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Interpreting the Effectiveness of Active Labor Market Policies in Combating Unemployment in OECD Countries Using a Causal Machine Learning Approach

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ABSTRACT

This study examines the effects of Active Labour Market Policies (ALMP) expenditures on unemployment in OECD countries. Using a large country-year panel dataset covering the period 2000–2022, policy effects were analyzed using causal machine learning methods. In this study, ALMP expenditures were treated as a continuous treatment variable expressed as a percentage of GDP, the unemployment rate was used as the outcome variable, and population size was included in the model as a confounding variable using logarithmic transformation. The average policy effect was estimated using the Double Machine Learning (DML) approach, while conditional mean treatment effects (CATE) were calculated using the Causal Forest method to reveal how the effects differed across countries and contexts. The findings show that ALMP expenditures significantly reduce the unemployment rate on average across the OECD. However, it was found that policy effects are quite heterogeneous across countries and contexts, with ALMP expenditures having much stronger unemployment-reducing effects in some countries, while marginal effects remained limited in others. The results highlight the inadequacy of a uniform policy approach in evaluating active labor market policies and emphasize the importance of context-sensitive, targeted policy designs.

Keywords: Active Labor Market Policies; Unemployment; OECD Countries; Policy Impact Analysis; Heterogeneous Treatment Effects; Causal Machine Learning; Double Machine Learning; Causal Forest

1. Introduction

Unemployment, as one of the most fundamental indicators of economic performance and social welfare, has long been a top priority for policymakers. Global economic crises, technological transformation, and demographic changes have profoundly impacted the structure of labor markets; these developments have led governments to develop more active and targeted policy tools to reduce unemployment (Bonoli, 2010; Martin, 2015). In this context, Active Labour Market Policies (ALMPs) stand out as key policy tools aimed at increasing the employability of unemployed individuals, accelerating their reintegration into the labor market, and especially reducing long-term unemployment.

The effects of ALMPs on unemployment have been the subject of extensive empirical literature, particularly in the context of OECD countries. Many macro-level studies show that ALMP expenditures, measured as a percentage of GDP, are associated with a decrease in unemployment rates (Sahnoun & Abdennadher, 2018; Hur, 2019). However, the findings vary significantly across countries, periods, and methods used. While some studies

report strong and statistically significant unemployment-reducing effects of ALMPs, others emphasize that the effects are limited or context-sensitive (Alegre, 2017; Karasová et al., 2019). This indicates that the effectiveness of ALMPs is not context-independent and universal.

One of the main limitations in the current literature is that the effects of ALMPs are mostly evaluated using a single average coefficient. However, labor markets vary greatly between countries in terms of institutional structure, governance quality, demographic characteristics, and level of economic development (Flaig & Rottmann, 2013). Considering this heterogeneous structure, it is expected that ALMP expenditures may be quite effective in some countries or specific contexts, while their marginal effects may be limited in others. Traditional approaches focusing on average effects can lead to incomplete or misleading results in policy evaluations by ignoring these differences (De Koning, 2001; Cronert, 2023).

In addition, defining the causal relationship between ALMP expenditures and unemployment presents methodological challenges. The fact that increases in unemployment rates can affect ALMP expenditures through pressure on public budgets raises problems of reverse causality and endogenity (Sahnoun & Abdennadher, 2022). Therefore, dynamic panel models, instrumental variable approaches, and difference-of-difference methods have been widely used in the literature. However, these methods often capture the heterogeneity in policy effects only to a limited extent.

In recent years, causal machine learning approaches, developed by combining causal inference and machine learning methods, offer powerful tools for overcoming these limitations. Methods such as Double Machine Learning (DML) and Causal Forest allow for the flexible control of highly dimensional and nonlinear confounding structures in observational data, enabling the estimation not only of average policy effects but also of context-sensitive conditional treatment effects (Conditional Average Treatment Effects, CATE) (Chen & Jing, 2025; Goller et al., 2025). With these features, causal machine learning approaches offer a significant methodological advancement for evaluating policies with heterogeneous effects, such as ALMP.

This study aims to fill this literature gap. Using a large country-year panel dataset covering OECD countries, the effects of ALMP expenditures on unemployment are examined within the framework of causal machine learning. In the first stage of the study, the average causal effect of ALMP expenditures on unemployment is estimated using the Double Machine Learning method. In the second and main stage, the Causal Forest approach is used to analyze how policy effects differ across countries and contexts, and conditional mean treatment effects are revealed.

