985). The age-wage profile and structural change in the japanese labor market for males,1964-1982. *The Journal of Human Resources*, *20*(1), 100-116.

Murphy, K. M., Shleifer, A., & Vishny, R. (1989, aug). Income distribution, market size, and industrialization. *The Quarterly Journal of Economics*, *104*(3), 537–564. https://doi.org/10.2307/2937810

Nehru, V. (1996). *The chinese economy: Fighting inflation, deepening reforms.* World Bank Publications.

Partridge, M. D. (1997). Is inequality harmful for growth? comment. *The American Economic Review*, *87*(5), 1019–1032. Retrieved from http://www.jstor.org/stable/2951339

Perotti, R. (1996, jun). Growth, income distribution, and democracy: What the data say. *Journal of Economic Growth*, *1*(2), 149–187. https://doi.org/10.1007/bf00138861

Persson, T., & Tabellini, G. (1994). Is inequality harmful for growth? *The American Economic Review*, *84*(3), 600–621. Retrieved from http://www.jstor.org/stable/2118070

Pesaran, M., & Smith, R. (1995, jul). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, *68*(1), 79–113. https://doi.org/10.1016/0304-4076(94)01644-f

Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association*, *94*(446), 621–634. https://doi.org/10.1080/01621459.1999.10474156

Ravallion, M., & Chen, S. (2007, jan). China's (uneven) progress against poverty. *Journal of Development Economics*, *82*(1), 1–42. https://doi.org/10.1016/j.jdeveco.2005.07.003

Ravallion, M., & Chen, S. (2021, aug). *Is that really a kuznets curve? turning points for income inequality in china* (Tech. Rep.). https://doi.org/10.3386/w29199

Romer, P. M. (1986, oct). Increasing returns and long-run growth. *Journal of Political Economy*, *94*(5), 1002–1037. https://doi.org/10.1086/261420

Romer, P. M. (1990, oct). Endogenous technological change. *Journal of Political Economy*, *98*(5, Part 2), S71–S102. https://doi.org/10.1086/261725

Saez, E., & Zucman, G. (2016, feb). Wealth inequality in the united states since 1913: Evidence from capitalized income tax data. *The Quarterly Journal of Economics*, *131*(2), 519-578. https://doi.org/10.1093/qje/qjw004

Solow, R. M. (1956, feb). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, *70*(1), 65–94. https://doi.org/10.2307/1884513

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, *39*(3), 312–320. Retrieved from

http://www.jstor.org/stable/1926047

Solt, F. (2019). *The Standardized World Income Inequality Database, Versions 8-9.* Harvard Dataverse. Retrieved from https://doi.org/10.7910/DVN/LM4OWF https://doi.org/10.7910/DVN/LM4OWF

Solt, F. (2020, may). Measuring income inequality across countries and over time: The standardized world income inequality database. *Social Science Quarterly*, *101*(3), 1183–1199. https://doi.org/10.1111/ssqu.12795

Stock, J. H., & Yogo, M. (2005, jun). Testing for weak instruments in linear IV regression. In *Identification and inference for econometric models* (pp. 80–108). Cambridge University Press. https://doi.org/10.1017/cbo9780511614491.006

Sørensen, A. (1999). R&d, learning, and phases of economic growth. *Journal of Economic Growth*, *4*(4), 429–445. https://doi.org/10.1023/a:1009871510523

Weil, D. N. (2007, aug). Accounting for the effect of health on economic growth. *The Quarterly Journal of Economics*, *122*(3), 1265–1306. https://doi.org/10.1162/qjec.122.3.1265

Zhao, Z. (2006). Income inequality, unequal health care access, and mortality in china. *Population and Development Review*, *32*(3), 461–483. Retrieved from http://www.jstor.org/stable/20058900

Zucman, G. (2013, jun). The missing wealth of nations: Are europe and the u.s. net debtors or net creditors? *The Quarterly Journal of Economics*, *128*(3), 1321–1364. https://doi.org/10.1093/qje/qjt012

