Effects of Income Inequality on Growth through Efficiency Improvement and Capital Accumulation.

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Abstract

In the present paper, the inverted-U shape relationship between growth and inequality found in Chen(2003), is reexamined. We decompose productivity growth into efficiency improvement, capital accumulation and technological progress and then ascertain their determinants by employing a fixed effects and dynamic panel models. In particular, this paper focuses on the question of how economic inequality affects capital accumulation and efficiency improvement. Key findings are that inequality enhances efficiency improvement as well as capital accumulation and then undermines them as inequality widens. However, other factors such as human capital, openness, and government consumption have different effects on them.

Keywords: Inequality, Growth, Fixed effects

JEL classification: E25, O4, O15, P3

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I. Introduction

Since the seminal work of Kuzmets (1955) asserting that inequality first rises and later falls as an economy develops, and that this is schematized as an inverted-U relationship between inequality and the level of per capita product, it has been widely and generally acknowledged that a country's level of economic inequality can been viewed as an outcome of its economic performance[1]. In recent years there has been increasing interest in the opposite causality, the question of how inequality affects economic growth. There seems, however, to be little agreement regarding the influence of inequality upon economic growth. Some research has found inequality to have negative effects on growth (e.g., Alesina and Perotti, 1996; Mo, 2000; Perotti, 1996; Persson and Tabellini, 1994; Sukiassyan, 2007). By contrast, positive effects have also been observed (e.g., Forbes, 2000; Li and Zou, 1998). An explanation for such discordance is that the negative relationship is found for less developed countries whereas a positive one is found for developed ones (Barro, 2000)[2]. An alternative explication is that growth rates first rise and then decline with an initial inequality (Chen, 2003). However, Chen (2003) does not control for unobservable fixed effects and the endogeneity problem that are expected to cause the estimation bias[3]. Therefore, we attempt to reexamine the finding which Chen (2003) provides by controlling for fixed effects and endogeneity.

If inequality has a critical effect on economic growth it would be cogent to ask what the channels are through which inequality affects growth. For instance, Mo (2000) investigated plausible channels such as human capital and political stability when the impact of income inequality on the growth rate is considered. A classical analysis of Kaldor (1956) argued that income distribution has a critical effect on capital accumulation, through which economic growth is affected. Besides capital accumulation, technology progress and its diffusion appears to make a contribution to economic growth (Segerstrom 1991, Yamamura et al., 2005). Accordingly, economic growth is considered to be attributed to several channels such as efficiency improvement, technological progress, and capital accumulation (Kumar and Russell,

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[1] Recent empirical study has provided evidence that while during the 1970s and 1980s the growth process was not accompanied by increases in inequality, during the 1990s a positive correlation between growth and inequality appeared (Lopez 2006).

[2] Banerjee and Duflo(2003) presents inconclusive results.

[3] Chen (2003) refers to a remaining issue as, " documenting evidence using a panel is an avenue for further research."

2002). The main aim of this paper is to examine the determinants, putting especial focus on economic inequality, of efficiency improvement and capital accumulation.

Existing literature (Yamamura and Shin 2007a, 2007b, 2007c, Zheng et al., 1998; 2003) has used data envelopment analysis to construct the production frontier and decompose labor-productivity growth into the three components of efficiency improvement, capital accumulation, and technological progress to more closely investigate economic growth. Additionally, through regression analysis they examined how various key independent variables have an effect on these components. Applying the above approach, we attempt to decompose inequality effects on growth after controlling for unobservable fixed effects and endogeneity.

The main findings of our estimation support the assertion of Chen (2003) and provide further evidence that: inequality enhances efficiency improvement as well as capital accumulation and then undermines them as inequality widens. However, other factors such as human capital, openness, and government consumption have different effects on efficiency improvement and capital accumulation, respectively. The organization of this paper is as follows: Section II briefly explains the strategy of the method used in the present paper and describes data sources. Regression functions are then presented. Section III discusses the results of the estimations. The final section offers concluding observations.

2. Methodorogy

1. Data

Definitions and the descriptive statistics used in this paper are presented in *Table 1*. Our data source for economic inequality measured by income inequality, Gini Coefficient, is collected from Deininger and Squire (1996)[4]. To estimate efficiency

[4] Gini coefficient is available from the World Bank HP (http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/0,,contentMDK:20699070~pagePK:64214825~piPK:64214943~theSitePK:469382,00.html). This data is widely used in previous works (e.g., Banerjee and Duflo 2003, Barro 2000, Forbes 2000, Li and Zou 1998). Recently, new indicators for inequality ((Duclos et al. 2004, Esteban et al. 2007) and ethnic composition (Montalvo and Reynal-Querol 2005) have been developed. However, the cross country panel data, which is called for the present paper, have not been constructed before.

improvement, capital accumulation, and technological progress by data envelopment analysis (abbreviated hereafter as DEA analysis), output, capital and labor data are required[5]. These data can be obtained from the Penn World Table from 1965 to 1990[6]. Following Yamamura and Shin (2007a), we construct a panel dataset from 1965 to 1990[7]. As explained later, using this dataset, we conduct a simple regression model in which the dependent variables are the percentage change between *t* and *t+1* years in output per worker, technology change, efficiency index, and the capital accumulation index.

Average years of school attainment, considered as human capital, are found in Easterly and Levine (1997)[8]. Trade as a share of GDP that is a proxy for openness, government consumption as a share of GDP, and investment as a share of GDP are collected from Dollar (2002)[9]. The ethnic fractionalization score is obtained from Matthew (1997)[10]. EM-DAT provides data of the number of natural disasters[11].

The data of these variables are unavailable for several years; therefore additional data were generated by interpolation based on an assumption of constant changing rates to construct the panel data[12].

2. Method

[5] The great advantage of DEA is that the frontier function requires no specification of functional form or distributional assumptions. DEA is widely used to evaluate the efficiencies of countries (e.g. Kumar and Russell (2002), Kruger (2003)) and industries (e.g. Zheng et al., 1998; 2003).

However, it should be noted that there are well known limitations to using this method. For more information concerning limitations, see "A Data Envelopment Analysis (DEA) Home Page"(www.emp.pdx.edu/dea/homedea.html). We appreciate a referee introducing us to this web site.

[6] The data are available from the Penn World Table HP：
http://pwt.econ.upenn.edu/php_site/pwt61_form.php

[7] Yamamura and Shin (2007a) preclude an implosion of the frontier over time.

[8] The data are available from the World Bank HP：
http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/0,,contentMDK:20700002~pagePK:64214825~piPK:64214943~theSitePK:469382,00.html

[9] These data are available from the World Bank HP：
http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/0,,contentMDK:20699374~pagePK:64214825~piPK:64214943~theSitePK:469382,00.html

[10] The data are available at http://www.wooster.edu/polisci/mkrain/ethfrac.html

[11] The data are available at http://www.em-dat.net/

[12] It must be noted these data might suffer from measurement errors when interpolation is conducted.

We estimate the extent of efficiency improvement, capital accumulation and technological progress by data envelopment analysis (DEA) and tripartite decomposition using country level panel data from 1965 to 1990. First, we estimate the production frontier by DEA. Two production frontiers derived from DEA can be decomposed into three components - efficiency improvement, capital accumulation and technological progress. This approach has an advantage over the growth accounting approach, in that we can further decompose total factor productivity growth, thereby obtaining more detailed information. Second, we take these variables as dependent variables and estimate their determinants by controlling unobservable individual and time effects through fixed effects and dynamic panel models.[13] This method allows us to assess how and to what extent inequality and additional crucial factors have effects on productivity growth through efficiency improvement and capital accumulation. That is, to examine whether and to what degree various factors determine productivity growth affect efficiency improvement and capital accumulation.

