Income Inequality and Total Factor Productivity: An Inverse-Parabolic Relationship

Altuğ Yıldız

Department of Economics

Rutgers, The State University of New Jersey

Abstract

This paper investigates the possibility of a non-linear relationship between income inequality and total factor productivity. Using unbalanced panel data including up to 62 countries over a period of 50 years (taken in five year increments), GMM estimation techniques were employed (namely the two-step difference GMM and the System GMM). Twenty different specifications under five different subsets were used for robustness. The inequality measure was statistically significant and positive and its squared value was statistically significant and negative in all regressions with the Gini measure, and the Top 10%'s share of income had the same signs but these were not always significant. The results establish an inverse-U relationship between income inequality and aggregate productivity, with the turning point being higher for developing (non-OECD) countries.

Introduction

Over the last few decades, high-income, advanced economies experienced steady rises in wealth and income inequality, accompanied by a decline in their growth rates of productivity (Paganetto, 2016). Figure 1 displays the trends in income inequality for some of those countries. Whereas some inequality is considered necessary to have the right incentives in place for adequate investment, growth, and the effective functioning of a free-market economy, inequality can be disrupting when left unchecked (Berg & Ostry, 2017). Addressing the adverse effects associated with excess inequality may well be the defining challenge of our time (Krugman, 2013).

Traditionally, the neoliberal textbook argument had been that inequality was by and large necessary for economic growth - higher incomes provide needed incentives for those more able to work harder and to invest. While earlier work posited a natural trade-off between equality and efficiency (Okun, 1975), this view has since been challenged on both theoretical and empirical grounds. Since then, theory has outlined several ways in which inequality in wealth and incomes can have complex effects on the macro-economy through the channels of consumption, savings, and investment.

There is ample research on this relationship - both empirical and theoretical. Perhaps not surprisingly, these employ a variety of methodologies and arrive at different conclusions.

This alone suggests that the relationship between income inequality and economic growth is much deeper and complex than previously considered. To summarize a few on the empirical side, Persson and Tabellini (1994), and Alesina and Rodrik (1994) find that inequality has a negative impact on economic growth. The findings of Wan et. al. (2006) support these results in the short, medium, and long runs for China. On the other hand, panel data studies by Li, Squire and Zou (1998), and Forbes (2000) find positive effects of inequality on economic growth, contradicting these previous findings. More recently, Marrero and Rodríguez (2013) also find a positive relationship.

Given the apparent non-triviality of the relationship, several papers have sought to dissect the different manners in which inequality and economic growth could be related. On this front, an IMF paper investigating the relationship between income inequality and the sustainability of economic growth finds that in the long run, sustaining economic growth and preventing rampant inequality go hand in hand (Berg & Ostry, 2017). Similarly, Halter et. al. (2011) find that while inequality might have growth-boosting effects on the economy in the short run, these are far outweighed by the negative effects that arise when inequality is sustained over time. Brueckner et. al. (2018) add yet another dimension and find that the effects of inequality on economic growth depend on a country's initial level of income. Namely, this last paper finds that greater income inequality boosts transitional growth in low-income economies, where the opposite effect is true for those countries in the high-income category.

Given that establishing unidirectional causality between these two variables of interest is problematic in itself, there has also been research published on the effects of growth on inequality (e.g. Gil-Alana et. al., 2019). Finally, there is also a case to be made for a non-linear relationship. A theoretical model developed by Benhabib (2003) finds increasing inequality from low levels can have growth enhancing effects through providing added incentives for investment. However, these effects are dominated by rent-seeking inefficiencies past some threshold of inequality, thereby suggesting that the relationship between inequality and growth might be mildly hump shaped. Paleologou (2019) uses a System GMM to identify such a threshold point of inequality, beyond which the variable starts having a negative impact on growth - displaying an inverted-U shape. These last papers naturally call to mind the Kuznets curve.

Many have written about the relationship between inequality and economic growth, perhaps none more famous than Simon Kuznets (1955). Using per capita national income as proxy for economic growth, Kuznets argued that the evolution of income inequality follows the different stages of economic development (Chen et. al., 2003). More specifically, as per capita income rises in developing nations, Kuznets argued, inequality will tend to rise in the initial stages of development, reach a crest, and then begin to fall. This results in an inverted-U shape when inequality is plotted against per capita income, the graph of which is commonly referred to as "The Kuznets Curve."

Despite its groundbreaking hypothesis, evidence on the Kuznets inverted-U is mixed. While early empirical research tends to back this hypothesis (see Barro, 1991; Ram, 1991; Anand, 1993), the development experience of the "East Asian Tigers" is a notable counter-example. Namely, these countries (among which Japan, South Korea, Thailand, Malaysia...) progressed through the stages of development while keeping a relatively equal income distribution as millions were lifted out of poverty. Furthermore, more recent empirical studies by Zhou & Li (2011), and Li & Zhou (2013) find a more complex relationship using both non-parametric and semi-parametric methods. All in all, they find that over a period of 40 years, the Kuznets curve holds until displaying a second upswing in inequality at higher levels of per capita income for more developed (OECD) countries, where the resultant image is one of several crests and troughs for non-OECD countries. In light of these findings, it is likely that the response of income inequality to some of the deeper variables that affect economic growth is less determinate than what Kuznets had imagined. For example, while major determinants of economic growth such as capital and labor input could have predictable effects on the income distribution, it is not unfathomable to think that the initial income distribution could in turn influence these inputs too.

Considering the difficulty of dissecting the effects of inequality on these deeper variables or vice versa, understanding the role of the income distribution in long-run economic growth remains a complex matter. That being said, diminishing returns to scale to both capital and labor imply that long-run economic growth is best achieved by changes in aggregate productivity. Hence, one could analyze the effects of inequality on long run economic growth by keeping these other factors of production constant. The Solow Residual (1957), also known as Total Factor Productivity (TFP), seeks to do just that. A popular measure of productivity in economic research due to its parsimonious nature, the Solow Residual aims to capture the rise in output as the main factors of production (capital and labor) are kept constant. In layman's terms, it indicates whether economic growth occurs due to increases in inputs to capital and labor, or because the existing factors of production are utilised more productively. This notion prompts the author to ask whether inequality could impact economic growth beyond its effects on the input of capital and labor, in other words, through its effects on aggregate productivity.

As with the case of economic growth, a simple thought exercise would suffice to establish that some inequality (as opposed to perfect equality) would have positive impacts on aggregate productivity given different levels of skill among the labor force. The more interesting question would then be to ask whether this relationship is linear, or indeed always positive. In fact, there might be several channels through which inequality beyond an efficient (productivity-maximizing) point could have detrimental effects on aggregate productivity. For example, the extremely poor in an increasingly unequal society may not have the necessary means to invest in their human capital through financing their (or their children's) education (Berg & Ostry, 2017; Garcia-Peñalosa, 2018). To this effect, an OECD research paper identifies that in countries with higher levels of inequality, the children of poorly-educated parents tend to perform worse academically than their socioeconomic counterparts in countries with less inequality (Paganetto, 2016). This loss of human capital can also be exacerbated by decreased effort from the existing labor force. Aghion and Bolton (1997) note that under limited-liability conditions, the residual claimant to accrued profits from an investment is the lender, meaning that borrowers (which are in larger part among high-inequality countries) may have less incentives to exert effort since they are less likely to reap the benefits (Garcia-Peñalosa, 2018).

