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TOURISM-DRIVEN ECONOMIES AND INCOME DISPARITY: INSIGHTS FROM A REGRESSION DISCONTINUITY DESIGN

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Abstract This paper aims to answer two questions: (1) Does overtourism incline countries to favorise the capital asset holder instead of workers in income distribution? (2) Does income inequality come hand in hand with overtourism? Employing Kaldor's theory of income distribution, this study adapts its theoretical framework to assess countries with a specialization in tourism. The analysis encompasses data from 115 developed countries over the period of 2000 to 2019. A Regression Discontinuity Design (RDD) methodology is utilized for the empirical investigation, categorizing key variables based on the exposure of a country's unit to a tourism-focused developmental strategy. The study reveals that adopting overtourism as a developmental strategy has led to increased inequality, characterized by a rising capital share and a declining labor share over time. Evidence supporting these findings is presented through both parametric and non-parametric Regression Discontinuity Design (RDD) analyses. Robustness checks and placebo tests corroborate these results.

Keywords
overtourism, developmental strategy, income distribution, regression discontinuity design (RDD), economic inequality

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1 Introduction

This paper seeks to investigate the potential causal relationship between developmental strategies focused on tourism and the phenomenon of overtourism, within the framework of income distribution and inequality across developed nations. Utilizing a robust and comparable dataset, we employ the RDD, a non-experimental comparison group method, to explore this relationship. Our central hypothesis posits that the pursuit of overtourism as a developmental strategy may exacerbate income inequality by prioritizing profit-led growth over wage-led growth, particularly in economies heavily reliant on tourism services. Insights into the relationship between wages, productivity, and investment, and the determination of whether the economy is driven by wages or profits, shed light on crucial dynamics within economic systems (Storm and Naastepad, 2013: 100-124). Analysis of the determinants of functional income distribution and the factors contributing to the decline in wage shares was explored (Stockhammer, 2013: 40-70).

Drawing from the Kaldorian perspective, our theoretical framework suggests that overtourism as a strategy may lead to an increase in capital's share of income at the expense of labor's share, especially in countries where national beauty and other comparative advantages prioritize tourism over other branches of economic activities.

Overtourism might seem beneficial for job creation at first glance, yet the effects on salaries and employment conditions can be complex and do not always benefit those in the tourism sector (Walmsley, Koens, and Milano, 2021: 1-15). The tendency for overtourism to suppress wages, along with issues surrounding the cost of living, exacerbates the struggles for employees in such environments. Peterson delves into the issues of economic isolation, environmental deterioration, and institutional ineffectiveness, coupled with income-driven social inequalities in the Caribbean island — one of the globe's regions most saturated with tourism (Peterson, 2023: 89-126). Given the prevalence of tourism-focused developmental strategies in many developed nations, it is essential to examine, as we do in this study, the global impact of tourism specialization on the structures of income distribution, particularly in relation to the labor-capital divide. Traditional trade theory posits that capital-abundant developed countries typically transition towards more capital-intensive industries, often leading to a smaller portion of income allocated to labor. On the other hand, labor-abundant developing countries are inclined to adopt labor-intensive industries, potentially resulting in a higher proportion of income for labor (Dao *et al.*, 2017: 1-72). While this subject is inherently intricate, our investigation focuses specifically on developed countries with prevalent overtourism. We employ a simplified categorization of factors to analyze the potential impact of tourism-centric developmental strategies on key economic indicators, such as labor and capital shares and income inequality, for a selection of developed countries from 2000 to 2019. By adopting this streamlined approach, we aim to provide a clearer understanding of the possible distributional consequences of overtourism.

Discussing the implications of theoretical insights drawn from Kaldor's perspective for specific development strategies, particularly concerning the weight of tourism, is a central focus of this inquiry. A notable challenge in evaluating development strategy models is the limited opportunity for experimentation with alternative strategies to validate outcomes, as one might with forecasting models (Granger, 1999: 1-99). However, as we choose in this paper, the implementation of suitable econometric techniques such as RDD facilitates the performance of stylized natural experiments. It was originally introduced (Thistlewaite and Campbell, 1960: 309-317) and subsequently enhanced (Hahn, Todd, and van der Klaauw, 2001: 201-209). RDD allows for precise causal inference in settings where randomized experiments are not feasible.

The paper is organized as follows: The first section provides an introduction to the topic and sets the stage for subsequent research. The second chapter offers a literature review that synthesizes relevant studies and theoretical perspectives on tourism and its impact on income distribution, setting the context for our analysis. In the third chapter, the methodology of the paper is presented in a structured manner. It begins with a theoretical outline grounded in the Kaldorian framework, which examines the complex interplay between tourism and income distribution. This section elaborates on the derivation of Kaldorian conditions that establish the connection between the weight of the tourism economy and the income share of capital, elucidating its implications for labor share and income inequality. The penultimate chapter outlines the identification strategy, describes the dataset, and proceeds with the empirical analysis, sharing the principal findings. The final section concludes the paper by summarizing the discussions and highlighting the implications of the findings for a nuanced understanding of the relationship between overtourism, income distribution, and socio-economic inequality.

2 Literature preview

A noticeable departure from the wage-led growth model, traditionally observed in larger economies like the US and the EU, renowned as bastions of developed nations, has become increasingly apparent. This trend is notably accentuated in smaller or more open economies, including certain EU member states, particularly when considering the influence of foreign trade, notably in the realm of tourism flows. As highlighted by scholars (Onaran and Galanis, 2013: 71-99), this phenomenon underscores a significant shift in economic dynamics. Moreover, studies (Hein and Mundt, 2013: 153-186) provide complementary insights into income distribution patterns and exacerbate the challenges associated with wage-led growth in developing contexts. Their analysis delves into the impact of financialization strategies on the financial and economic crisis, shedding light on the potential for wage-led recovery strategies. By examining the interplay between financialization, income distribution, and economic crises, their research offers valuable perspectives on the complexities faced by developing economies striving for equitable growth. Given the pivotal role of tourism in numerous economies, our research highlights how income distribution dynamics intertwine with inequality, particularly under the influence of international tourism. This intersection underscores the relevance of our topic, as it explores the potential amplification of effects within the context of overtourism and developmental strategies, thus presenting an intriguing perspective for readers.

While a consolidated database for a comprehensive analysis of the empirical relationship, as suggested by Kaldor's theory, remains elusive, several studies have approached this issue from diverse perspectives. For instance, one of these developed a computable general-equilibrium (CGE) model specific to Brazil's tourism sector, examining earnings disparities among different labor categories within the industry and the resultant impact on income distribution across households of varying socioeconomic strata (Blake *et al.*, 2008: 107-126). In the case of low-income countries, the rationale behind utilizing tax revenues to support tourism promotion often hinges on the belief that tourism expansion will lead to improved income distribution, particularly by bolstering demand for low-skilled labor. This hypothesis was subjected to scrutiny by (Wattanakuljarus and Coxhead, 2008: 929-955) through an applied general-equilibrium model tailored to Thailand's heavily tourism-dependent economy.

