

Threshold Effects of Inequality on Economic Growth in the US States: The Role of Human Capital to Physical Capital Ratio[#]

Oğuzhan Çepni^{*}, Rangan Gupta^{**} and Zhihui Lv^{***}

Abstract

Theory suggests that the effect of inequality on growth varies with the level of economic development, as captured by the ratio of human capital to physical capital. In particular, the effect is shown to be positive at lower levels of this ratio, and turns negative beyond a threshold in such models. Using a comprehensive panel of annual data for the 48 contiguous US states over the period 1948 to 2014, we find overwhelming evidence in support of this theory, unlike prior work on this topic. Hence, our paper highlights the importance of accurately measuring the process of economic development using data on human capital and physical capital, instead of using proxies that are not theoretically consistent. Understandably, if not done so, policymakers would end up undertaking incorrect decisions.

JEL Codes: C23, C24, E24, O11, O15.

Keywords: Inequality, Economic Growth, Ratio of Human Capital to Physical Capital, Panel Threshold Model, State-Level Data of the United States.

[#] We would like to thank an anonymous referee for many helpful comments. However, any remaining errors are solely ours.

^{*} Central Bank of the Republic of Turkey, Anafartalar Mah. Istiklal Cad. No:10 06050, Ankara, Turkey.
Email: Oguzhan.Cepni@tcmb.gov.tr.

^{**} Corresponding author. Department of Economics, University of Pretoria, Pretoria, 0002, South Africa.
Email: rangan.gupta@up.ac.za.

^{***} KLASMOE & School of Mathematics and Statistics, Northeast Normal University, Changchun 130024, China. Email: luzh694@nenu.edu.cn.

1. Introduction

In a major contribution to the theoretical relationship between growth and inequality, Galor and Moav (2004) argue that human capital accumulation endogenously replaces physical capital accumulation in the transition of an economy from a less developed to a developed state. The authors argue that in the early stage of development, the rate of return on physical capital is higher relative to that on human capital, which causes inequality to channel resources to owners of capital with higher marginal propensity to save, in the presence of credit market imperfection, and in the process results in increased physical capital accumulation and growth. However, in the later stage, the return on human capital is higher compared to physical capital, and thus, human capital accumulation drives economic growth, and equality reduces the adverse effects of credit constraints on human capital investment to result in an increase in economic growth. Hence, this theoretical framework of Galor and Moav (2004) implies a nonlinear relationship between inequality and economic growth.

Though conventional wisdom suggests the United States (US) is a land of equal opportunity, where those who work hard can succeed, the past three-and-a-half decades have witnessed growing income inequality due to variety of reasons (see for example, Berisha and Meszaros (2017, 2018), and Berisha et al., (2017) for further details in this regard involving aggregate and state-level data analyses). Hence, the impact of inequality on economic growth is an equally important question for the US, just like any other economy in the world (see for example in this regard, Chang et al., (2018, forthcoming) and Ben Nasr et al., (2019a) for detailed literature reviews on the impact of inequality on growth for the US). Against this backdrop, the objective of our paper is to empirically test the above-mentioned theoretical predictions based on state-level data of the 48 contiguous states of the economy of the US covering the annual period of 1948 to 2014. From the perspective of the econometric methodology, we employ the technique of threshold regression with instrumental variables, as suggested by Caner and Hansen (2004), which in turn captures any threshold effect endogenously in the inequality-growth relationship without fixing the threshold values. At this stage, it must be emphasized that, while there is likely to be lot of homogeneity when looking at state-level rather than cross-country data in terms of the way the inequality (as well as income) variables are collected and measured, as well as in terms of institutions, political process, and social climate, there is widespread evidence that the states of the US differ markedly in terms of their levels of growth and inequality (Bittencourt, 2019), and hence nonlinearity cannot be ignored. The homogeneity along the abovementioned dimensions however, helps in the fact that we need lesser control variables to analyze the relationship between inequality and growth, and also that the estimated coefficients are stable across observations that belong to the same income regime is more justifiable when state data is used. Further, there is strong evidence that there exists convergence clubs and clustering of income and inequality in the US states (Choi and Wang, 2015; Gogas et al., 2017; Apergis et al., 2018), and hence, there are likely to be regimes or nonlinearity in the relationship between growth and inequality. Finally, the theory of Galor and Moav (2004) which argues that human capital accumulation endogenously

replaces physical capital accumulation in the transition of an economy from a less developed to a developed state, requires an underlying channel of high mobility of factors - the possibility of which is more likely within the states of a country than across countries. Overall, one cannot overlook the possibility of a nonlinear relationship between inequality and growth within the US states, even though there exists homogeneity in terms of multiple factors.¹

