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Research Article

Macroeconomic indicators affect the NEET: A panel data analysis for BRICST countries

NEET'i etkileyen makroekonomik göstergeler: BRICST ülkeleri için panel veri analizi

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Abstract

The study examines the impact of real GDP per capita (GDP), inflation rate (INF), the share of education expenditure in GDP (EDU), and the proportion of wage and salaried workers in total employment (WAGE) on NEET rates in Brazil, Russia, India, China, South Africa, and Türkiye (BRICST) from the data 1999 to 2023 using the Augmented Mean Group Estimator. According to the test results, a 1% increase in GDP reduces NEET rates by 0.008% and 0.0009% in India and China, respectively. A 1% increase in INF increases NEET rates in Russia and India by 0.029% and 0.424%, respectively. A 1% increase in EDU reduces NEET rates in Russia and Turkey by 2% and 7%, while in China, Brazil and South Africa, NEET rates are increased by 9%, 3% and 0.003%, respectively. A 1% increase in WAGE reduces NEET rates by 0.5% in Russia and 0.11% in South Africa. However, a 1% increase in WAGE in India increases NEET rates by 1.2%. The study reveals that macroeconomic indicators are valuable tools for producing NEET policies in BRICST.

Keywords: NEET, Augmented Mean Group Estimator, BRICST, Macroeconomic Indicators

Jel Codes: E24, C01, E2, E00

Öz

Bu çalışmada 1999-2023 yılı arasındaki veriler kullanılarak Brezilya, Rusya, Hindistan, Çin, Güney Afrika ve Türkiye için kişi başına düşen reel GSYİH (GDP), enflasyon oranı (INF), eğitim harcamalarının GSMH'a oranı (EDU), ve ücretli ve maaşlı çalışan işçilerin toplam işgücüne oranı (WAGE) gibi değişkenlerin NEET oranlarına olan etkisi Arttırılmış Ortalama Grup tahmincisi yardımıyla araştırılmıştır. Test sonuçlarına göre Hindistan ve Çin'de GDP'de görülen %1'lik artış NEET oranlarını sırasıyla %0.008 ve %0.0009 oranında azaltmaktadır. INF'da görülen %1'lik artış ise Rusya ve Hindistan'da NEET oranlarını %0.029 ve %0.424%oranında artırmaktadır. EDU'da görülen %1'lik artış Rusya ve Türkiye'de NEET oranlarını %2 ve %7 oranında azaltırken; Çin, Brezilya ve Güney Afrika'da NEET oranlarını sırasıyla %9, %3 ve %0.003 oranında artırmaktadır. WAGE'de görülen %1'lik bir artış, Rusya'da NEET oranlarını %0.5 Güney Afrika'da ise %0.11 oranında azaltmaktadır. Ancak Hindistan'da WAGE'de görülen %1'lik artış artış NEET oranını %1.2 oranında artırmaktadır. Çalışma, BRICST ülkeleri için söz konusu değişkenlerin NEET oranlarını azaltmak için kullanışlı araçlar olduğunu ortaya çıkarmıştır.

Anahtar Kelimeler: NEET, Arttırılmış Ortalama Grup Tahmincisi,BRICST, Makroekonomik Göstergeler

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Introduction

The concept of NEET, which originated in the United Kingdom and stands for "neither in employment nor in education or training," is a statistical term used to understand young people's employment and educational status. This term, which refers to individuals who are "neither employed, in education nor training", is also used to describe those commonly referred to as "stay-at-home youth." Reducing NEET rates is crucial for countries to combat unemployment and achieve economic growth. According to the OECD (2016), the NEET rate in a country increases when young people aged 15-29 are not enrolled in an educational institution, are not receiving vocational training, or are not employed. An increase in a country's NEET rate reduces productivity, negatively impacts production capacity, and slows economic growth. Therefore, recent efforts have been made to minimise NEET rates.