Proposing a different channel through which inequality can hinder productivity, Basu & Stiglitz (2016) suggest that societies with greater levels of inequality are less likely to undertake productivity-enhancing, long-term public investments. Halter et. al. (2011) expand on this, stating that the decisive voter supplies less physical or human capital when there is higher asset-inequality in an economy, making them more likely to favor direct, lump-sum transfers from the government over long-term, potentially productivity-boosting public investments. Finally, excess inequality might also have long-term destabilizing effects on the macroeconomy through negative externalities. These include (but are not limited to) decreasing social mobility (which in turn causes under-investment in human capital and could lead to the aforementioned effects), inciting social unrest (causing under-investment in the economy both internal and external), and incentivizing increased rent-seeking behavior (causing a misallocation of valuable economic resources) (Paganetto, 2016). These seem to suggest that as was the case with economic growth, curbing rampant inequality goes hand in hand with sustaining aggregated productivity. Indeed, micro-level evidence points in the same direction: Gang et al. (2022) find that gender-based inequality among enterprise owners is associated with measurable productivity gaps in India's informal sector, suggesting that distributional factors operate through productivity channels even at the firm level.

The research question is made all the more relevant by the complex nature of empirical findings. While there is an abundance of research on the interplay between income inequality on economic growth as noted earlier, research on the effects of inequality on productivity is scant. Even so, combining economic theory with a review of existing literature should act as a compelling start. Hence, using unbalanced panel data including up to 62 countries over a period of 50 years (taken in five year increments), this paper sets out to investigate whether inequality has a decreasingly positive effect on aggregate productivity, displaying a hump-shaped curve similar to that of Kuznets.

The paper is organized in the following manner. The next two sections will outline the methodology and describe the data. The ensuing section will present and discuss the results. The penultimate section will highlight limitations associated with this study and propose extensions to enrich its scope. The final section will conclude.

Methodology

It is commonly acknowledged that when the lagged version of the dependent variable is included as a regressor, standard panel data techniques such as random effects or within group estimations are viable to yield inconsistent estimates, especially in small sample sizes (Bond et. al., 2001). As a result, dynamic panel data is more and more commonly estimated via difference and system Generalized Method of Moments (GMM) (Holtz-Eakin, Newey & Rosen, 1988; Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998).

The difference (Arellano & Bond, 1991) and system (Arellano & Bover, 1995) GMM estimators have been rigorously outlined in literature (for further detail, see the original papers by Arellano & Bond; Bond, 2002; Croissant & Millo, 2008; or Roodman, 2009). Both estimators are designed for panel data that is short, either balanced or unbalanced, to fit linear models with a dynamic dependent variable, fixed effects, and additional controls in the lack of good external instruments. They are flexible in application and deal with modeling concerns (such as fixed effects and endogenous regressors) while avoiding dynamic panel bias (Nickell, 1981). The resulting equation takes some version of the form:

$$y_{i,t} = \alpha y_{i,t-1} + \beta x'_{i,t} + \mu_i + \nu_{i,t}$$

$$E(\mu_i) = E(\nu_{i,t}) = E(\mu_i \nu_{i,t}) = 0$$

where i indexes the observational units, t is for time, and x is a vector of independent variables, possibly including controls or further lags of y. The fixed effects are given by μ_i, the idiosyncratic error term by $v_{i,t}$, and these are orthogonal by assumption. Both difference and system estimators fit this model using linear GMM. The former carries estimation after first-differencing the data in order to eliminate the fixed effects (hence the name), while the latter augments the difference GMM by carrying estimation simultaneously at levels and in differences, with these two equations being distinctively instrumented (Roodman, 2009). The validity of these instruments then hinges on homoskedasticity and the non-existence of serial correlation in the idiosyncratic error term. If these conditions are broken, even though the "one-step" difference GMM estimator remains consistent, the weighting matrix of moments is no longer a consistent estimate of the "true" weighting matrix, leading to an efficiency loss (Croissant & Millo, 2008). The "two-step" difference GMM partly resolves this problem by using the residuals recovered from the one-step estimate in its weighting matrix. This accounts for any problems that might arise due to unobserved heterogeneity among countries and the issue of a lagged dependent variable used as a regressor. However, the fact that within-country inequality is presumably highly persistent while across-country inequality displays considerable variation can weaken the instruments and thereby reinforce endogeneity bias (Staiger & Stock, 1997). When the analysis makes use of persistent series in which the lagged levels of the variables are weak instruments for future variation, the system GMM carries the most benefit over the difference GMM (Blundell & Bond, 1998, 2000; Blundell, Bond & Windmeijer, 2000). Namely, it adds extra moment conditions on the level equation along with the moment conditions in the first-differenced equation to then carry out estimation with a general weighting matrix and address these problems. Hence, this paper will estimate the previously outlined relationship between income inequality and TFP via both a difference (in two-steps) and a system GMM.

Data & Descriptive Statistics

Throughout this study, income inequality is operationalized using the Gini Index, although the top 10%'s share of total income is also used as a robustness check. Note that the square of the relevant inequality variable is also included as a regressor to check if a non-linear, quadratic relationship exists as previously hypothesized. Furthermore, the Solow Residual is taken as a measure of TFP.

A variety of open-access databases were used in this research. The Standardized World Income Inequality Database (SWIID) was used for the Gini coefficients (reported at post tax and transfer levels). The SWIID uses Bayesian methods to standardize observations collected from a wide variety of sources such as but not limited to the OECD Income Distribution Database, the Socio-Economic Database for Latin America and the Caribbean (compiled by the World Bank and CEDLAS), Eurostat, PovcalNet (also compiled by World Bank), the UN Economic Commission for Latin America and the Caribbean, and global national statistical offices. Data from the Luxembourg Income Study serves as the standard. This database is used because it achieves utmost comparability of the income inequality data that is freely available for the largest possible sample of countries and years (Solt, 2020). The particular estimate for the Gini Index is equivalized (scaled by square root) using households' post tax and transfer disposable income. The top 10%'s shares of national income (reported at pre tax levels) were taken from the World Inequality Database. Furthermore, data on total factor productivity was retrieved from the latest version of the Penn World Table (version 9.1), with the variable being reported at constant national prices indexed at the year 2011. Population growth and unemployment were chosen as suitable controls as they provided the most overlap with data availability. For any year t, the former is defined as the exponential rate of growth of midyear population from year t-1 to t, expressed as a percentage, where the latter is defined as a percentage of the total labor force in a country in any given year. Population growth data was taken from the World Development Indicators, which uses a combination of statistics from the UN Population Division, census reports and other statistical publications from national statistical offices, and Eurostat, where data for unemployment was retrieved from the ILOSTAT database, and complemented with data from the IFS database when observations were lacking.

