The Impact of Employment Protection on Income Inequality

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Abstract

The paper addresses the relationship between income inequality and employment protection using an unbalanced panel of 32 countries from 1985-2019. Unlike other studies, we consider employment protection to be a slowly changing variable. In the presence of time-invariant variables, standard OLS regression does not provide valid estimates. To this end, we adopt a two-stage method suggested by Pesaran and Zhou (2018), and we extend this method in the case where some of the regressors are endogenous. To allow for endogeneity, we use a free instrument method based on copula theory. Monte Carlo simulations show that our estimator outperforms the standard two-stage estimator in the case of endogeneity. Results demonstrate that EPL measurements decrease significant income inequality differences. Nevertheless, the higher the protection against dismissals in regular labor holders decreases income inequality before and after redistribution policies. However, strengthening the protection of temporary labor holders cannot provide a straightforward relationship with income inequality indices. The other income inequality determinants follow the existing literature on their impact on income distribution.

Keywords: Income Inequality, Labor market, Employment protection legislation

Contents

1 Introduction

Recently, across many countries, income inequality – as measured by the Gini coefficient – has risen. Addressing the rising trend in income inequality is a formidable challenge for most countries worldwide Atkinson (2015),Tridico (2017). Understanding the reasons behind the rising trend of income inequality is crucial for policy design to achieve economic growth and social cohesion. Trade and financial globalization Stolper and Samuelson (1941), Jaumotte et al. (2013), Furceri and Loungani (2018), Furceri and Ostry (2019) and the spread of technological changes Acemoglu and Autor (2010)Jaumotte et al. (2013), Dabla-Norris et al. (2015), Furceri and Ostry (2019) are considered as traditional explanations behind the high levels of income differences across countries. However, a worldwide tendency to reform many sectors of the economy and the increase of income inequality varies among advanced economies push policymakers to identify the role of institutional reforms on income inequality Jaumotte and Osorio Buitron (2015).

Structural reforms should be considered an essential factor influencing inequality Furceri and Ostry (2019). Significantly reforming the labor market has been one of the most "popular" policy interventions for governments to challenge possible labor demand and supply shocks. Many reforms in institutions related to the regulatory framework for lay-offs, the level of the minimum wage, or even the strength of trade unions had a significant distribution effect on income in the last decades Checchi and García-Peñalosa (2014), DiNardo et al. (1996), Lee (1999), Machin and Wadhwani (1991), Card (2001), Jaumotte et al. (2013), Fortuna and Neto (2021), raising questions about the extent to which labor market reforms affect income inequality. Over the years, numerous studies have analyzed inequality and labor market reforms. The majority of these studies support the notion that strengthening the labor market (i.e., increasing the difficulty of dismissals and hirings under fixed-term contracts, increasing the minimum wage) income inequality follows a decreasing trend (Koeniger et al. (2007); Jaumotte et al. (2013);

Fortuna and Neto (2021); Checchi and García-Peñalosa (2014); and Calderon and Chong (2009)). However, that hypothesis should not be considered as a rule, as there is a part of the literature suggesting mixed results or even a more positive upward relationship between some labor market institutions and income inequality (Lewis (1963);Fortuna and Neto (2021);Checchi and García-Peñalosa (2014); Bosio (2014)).

The literature on the effect of labor market institutions is mainly focused on minimum wage and unions. Nevertheless, the literature on the impact of employment protection legislation (EPL) is scant and relatively recent, and it has been driven mainly by attempts to examine the high and persistent unemployment rate (Bassanini and Duval (2006)). Despite this, when it comes to the distributional impact of EPL on income, most available studies suggest that strengthening the EPL tends to decrease income inequality (Koeniger et al. (2007); Perugini and Pompei (2016), Perugini and Pompei (2017), Checchi and García-Peñalosa (2014)). However, some studies, such as Fortuna and Neto (2021) for regular contract holders (i.e., those with permanent employment and regular wages) and Bosio (2014) considering the role of firing costs, have found that EPL can widen income inequality.

The primary purpose of this paper is to shed new light on the role of employment protection legislation on the evolution of income inequality using an updated dataset of 32 OECD countries for a period between 1985 to 2019 by contributing to the following areas: (1) Taking into account that the level of income inequality depends on its previous values, we consider a dynamic regression analysis to produce more valid results, as it emphasizes the ripple effect the income inequality in lagged terms variables can have on income inequality measurements. (2) Differently from the other studies using panel data Fortuna and Neto (2021), Koeniger et al. (2007), Checchi and García-Peñalosa (2014), we take into account that EPL is a slowly changing variable. Using slowly changing variables will not provide valid empirical estimates as it eliminates all the time-invariant regressors. To get rid of this issue, we use a two-stage estimation procedure to identify the coefficients of time-invariant regressors, including fixed effects based on Kripfganz and Schwarz (2019) and Pesaran and Zhou (2018).

Following, Kripfganz and Schwarz (2019) and Pesaran and Zhou (2018), in the first stage, we run a regression of income inequality measurements on time-varying explanatory variables. The residuals computed from the first stage regression are then averaged over time and used as the dependent variable in a cross-section OLS regression that includes an intercept and the vector of time-invariant regressors. (3) We expand the method suggested by Kripfganz and Schwarz (2019) and Pesaran and Zhou (2018) by allowing for the presence of endogenous variables in the first stage of regression analysis. By ignoring the presence of possible endogeneity in the first regression, we get inconsistent parameter estimates leading to incorrect residuals, affecting thus the estimates in the second stage analysis. We show by using Monte Carlo simulations that by ignoring endogeneity in the first-stage regression, we get severely size-distorted parameters in the second-stage regression. Alternatively, we employ an Instrumental Free approach following Yang et al. (2022) who suggested a generalized two-stage copula endogeneity correction method (2sCOPE). The reasons why we do not use the standard IV approach are that the use of the IV approach requires suitable instruments, which have always been challenging, and that the potential IVs are correlated with endogenous regressors.

Our study demonstrates that employment protection significantly influences income distribution. Strengthening employment protection has a pronounced effect in reducing income inequality, particularly for workers in regular labor contracts, giving further support to the existing literature Koeniger et al. (2007), Checchi and García-Peñalosa (2014), and Fortuna and Neto (2021) and contrary to Leonardi (2006) and Heywood et al. (2018). Increasing the cost against dismissals has a negative effect on income inequality. However, the effect of strengthening EPL on temporary contracts in income differences needs to be clarified, raising the need to investigate further the distributional impact of reforming the protection in temporary labor contracts. Moreover, both EPL measures appear linked to a decreasing trend in income inequality differences across countries. The empirical findings regarding the additional explanatory variables align with the existing literature.

The paper's structure is organized as follows: Section 2 provides an extensive review of the literature on the distributional impact of employment protection on income inequality. Section 3 describes the empirical specification, and Section 4 presents the design of the Monte Carlo simulation. Section 5 describes the dataset used for the analysis, and Section 6 presents the empirical results. Finally, Section 7 provides a robustness check utilizing a principle component analysis. The paper concludes by summarising the findings and their implication for future research and policy considerations.

2 Literature Review

The existing literature on the impact of (EPL) on income inequality is relatively recent and primarily focuses on wage distribution within developed countries. EPL encompasses a variety of dimensions, including regulations related to severance payments, mandated notice periods, hiring and firing decisions, restrictions on the use of fixed-term contracts, and mandates for training within firms. From a theoretical standpoint, the influence of EPL on income inequality is complex. The nexus between employment protection and the degree of income inequality is a multifaceted topic. Several theoretical frameworks provide insights into how employment protection can impact income inequality. The *Insider-Outsider Theory* (Lazear (1990)) posits that strict employment protection can lead to a labor market divide, creating "insiders" and "outsiders." Insiders, typically well-protected and well-paid workers, benefit from these regulations, while outsiders, often less protected and lower paid, face a more precarious labor market situation. This division may exacerbate income inequality within the labor market by favoring insiders.

Shapiro and Stiglitz (1984) introduces an alternative perspective, the *Efficiency-Wage Theory*. Based on *Efficiency-Wage Theory*, employment protection can foster the practice of offering efficiency wages. Efficiency wages are higher salaries employers pay to incentivize worker compliance and maintain high productivity. Under this theory, strict employment protection may encourage employers to offer higher wages, thereby improving the income of less-skilled workers and potentially reducing income inequality. EPL often provides a legal framework for forming labor unions and collective bargaining agreements. Unions negotiate for higher wages and better working conditions on behalf of their members. Empirical studies, such as Freeman and Medoff (1984), have shown that unionized workers tend to earn higher wages and experience reduced income inequality compared to non-unionized workers. Nevertheless, workers with permanent contracts have an advantage in bargaining for higher wages compared to those with temporary contracts Güell (2000).