This study aims to determine which macroeconomic variables can effectively reduce NEET rates in BRICST countries. Thus, the study examines whether key macroeconomic indicators such as per capita income, education expenditures, inflation rates, and salaried employees effectively reduce NEET rates. For this purpose, the effects of selected macroeconomic indicators on NEET rates were analysed using the Augmented Mean Group Estimator method for BRICST countries. As a result, it was concluded that macroeconomic variables are effective in reducing NEET rates.

Conceptual Framework of NEET

NEET is an acronym meaning "not in employment, education, or training," researchers in the United Kingdom first used it in the 1980s. The category includes individuals who would traditionally be counted in a country's unemployment numbers, such as those who are unemployed but looking for work. Still, it also applies to those who have stopped applying for jobs. According to OECD, the NEET rate, which is calculated as the proportion of 15–29-year-olds that are classified as NEET, NEET rates by five-year age groups, for 15–19-year-olds, 20–24-year-olds, and 25–29-year-olds and gender differences in NEET rates, which disaggregates the overall NEET rate for men and women (OECD, 2016, p.17). Traditionally, employment and unemployment statistics have been used to describe labour markets, focusing on employed individuals and those actively seeking work. However, analysing labour market participation among young people requires a different approach, mainly because:

1. Many young individuals are still in formal education or training at schools, colleges, universities, or other institutions.

2. Another segment consists of young people who are neither employed (whether unemployed or outside the labour force) nor participating in any form of education or training, referred to as NEETs.

The NEET rate measures the proportion of a subpopulation not employed or involved in education or training. This group can be further categorised into those unemployed and those outside the labour force—individuals who neither have a job nor are actively seeking employment (Eurostat,2024).

According to Figure 1, the youth population may be divided into active and inactive populations. The active population is divided into two: employed and unemployed. Suppose the population referred to as unemployed has not received any education or training in the four weeks preceding the survey or is not currently receiving any education or training. In that case, they can be defined as "NEET".

The inactive population is divided into two groups: the population that has received education or training in the last four weeks or is currently receiving education or training, or the population that has not received education or training in the previous four weeks or is not presently receiving education or training. If the youth population has no education or training in the four weeks or is not currently receiving any education or training, they are referred to as NEET. More than a fifth of people worldwide between the ages of 15 and 24, 21.7%, were considered NEETs in 2023 (ILO,2023).