As mentioned in the previous section, the variables are likely to be highly persistent in nature. Hence, five year averages were computed for all of them. For each country to have an entry, a minimum of three data-points were required in computing these averages. For example, averages for years 1981 through 1985 were coded as the five year average standing in 1985, those for years 1986 until 1990 were coded as the five year average in 1990, and so on. Furthermore, the Gini data-set[15] consists of those countries with at least a 5% change in their Gini Indices from their point of lowest inequality throughout the time

[15] Countries included: Argentina, Australia, Austria, Belgium, Bolivia, Brazil, Bulgaria, Burkina Faso, Canada, Chile, China, Costa Rica, Côte d'Ivoire, Denmark, Dominican Republic, Ecuador, Egypt, Finland, France, Germany, Greece, Guatemala, Honduras, Hong Kong, Hungary, Iceland, India, Indonesia, Iran, Ireland, Israel, Italy, Japan, Kenya, Lesotho, Luxembourg, Malaysia, Mauritania, Mexico, Netherlands, New Zealand, Norway, Panama, Paraguay, Peru, Poland, Republic of Korea, Romania, Sierra Leone, Singapore, Spain, Sri Lanka, Sweden, Switzerland, Tanzania, Thailand, Tunisia, Turkey, United Kingdom, United States, Uruguay, Venezuela.

period under consideration. This was done in order to focus the analysis on those countries whose inequality levels showed discernible change in an otherwise more comprehensive data-set. In contrast, the data-set using top shares of income (henceforth named Top Shares[16]) was not parcelled in the same manner due to the already more limited number of observations and a relatively higher variation across the board. The two data-sets thus allow the analysis to be run at both pre-tax, and post-tax and transfer levels of income, as well as with different subsets of countries. The tables in the appendix outline some descriptive statistics for the two.

Each data-set had entry points going back to 1965 (and up to 2015), and the countries included are as outlined in the footnotes earlier in this section (the Gini data-set consisted of 62 countries, to the Top Shares' 59). Table 1 displays some summary statistics for the Gini data-set. It includes 503 observations for all variables except the unemployment rate (Unemp), where fewer data points were available. For the countries in question, TFP ranges from a minimum of 0.481 (Korea, 1970) to a maximum of 2.176 (Mauritania, 1990), with a sample mean of 0.968. The Gini Index has a sample minimum value of 20.52 (Finland, 1985), a maximum of 53.32 (Peru, 1985) and a sample mean of 36.83. Note that this baseline data-set was later parcelled into smaller subsets as a robustness check. Summary statistics for these are given in the appendix. Table 2 presents the same summary

---

[16] Countries included: Australia, Austria, Belgium, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cameroon, Canada, Central African Republic, Chile, China, Cyprus, Denmark, Egypt, Finland, France, Germany, Greece, Hungary, Iceland, India, Ireland, Italy, Japan, Kenya, Lesotho, Luxembourg, Malta, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Netherlands, New Zealand, Niger, Nigeria, Norway, Poland, Portugal, Qatar, Republic of Korea, Romania, Senegal, Sierra Leone, Singapore, South Africa, Spain, Sweden, Switzerland, Tanzania, Thailand,Tunisia, Turkey, United Kingdom, United States, Zimbabwe.

statistics for the Top Shares data-set. It includes a maximum of 366 observations for TFP and population growth (PopG), with 361 observations available for the top 10%'s share of total income (Top10)[17] and only 310 observations for unemployment. The TFP figure here had the same maximum value and almost the same sample mean as the Gini data-set, despite a lower minimum value of 0.451 (Nigeria, 1990). The inequality variable of interest in this second data-set had a minimum of 0.161 (Hungary, 1985), a maximum of 0.709 (Namibia, 2005), and a sample mean of 0.387. The unemployment statistics of the two data-sets were not too dissimilar however, population growth showed much more variation in the Top Shares data-set with a maximum of 15.263 (Qatar, 2010) compared to Table 1's 4.164 (Sierra Leone, 2005).

To see how the variables of interest evolve with respect to one another at first glance, Figures 2 & 3 plot the relevant income inequality variable (Gini Index and top 10%'s share respectively) against TFP. Figure 4 complements these by plotting residualized TFP - that is, TFP net of time fixed effects and the controls - against the Gini index, with decile means overlaid alongside a quadratic fit, so as to more cleanly isolate the partial relationship between inequality and productivity.

While the graphs don't reveal too much, there seems to be a slightly positive relationship between income inequality and TFP, with the latter commencing its peak after the mean value of the relevant inequality measure, and coming back down. The peak being at approximately around the mean is promising in terms of revealing the quadratic, inverse-U

---

[17] It should come as no surprise that this latter measure of inequality was initially reported much less frequently than its more common predecessor in the Gini Index.

relationship previously posited. In line with this, the binned means in Figure 4 trace a mild but discernible hump shape, rising to a peak at around a Gini of 33-35 before declining steadily thereafter, thereby lending preliminary descriptive support to the previously posited inverse-parabolic relationship between the two. The next section presents an empirical analysis to place these preliminary observations under econometric scrutiny.

Results

The tables in the appendix present results for the difference and System GMM estimations previously outlined. Table 3 makes use of the comprehensive Gini data-set. The first two columns hold results for the difference GMM (with and without time dummies, respectively), and the latter two for the System GMM, in the same manner. Table 4 parcels this first data-set into OECD (regressions 1, 2, 5, 6) and non-OECD (regressions 3, 4, 7, 8) countries, and the difference/System GMM is separated into four columns each. Table 5 limits the analysis to a smaller time period (starting in 1990), and Table 6 uses the alternate inequality measure in the top 10%'s share of total income. In all of these regressions, the standard errors are clustered, heteroskedasticity robust, and the Windmeijer (2005) correction is applied. Statistics for the Arellano-Bond (1991) autocorrelation test of order 2 (since the models are in first differences) and the Hansen-Sargan over-identification test are reported.

On this note, and before discussing the results, it is worthwhile to address the issue of instrument proliferation. Namely, with GMM estimation, the number of instruments grows with the time dimension. Hence, estimation with popular software packages is liable to generate numerous instruments, which can over-fit the instrumented variables and yield biased coefficient estimates (Roodman, 2009).

The Hansen (1982) J-test is an industry standard specification check on this front, however, Andersen & Sorensen (1996), and Bowsher (2002) document that instrument proliferation weakens the test by virtue of this over-fitting problem. A high p-value on the Hansen test is normally the backbone of researchers' arguments for the validity of their GMM results. There is also a tendency to view p-values above the conventional the thresholds of 0.05 or 0.10 with complacency. Roodman (2009) argues that while those thresholds are deemed to be conservative when it comes to coefficient estimates, they are lax in ruling out correlation between the error term and the instruments. Hence, a p-value above 0.25 should raise questions, noting the fact that the test can often yield a p-value of 1.00 as a tell-tale sign of instrument proliferation, vitiating its ability to detect the issue.

The tables reveal certain trends. First of all, the first lag of TFP is usually a positive, significant predictor, and while population growth proves insignificant in all regressions, unemployment is at times a significant predictor. Before any in depth look, we can also notice that across the 5 different subsets and data-sets and the 20 regressions, the Gini measure is always positive and significant, and its square is negative as well as significant. In fact, the coefficients on Gini^2 is -0.07 for most of the time, and the coefficient on Gini fluctuates around the 4-5 range. When the relevant inequality measure is the top 10%'s share of total income, the inequality measure loses statistical significance in all but one regression but remains positive, and its squared value remains negative and significant. Hence, it could be said that while the effects of income inequality on TFP are decreasingly positive, they are decreasing at a very slow rate.