2..2 DEA

We introduce the methodologies used to analyze the productivity and decomposition. DEA is a nonparametric method to construct a production frontier and associated productive efficiency indexes for the whole data set. The approach to obtaining the production function is to envelop all scattered data on the dimension of input and output factors in the convex cone, and then the upper boundary of this set represents the production frontier as the best practice. This method has advantages over other methods as it requires no specification of functional forms, except that it needs to assume returns to scale of technology. In this case, we assume constant-returns-to-scale technology with three variables: capital stock (K) and labor (L) as aggregate inputs and output (Y) as the aggregate output. To express this production function in two dimensions, we modify (a linear homogeneous) production process in which output per labor $(y = Y/L)$ can be produced by capital per worker $(k = K/L)$. Thus, we let (k_t^i, y_t^i), $t = 1,\ldots,T$, $i = 1,\ldots,I$, represent T observations on these two variables for each of I countries.

[13] Some prior researches used the panel data to employ fixed effects model (Banerjee and Duflo 1996, Forbes 2000, Li and Zou 1998) and dynamic panel model (Banerjee and Duflo 1996, Forbes 2000, Skiassyan 2007).

We briefly describe the concept of the DEA method in Figure 1 without specific mathematical explanation. In this $\langle k, y \rangle$ space of scalar input and output, there are 20 scattered points of $\left(k_t^i, y_t^i\right)$ that represent observations in a given period for some hypothetical economy. The best-practice production frontier can be constituted by enveloping upper boundaries of these observations given the level of inputs (6 points in this case) to make a convex cone. Thus, this production frontier represents the maximum feasible outputs given inputs. Let $\bar{y}_t(k_t)$ denote the maximum output that we can produce with capital stock k_t in period t.

Now, we utilize the output-based efficiency indexes that can be obtained from measuring the distance between the observed output level and the level on the frontier given an input level. Such an index for i countries at time t is defined by

$$e\left(k_t^i, y_t^i\right) = \min\left\{\theta \mid \left(k_t^i, y_t^i/\theta\right) \in S_t\right\} \tag{2-1}$$

where S_t indicates the CRS production set. For example, the output-based efficiency level of one observation $e(k_t, y_t)$ at point B in Figure 1 is the ratio of actual output y_t to the production frontier level $\bar{y}_t(k_t)$, that is, $e(k_t, y_t) = y_t / \bar{y}_t(k_t)$=BC/AC. It is less than or equal to 1 and takes the value of 1 if and only if the observation is on the production frontier. The greater the value of the efficiency index, the more it is efficient and the nearer to the production frontier. This index indicates the relative efficiency to the best practice of points at a given period. It also has advantages of measuring productivity shortfall and catch-up relative to the best-practice frontier.

< FIGURE 1 >

If each of the production frontiers is constructed for any two years, we can then decompose productivity growth between two periods into three components. The tripartite decomposition method is conceptually described between two period technologies in Figure 2. We consider the two periods as the base period a and the current period b.

< FIGURE 2 >

y_a and k_a represent output and capital stock per capita, respectively, in period a. $\bar{y}_a(k_a)$ is the potential output in period a. Let us define the value of the efficiency indexes in period a as $e_a \equiv y_a / \bar{y}_a(k_a)$.

The ratio of per capita outputs in periods a and b is calculated by definition as

$$\frac{y_b}{y_a} = \frac{e_b \times \bar{y}_b(k_b)}{e_a \times \bar{y}_a(k_a)}. \tag{2-2}$$

An equivalent way of writing the right hand side of (2-2) is

$$\frac{y_b}{y_a} = \frac{e_b}{e_a} \times \left(\frac{\bar{y}_b(k_b)}{\bar{y}_a(k_b)} \times \frac{\bar{y}_b(k_a)}{\bar{y}_a(k_a)} \right)^{\frac{1}{2}} \times \left(\frac{\bar{y}_a(k_b)}{\bar{y}_a(k_a)} \times \frac{\bar{y}_b(k_b)}{\bar{y}_b(k_a)} \right)^{\frac{1}{2}} = \mathrm{E} \times \mathrm{T} \times \mathrm{K} \tag{2-3}$$

where E stands for efficiency change, T is technological change and and K is the capital accumulation change, between two periods. Output changes for the two periods can be decomposed in efficiency, technological and capital accumulation changes. The efficiency change is the change in the distance from the frontier. The technological change is the shift in the frontier. The capital accumulation change is the movement along the frontier.

We diagrammatically explain the decomposition identity (2-3) in Figure 2. The points B and G represent feasible input-output combinations in period a and b, respectively. Multiplying the top and bottom by $\bar{y}_a(k_b)$ or $\bar{y}_b(k_a)$, we obtain

$$\frac{\mathsf{EG}}{\mathsf{AB}} = \frac{\mathsf{EG/EH}}{\mathsf{AB/AC}} \times \frac{\mathsf{EH}}{\mathsf{EF}} \times \frac{\mathsf{EF}}{\mathsf{AC}} \tag{2-4}$$

or

$$\frac{\mathsf{EG}}{\mathsf{AB}} = \frac{\mathsf{EG/EH}}{\mathsf{AB/AC}} \times \frac{\mathsf{AD}}{\mathsf{AC}} \times \frac{\mathsf{EH}}{\mathsf{AD}}, \tag{2-5}$$

respectively. The geometric average of (2-4) and (2-5) is

$$\frac{\mathsf{EG}}{\mathsf{AB}} \approx \frac{\mathsf{EG/EH}}{\mathsf{AB/AC}} \times \left(\frac{\mathsf{EH}}{\mathsf{EF}} \times \frac{\mathsf{AD}}{\mathsf{AC}} \right)^{\frac{1}{2}} \times \left(\frac{\mathsf{EF}}{\mathsf{AC}} \times \frac{\mathsf{EH}}{\mathsf{AD}} \right)^{\frac{1}{2}}. \tag{2-6}$$

Let $\mathrm{E} \equiv \frac{\mathsf{EG/EH}}{\mathsf{AB/AC}}$, $\mathrm{T} \equiv \left(\frac{\mathsf{EH}}{\mathsf{EF}} \times \frac{\mathsf{AD}}{\mathsf{AC}} \right)^{\frac{1}{2}}$ and $\mathrm{K} \equiv \left(\frac{\mathsf{EF}}{\mathsf{AC}} \times \frac{\mathsf{EH}}{\mathsf{AD}} \right)^{\frac{1}{2}}$, then (2-6) is the same with (2-3).

We now switch attention to Figure 1 that simply illustrates the DEA. The technology frontier is depicted by connecting the most efficient point, when the vertical and horizontal axes stand for output over labor and capital over labor, respectively. Technological progress is considered as the shift of the productivity frontier that solely results from the level of the efficiency on the frontier. To put it another way, apart from the most efficient country, no other country not affects technological progress since technological progress is externally determined for them. Hence the estimation results seem to encounter difficulty in interpreting when technological progress is taken as a dependent variable. This is why the estimation results of technological progress are not paid much attention and not interpreted, although they are reported in *Table A1* and *A2* of the APPENDIX.

3. Specification of the Regression Function

We now formulate a regression function which take the labor-productivity growth(changes of the output per worker), the efficiency change and capital accumulation as the dependent variables.