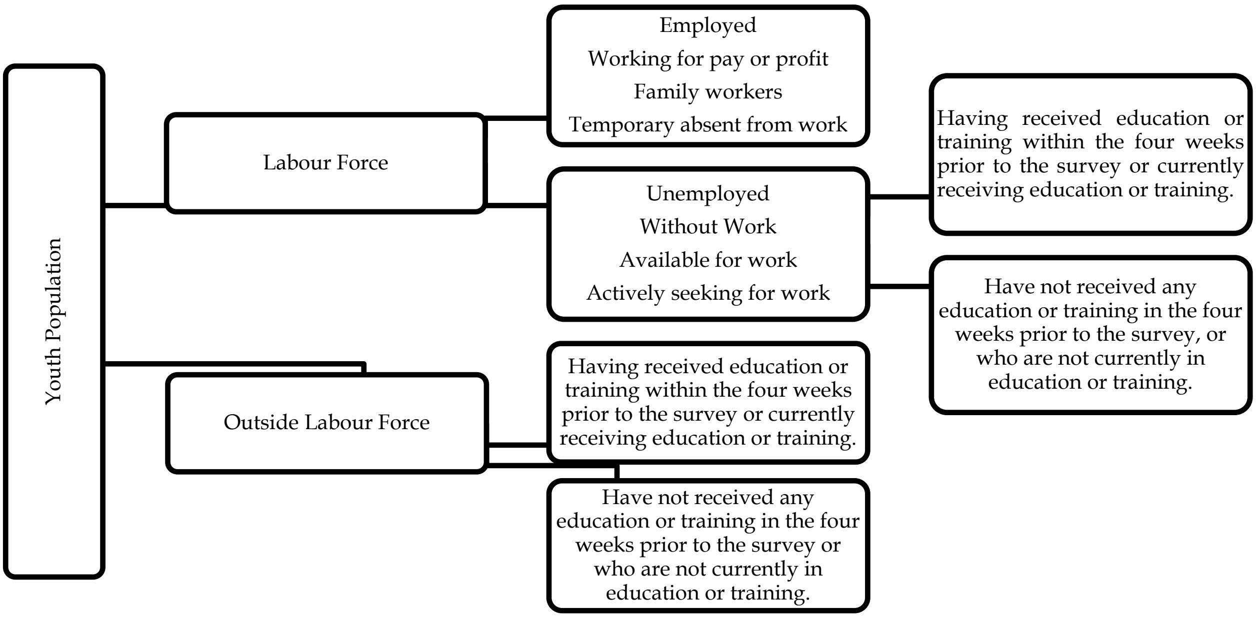

Figure 1: Diversification Chart for the Youth Population

Source: Bardak, U. et. al (2015)

A high NEET ratio has some defects, both economically and socially. For example, NEETs represent a significant loss of potential economic contribution. When young people are not engaged in productive activities, their skills may deteriorate, reducing their employability in the future. This also translates into a lesser-skilled workforce, which can affect the country's competitive edge globally. On the other hand, prolonged disengagement can lead to social exclusion, mental health issues, and increased susceptibility to anti-social behaviour and crime. It can also perpetuate cycles of poverty and inequality in society. NEET ratio also claims evidence for blooming future concerns. As the global economy evolves, the demand for skilled labour increases. NEETs may find it increasingly difficult to secure employment without proper education or training, particularly in a technologically advancing job market. This could lead to increased long-term unemployment.

Literature review

The Not in Education, Employment, or Training (NEET) rate has emerged as a critical socio-economic indicator reflecting youth populations' vulnerabilities across different economies. Understanding its relationship with macroeconomic factors is essential for policymakers addressing youth unemployment, economic productivity, and social mobility. This literature review examines the existing research on the interplay between NEET rates and macroeconomic indicators such as GDP growth, inflation, unemployment rate and wages, public policies and education levels.

NEET rates are often correlated with general unemployment trends, particularly youth unemployment. Scarpetta et al. (2010) highlight that rigid labour markets with high entry barriers, such as stringent employment protection legislation, contribute to prolonged youth inactivity. Conversely, economic downturns, such as the 2008 financial crisis, significantly increased NEET rates across developed economies (Bell and Blanchflower, 2011, p.241).

A crucial determinant of NEET rates is the degree of alignment between educational systems and labour market needs. Investment in education plays a vital role in reducing NEET rates. Bynner and Parsons (2002) argued that countries with higher public expenditure on education tend to have lower NEET rates, as they provide better vocational training and skill development programs. According to McQuaid et al. (2012), economies with weak vocational training and apprenticeship programs tend to have higher NEET rates as graduates struggle to secure relevant employment. In contrast, countries like Germany and Switzerland, which emphasise dual education systems, report lower NEET rates due to their emphasis on skill acquisition and work experience. Moreover, social protection measures, including unemployment benefits and conditional cash transfers, can prevent long-term detachment from education and the labour market (Görlich et al., 2013, p. 8). Similarly, a study by Quintini and Martin (2014) demonstrated that increasing funding for education and training programs effectively reduces the transition period between school and employment, decreasing the likelihood of youth falling into the NEET category.

Public policies play a pivotal role in mitigating NEET rates. Active labour market policies (ALMPs), such as targeted training programs, wage subsidies, and youth employment guarantees, have reduced NEET prevalence in several OECD countries (Martin, 2015). The role of inflation in influencing NEET rates remains ambiguous. While some research suggests that moderate inflation can stimulate economic activity and reduce youth unemployment (Blanchard, 2018), other studies argue that high inflation erodes real wages and discourages labour market participation, increasing NEET prevalence (Kahn, 2015, p.303). The impact of inflation may also depend on government policies, such as minimum wage regulations and social protection programs.