All of that being said, we can also see that the performance of these regressions on the relevant tests varies significantly from one specification to the next. Namely, looking at Table 3, the difference GMM performs well on the J-test but the Arellano-Bond autocorrelation test reveals serial correlation in errors in all four specifications. Table 4 presents regression results that show the OECD and non-OECD data-sets. Here, regression 1 does well on the J-test and rejects the null of serial correlation in the errors at the 5% level, but fails to do so at the 10% level. Regressions 2, 5, and 6 suffer from autocorrelation, and regressions 3, 5, 7 and 8 are over-identified. Regression 4 reports a J-test statistic of 0.37 which is higher than Roodman's (2009) rule of thumb, but not so high that the issue is glaring; it does not seem to suffer from autocorrelation either. The most promising specification in Table 5 is the System GMM with no time dummies (regression 4), and the difference GMM with no time dummies in Table 6 also performs quite desirably (with a J-test statistic of 0.24 and no serial correlation), especially considering that this is the only specification where the top shares' inequality measure is statistically significant.

Having established that the relationship between inequality and TFP is somewhat of an inverted-U, it could be worthwhile to ask where the turning point is from a policy standpoint. Looking at the regressions that performed well econometrically and yielded significant results (regressions 1 and 4 in Table 4, regression 4 in Table 5, and regression 2 in Table 6) and using some simple algebra, the "productivity maximising" point of income inequality can be extracted. Looking at Table 5, since the 1990's, this figure is approximately a Gini index of 39.7, which is just a bit higher than the sample mean (37.4). For the OECD countries, this figure is approximately 36.6, where the number is much higher for non-OECD countries, at 50.4. Both of these are beyond the 75^th% of their respective sample means, and the higher figure for non-OECD countries call to mind

Kuznets' hypothesis about increasing inequality being a part of the development process. Finally, Table 6 reveals an optimal figure of 0.37, which is just below its sample mean of 0.39, meaning once the top 10% of a population earn approximately two-fifths of a nation's total income, income inequality starts to become productivity-decreasing.

^{2t}hThat being said, these findings also speak to a deeper question: is it necessary for a developing economy to go through a period of increased inequality on its path to development? The higher turning point for non-OECD countries (a Gini of 50.4) might at first glance suggest that developing economies need to 'tolerate' more inequality before productivity gains begin to taper off. However, what is observed need not be what is inevitable. Namely, the Kuznets curve, while an influential hypothesis, need not be a predetermined trajectory that all developing economies must follow. The experience of the East Asian Tigers (as noted in the introduction) demonstrates that rapid development can occur alongside a relatively equal income distribution, and more recent evidence from countries such as Poland and the Czech Republic further suggests that the inverted-U is by no means a foregone conclusion. On this front, what seems to matter is not the level of inequality per se but the underlying source of that inequality. As Benhabib (2003) argues, inequality that arises from productive incentives – where higher returns reward innovation, risk-taking, and human capital investment – could be growth and productivity enhancing. Conversely, inequality that stems from rent-seeking behavior, institutional capture by elites, or the exclusion of large segments of the population from economic opportunity is likely to be productivity-destroying, as it diverts resources away from productive uses and towards the preservation of existing power structures. These seem to suggest that the inverse-parabolic relationship identified in this paper could be interpreted as capturing precisely this transition: at lower levels, inequality reflects the incentive effects that reward productive effort, but past the turning point, the rent-seeking and institutional capture channels begin to dominate, pulling aggregate productivity downward. Hence, the policy implication is not that developing economies must accept rising inequality as a necessary cost of development, but rather that the astute policymaker should seek to foster the kind of inequality that reflects productive incentives while curbing the kind that reflects elite extraction and rent-seeking inefficiencies.

Limitations & Extensions

The results seem to reveal an inverse-parabolic relationship does exist between income inequality and total factor productivity, with some estimates being more robust than others. That being said, these are only as strong as the methodology design. In this regard, as with any research, this paper has its limitations, and so can benefit from a few extensions.

First, a note must be made on causal inference. While randomized control trials are considered the gold standard in this regard, given their elusive nature in policy-relevant topics such as this, the GMM approach is a good alternative. Becker (2016) finds that not only does this kind of instrumental variable approach help establish causality (assuming the instruments are valid), but it can also help address measurement error in the variable of concern, omitted variable bias, and simultaneity bias too. On this note, the limitations and caveats associated with the dependent and independent variables are in no doubt important limiting factors to consider, albeit somewhat dealt with through the estimation technique.

Measurement Error

Total Factor Productivity

TFP is estimated by using index number techniques and is derived as a residual. Hence, it is more of a "measure of our ignorance," with plenty of potential for measurement error (Hulten, 2000). Due to its parsimonious nature, TFP is thus both a measure of immense utility and practicality for economic research, but also one fraught with many shortfalls. For example, Hall (1988) underlines that in the presence of imperfect competition, the residual provides a biased estimate of productivity. On this front, it must be stated that if the errors in its computation were randomly distributed, the unwanted parts of the residual figure would cancel out, thereby resulting in an unbiased estimate. However, both New Economy and Environmentalist arguments base themselves on the notion that these errors are not, in fact, randomly distributed. The former posits that the bias is downwards due to the unmeasured gains in product quality over time, while the latter is based on the idea that environmental costs of growth are under-reported, thereby biasing the measure upwards (Hulten, 2000). Furthermore, Van Beveren (2010) points out issues related with empirical methods seeking to estimate the residual. To this point, she not only underscores issues related with simultaneity and selection bias (issues that are widely recognized), but also less highlighted problems regarding the use of deflated input and output values in estimating firm level productivity, as well as endogeneity issues arising from the particular products chosen in its calculation.

A further caveat worth noting pertains to labor quality. As Jorgenson and Griliches (1967) point out, the Solow residual is computed by treating labor as a homogeneous input -

capturing its quantity (in terms of workers or hours) but not its quality (in terms of education, experience, or skill composition). Hence, to the extent that labor quality improves over time, the residual will tend to absorb these improvements, thereby conflating gains in pure productive efficiency with unmeasured human capital accumulation. On this front, it must be stated that this limitation is particularly pertinent in the context of this paper, given that human capital investment is one of the primary channels through which income inequality is theorized to affect aggregate productivity (Berg & Ostry, 2017; García-Peñalosa, 2018). That being said, it is worthwhile to note that this concern does not so much invalidate the findings as it refines their interpretation. Namely, if inequality shapes human capital accumulation, and this in turn registers in the residual, then the inverse-parabolic relationship identified herein remains a meaningful characterization of how inequality ultimately feeds through into aggregate productivity - even if the precise decomposition of the residual between its pure efficiency and labor quality components remains elusive.

A related concern pertains to cross-country heterogeneity in TFP measurement. Even when drawn from a harmonized source such as Penn World Table version 9.1, cross-country TFP comparisons rely on price deflators, purchasing power parity conversions, and factor share assumptions that may not be fully comparable across economies with very different production structures, sectoral compositions, and statistical capacities. In this regard, the descriptive statistics reveal a wide range of TFP values across the sample - from a minimum of 0.451 in Nigeria to a maximum of 2.176 in Mauritania - which, whilst partly reflective of genuine productivity differences, could also in part capture measurement discrepancies rooted in these comparability issues. On this front, the GMM estimator does partially address the concern, in that the country fixed effects absorbed by first-differencing remove time-invariant cross-country heterogeneity, and the OECD/non-OECD parcelling in Table 4 accounts for the most systematic structural differences across country groups. That being said, residual heterogeneity in factor shares or deflation procedures across the sample remains a caveat. Hence, future work could seek to address this - perhaps by employing country-specific production function estimates or alternate productivity databases such as the "long-term productivity" database by Banque de France, albeit at the cost of a considerably more limited cross-sectional scope, as noted in the Extensions below.