In this respect, the study offers three main contributions. First, it re-evaluates the effect of ALMP expenditures on unemployment within a causal framework using a large panel dataset for OECD countries. Second, it presents empirical evidence that policy effects are not homogeneous, revealing the limitations of policy evaluations based on mean effects. Third, it provides a methodological contribution to the literature by demonstrating how causal machine learning methods can be used in the macro-level analysis of labor market policies.

The rest of the study is structured as follows: The second section summarizes the relevant literature and discusses the relationship of this study to existing studies. The third section introduces the dataset and methods used in detail; this is followed by empirical findings, discussion, and policy implications. The final section summarizes the findings and offers suggestions for future research.

2. Literature Review

2.1. Active Labour Market Policies and Unemployment

The effects of Active Labour Market Policies (ALMP) on unemployment have long been debated in the empirical literature, particularly in the context of OECD countries. Early studies have emphasized that ALMP expenditures have the potential to reduce unemployment rates, but that this effect varies significantly across countries and periods (Martin, 2015; Bonoli, 2010).

Macro-level panel data analyses show that when ALMP expenditures are used as a percentage of GDP, they are associated with a decrease in unemployment rates (Sahnoun & Abdennadher, 2018; Hur, 2019). However, this relationship is often not one-way. It has been shown that increases in the unemployment rate, especially during periods of economic recession, can increase pressure on public finances and thus limit ALMP expenditures (Sahnoun & Abdennadher, 2022). This bidirectional relationship makes it difficult to define the causal link between ALMP and unemployment, placing the issue of endogenity at the center of the literature.

2.2. Program Types, Time Horizon, and Impact Differentiation

The effectiveness of ALMPs depends not only on the total expenditure level but also on the program types and time horizons. Meta-analyses show that training programs and public employment services (PES) have more lasting unemployment-reducing effects in the long term, while wage subsidies can produce strong effects in the short term but weaken over time (Card, Kluve & Weber, 2010; Vooren et al., 2019).

These differences regarding program types become more pronounced, especially for disadvantaged groups. It has been reported that training and targeted support programs have more lasting effects on long-term unemployed and low-skilled individuals; in contrast, direct public employment programs often have limited or negative results (Kluve et al., 2007; Escudero, 2018). These findings indicate that ALMP assessments should go beyond total expenditure indicators.

2.3. Cross-Country Heterogeneity and Context Dependence

Recent literature highlights that the effects of ALMPs on unemployment are significantly heterogeneous across countries. Comparative studies covering OECD countries show that factors such as economic conditions, quality of governance, and institutional structure strongly shape the effectiveness of ALMPs (Flaig & Rottmann, 2013; Karasová et al., 2019).

In particular, ALMPs have been found to produce stronger unemployment-reducing effects in countries with high quality of governance and budgetary stability (Sahnoun & Abdennadher, 2023; Sahnoun & Abdennadher, 2025). In contrast, in countries with mature labor markets and relatively low unemployment rates, the impact of marginal increases in

ALMP expenditures remains limited (Alegre, 2017). This situation demonstrates that policy evaluations based on average effects can be misleading and that heterogeneity should be analyzed directly.

2.4. Methodological Approaches in ALMP Research

The methods used in the ALMP literature have undergone a significant transformation over time. While early studies relied heavily on fixed-effects regressions and dynamic panel GMM models, more recently, Difference-in-Differences (DiD) and Instrumental Variables (IV) approaches have been widely used to address the endogenousity issue (Altavilla & Caroleo, 2006; Sahnoun & Abdennadher, 2018).

However, a large portion of these traditional methods report policy effects using a single mean coefficient and can only capture heterogeneity to a limited extent. This limitation creates a significant methodological gap in the evaluation of context-sensitive policies such as ALMP (De Koning, 2001; Cronert, 2023).

2.5. Causal Machine Learning in ALMP Research

To address this methodological gap, causal machine learning approaches have begun to be incorporated into the ALMP literature in recent years. Methods such as Double Machine Learning (DML) and Causal Forest allow for the flexible control of high-dimensional and nonlinear confounding structures while simultaneously enabling the prediction of heterogeneous treatment effects (Chen & Jing, 2025).