Another important indicator that may affect NEET rates is social welfare spending. Welfare policies can also influence NEET rates by supporting youth engagement in education and employment or creating disincentives for participation in the labour market. Thus, the relationship between social welfare spending and NEET rates is complex. Some studies suggest that higher welfare spending reduces financial barriers for youth to continue education or seek training. For example, Hämäläinen et al. (2017) found that targeted social policies in Nordic countries helped reduce NEET rates by providing financial support and career counselling services. A study by Berloffa et al. (2019) suggests that generous welfare systems may inadvertently encourage prolonged inactivity among young individuals, particularly in high-income countries. However, other research, such as Furlong (2006), argues that overly generous welfare policies can prevent non-incentive youth from actively seeking employment or further education, leading to higher NEET rates in specific contexts.

Additionally, studies by the OECD (2016) show that countries with high long-term unemployment rates often exhibit persistent NEET problems, indicating structural inefficiencies in job creation and matching skills. Similarly, O'Higgins (2017) emphasises that during periods of economic growth, youth unemployment and inactivity decrease due to increased labour demand and more significant investment in human capital.

Bingöl (2020) conducted a study on NEET in the Fragile Five. This study analyses the impact of macroeconomic indicators on NEET rates in Brazil, India, Indonesia, South Africa, Türkiye, and Russia from 2005 to 2018 using panel data analysis, finding that while HDI and FDI increase NEET, GDP and education expenditures decrease it.

Furthermore, a study by Eurofound (2021) indicated that youth in countries with high structural unemployment face prolonged NEET status due to a lack of entry-level job opportunities.

According to Ripamonti and Barberis (2021), higher levels of human capital correlate with increased salaries, highlighting a wage differential between skilled and unskilled workers. This suggests that individuals with lower educational attainments or skills are more susceptible to becoming NEET, potentially due to limited access to well-paying jobs.

According to Maynou et al. (2022), the unemployment rate and the percentage of early leavers from education and training are the main drivers of NEET rates in 274 European regions from 2000 to 2019.

Several studies suggest a strong inverse relationship between NEET rates and GDP growth. According to Eurostat (2024), countries with higher GDP per capita tend to have lower NEET rates, as economic expansion generates employment and educational opportunities.

The literature indicates that macroeconomic factors influence NEET rates, including GDP growth, unemployment, inflation, education systems, and labour market policies. While economic expansion tends to lower NEET rates, structural challenges such as skill mismatches and labour market rigidities remain persistent concerns. Future research should focus on longitudinal studies assessing the long-term impact of policy interventions and economic fluctuations on NEET trends to formulate more effective youth employment strategies.

Empirical analysis

Data

In this study, NEET rates, Gross Domestic Product per Capita, Inflation Rate (consumer prices) %, education expenditures (% of GNI), wage and salaried workers data have been retrieved from the World Bank database from 1999 to 2023 for Brazil, Russian Federation, India, China, South Africa and Türkiye.

Table 1: Variables and Data Source

Variables	Explanation of Variables	Source
NEET	Share of youth not in education, employment or training, total (% of youth population)	World Bank Database
GDP	GDP per capita (constant 2015 US$) (% change)	World Bank Database
INF	Inflation, consumer prices (annual %)	World Bank Database
EDU	Adjusted savings: education expenditure (% of GNI)	World Bank Database
WAGE	Wage and salaried workers, total (% of total employment) (modelled ILO estimate)	World Bank Database

$$NEET=f\ (GDP, INF, EDU, WAGE) \quad (1)$$

$$NEET_{it} = \beta_0 + \beta_1 GDP_{it} + \beta_2 INF_{it} + \beta_3 EDU_{it} + \beta_4 WAGE_{it} + \varepsilon_{it} \quad (2)$$

$$\varepsilon it\ = \mu it + uit \quad (3)$$

$$i=1,\dots\dots\dots, N\ ;\ t{:}\ 1,\ \dots\dots\dots\dots, T \quad (4)$$

Equation (1) represents the function of the NEET, as retrieved from related literature. The subscript i represents countries in the given equations, while the subscript t denotes time. The coefficient β corresponds to the estimated parameter, and u represents the error term. Given the utilisation of panel data, both i and t are incorporated as subscripts within the model. In Equation 2, the dependent variable is the NEET percentage, whereas the independent variables include GDP, INF, EDU, and WAGE.