The labor share represents the portion of national income attributed to labor (Luebker, 2007: 1-15). However, some scholars have raised critiques regarding the oversimplified binary classification of income into labor and capital categories used in these calculations, arguing that such a distinction is becoming increasingly artificial. They posit that in contemporary economic landscapes, labor and capital are not strictly mutually exclusive, with economic agents often deriving income from multiple sources (Krueger, 1999: 45-51).

Within the domain of economic research, the intricate interplay between income distribution and tourism specialization has received relatively limited attention. Notable exceptions include the work, that explored the performance of the tourism sector and its impact on economic growth distribution within the lake regions of the United States (Marcouiller, Kim, and Deller, 2004: 1031-1050). Various case studies have explored the connection between Kaldor's income distribution theory and economic conditions, albeit from diverse perspectives. For instance, one of the studies expanded Kaldor's framework to incorporate workers' debt accumulation and their pursuit to match rentiers' consumption levels (Ryoo and Kim, 2014: 585-618).

For instance, one of the studies expanded Kaldor's framework to incorporate workers' debt accumulation and their pursuit to match rentiers' consumption levels (Ryoo and Kim, 2014: 585-618). Another study sought to empirically test Kaldor's effects within less developed countries, focusing on income distribution dynamics (Cook, 1995: 71-82). Subsequently, one paper synthesized several theories explaining functional income distribution, including Kaldor's, while reviewing empirical literature on the persistent decline in the wage share of national income since the 1980s (Dünhaupt, 2014: 1-36). A growth model was developed rooted in Kaldorian principles, integrating both Kaldor's income distribution theory and the concept of endogenous technical progress (Palely, 2013: 319-345). Another study derived income distribution between units using an information-theoretic approach within the neo-Keynesian distribution theory framework (Das and Martin, 2012: 136-146). Additionally, a following study analyzed the influence of aggregate demand fluctuations on income distribution, considering a model consistent with stock ownership and segmented into two classes, where income distribution is endogenously determined by aggregate demand levels, a key aspect of Kaldorian economics (Ryoo, 2015: 429-457).

The discourse surrounding the determinants of distributional impacts on demand and growth has been significantly shaped by the seminal work of (Marglin and Bhaduri, 1991: 123-163). One prevailing insight posits that global economic integration tends to undermine the feasibility of a wage-led growth strategy, as argued by (Razmi, 2016: 516-538). Some authors characterized a profit-led growth pattern as "exhilarationist" (Bhaduri and Marglin, 1990: 375-393); others investigate the interplay between growth and inequality within the Bhaduri-Marglin Model's growth regimes, revealing bidirectional causal relationships and their implications for economic and social stability, providing insights into contemporary economic and social crises (see Molero-Simarro, 2017: 367-390).

3 Metodology

3.1 The Equilibrium Effect of Tourism on Income Distribution

Drawing heavily on the exposition provided in the work (Candela and Figini, 2012: 73-130), our study's formulation of the relationship between tourism and income distribution is rooted in the principles of Kaldor's model (Kaldor, 1956: 83-100), underscoring our commitment to academic rigor through precise attribution and enabling readers to trace the conceptual lineage of our analytical framework.

In our empirical study, we adapt a Keynesian open economy model to include tourism, examining how a steady inflow of tourists affects national income distribution. By incorporating Kaldor's insights on saving propensities across income groups, we explore the equilibrium impact of tourism expansion on the functional distribution of income, ensuring a coherent transition to the model's practical application without overwhelming readers with complexity.

Kaldor's model provides a pivotal framework for understanding the functional distribution of income between capital and labor, which is particularly relevant in the context of an expanding tourism industry. The model posits that the propensities to save out of profits (sc) and wages (sw) differ, typically with sc > sw, leading to varying effects on income distribution as the economy evolves.

The burgeoning sector of tourism holds particular significance within the macroeconomic landscape, as its growth, driven by international demand, has become a substantial contributor to the GDP of numerous countries. Its expansion carries weighty implications for macroeconomic indicators and the allocation of national income, underscoring its vital role in shaping economic fortunes.

In Kaldor's model, the relationship between the size of the tourism sector and the distribution of income is defined by a first-order condition:

$$\partial Q_c / \partial q = 1/(s_c - s_w) > 0,$$

This condition indicates that an increase in the tourism output ratio, q, is expected to lead to an increase in the profit share, Qc, under the assumption that the propensity to save from profits is greater than from wages.
This states that, ceteris paribus, as q increases—indicating a higher relative size of the tourism sector—the profit share (Qc) in the national income also increases, given that:

$$\partial Q_c / \partial q > 0$$

The repercussions of a larger tourism sector within an economy, as dictated by the condition, point to a shift in national income distribution towards profits at the expense of wages. This phenomenon highlights several critical considerations: firstly, the transition towards a tourism-centric economy can alter income distribution, privileging capital holders; secondly, increasing international tourism might lead to income redistribution, potentially intensifying inequality if the industry leans towards capital intensiveness; and finally, the necessity for economic policymakers to strike a judicious balance between fostering tourism growth and preserving fair income distribution.

3.2 Methodological Consideration for Econometric Analysis

In our econometric analysis, we explore the impact of tourism on income distribution, drawing inspiration from Kaldor's model, which suggests a probable positive association between the tourism sector's growth and the economy's profit share. Instead of elasticity, we aim to measure the responsiveness of the profit share to variations in the tourism sector's scale. The equation:

$$\partial Q_c / \partial q * q/Q_c = 1/(s_c - s_w) * q/Q_c,$$

is central to our examination of how changes in tourism activity affect profit distribution. Should our analysis yield a positive coefficient, it would indicate that a burgeoning tourism sector not only raises the profit share but may also exacerbate income inequality by tilting the balance in favor of capital owners over labor. Furthermore, this predicted outcome would suggest a corresponding negative trend in the labor share, highlighting the dichotomy in income distribution as tourism intensifies.

3.3 Identification strategy

In our research, we will extensively utilize the RDD technique as our primary methodological approach. The RDD methodology was brought to the fore in economic research following a study that analyzed the impact of certain variables on a predicted outcome by contrasting control and intervention groups (Angrist and Lavy, 1999: 533-575). The RDD methodology was further refined by a study in 2001, and cases with a discrete running variable were addressed in 2008 (Hahn *et al.*, 2001: 201-209; Lee and Card, 2008: 655-674). Comprehensive reviews of RDD, along with detailed discussions on the nuances of control and intervention within RDD frameworks, have been provided in subsequent works (Imbens and Lemieux, 2008: 615-635; Lee and Lemieux, 2010: 281-355).