In particular, the Causal Forest approach offers a significant advantage in terms of targeted policy design by revealing in which contexts policy effects are strengthened or weakened. Micro-level applications have shown that the effects of education and employment programs vary considerably across different groups (Cockx et al., 2023; Goller et al., 2025). However, the application of these approaches to macro-level, country-year panel data is still limited.

2.6. Literature Gap and Contribution of the Present Study

The current literature points to three main gaps. First, the effects of ALMPs on unemployment are often examined at the average level, with inter-country heterogeneity treated as a secondary issue. Second, the use of causal machine learning methods in ALMP analyses is largely limited to micro datasets. Third, the number of studies systematically revealing how policy effects vary in a context-sensitive manner is limited (Bredgaard, 2015; Cronert, 2023).

This study examines the effects of ALMP expenditures on unemployment within a causal machine learning framework using a broad country-year panel covering OECD countries, aiming to fill these gaps. While the average effect is estimated using the Double Machine Learning method, heterogeneity in policy effects is directly analyzed using the Causal Forest approach. In this respect, the study offers both an empirical and methodological contribution to the ALMP literature.

3. Method

3.1. Data Set and Scope

This study examines the effects of Active Labour Market Policies (ALMP) on unemployment using a country-year panel dataset covering OECD countries. The analysis

period covers the years 2000–2022, and the dataset provides a large panel sample encompassing most OECD countries (approximately 26,000 country-year observations). The country name variable was retained in the dataset to improve the visual presentation and interpretability of the findings; the country code was used as a matching key for consistency in the merging operations.

The outcome variable in the analysis is the unemployment rate. ALMP expenditures were used as the intervention/treatment variable, and this variable, originating from the OECD, was modeled as a continuous variable as a percentage of GDP. Population size was used as the confounder variable; to better capture scale effects and balance the distribution, a logarithmic transformation was applied to the population variable and it was included in the analysis in log(population) form.

3.2. Data Sources and Variable Definition

The data infrastructure of the study was created from two main sources:

• *OECD (ALMP):* ALMP expenditures were taken from the OECD database and measured as a percentage of GDP. This measurement was preferred because it increases comparability between countries. The variable is a normalized indicator of expenditures on publicly funded active labor market programs according to economic size.

• *World Bank (World Development Indicators – WDI)*: Unemployment rate and population data were obtained from World Bank WDI sources. The unemployment rate was measured as the share of unemployed people in the total labor force (%). The population variable represents the total population, and a log transformation was applied in the analysis. The variables can be summarized as follows:

• *Outcome (Y):* Unemployment rate (%)
• *Treatment (T):* ALMP expenditure (percentage of GDP, continuous)
• *Confounder (X):* log(population)

3.3. Data Set Creation and Preprocessing Steps

The panel data set was created by consistently combining variables from different sources at the country-year level. In this process, the country code was used as the common key to reduce joining errors and eliminate the effect of possible spelling differences in country names. The process followed is summarized as follows:

First, the ALMP expenditure series from the OECD was organized by country code and year, and non-country records, such as OECD aggregate rows, were removed from the data set. This step is critical to ensure that the unit of analysis is defined as "country". Then, the World Bank unemployment series was converted to long format (country-year observations) and filtered to match OECD country codes. Similarly, the population series was also converted to country-year format and restricted to OECD country codes.

In the final stage, unemployment and population data were combined via country name-country code-year; and the OECD ALMP data was added to the panel structure using the inner join method at the country code-year key. This choice ensured a consistent sample in terms of the treatment definition by excluding country-year observations for which ALMP data was not available. The dataset was limited to the period 2000–2022. Additionally, a

confounding variable to be used in the model was obtained by applying a natural logarithm transformation to the population variable.

3.4. Causal Machine Learning Framework

This study utilizes causal machine learning methods, going beyond classical linear regression approaches, to evaluate the impact of ALMP expenditures on unemployment. The main goal is not only to estimate the average effect (ATE) but also to reveal the effects (heterogeneity) that may vary across countries and contexts. Accordingly, the analysis consists of two components:

1. Double Machine Learning (DML) for Average Treatment Effect (ATE)
2. Causal Forest approach for Conditional Average Treatment Effects (CATE)

These two approaches together provide the opportunity to examine the policy effect both at the "general average" level and at the "in which contexts is it stronger/weaker" level.

