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Examining the Effect of Investment, Taxation on Low-Wage Earners, and Productivity (GDP Per Capita) on Income Inequality in Germany, Greece, Ireland, Portugal, and the UK during the Period 2009-2023 Using Panel Data Analysis

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Abstract: ***This study investigates the effects of investment, taxation on low-wage earners, and productivity (measured by real GDP per capita) on income inequality in Germany, Greece, Ireland, Portugal, and the United Kingdom from 2009 to 2023. Employing panel data analysis with a fixed effects model and pooled OLS for comparison, the study uses the quintile share ratio (S80/S20) from EU-SILC as the measure of inequality. The findings indicate that productivity has a statistically significant negative impact on income inequality, whereas taxation and investment variables show no consistent effects. These results highlight the importance of structural productivity growth over fiscal or investment policy in influencing income distribution across advanced European economies.***

Keywords: income inequality, panel data analysis, taxation, foreign investment, GDP per capita

Index of acronyms:
FDI: Foreign Direct Investment
IID: Income Inequality Distribution
GLS: Generalized Least Squares
SUR: Seemingly Unrelated Regressions

1. Introduction

Income inequality has re-emerged as a central concern in advanced economies, particularly in the aftermath of the 2008 global financial crisis and the subsequent European sovereign debt crisis. While the European Union has long promoted social cohesion and convergence, distributive outcomes across member states remain heterogeneous, reflecting differences in fiscal capacity, labor market structures, and integration into international capital markets. Germany, Greece, Ireland, Portugal, and the United Kingdom offer a compelling comparative sample, as they combine diverse welfare state models with distinct post-crisis adjustment trajectories.

The economic literature identifies multiple channels through which inequality is shaped. Fiscal policy, particularly taxation and transfers, directly influences disposable incomes, with taxes on low-wage earners playing a critical role in labor market incentives and the distribution of net earnings. International investment flows affect the structure of production, capital intensity, and wage dynamics, while productivity growth—proxied by real GDP per capita—remains central to long-term improvements in living standards. Understanding the interaction of these factors is essential for designing policies that balance equity and efficiency.

This study employs a panel data framework to analyze the joint effects of investment, taxation on low-wage earners, and productivity on income inequality between 2009 and 2023. By applying a fixed effects model, the analysis accounts for unobserved country-specific characteristics, allowing for a more precise identification of the drivers of inequality in the selected European economies.

2. Literature Review

Income inequality has remained a central concern in both academic research and policymaking, particularly within the European Union (EU) and comparable economies. The literature highlights multiple economic, social, and institutional factors that shape inequality outcomes, ranging from redistributive fiscal policy and taxation, to globalization, structural transformation, and demographic dynamics.

The effectiveness of redistributive fiscal policy has been a recurring theme in the European context. Wildowicz-Szumarska (2022) examined the EU-28 over the period 2005–2017 and found that social transfers are significantly more effective than direct taxes in reducing income inequality. Liberal welfare regimes exhibited the steepest increases in inequality, while social-democratic regimes proved more resilient. This suggests that institutional design matters as much as fiscal volume in shaping redistributive outcomes. Similarly, Ulu (2018), analyzing OECD countries, showed that government social spending directly reduces inequality, with greater effectiveness than education expenditures. These findings reinforce the idea that transfers remain the cornerstone of redistributive systems. At the same time, taxation policies affect both redistribution and growth. Balasoiu, Chifu, and Oancea (2023) demonstrated that corporate income taxes significantly depress economic growth, while personal income taxes hinder growth in countries with low fiscal efficiency. These results highlight the trade-off between equity and efficiency in fiscal design. By contrast, Erauskin (2020) focused on the labor share of income, finding that its relationship with inequality is heterogeneous: in “old” EU members, labor share has no significant link with inequality, while in “new” members, higher labor share can paradoxically increase inequality due to structural differences in labor markets. Taken together, these studies underline the nuanced role of redistributive instruments: while transfers generally reduce inequality, the effects of taxation and labor market dynamics vary depending on institutional context and stage of development.