Note that the Galor and Moav (2004) model has already been tested for the US at state-level by Lin et al., (2014) based on per capita real income as the threshold variable that serves as a proxy for development. However, these authors show that the effect of inequality on growth is significantly negative at lower levels of development, and then turns significantly positive at higher levels of development. In other words, Lin et al. (2014) detect evidence that is opposite to the claims of the theoretical model.² Realizing that the invalidity of the theoretical models could be due to the usage of a proxy for the process of development, we construct explicit measures of human capital to physical capital, and investigate how the effect of inequality on growth changes based on the transition from low to high values of the human capital to physical capital ratio. Hence, we are more precise in terms of matching the theoretical model dealing with the relative change in human capital as compared to physical capital in the process of economic development. Thus, our empirical study can be considered to be an extension of the work of Lin et al., (2014) by being theoretically more consistent. While such an empirical framework has been considered by Bhatti et al., (2015) for 82 countries to provide support for the theoretical model of Galor and Moav (2004), to the best of our knowledge, this is the first paper to use human capital-to-physical capital ratio in order to investigate the threshold effects of inequality on economic growth for the state-level data of the US. The remainder of the paper is organized as follows: Section 2 discusses the data and the methodology adopted for the empirical analysis, with Section 3 presenting the results, and section 4 concluding the paper.

2. Data and Methodology

2.1 Data

This study makes use of 48 (barring Alaska and Hawaii) contiguous state-level US data at annual frequency data over the period of 1948 to 2014. The dependent variable in our econometric analysis, denoted by “*GROWTH*,” is the annual growth rate of real per capita state income. Nominal state income per capita is derived from the Regional Economic Accounts of the Bureau of Economic Analysis (BEA), and is deflated using the overall consumer price index (CPI) of the US economy, with the latter derived from the FRED database of the Federal Reserve Bank of St. Louis. Inequality is represented by the Gini coefficient (*GINI*) as in Bhatti et al., (2015) which shows how far a country's wealth or income distribution deviates from a complete equal distribution. The data on

¹ We would like to thank the anonymous referee for directing us to clarify this issue.

² Lin et al., (2009) had earlier obtained similar results at the country-level, again based on per capita real income as a proxy for the process of development.

this measure of inequality is available from the website of Professor Mark W. Frank at: https://www.shsu.edu/eco_mwf/inequality.html, and is based on the paper by Frank (2009). In addition, log of initial value of real per capita income (*LY0*) is included to control for convergence, whereas population growth (*POPG*) is included to incorporate the demographic effects, with the levels of the latter variable also derived from the Regional Economic Accounts database of the BEA. We use log of high school attainment (i.e., the total number of high school graduates divided by the total state population) to per capita capital stock (*HKH*), and log of college attainment (i.e., the total number of college graduates divided by the total state population) to per capita capital stock (*HKC*) as two proxies of our threshold variable (*HK*). The high school and college attainments data is based on Frank (2009) and is again derived from the website of Professor Frank, while the real capital stock data comes from Garofalo and Yamarik (2002) and Yamarik (2013).³

2.2 Methodology

In order to investigate whether and to what extent the level of economic development affects the impact of inequality (x) on growth (y), we introduce non-linearity by utilizing a panel threshold model which allows the slope coefficients to be regime dependent. In particular, we consider the following panel threshold model of Hansen (1999):

$$y_{it} = \mu_i + \beta_2 x_{it} I(q_{it} \leq \gamma) + \beta_1 x_{it} I(q_{it} > \gamma) + \theta' z_{it} + e_{it} \quad (1)$$

where $I(\cdot)$ is an indicator function, q_{it} is the threshold variable (*HKC* or *HKH*), and γ is the threshold parameter that divides the equation into different regimes, and z_{it} is a set of growth determinants, which in our case is *LY0*, *POPG*, and *HKH* or *HKC* and x_{it} is a measure of income inequality (GINI). The error term e_{it} is assumed to be distributed with mean zero and variance σ^2 . Then, we can estimate the threshold value γ by minimizing the concentrated sum of squared residuals denoted by $S_1(\gamma)$.