To estimate the relationship between labor-productivity growth and inequality we use the following standard equation:

$$GR_{i,t\text{-}to} = \alpha_1\, LGDP_{it0} + \alpha_2 GINI_{it0} + \alpha_3\, GINI2_{it0} + \alpha_4\, HC_{it0} + \alpha_5 OPEN_{it0} + \alpha_6\, GOV_{it0} + \alpha_7\, INVS_{it0} + \alpha_8\, EHETE_{it0} + \alpha_9\, DISA_{it0} + \varepsilon_i + v_t + u_{it}\,,$$

ε_t ,v_i,u_{it} represent the following unobservable effects: the t's year-specific effects and the i's prefecture-specific effects, and the error term, respectively. $t0$ is the lagged year of the t's year. v_i includes a time-invariant feature, which is controlled for in the fixed effects model. The structure of the data set used in this study is a panel. We employed the fixed effects model to reduce the omitted variable bias caused by time invariant features of countries (Banerjee and Duflo, 2003; Forbes, 2000; Li and Zou, 1998). Development stages are considered to be covered in ε_t, and I incorporated in each year's dummy variables to restrain the time-specific effects (Forbes, 2000; Li and

Zou, 1998). The stage of development seems to be correlated with growth and inequality at the same time, causing the spurious correlation problem. Inclusion of year dummies is thought to alleviate this problem. As well as year dummies, some explanatory variables such as proxies for human capital and openness appear to control for possible sources of spurious correlation since they stand for the stage of development[14]. To address potential endogenous problems with lagged independent variables, we also carry out the dynamic panel estimation developed by Arellano-bond (Baltagi, 2005), since dynamic panel models allow past realizations of a dependent variable to affect its current level. Lagged $GR_{i,t-to}$ replaces $LGDP_{it0}$ as independent variables when a dynamic model is employed.

As argued by Kuznets (1955), economic inequality is likely to be under the influence of economic growth. If this is the case, the coefficients of *GINI* and *GINI2* would suffer from an endogeneity bias. With a view to alleviating this problem, we employ the fixed effects 2sls model and its results are presented in columns (3) and (6) of *Tables 2, 3, 4,* and *Table A1.* The instruments used are year dummies and cross products of an 80s dummy and legal origin dummies such as English common law and French commercial code dummies. The 80s dummy takes 1 if years are from 1980 to 1989, otherwise it takes 0. The legal origin dummies are obtained from La Porta et al. (1999). When the dynamic panel estimation is conducted, *GINI* and *GINI2* are also treated as endogenous explanatory variables, and we use the level of these for two periods or more as additional instruments (Arellano, 2003).

Independent variables are explained in the sections that follow.

3.1. Gini coefficient

LGDP stands for the output per worker, *GINI* and *GINI2* represent the Gini coefficient of per capita income and its square, respectively; *GINI* and *GINI2* are incorporated into the function as above to capture the income inequality effects in the base year *t0* after controlling for the initial output level and various control variables

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[14] Previous research include the variables used in this paper and additionally control for various factors concerning institutional and economic conditions (Barro, 2000; Banerjee and Duflo, 2003; Forbes, 2000; Perotti, 1996; Persson and Tabellini, 1994). Institutional and geographical features can be controlled by fixed effects estimation. Further, sample size seriously decreases if additional variables are incorporated. This is why we use only the important variables that are frequently used in the relevant literature.

mentioned later. In conjecture based upon a political economy argument, the redistribution of resources from the rich to the poor is less likely to be called for in the case where income is equally distributed. If this is the case, economic growth accompanied with income inequality is induced since the incentive for skilled workers to work harder and for entrepreneurs to generate innovation is strengthened. As a consequence, in the subsequent stage, income inequality leads to a system where the majority vote to favor redistribution through explicit transfer payments, public expenditure programs, and regulatory policy. The incentive to work and invest is thus weakened, resulting in economic growth being hampered. What is more, assuming that the conditions are under an imperfection of credit market, investors are limited in their access to credit, leading to lower investment and then a reduction of economic growth. As discussed above, an inverted-U relationship between income inequality and economic growth emerges via various channels. When the incentive to work diminishes, efficiency deteriorates even if the country possesses high technology. The inverted-U relationship holds presumably due to the degree of the incentive for workers when efficiency improvement is examined. On the other hand, when the incentive to invest is reduced, capital formation is impeded, the inverted-U relationship holds probably thanks to the degree of the incentive to invest when capital accumulation is assessed[15]. According to Chen (2003), the coefficients of *GINI* and *GINI2* take positive and the negative signs, respectively. As well, the absolute value of *GINI* is smaller than that of *GINI2* if an inverted-U relationship holds in each estimation.

3.2. Additional Control variables.

HC denoting schooling years is taken as an indicator of human capital, which has frequently been used as an explanatory variable in previous research. Higher education is likely to promote economic growth through various plausible channels. For instance, more educated people are apt to generate technological progress and facilitate the learning of new technology from others. Nevertheless, the relationship between capital accumulation and *HC* seems to be ambiguous. Hence, *HC* is predicted to take a positive sign when productivity growth and efficiency improvement are examined.

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[15] Although proxy for investment is included in the estimation function, incentive to invest appears to have a critical effect upon capital accumulation if the proxy fails to fully capture the impact of investment.

A country's import and export share of GDP represented as *OPEN* is incorporated in the function since trade is among the key factors determining growth (Frankel and Aten, 2002). The technological knowledge and the various materials used for products are more inclined to flow into a country from abroad when that country is more open to foreign ones; thereby smoothing efficiency improvement and capital accumulation. Openness also seems to serve as a proxy for the degree of competition, leading to the acceleration of efficiency improvement. Accordingly, the sign of *OPEN* is expect to be positive, in particular when efficiency improvement is assessed.

As regards *GOV* standing for a government's share of GDP, the relative presence of the government will be inversely related with productivity growth through deterioration of efficiency, in large part due to an inefficient distribution of resources. On the other hand, the government is more inclined to enhance public investment to give a lift to the economy with the object of gaining wider support among the people. As a result, the larger the presence of the government becomes, the higher the degree of capital accumulation becomes. Hence, signs of *GOV* are predicted to be negative in estimations of efficiency improvement but be positive in those of capital accumulation.

INVS standing for the investment share of GDP would, as a matter of course, enhance capital accumulation so that its sign is thought to be positive in estimations of capital accumulation, whereas it is uncertain in those of efficiency improvement.

To include how ethnic heterogeneity influences on growth, the function includes ethnic fractionalization represented as *EHETE*. It is increasingly acknowledged that ethnic heterogeneity reduces the incentives for collective action (Alesina and La Ferrara 2000) and hampers economic growth (Montalvo and Reynal-Querol. 2005). This is likely to have an influence on efficiency improvement and capital accumulation as follows. Capital accumulation is not promoted as a consequence of the lack of collective action calling for the provision of local public goods. On the other hand, intuitively worker homogeneity is required for the smooth transmission of knowledge. Ethnic fractionalization thus hampers knowledge spillover, resulting in deteriorating efficiency. This leads us to expect *EHETE* to take a negative sign in each of the estimations.

There has been recent research on the impact of natural disasters on economic growth (Skidmore and Toya 2002). To include this effect, *DISA,* standing for the number of natural disasters, is included. It seems obvious that disasters cause damage to physical capital, thereby impeding capital accumulation. On the other hand, Skidmore and Toya (2002) asserted that disasters provide an impetus to adopt new technologies, resulting in economic growth. If so, *DISA* is though to be positive when efficiency improvement and economic growth is examined.

Further reports have pointed out the importance of other variables such as institutional characteristics (Tabellini 2005). This paper controls for them through a fixed effects model that capture these time invariant features.

3. Estimation Reusults

1. Results of Fixed Effects Estimation

The estimation results of the fixed effects model with year dummies for productivity growth, efficiency improvement, and capital accumulation are reported in *Tables 2, 3* and *4*, respectively. In columns (2), (4), (6), and (8) in each of the tables, the results of the fixed effects 2sls model are presented.