Beyond fiscal policy, macroeconomic fundamentals also influence income distribution. Bucevska (2019) investigated EU candidate countries and found that unemployment, low economic development, and low investment rates increase inequality, whereas government indebtedness surprisingly reduces it. Education and demographic variables such as population growth also play a central role. Malerba and Spreafico (2013) further developed a framework for advanced EU economies, identifying short-term determinants of inequality across 25 member states. Their findings stressed the difficulty of isolating the relative impact of structural versus cyclical forces, but highlighted education and labour market conditions as critical levers.

Another strand of literature emphasizes globalization and trade integration as drivers of inequality. Asteriou, Dimelis, and Moudatsou (2014) showed that in the EU, trade openness, R&D, and FDI reduced inequality after 2010, though earlier periods saw globalization—particularly financial openness—exacerbating inequality. Similarly, Çelik and Basdas (2010) analyzed different country groups and confirmed that FDI inflows reduce inequality in developing countries but worsen it in developed ones, indicating that the effect of globalization depends on domestic absorptive capacity. Gabrisch (2009) focused on vertical intra-industry trade between the EU and Central-East European countries, showing that technological differences foster trade but can alter income distribution within countries, consistent with neo-Ricardian rather than Heckscher-Ohlin dynamics. These insights connect globalization to structural change and its distributive consequences.

Entrepreneurship also shapes inequality in complex ways. Ragoubi and El Harbi (2018) found evidence of an inverted U-shaped relationship between entrepreneurship and inequality, in line with the Kuznets hypothesis. At early stages of development, entrepreneurship can increase inequality, but as economies mature, it contributes to greater equality. Importantly, the relationship is moderated by institutional quality, governance, and innovation systems, underlining the role of broader structural factors.

3. Methodology and Data

3.1 Methodology

The methodology used in this research is the panel data analysis because it allows studying the *dynamics of changes* in the data. The fact that we use time series of different cross section variables provides greater flexibility in terms of degrees of freedom. Panel data analysis with fixed effects controls for unobserved, time-invariant heterogeneity across variables, in our case, Income Inequality Distribution, Tax on low wage earners, International Investment Position, and real GDP, by allowing each entity to have its own intercept. This method helps us isolate the impact of explanatory variables on the dependent variable by accounting for individual-specific characteristics that do not change over time.

The model that we used to estimate the panel analysis approach can be written as:

$y\_it = a\_it + 〚x'〛\_it\ \beta\_i + \varepsilon\_it$ (1)

Where, y_{it} is the dependent variable, and x_{it} and β_i are vectors of non-constant regressors, while the parameters are i=1,2,…n cross-sectional units.

The variables of the panel analysis are described in the following section, 3.2.

Pooled Ordinary Least Squares (OLS) regression is one of the simplest approaches to analyzing panel data. Panel data, also known as longitudinal data, consists of observations on the same individuals, firms, countries, or other entities over multiple time periods. In essence, pooled OLS treats panel data as if it were a single, large cross-sectional dataset. It completely ignores the panel structure, meaning it does not account for the fact that the observations for a given entity across different time periods might be correlated, or that there might be unobserved characteristics specific to each entity that influence the outcome.

The general form of a pooled OLS model for panel data is:

$y_{it}=\beta_0+\beta_1 x1_{it}+\beta_2 x2_{it}+\cdots+\beta_k xk_{it}+u_{it}$

Where:
- y_{it} is the dependent variable for individual i at time t.
- k_{it} are the independent variables for individual i at time t.
- β_0 is the intercept.
- The coefficients for the independent variables are assumed constant across all individuals and all time periods.
- u_{it} is the error term for individual i at time t.

The key characteristics of Pooled OLS in panel analysis are the Homogeneity Assumption, the fact that it ignores panel structure, and its simplicity. Pooled OLS in panel analysis is especially appropriate when our primary interest is only in estimating average effects across all individuals and periods, without trying to understand how changes *within* an individual over time affect the outcome.