The *human capital theory* posits that permanent workers may secure a wage premium due to their investments in firm-specific human capital. These investments are encouraged by their strong attachment to a particular firm (Becker (1964)). As permanent workers accumulate firm-specific skills, their productivity, and wage-earning potential increase and essentially may lead to a reduction in income disparities within the firm and across the labor market. Finally, based on the equalizing theory of Rosen (1986), workers under temporary contracts are more likely to secure a wage premium as compensation for working under a less desirable labor contract. This compensation can be viewed as an equalizing mechanism, potentially leading to a lower wage gap between temporary and regular contract workers (Rosen (1986)).

Empirical studies have explored the impact of employment protection on income inequality, often yielding mixed results. These studies shed light on the complex dynamics within labor markets, where the strength of employment protection regulations can impact income distribution.

The study of Koeniger et al. (2007) is an essential contribution to labor economics and the study of income inequality.Koeniger et al. (2007) utilize cross-country panel data to examine the relationship between the labor market in.Koeniger et al. (2007) utilize cross-country panel data to explore the relationship between labor market institutions and wage inequality over time. The analysis highlights the noteworthy role of employment protection in shaping wage inequality. Their findings suggest that stringent employment protection laws against lay-offs are associated with reduced wage disparities between skilled and unskilled workers. Higher employment protection EPL can provide workers with job security, potentially reducing income disparities by preventing income losses due to job loss. Similarly, Checchi and García-Peñalosa (2014) investigates the impact of various labor market institutions on income inequality, including employment protection. The key findings from their panel empirical analysis suggest that labor market institutions, particularly employment protection, play a pivotal role in mitigating income inequality. The empirical estimates indicate that strengthening EPL is related to robust lower income inequality and unemployment, giving further empirical support on Koeniger et al. (2007). Their research highlights that employment protection can act as a mechanism to protect the vulnerable segments of the labor force, which, in turn, contributes to a more equal income distribution.

Fortuna and Neto (2021) using data from 35 OECD countries for the 1993-2017 period, evaluate the impact of labor market institutions on income inequality. Their study emphasizes the effect of employment protection legislation on income distribution. Stricter employment protection laws are associated with a decrease in income inequality. In particular, considering temporary or regular contract holders, they observe that higher protection for temporary contract holders decreases inequality. Still, the protection for regular contract holders cannot provide robust, statistically significant evidence. Considering that EPL has different income inequality effects among temporary and regular labor contract holders, Perugini and Pompei (2016, 2017); and Perugini (2020) analyze the impact of EPL on wage differences before and after the outburst of the economic crisis of 2008. In particular, Perugini and Pompei (2016) estimates the different distributional effects of regular and temporary contracts, considering additionally the role of education. While increasing protection on dismissals makes the wage distribution less equal for temporary and permanent workers, reforms aimed to increase the protection on using temporary contracts have an equalizing effect, especially for low and medium-educated workers. Perugini (2020) extend the analysis on income differences, observing that the deregulation of EPL increases the wage inequality between males and females, especially when we consider workers' temporary positions.

Following the empirical analysis of Perugini and Pompei (2016, 2017), examined the impact of both hiring and firing regulations on wage disparities in conjunction with other labor market institutions. The empirical evidence supports the existence of a negative wage gap between temporary and regular positions. However, the deregulation of firing and hiring rules after the financial crisis of 2007 narrowed the average wage gap between temporary and regular positions at every educational level. Nevertheless, the wage gap between temporary and regular positions is smaller as the education level decreases. The fundamental explanation behind these results is that only workers in regular positions can earn a wage premium due to the complementarities between informal firm-specific skills and formal education.

Additionally, Blanchard and Landier (2002) and Nunziata and Staffolani (2007) provided empirical evidence suggesting that reforms aimed to deregulate regular labor contracts in favor of temporary contracts will increase income inequality. While the share of employees will increase, the fact that they are employed in contracts with lower bargaining power deteriorates their ability to demand higher income shares and, thereby, increases the inequality gap.

Emphasizing on temporary labor contracts Andrea Albanese and Gallo (2020) and Bosio (2014) provided different results on the effect of EPL on wage inequality. Specifically, Bosio (2014) observed that workers under temporary contracts face lower wages than regular contract workers. In temporary contracts, wage inequality increases due to the deterioration in the wages of low-paid workers who bear the cost of higher employment protection. On the contrary, Andrea Albanese and Gallo (2020) provides a positive relationship between EPL in temporary contracts and income disparities. The empirical estimates see that the deregulation in the use of temporary contracts decreases inequality due to a wage premium in favor of temporary workers as compensation for working under a less desirable labor contract, giving empirical support to the equalizing theory of Rosen (1986). Leonardi (2006) explores the role of firing costs on wage differentials, considering specifically the role of severance payments, not an aggregate indicator as in the studies mentioned above. The empirical analysis of Leonardi (2006) sees that an increase in severance payments decreases wages at the entry level, making workers pay a part of the dismissal cost to protect themselves, increasing wage inequality.

Recently, Wiese et al. (2024) provide an alternative methodological approach to investigate the impact of EPL and other reforms on income inequality, considering 25 OECD countries from 1970 to 2020. Utilizing a narrative-based dataset updated from), they focus on the precise timing and nature of major legislative and regulatory changes. This methodological approach is critical for capturing the causal impacts of EPL on inequality, using the Augmented Inverse Probability Weighted (AIPW) estimator to correct for potential endogeneity in reform implementation. This method revealing a small but statistically significant increase of about 0.5% in the disposable Gini coefficient nine years post-reform. This nuanced analysis underscores the complex trade-offs between labor market flexibility and income distribution, providing critical insights for policymakers on the broader economic impacts of labor market reforms.

Essentially, the role of employment protection by referring both to regulations concerning hirings and firings needs to be clarified, as EPL can change income inequality either negatively (in most cases) or positively. The relationship between EPL and income distribution depends on various factors, including the specific policies, labor market context, and the level of education of the workforce. Therefore, there is a clear need to continue investing in studying this relationship. In the following sections, we analyze the methodology and the data we use to identify empirically the impact of employment protection on income inequality.

3 Methodology

The main objective of this study is to empirically estimate the effect of EPL on income inequality after controlling for other exogenous factors that change income distribution. The following dynamic regression model can summarize our baseline empirical specification model:

$$\Upsilon_{it} = \lambda \Upsilon_{it-1} + \chi'_{it}\beta + \Theta'_{it}\gamma + \varepsilon_{it} \tag{1}$$

$$\epsilon_{it} = \alpha_i + \upsilon_t \tag{2}$$

with units *i=1,2,...,N* and a fixed number of time periods *t=1,2,...,T* .

The dependent variable Υ_{it} refers to income inequality measurement. Where χ_{it} is a $K_x > 1$ vector of time-variant explanatory variables, $Theta'_{it}$ is a $K_\Theta > 1$ vector of time-invariant or slow changing variables, and α_i describes an unobserved individual specific effect. We use explanatory time-variant variables that include the logarithm of real GDP per capita in linear and squared terms, the logarithm of human capital, trade, and financial openness, the unemployment level, the inflation rate, and government expenditures as a percentage of GDP. As explanatory time-invariant variables, we use the EPL measurements and an index of democratization. We describe the dependent and explanatory variables in detail below.

In our analysis, estimating time-invariant or slowly-changing variables as independent variables is challenging, which is notably the case for EPL and Democracy. While a fixed effect estimation procedure can identify the slope coefficient of time-variant variables in the presence of slowly changing (time-invariant) variables, the fixed effect model absorbs most of their explanation, providing non-significant results Beck (2001). To provide robust estimates, we follow a two-stage estimation procedure to identify the coefficients of time-invariant regressors based on Kripfganz and Schwarz (2019) and Pesaran and Zhou (2018). In the first stage, we estimate the coefficients of the time-varying regressors as Kripfganz and Schwarz (2019) proposed. The combined residuals of the first stage panel regression are then averaged over time and used as a dependent variable in a cross-section OLS regression, including an intercept and the vector of time-invariant regressors.