Put differently, the procedure searches over the whole sample and finds the estimate of threshold value $\hat{\gamma}$ that minimizes the concentrated sum of squared residuals. The least squares estimator of parameter γ is then obtained by:

$$\hat{\gamma} = \underset{\gamma}{\operatorname{argmin}} S_1(\gamma) \quad (2)$$

Moreover, it is crucial to determine whether there exists a threshold effect. To this end, we implement the likelihood ratio test suggested by Hansen (1999) to test the null hypothesis of no threshold effect:

$$\begin{aligned} H_0: \beta_1 &= \beta_2 \\ H_1: \beta_1 &\neq \beta_2 \end{aligned}$$

The F -statistic is constructed as

$$F_1 = \frac{S_0 - S_1(\hat{\gamma})}{\hat{\sigma}^2} \quad (3)$$

where S_0 is the residual sum of squares of the linear model. Since the threshold

³ We would like to thank Professor Steven Yamarik for kindly sharing the updated version of the data with us.

parameter is not identified and estimated endogenously, the asymptotic distribution of test statistics is not standard due to the existence of the nuisance parameter. In this regard, Hansen (1996) propose a bootstrap methodology where p -values are asymptotically valid.

Based on the estimated threshold value $\hat{\gamma}$, the whole sample is split into the two indicated subsamples, and then the generalized least squares (GLS) method is utilized to obtain the coefficient estimates of (1) in each subsamples.

3. Empirical Results

In this section, we turn to discuss the threshold regression results to analyze the nonlinear effect of the income inequality ($GINI$) on growth, by allowing our threshold variable to be the different measures of the HK ratio for schooling i.e., HKC or HKH . Note that, given issues of endogeneity (Ben Nasr, 2019b; Hailemariam and Dzhumashev, 2019), we instrumented the $GINI$ variable using the method suggested Caner and Hansen (2004) by estimating a linear model for our particular measure of inequality as a function of one lag each of inequality, $POPG$, $LY0$, and HKH or HKC (depending upon which HK variable we are using as the threshold), and $LY0$, and then use the fitted inequality from this regression in the growth equation, besides one lag each of $POPG$, $LY0$, and HKH or HKC as additional controls.

Table 1 summarizes the estimates of the threshold parameter and the regression coefficients, using different threshold variables, i.e., HKH or HKC . According to the estimated threshold value of γ , the whole sample can be divided into two subsamples. The estimators for the threshold parameter $\hat{\gamma}$ occur at -6.724 and -8.399 for HKH and HKC respectively,⁴ and the estimators for threshold parameter are statistically significant. According to Son (2010), HK ratios are expected to be relatively low for developing countries due to low levels of education when compared to developed countries. Building on this view, we classify US states falling into the $HKH_{i,t}$ or $HKC_{i,t} > \gamma$ regime as high-educated states, while the states for which $HKH_{i,t}$ or $HKC_{i,t} \leq \gamma$ regime holds, we can categorize them as the low-educated states.

⁴ Note that the HKH and HKC variables are in logarithms, with the raw values of HKH and HKC being fractions (as physical capital stock is larger than human capital stock), and hence, the thresholds which provide the logarithmic values for HKH and HKC are negative, and translates into 0.0012 and 0.0002 respectively for the raw data.

Table 1: Threshold model estimates using *HKH* and *HKC* measures

Threshold Estimation	Model 1 (<i>HKH</i>)		Model 2 (<i>HKC</i>)	
$\hat{\gamma}$	-6.724		-8.399	
<i>LM</i> stat.	32.32		35.17	
<i>p</i> -value	0.001		0.001	
Growth Equation	$HKH \leq \hat{\gamma}$	$HKH > \hat{\gamma}$	$HKC \leq \hat{\gamma}$	$HKC > \hat{\gamma}$
\widehat{GINI}_{it}	0.0682** (0.031)	-0.0249* (0.014)	0.0855** (0.034)	-0.0291** (0.012)
HKH_{it-1}	0.0121*** (0.004)	0.0265*** (0.007)	0.0149*** (0.005)	0.0155*** (0.003)
$POPG_{it-1}$	0.0277 (0.084)	0.0395 (0.073)	0.0599 (0.081)	-0.0443 (0.056)
LYO_{it-1}	-0.0254*** (0.004)	-0.0124*** (0.002)	-0.0248*** (0.004)	-0.0201*** (0.004)
Constant	0.1880*** (0.031)	0.2640*** (0.051)	0.2235*** (0.046)	0.2551*** (0.037)
Observations	1419	1749	1223	1945

Note: The dependent variable is *GROWTH*,” i.e., the annual growth rate of real per capita state income, and \widehat{GINI} is the instrumented measure of inequality. The robust standard errors reported in parentheses. ***, **, * indicates significant at 1%, 5% and 10% level, respectively.