On this front, a static fixed effects model was also estimated as a means of robustness, so as to examine whether the main results are contingent on the inclusion of the lagged dependent variable. The results are presented in Table 10. Whilst the specification with time dummies (FE 1) yields insignificant coefficients on both the Gini index and its square - a result that is not altogether surprising, given that time fixed effects absorb a considerable share of the common variation in TFP across countries in a static setting - the specification without time dummies (FE 2) corroborates the main finding, yielding a positive and significant coefficient on the Gini index and a negative and significant coefficient on its square, with magnitudes broadly in line with those obtained via the GMM approach in Table 3. Hence, whilst the loss of significance in FE (1) warrants acknowledgement, the robustness of the inverse-parabolic relationship in FE (2) lends further credence to the main claim. That being said, the dynamic GMM specification remains the preferred one on both theoretical and econometric grounds, for at least three reasons. First, both income inequality and TFP are highly persistent series - a fact that, as noted in the Data section, motivates the use of five-year averages - and the inclusion of the lagged dependent variable is warranted precisely to address the dynamic panel bias that would otherwise arise in its absence (Nickell, 1981). Second, and relatedly, it is worthwhile to note that even where FE (2) yields significant results, the standard errors on the Gini index are approximately six times larger than those reported in the GMM specifications of Table 3 (1.37 versus approximately 0.22–0.23), underscoring the considerably greater efficiency of the dynamic estimator. Third, the GMM approach instruments for the potential endogeneity of the inequality variable via its lagged levels and differences - a concern that the static fixed effects estimator does not address, and one that, as outlined in the Methodology section, constitutes a further motivation for the GMM approach adopted in this paper.

Income Inequality

Measuring income inequality is not a straightforward a task. Since inequality is a function of the distribution of income, wealth, and other similar factors, there exist several measures that seek to fully capture its many nuances. All of these measures aim to produce a single number to characterize such a complex concept in order to facilitate analyses; the information contained in any single one of them is therefore limited in nature. Although the relative ease with which the Gini index is computed speaks to its practicality, it also comes with several caveats. First and foremost, one must bear in mind that the widely used Gini index is a *relative* measure of income. This means that different income distributions can yield the same outcome, and that different definitions of income can produce very different coefficients for the same population. As an example of the former, Osberg (2017) constructs a two-class scenario showing how varying the size of the rich and the poor populations in specific ways can leave the Gini unchanged. Illustrating how societies that look completely different can produce the same coefficient, he shows that changing income distributions while retaining the same Gini measure can yield to variations in the rich-to-poor income ratio by a factor of 12, and variations in the top 1%'s share of total income by a staggering factor of 16. As for the latter, Deininger & Squire (1996) show the degree to which the Gini index can vary for the same population depending on whether the individual or the household is taken as the relevant entity whose income is measured. Another caveat associated with the Gini is that the index doesn't contain any information about wealth inequalities, which may well be more informative about the overall economic structure of a given society. In this regard, Domeij & Klein (2002) show how (and why) a country like Sweden can simultaneously have relatively low income inequality as measured by the Gini index, whilst still experiencing high levels of wealth disparity. As Deltas (2003) points out, the Gini index might also fall short econometrically, in that it is liable to be biased downwards for small sample sizes. As such, there have been several other measures suggested and employed in its stead in recent literature, including various top shares of income, which this study also employs as a means of robustness (Pikkety, 2014).

Extensions

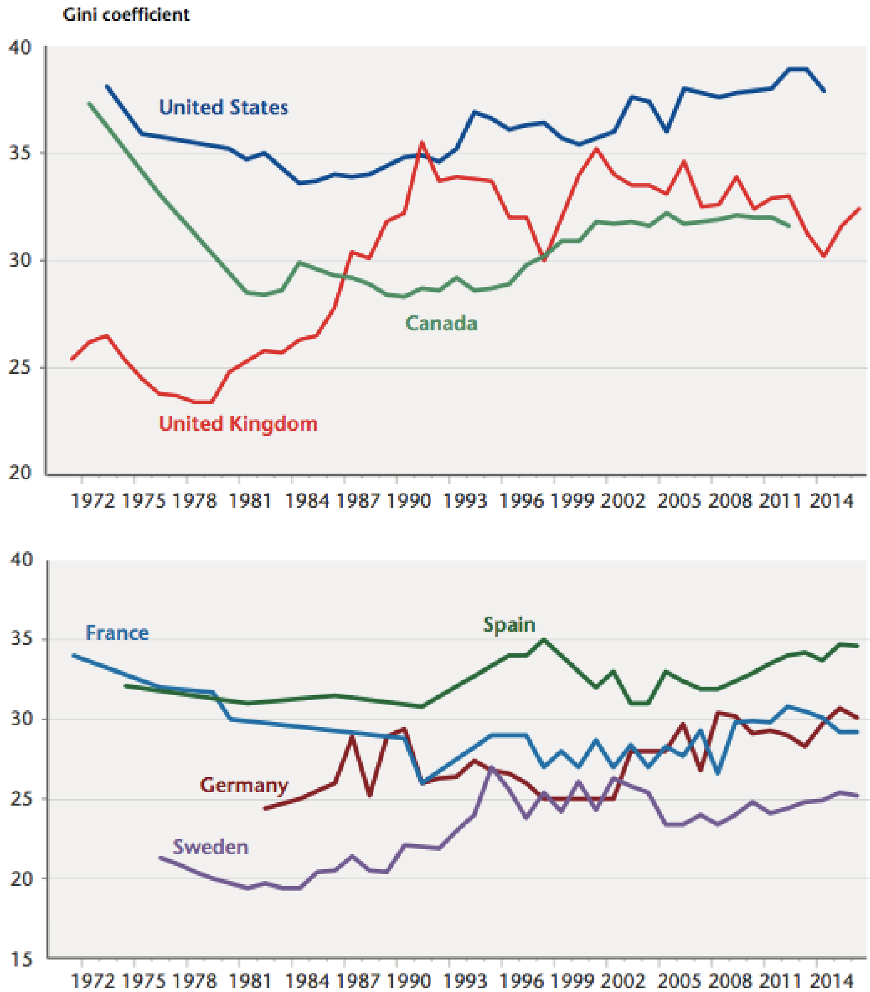
Although two different measures for income inequality were used for robustness, more steps can be taken to increase the scope of this study. Namely, a natural next step would be to see how inequalities in capital and labor income separately affect total factor productivity. Another measure to consider would be wealth inequality. Similarly, using different productivity measures and seeing how these are affected by the different inequality measures could be a natural next step. Labor productivity would be one obvious choice, and could be of even more interest in terms of manifesting the effects of rampant inequality through the channels suggested earlier in this paper. With regards to the measure employed herein, a non-standardized version of the TFP could be used as a robustness check. While there are alternate open-access databases to consider (such as the "long term productivity" database by Banque de France) these would seriously limit the scope of the current undertaking (especially in terms of cross-sectionals). In fact, the researcher is likely to run into problems of data availability with any of these extensions. Hence, while the scope of this project can be extended by using these different measures for inequality or productivity, the analysis would also need to be much more limited cross-sectionally.