In columns (1), (2), (5), and (6) in each table, results are presented when the square term of the gini coefficient *GINI2* is not included in the functions. From them, we can obtain results in respect to the linear effect of inequality on growth. From columns (5) to (8), a lagged dependent variable is incorporated instead of the initial levels of per capita product, efficiency, and per capita capital, in *Tables 2, 3*, and *4*, respectively. Also, the estimation results of technology progress are proposed in Tables A1 and A2 (Appendix) for reference.

We now discuss *Table2.* Before we examine the inverted-U shape, the linear effect of inequality is more precisely investigated. *GINI* yields negative signs in columns (1) and (5), while it yields positive signs in columns (2) and (6). These results are not, with exception of column (1), statistically significant. We interpret this result that an effect of inequality depends on whether its endogeneity is controlled for. Looking at the results when *GINI2* is incorporated reveals that *GINI* and *GINI2* produce statically significant positive and negative signs, respectively. As well, the magnitude of *GINI* is smaller than that of *GINI2.* These results are consistent with the findings of Chen (2002) that the relationship between inequality and growth demonstrates an inverted-U shape. Furthermore, compared with the results of the fixed effects estimation, their absolute values are larger when fixed effects 2sls estimation is conducted. Mitigation of endogeneity is thus thought to cause the U-inverted association to be more pronounced. With respect to the effects of human capital and openness, *HC* and *OPEN, respectively,* generally take, with the exception of columns (2) and (4), positive signs, being almost statistically significant at the 1 % level, which is in line with our expectation. The signs of *GOV, INVS, EHETE* and *DISA* are varied according to the specifications. Although from this we cannot derive a particular conjecture, the effects arising from efficiency improvement and capital accumulation seem to neutralize each other, assuming that the effect of efficiency improvement is opposed to that of capital accumulation.

Table 3 provides similar results to those of *Table 2* as regards *GINI* and *GINI2.* These tell us that the linear effects of inequality on efficiency are indecisive and ambiguous, with inequality first improving efficiency and then reducing it. What is more, *GINI* is smaller than *GINI2.* These results are consonant with the argument put forward in the previous section. As expected, *HC* and *OPEN* almost, with some exceptions, take significant positive signs, suggesting that human capital and openness promote and accelerate efficiency improvement. *GOV, INVS*, and *ETHE* generally produce negative signs, despite being statistically insignificant. This seems to be compatible with our expectation, as previously noted. We found it interesting that the sign of *DISA* becomes positive despite not having statistical significance. This suggests, as argued by Skidmore and Toya (2002), that disasters provide a catalyst to ameliorate efficiency through the adaptation of new technologies.

We now turn to consider *Table 4* detailing the capital accumulation. We found coefficient of *GINI* to consistently take a negative sign when a linear specification is estimated, while the results of *GINI* and*GINI2,* when included in the same function, share similarities when examining efficiency improvement. This implies that the negative effect stemming from inequality outweighs the positive effect from it, even though both effects exists as earlier expected and illustrate the inverted-U shape relation ship between inequality and capital accumulation. *HC* and *OPEN* yield negative signs; therefore, they fail to enhance capital accumulation. Signs of *GOV* varied depending on the specification; therefore, the effect of the government share remains unclear. *INVS* generally yields a positive sign and therefore investment instigates capital accumulation, which is congruous with that intuition and expectations. We are intrigued by the results concerning ethnic fractionalization and natural disasters; *EHETE* and *DISA* almost produced significant negative signs. The results for *EHETE* lead us to conjecture that ethnic fractionalization reduces incentives to take collective action, thereby causing the free rider problem, resulting in a scarcity of local public goods. On the other hand, occurrences of natural disasters cause damage to various types of infrastructure, resulting in impediments to capital accumulation.

2. Results of Dynamic Panel Estimations

Tables 5, 6, and *7* report the results of the dynamic panel model with year dummies for productivity growth, efficiency improvement, and capital accumulation, respectively. In columns (2) and (4), we incorporate both the first and second lagged variables. A test for the hypothesis that there is no second-order serial correlation for the disturbance of the first-differenced equation is important because the consistency of the estimator relies on there being no second-order serial correlation.

We begin by discussing the results presented in *Table 5*. The test for the second order serial correlation does not reject the null hypothesis that there is no second order serial correlation in columns (2) and (4). Accordingly, careful attention needs to be paid to the results of (2) and (4). We see that the signs of *GINI* are negative and statistically significant in column (2), implying that inequality hampers productivity growth. What is more, *GINI* and *GINI2* take significant positive and negative signs, respectively, and *GINI* is smaller than *GINI2*, which is equivalent to the results in *Table 2*. These results make evident the argument of Chen (2002) that there is an inverted-U shape relationship between inequality and growth. Taking then results for *GINI* and *GINI2* together, the negative effects of inequality outweigh the positive ones, so that inequality has a negative impact on productivity growth. Both *HC* and *OPEN* produce results that human capital and openness have positive effects on productivity growth, which is equivalent to those of *Table 2.* Consistent with our expectation, *EHETE* takes negative signs, despite being statistically insignificant. Despite the statistical insignificance, the positive sign of *DISA* is thought to reflect that its positive effect on efficiency improvement through an increasing impetus to adopt new technology dominated its negative effect on capital accumulation via the damage to physical capital, as discussed earlier. As a whole, the results in *Table 5* reinforced those in *Table 2.*

In *Table 6,* the estimation results in columns (2) and (4) pass the second order correlation test. Hence, it should be noted that the results in columns (1) and (3) suffer from estimation bias. The results of *GINI* and *GINI2* are equivalent to those in *Table 3*, implying that there is an inverted-U shape relationship between inequality and efficiency improvement. The negative signs of *GINI* in columns (1) and (2) reflect that the negative impact of inequality exceeds any positive influence. We found the signs of *EHETE* and *DISA* to be negative and positive, respectively, which is consistent with the prediction. Nevertheless their lack of statistical significance persists under different specifications, not only in *Table 6* but also in *Table 3*. Our interpretation is that the insignificance of *EHETE* seems to suffer from measurement error, while that of *DISA* may reflect that the number of disasters fails to reflect the extent to which disasters caused damage.

Only columns (1) and (3) of *Table 7* pass the second order correlation test. Accordingly, we mainly discuss the results in columns (1) and (3) rather than those in columns (2) and (4). The estimation results for *GINI* and *GINI2* are equivalent to those in *Table 4,* and therefore are robust to alternative specifications and estimation methods. In short, the U-shaped association between inequality and capital accumulation is shown to be valid. Consistent with our anticipation, *COV* and *INVS* take significant positive signs. We found the sign of *EHETE* to be negative, implying that a reduction of the incentive to take the collective action required for achieving public good stems from ethnic fractionalization, which is in line with previous reports (Alesina, et.al., 1999; Alesina and La Ferrara, 2000).

We have so far examined the determinants of productivity growth, efficiency improvement and capital accumulation. The combined results presented above strongly supported an inverted U-relationship between inequality and productivity growth. This arises not only from efficiency improvement but also from capital accumulation. Furthermore, it is noteworthy that some control variables have an effect on efficiency improvement and capital accumulation; even if they seemingly fail to affect productivity growth because their effects from different channels neutralize each other.

4. Concluding Remarks

While an increasing number of researchers have shown interest in whether inequality is really harmful for economic growth, the results so far reported vary and there seems little agreement about the effect. Therefore, the question of how inequality affects economic growth remains open. In the present paper, an inverted-U shape relationship, as put forward by Chen (2003), between growth and inequality has been reexamined in more detail.