In our approach, we use the Fixed effect model, which accounts for unobserved, time-invariant individual-specific effects by allowing each individual to have their own intercept. It effectively "sweeps out" these fixed effects. The Fixed effects model is preferred when the unobserved individual effects are correlated with the independent variables (the primary concern with pooled OLS).

3.2 Data

3.2.1 IID (Income Inequality Distribution)

The ratio of total income received by the 20 % of the population with the highest income (top quintile) to that received by the 20 % of the population with the lowest income (lowest quintile). Income must be understood as equivalised disposable income.

The European Union Statistics on Income and Living Conditions (EU-SILC) collects timely and comparable multidimensional microdata on income, poverty, social exclusion and living conditions.

The EU-SILC collection is a key instrument for providing information required by the European Semester and the European Pillar of Social Rights, and the main source of data for microsimulation purposes and flash estimates of income distribution and poverty rates.

The information collected in EU-SILC pertains to the following types of statistical units: private households and persons living in these households. Annex II of Commission EU regulation 2019/2242 defines the specific statistical units per variable and specifies the content of the quality reports on the organization of a sample survey in the income and living conditions domain pursuant to EU regulation 2019/1700 of the European Parliament and of the Council.

The target population is the private households and all persons composing these households having their usual residence in the national territory. A private household means a person living alone or a group of persons who live together, providing oneself or themselves with the essentials of living.

3.2.2 Tax on low wage earners-low wage trap

It measures the percentage of gross earnings which is taxed away through the combined effects of income taxes, social security contributions and any withdrawal of benefits when gross earnings increase from 33% to 67% of the average worker. This structural indicator is available for single persons without children and one-earner couples with two children.

Information on net earnings (net pay taken home, in absolute figures) and related tax-benefit rates (in %) complements gross earnings data with respect to disposable earnings. The transition from gross to net earnings requires the deduction of income taxes and employee's social security contributions from the gross amounts and the addition of family allowances, if appropriate.

The amount of these components and therefore the ratio of net to gross earnings depend on the individual situation. A number of different family situations are considered, all referring to an average worker. Differences exist with respect to the number of workers/earners (only in the case of couples), number of dependent children, and level of gross earnings, expressed as a percentage of the gross earnings of an average worker.

The data refer to an average worker at national level for different illustrative cases, defined on the basis of the number of earners (only in the case of couples), number of dependent children, and level of gross earnings, expressed as percentage of the average earnings of an average worker. The low wage trap measures the percentage of gross earnings which is taxed away through the combined effects of income taxes, social security contributions, and any withdrawal of benefits when gross earnings increase from 33% to 67% of the average worker. It is defined as the difference between gross earnings and net income increases resulting from additional work effort, expressed as a percentage of the increase of gross earnings. This indicator is available for single persons without children and one-earner couples with two children aged 4 and 6 years. Gross and net earnings and the transition components are expressed in Euro, national currency (if different) and Purchasing Power Standards (PPS), all other indicators are in %. PPS are applied in order to remove the effect of differences in price levels between the countries and are on the basis of household final consumption expenditure in each country.

3.2.3 Direct investment - annual data, million units of national currency

The international investment position (IIP) is a statistical statement that shows at a point in time the value and composition of: -financial assets of residents of an economy that are claims on non-residents and gold bullion held as reserve assets, and -liabilities of residents of an economy to non-residents. The difference between an economy’s external financial assets and liabilities is the economy’s net IIP, which may be positive or negative.

According to the functional category, the cross-border financial positions are classified as: 1) For the assets - Direct investment; Portfolio investment; Financial derivatives and employee stock options; Other investment and Reserve assets 2) For the liabilities - Direct investment; Portfolio investment; Financial derivatives and employee stock options and Other investment. The financial positions are further classified according to the different instruments. The data on direct investment are expressed in million units of national currency. The indicator is based on the Eurostat data from the Balance of payment statistics, these data are quaterly reported to the ECB by the EU Member States.