Methodology

Addressing cross-sectional dependence and heterogeneity in panel data models in econometric analysis is crucial for obtaining reliable estimates. Traditional estimators often fall short when dealing with these complexities, especially in macroeconomic contexts where unobserved common factors can influence cross-sectional units simultaneously. Eberhardt and Teal (2010) introduced the Augmented Mean Group (AMG) estimator to tackle these challenges. The AMG estimator enhances the traditional Mean Group approach by incorporating a 'common dynamic process' into the regression model, accounting for unobserved common factors that may induce cross-sectional dependence. This method involves a two-step procedure: first, estimating a pooled regression in the first differences to capture common dynamic effects, and second, including these effects in group-specific regressions to obtain heterogeneous slope coefficients. By doing so, the AMG estimator provides a robust framework for analysing nonstationary panel data with heterogeneous slopes and cross-sectional dependence. It is particularly suitable for empirical studies in macroeconomics and international comparisons. This study initially conducted heterogeneity, cross-sectional dependency, and unit root tests. Based on the results, coefficient estimators were derived using the AMG method, one of the most appropriate estimation techniques (Eberhardt and Teal, 2010).

There are many specific reasons why this method was chosen in the study. The AMG method effectively deals with cross-sectional dependence, which is common in macroeconomic panel data since economies are often interconnected through trade, investment, and policy spillovers. In the case of BRICST countries, economic shocks in one country can impact others, making AMG a robust choice. Besides, unlike traditional panel data models, AMG allows for heterogeneous slope coefficients across countries. Since BRICST economies have different economic structures, labour market policies, and education systems, AMG helps capture these differences more accurately. In addition, macroeconomic indicators such as GDP per capita, education expenditures, and inflation rates often exhibit non-stationarity and long-run equilibrium relationships. AMG can effectively estimate long-run coefficients, making it superior to standard panel models that may suffer from spurious regression issues. As a novelty, AMG is well-suited for small and medium-sized panels like BRICST while still maintaining efficiency in estimation.

Since the research data were not collected from participants using techniques such as surveys, interviews, observations, experiments, or discussions but rather obtained from World Bank Databank publicly available sources, this study falls under research that does not require ethical committee approval.

Coefficient heterogeneity

In empirical economic research, it is essential to recognise and account for coefficient heterogeneity, particularly when analysing panel data. This heterogeneity refers to differences in slope coefficients among cross-sectional units, such as countries, firms, or individuals, within a panel dataset. Failing to consider these variations can result in biased and inconsistent estimates, which may mislead policy recommendations and theoretical interpretations. (Pesaran and Smith, 1995).

Panel data models traditionally assume homogeneity of coefficients, particularly in pooled ordinary least squares (OLS) and fixed-effects models. However, this assumption often oversimplifies the reality of diverse cross-sectional units. For instance, in macroeconomic studies, countries exhibit different levels of development, institutional quality, and resource endowments, all of which influence the relationship between variables differently (Eberhardt and Teal, 2010). Coefficient heterogeneity acknowledges these differences and allows for more nuanced and accurate econometric modelling.

The recognition of coefficient heterogeneity has broad implications for applied research. For instance, in growth studies, the relationship between economic growth and its determinants, such as trade openness or human capital, may vary significantly across countries due to structural characteristics and policy environment differences. Failure to account for this heterogeneity risks drawing generalised conclusions that may not be held in specific contexts (Pesaran et al., 1996).

H_0 = There is homogeneous slope.

H_1 = There is no homogeneous slope.

In our study, we use the Pesaran and Yamagata coefficient homogeneity test.

Table 2: Coefficient Heterogeneity

Test	Test Statistics	Prob.
Delta	5.932	0,000***
Delta $_{adj}$	6.812	0,000***

Note: ***, ** show rejection of the null hypothesis at the 1% and 5% levels of significance, respectively.