Earlier reports have scarcely analyzed plausible channels through which economic inequality has effects on growth, although a number of works have tried to explore the relationship between inequality and growth. In an attempt to shed light on this, we first decomposed productivity growth into efficiency improvement, capital accumulation and technological progress. Second we proceeded to ascertain their determinants by employing fixed effects and dynamic panel models. Particularly, in this paper the main emphasis fell on the question of how economic inequality affects capital accumulation and efficiency improvement. Our main findings, which are invariant to alternative specifications and estimation methods, are as follows.

(1) Inequality enhances efficiency improvement as well as capital accumulation and then undermines them as inequality widens. Consequently, an inverted-U shape relationship between inequality and growth holds, in agreement with Chen (2003).

(2) Human capital and openness promote efficiency improvement, while investment and government consumption enhances capital accumulation. Ethnic fractionalization hampers both.

Findings as above make evident the inverted-U relationship between inequality and not only capital accumulation but also efficiency improvement, and that additional determinant factors lead to different outcomes for efficiency improvement and capital accumulation. The findings suggest that the factors are seemingly unrelated with productivity growth, since effects through the efficiency improvement channel and those from capital accumulation neutralize each other. For instance, a factor such as openness is positively associated with efficiency improvement, but inversely with capital accumulation. Necessarily, attention should also be paid to whether factors have effects on these channels even when they do not have a significant effect on productivity growth.

A limitation of the present paper is that it is limited to an empirical analysis and the estimation results seem to suffer from the omission of relevant variables. Hence, it will be worthwhile to use the theoretical model to explore why this is the case; investigating whether a newly developed income inequality index such as a polarization index (Duclos et al. 2004, Esteban et al. 2007), affects efficiency improvement and capital accumulation. As well, how other socio-economic factors are related to them needs to be examined. These are the major issues remaining to be addressed in our future studies.

References

Alesina,A., R.Baqir., and W. Easterly., 1999. Public goods and ethnic divisions, Quarterly Journal of Economics. 114, 1243-1284.

Alesina,A. and R. Perotti., 1996. Income distribution, political instability, and investment, European Economic Review. 40, 1203-1228.

Alesina,A. and E. La Ferrara., 2000. Participation in heterogeneous communities, Quarterly Journal of Economics. 115, 1203-1228.

Arellano, M., 2003. Panel Data Econometrics: Advanced Texts in Econometrics. Oxford University Press, New York.

Baltagi, B.,2005. Econometric Analysis of Panel Data. Chippenham, John Wiley and Sons.

Banerjee, A. and E.Duflo., 2003. Inequality and growth: What can the data say? Journal of Economic Growth. 8, 267-299.

Banker R D A, A.Charnes, and W.W.Cooper., 1984. Models for Estimating Technical and Scale Efficiencies. Management Science. 30, 1078-1092.

Barro, R.J., 2000. Inequality and growth in a panel of countries. Journal of Economic Growth. 5, 5-32.

Chen, B.L., 2003. An inverted-U relationship between inequality and long-run growth. Economics Letters. 78, 205-212.

Cooper W W, M.S.Lawrence., and K.Tone., 2000. Data Envelopment Analysis. Boston ,Kluwer Academic Press.

Deininger, K. and L. Squire., 1996. A New Data Set Measuring Income Inequality. World Bank Economic Review. 10, 565-591.

Dollar,D and A. Kraay., 2003. Institutions, Trade and Growth, Journal of Monetary Economics. 50,133-162.

Duclos, J-Y., J. Esteban., and D. Ray., 2004. Concepts, Measurement, Estimation. Econometrica. 72, 1732-1772.

Esteban, J., C. Gradin., and D. Ray., 2007. An Extension of a Measure of Polarization with an Application to the Income Distribution of Five OECD Countries. Journal of Economic Inequality. 5, 1-19.

Easterly,W. and R.Levine's., 1997. Africa's Growth Tragedy: Policies and Ethnic Divisions. Quarterly Journal of Economics. 112, 1203-50.

EM-DAT: The OFDA/CRED International Disaster Database, www.em-dat.net,

Université Catholique de Louvain, Brussels, Belgium.
Färe R, S.Grosskopf., M.Norris., and Z.Zhang., 1994. Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries. American Economic Review. 84, 66-83.
Färe R, S.Grosskopf., and P.Roos., 1996. On two Definitions of Productivity. Economics Letters. 53, 269-274.
Forbes, K., 2000. A reassessment of the relationship between inequality and growth. American Economic Review. 90, 869-886.
Frankel, J.A. and D. Romer., 1999. Does Trade Cause Growth?, American Economic Review. 89, 379-399.
Heston, A., Summers,R., Aten, B., 2002. Penn World Table Version 6.1, Center for International Comparisons at the University of Pennsylvenia (CICUP), Taken from the ISP web page, http://pwt.econ.upenn.edu/
Kaldor, N., 1956. Alternative Theories of Distribution, Review of Economic Studies. 23, 83-100.
Kruger J., 2003. The Global Trends of Total Factor Productivity. Evidence from the Nonparametric Malmquist Index Approach. Oxford Economic Papers. 55, 265-286.
Kumar, S., and R.R.Russell., 2002. Technological Change, Technological Catch-up, and Capital deepening: Relative Contributions to Growth and Convergence. American Economic Review 92, 527-548.
Kuznets, S., 1955. Economic Growth and Income Inequality, American Economic Review, 45,1-28.
La Porta, R., F. Lopez-de-Silanes., A. Shleifer and R. Vishny., 1999. The Quality of Government. Journal of Law, Economics, and Organization. 15, 222-275.
Li, H. and H. Zou., 1998. Income inequality is not harmful for growth: Theory and evidence. Review of Development Economics. 2, 318-334.
Lopez, H., 2006. Growth and inequality: Are the 1990s different?. Economics Letters. 93, 18-25.
Matthew,K., 1997. State-Sponsored Mass Murder: The Onset and Severity of Genocides and Politicides. Journal of Conflict Resolution. 41,3:331-360.
Mauro, P., 1995. Corruption and Growth. Quarterly Journal of Economics. 110, 681-712.
Mo, P.H., 2000. Income inequality and economic growth. Kyklos. 53, 293-316.
Montalvo, J.G., and M. Reynal-Querol., 2005. Ethnic Diversity and Economic Development. Journal of Development Economics. 76, 293-323.

Perotti, R., 1996. Growth, income distribution, and democracy: What the data say. Journal of Economic Growth. 1, 149-187.

Persson, T. and G.Tabellini., 1994. Is inequality harmful for growth? American Economic Review 84, 600-621.

Segerstrom, P.S., 1991. Innovation, Imitation, and Economic Growth, Journal of Political Economy. 99, 807-827.

Sukiassyan, G., 2007. Inequality and growth: What does the transition economy data say?. Journal of Comparative Economics. 35, 35-56.

Tabellini, G., 2005. The Role of the State in Economic Development. Kyklos. 58, 283-303.

Skidmore, M., and H. Toya., 2002. Do Natural Disaster Promote Long-Run Growth. Economic Inquiry, 40, 664-687.

Yamamura, E. and I.Shin., 2007a. Technological Change and Catch-up and Capital deepening: Relative Contributions to Growth and Convergence: Comment. Economics Bulletin. 15 (3), 1-8.

Yamamura, E. and I.Shin., 2007b. The benefit of efficiency improvement on growth and convergence: A study using Japan panel data. Forthcoming in Economics Letters.

Yamamura, E. and I.Shin., 2007c. Dynamics of Agglomeration Economies and Regional Industrial Structure: The Case of the Assembly Industry of the Greater Tokyo Region, 1960-2000. Forthcoming in Structural Change and Economic Dynamics. 18, 483-489.

Yamamura, E., T. Sonobe., and K. Otsuka., 2005. Time path in innovation, imitation, and growth: the case of the motorcycle industry in postwar Japan. Journal of Evolutionary Economics. 15, 169-186.