To deal with possible endogeneity problems in the first stage regression arising from simultaneity issues, we employ an Instrumental Free approach following Yang et al. (2022) and Park and Gupta (2012). Park and Gupta (2012) proposed a copula correction method that directly models the dependence between the structural error and the endogenous regressor via copula. Following other IV-free methods, the application of the copula correction method has two vital requirements: the distinctiveness between the distribution of endogenous regressors and the structural error, i.e., the non-normality assumption of the endogenous regressors and the non-correlation between the linear combination of copula transformation of endogenous regressors and exogenous regressors. The non-normality assumption in the endogenous threshold variable reduces the correlation between the original threshold variable and its copula transformation, see also Christopoulos et al. (2021). In economic studies, both requirements are too strong, making less applicable the use of a copula correction method.

Yang et al. (2022) extend the analysis of Park and Gupta (2012) suggesting a generalized two-stage analysis (2sCOPE) relaxing the above two requirements, that is, the non-correlation between the linear combination of copula transformation of endogenous regressors and exogenous and the non-normality assumption of endogenous regressor. According to Yang et al. (2022)), the non-normality of endogenous regressors is not required as long as at least one correlated exogenous regressor is not normally distributed. The 2sCOPE correction method addresses endogeneity by adding residuals obtained by regressing latent copula data for each endogenous regressor on the latent copula data for the exogenous regressors as generated in the structural regression model. In our analysis, we consider endogenous variables, unemployment, and human capital. Unemployment and human capital are determined simultaneously with income inequality, which generally correlates with the error term, leading to bias and inconsistent estimates.[1].

The 2sCOPE approach as propsed by Yang et al. (2022),is particularly advantageous over conventional methods such as Augmented Inverse Probability Weighting (AIPW) as used in Wiese et al. (2024) to correct potential biases arising from non-random implementation of labor and product market reforms across countries. Our approach allow us to model the joint distribution between potentially endogenous regressors and the error term directly, offering flexibility in capturing nonlinear interactions and dependencies beyond traditional linear models. This method enhances the robustness of our estimates and reduces reliance on external instruments, which are often hard to justify and can limit the efficacy of traditional instrumental variable techniques. Given the intricate nature of economic relationships and policy impacts, the copula approach provides a more nuanced and reliable analysis, leading to more precise policy insights into the effects of EPL on income inequality.

Next, we describe our empirical method to allow for endogeneity, which is summarized in detail in the following steps:

- Step 1: Time-Varying Regression Model

$$\Upsilon_{it} = \lambda \Upsilon_{it-1} + X'_{1it}\beta_1 + X'_{2it}\beta_2 + \varepsilon_{it} \tag{3}$$

$$\varepsilon_{it} = \alpha_i + \upsilon_t \tag{4}$$

where X'_{1it} are time-varying endogenous variables, and X'_{2it} is a time-varying dependent variable potentially endogenous with X'_{1it}. α_i describes an unobserved individual specific

[1]We conducted three normality tests for the endogenous variables, and we concluded that both variables are not normally distributed, allowing us to implement the 2sCOPE method

effect. The empirical methodology is based on the following assumptions:

- Assumption 1. The structural error υ_t follows a normal distribution;
- Assumption 2. χ_{1it} and structural error υ_t follow a Gaussian copula;
- Assumption 3. $E(\chi_{1it'}, \upsilon_t) \not\equiv 0$
- Assumption 4. $E(\chi_{1it'}, \chi_{2it'}) = 0$

The 2sCOPE empirical specification as suggested by Yang et al. (2022) jointly models the endogenous regressors X'_{1t}, the correlated exogenous variable, X'_{2t} and the error term ε_t adopting a Gaussian copula model. According to Sklar's theory Sklar (1959) that there is a Copula function C(.,.) for both χ_{1it} and υ_{it} such that

$$F(\chi_{1it,\upsilon_{it}}) = C(H(\chi_{1it}), J(\upsilon_{it})) = C(U_{\chi_1}, U_\upsilon)$$

where $U_\chi = H(\chi_{1it})$, $U_\upsilon = H(\upsilon_{it})$. Thus, the copula depicts the marginal CDFs of the endogenous regressor χ_{1it} and the error term υ_{it} to their joint CDF and makes it possible to model independently the marginals and correlations of these random variables. Essentially, under the Gaussian Copula assumption $(\chi^*_{1t},\ \chi^*_{2t},\ ,\epsilon_t)$ follows the multivariate normal distribution :

$$\begin{pmatrix} \chi^*_{1t} \\ \chi^*_{2t} \\ \varepsilon^*_t \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \varrho_{\chi_1\chi_2} & \varrho_{\chi_1\varepsilon} \\ \varrho_{\chi_1\chi_2} & 1 & 0 \\ \varrho_{\chi_1\varepsilon} & 0 & 1 \end{pmatrix} \right]$$

,

where $\chi^*_{1t} = \Phi^{-1}(K(\chi_{1t}))$, $\chi^*_{2t} = \Phi^{-1}(M(\chi_{2t}))$, and $\varepsilon^*_t = \Phi^{-1}(N(\varepsilon_t))$ and $K(\chi_{1it})$,$M(\chi_{2it})$ and $N(\varepsilon_{it})$ are the marginal CDFs of χ_{1it}, χ_{2it} and ε_{it}.

As a result, we derive the following system of equations:

$$\Upsilon_{it} = \lambda \Upsilon_{it-1} + X'_{1it}\beta_1 + X'_{2it}\beta_2 + \varepsilon_{it} \tag{5}$$

$$\chi^*_{1t} = \chi^*_{2t}\zeta + \eta_t \tag{6}$$

where η_t and ε_{it} are correlated due to endogeneity of χ^*_{1t} and equation (6) expresses the copula transformation of χ^*_{1t} as a linear combination of observed and unobserved variables. The term η_t can be considered as a control function to address endogeneity in order for the structural error term ε_{it} to become independent of both χ^*_{1t} and χ^*_{2t}

We rewrite the Gaussian Copula model as follows:

$$\begin{pmatrix} \chi^*_{2t} \\ \chi^*_{2t} \\ \varepsilon^*_t \end{pmatrix} = \left[\begin{pmatrix} 1 & 0 & 0 \\ \varrho_{\chi_1\chi_2} & \sqrt{1-\varrho^2_{\chi_1\chi_2}} & 0 \\ \varrho_{\chi_1\epsilon} & \frac{-\varrho_{\chi_1\chi_2}\varrho_{\chi_1\varepsilon}}{\sqrt{1-\varrho^2_{\chi_1\chi_2}}} & \sqrt{1-\varrho^2_{\chi_1\varepsilon} - \frac{\varrho^2_{\chi_1\chi_2}\varrho^2_{\chi_1\varepsilon}}{1-\varrho^2_{\chi_1\chi_2}}} \end{pmatrix} \cdot \begin{pmatrix} w_{1t} \\ w_{2t} \\ w_{3t} \end{pmatrix} \right]$$

,

$$\begin{pmatrix} w_{1,t} \\ w_{2,t} \\ w_{3,t} \end{pmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \right)$$

Considering the above joint normal distribution for (X^*_{1t},X^*_{2t},ϵ^*_t) and $\epsilon^*_t = \sigma_\varepsilon \varepsilon_t$, we can derive $\chi^*_{1t} = \varrho_{\chi_1\chi_2}\chi^*_{2t} + \sqrt{1-\varrho^2_{\chi_1\chi_2}}\, w_{2,t} = \varrho_{\chi_1\chi_2}\chi^*_{2t} + \eta_t$, which basically describes the ζ from equation (6) is $\varrho_{\chi_1\chi_2}$ and $\eta_t = \sqrt{1-\varrho^2_{\chi_1\chi_2}}\, w_{2,t}$ and

Based on Yang et al. (2022), the construction of the above equation for the dependent variable helps us to overcome the arising endogeneity problem by simply adding the estimate of the error term η_t from the first stage regression as generated regressor to the outcome regression instead of using χ^*_{1t} and χ^*_{2t}

$$\Upsilon_t = \lambda\Upsilon_{t-1} + \chi_{1t}\beta_1^{'} + \chi_{2t}\beta_2^{'} + \frac{\sigma_\varepsilon \varrho_{\chi 1\varepsilon}}{1-\varrho^2_{\chi_1\chi_2}}\chi^*_{1t} + \frac{\sigma_\varepsilon \varrho_{\chi_1\chi_2}\varrho_{\chi 1\varepsilon}}{1-\varrho^2_{\chi_1\chi_2}}\chi^*_{2t} + \sigma_\varepsilon\sqrt{1-\varrho^2_{\chi 1\varepsilon} - \frac{\varrho^2_{\chi_1\chi_2}\varrho^2_{\chi 1\varepsilon}}{1-\varrho^2_{\chi 1\chi_2}}}w_{3t}$$

$$\Upsilon_t = \lambda\Upsilon_{t-1} + \chi_{1t}\beta_1^{'} + \chi_{2t}\beta_2^{'} + \frac{\sigma_\varepsilon \varrho_{\chi 1\varepsilon}}{1-\varrho^2_{\chi_1\chi_2}}\eta_t + \sigma_\varepsilon\sqrt{1-\varrho^2_{\chi 1\varepsilon} - \frac{\varrho^2_{\chi_1\chi_2}\varrho^2_{\chi 1\varepsilon}}{1-\varrho^2_{\chi 1\chi_2}}}w_{3t} \qquad (7)$$

.