Our identification strategy hinges on the utilization of a RDD to gauge the impacts of developmental strategies leading to overtourism on income distribution and inequality (as measured by the Gini coefficient), specifically delineating the labor and capital shares across developed countries. Guided by our theoretical framework, which emphasizes steady-state effects, we hypothesize that countries grappling with overtourism may witness an increase in the capital share of income distribution, accompanied by a corresponding decrease in labor share, and rising inequality. In the data section of our study, we will use a proxy variable that better encapsulates the profit share within our dataset. Moving forward, we will refer to this as the 'capital share' to align with the terminologies applied in later sections of our analysis. This analysis rests on the assumption that countries near the cutoff point exhibit similarity in all other aspects, with their initial product share in income distribution serving as the primary distinguishing factor.

This theoretical framework posits that overtourism induces profit-led rather than wage-led growth in economies. Our units of analysis are developed countries, where those with a per capita TDI below the 75th percentile are contrasted with those above this threshold—considered as undergoing treatment. The running variable in our study is the country's per capita TDI, with the 75th percentile serving as the cutoff point for treatment if surpassed. The Tourism Development Index (TDI) captures a nation's appeal not solely through its natural landscapes and attractions but also through its cultural heritage and distinctive contributions within the context of historical cumulative causation. It serves as a measure of the symbiotic relationship between a country's resources and its ability to attract visitors. It is crucial to note that, consistent with RDD principles, receiving treatment—associated with overtourism—is presumed to depend solely on whether a country's TDI per capita is below the fixed threshold (75th percentile of the sample).

Our identification strategy capitalizes on the natural experiment created by the marginal differences above or below the per capita TDI, which serves as the critical determinant of categorizing a country as affected by overtourism. This sharp RDD approach is akin to a local randomized experiment (Lee and Lemieux, 2010: 281-355). An RDD identification strategy is credible if units cannot precisely manipulate the running variable—the variable whose threshold value dictates treatment eligibility. Given that the TDI over the population ratio is influenced by a country's population size and a chosen developmental strategy enacted *ex-post* by the Ministry of Tourism and other authorities, it is implausible that it could be manipulated by country agents to ensure inclusion in the treatment regime associated with overtourism.

By sorting the available dataset of developed nations into two groups—one representing observations under the 'intervention' of overtourism and the other comprising control countries—we can observe and evaluate the impacts of these strategies akin to forecasting models, albeit with a retrospective focus on past data and trends.

As we employ RDD to assess the impact of tourism overspecialization on income distribution, focusing particularly on labor or capital share, along with inequality as outcome variables, we begin with the following premises.
Let's suppose we have a running variable X_s, where s =1,…,S indexes countries. Define D_s as:

$$D_s=1[X_s > c\ ] \tag{1}$$

where 1[·] is the indicator function and c represents the 0.75 quantile, denoting the threshold of the TDI per capita in our dataset. Let Y_{is} denote the response variable of interest for country i=1,…,N in country s, with $Y_{is}(1)$ representing treated countries and Y_{is} (0) representing untreated countries. The average potential outcomes at the threshold c can be expressed as:

$$\mathrm{E}[Y_{is}(1)|\ X_s= c] \tag{2}$$

and

$$\mathrm{E}[Y_{is}(0)|X_s= c] \tag{3}$$

We aim to estimate the limit of the expected outcomes as X_s approaches c from above and below:

$$\lim X_s\rightarrow c-\ \mathrm{E}[Y_{is}|X_s] \tag{4}$$

and

$$\lim X_s\rightarrow c+\ \mathrm{E}[Y_{is}|X_s] \tag{5}$$

which corresponds to:

$$\lim X_s \rightarrow c- \mathrm{E}[Y_{is}(1)-Y_{is}(0) \mid X_s = c] \tag{6}$$

and

$$\lim X_s \rightarrow c+ \mathrm{E}[Y_{is}(1)-Y_{is}(0) \mid X_s = c] \tag{7}$$

This concept is implemented within a regression framework. Potential outcomes can be written as (Lee and Card, 2008: 655-674):

$$Y_{is}^{L} = \alpha^{L} + (X_s - c)\beta^{L} + \epsilon_{is} \tag{8}$$

for observations to the left of the threshold, and

$$Y_{is}^{R} = \alpha^{R} + (X_s - c)\beta^{R} + \epsilon_{is} \tag{9}$$

for observations to the right of the threshold, where β^L and β^R are the regression coefficients associated with the running

variable. We can combine these potential outcomes as:

$$Y_{is} = Y_{is}^{L}(1 - D_s) + Y_{is}^{R} D_s \tag{10}$$

which implies that the regression model is:

$$Y_{is} = \alpha^{L} + D_s(\alpha^{R} - \alpha^{L}) + D_s(X_s - c)\beta^{R} + (1 - D_s)(X_s - c)\beta^{L} + \epsilon_{is} \tag{11}$$

The RDD estimate of the impact of tourism overspecialization is given by the coefficient $(\beta^R - \beta^L)(c - \overline{X})$ associated with the treatment dummy D_s in the regression model, allowing for different slopes on either side of the threshold. We expect β^L>0 and β^R<0, along with D_s<0 when measuring the impact of treatment on labor share, and the opposite if capital share and Gini inequality are the outcome variables. From the RDD estimate perspective, we would like to stress, within our identification strategy section, that D_S represents the Treatment Effect; β^L denotes the Control Slope, and β^R signifies the Treatment Slope. These values are crucial for interpreting the impact of tourism overspecialization on income distribution and inequality as observed in our empirical analysis.

3.4 About the data

The dataset comprises a comprehensive selection of 115 developed nations over the period from 2000 to 2019. While all countries are included, some have missing data for certain years. No imputation was made for these gaps; analyses were conducted using the available data. The countries represented span multiple continents, ranging from various European nations to countries in the Americas, Africa, Asia, and Oceania. For an exhaustive list of the countries included in this study, see Appendix.

The primary focus of the dataset is to explore the distribution of GDP factor shares between labor and capital, expressed as a percentage over the observed period. The labor share of GDP data utilized in our analysis is obtained from the 'pwt10.0' dataset available in the R programming language (Zeileis, 2023: 1-7), with the original data sourced from the Groningen Growth and Development Centre (2023). The capital share is then computed as the residual of one minus the labor share, accounting for the entire GDP composition. Given the presence of statistical anomalies, robust data processing techniques were applied, culminating in the creation of the winsorized variables labsh and capsh, which mitigate the influence of outliers and offer a refined representation of the underlying economic dynamics.

The Gini coefficient, as well as control variables, are sourced from the World Development Indicators (WDI), extracted using the WDI package (version 2.7.8) in the R programming language (Arel-Bundock, 2022: 1-8). This tool facilitates the retrieval of data from the extensive databases hosted by the World Bank.

The Tourism Development Index (TDI), our running variable, is constructed by combining total tourist arrivals with tourism receipts using the WDI package. These components are equally weighted and normalized by the population to determine per capita values. For enhanced utility in econometric analysis, the TDI has been converted into a standardized index after rescaling the per capita figures.

In the dataset, the median values serve to illustrate the central position of data points for both treated and untreated groups, mitigating the influence of extreme values. Table 1 reveals that the median value of the TDI for the treated group is 168.3 index units, signaling that tourism's economic influence is greater than this level in half of these countries. The treatment threshold for the running variable begins at roughly 84.5 index units.