Zheng, J., X.Liu., and A.Bigsten., 1998. Ownership Structure and Determinants of Technical Efficiency: An Application of Data Envelopment Analysis to Chinese Enterprises (1986-1990). Journal of Comparative Economics. 26, 465-484.

Zheng, J., X.Liu., and A.Bigsten., 2003. Efficiency, Technical Progress, and Best Practice in Chinese State Enterprises (1980-1994), Journal of Comparative Economics. 31, 134-152.

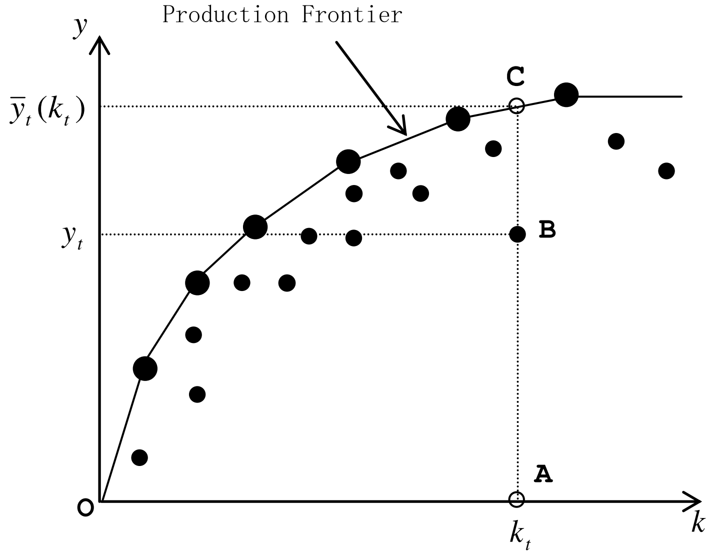

Fig.1. Data Envelopment Analysis Method

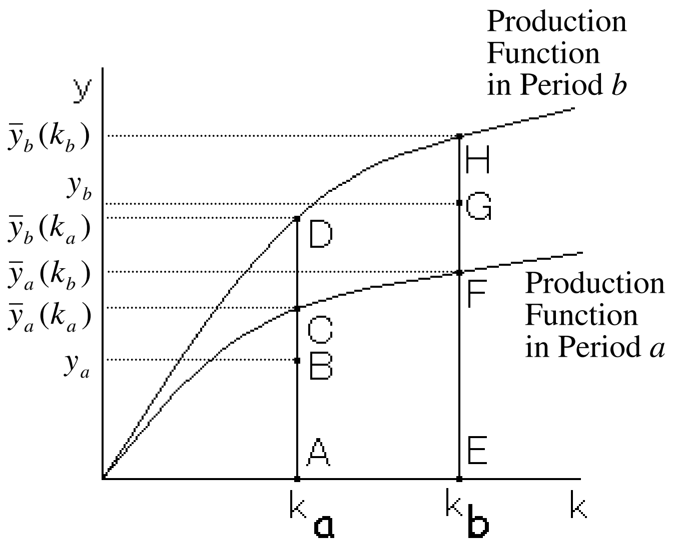

Fig.2. Illustration of Tripartite Decomposition

Table 1

Descriptive Statistics

Variables	Definition	Sources	Mean	S.D
GR	Growth rate of output per worker	Penn & world table	0.98	5.24
EFCH	Efficiency improvement rate	Author's calculation using data of Penn & world table	$0.01*10^{-2}$	$4.88*10^{-2}$
KLCH	Capital deepening rate	Author's calculation using data of Penn & world table	$1.24*10^{-2}$	$2.04*10^{-2}$
TNCH	Technological progress rate	Author's calculation using data of Penn & world table	$0.76*10^{-2}$	$1.53*10^{-2}$
GINI	Gini coefficients of per capita income	World Bank HP	0.39	0.08
HC	Log of 1 + average years of school attainment	Easterly and Levine (1997)	1.75	0.43
OPEN	Trade as a share of GDP	Dollar (2002)	0.38	0.37
GOV	Government consumption as a share of GDP	Dollar (2002)	0.20	0.08
INVS	Investment as a share of GDP	Dollar (2002)	0.20	0.08
EHETE	Ethnic Fractionalization Score	Matthew (1997)	0.36	0.28
DISA	Number of natural disasters	EM-DAT：the International Disaster Database	1.33	2.26

Notes: [a] Per Millions

[b] In Yens

[c] In Million Yens

[d] In Yens per liter

Table 2

Growth and Inequality (Fixed Effects Model)

	(1)GR FE	(2)GR FE2sls	(3) GR FE	(4)GR FE2sls	(5)GR FE	(6)GR FE2sls	(7) GR FE	(8)GR FE2sls
LGDP	-3.19	-5.45**	-5.62**	-12.5**				
	(-1.51)	(-2.54)	(-2.70)	(-4.16)				
GR_1					0.13**	0.20**	0.06	-0.01
					(2.75)	(4.10)	(1.24)	(-0.90)
GINI	-20.3*	1.62	275.6**	1000.0**	-16.5	8.29	230.0**	857.6**
	(-1.79)	(0.07)	(5.33)	(4.60)	(-1.45)	(0.34)	(4.34)	(2.75)
GINI2			-375.6**	-1389.7**			-316.0**	-1200**
			(-5.85)	(-4.14)			(-4.75)	(-2.73)
HC	17.2**	-4.31	19.5**	18.6**	15.2**	-5.87	17.8**	9.50
	(2.98)	(-0.92)	(3.50)	(2.47)	(2.64)	(-1.29)	(3.16)	(1.23)
OPEN	4.84	-0.91	10.4**	22.1**	4.32	-1.53	8.84**	15.3**
	(1.59)	(-0.34)	(3.34)	(3.72)	(1.43)	(-0.59)	(2.86)	(2.23)
GOV	56.8*	-0.52	26.5	-128.9**	52.9*	-1.52	32.1	-124.8**
	(1.96)	(-0.02)	(0.94)	(-3.18)	(1.84)	(-0.06)	(1.13)	(-2.35)
INVS	14.4	7.15	-1.74	-75.2**	10.7	3.23	-3.38	-75.8*
	(0.93)	(0.42)	(-0.11)	(-2.77)	(0.69)	(0.20)	(-0.22)	(-2.19)
EHETE	-22.0	12.0	-8.82	65.2	-38.8	-18.0	-45.6	-21.5
	(-0.48)	(0.26)	(-0.20)	(1.14)	(-0.90)	(-0.41)	(-1.08)	(-0.42)
DISA	0.15	-0.003	0.06	-0.23	0.14	-0.005	0.07	-0.25
	(1.11)	(-0.03)	(0.51)	(-1.32)	(1.06)	(-0.04)	(0.57)	(-1.37)
Year dummy	Yes	No	Yes	No	Yes	No	Yes	No
Sample	466	466	466	466	466	466	466	466
Groups	31	31	31	31	31	31	31	31

Notes: Numbers in parentheses are t-statistics. * and ** indicate significance at 5 and 1 per cent levels respectively (one-sided tests). In each estimates, year dummies are included, but not reported to save the space. We employ the fixed effects 2sls model and its results are presented in columns (3) and (6). The instruments used are year dummies and cross products of 80s dummy and legal origin dummies such as English common law dummy and French commercial code dummy.