Essentially, based on Yang et al. (2022), the construction of the above equation for the dependent variable helps us to overcome the arising endogeneity problem by simply adding the estimate of the error term η_t from the first stage regressions (6) as generated regressors to the outcome regression instead of using χ^*_{1t}.

In a dynamic regression model, in which is included a lagged dependent variable, the OLS estimator is biased and inconsistent because of the correlation of the lagged dependent variable with the individual specific effect. Instead of using OLS or within-group estimators, we estimate equation (7) by implementing a bias-corrected Least Square Dummy Variable' (BCLSDV) estimation technique. The bias of the LSDV estimator is approximated following Bruno (2005) and Bun and Kiviet (2003) methodology. Additionally, in order to increase the robustness of our results, we adopted IV - Anderson and Hsiao estimates Anderson and Hsiao (1981).

Regressing equation (7) we compute FE residuals, denoted by $\hat{\text{b}}$ and the associated residuals ϵ, defined by

$$\epsilon_{it} = \Upsilon_{it} - (\widehat{\lambda}\Upsilon_{it-1} + \widehat{\beta_{1t}}\chi_{1it} + \widehat{\beta_{2t}}\chi_{2it})$$

Computing the time averages of the residuals in step 1,

$$\bar{\hat{\epsilon}} = T^{-1} \sum_{t=1}^{T} \widehat{\epsilon_{it}}$$

we continue with a cross-section OLS regression of EPL measurements and democracy on the computed residuals in step 1.

- Step 2: Time-Invariant Regression Model :

$$\widehat{\epsilon_i} = \delta + EPL_i'\gamma_1 + Democracy_i'\gamma_2 + \zeta_i \tag{8}$$

where EPL_i' is a $K_{EPL} > 1$ vector of EPL indices and is a vector $K_{Democracy} > 1$ measuring the level of democracy and δ an intercept.

The empirical estimates are presented in section 6. In the following section, 4, we present the design of the Monte Carlo simulation to examine the extent to which endogeneity is likely to distort the predicted values in the second stage. The dataset we used in the aforementioned empirical specification is laid out in Section 6.

4 Monte Carlo Simulation

In this section, we investigate the extent to which the estimated parameters in the second stage are likely to be distorted when endogeneity is ignored in the first-stage regression using an artificial data set. For the first stage regression, the DGP we consider to generate our simulated data set is like Kiviet et al. (2017) and Yang et al. (2022):
First Stage Regression:

$$y_{it} = \phi y_{it-1} + \beta_1 \chi_{1it} + \beta_2 \chi_{2it} + \alpha_i \upsilon_{it} \tag{9}$$

$$\chi_{1it} = \varrho_1 \alpha_i + \nu_{1it} \tag{10}$$

$$\chi_{2it} = \varrho_2 \alpha_i + \nu_{2it} \tag{11}$$

We make the following further assumptions:

$$\alpha_i \sim U(-1,1), \chi_{2it} \sim IIDN(0,1)), \nu_{1it} \sim N(0,1)), \nu_{2it} \sim N(0,1)) \tag{12}$$

$$\chi_{1it} \sim U(-1,1) \tag{13}$$

With

$$E(\upsilon_{it}|\chi_{2it}) = 0 \tag{14i}$$

$$E(\upsilon_{it}|\chi_{1it}) \neq 0 \tag{14ii}$$

$$E(\chi_{1it}|\chi_{2it}) \neq 0 \tag{14iii}$$

The assumptions in (12) are standard in dynamic panel data econometrics; see, for example, Hsiao and Zhang (2015) and Kiviet et al. (2017). Assumption (14i) states that the random variable χ_{2it} is uncorrelated (exogenous) with the error term υ_{it} while (14ii) argues that the random variable χ_{1it} is correlated (endogenous) with the error term υ_{it}. Assumption (14iii) means that the exogenous variable χ_{2it} is correlated with the endogenous variable χ_{1it} . This assumption is based on Yang et al. (2022) who claim that the 2sCOPE estimator is biased when the copula transformation of the endogenous random variable $P^*_{\chi_{1it}}$ is correlated with the exogenous variable χ_{1it}. This is expected to happen when several independent variables predict movements in the dependent variable.

The non-normality assumption (13) is essential for all results; see Park and Gupta (2012) and Yang et al. (2022). Adding the copula transformation of endogenous regressor as an additional regressor will cause perfect co-linearity with the original variable, leading to identification problems. Finally, we choose a process with high persistence $\lambda = 0.90$ while for the values of β_1, β_2, ϱ_1, ϱ_2, we set $\beta_1 = 0.50$, $\beta_2 = 0.25$,$\varrho_1 = \varrho_2 = 0.75$. We set the dependence between the endogenous variable and the error term equal to 0.70 while the correlation between the endogenous and the exogenous variable equals 0.50; see also Yang et al. (2022). Following Hsiao and Zhang (2015) we consider cases with small N, large T ($N = 20$,$T = 40$,100) and small T, large N ($N = 40$,100,$T = 20$).

Second Stage Regression:

In the second stage of regression, we estimate the following model:

$$\ddot{\upsilon}_i = \gamma_0 + \gamma_1 \chi_{3i} + w_i \tag{14}$$

where $\ddot{\upsilon}$ shows the average value per unit of composed errors from the first stage regression,χ_{3i} is a normally distributed random variable with zero mean and unity variance while w_i is a statistical noise. Finally, γ_0 and γ_1 are parameters to estimate. We assume the correlation between the existing variable $\ddot{\upsilon}_i$and the random variable χ_{3i} is equal to 0.60. To generate a predefined correlation between a random variable and an existing one, we consider that for vectors with mean zero, their correlation equals the cosine of their angle. A detailed description of this method is provided in Appendix-A.1.

Given the inconsistency of the Least Square Dummy Variable Estimator (LSDVE) for dynamic panel models, we employ the Anderson and Hsiao (1981), Anderson and Hsiao (1982) simple instrumental variable estimator. Arellano (1989) has shown that this estimator performs better when the level of the lagged dependent variable is used as an instrument. We carry out 1000 MC iterations using different combinations of N and T. In each iteration, we estimate parameters λ, β_1, β_2 based on model (9) or its extended version with P^*_{x1it}. In Table 1, we report the average values of the bias of the estimates of

λ, β_1, β_2, from its true value (denoted as BIAS), the mean square error (MSE) as well as the mean values of γ_0 and γ_1 under the assumption that χ_{1it} is generated from a uniform distribution with parameters (-1,1) while in Table **??** we consider that the endogenous variable χ_{1it} follows a t distribution with 5 degrees of freedom that is $\chi_{1it} \sim t_{df}$, $df = 5$. The t distribution can show if our method is robust to a misspecification of the true distribution of χ_{1it}. In both Tables, we present simulated results for the case we ignore the endogeneity of χ_{1it} when estimating models (9) and (14), and for the case we control for it. From these tables, several conclusions can be drawn.