Appendix A Supplementary Tables And Figures

Table A1: Data Sources and Description of Variables

Variable	Unit	Indicators Instruction	Symbol	Resources
GNI per capita growth (annual)	%	Annual percentage growth rate of GNI per capita based on constant local currency. GNI per capita is gross national income divided by midyear population.	GROWTH	
Gini coefficient	%	The World Bank estimates the Gini coefficient that is on a scale from 0 to 100, with a higher score indicating more inequality.	GINI	
Residents' Patent applications	one-unit	Patent applications are worldwide patent applications filed through the Patent Cooperation Treaty procedure or with a national patent office for exclusive rights for an invention.	PATENT	
Adjusted savings: consumption of fixed capital (% of GNI)	%	Consumption of fixed capital represents the replacement value of capital used up in the process of production.	CAPITAL	
School enrollment, tertiary (% gross)	%	Gross enrollment ratio is the ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the level of education shown. Tertiary education, whether or not to an advanced research qualification, normally requires, as a minimum condition of admission, the successful completion of education at the secondary level.	EDUCATION	The World Development Indicators 2021 of the World Bank.
Age dependency ratio, old (% of working-age population)	%	Age dependency ratio, old, is the ratio of older dependents–people older than 64–to the working-age population–those ages 15-64. Data are shown as the proportion of dependents per 100 working-age population.	OLD	
Prevalence of HIV, total (% of population ages 15-49)	%	Prevalence of HIV refers to the percentage of people ages 15-49 who are infected with HIV.	HIV	
Armed forces personnel (% of total labor force)	%	Armed forces personnel are active duty military personnel, including paramilitary forces if the training, organization, equipment, and control suggest they may be used to support or replace regular military forces.	MILITARY	
School enrollment, primary (gross), gender parity index	%	Gender parity index for gross enrollment ratio in primary education is the ratio of girls to boys enrolled at primary level in public and private schools.	GPI	
Life expectancy at birth, total	year	Life expectancy at birth indicates the number of years a newborn infant would live if prevailing patterns of mortality at the time of its birth were to stay the same throughout its life.	HEALTH	
Final consumption expenditure (% of GDP)	%	Final consumption expenditure (formerly total consumption) is the sum of household final consumption expenditure (private consumption) and general government final consumption expenditure (general government consumption).	CONSUMPTION	
GDP per capita	constant 2010 US$	GDP per capita is gross domestic product divided by midyear population. Data are in constant 2010 U.S. dollars.	GDP	

Variable	Unit	Indicators Instruction	Symbol	Resources
Post-tax Gini coefficient	%	The Standardized World Income Inequality Database (SWIID) takes a Bayesian approach to standardizing observations collected from the OECD Income Distribution Database, the Socio-Economic Database for Latin America and the Caribbean generated by CEDLAS and the World Bank, Eurostat, the World Bank's PovcalNet, the UN Economic Commission for Latin America and the Caribbean, national statistical offices around the world, and many other sources. Estimate of Gini coefficient of inequality in equivalized (square root scale) household disposable (post-tax, post-transfer) income, using Luxembourg Income Study data as the standard.	GINI	Solt, Frederick, 2019, "The Standardized World Income Inequality Database, Versions 8-9", https://doi.org/10.7910/DVN/LM4OWF, Harvard Dataverse, V6.
Pre-tax Gini coefficient	%	Estimate of Gini coefficient of inequality in equivalized (square root scale) household market (pre-tax, pre-transfer) income, using Luxembourg Income Study data as the standard.	GINI	

Table A2: Descriptive Statistics
(A) Common Sample of Five Basic Variables of Panel A

	GROWTH	GINI	PATENT	CAPITAL	EDUCATION
Mean	2.28	36.37	14689.33	14.54	52.54
Median	2.19	34.60	651.00	14.97	54.50
Maximum	16.53	63.40	1204981.00	43.19	142.85
Minimum	-16.05	22.20	1.00	1.68	1.60
Std. Dev.	4.12	8.50	74333.40	4.52	23.98
Jarque-Bera	314.11	108.65	595048.30	283.14	4.40
Probability	0.00	0.00	0.00	0.00	0.11
Common Observations	961	961	961	961	961