This study adopts a causal machine learning framework that combines Double Machine Learning and Causal Forest methods, which have been increasingly used to estimate causal effects and treatment effect heterogeneity in observational settings. Double Machine Learning provides orthogonalization-based estimators that are robust to high-dimensional confounding, while Causal Forest enables the direct estimation of heterogeneous treatment effects across contexts (Chernozhukov et al., 2018; Chen & Jing, 2025).

3.5. Estimation of Mean Effectwith Double Machine Learning

The DML framework was used to estimate the mean treatment effect. The DML approach aims to estimate the treatment effect more robustly while flexibly controlling the effect of confounders, which are common in observational data. In this study, since the treatment variable *T* (ALMP, %GDP) is continuous, the DML specification suitable for continuous treatment was used.

In DML, there is an estimation of two "nuisance" functions: the outcome model and the treatment model. In this study, these auxiliary models were estimated with LassoCV (L1-regularized) linear models to limit overfitting in small samples and to provide stable estimation. The main advantage of DML is that despite the possible prediction errors in these auxiliary models, the treatment effect is estimated through an "orthogonal" moment condition, thus reducing bias. To increase the generalizability of the model and reduce the bias that may arise from both learning and evaluating the auxiliary models on the same data, 5-fold cross-fitting was applied. In this procedure, the data was divided into five parts; in each step, auxiliary models were learned with four parts, the orthogonalized treatment effect was calculated on the remaining part, and the process was repeated for all layers. The resulting ATE estimate provides a more robust average measure of policy impact under observational data conditions.

The Double Machine Learning approach builds on recent advances in causal inference that combine machine learning with semiparametric estimation to address endogeneity and model misspecification. By employing orthogonal moment conditions and cross-fitting, DML yields consistent estimates of average treatment effects even in the

presence of complex confounding structures (Chernozhukov et al., 2018; Chen & Jing, 2025).

3.6. Estimation of Heterogeneous Effects with Causal Forest

Expressing the average effect with a single coefficient is often insufficient for policies shaped by national institutions, demographics, and labor market structures, such as ALMP. Therefore, the main focus of this study is the estimation of conditional mean treatment effects (CATE), which show how ALMP effects differ in the country context.

For this purpose, the Causal Forest approach was used. Causal Forest is a tree-based causal learning method that focuses on directly estimating the treatment effect. The method estimates treatment effects that can vary by making local comparisons between similar observations. In this study, CATEs were obtained, especially under the condition of the log(population) variable, which represents the scale and country context.

Causal Forest estimates utilize auxiliary models to control for systematic patterns in outcomes and treatment processes; thus, heterogeneity estimates rely not solely on correlation but on a comparative logic closer to a causal framework. The resulting CATE estimates were first examined as distributions at the observational level; then, country-by-country averages were taken to create an inter-country heterogeneity map to strengthen policy interpretation. This approach allows for a data-driven answer to the question, "Does ALMP have the same effect in every country?"

In summary, the impact of ALMP expenditures on unemployment was examined using causal machine learning tools with a broad OECD country-year panel. The average impact was estimated within the DML framework (with LassoCV auxiliary models and 5-fold cross-fitting); the main contribution of the study is that heterogeneous impacts were revealed at the CATE level using the Causal Forest method. This two-tiered approach aims to directly contribute to policy design discussions by considering both the overall policy impact and the country-specific varying impacts together.

The Causal Forest method, extending the random forest framework to causal inference, is specifically designed to estimate conditional average treatment effects through local comparisons among similar observations. This approach has been shown to be particularly effective in uncovering treatment effect heterogeneity in labor market policy evaluations (Athey & Imbens, 2016; Goller et al., 2025; Cockx et al., 2023).

4. Results

This section presents the effects of spending on active labor market policies (ALMP) on the unemployment rate, based on findings obtained within the framework of causal machine learning. The findings are addressed in two stages. First, the average causal effect of ALMP spending is examined using the Double Machine Learning (DML) method, and then how this average effect differs across countries and contexts is evaluated through conditional mean treatment effects (CATE).