Table 1: Results for the endogenous variable χ_{1it} assuming a uniform distribution with parameters (-1, 1)

Scenario		**Bias**			**Mean Squared Error (MSE)**			**Mean Values**	
N	**T**	λ	β_1	β_2	λ	β_1	β_2	γ_0	γ_1
Ignore Endogeneity of χ_{1it}									
20	40	0.049	1.756	-0.311	0.005	3.126	0.104	-0.0007	1.555
20	100	0.073	1.715	-0.307	0.006	2.960	0.097	-0.0007	1.501
40	20	0.003	1.837	-0.312	0.003	3.416	0.105	0.0003	2.402
100	20	0.004	1.834	-0.309	0.001	3.381	0.099	-0.0008	3.828
Controlling for the Endogeneity of χ_{1it}									
20	40	0.048	0.173	-0.026	0.005	0.453	0.021	-0.001	0.860
20	100	0.072	0.140	-0.213	0.006	0.167	0.008	-0.002	0.816
40	20	0.0004	0.196	-0.017	0.003	0.812	0.023	-0.0004	1.383
100	20	0.0009	0.127	-0.002	0.001	0.192	0.009	-0.0002	2.118
Notes: The table presents average BIAS and MSE for λ, β_1, β_2, and mean values of γ_0, γ_1 over 1000 iterations.									

Table 2: Monte Carlo Simulation results for the endogenous variable χ_{1it} following a t-distribution (df=5)

Scenario		**Bias**			**Mean Squared Error (MSE)**			**Mean Values**	
N	**T**	λ	β_1	β_2	λ	β_1	β_2	γ_0	γ_1
Ignore Endogeneity of χ_{1it}									
20	40	0.044	0.833	-0.325	0.005	0.705	0.116	0.0003	1.991
20	100	0.071	0.793	-0.317	0.006	0.634	0.104	-0.0006	1.923
40	20	-0.009	0.885	-0.327	0.003	0.794	0.118	0.004	3.103
100	20	-0.008	0.871	-0.321	0.001	0.763	0.107	-0.008	4.973
Controlling for the Endogeneity of χ_{1it}									
20	40	0.044	0.259	-0.095	0.005	0.253	0.049	-0.0009	1.451
20	100	0.071	0.125	-0.046	0.006	0.089	0.017	-0.002	1.298
40	20	-0.009	0.294	-0.094	0.003	0.323	0.055	-0.0008	2.291
100	20	-0.009	0.177	-0.043	0.001	0.114	0.020	-0.002	3.416
Notes: The table presents average BIAS and MSE for λ, β_1, β_2, and mean values of γ_0, γ_1 over 1000 iterations.									

(a) As expected, the IV estimator works remarkably well in reducing the bias of λ, see Anderson and Hsiao (1981), Anderson and Hsiao (1981), and Hsiao and Zhou (2017).

(b) For the case, we ignore the endogeneity of random variable χ_{1it} both β_1, β_2 are severely biased as it is indicated by the BIAS and MSE metrics. The bias slightly increases as N grows larger, indicating that the biases do not disappear as N or T increases.

(c) These results hold for the student's t distribution as well.

(d) The 2sCOPE estimator clearly deals with the problem of endogenous random variable χ_{1it} demonstrating thus that the average β_1, β_2 values are very close to the true ones. In other words, by using the 2sCOPE method, the implying regressor endogeneity is correctly detected.

(e) The performance of the method improves with N, implying more accurate estimations of β_1 and β_2

(f) The 2sCOPE estimator can successfully control for the endogeneity bias problem of the random variable χ_{1it} even in the case this variable follows a t-distribution.

(g) The estimation of the augmented model (9) controlling for endogeneity exerts an important influence on the estimates of the second stage regression that is γ_0 and γ_1. For instance, in the case that the endogenous variable follows a uniform distribution with parameters (-1,1) with N=20 and T=40, the mean value for γ_1 equals 1.555 and 0.860 for the ignore and allow for endogeneity case, respectively. Similar differences can be documented for the case that the endogenous variable follows a student t distribution.

From the above results, we can conclude that for dynamic panel models that combine some varying endogenous regressors with some invariant exogenous ones and thus a two-stage estimation procedure should be adopted, the size of the estimated parameters of the second stage regression is not correct when we ignore the presence of endogeneity leading, thus, to erroneous statistical inference.

5 Data

To explore empirically the relationship between employment protection legislation and income inequality, we proceed along with an unbalanced panel of data consisting of 32 OECD countries over the period 1985 to 2019. This section describes the data used and the reason for choosing these variables in the empirical specification.

5.1 Data on Income Inequality

To estimate the relationship between income inequality and Employment Protection Legislation we consider as a dependent variable the Gini coefficient. Even though

Kuznets (1955) suggested that the most appropriate measure of inequality should be based on gross (rather than net) incomes, we employ the Gini coefficient of inequality of both pre-tax,pre-transfer (gGini) and disposable income (nGini) proposed by Solt (2020). Solt (2020) develops the Standardized World Income Inequality database considering both the inequality of pre-tax, pre-transfer, and post-tax, post-transfer (disposable) household income. The disposable income (contrary to market-based income) inequality measures the level of income disparities after accounting for the redistribution policy of the government through taxes, transfer, and fiscal policies. The specification of Solt (2020) offers an internationally comparable measure of disposable income inequality, which stems from the government's implementation of redistributive policies and measures.

Figure 1 shows the data on net and gross Gini measurements. The index lies between 0 and 100; values close to 100 indicate less equal income distribution. In many economies, both series are trending upwards (i.e., Italy, Japan, Hungary, New Zealand, United States, United Kingdom). In countries such as Slovak Republic, Mexico, and Portugal, both Gini coefficient measurements are trending downwards. Additionally, we can observe that in Germany, Sweden, Denmark, Belgium, and the Netherlands, the redistributive schemes are effective as the ratio of average gross-to-net Gini strongly exceeds 1.

5.2 Data on Employment Protection Legislation

The key explanatory variable of our analysis is the Employment Protection Legislation. EPL is a set of mandatory restrictions upon dismissals and the requirements of employees. In our analysis, labor market protection relies on three different measures of EPL from OECD (2020) [2]. In particular, we consider the regulation on the use of fixed-term and temporary work agency contracts including hiring regulations. The

[2]Source: See OECD (2020), OECD Employment Outlook, Chapter 3.

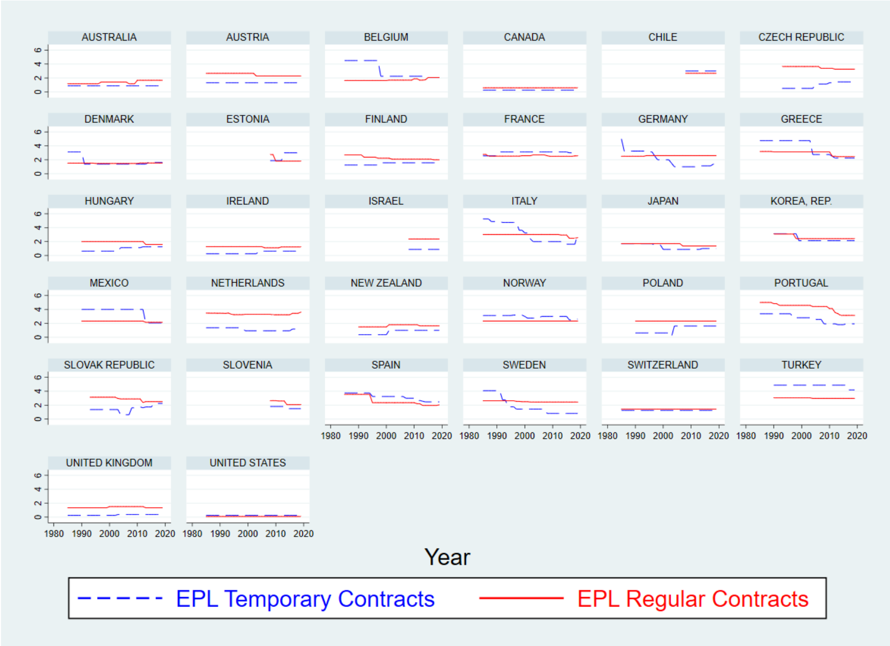
Figure 1: Gini Coefficients, Gross and Net

Notes: Blue (red) line indicates Net (Gini) coefficients.
Source: Solt (2020)

overall EPL for dismissing regular workers assigns a weight of 5/7 to individual dismissals and 2/7 to collective dismissals. Regulation of temporary contracts includes hiring regulations for fixed-term and temporary work agency contracts.