The median labor share of GDP (labsh) for treated countries is 0.573, implying that labor accounts for 57.3% of GDP, which is higher than the untreated median of 52.1%. Conversely, the median share of GDP allocated to capital (capsh) is lower in treated nations at 0.427, compared to an untreated median of 0.479, suggesting a lesser proportion of GDP is captured by capital owners in countries with higher tourism dependency. Regarding income inequality, as measured by the Gini coefficient, the median value for treated countries stands at 0.476, below the untreated median of 0.535, indicating lower income disparity in nations more dependent on tourism.

Regarding the control variables, the median population (pop) for the treated group is 3,526 (in thousands), which is smaller than the untreated group's median of 9,506, indicating that countries in the treated group tend to have lower population sizes. However, when it comes to GDP per capita (gdppc), the treated group appears more affluent, with a higher median value of 32,626.307 USD compared to the untreated group's median of 25,424.059 USD.

For other variables such as the urbanization rate (urb), education expenditure (% of GDP) (educ), health expenditure (% of GDP) (health), employment rate (emp), and tax revenue (% of GDP) (tax), the differences between the treated and untreated groups are relatively minor when comparing median values. The dependency ratio (depenage) quantifies the balance between those not in the workforce due to age and those within the working-age bracket. This indicates a relative homogeneity in these factors, with both groups exhibiting comparable median and mean values.

These median figures are key to understanding the economic attributes of countries with differing degrees of tourism dependency, especially in the analysis carried out using the RDD method.

4 Regression Discontinuity: Estimation Results

4.1 Evaluating Regression Discontinuity Prerequisites

For a RDD to be utilized effectively, several key conditions must be met. First, there must be a sharp change in the outcome variable at the cutoff, attributable to the treatment effect and not to other factors. This requires that other covariates must be smooth at the threshold, ensuring that any discontinuity in the outcome can be confidently isolated to the treatment effect. Second, the ability to manipulate the assignment variable must be limited, ensuring that treatment allocation is effectively random and not systematically biased. These conditions, taken together, help to confirm the absence of confounding factors that could affect the outcome and ensure the integrity of the RDD, as other covariates should not exhibit jumps at the cutoff point that could confound the estimated treatment effect (Lee and Lemieux, 2010: 281-355).

The RDD approach we're considering addresses some of the endogeneity issues, particularly those related to treatment assignment. It does not impose stringent conditions on the endogeneity of the treatment variable. By focusing on observations near the cutoff point for treatment assignment, RDD exploits a more exogenous variation in the treatment, providing a cleaner estimate of the causal effect of the policy.

4.2 Rule-Based Treatment Assignment (determining sharp or fuzzy design)

Before proceeding with the intended RDD analysis, it is essential to verify if the treatment assignment within our study's context adheres to a rule-based criterion. To qualify for the developmental strategy addressing overtourism, countries must reach or exceed the 0.75 quantile on the TDI per capita. Those falling below this cut-off are not selected for the developmental strategy. This clear-cut 0.75 quantile threshold enables us to infer that the inclusion in the developmental strategy is, in fact, rule-based.

At this juncture, it is necessary to determine if our RDD is characterized as fuzzy or sharp. Considering that the eligibility for the developmental strategy was dictated by a predetermined rule, we must scrutinize the enforcement of this rule among the countries under observation. The decisive threshold has been established at the 0.75 quantile on the TDI. We must investigate whether there were any instances where countries slightly above this threshold were excluded from the strategy due to administrative errors, or if any countries just below were allowed to participate. Assuming that such anomalies are highly unlikely, we can presume that our RDD approach is of a sharp nature.

4.3 Integrity of the Running Variable (checking for cutoff manipulation)

To ensure the validity of our RDD approach, it is crucial to verify that there has been no manipulation of the running variable, which in this case is the TDI. Countries clustering unnaturally around the cutpoint could indicate manipulation. Our initial assessment suggests that countries do not gain a particular advantage by being just above or below the threshold, and considering the complexity of a country's economy, we tentatively assume an absence of manipulation.

Nonetheless, to proceed with sound premises, we will conduct the McCrary density test (McCrary, 2008: 698-714). This test will arrange the data into bins and calculate the average and confidence intervals for these bins. A significant gap in confidence intervals around the 0.75 quantile cutpoint would suggest potential manipulation. Conversely, overlapping confidence intervals would indicate that the distribution around the threshold is not statistically different from the rest of the data, affirming the absence of manipulation. The McCrary density test results, shown in Figure 1, demonstrate overlapping confidence intervals, thus confirming that there is no evidence of data manipulation.

The McCrary density test results confirm the suitability of RDD for our analysis, showing no manipulation at the cutoff, as evidenced by a more formal robust t-test with a p-value of 0.857.

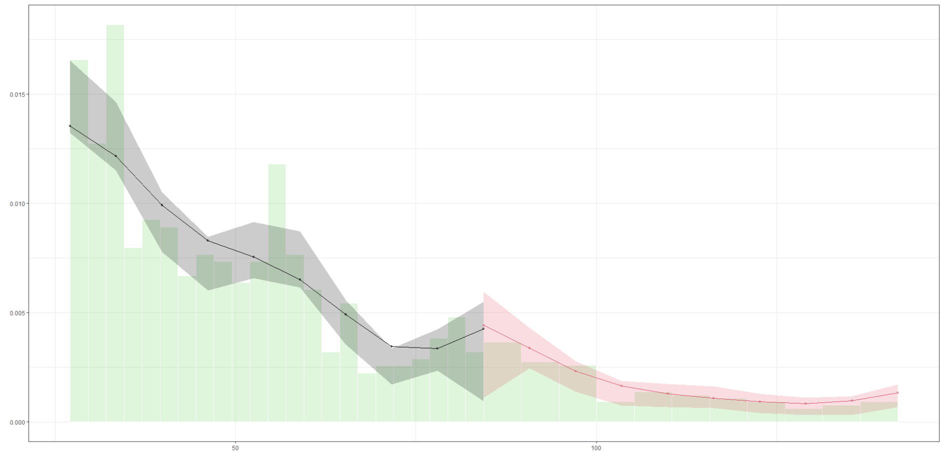

Figure 1: Assessing Running Variable (TDI) Manipulation with McCrary Density Test Plot
Source: Authors' calculation.

4.4 Visual Analysis and Preliminary Checks

After confirming the absence of manipulation in the running variable using the McCrary density test, we proceed to a visual examination of the data. This visual analysis aids in understanding the relationships between outcome variables, such as the labor share, capital share, and Gini indicator, and the running variable — the TDI per capita.

To visualize the relationships between outcome variables (labor share, capital share, Gini indicator) and the running variable (TDI per capita), we plotted data for countries on either side of the cutoff (75% of the running variable). These figures help assess the likelihood of significant policy effects. In the plots, a clear division separates the treated and non-treated countries, with a parametric polynomial regression model and 95% confidence bands illustrating the differences.