4.1. Average Treatment Effect: Double Machine Learning Findings

The results obtained using the Double Machine Learning (DML) approach show that ALMP spending has a statistically significant and economically noteworthy average effect on the unemployment rate across OECD countries. According to the estimated mean

treatment effect (ATE), a one-unit increase in ALMP spending as a percentage of GDP is associated with an average decrease of approximately 0.5 percentage points in the unemployment rate. The fact that the confidence interval does not include zero indicates that this effect is statistically significant.

This finding demonstrates that active labor market policies play an average role in reducing unemployment and does not support generalizations that ALMPs are ineffective at the macro level. However, when DML results are considered alone, they imply the assumption that this average effect is valid for all countries and contexts. As will be shown in the next subsection, this assumption should be strongly questioned.

4.2. Conditional Mean Treatment Effects: Causal Forest Findings

To go beyond the average effect, the effects of ALMP expenditures on unemployment were examined at the conditional mean treatment effects (CATE) level using the Causal Forest method. This approach assumes that the policy effect is not homogeneous across countries and contexts and aims to reveal heterogeneity by utilizing local comparisons between similar observations.

Figure 1 shows the distribution of CATE values estimated using the Causal Forest method for all country-year observations. The distribution reveals that the effects of ALMP expenditures on unemployment vary over a wide range. While some observations show that increases in ALMP are associated with a very strong decrease in unemployment, in other contexts the effect is seen to be weaker or even negative. This finding indicates that considering ALMP as a “uniform” policy tool can be misleading.

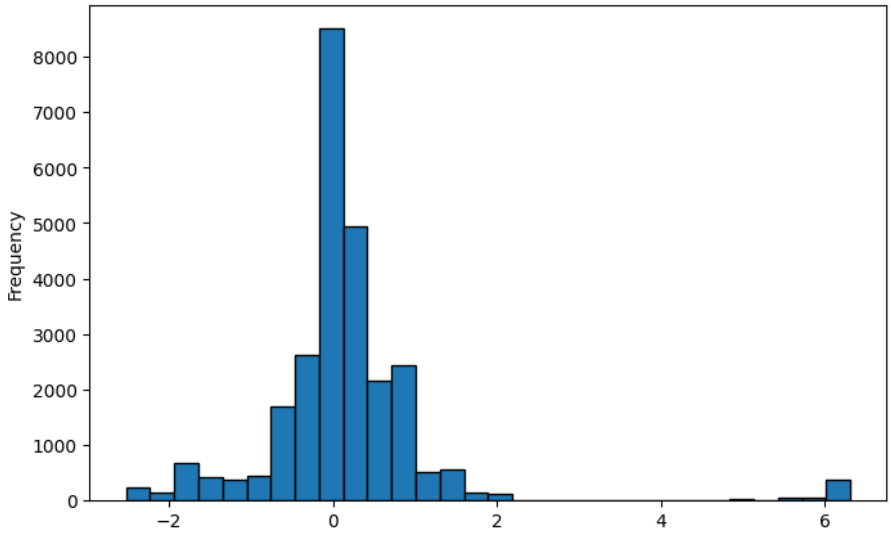

Figure 1. Distribution of conditional mean treatment effects (CATE) of ALMP expenditures on unemployment.

4.3. Heterogeneity in Population Context

To examine in which contexts the ALMP effects are strengthened, CATE estimates were evaluated together with the logarithm of the population size. Figure 2 shows the distribution of CATE estimates according to the log(population) variable and reveals the contextual heterogeneity in policy effects. The graph shows that ALMP effects are more variable and in some cases quite strong, especially in countries with medium and high

population sizes. In contrast, it is observed that ALMP effects are relatively more limited and concentrated in a narrower band in countries with smaller populations.

This finding suggests that ALMP may be closely related to scale effects and that policy design should be evaluated together with the demographic size of the country.