An inspection of Table 1 leads to a number of observations. First, the coefficient estimates on the inequality measure are significantly different from zero across both-regimes, reflecting that income inequality and economic growth are not linearly related. Second, regardless of the selected threshold HK measure, the coefficients of inequality measures are negative in low-educated states, whereas the estimated coefficients are positive in high-educated states. This finding implies that the relationship between inequality and growth varies based on the level of the ratio of human capital to physical capital, as suggested by the theoretical model of Galor and Moav (2004).⁵ Third, the estimated coefficients on the inequality measure are bigger in low-educated states than in high-educated states implying that the positive effect of inequality on growth is larger in low-educated states, than the negative impact on high-educated states. Based on the

⁵ As a preliminary analysis, we estimated a linear model with an interaction term involving inequality and the two HK variables separately. The results of regressions with interaction term strongly confirmed that the marginal effect of inequality on growth constantly changed as *HKH* or *HKC* increased. When *HKH* or *HKC* is relatively, inequality and growth were found to be positively related, but as *HKH* or *HKC* increased along the process of economic development, the relationship became less positive over time. In other words, the statistically significant negative coefficient on the interaction term suggested that at higher levels of economic development, the link between inequality and growth may eventually turn from positive to negative – an observation formally confirmed by the nonlinear model. Complete details of these results are available upon request from the authors.

coefficients, a 1-Gini point reduction in inequality would increase economic growth by about 0.3 percentage point in the high-educated states, while the same would reduce growth in low-educated states between the range of 0.7 to 0.9 percentage points depending on whether the threshold is *HKH* or *HKC* respectively. Fourth, the ratio of human capital to physical capital is found to be growth enhancing, though population growth has no significant effects. Finally, there is strong evidence of convergence across the states, given the negative and significant coefficient of the initial level of income.

4. Conclusion

The theoretical framework of Galor and Moav (2004) suggests a nonlinear relationship between inequality and economic growth, along the process of economic development as captured by the ratio of human capital to physical capital. This model tend to suggest that while the effect is positive below a certain threshold of the ratio of human to physical capital, the effect turns negative thereafter. Our paper examines whether the effect of inequality on growth varies with the level of economic development. Using a comprehensive panel of annual data for the 48 contiguous US states over the period 1948–2014, where the process of development is captured by newly-constructed measures of human capital and physical capital, we find overwhelming evidence in support of threshold effects in the relationship between inequality and growth. Our analysis shows that while the effect of inequality on growth is significantly positive at lower levels of development, this effect turns significantly negative at higher levels of development. Our theory-consistent result is in contrast to prior work on the US states, which, based on a proxy for the level of development, produced a diametrically opposite conclusion. We thus highlight the need to use data that corresponds exactly to the theory, before validating or invalidating such models. Understandably, if this is not done, policy recommendations are likely to be incorrect. In this regard, we can conclude that that in devising policies for redistribution, states need to take into account their position in the developmental process, as captured by the human capital to physical capital ratio. If the states are above the threshold value of this ratio, then greater redistribution is likely to generate not only greater equality, but also faster economic growth. However, if the states are below this threshold, then policymakers should be cautious in implementing redistributive policies via distortionary taxes, since this would negatively impact the dominant physical capital (relative to human capital) investment and reduce growth.

References

- Apergis, N., Christou, C., Gupta, R., & Miller, S.M. (2018). Convergence in Income Inequality: Further Evidence from the Club Clustering Methodology across States in the U.S. *International Advances in Economic Research*, 24 (2), 147–161.
- Ben Nasr, A., Balcilar, M., Gupta, R., & Akadiri, S. S. (2019). Asymmetric effects of inequality on real output levels of the United States. *Eurasian Economic Review*. DOI: <https://doi.org/10.1007/s40822-019-00129-x>.
- Ben Nasr, A., Mehmet Balcilar, M., Akadiri, S S., & Gupta, R. (2019). Kuznets Curve for the US: A Reconsideration Using Cosummability. *Social Indicators Research*:

An International and Interdisciplinary Journal for Quality-of-Life Measurement, 142(2), 827-843.