Our primary goal at this stage is to validate the RDD's applicability to our study, rather than measure the exact discontinuity (D) at the cutoff. While the behavior of outcome variables near the cutoff might seem misleading at first glance, the visual plots are not conclusive but serve as a preliminary check. Any observed jumps at the cutoff support the anticipated treatment effect and warrant further analysis using RDD.

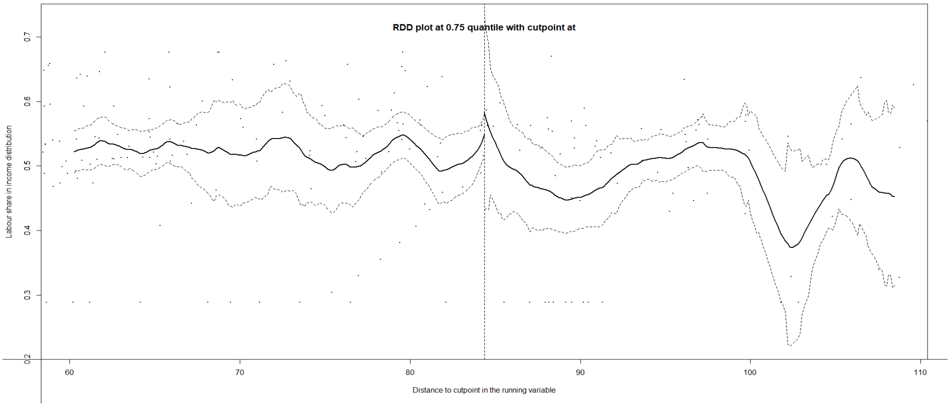

Figure 2: Regression Discontinuity Design (RDD) Plot of Labor Share in Income Distribution as Outcome at Cutpoint

Source: Authors' calculation.

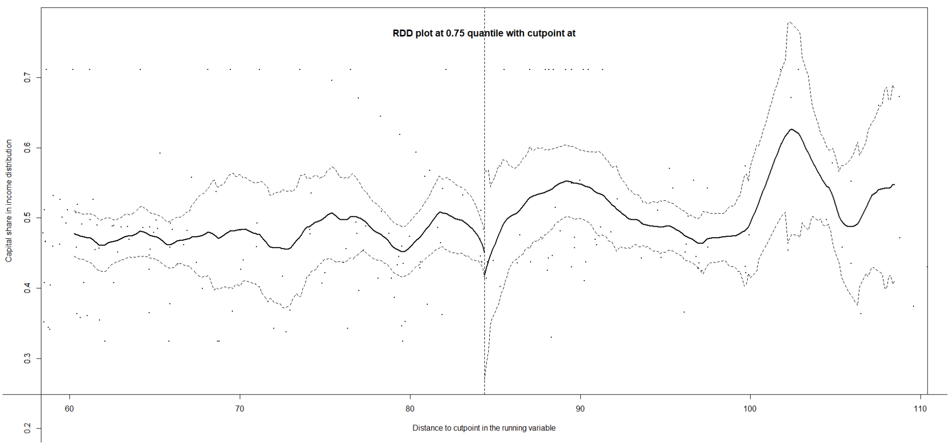

Figure 3: Regression Discontinuity Design (RDD) Plot of Capital Share in Income Distribution as Outcome at Cutpoint

Source: Authors' calculation.

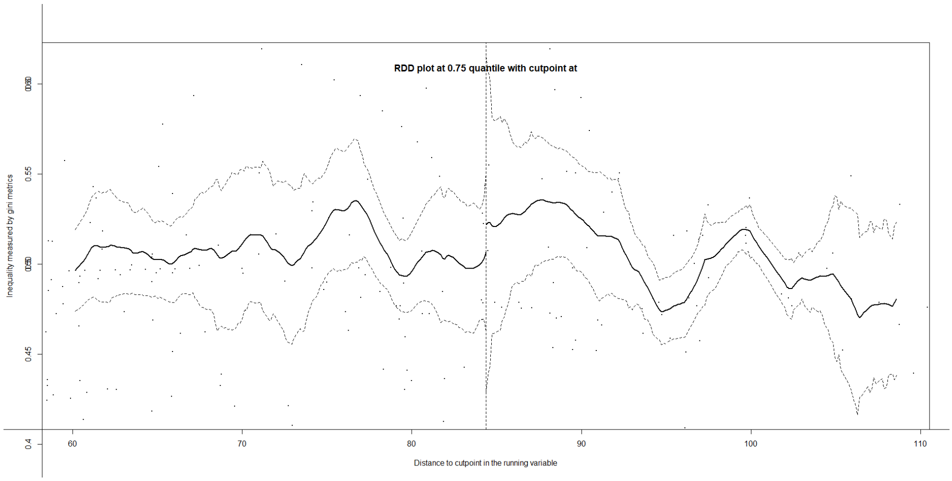

Figure 4: Regression Discontinuity Design (RDD) Plot of Gini Inequality Metrics in Income Distribution as Outcome at Cutpoint

Source: Authors' calculation.

The graphical analysis serves as a precursor to more rigorous testing, offering a visual inspection to ensure that no gross violations of the RDD assumptions are evident. The presence of a discernible jump at the cutoff aligns with the expectation of a treatment effect under the RDD framework. In summary, the non-parametric analysis, bolstered by visual evidence and robust statistical validation, compellingly supports the use of RDD in our study. This approach will enable us to explore the impact of overtourism on key economic indicators such as labor share, capital share, and the Gini coefficient. It is this indication of discontinuity—which non-parametric methods have satisfactorily captured—that reinforces our confidence in the appropriateness of RDD for further analysis.

4.5 Smoothness Checks for Covariates at the Cutoff

Following the methodology outlined in their work, we've conducted robustness checks to validate our RDD approach (Imbens and Lemieux, 2008: 615-635). As previously verified, the assignment to treatment at the cutoff is as good as random, a crucial assumption for RDD. Furthermore, to ensure demographic and socioeconomic covariates do not bias treatment effects at the overtourism threshold, we performed balance tests on key variables ("pop", "educ", "health", "emp", "depenage", "tax", "urb", and "gdppc"). Table 2 confirms the absence of significant differences for all variables at the cutoff, supporting the assumption that these covariates are smoothly distributed, which strengthens our study's internal validity.

4.6 Parametric RDD Estimation

Our parametric RDD estimation results, as shown in Table 3, were obtained using the optimal bandwidth selected by the Imbens and Kalyanaraman (IK) method (Imbens and Kalyanaraman, 2012: 933-959). This approach minimizes the mean squared error, balancing bias and variance in the estimation of the treatment effect at the cutoff. When applying a parametric RDD estimator, we obtained control and treatment slope coefficients that align with Kaldor's theory of income distribution and the consequent effects on the dynamics of labor share, capital share, and inequality indicators.

In the RDD analysis at the 0.75 quantile, the labor share (labsh) does show a significant negative Treatment Effect, in line with Kaldorian expectations that the treatment would reduce the labor share. The Control Slope is positive, suggesting an increase in labor share below the cutpoint, while the negative Treatment Slope indicates a decrease above the cutpoint, further supporting Kaldorian theory.