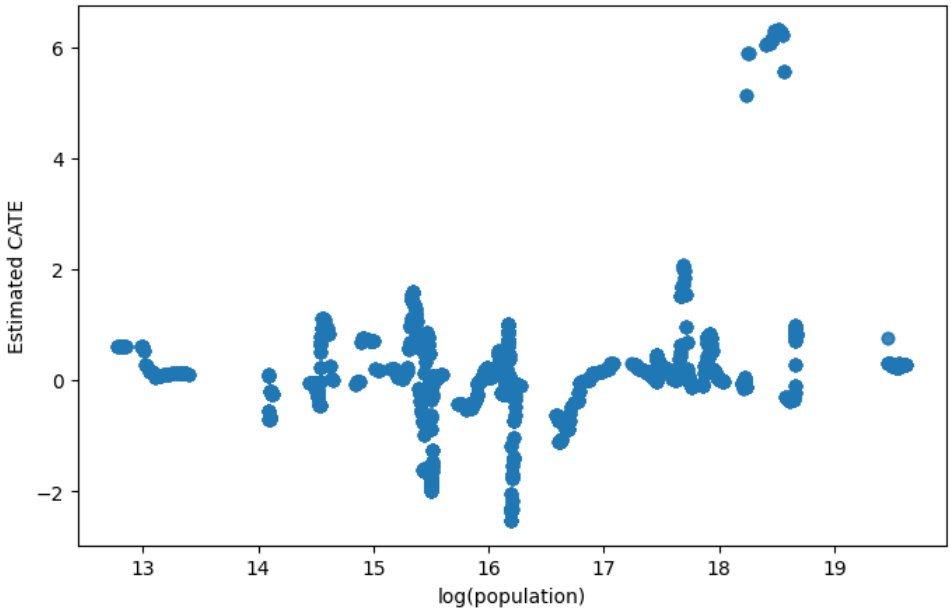

Figure 2. Variation of conditional effects of ALMP on unemployment in the context of population.

4.4. Country-Specific Conditional Average Effects

To make CATE estimates more interpretable from a policy perspective, conditional effects have been summarized by averaging them at the country level. Figure 3 shows the ten OECD countries with the highest average conditional effects of ALMP expenditures on unemployment. The high ranking of countries such as Turkey, Mexico, Korea, and Japan reveals that the unemployment-reducing effect of ALMP expenditures is relatively stronger in these countries.

In contrast, the results presented in Figure 4 show that the average conditional effects of ALMP expenditures are weaker or negative in countries such as Greece, Slovakia, the Netherlands, and Switzerland. These countries generally have more mature labor markets, and it is thought that the marginal effects of ALMP expenditures may have reached saturation. This shows that the effectiveness of ALMP depends not only on the level of expenditure but also on the institutional structure and policy design.

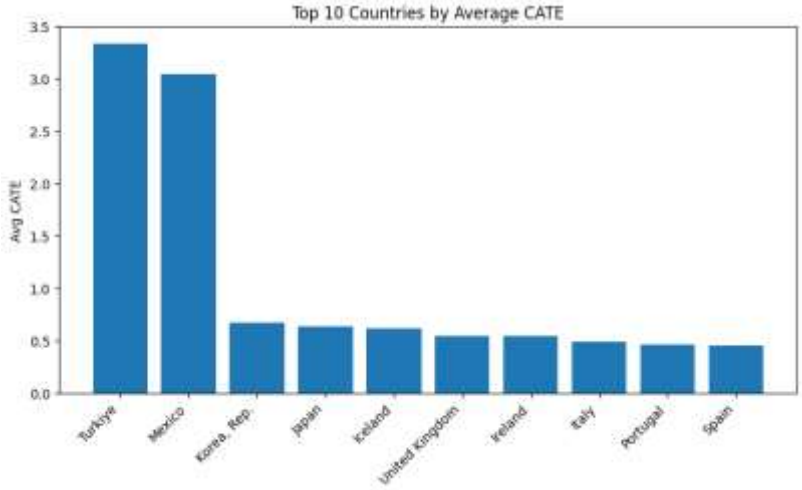

Figure 3. Countries with the highest average conditional effects of ALMP expenditures on unemployment.