Figure 2 shows the data on employment protection in temporary and regular contracts. The range of indicators lies between 0 and 6; higher values of the above indices insinuate more regulations on the procedures involved in hirings and lay-offs making the labor market more regulated. Compared to other countries, the United States, the United Kingdom, Switzerland, and Canada have fewer rights regarding unfair dismissals after the outburst of economic crises, such as Greece, Portugal, and Spain, which had to deregulate the laws against collective dismissals. Additionally, considering hiring regulations for temporary workers, there are countries (i.e., Belgium, Greece, Sweden, and Portugal) that reduced restrictions on temporary contracts. In others, though, there have been sustained increases in the regulation for hiring temporary workers. (i.e., Poland, Italy, and Slovak Republic).

Figure 2: EPL , Temporary and Regular Contracts



Notes: Solid (dash) line indicates EPL in Regular (Temporary) Contracts.
Source: OECD (2021)

5.3 Control Variables

As mentioned in section 3, the first step of empirical specification requires a set of time-varying regressors that affect income distribution. In this subsection, we briefly present the set of macroeconomic variables that we will augment in time-varying regression analysis, as well as their relation with income distribution based on previous studies. As we saw above, the level of income inequality varies across countries and within the same income groups. Based on Furceri and Ostry (2019), the level of development, unemployment, and globalization can be considered as important determinants of income inequality.

Following Furceri and Ostry (2019), the logarithm of real GDP per capita in linear and squared terms captures the role of economic development in inequality. Economic development is one of the most significant factors in explaining income inequality evolution. The well-known work of Kuznets (1955) highlighted an inverted-U relationship between growth and inequality. Alesina and Rodrik (1994) and Alesina and Perotti (1996) suggested a negative relationship between economic growth and inequality whereas Barro (2000) found inconclusive results. At the same time, Angeles (2010) and Savvides and Stengos (2000) provided evidence for a U-shaped relationship between income inequality and GDP. Considering that higher unemployment rates tend to increase inequality by affecting wages negatively (Cysne (2009); Acemoglu (1999), following Furceri and Ostry (2019), Koeniger et al. (2007) and Checchi and García-Peñalosa (2014) we augment our analysis with the unemployment level, through which it appears that income inequality increases the lower the employment rate is.

Trade and financial globalization affect differently the income distribution. Considering an index of Financial globalization, which is measured by capital flows and stocks of foreign assets and liabilities, we control for the effect of financial openness on income differences. However, the impact of financial globalization varies depending on the situation and circumstances. Financial globalization can either affect positively (Jaumotte et al. (2013); Furceri and Loungani (2018); Asteriou et al. (2014) or negatively the income inequality (Hamori and Hashiguchi (2012) and Clarke et al. (2006)). Nevertheless, empirical shreds of evidence provided a non-linear hypothesis of finance on income inequality (Greenwood and Jovanovic (1990) depending on the level of economic development. How trade globalization relates to income inequality has been examined in many empirical studies with mixed results (especially for advanced economies Autor et al. (2013) and Dauth et al. (2014)). Based on Stolper and Samuelson (1941) theorem, trade openness works in favor of higher-skilled workers, leading to higher income distribution. Roser and Cuaresma (2016) and Meschi and Vivarelli (2009) provided evidence for a positive relationship between income inequality and trade openness, while Jaumotte et al. (2013) suggested a narrowing inequality effect of trade. Following the empirical analysis of Furceri and Ostry (2019), we use the sum of exports and imports of goods of (%GDP) and an overall index of foreign direct investment, international debt, income payments, and reserves to capture trade and financial globalization, respectively.

Based on the human capital model, the level of schooling affects earning distribution Mincer (1974). The logarithm term of human capital is an index for education based on the average years of schooling Barro and Lee (2013). It is expected that human capital decreases income inequality (Gregorio and Lee (2002), Calderon and Chong (2009), Katz and Murphy (1992) and Woo (2018)). A major determinant of income inequality can be considered technological change. Technological progress, which is measured by the gross fixed capital formation (% GDP), is a proxy for skill-biased technological progress Checchi and García-Peñalosa (2014). Technological progress is considered a traditional factor of rising income inequality in recent decades (Autor et al. (1998) and Acemoglu (2003)).

The variation of government policies across countries can be considered a significant factor explaining cross-country variation in inequality Furceri and Ostry (2019). To capture the role of fiscal policy, we augment in our model the size of government Furceri and Ostry (2019) taking into account the government expenditures (% GDP). Even though Maestri and Roventini (2012) provided evidence of a widening inequality effect, Chatterjee and Turnovsky (2012), Furceri and Ostry (2019) suggested a narrowing inequality effect of government spending in inequality in the short run and a widening inequality effect in the long run. Earlier literature on the impact of inflation on income inequality has been well studied Doumbia and Kinda (2019), Furceri and Ostry (2019). Inflation, as measured by the GDP deflator Furceri and Ostry (2019), is more costly for lower-income workers compared to other income groups, increasing the inequality gap. Liquid assets are more likely to decrease in the presence of inflation, leading to a transfer of wealth from the poorest population and increasing inequality (Erosa and Ventura (2002); Albanesi (2007)).

Finally, considering an index of democratization, we capture the role of institutions on income disparities. While democracy can potentially contribute to reducing income inequality through political representation, redistribution policies, and promoting equal opportunities, the effectiveness of these mechanisms can be influenced by various contextual factors. The results are mixed for net and gini coefficients Kammas and Sarantides (2019), Sirowy and Inkeles (1990), Acemoglu et al. (2015), Boix (2003). The indicator of democracy is used in the second stage regression as it is considered a time-invariant variable. The empirical estimates of the underlined methodology in section 3 are presented below.

6 Results

Table 3 shows the empirical evidence of the regression of net and gini coefficients on time-varying variables (as mentioned in section 3). The analysis employs the BCLSDV empirical estimation approach. Columns (1) and (2) present the empirical estimates ignoring the potential endogeneity bias, while columns (3) and (4) display the results after addressing endogeneity bias, using the 2sCOPE methodology proposed by Yang et al. (2022). The empirical evidence reveals a significant (non-significant) U-shaped relationship between net (gross) gini and GDP per capita. This finding lends support to the concept of an S-curved relationship between income inequality and GDP per capita, in line with prior studies such as Angeles (2010), Savvides and Stengos (2000), Piketty (2014), Tribble (1999). Specifically, during the initial stages of economic development, income inequality tends to increase, aligning with the notion of an inverted U-shaped relationship, as suggested by Kuznets (1955)). However, after reaching a certain level of development, income inequality (advanced economies) initially decreases as GDP per capita increases, but then increased GDP per capita is linked to a worsening of income inequality.

Higher unemployment level has a robust positive effect on income inequality, indicating that it is necessary for economies to improve employment rates in order to decrease income disparities. Turning to globalization indices, we observe distinct effects of the impact of financial and trade globalization on income inequality. Notably, trade globalization displays a higher net coefficient (with non-significant results for the Gini index). This result aligns with the findings of Roser and Cuaresma (2016), giving further empirical support to the Stolper-Samuelson theorem Stolper and Samuelson (1941), which posits that increased international integration is associated with a wage premium to skilled labor, increasing income inequality in developed economies.

Table 3: **Time-Variant Regression (1st Stage)**

VARIABLES	**Gross Gini (1)**	**Net Gini (2)**	**Gross Gini (3)**	**Net Gini (4)**
GDP per capita	-0.805	**-3.108****	-1.120	**-3.175****
	(1.579)	(1.435)	(1.592)	(1.479)
GDP per capita (sq)	0.0534	**0.155****	0.0634	**0.151****
	(0.0766)	(0.0693)	(0.0774)	(0.0718)
Human Capital (log)	**-2.774*****	**-1.990*****	**-2.232*****	**-0.943**
	(0.592)	(0.542)	(0.818)	(0.758)
Financial Glob.	**-0.00521****	**-0.00517****	**-0.00489****	**-0.00485****
	(0.00213)	(0.00202)	(0.00220)	(0.00208)
Trade Glob.	0.00228	**0.00677*****	0.00217	**0.00640*****
	(0.00249)	(0.00225)	(0.00239)	(0.00220)
Unemployment	**0.0329*****	**0.0202*****	**0.0243***	**0.0257****
	(0.00607)	(0.00555)	(0.0133)	(0.0122)
Inflation	0.000585	0.000321	0.000853	0.000686
	(0.00201)	(0.00185)	(0.00204)	(0.00189)
Gov. Spendings	**0.0866*****	**0.0430*****	**0.0854*****	**0.0408*****
	(0.00936)	(0.00867)	(0.00923)	(0.00855)
Tech Progress	0.00676	0.00656	0.00523	0.00303
	(0.00556)	(0.00509)	(0.00596)	(0.00551)
resUnemploymentGDP			0.0281	-0.0450
			(0.0520)	(0.0475)
resHumanCapitalGDP			-0.0739	**-0.141****
			(0.0700)	(0.0648)
Observations	888	888	886	886
No. Countries	32	32	32	32
Endogeneity Correction	NO	NO	YES	YES