For the capital share (labsh), the significant positive Treatment Effect contrasts with Kaldorian expectations, as it suggests an increase in capital share due to the treatment. The negative Control Slope indicates a decrease in capital share below the cutpoint, while the positive Treatment Slope suggests a marginal increase above the cutpoint, which does align with Kaldorian theory.

Regarding income inequality, as indicated by the Gini coefficient, the significant intercept suggests a high baseline level of inequality. The Treatment Effect is positive but less significant, and the negative Control Slope indicates a reduction in inequality below the cutpoint. The Treatment Slope is positive but not statistically significant, suggesting that the treatment may not have a clear impact on inequality above the cutpoint.

Overall, the parametric RDD results indicate significant effects of the treatment on labor and capital shares consistent with Kaldorian theory, while the impact on inequality as measured by the Gini coefficient is less clear. These findings suggest that the treatment should consider its potential impact on the distribution of income between labor and capital, as well as on the overall level of inequality

4.7 Optimal Bandwidth in Non-Parametric RDD Estimation

In our study, we implement non-parametric estimation for RDD by adopting local linear regression techniques. This method is applied separately to data on either side of the cut-off point. Choosing an appropriate bandwidth is crucial, as it influences the trade-off between the estimator's precision and bias. A larger sample size within the bandwidth can improve the accuracy of the regression but may also increase the bias due to a greater disparity between the treatment and control groups. Therefore, a narrower bandwidth is generally preferred when a large sample size is available.

While there are several heuristic methods for selecting the bandwidth, we use an approach that aims to determine an asymptotically optimal bandwidth, which is designed to strike a balance between the estimator's variance and squared bias, hence optimizing the mean squared error. To assess the robustness of our results, we conduct a sensitivity analysis by varying the bandwidth around its optimal value.

In addition to varying the bandwidth, we explore three different kernel functions: Gaussian, Epanechnikov, and rectangular. Each kernel shape can yield different estimates of the treatment effect for our outcome variables, and this variation allows us to examine the sensitivity of our results to the choice of kernel.

The results from the non-parametric RDD, as shown in Table 4, validate a notable and positive treatment effect on the capital share within income distribution, consistent across a range of bandwidths and kernel types. The consistency of the treatment effect, with coefficients ranging from 0.060 to 0.067, underscores the model's robustness. P-values below 0.01 across all cases strengthen the evidence against the null hypothesis, underscoring the robustness of our findings. The positive treatment effect supports Kaldor's theoretical expectations, with the analysis providing strong evidence that the treatment correlates with an increase in the capital share at the 0.75 quantile of income distribution.

The non-parametric RDD regression data, as displayed in Table 5, indicate a consistent decline in the labor income share specifically at the 0.75 quantile. This is characterized by a negative treatment effect that persists over different bandwidths and kernel choices. The effects range narrowly from -0.060 to -0.067, maintaining significance at the highest confidence level in each instance. This suggests a consistent and substantive shift in the distribution of income away from labor following the treatmen. The results confidently point to a treatment-induced shift. The negative coefficients, alongside the negligible p-values, affirm a reduction in labor's share post-treatment.

These findings give credence to theoretical models that predict shifts in income distribution mechanisms, particularly within specialized economic contexts such as those reliant on tourism. The uniformity and strength of the results across different specifications highlight the potential impact of the treatment on labor share dynamics, warranting attention for policy considerations.

The consistent negative treatment effect on the labor share within the income distribution, as shown by the non-parametric RDD regression results, serves as a validation of our Kaldorian hypothesis. The hypothesis anticipates changes in the distribution of income between capital and labor in response to economic interventions or shifts. The significant and stable reduction in labor's share across all tested kernels and bandwidths confirms the expected outcome as predicted by Kaldorian theories, specifically reflecting the dynamics within economies with unique structures, such as those heavily influenced by tourism. This validation underscores the relevance and applicability of Kaldorian principles to contemporary income distribution analysis and supports their use in understanding the ramifications of economic policies.

The symmetry observed in the treatment effects across both labor and capital share outcomes may stem from the treatment's systemic impact on income distribution dynamics. This symmetry suggests that the treatment affects both labor and capital factors in a balanced manner, but in opposite directions, possibly reflecting underlying economic mechanisms that influence the redistribution of income. Additionally, the proximity in treatment effect magnitudes for both outcomes indicates a consistent response to the treatment intervention, further reinforcing the notion of symmetry in the observed outcomes.

Table 6 shows that the treatment effect, denoted by D, on inequality—quantified using the Gini coefficient—is positive, indicating a rise in inequality following the treatment. The effect is statistically significant at varying levels across different kernels and bandwidths. With bandwidths increasing, the significance level of the treatment effect strengthens, and the coefficient rises from 0.026 to 0.033. At the widest bandwidth and with all kernel types, the treatment effect is most significant (p-value of 0.001), indicating robustness against the null hypothesis at the 1% level. However, given the trend of increasing significance with larger bandwidths, the results suggest a clear relationship between the treatment and a rise in Gini-measured inequality at the 0.75 quantile cutpoint.

The consistent significance levels across the various bandwidths and kernels in Table 4-6, signal a reliable treatment effect on the outcome variables. This consistency implies that the detected variation in the outcomes—be it inequality, labor share, or Gini variable—is not driven by the choice of bandwidth. The robustness of these results strengthens the inference that the treatment has a substantive connection with an increase in overtourism, influencing the different outcome metrics under study.

4.8 Robustness Assessment

We reevaluate the strength of our evidence by employing local polynomial Regression Discontinuity (RD) point estimators with robust bias-corrected confidence intervals and inference procedures developed in several studies (Calonico, Cattaneo, and Titiunik, 2014: 2295-2326; Calonico, Cattaneo, and Farrell, 2018: 767-779; Calonico *et al.*, 2019: 442-451; Calonico, Cattaneo, and Farrell, 2020: 1258-1282).

Our findings reported in Table 7 indicate that the developmental strategy employed to manage overtourism has a positive impact on the increasing trend of capital's share in income distribution, as reflected in the Gini coefficient for inequality.

The preferred quadratic model strikes an optimal balance between detail and generalizability, effectively capturing the treatment's impact without overfitting. The model's significance is consistent across polynomial orders and bandwidths, indicating robust effects on income distribution. The data reveal that overtourism policy in developed countries leads to a notable decrease in labor share of income by 0.100 units and an increase in capital share and Gini coefficient by 0.091 and 0.068 units, respectively, at the cutoff point. These robust and statistically significant results suggest that such policies have a significant and lasting influence on equity and income allocation.

4.9 Validity Checks: Placebo Tests

To further evaluate the robustness of our earlier assessments related to the output variables, we conducted a placebo test by examining the non-parametric estimation results at different quantiles which served as alternative cutpoints. This approach allows us to see whether the significance of our findings holds at these various assumed critical points, beyond the primary cutpoint of interest. The following table, Table 8, presents the results of the placebo test, which is used to assess the validity of the causal inferences drawn from the main analysis.