3.2.4 Real GDP per capita

The indicator is calculated as the ratio of real GDP (GDP adjusted for inflation) to the average population of a specific year, where GDP is expressed in millions and population is expressed in thousands. GDP measures the value of the total final output of goods and services produced by an economy within a certain period of time. It includes goods and services that have markets (or which could have markets) and products which are produced by general government and non-profit institutions. It is a measure of economic activity and is commonly used as a proxy for the development in a country’s material living standards. However, it is not a complete measure of economic welfare. For example, GDP does not include most unpaid household work. Neither does GDP take account of negative effects of economic activity, like environmental degradation.

For UK data, our source was the Office for National Statistics (ONS) - UK's Official Statistical Agency: The ONS is the primary source for UK economic data. They publish various GDP series, including real GDP per capita (often referred to as "chained volume measures" or CVM).

4. Empirical Results

Firstly, we ran a Panel analysis with fixed effects, but heteroscedasticity was present, as we can see from the results of Table 1:

(Table1: panel analysis with fixed effects and explanatory results)

The constant and GDP values are significant at 1% (as p value is less than 0,01%). Since the p-value of joint test on named regressors is greater than 1%, we can safely say that all independent variables are not jointly significant in explaining the dependent variable IID. Since the p-value for the Test for differing group intercepts is greater than 1%, the group of independent variables does not have a common intercept.

Test for evaluating the validity of the fixed effects model:
Distribution-free Wald test for heteroskedasticity -
Null hypothesis: the units have a common error variance
Asymptotic test statistic: Chi-square (5) = 267.543
with p-value = 9.43196e-56

The above indicates the presence of heteroscedasticity, i.e., the error variance is not constant across observations or units.

After that, we ran a Pooled OLS model with robust standard errors. Results were as follows in Table 2:

(Table 2: Pooled OLS, using 44 observations)

The only statistically significant results were of GDP. The analysis was repeated using lagged TLW and TI variables, but we received identical results (Table 3). Therefore, by using the OLS model, the only variable that significantly affects IID is GDP.

(Table 3: Pooled OLS, using 39 observations)

What we notice again is that GDP consistently emerges as a statistically significant predictor of the dependent variable (IID), even with lagged explanatory variables and robust standard errors. The lagged TLW (TLW_1) and lagged TI (TI_1) are not statistically significant, suggesting:

a) There's no strong evidence of delayed (lagged) effects from these variables.
b) TI_1 has almost no effect ($p = 0.93$, $t \approx 0$).
   - R-squared is high (0.80) → our model explains ~80% of the variation in IID.
   - Durbin-Watson = 1.063 → suggests possible positive autocorrelation, though we are already using HAC robust errors, which compensates for this.
   - rho = 0.29 → mild within-panel correlation (which is not very strong).

Using pooled OLS with heteroskedasticity- and autocorrelation-consistent standard errors, we find that GDP has a statistically significant negative effect on IID ($p < 0.001$). Neither lagged TLW nor TI shows a significant influence, suggesting no detectable delayed effect from labor wages or tax incentives on IID within the observed period.

5. Conclusions

This research investigated the impact of investment, taxation on low-wage earners, and productivity on income inequality in Germany, Greece, Ireland, Portugal, and the United Kingdom during 2009–2023. The results indicate that real GDP per capita exerts a robust and negative effect on inequality, underscoring the central role of productivity growth in shaping distributive outcomes.

By contrast, neither the tax burden on low-wage earners nor international investment displayed significant effects, even when accounting for lagged relationships. These findings suggest that, within the observed period, structural growth dynamics outweigh the direct influence of fiscal burdens or capital inflows on income inequality.

From a policy perspective, the results highlight that measures enhancing productivity and sustainable growth may constitute the most effective route to reducing inequality in advanced European economies. While taxation and investment policies remain relevant for efficiency and employment, their distributive effects appear contingent on broader institutional and structural conditions.