According to Table 2, we have to reject the null hypothesis. Slope coefficients are heterogeneous. It should be used as a test to consider heterogeneity.

The Mean Group (MG) estimator, proposed by Pesaran and Smith (1995), addresses coefficient heterogeneity by estimating individual regressions for each cross-sectional unit and then averaging the results. While this method captures heterogeneity, it does not account for cross-sectional dependence arising from standard shocks or spillover effects. Building on the MG framework, Eberhardt and Teal (2010) introduced the Augmented Mean Group (AMG) estimator, which incorporates a standard dynamic process into the regression model to account for unobserved factors influencing all units simultaneously. The AMG estimator thus balances the need for heterogeneity and dependence, providing more robust and reliable results in panel data settings.

In conclusion, addressing coefficient heterogeneity in panel data analysis is essential for producing accurate and meaningful results. Methods like the AMG estimator represent significant econometrics advancements, allowing researchers to model complex relationships while accounting for unit-specific differences and standard shocks. Integrating heterogeneity into econometric frameworks will remain a cornerstone of robust and reliable analysis as empirical research evolves.

Cross-section dependence test

Cross-sectional dependence is a significant concern in panel data analysis, especially when working with macroeconomic and regional datasets, where individual units—such as countries or regions—are often interconnected. Neglecting cross-sectional dependence can lead to biased and inconsistent estimations, compromising results' reliability (Pesaran, 2004, p.1). This dependence arises when the error terms or residuals of cross-sectional units are correlated due to standard shocks, spillover effects, or unobserved factors. For instance, in studies focusing on global trade, the economic conditions of one country may directly influence others through trade flows, financial markets, or synchronised policy changes. Consequently, assuming that cross-sectional units are independent, as often in traditional panel data models, becomes impractical in many empirical applications.

Researchers typically employ tests such as the Breusch-Pagan LM test (1980) or the Pesaran CD test (2004) to examine the presence of cross-sectional dependence in a dataset. When the time dimension (T) of the panel is smaller than the cross-sectional dimension (N) (T < N), the bias-corrected scaled LM test is recommended. Simulation studies by Baltagi et al. (2012) suggest that this test is well-suited for micro-panel datasets with a large cross-section (N) and a smaller time dimension (T).

In this study, the time dimension (T) is 25, while the cross-sectional dimension (N) is 6 (T = 25, N = 6). Given this structure, the bias-corrected scaled LM test was applied to appropriate accounts for cross-sectional dependence in the dataset.

H_0 = No cross-section dependency. (There is no correlation between units)

H_1 = There is cross-section dependency. (There is a correlation between units)

Table 3: Cross-Section Dependence (CSD) Tests

Variables /CSD Tests	**NEET** **p-value**	**GDP** **p-value**	**INF** **p-value**	**EDU** **p-value**	**WAGE** **p-value**
Breusch Pagan LM	0.000***	0.000***	0.000***	0.000***	0.000***
Pesaran CD	0.1774	0.000***	0.000***	0.000***	0.2980
Bias Corrected Scaled LM	0.000***	0.000***	0.000***	0.000***	0.000***
Pesaran Scaled LM	0.000***	0.000***	0.002***	0.000***	0.000***

Note: ***, ** show rejection of the null hypothesis at the 1% and 5% levels of significance, respectively.

According to Table 3, the Bias Corrected Scaled LM test results are that the null hypothesis will be rejected, and the alternative hypothesis will be accepted. Cross-section dependence exists, and there is a correlation between units.

Unit root test

Unit root tests in literature are broadly categorised into two groups: First-generation tests, which assume no correlation among panel units, and second-generation tests, which are specifically designed to account for cross-sectional dependence. Given the correlation among units in this study, a second-generation unit root test was employed, with a preference for the method proposed by Pesaran (2003).