The placebo test results for the output variables capsh, labsh, and the Gini coefficient at specified quantiles revealed a consistent pattern of non-significance. None of the estimates for capsh at the 0.15, 0.3, 0.45, 0.6, and 0.9 quantiles demonstrated statistical significance, with p-values stretching from 0.172 to 0.878. labsh followed a similar trend, showing no statistically significant estimates at these quantiles, accompanied by p-values ranging from 0.198 to 0.878. Likewise, the Gini coefficient estimates across the same quantiles did not yield significant effects, as indicated by p-values that fell between 0.116 and 0.531. This uniformity in the results across different quantiles suggests that the effects observed at our primary cutpoint are specific and not replicated when alternative cutpoints are considered.

5 Discussion

Many developed nations actively pursue tourism industry opportunities as a means to strengthen their local economies. Policymakers frequently highlight the positive economic impacts to justify the development of tourism in areas facing economic challenges. However, there is often insufficient consideration of the macroeconomic perspective—how the relative economic gains or losses are distributed among different factors of production. This oversight is critical in understanding the broader implications of tourism as a developmental strategy. The research findings suggest that in countries dependent on tourism, an increase in overtourism correlates with ongoing inequality in how income is distributed across the population. This phenomenon can be partially explained by the shift in income distribution between capital and labor, with a tilt towards capital owners at the expense of laborers due to overtourism. The implication is that specific attributes of the overtourism sector within nations that have well-established tourism industries are exacerbating income inequality. Our research corroborates the discoveries made by other authors' contributions, which uncovered that counties in the US with economies reliant on tourism services exhibit higher levels of income inequality compared to counties less dependent on tourism (Lee, 2009: 33-45). Additionally, Lee noted that the rate of inequality growth in these tourism-dependent counties surpasses the national average. The issue of overtourism was addressed from a sociological research perspective – in one of the works – framing it as an archetype within a profit-oriented system and highlighting the adverse effects on tourism workers within a neoliberal or free-market capitalist context (Walmsley, Koens, and Milano, 2022: 1-15). Our findings, derived from an econometrically focused investigation, align with these observations, indicating a commonality in outcomes despite our differing methodological approaches. One particular study discerned that the impact of tourism on income inequality varies significantly between developing and developed nations (Fang *et al.*, 2021: 1669-1691). Their findings suggest that while tourism indicators tend to exert a negative and statistically meaningful influence on income disparity in developing countries, they appear to have a negligible effect in more developed nations. These results stand in stark contrast to our own, where our RDD approach has uncovered evidence that suggests the opposite. It is important to consider the difference in methodologies; Fang *et al.* employed a panel data integration technique to gauge these effects, which differs from the analytical approach we took in our study.

The labor share of income, which encompasses the portion of national income paid out as wages and benefits to workers, has been on a decline across numerous nations. This downturn began in the 1980s for advanced economies, plunging to a fifty-year low around the 2008–09 global financial crisis and has since failed to make a significant recovery (Dao *et al.*, 2017: 1-72). Our research points out that this trend is exacerbated particularly in developed countries where overtourism strategies are predominant. We aim to explore the reasons behind this shift towards a rising capital share, growing inequality, and the diminishing labor share in the income distribution landscape.

Recipients of capital income are a heterogeneous group, ranging from corporate entities with dispersed ownership reaping dividends to small-scale accommodation landlords reaping rents and banks accruing interest revenue. In the context of a development strategy centered around overtourism, these small-scale landlords are instrumental in contributing to the rise in capital income share. This undoubtedly bolsters the capital gains within the economic framework as compared to labor gains, which relatively diminish. Moreover, this complexity is intensified by the presence of lower wages in segments of the service sector that are characterized by lower productivity, further skewing the balance in favor of capital over labor.

Our in-depth analysis reveals that the strategy we have examined significantly influences how income is divided between workers and capital providers, such as investors. This finding is in line with the economic principles proposed by Nicholas Kaldor. However, the effects on overall economic inequality, which we assess using the Gini coefficient, are less definitive. This suggests that when designing policies to address challenges like overtourism, which have profound economic implications, policymakers need to carefully consider the potential impact on the distribution of income between labor and capital, as well as the consequences for overall inequality.

6 Conclusion

This research evaluates how overtourism affects income distribution within the context of Kaldor's growth conjectures, applying a causal analysis framework that leverages a non-experimental comparison group approach. Our comparative study involves developed countries exposed to overtourism (the treated group) versus those that are not (the control group), using a RDD for empirical analysis. We constructed a bespoke dataset for the period of 2000 to 2019 encompassing countries affected by overtourism, ensuring it aligns with our theoretical construct and intervention identification strategy. The impact of overtourism's developmental policies has been scrutinized using both non-parametric and parametric RDD techniques.

The findings highlight that the strategic approach to overtourism is linked to a notable upward shift in the capital share of income distribution and affects the Gini coefficient—a metric for inequality. An increase by about 0.06-0.067 percentage points per annum in capital share was detected using the non-parametric approach. In contrast, a smaller, marginally significant effect of approximately 0.0003 percentage points per annum was recorded with the parametric approach, with the capital share designated as the dependent variable. Further, our results indicate a corresponding adverse effect on the labor share that is symmetrically opposite to that of the capital share in terms of size.

When considering the Gini coefficient, the impact estimated by the non-parametric model stands at an annual change of 0.026-0.033 percentage points. The variances observed between non-parametric and parametric model outcomes may stem from different prioritization of data points adjacent to the RDD threshold, with non-parametric models assigning greater weight. The statistical significance and robustness of our estimates are upheld across different model specifications. Additionally, the application of a placebo test has corroborated the validity of the causal inferences drawn in this study.

Thus, the divergence in the shares of production factors observed during the two-decade period from 2000 to 2019 can be linked to the impact of overtourism in developed countries.

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Appendix

Table 1: Descriptive Statistics for Outcome, Running, and Control Variables

Variable		Treated Mean	Treated Median	Untreated Mean	Untreated Median
Outcome Variable					
Worker Share	labsh	0.546	0.573	0.499	0.521
Capitalist Share	capsh	0.454	0.427	0.501	0.479
Gini coeficient		0.494	0.476	0.540	0.535
Running Variable					
Tourism Depen-dency weighted Index	tdi	259.3	168.3	29.019	32.601
Control Variables					
Population (pop)	pop	8.492	3.526	29.494	9.506
Urbanization Rate (urb)	urb	72.9	69.678	73.861	75.814
Education Expenditure (% GDP) (educ)	educ	4.802	4.923	4.7	4.757
Health Expenditure (% GDP) (health)	health	5.706	5.549	5.684	5.572
Employment Rate (emp)	emp	55.667	56.055	56.392	56.587
Dependency Ratio (depenage)	depenage	45.622	46.8	50.403	50.21
Tax Revenue (% GDP) (tax)	tax	29.888	32.621	26.276	26.518
GDP per Capita (gdppc)	gdppc	39203.88	32626.307	31536.651	25424.059

Source: Authors' calculation.