(B) Individual Samples of All Variables of Panel A

	GROWTH	GINI	PATENT	CAPITAL	EDUCATION	OLD	HIV	MILITARY	GPI	HEALTH	CONSUMPTION
Mean	1.95	38.53	11091.13	11.74	27.84	11.20	1.99	1.45	94.00	66.42	82.10
Median	2.13	36.40	225.50	11.39	21.38	7.81	0.30	0.98	98.36	68.86	80.46
Maximum	45.31	65.80	1393815.00	47.93	142.85	46.17	28.90	35.05	141.15	84.21	236.86
Minimum	-47.39	20.70	1.00	0.59	0.00	0.80	0.10	0.00	37.96	26.17	11.61
Std. Dev.	5.07	9.23	63220.16	5.41	24.66	6.99	4.44	1.64	11.48	10.03	16.75
Jarque-Bera	15292.26	115.47	5038285.00	1082.52	617.32	1548.67	34942.48	492069.10	7556.22	453.30	42711.71
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Overall Observations	4063	1693	3190	5567	4031	6201	3489	4137	4858	6221	5141

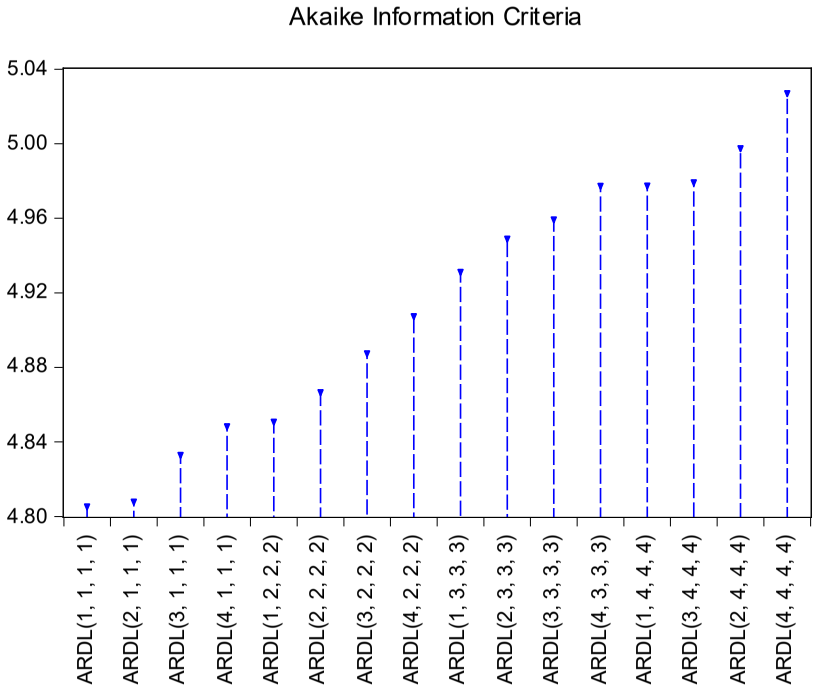
(C) Descriptive Statistics of Panel B

	GROWTH	GINI_post-tax	GINI_pre-tax	GDP
Mean	2.36	37.15	47.54	20259.91
Median	2.41	34.10	47.70	15706.77
Maximum	12.84	54.90	63.70	57911.23
Minimum	-19.34	20.30	30.60	946.88
Std. Dev.	3.41	9.25	6.15	16118.90
Jarque-Bera	772.60	52.30	20.58	79.00
Probability	0.00	0.00	0.00	0.00
Overall Observations	864	864	864	864