*Bootstrap standard errors in dynamic panel analysis and reported, *** Significance at 1%, ** Significance at 5%, * Significance at 10%*

Examining the impact of financial globalization, it is apparent that the attraction of foreign capital leads to a reduction in both the net and gross gini coefficients by facilitating countries to invest more. This findings supports the studies of Beck et al. (2007), Hamori and Hashiguchi (2012), Clarke et al. (2006). Additionally, education exerts a notable and statistically significant effect on income distribution. Other things equal, an increase in the level of human capital serves to diminish educational inequality and thereby income differences as posited by Gregorio and Lee (2002), Katz and Murphy (1992), and Calderon and Chong (2009). Conversely, higher levels of government spending, i.e., spending for public services, have a widening inequality effect. This may be attributed to the possibility that conventional measures of income inequality may not adequately account for the narrowing inequality effect of health and education as suggested by Maestri and Roventini (2012). Finally, GDP deflator and skill technological progress fail to yield a robust positive effect on income inequality.

Table 4: Time-Invariant Regression (2nd Stage) - OLS

VARIABLES	resgross (I)	resnet (II)	resgross (III)	resnet (IV)
EPL Temp	**-0.131****	**-0.0860***	**-0.129****	**-0.0806***
	(0.0593)	(0.0454)	(0.0585)	(0.0461)
EPL Reg	**-0.214*****	**-0.180*****	**-0.204*****	**-0.164****
	(0.0766)	(0.0622)	(0.0735)	(0.0702)
Democracy	-0.0295	-0.0212	-0.0311	-0.0227
	(0.0459)	(0.0391)	(0.0472)	(0.0386)
No. of Countries	32	32	32	32
R-squared	0.444	0.436	0.436	0.408
Copula 1st Stage	NO	NO	YES	YES

*Bootstrap standard errors in dynamic panel analysis and reported,*** Significance at 1%, ** Significance at 5%, * Significance at 10%*

Table 4 shows the results for the time-invariant regression analysis of the averaged residuals derived from the first-stage regression on EPL for temporary and regular contracts and democracy. In columns (I) and (II), we use the residuals ignoring endogeneity bias in the first-stage regression, whereas in columns (III) and (IV), we have controlled for the endogeneity. Overall, the OLS empirical estimates suggest a negative relationship between EPL for temporary and regular labor holders and Gini coefficients, reinforcing the findings of Koeniger et al. (2007), Checchi and Garcia-Penalosa (2010), Perugini and Pompei (2016). However, the democratization index fails to provide a robust negative effect on income inequality, indicating that the level of democracy has no significant impact on income distribution.

In detail, decreasing the flexibility of using temporary contracts demonstrates a weak but statistically significant negative effect on income inequality, aligning with Perugini and Pompei (2016). A plausible could be rooted in bargaining theory, as temporary labor holders may gain greater bargaining power to demand higher wages and potentially decrease income inequality. Simultaneously, an increase in dismissal costs is associated with a significant adverse effect on income inequality, giving further support to the empirical analysis of Koeniger et al. (2007), Checchi and García-Peñalosa (2014). Strengthening protection against lay-offs enhances the protection for less-protected and lower-paid workers, reducing the division of the labor market between "insiders" and "outsiders" and thereby decreasing income disparities.

The findings are confirmed even if we consider the IV - Anderson and Hsiao (1981) estimates in the first-stage regression analysis. These estimates are presented in Tables 1c & 2c in the A.2 Appendix. Specifically, our estimates demonstrate that increasing employment protection for regular contracts can have a substantial impact on reducing income inequality. However, we did not observe any significant effect of higher employment protection for temporary contracts on the net Gini coefficient, Increasing the need to invest further in the impact of EPL on net income disparities.

From the OLS estimates, it is straightforward that income inequality is inversely related to EPL measurements. Extending further our analysis, we investigate if EPL policies help countries to converge to similar levels of income inequality. Thereby, we regress the ratio of time-averaged residuals for each country on the maximum residuals value in the sample using as explanatory variables the EPL measurements and democratization index. Given the bounded nature of the dependent variable, which ranges between 0 and 1, we apply Tobit estimates. [3]

In the second stage of time-invariant regression, we estimate the following model:

[3] Tobit estimates Tobin (1958), in theory, are considered superior to OLS estimates when dealing with bounded data, even though both estimates closely align. Tobit models offer the advantage of producing robust results in cases where the sample may not be entirely representative of the entire population.

■ Tobit Regression model

$$\frac{\widehat{\epsilon}}{max\widehat{\epsilon}_i} = \delta + EPL_i'\gamma_1 + Democracy_i'\gamma_2 + \zeta_i \tag{15}$$

Table 5: Time-Invariant Regression (2nd Stage) - TOBIT

VARIABLES	ratio gross (V)	ratio net (VI)	ratio gross (VII)	ratio net (VIII)
EPL Temp	**-2.094****	**-0.476***	**-1.577****	**-0.444***
	(1.023)	(0.262)	(0.793)	(0.246)
EPL Reg	**-3.418*****	**-0.994*****	**-2.503****	**-0.902****
	(1.254)	(0.322)	(1.157)	(0.363)
Democracy	-0.471	-0.117	-0.381	-0.125
	(0.765)	(0.227)	(0.526)	(0.204)
No Countries	32	32	32	32
R-squared	0.444	0.436	0.436	0.408
Copula 1st Stage	NO	NO	YES	YES

*Bootstrap standard errors in dynamic panel analysis and reported, *** Significance at 1%, ** Significance at 5%, * Significance at 10%*

Columns (V), (VI), (VII), and (VIII) of Table 5 provide the empirical evidence of the Tobit regression model. The results obtained by eq.15 increase the validity of our baseline results and highlight the substantial influence of employment protection policies to reduce income differences. In particular, the results indicate a persistent pattern of income inequality reduction across the countries in our dataset. Thereby, we can assume that the implementation of stricter employment protection regulations in both regular and temporary labor contracts can lead to a significant decrease in income disparities in high-income inequality countries. Consequently, these countries may be on a path to align their income inequality levels with those of low-income inequality nations.

7 Robustness Check

We perform one type of robustness check on the effect of EPL on income inequality, providing a principle component analysis on the Time-Varying regression as explained in section 3. During the estimation procedure, except for the possible endogeneity

Table 6: Time-Variant Regression (1st Stage) - PCA

	(A)	**(B)**	**(C)**	**(D)**
VARIABLES	**gGini**	**nGini**	**gGini**	**nGini**
GDP per capita	**-5.454*** **	**-6.728*** **	**-5.127*** **	**-6.929*** **
	(1.487)	(1.278)	(1.556)	(1.374)
GDP per capita (squared)	**0.241*** **	**0.307*** **	**0.221*** **	**0.319*** **
	(0.0730)	(0.0623)	(0.0772)	(0.0680)
Weighted Component	**0.194*** **	**0.102*** **	**0.285** **	0.0586
	(0.0348)	(0.0292)	(0.133)	(0.119)
rescomponentgdpt			-0.0706	0.0345
			(0.0965)	(0.0863)
Observations	888	888	886	886
No. of Countries	32	32	32	32
Endogeneity Correction	NO	NO	YES	YES

Bootstrap standard errors in dynamic panel analysis and reported,
**** Significance at 1%, ** Significance at 5%, * Significance at 10%*

problem, we have to deal with multicollinearity Farrar and Glauber (1967). Considering that during the first step of regression analysis, a set of explanatory variables are approximately linear related, we adopted a principle component analysis (PCA) to control the multicollinearity problem. PCA dimensionality reduction technique removes multicollinearity from the dataset and preserves the maximum variance.

For our analysis, we calculated a weighted average component (Weighted Component) for the first four components (explaining the 86,59%) from a set of time-varying variables, including the logarithm term of human capital, the government expenditures in the percentage of GDP, the unemployment, the trade, and financial openness, the inflation, and skill-biased technological progress.