Table 2 : Covariate Balance Check for RDD Estimation

Dependent Variable	Bandwidth(h)	rho (h/b)	Estimate [P-Value]
pop	11.969	0.566	-0.552 [0.954]
educ	15.229	0.653	-0.431 [0.319]
health	17.804	0.657	0.573 [0.144]
emp	19.178	0.603	1.798 [0.412]
depenage	11.875	0.613	-6.117 [0.057]
tax	22.143	0.627	3.693 [0.067]
urb	18.515	0.629	-0.910 [0.820]
gdppc	16.576	0.569	12692.345 [0.146]

Note: Robust p-values are enclosed in square brackets. Bandwidth is measured in index points. The running variable at the 0.75 quantile cutpoint is TDI.
Source: Authors' calculation.

Table 3: Parametric RDD Regression Results for Various Outcome Variables Using IK Optimal Bandwidth

Variable/ Outcome	Intercept	Treatment Effect	Control Slope	Treatment Slope
labsh	0.538*** [0.000]	-0.074*** [0.000]	0.001*** [0.000]	-0.001* [0.092]
capsh	0.462*** [0.001]	0.074*** [0.001]	-0.001*** [0.001]	0.0003* [0.092]
Gini	0.487*** [0.000]	0.037** [0.010]	-0.001*** [0.000]	0.001 [0.990]

Note: Statistical significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust p-values are enclosed in square brackets. Bandwidth is measured in index points. The running variable at the 0.75 quantile cutpoint is TDI. Source: Authors' calculation.

Table 4: Non-parametric estimation of the differences between treated and non-treated countries (capital share in income distribution as outcome)

Bandwidth	Gaussian	Epanechnikov	Rectangular	No.of.obs.
50.409	0.060*	0.062*	0.067*	486
	[0.006]	[0.006]	[0.007]	
67.212	0.062***	0.067***	0.064***	821
	[0.000]	[0.000]	[0.000]	
84.015	0.064***	0.061***	0.063***	1093
	[0.000]	[0.000]	[0.000]	

Note: *, **, *** = significant at 10%, 5%, 1% level, respectively; p-values are enclosed in square brackets. Bandwidth is measured in index points. The running variable at the 0.75 quantile cutpoint is TDI.
Source: Authors' calculation.

Table 5: Non-parametric estimation of the differences between treated and non-treated countries (labour share in income distribution as outcome)

Bandwidth	Gaussian	Epanechnikov	Rectangular	No.of.obs.
50.409	-0.060*	-0.062*	-0.067*	486
	[0.006]	[0.006]	[0.006]	
67.212	-0.062***	-0.067***	-0.064***	821
	[0.000]	[0.000]	[0.000]	
84.015	-0.064***	-0.061***	-0.063***	1093
	[0.000]	[0.000]	[0.000]	

Note: *, **, *** = significant at 10%, 5%, 1% level, respectively; p-values are enclosed in square brackets.Bandwidth is measured in index points. The running variable at the 0.75 quantile cutpoint is TDI.
Source: Authors' calculation.

Table 6: Non-parametric estimation of the differences between treated and non-treated countries (inequality measured by Gini metrics as outcome)

Bandwidth	Gaussian	Epanechnikov	Rectangular	No.of.obs.
567.105	0.026*	0.026*	0.026*	612
	[0.067]	[0.067]	[0.067]	
756.140	0.028**	0.028**	0.028**	966
	[0.012]	[0.012]	[0.012]	
945.175	0.033***	0.033***	0.033***	1113
	[0.001]	[0.001]	[0.001]	

Note: *, **, *** = significant at 10%, 5%, 1% level, respectively; p-values are enclosed in square brackets.Bandwidth is measured in index points. The running variable at the 0.75 quantile cutpoint is TDI.
Source: Authors' calculation.

Table 7: Polynomial Regression Discontinuity (RD) Estimation with Robust Bias-Corrected Confidence Intervals

Outcome variable	Polynomial Order	Bandwidth(h)	rho (h/b)	Point Estimate (Bias-Corrected)
Labour share in income distribution	Linear (p = 1)	10.798	0.527	-0.068** [0.014]
	Quadratic (p = 2)	15.335	0.688	-0.100*** [0.004]
	Cubic (p = 3)	21.910	0.813	-0.108*** [0.005]
Capital share in income distribution	Linear (p = 1)	10.087	0.534	0.065*** [0.008]
	Quadratic (p = 2)	15.335	0.662	0.091*** [0.002]
	Cubic (p = 3)	21.910	0.806	0.101*** [0.003]
Gini coefficients	Linear (p = 1)	12.265	0.523	0.035** [0.019]
	Quadratic (p = 2)	13.068	0.612	0.068*** [0.001]
	Cubic (p = 3)	20.490	0.701	0.073*** [0.000]

Note: *, **, *** = significant at 10%, 5%, 1% level, respectively; robust p-values are enclosed in square brackets.Bandwidth is measured in index points. The running variable at the 0.75 quantile cutpoint is TDI.

Table 8: Results of the Placebo Test

Quantile	capsh	labsh	Gini
	Estimate [P-value]	Estimate [P-value]	Estimate [P-value]
0.15	0.003 [0.878]	-0.003 [0.878]	-0.011 [0.531]
0.3	-0.005 [0.777]	0.005 [0.777]	-0.018 [0.238]
0.45	0.010 [0.601]	-0.010 [0.601]	0.034 [0.116]
0.6	-0.039 [0.198]	0.039 [0.198]	-0.037 [0.202]
0.9	-0.040 [0.172]	0.040 [0.262]	0.043 [0.210]

Note: Robust p-values are enclosed in square brackets. The running variable at the various designed placebo quantile cutpoints is TDI.
Source: Authors' calculation.

The Dataset: A Global Compilation of Developed Countries

Europe: Austria, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Denmark, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Russian Federation, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine, United Kingdom.

Americas: Argentina, Aruba, Barbados, Bermuda, Brazil, Canada, Cayman Islands, Chile, Colombia, Costa Rica, Curacao, Dominican Republic, Ecuador, Guatemala, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Suriname, Trinidad and Tobago, United States, Uruguay.

Africa: Angola, Benin, Botswana, Burkina Faso, Burundi, Cabo Verde, Cameroon, Djibouti, Egypt, Eswatini, Gabon, Guinea, Kenya, Lesotho, Malawi, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, South Africa, Sudan, Togo, Uganda, Zimbabwe.

Asia: Armenia, Azerbaijan, Bahrain, China, India, Indonesia, Iraq, Israel, Japan, Jordan, Kazakhstan, Kuwait, Lebanon, Malaysia, Mongolia, Philippines, Qatar, Saudi Arabia, Singapore, Sri Lanka, Tajikistan, Thailand, United Arab Emirates, Uzbekistan.

Oceania: Australia, Fiji, New Zealand.