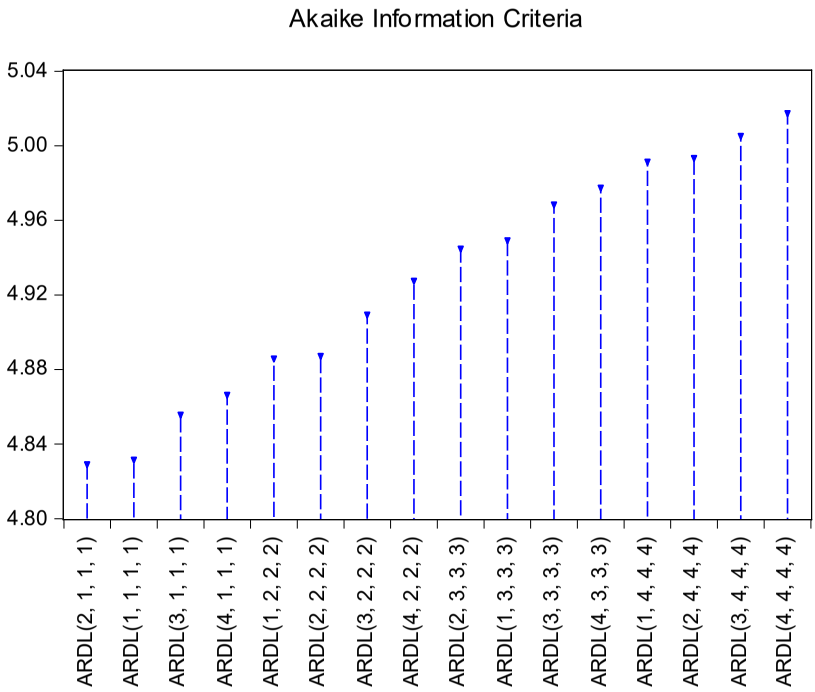
Table A3: Weak Instrumenting Test in Heteroskedasticity

	Dependent variable: *GINI*			
Explanatory variable	(1)FGLS	(2)FGLS	(3)FGLS	(4)FGLS
CONSTANT	47.33***	47.92***	47.74***	48.87***
	(0.22)	(0.48)	(0.38)	(0.78)
OLD	-0.58***	-0.44***	-0.60***	-0.39***
	(0.01)	(0.02)	(0.02)	(0.04)
Log PATENT		0.14***		0.15*
		(0.04)		(0.09)
CAPITAL		-0.29***		-0.40***
		(0.04)		(0.05)
EDUCATION		-0.004		-0.02
		(0.007)		(0.01)
GLS weights	Cross-section weights	Cross-section weights	Period weights	Period weights
R^2	0.60	0.60	0.33	0.30
Adjusted R^2	0.60	0.59	0.32	0.30
F-statistic	2533.42	388.20	808.48	114.73
Prob(F-statistic)	0.00	0.00	0.00	0.00
Number of observations	1680	1058	1680	1058
Number of countries	159	107	159	107

Note: *** indicates $p < 0.01$, ** indicates $p < 0.05$, * indicates $p < 0.1$. Standard deviations of estimate coefficients of variables are in parentheses. We estimate feasible GLS specifications assuming the presence of country-level heteroskedasticity in column (1)- (2). Similarly, Period weights allow for yearly heteroskedasticity in column (3)- (4).



(A) Akaike Information Criteria in Column (22)



(B) Akaike Information Criteria in column (23)

Fig. A1: Akaike Information Criteria in PMG Estimation

Appendix B Local Moran's Index Statistic

Anselin (1995) presents Local Moran's I statistic (I_i), also known as local indicator of spatial association (LISA). It is a local indicator that describes spatial connections and is used to examine whether there is a cluster of related or unrelated observations. Local Moran's I statistic is used to measure the degree of spatial correlation of an economic attribute between country i and its neighboring country j, defined as:

$$I_i = \frac{(x_i - \bar{x})}{s_i^2} \sum_{j=1,\ j \neq i}^{n} w_{i,j} \left(x_j - \bar{x}\right), \qquad i = 1, 2 \cdots n,$$

where x_i is an attribute for feature i, $\bar{x}$ is the mean of the corresponding attribute, $w_{i,j}$ is the spatial weight between feature i and j, and

$$S_i^2 = \frac{1}{n-1} \sum_{j=1,\ j \neq i}^{n} \left(x_j - \bar{x}\right)^2 - \bar{x}^2$$

with n equating to the total number of features.