Pesaran (2003) introduced an innovative approach to testing unit roots in panel data, mainly when errors exhibit serial dependence and cross-sectional correlation. To address this, the standard Dickey-Fuller (DF) or Augmented Dickey-Fuller (ADF) regressions were extended by incorporating the first differences of individual series and the cross-sectional averages of lagged levels. The methodology is based on computing each panel unit's mean of individual DF or ADF t-statistics. The null hypothesis assumes that all series are nonstationary.

Pesaran introduced the Cross-Sectionally Augmented Dickey-Fuller (CADF) statistics to correct cross-sectional dependence, integrating the cross-sectional averages of lagged levels and first differences into the standard unit root regressions. Additionally, a truncated version of the CADF statistics, which preserves finite first and second-order moments, minimises size distortions, particularly in models affected by serial correlation in residuals and linear trends.

When implementing the Pesaran CADF-CIPS statistics, the Schwarz Information Criterion (SIC) was used to determine the optimal lag length for the variables. This selection process enhances the reliability of the results, ensuring robustness in the presence of cross-sectional dependence.

Table 4: Unit Root Test Results for Variables

Variables	NEET I(1)	LGDP I(0)	INF I(0)	EDU I(0)	WAGE I(1)
Schwarz Info Criteria	3.196296 (3rd Lag)	14.27599 (2nd Lag)	6.509092 (1st Lag)	-0.267937 (1st Lag)	4.532616 (4th Lag)
Unit Root Test Results Pesaran CD (2nd Gen)	-4.031 (0.000)***	-3.524 (0.001)***	-3.161 (0.012)**	-3.713 (0.000)***	-2.208 (0.014)**

Note: ***, ** show rejection of the null hypothesis at the 1% and 5% levels of significance, respectively.

In Table 4, it was observed in the unit root calculations made with the level values of the variables in the model that NEET and WAGE contain unit roots. They are nonstationary. So, we need to make a difference and make them stationary. Other than NEET and WAGE, different variables are stationary on their level.

Panel cointegration test

Panel cointegration tests are crucial in analysing long-term relationships among variables in panel data models. These tests assess whether nonstationary variables exhibit cointegration, meaning they share a stochastic trend over time. Traditional cointegration tests, such as those developed by Pedroni (1999), evaluate cointegration by analysing the residuals of estimated panel regressions while allowing for heterogeneity across cross-sectional units. However, these tests often assume cross-sectional independence, which may not be held in many real-world applications. Westerlund (2007, 2008) proposed panel cointegration tests that account for cross-sectional dependence by incorporating bootstrap techniques and error correction mechanisms to overcome this limitation. These tests offer greater flexibility compared to earlier approaches, as they do not require all variables to be nonstationary, making them particularly suitable for empirical research in economics and finance, especially when dealing with heterogeneous panels that exhibit cross-sectional dependencies.

In this study, the model variables were tested for stationarity in the same order, and it was further examined whether the error terms of the regression constructed with these variables were stationary at level values. If the error terms remain stationary at level values, it suggests the existence of cointegration among the variables. To confirm the presence of cointegration, the Westerlund (2008) test was applied. The test results led to rejecting the null hypothesis, thereby establishing a long-run cointegrating relationship among the model variables.

- H_o: No Cointegration
- H_1: Same Panels are cointegrated

Table 5: Westerlund ECM Panel Cointegration Test

Hypothesis	Test	Bootstrap Prob.	Statistics
H_o: No cointegration	Westerlund	0,0234**	1.9880

Note: ***, ** show rejection of the null hypothesis at the 1% and 5% levels of significance, respectively.

According to Table 5, cointegration exists. Thus, the null hypothesis should be rejected; a long-run relationship exists between the variables.

Augmented Mean Group (AMG) estimator

The Augmented Mean Group (AMG) estimator, introduced by Eberhardt and Teal (2010), is a robust estimation technique designed to account for cross-sectional dependence and heterogeneity in panel data models. Traditional panel estimation methods often assume homogeneity across units, which may lead to biased results when heterogeneity and cross-sectional correlation are present. The AMG estimator addresses this issue by incorporating a standard dynamic process, allowing unit-specific heterogeneity while controlling unobserved common factors (Eberhardt and Bond, 2009, p.11). This makes AMG particularly suitable for empirical analyses where structural differences exist among cross-sectional units and cross-sectional dependence is a concern. Studies employing AMG highlight its effectiveness in estimating long-run relationships in dynamic heterogeneous panels while mitigating bias from correlated unobserved shocks (Bond and Eberhardt, 2013, p.2).