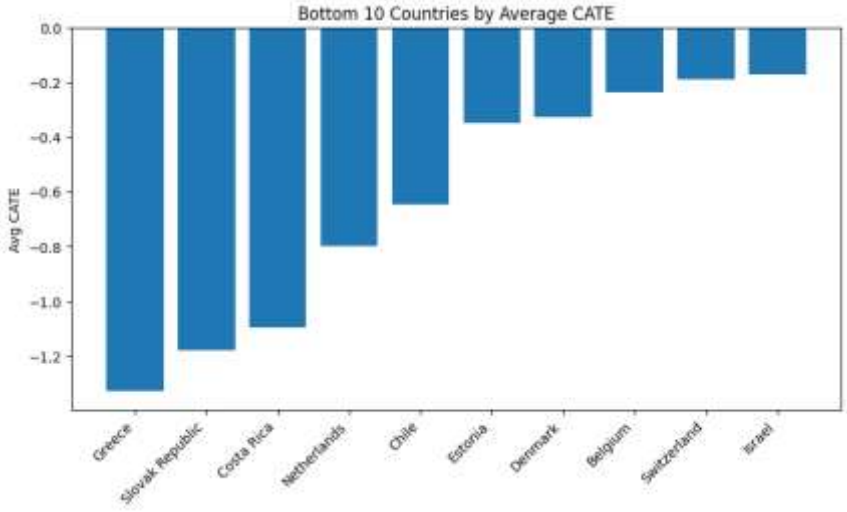

Figure 4. Countries with the lowest average conditional effects of ALMP expenditures on unemployment.

4.5. General Assessment of Findings

When the findings are considered together, it is seen that ALMP expenditures reduce the unemployment rate on average across OECD countries, but this effect is significantly heterogeneous between countries and contexts. Although the average treatment effect is significant, the Causal Forest results reveal that this average does not fully reflect the policy reality. It is observed that ALMP expenditures can produce much stronger effects, especially in developing OECD economies and in certain demographic contexts, while marginal returns remain limited in some mature economies. These findings show that in evaluating active labor market policies, the question of "in what context and under what country conditions the expenditure is made" should be prioritized rather than the question of "how much is spent".

5. Discussion

This study examines the effects of spending on active labor market policies (ALMP) on unemployment across a broad panel of countries-years covering OECD countries using

causal machine learning methods. The findings reveal that ALMP spending reduces the unemployment rate on average, but this effect is significantly heterogeneous across countries and contexts. These results empirically confirm the issues of context dependence and heterogeneous effects, which have long been debated but often addressed in a limited way in the ALMP literature.

The mean treatment effect (ATE) obtained using the Double Machine Learning (DML) method shows that ALMP spending significantly reduces the unemployment rate across OECD countries. This finding is largely consistent with previous studies that point to the unemployment-reducing effects of ALMP spending in macro-level panel data analyses (Sahnoun & Abdennadher, 2018; Hur, 2019; Martin, 2015). Literature findings, particularly those suggesting that measuring ALMP expenditures as a ratio to GDP increases cross-country comparability and produces more consistent results, support the approach of this study. However, it appears that this average effect alone is not a sufficient indicator of policy effectiveness, as reported in the literature. As previously highlighted by Alegre (2017) and Karasová et al. (2019), the marginal effects of ALMP expenditures may remain limited or reach saturation in some countries. This study also demonstrates that even if the average effect is positive and significant, this effect is not uniformly applicable to all countries.

5.1. Heterogeneous Effects and Inter-Country Differentiation

The main contribution of the study is the heterogeneous treatment effects revealed by the Causal Forest method. The obtained CATE distributions show that the effects of ALMP expenditures on unemployment vary widely, being quite strong in some countries and limited or even negative in others. This finding directly aligns with the theoretical and empirical literature indicating that the effectiveness of ALMPs is not context-independent (Bonoli, 2010; Cronert, 2023).

The observation of higher average conditional treatment effects, particularly in countries such as Turkey, Mexico, Korea, and Japan, suggests that ALMPs can provide higher marginal utility in economies undergoing structural transformation. The more heterogeneous labor markets in these countries, along with their young and dynamic population structures, allow ALMPs to produce more visible results through targeted programs. This interpretation is also consistent with meta-analysis findings showing that ALMPs are more effective in addressing disadvantaged groups and structural unemployment (Card et al., 2010; Vooren et al., 2019).

Conversely, the weak or negative conditional effects of ALMP expenditures in countries such as Greece, the Netherlands, and Switzerland suggest that the marginal effectiveness of active policies may decrease in mature labor markets. This supports studies emphasizing that ALMP effectiveness depends not only on the amount of expenditure but also on institutional structure, governance quality, and policy design (Flaig & Rottmann, 2013; Sahnoun & Abdennadher, 2023).