Concluding Remarks

This research adds to the body of literature on the relationship between inequality and economic growth. Considering the complexities associated with doing so, it keeps capital and labor input constant and focuses on productivity (as proxied by TFP) as the determinant of long-term growth. The results are driven by GMM estimation using unbalanced panel data of up to 62 countries over a period of 50 years and establish that income inequality has a decreasingly positive effect on aggregate productivity. 20 different specifications in 5 different data-sets are used to drive these results and the regressions, once subjected to rigorous testing, reveal some robustness. This implies that beyond a certain threshold, income inequality hinders productivity and adversely affects long-term prosperity. As decreasing growth of productivity and an increasing divide in income distributions are likely to stay realities for the foreseeable future, this paper draws an important result in establishing a way in which the two could be inter-connected. The astute policy-maker could thus use this research as a starting point to determine this threshold value of inequality, and aim for policies that would target a “productivity-maximising” level of inequality.

Tables and Figures

Figure 1 - Rising Income Inequality in Advanced Economies



Source: https://www.wider.unu.edu/project/wiid-world-income-inequality-database.

Table 1: Summary Statistics – Gini Index

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
TFP	503	0.97	0.19	0.48	0.89	1.02	2.18
Gini Index	503	36.83	8.77	20.52	28.93	43.95	53.32
Unemp	349	7.22	4.86	0.58	3.86	9.18	37.74
PopG	503	1.33	0.99	-1.29	0.54	2.00	4.16

Table 2: Summary Statistics – Top Shares

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
TFP	366	0.97	0.18	0.45	0.89	1.02	2.18
Top 10%	361	0.39	0.11	0.16	0.31	0.46	0.71
Unemp	310	7.76	5.88	0.41	3.81	9.52	37.74
PopG	366	1.20	1.33	-1.29	0.43	1.78	15.26

Figure 2 - TFP and Income Inequality – Gini Index

Figure 3 - TFP and Income Inequality – Top 10%'s Share of Income

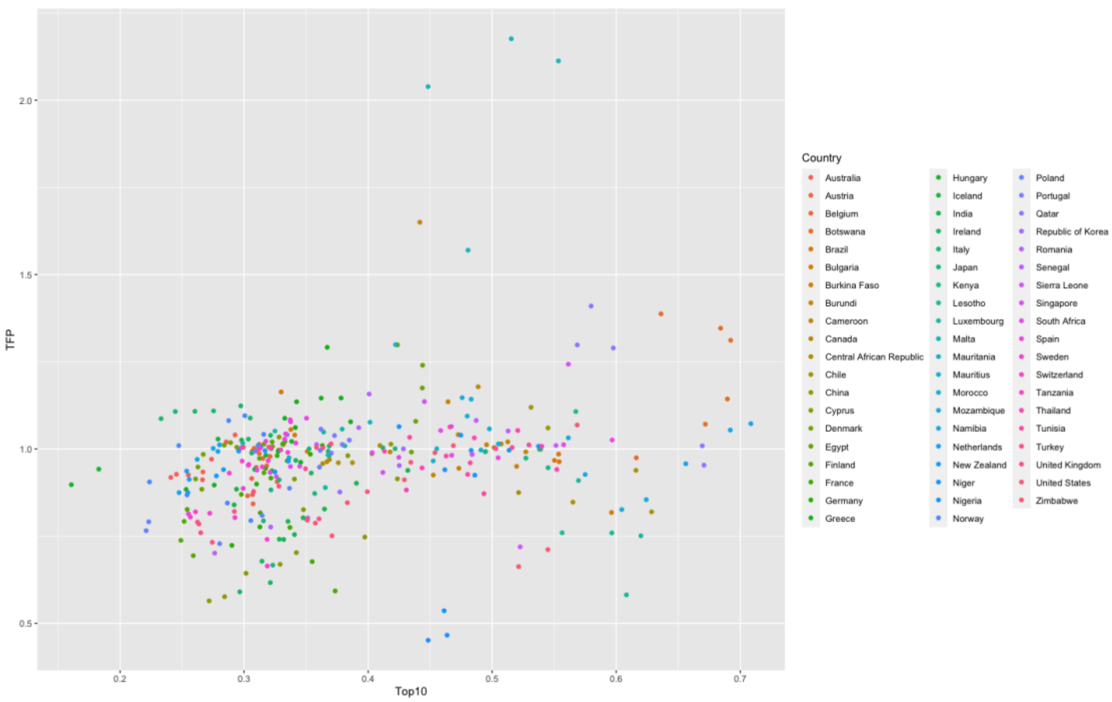


Figure 4 – Residualized TFP and Income Inequality – Gini Index

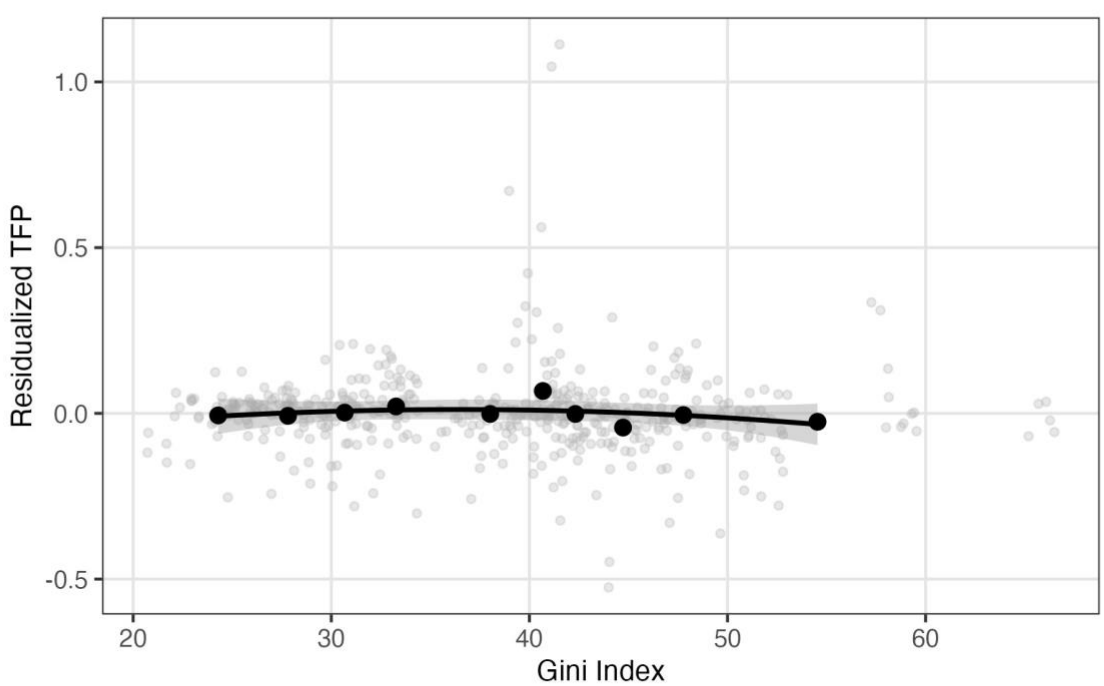


Table 3: GMM Regression Results – Gini Index

	Diff (1)	Diff (2)	Sys (3)	Sys (4)
TFP_{t-1}	0.42***	0.22***	0.22***	0.24***
	(0.10)	(0.07)	(0.05)	(0.02)
Gini	4.95***	4.97***	4.95***	4.94***
	(0.22)	(0.23)	(0.22)	(0.23)
$Gini^2$	-0.06***	-0.06***	-0.06***	-0.06***
	(0.00)	(0.00)	(0.00)	(0.00)
Unemp	-0.33	-0.36	-0.25	-0.28
	(0.28)	(0.35)	(0.30)	(0.31)
PopG	-0.18	-0.37	0.09	-0.64
	(1.88)	(2.46)	(1.74)	(1.47)
Time Dummies	Yes	No	Yes	No
Hansen-Sargan J-test	0.16	0.16	0.85	0.72
Autocorrelation Test (2)	0.02**	0.01***	0.04**	0.02**
No. of Instruments	27	17	36	26