Table 3

Efficiency Improvement and Inequality (Fixed Effects Model)

	(1)EFCH FE	(2)EFCH FE2sls	(3) EFCH FE	(4)EFCH FE2sls	(5)EFCH FE	(6)EFCH FE2sls	(7) EFCH FE	(8)EFCH FE2sls
ELEV	-0.08**	-0.06**	-0.12**	-0.24**				
	(-3.87)	(-2.78)	(-5.57)	(-4.41)				
EFCH_1					0.14**	0.19**	0.10*	0.01
					(3.01)	(3.91)	(2.21)	(0.14)
GINI	-0.22*	0.36	2.53**	10.2**	-0.14	032	1.40**	6.20**
	(-2.05)	(1.50)	(4.90)	(3.81)	(-1.27)	(1.40)	(2.73)	(2.51)
GINI2			-3.53**	-13.8**			-1.99**	-8.21**
			(-5.45)	(-3.73)			(-3.07)	(-2.39)
HC	0.16**	-0.03	0.18**	0.15*	0.13**	-0.02	0.15**	0.09
	(2.92)	(-0.77)	(3.44)	(2.05)	(2.38)	(-0.52)	(2.68)	(1.36)
OPEN	0.09**	0.04*	0.13**	0.25**	0.08**	0.04*	0.11**	0.17**
	(3.09)	(1.82)	(4.69)	(4.01)	(2.81)	(1.74)	(3.67)	(2.88)
GOV	0.12	-0.09	-0.13	-1.45**	0.10	-0.05	-0.04	-0.90
	(0.46)	(-0.38)	(-0.48)	(-3.15)	(0.38)	(-0.25)	(-0.16)	(-2.09)
INVS	0.04	0.05	-0.06	-0.62**	-0.05	-0.01	-0.15	-0.56
	(0.32)	(0.35)	(0.43)	(-2.35)	(-0.38)	(-0.09)	(-1.01)	(-1.96)
EHETE	-0.15	-0.16	-0.15	0.02	-0.14	-0.10	-0.18	-0.15
	(-0.36)	(-0.38)	(-0.39)	(0.05)	(-0.34)	(-0.23)	(-0.44)	(-0.33)
DISA	0.001	0.004	0.0009	-0.001	0.001	0.0004	0.0009	-0.001
	(1.24)	(0.35)	(0.73)	(-1.06)	(0.98)	(0.34)	(0.67)	(-0.66)
Year dummy	Yes	No	Yes	No	Yes	No	Yes	No
Sample	466	466	466	466	466	466	466	466
Groups	31	31	31	31	31	31	31	31

Notes: Numbers in parentheses are t-statistics. * and ** indicate significance at 5 and 1 per cent levels respectively (one-sided tests). In each estimates, year dummies are included, but not reported to save the space. We employ the fixed effects 2sls model and its results are presented in columns (3) and (6). The instruments used are year dummies and cross products of 80s dummy and legal origin dummies such as English common law dummy and French commercial code dummy.

Table 4

Capital Deepening and inequality (Fixed Effects Model)

	(1)KLCH FE	(2)KLCH FE2sls	(3) KLCH FE	(4)KLCH FE2sls	(1)KLCH FE	(2)KLCH FE2sls	(3) KLCH FE	(4)KLCH FE2sls
KLEV	0.02**	0.01**	0.02**	0.04**				
	(3.88)	(2.51)	(4.74)	(3.09)				
KLCH_1					0.72**	0.73**	0.71**	0.66**
					(21.3)	(22.0)	(20.7)	(13.5)
GINI	-0.03	-0.31**	0.55**	2.51**	-0.01	-0.09*	0.19*	0.77*
	(-1.11)	(-4.89)	(4.51)	(2.39)	(-0.99)	(-2.27)	(2.19)	(2.10)
GINI2			-0.74**	-4.02**			-0.26**	-1.25**
			(-4.86)	(-2.71)			(-2.46)	(-2.38)
HC	-0.008	-0.04**	-0.008	-0.02	0.01	-0.004	0.01*	0.01
	(-0.62)	(-3.45)	(-0.60)	(-1.20)	(1.53)	(-0.61)	(1.68)	(1.06)
OPEN	-0.02**	-0.05**	-0.01*	-0.005	-0.003	-0.01**	0.0001	0.005
	(-3.45)	(-6.58)	(-2.26)	(-0.24)	(-0.66)	(-2.39)	(0.03)	(0.62)
GOV	0.39**	-0.001	0.34**	-0.42*	0.12**	-0.002	0.10*	-0.12*
	(5.70)	(-0.02)	(5.07)	(-2.28)	(2.53)	(-0.07)	(2.20)	(-1.82)
INVS	0.18**	0.06	0.15**	-0.28	0.05	0.01	0.04	-0.06
	(4.79)	(1.54)	(4.11)	(-1.53)	(2.04)	(0.42)	(1.60)	(-1.48)
EHETE	-0.32**	-0.09	-0.36**	-0.28	-0.16*	-0.11	-0.16*	-0.0005*
	(-2.87)	(-0.78)	(-3.32)	(-1.36)	(-2.25)	(-1.50)	(-2.30)	(-1.81)
DISA	-0.0004	-0.001**	-0.0006*	-0.001**	0.0002	-0.0002	-0.00004	-0.05
	(-1.49)	(-2.93)	(-2.03)	(-2.96)	(0.11)	(-1.04)	(-0.20)	(-0.92)
Year dummy	Yes	No	Yes	No	Yes	No	Yes	No
Sample	466	466	466	466	466	466	466	466
Groups	31	31	31	31	31	31	31	31

Notes: Numbers in parentheses are t-statistics. * and ** indicate significance at 5 and 1 per cent levels respectively (one-sided tests). In each estimates, year dummies are included, but not reported to save the space. We employ the fixed effects 2sls model and its results are presented in columns (3) and (6). The instruments used are year dummies and cross products of 80s dummy and legal origin dummies such as English common law dummy and French commercial code dummy.

Table 5

Growth and Inequality (Dynamic Panel Model)

	(1) GR	(2) GR	(3) GR	(4) GR
GR_1	0.12** (2.70)	0.13** (2.84)	0.06 (1.27)	0.06 (1.37)
GR_2		-0.06 (-1.42)		-0.13** (-2.80)
GINI	-17.3 (-1.54)	-18.8* (-1.66)	230.1** (4.43)	266.7** (4.97)
GINI2			-316.0** (-4.85)	-366.6** (-5.42)
HC	18.1** (3.06)	18.7** (3.14)	17.8** (3.23)	19.3** (3.48)
OPEN	5.17* (1.72)	5.08* (1.69)	8.84** (2.93)	9.36* (3.09)
GOV	53.0* (1.86)	56.3* (1.93)	32.1 (1.16)	35.1 (1.26)
INVS	7.76 (0.51)	8.69 (0.56)	-3.38 (-0.23)	-3.78 (-0.25)
EHETE	-37.3 (-0.88)	-37.7 (-0.88)	-45.6 (-1.11)	-47.3 (-1.15)
DISA	0.14 (1.04)	0.15 (1.09)	0.07 (0.59)	0.08 (0.62)
Year dummy	Yes	Yes	Yes	Yes
Serial correlation				
First order (P-value)	0.00	0.00	0.00	0.00
Second order (P-value)	0.02	0.12	0.00	0.73
Sample	435	435	435	435
Groups	28	28	28	28

Notes: Numbers in parentheses are t-statistics. * and ** indicate significance at 5 and 1 per cent levels respectively (one-sided tests). In each estimates, year dummies are included, but not reported to save the space.