- Berisha, E., & Meszaros, J. (2017). Household debt, economic conditions, and income inequality: A state level analysis. *The Social Science Journal*, 54(1), 93-101.
- Berisha, E., & Meszaros, J. (2018). Household debt, expected economic conditions, and income inequality. *International Journal of Finance & Economics*, 23(3), 283-295.
- Berisha, E., Meszaros, J., & Olson, E. (2017). Income Inequality, Equities, Household Debt, and Interest Rates: Evidence from a Century of Data. *Journal of International Money and Finance*, 80, 1-14.
- Bittencourt, M., Chang, S., Gupta, R., & Miller, S. M. (2019). Does Financial Development Affect Income Inequality in the U.S. States? A Panel Data Analysis. *Journal of Policy Modeling*. DOI: <https://doi.org/10.1016/j.jpolmod.2019.07.008>.
- Bhatti, A. A., Haque, M. E., & Osborn, D. R. (2015). Threshold Effects of Inequality on the Process of Economic Growth. Centre for Growth and Business Cycle Research Discussion Paper Series, No. 205, Economics, University of Manchester.
- Caner, M., & Hansen, B. E., (2004). Instrumental variable estimation of a threshold model. *Econometric Theory*, 20(5), 813-843.
- Chang, S., Gupta, R., & Miller, S. M. (2018). Causality between Per Capita Real GDP and Income Inequality in the U.S.: Evidence from a Wavelet Analysis. *Social Indicators Research: An International and Interdisciplinary Journal for Quality-of-Life Measurement*, 135(1), 269-289.
- Chang, S., Hsiao-Ping, C., Gupta, R., Miller, S. M. (Forthcoming). Causality between Output and Income Inequality across US States: Evidence from a Heterogeneous Mixed Panel Approach. *Journal of Income Distribution*.
- Choi, C-Y., & Wang, X. (2015). Discontinuity Of Output Convergence Within The United States: Why Has The Course Changed? *Economic Inquiry*, 53(1), 49-71.
- Frank, M. W. (2009). Inequality and Growth in the United States: Evidence from a New State-Level Panel of Income Inequality Measures. *Economic Inquiry*, 47 55–68.
- Galor, O., & Moav, O., (2004). From physical to human capital accumulation: Inequality and the process of development. *The Review of Economic Studies*, 71(4), 1001-1026.
- Garofalo, G. A., & Yamarik, S. (2002). Regional convergence: Evidence from a new state-by-state capital stock series. *Review of Economics and Statistics*, 84(2), 316-323.
- Gogas, P., Gupta, R., Miller, S.M., Papadimitriou, T., & Sarantitis, G.A. (2017). Income Inequality: A State-by-State Complex Network Analysis. *Physica A: Statistical Mechanics and its Applications*, 483, 423-437.
- Hansen, B. E. (1996). Inference when a nuisance parameter is not identified under the null hypothesis. *Econometrica*, 64, 413-430.
- Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics*, 93(2), 345-368.
- Hailemariam, A., & Dzhumashev, R. (2019). Income Inequality and Economic Growth: Heterogeneity and Nonlinearity. *Studies in Nonlinear Dynamics & Econometrics*. DOI: <https://doi.org/10.1515/snde-2018-0084>.

- Lin, S. C., Huang, H-C., Kim, D. H., & Yeh, C.-C. (2009). Nonlinearity between inequality and growth. *Studies in Nonlinear Dynamics & Econometrics*, 13(2), Article No. 3.
- Lin, Y-C., Huang, H-C., & Yeh, C-C. (2014). Inequality-growth nexus along the development process. *Studies in Nonlinear Dynamics & Econometrics*, 18(3), 237-252.
- Son, H. H. (2010). Human capital development. Asian Development Bank Economics Working Paper Series No. 225.
- Yamarik, S. (2013). State-Level Capital and Investment: Updates and Implications. *Contemporary Economic Policy*, 31(1), 62-72.