5.2. Population Context, Scale Effects, and Institutional Structure

Examining CATE estimates in the context of population size reveals that ALMP effects exhibit higher variance, particularly in medium and large-population countries. This finding suggests that ALMPs may be closely related to scale effects. The more fragmented

and heterogeneous labor market in large-population countries allows ALMPs to produce strong effects in specific subgroups, while policy effects are concentrated in a narrower band in small-population countries.

These results are consistent with the literature highlighting the role of governance quality and administrative capacity on ALMP effectiveness (Sahnoun & Abdennadher, 2025). Especially in large-scale labor markets, the targeting accuracy and implementation capacity of policy design can be more decisive than the level of expenditure itself.

5.3. Discussion of Methodological Contribution

The findings of this study clearly reveal the limitations of average-effect-focused approaches commonly used in the ALMP literature. While dynamic panel GMM, DiD, or IV-based analyses have made significant contributions to addressing the endogenousity issue, they often overlook heterogeneity in policy effects (Altavilla & Caroleo, 2006; De Koning, 2001).

The causal machine learning approach used in this study, particularly the combination of Double Machine Learning and Causal Forest, allows for both robust estimation of the average effect and direct analysis of heterogeneity. In this respect, the results obtained demonstrate that causal machine learning methods offer a significant methodological advantage in evaluating context-sensitive policies such as ALMP. The findings of similar studies at the micro level (Cockx et al., 2023; Goller et al., 2025) support the macro-level results of this study.

Overall, the findings of this study indicate that ALMPs can be an effective tool in combating unemployment across OECD countries, but that this effectiveness varies in a context-sensitive manner. While the average treatment effect is positive and significant, the Causal Forest results reveal that this average does not fully reflect policy reality. This suggests that ALMP assessments should prioritize questions such as "in what context, in which country, and under what institutional conditions is spending done" rather than "how much is spending done."

6. Conclusion

This study examines the effects of spending on active labor market policies (ALMPs) on unemployment using causal machine learning methods with a large country-year panel dataset covering OECD countries. The findings reveal that ALMP spending has an average effect of reducing the unemployment rate, but this effect varies significantly across countries and contexts. This result clearly shows that ALMPs cannot be considered a uniform and universal policy tool in combating unemployment.

The average treatment effect estimated using the Double Machine Learning method confirms that active policies have the potential to reduce the unemployment rate across the OECD. However, the conditional average treatment effects obtained using the Causal Forest approach reveal that this average result does not fully reflect the policy reality. While some countries showed quite strong unemployment-reducing effects from ALMP spending, others had limited or weak marginal effects. This indicates that policy effects are context-sensitive and should be evaluated in conjunction with country characteristics.

Particularly in countries undergoing structural transformation, where labor markets are more heterogeneous and certain vulnerable groups are concentrated, ALMP expenditures appear to yield higher marginal benefits. Conversely, in countries with mature and institutionalized labor markets, quantitative increases in active policies seem to have limited effects on unemployment. This finding suggests that policy design, targeting accuracy, and institutional context, rather than expenditure levels, are the determining factors in ALMP assessments.

In this context, the study offers important implications for policymakers. Firstly, the effectiveness of ALMPs should be considered not through a "more spending" approach, but through an understanding of "better-designed programs in a more appropriate context." Increased spending without considering the demographic structure of countries, the institutional characteristics of the labor market, and administrative capacity makes it difficult to produce the expected results. Therefore, targeted, flexible, and context-sensitive policy frameworks should be adopted in ALMP design.

Another important contribution of the study concerns the methods used in evaluating labor market policies. Traditional average-effects-focused approaches may be insufficient in analyzing policies that produce heterogeneous effects, such as ALMPs. This study provides a methodological contribution to the literature by demonstrating the capacity of causal machine learning methods to address both average and context-sensitive policy effects within the same framework. The use of the Causal Forest approach, particularly in macro-level panel data, makes the differentiation in policy effects more visible.

Finally, the findings of this study offer important clues for future research. Analyses conducted with more detailed datasets that disaggregate program types can reveal which components of ALMPs are more effective in which contexts. Furthermore, the more comprehensive inclusion of variables such as institutional quality, governance indicators, and labor market flexibility in the model will contribute to a better understanding of the mechanisms of policy impact. In this respect, the study aims to make a lasting contribution to the literature by emphasizing the importance of context-sensitive and evidence-based approaches in evaluating active labor market policies.

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