*Note: Coefficients multiplied by 10^2. *p<0.1; **p<0.05; ***p<0.01*

Table 4: GMM Regression Results – OECD vs non-OECD

	Diff (1)	Diff (2)	Diff (3)	Diff (4)	Sys (5)	Sys (6)	Sys (7)	Sys (8)
	OECD	*OECD*	*non-OECD*	*non-OECD*	*OECD*	*OECD*	*non-OECD*	*non-OECD*
TFP_{t-1}	2.26***	0.33***	0.21	0.16	2.60***	0.28***	-0.02	0.17***
	(0.41)	(0.10)	(0.18)	(0.16)	(0.40)	(0.08)	(0.07)	(0.01)
Gini	5.12***	5.18***	3.87***	4.03***	5.22***	5.00***	3.97***	3.95***
	(0.26)	(0.39)	(0.41)	(0.37)	(0.27)	(0.39)	(0.32)	(0.34)
$Gini^2$	-0.07***	-0.07***	-0.04***	-0.04***	-0.08***	-0.07***	-0.04***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Unemp	0.66***	0.52	-0.37	-0.52	0.68***	1.15***	-0.37	-0.38
	(0.15)	(0.44)	(0.42)	(0.41)	(0.16)	(0.41)	(0.41)	(0.33)
PopG	-0.06	1.88	0.76	-0.02	0.10	0.78	0.78	0.84
	(1.93)	(2.91)	(2.82)	(3.74)	(1.79)	(3.49)	(2.55)	(2.38)
Time Dummies	Yes	No	Yes	No	Yes	No	Yes	No
Hansen-Sargan J-test	0.26	0.38	0.78	0.37	0.99	0.46	0.99	0.91
Autocorrelation Test (2)	0.07*	0.01**	0.17	0.11	0.01**	0.02**	0.16	0.21
No. of Instruments	27	17	27	17	36	26	36	26

*Note: Coefficients multiplied by 10^2. *p<0.1; **p<0.05; ***p<0.01. Columns (1,2,5,6): OECD; Columns (3,4,7,8): non-OECD.*

Table 5: GMM Regression Results – 1990-2015

	Diff (1)	Diff (2)	Sys (3)	Sys (4)
TFP_{t-1}	1.17**	0.30***	0.30***	0.29***
	(0.46)	(0.01)	(0.10)	(0.01)
Gini	5.36***	5.60***	5.46***	5.56***
	(0.17)	(0.15)	(0.17)	(0.16)
$Gini^2$	-0.07***	-0.07***	-0.07***	-0.07***
	(0.00)	(0.00)	(0.00)	(0.00)
Unemp	0.06	-0.53**	-0.21	-0.38**
	(0.28)	(0.24)	(0.25)	(0.17)
PopG	2.99	-2.69	-0.67	-0.64
	(2.82)	(3.30)	(1.87)	(1.53)
Time Dummies	Yes	No	Yes	No
Hansen-Sargan J-test	1	0.13	0.99	0.32
Autocorrelation Test (2)	0.47	0.01***	0.07*	0.15
No. of Instruments	17	12	21	16

*Note: Coefficients multiplied by 10^2. *p<0.1; **p<0.05; ***p<0.01*

Table 6: GMM Regression Results – Top Shares

	Diff (1)	Diff (2)	Sys (3)	Sys (4)
TFP_{t-1}	0.73***	0.97***	0.88***	1.00***
	(0.16)	(0.02)	(0.06)	(0.04)
top 10%	0.20	0.33***	0.18	0.21
	(0.24)	(0.06)	(0.16)	(0.16)
top $10\%^2$	-0.46**	-0.45***	-0.53***	-0.44*
	(0.19)	(0.07)	(0.14)	(0.23)
Unemp	0.00	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
PopG	0.01	-0.01*	0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Time Dummies	Yes	No	Yes	No
Hansen-Sargan J-test	0.00***	0.24	0.00***	0.00***
Autocorrelation Test (2)	0.46	0.94	0.08*	0.81
No. of Instruments	27	17	36	26

*Note: *p<0.1; **p<0.05; ***p<0.01*

Table 7: Summary Statistics – OECD

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
TFP	224	0.93	0.13	0.53	0.87	1.01	1.29
Gini Index	224	29.53	5.17	20.52	25.91	32.04	47.52
Unemp	179	7.14	3.87	1.21	4.53	8.80	24.23
PopG	224	0.69	0.52	-0.55	0.34	1.07	2.33

Table 8: Summary Statistics – Non-OECD

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
TFP	285	0.99	0.23	0.48	0.90	1.05	2.18
Gini Index	285	42.58	6.38	21.70	39.48	47.32	53.32
Unemp	173	7.22	5.70	0.58	3.45	9.43	37.74
PopG	285	1.81	0.98	-1.29	1.26	2.56	4.16

Table 9: Summary Statistics – 1990-2015

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
TFP	359	0.98	0.15	0.58	0.93	1.02	2.18
Gini Index	359	37.36	8.62	20.72	29.85	44.58	53.30
Unemp	323	7.30	4.94	0.58	3.90	9.29	37.74
PopG	359	1.22	0.95	-1.29	0.49	1.84	4.16

Table 10: FE Robustness Check – No Lagged TFP

	FE (1)	FE (2)
Gini	3.24	5.32***
	(2.61)	(1.37)
Gini²	-0.03	-0.05***
	(0.03)	(0.02)
Unemp	-0.71***	-0.76***
	(0.24)	(0.26)
PopG	-1.73*	-1.60*
	(0.90)	(0.89)
Time Dummies	Yes	No
N obs	463	463
R^2 (within)	0.071	0.114

*Note: Coefficients multiplied by 10^2. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at country level in parentheses.*

References

- Aghion, P., & Bolton, P. (1997). A trickle-down theory of growth and development with debt overhang. *Review of Economic Studies*, *64*, 151–172.
- Alesina, A., & Rodrik, D. (1994). Distributive politics and economic growth. *The Quarterly Journal of Economics*, *109*(2), 465–490.
- Anand, S., & Kanbur, S. M. R. (1993). The Kuznets process and the inequality–development relationship. *Journal of Development Economics*, *40*(1), 25–52.
- Andersen, T. G., & Sorensen, B. E. (1996). GMM estimation of a stochastic volatility model: A Monte Carlo study. *Journal of Business and Economic Statistics*, *14*, 328–352.
- Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies*, *58*, 277–297.
- Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, *68*, 29–51.
- Barro, R. J. (1991). Economic growth in a cross section of countries. *The Quarterly Journal of Economics*, *106*(2), 407–443.
- Basu, K., & Stiglitz, J. E. (2016). *Inequality and growth* (World Bank Publications No. 24983). The World Bank.
- Beck, T., & Levine, R. (2004). Stock markets, banks, and growth: Panel evidence. *Journal of Banking and Finance*, *28*, 423–442.
- Becker, O. S. (2016). Using instrumental variables to establish causality. *IZA World of Labor*, *1*.
- Benhabib, J. (2003). The tradeoff between inequality and growth. *Annals of Economics and Finance*, *4*, 491–507.
- Berg, A. G., & Ostry, J. D. (2017). Inequality and unsustainable growth: Two sides of the same coin? *IMF Economic Review*, *65*(4), 792–815.
- Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*, 115–143.
- Blundell, R., & Bond, S. (2000). GMM estimation with persistent panel data: An application to production functions. *Econometric Reviews*, *19*, 321–340.
- Blundell, R., Bond, S., & Windmeijer, F. (2000). Estimation in dynamic panel data models: Improving on the performance of the standard GMM estimator. In B. Baltagi (Ed.), *Advances in econometrics* (Vol. 15, pp. 53–91). JAI Elsevier Science.
- Bond, S. (2002). *Dynamic panel data models: A guide to micro data methods and practice* (Working Paper 09/02). Institute for Fiscal Studies.