We follow the same estimation procedure as mentioned in section 3 and the results reported in Table 6 and Table 7 for both net and gross gini measurements. While in columns (A) and (B), we ignore endogeneity, in columns (C) and (D), we control for the endogeneity in the time-varying regression using the 2sCOPE (Table 6). The findings suggest that income inequality may follow a U-shaped trajectory, with decreasing inequality followed by a potential increase in inequality at higher economic

Table 7: Time-Invariant Regression (2nd Stage) - PCA

	(A')	**(B')**	**(C')**	**(D')**
VARIABLES	**resgross**	**resnet**	**resgross**	**resnet**
EPL Temp	-0.0153	0.0400	-0.0122	0.0408
	(0.0330)	(0.0354)	(0.0350)	(0.0401)
EPL Reg	**-0.1000***	**-0.122****	**-0.103***	**-0.123***
	(0.0589)	(0.0589)	(0.0609)	(0.0645)
Democracy	**0.0884*****	-0.0113	**0.0867*****	-0.0120
	(0.0280)	(0.0366)	(0.0315)	(0.0336)
No. of Countries	32	32	32	32
R-squared	0.401	0.163	0.393	0.161
Copula 1st Stage	NO	NO	YES	YES

Bootstrap standard errors in dynamic panel analysis and reported,
**** Significance at 1%, ** Significance at 5%, * Significance at 10%*

development levels, giving further empirical support to baseline results. After controlling for endogeneity, the weighted component provides a significant positive effect on income inequality only for the gross Gini coefficient. Similar results are obtained even when we do not deal with possible endogeneity problems for both net and gross Gini coefficients.

The OLS empirical estimates of the Time-Invariant regression analysis provide mixed results (see Table 7). The increase in the protection against dismissals provides a robust negative relationship with gross coefficient, giving further empirical support to the baseline results and the existing literature Koeniger et al. (2007), Checchi and García-Peñalosa (2014) and Fortuna and Neto (2021). On the other hand, the empirical estimates on the distributional impact of EPL on temporary labor holders failed to support a positive impact on income inequality. Finally, regarding the distributional effect of democracy, it appears that income inequality has an upward trend after redistribution (net Gini index). Based on Acemoglu et al. (2015), higher levels of democratization tend to increase income disparities "*when the economies have already undergone a significant structural transformation* as carried out in total the advanced economies.

8 Conclusion

Recently, the causes and the consequences of income inequality have garnered increased attention in understanding the determinants of income inequality. Trade and financial globalization and the spread of technological changes are widely acknowledged as driving forces behind rising income disparities across countries. Employment protection legislation (EPL) is a critical component of labor market regulations that can shape income disparities.

This analysis employs a rigorous dynamic empirical approach to examine the interplay between employment protection and income inequality. In contrast to prior research, we consider that employment protection is a slowly changing variable. Traditional OLS regression doesn't yield accurate estimates in the context of time-invariant variables. To address this, we employ a two-stage method proposed by Pesaran and Zhou (2018), and we extend this method in the case where some of the regressors are endogenous. To allow for endogeneity, we use a free instrument method based on copula theory. Through Monte Carlo simulations, our analysis demonstrates that our estimation method outperforms the standard two-stage estimator in the case of endogeneity.

As employment protection measurements, we use two indices: one that captures the protection against dismissals for regular labor holders and the other that captures the protection on using temporary labor contracts. The results indicate that higher employment protection for regular contracts significantly decreases income inequality. In contrast, the role of employment protection in temporary labor holders fails to provide a robust relationship with Gini indices. So, further research is needed to thoroughly examine employment protection's impact, particularly in the context of temporary labor contracts. Our empirical findings additionally highlighted that EPL can reduce income inequality disparities across countries.

Turning to other determinants of income inequality, economic development as measured by GDP per capita demonstrates a U-shaped association with income inequality. This result signifies that following a particular threshold of development, further economic expansion tends to exacerbate the disparity between low and high-wage earners. Furthermore, while an increase in trade globalization increases income inequality, financial globalization yields a converse effect by enabling the economies to attract investments and stimulate economic growth. The accumulation of human capital decreases income inequality, whereas increased government spending widens income income disparities.

The empirical findings from this analysis have significant policy implications. Well-designed employment protection measures can serve as a potent tool in addressing income inequality. Policymakers should consider the role of EPL in crafting labor market policies that promote economic fairness and social justice. However, it is crucial to recognize that a one-size-fits-all approach may not be appropriate, and policy interventions should be tailored to the specific socio-economic context of each country.

A Appendix

A.1 Monte Carlo Simulation

In order to generate a correlation between an existing variable and a randomly distributed variable with zero mean and unity variance, we apply the following steps:

1. Get the fixed vector υ_i and a random χ_{i3}
2. Center both vectors (mean 0), giving vectors $\dot{\upsilon}_i, \dot{\chi}_{i3}$
3. Make $\dot{\chi}_{i3}$ orthogonal to $\dot{\upsilon}_i$ (projection onto orthogonal subspace), giving $\dot{\chi}_{i3}\perp$
4. Scale $\dot{\chi}_1$ and $\dot{\chi}_2$ to length 1, giving $\overline{\upsilon}_i$ and $\overline{\chi}_{i3}\perp$
5. The term $(\overline{\chi}_{i3}\perp + (\frac{1}{tan(\theta)})\overline{\upsilon}_i)$ is the vector whose angle to $\overline{\upsilon}_i$ is θ, and whose correlation with $\overline{\upsilon}_i$ thus is r. This is also the correlation to υ_i since the linear transformations leave the correlation unchanged.

A.2 Anderson and Hsiao Estimates

Table 2: 1st Stage Regression - IV Anderson & Hsiao

VARIABLES	gGini (A)	nGini (B)	gGini (C)	nGini (D)
GDP per capita	**-6.393*** **	**-6.950*** **	**-6.933*** **	**-7.338*** **
	(1.598)	(1.398)	(1.645)	(1.431)
GDP per capita (squared)	**0.329*** **	**0.337*** **	**0.347*** **	**0.350*** **
	(0.0775)	(0.0672)	(0.0800)	(0.0692)
Human Capital (log)	**-3.004*** **	**-2.381*** **	**-2.074*** **	**-1.583** **
	(0.571)	(0.536)	(0.728)	(0.684)
Financial Globalization	0.000517	0.00211	0.00114	0.00243
	(0.00210)	(0.00201)	(0.00212)	(0.00202)
Trade Globalization	**0.00445** **	**0.00682*** **	**0.00393* **	**0.00648*** **
	(0.00222)	(0.00207)	(0.00223)	(0.00208)
Unemployment	**0.0373*** **	**0.0156*** **	**0.0283*** **	**0.0214** **
	(0.00546)	(0.00490)	(0.0108)	(0.0100)
Inflation	0.000296	-0.000556	0.000778	-0.000220
	(0.00190)	(0.00178)	(0.00191)	(0.00179)
Government Spending	**0.0915*** **	**0.0354*** **	**0.0874*** **	**0.0328*** **
	(0.00865)	(0.00820)	(0.00884)	(0.00838)
Technological Progress	0.00671	0.00337	0.00565	0.00243
	(0.00469)	(0.00440)	(0.00524)	(0.00491)
resHumanCapitalGDP			**-0.118* **	**-0.101* **
			(0.0609)	(0.0566)
resUnemploymentGDP			0.0327	-0.0341
			(0.0430)	(0.0403)
Observations	888	888	886	886
No of countries	32	32	32	32

*Standard errors in dynamic panel analysis reported. *** Denotes significance at 1%, ** at 5%, and * at 10%*

Table 3: 2nd Stage Regression - IV Anderson & Hsiao

VARIABLES	resgross (A)	resnet(B)	resgross (C)	resnet (D)
EPL Temp	-0.112	0.101	**-1.951** **	0.107
	(0.0847)	(0.133)	(0.788)	(0.125)
EPL Reg	**-0.234** **	**-0.378** **	**1.489* **	**-0.365** **
	(0.109)	(0.164)	(0.830)	(0.167)
Democracy	**-0.0277**	**-0.180* **	**1.953*** **	**-0.181* **
	(0.0720)	(0.108)	(0.717)	(0.103)
Observations	32	32	32	32
R-squared	0.305	0.283	0.503	0.275
Endogeneity Correction	NO	NO	YES	YES

*Standard errors in dynamic panel analysis reported. *** Denotes significance at 1%, ** at 5%, and * at 10%*

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