Table 6

Efficiency Improvement and Inequality (Dynamic Panel Model)

	(1) EFCH	(2) EFCH	(3) EFCH	(4) EFCH
EFCH _1	0.13**	0.15**	0.10*	0.11**
	(2.99)	(3.21)	(2.26)	(2.46)
EFCH _2		-0.09*		-0.13**
		(-2.05)		(-2.79)
GINI	-0.14	-0.17	1.41**	1.70**
	(-1.30)	(-1.53)	(2.79)	(3.27)
GINI2			-1.99**	-2.40**
			(-3.14)	(-3.68)
HC	0.16**	0.17**	0.15**	0.17**
	(2.74)	(2.93)	(2.74)	(3.05)
OPEN	0.08**	0.09**	0.11**	0.12**
	(3.20)	(3.13)	(3.76)	(4.07)
GOV	0.10	0.12	-0.04	-0.05
	(0.38)	(0.43)	(-0.16)	(-0.20)
INVS	-0.06	-0.06	-0.15	-0.17
	(-0.44)	(-0.44)	(-1.03)	(-1.16)
EHETE	-0.14	-0.19	-0.18	-0.25
	(-0.35)	(-0.46)	(-0.45)	(-0.61)
DISA	0.001	0.001	0.0009	0.001
	(0.95)	(1.08)	(0.68)	(0.81)
Year dummy	Yes	Yes	Yes	Yes
Serial correlation				
First order (P-value)	0.00	0.00	0.00	0.00
Second order (P-value)	0.02	0.48	0.01	0.96
Sample	435	435	435	435
Groups	28	28	28	28

Notes: Numbers in parentheses are t-statistics. * and ** indicate significance at 5 and 1 per cent levels respectively (one-sided tests). In each estimates, year dummies are included, but not reported to save the space.

Table 7

Capital Deepening and Inequality (Dynamic Panel Model)

	(1) KLCH	(2) KLCH	(3) KLCH	(4) KLCH
KLCH_1	0.72**	0.76**	0.71**	0.74**
	(22.1)	(16.4)	(21.7)	(16.9)
KLCH_2				-0.05
				(-1.15)
GINI	-0.01	-0.05	0.19*	0.19*
	(-1.03)	(-1.25)	(2.29)	(2.23)
GINI2			-0.26**	-0.26**
			(-2.57)	(-2.49)
HC	0.01	0.01	0.01*	0.01
	(1.30)	(1.13)	(1.75)	(1.60)
OPEN	-0.003	-0.004	0.001	-0.002
	(-0.79)	(-0.86)	(0.04)	(-0.04)
GOV	0.12**	0.13**	0.10*	0.11**
	(2.62)	(2.66)	(2.30)	(2.35)
INVS	0.05*	0.05*	0.04*	0.04*
	(2.16)	(2.18)	(1.67)	(1.71)
EHETE	-0.16**	-0.15*	-0.16**	-0.16*
	(-2.32)	(-2.17)	(-2.41)	(-2.27)
DISA	0.0003	0.0001	-0.0004	-0.0006
	(0.15)	(0.07)	(-0.21)	(-0.27)
Year dummy	Yes	Yes	Yes	Yes
Serial correlation				
First order (P-value)	0.00	0.00	0.00	0.00
Second order (P-value)	0.13	0.01	0.13	0.01
Sample	435	435	435	435
Groups	28	28	28	28

Notes: Numbers in parentheses are t-statistics. * and ** indicate significance at 5 and 1 per cent levels respectively (one-sided tests). In each estimates, year dummies are included, but not reported to save the space.

APPENDIX

Table A 1

Technological Progress and Inequality (Fixed Effects Model)

	(1) TNCH FE	(2) TNCH FE2sls	(3) TNCH FE	(4) TNCH FE2sls	(5) TNCH FE	(6) TNCH FE2sls	(7) TNCH FE	(8) TNCH FE2sls
TNLEV	-0.009	-0.02*	-0.004					
	(-0.94)	(-2.18)	(-0.44)					
TNCH_1				-0.02	0.12**	0.06	0.11**	0.01
				(-0.08)	(2.63)	(1.27)	(2.37)	(0.23)
GINI	0.01	0.04	0.31**	0.06	0.009	-0.01	0.29*	1.34**
	(0.65)	(0.73)	(2.47)	(0.07)	(0.36)	(-0.27)	(2.29)	(2.53)
GINI2			-0.37**	-0.01			-0.35*	-1.92**
			(-2.39)	(-0.01)			(-2.27)	(-2.58)
HC	0.0001	-0.008	0.002	-0.008	0.001	-0.01	0.003	0.01
	(0.01)	(-0.73)	(0.16)	(-0.61)	(0.12)	(-1.25)	(0.25)	(0.74)
OPEN	-0.03**	-0.02**	-0.02**	-0.02*	-0.02**	-0.03**	-0.02**	-0.004
	(-4.06)	(-3.71)	(-3.34)	(-1.97)	(-3.63)	(-4.25)	(-2.93)	(-0.31)
GOV	0.10	0.09	0.08	0.09	0.10	0.04	0.07	-0.14
	(1.50)	(1.44)	(1.15)	(0.54)	(1.44)	(0.71)	(1.06)	(-1.43)
INVS	0.03	0.01	0.01	0.01	0.03	0.002	0.01	-0.12*
	(0.90)	(0.37)	(0.50)	(0.15)	(0.92)	(0.07)	(0.47)	(-1.81)
EHETE	0.0009	0.09	-0.03	0.09	-0.06	-0.04	-0.07	-0.02
	(0.01)	(0.73)	(-0.28)	(0.49)	(-0.66)	(-0.38)	(-0.70)	(-0.22)
DISA	0.0006*	0.0004	0.0005	0.0004	0.0005	0.0003	0.0005	0.00004
	(1.81)	(1.20)	(1.58)	(0.94)	(1.76)	(1.05)	(1.53)	(0.11)
Year dummy	Yes	No	Yes	No	Yes	No	Yes	No
Sample	466	466	466	466	466	466	466	466
Groups	31	31	31	31	31	31	31	31

Notes: Numbers in parentheses are t-statistics. * and ** indicate significance at 5 and 1 per cent levels respectively (one-sided tests). In each estimates, year dummies are included, but not reported to save the space. We employ the fixed effects 2sls model and its results are presented in columns (3) and (6). The instruments used are year dummies and cross products of 80s dummy and legal origin dummies such as English common law dummy and French commercial code dummy.

Table A2

Technological Progress and Inequality (Dynamic Panel Model)

	(1) TNCH	(2) TNCH	(3) TNCH	(4) TNCH
TNCH_1	0.12**	0.10*	0.11**	0.09*
	(2.70)	(2.17)	(2.45)	(1.93)
TNCH_2		0.17**		0.16**
		(3.72)		(3.58)
GINI	0.01	0.002	0.29**	0.24*
	(0.41)	(0.08)	(2.37)	(1.99)
GINI2			-0.35**	-0.31*
			(-2.35)	(-2.02)
HC	0.0003	0.004	0.003	0.006
	(0.03)	(0.30)	(0.26)	(0.49)
OPEN	-0.02**	-0.02**	-0.02**	-0.01*
	(-3.78)	(-2.89)	(-3.03)	(-2.29)
GOV	0.10	0.09	0.07	0.07
	(1.49)	(1.36)	(1.10)	(1.02)
INVS	0.03	0.03	0.01	0.01
	(0.97)	(0.81)	(0.49)	(0.40)
EHETE	-0.07	-0.12	-0.07	-0.12
	(-0.70)	(-1.23)	(-0.72)	(-1.23)
DISA	0.0005*	0.0006*	0.0005	0.0005
	(1.82)	(1.82)	(1.58)	(1.61)
Year dummy	Yes	Yes	Yes	Yes
Serial correlation				
First order (P-value)	0.00	0.00	0.00	0.00
Second order (P-value)	0.00	0.00	0.00	0.00
Sample	435	435	435	435
Groups	28	28	28	28

Notes: Numbers in parentheses are t-statistics. * and ** indicate significance at 5 and 1 per cent levels respectively (one-sided tests). In each estimates, year dummies are included, but not reported to save the space.