- Bond, S. R., Hoeffler, A., & Temple, J. (2001). *GMM estimation of empirical growth models* (Discussion Paper No. 2048). Centre for Economic Policy Research.
- Bowsher, C. G. (2002). On testing overidentifying restrictions in dynamic panel data models. *Economics Letters*, *77*, 211–220.
- Bräuninger, M., & Pannenberg, M. (2002). Unemployment and productivity growth: An empirical analysis within the augmented Solow model. *Economic Modelling*, *19*, 105–120.
- Brueckner, M., & Lederman, D. (2018). Inequality and economic growth: The role of initial income. *Journal of Economic Growth*, *23*(3), 341–366.
- Calderon, C. A., Chong, A., & Loayza, N. V. (2002). Determinants of current account deficits in developing countries. *Contributions to Macroeconomics*, *2*.
- Carkovic, M., & Levine, R. (2005). Does foreign direct investment accelerate economic growth? In T. Moran, E. Graham, & M. Blomstrom (Eds.), *Does foreign direct investment promote development?* (pp. 195–220). Institute for International Economics.
- Chen, L., Fukuda-Parr, S., & Seidensticker, E. (2003). Human insecurity in a global world: Studies in global equity. *Journal of Human Development*, *4*(2).
- Croissant, Y., & Millo, G. (2008). Panel data econometrics in R: The plm package. *Journal of Statistical Software*, *27*(2), 1–43.
- Deininger, K., & Squire, L. (1996). A new data set measuring income inequality. *World Bank Economic Review*, *10*(3), 565–591.
- Deltas, G. (2003). The small-sample bias of the Gini coefficient: Results and implications for empirical research. *The Review of Economics and Statistics*, *85*(1), 226–234.
- Domeij, D., & Klein, P. (2002). Public pensions: To what extent do they account for Swedish wealth inequality? *Review of Economic Dynamics*, *5*(3), 503–534.
- Forbes, K. J. (2000). A reassessment of the relationship between inequality and growth. *American Economic Review*, 869–887.
- García-Peñalosa, C. (2018). Inequality in macroeconomic models. *Revue de l'OFCE*, *0*(3), 93–115.
- Gil-Alana, L. A., Skare, M., & Druzeta-Prziklas, R. (2019). Measuring inequality persistence in OECD 1963–2008 using fractional integration and cointegration. *The Quarterly Review of Economics and Finance*, *72*, 65–72.
- Hall, R. E. (1988). The relation between price and marginal cost in U.S. industry. *Journal of Political Economy*, *96*, 921–947.
- Halter, D., Oechslin, M., & Zweimüller, J. (2011). *Inequality and growth: The neglected time dimension* (IEW Working Paper No. 507). University of Zurich.

- Hansen, L. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, *50*, 1029–1054.
- Holtz-Eakin, D., Newey, W., & Rosen, H. S. (1988). Estimating vector autoregressions with panel data. *Econometrica*, *56*, 1371–1395.
- Jorgenson, D. W., & Griliches, Z. (1967). The explanation of productivity change. *The Review of Economic Studies*, *34*(3), 249–283.
- Hulten, C. R. (2000). *Total factor productivity: A short biography* (NBER Working Paper No. 7421).
- International Labour Organization. (2020). *ILOSTAT database*. https://ilostat.ilo.org/
- International Monetary Fund. (2020). *International financial statistics*. https://data.imf.org/
- Krugman, P. (2013, December 15). Why inequality matters. *The New York Times*.
- Kuznets, S. (1955). Economic growth and income inequality. *The American Economic Review*, *45*(1), 1–28.
- Li, H., Squire, L., & Zou, H. (1998). Explaining international and intertemporal variations in income inequality. *The Economic Journal*, *108*(446), 26–43.
- Li, K.-W., & Zhou, X. (2013). A nonparametric and semiparametric analysis on inequality and development: Evidence from OECD and non-OECD countries. *Economic and Political Studies*, *1*(2), 55–79.
- Marrero, G. A., & Rodríguez, J. G. (2013). Inequality of opportunity and growth. *Journal of Development Economics*, *104*, 107–122.
- Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, *49*(6), 1417–1426.
- Nichols, A., Mitchell, J., & Lindner, S. (2013). *Consequences of long-term unemployment*. The Urban Institute.
- Okun, A. (1975). *Equality and efficiency: The big tradeoff*. Brookings Institution Press.
- Osberg, L. (2017). On the limitations of some current usages of the Gini index. *Review of Income and Wealth*, *63*(3), 574–584.
- Paganetto, L. (2016). *Stagnation versus growth in Europe*. Springer.
- Paleologou, M. S. (2019). In search of thresholds in the household income inequality–growth relationship. *Economics of Transition and Institutional Change*, *27*(4), 989–1008.
- Penn World Table. (2020). *Penn World Table* (Version 9.1). University of Groningen. https://www.rug.nl/ggdc/productivity/pwt/
- Persson, T., & Tabellini, G. (1994). Growth, distribution and politics. *European Economic Review*, *36*(2), 593–602.

- Piketty, T. (2014). *Capital in the twenty-first century* (A. Goldhammer, Trans.). Harvard University Press.
- Pritchett, L. (1996). *Population growth, factor accumulation, and productivity* (Policy Research Working Paper No. 1567). The World Bank.
- Ram, R. (1991). Kuznets's inverted U-hypothesis: Evidence from a highly developed country. *Southern Economic Journal*, *57*, 1112–1123.
- Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, *71*(1), 135–158.
- Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, *39*(3), 312–320.
- Solt, F. (2020). Measuring income inequality across countries and over time: The Standardized World Income Inequality Database. *Social Science Quarterly*. SWIID Version 8.3.
- Staiger, D., & Stock, J. H. (1997). Instrumental variables regressions with weak instruments. *Econometrica*, *65*, 557–586.
- Standardized World Income Inequality Database. (2020). https://fsolt.org/swiid/
- Van Beveren, I. (2012). Total factor productivity estimation: A practical review. *Journal of Economic Surveys*, *26*(1), 98–128.
- Wan, G., Lu, M., & Chen, Z. (2006). The inequality–growth nexus in the short and long run: Empirical evidence from China. *Journal of Comparative Economics*, *34*(4), 654–667.
- Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, *126*(1), 25–51.
- World Bank. (2020). *World development indicators*. https://datacatalog.worldbank.org/
- World Income Inequality Database. (2020). https://www.wider.unu.edu/project/wiid
- World Inequality Database. (2020). https://wid.world/
- Zhou, X., & Li, K.-W. (2011). Inequality and development: Evidence from semiparametric estimation with panel data. *Economics Letters*, *113*(3), 203–207.