Future research should incorporate a wider set of fiscal instruments, such as social transfers and progressive taxation, and differentiate between forms of capital inflows to capture their heterogeneous effects. Extending the analysis across a larger group of economies and longer time horizons would further strengthen the generalizability of these conclusions.

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Author Profile

Dr Dimitris Kalimeris holds a PhD in Economics and Finance from the University of Macedonia, Greece, and has extensive academic and professional experience in economics, finance, administration, and teaching. He has also pursued postgraduate studies in Business Management at Kingston University, UK, and a Master's degree in Information Systems at University of Macedonia. His research interests include taxation, fiscal policy, macroeconomic stability, and the interaction between investment and income distribution. Skilled in statistical and econometric analysis (E-Views, Stata, SPSS, Minitab), he combines academic expertise with practical knowledge in financial and tax analysis, human resources, and e-commerce.

Appendix

List of tables:
1) Table1: panel analysis with fixed effects and explanatory results
Fixed-effects, using 44 observations
Included 5 cross-sectional units
Time-series length: minimum 4, maximum 10
Dependent variable: IID

	Coefficient	*Std. Error*	*t-ratio*	*p-value*
Const	6.59449	1.30765	5.043	<0.0001***
TLW	−0.0152390	0.0401343	−0.3797	0.7064
TI	−2.47146e-07	6.46069e-07	−0.3825	0.7043
GDP	−2.77420e-05	9.78734e-06	−2.834	0.0075***

Mean dependent var	5.009545		S.D. dependent var	0.712441
Sum squared resid	4.517136		S.E. of regression	0.354226
LSDV R-squared	0.793035		Within R-squared	0.204702
LSDV F (7, 36)	19.70605		P-value(F)	1.47e-10
Log-likelihood	−12.35444		Akaike criterion	40.70888
Schwarz criterion	54.98240		Hannan-Quinn	46.00219
Rho	0.431557		Durbin-Watson	0.902186

Joint test on named regressors -
Test statistic: F (3, 36) = 3.08868
with p-value = P (F (3, 36) > 3.08868) = 0.0391927
Test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: F (4, 36) = 0.246939
with p-value = P (F (4, 36) > 0.246939) = 0.909631

2) Table 2: Pooled OLS, using 44 observations
Included 5 cross-sectional units
Time-series length: minimum 4, maximum 10
Dependent variable: IID
Robust (HAC) standard errors

	Coefficient	Std. Error	t-ratio	p-value
const	6.35195	0.190490	33.35	<0.0001***
TLW	−0.0111648	0.00731248	−1.527	0.2015
TI	−1.07369e-07	1.67741e-07	−0.6401	0.5569
GDP	−2.53238e-05	6.65705e-07	−38.04	<0.0001***

Mean dependent var	5.009545		S.D. dependent var	0.712441
Sum squared resid	4.641076		S.E. of regression	0.340627
R-squared	0.787356		Adjusted R-squared	0.771408
F(3, 4)	2829.412		P-value(F)	4.16e-07
Log-likelihood	−12.94994		Akaike criterion	33.89988
Schwarz criterion	41.03664		Hannan-Quinn	36.54653
rho	0.452858		Durbin-Watson	0.876344

3) Table 3: Pooled OLS, using 39 observations
Included 5 cross-sectional units
Time-series length: minimum 3, maximum 9
Dependent variable: IID
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*
const	6.29489	0.326504	19.28	<0.0001***
TLW_1	−0.0124895	0.0132221	−0.9446	0.3984
TI_1	−2.94833e-08	3.14198e-07	−0.09384	0.9298
GDP	−2.39550e-05	1.46573e-06	−16.34	<0.0001***

Mean dependent var	4.958205		S.D. dependent var	0.690507
Sum squared resid	3.628919		S.E. of regression	0.321999
R-squared	0.799711		Adjusted R-squared	0.782543
F(3, 4)	7566.571		P-value(F)	5.82e-08
Log-likelihood	−9.033377		Akaike criterion	26.06675
Schwarz criterion	32.72100		Hannan-Quinn	28.45424
rho	0.291176		Durbin-Watson	1.063011