The AMG method was introduced to overcome these limitations by incorporating a "common dynamic process" into the estimation framework. This dynamic process accounts for the unobserved common factors that drive cross-sectional dependence. The method is particularly effective in scenarios where the data exhibits non-stationarity and heterogeneity in slope coefficients. By augmenting the traditional Mean Group (MG) estimator, AMG allows for unit-specific slope coefficients while controlling for standard shocks and spillovers. This makes it suitable for datasets with diverse units, such as countries or firms, where structural and policy differences are prominent.

The AMG estimator follows a two-step procedure. First, a pooled regression in first differences is conducted to estimate the standard dynamic process. This step captures the shared time-specific effects that influence all cross-sectional units. Second, these effects are additional regressors in unit-specific regressions to estimate heterogeneous slope coefficients. This process yields robust estimates of individual and common effects, making the AMG method exceptionally reliable for analysing long-term relationships in the presence of cross-sectional dependence.

Table 6: Augmented Mean Group Estimator Coefficient Estimations Results

Codes	**Countries**	**GDP**	**INF**	**EDU**	**WAGE**
0	BRICST Overall	-.0021088 (0.093)*	0.0609549 (0.449)	0.9220644 (0.689)	0.1547617 (0.562)
1	Brazil	-16.7221 (0.104)	0.0342042 (0.833)	3.024411 (0.001)***	0.4243325 (0.339)
2	Russia	-1.552134 (0.300)	0.0295902 (0.002)***	-2.064104 (0.000)***	-.5973865 (0.018)**
3	India	-0.0082585 (0.016)**	0.4244099 (0.074)*	1.992171 (0.300)	1.236772 (0.001)***
4	China	- 0.000907 (0.008)***	-0.1637349 (0.222)	9.847898 (0.028)**	-0.009929 (0.959)
5	South Africa	-0.0006346 (0.230)	0.0783473 (0.523)	0.0035035 (0.001)***	-0.1112642 (0.038)**
6	Türkiye	-0.0006522 (0.559)	-0.0363447 (0.459)	-7.00509 (0.002)***	-0.0279956 (0.946)

Note: ***, **,* show rejection of the null hypothesis at the 1%, 5% and 10% significance levels, respectively.

According to Table 6, when all countries are evaluated together, only the GDP variable is found to be statistically significant. However, when significance is assessed separately for each country, the following results emerge: In Brazil, the EDU variable is statistically significant for 1%. For Russia, the INF and EDU variables are statistically significant at 1%, and WAGE is statistically significant at 5%, respectively. The GDP, INF, and WAGE variables show statistical significance for India: 5%, 10% and 1%, respectively. China's WAGE and EDU variables are statistically significant, 5% and 5% respectively. When looking for South Africa, the EDU and WAGE variables are statistically significant at 1% and 5%. As a last one for Türkiye, only the EDU variable is statistically significant at 1%. These findings indicate that the impact of macroeconomic variables on the dependent variable varies across countries.

Findings and discussions

This study examines the macroeconomic variables that influence the proportion of young individuals classified as NEET, meaning those who are neither in education, employment, nor training. The study focuses on BRICST countries as the sample and utilises data from 1999-2023. To ensure more unbiased results in panel datasets characterised by heterogeneous slope coefficients and cross-sectional dependence, the Augmented Mean Group (AMG) Estimator proposed by Eberhardt and Teal (2010) was employed for coefficient estimation.

In this context, the study investigates the relationship between the share of youth not in education, employment, or training, total (% of youth population) and the macroeconomic variables: GDP per capita (constant 2015 US$) (% change), inflation (consumer prices, annual %), adjusted savings: education expenditure (% of GNI), and wage and salaried workers in total.

According to overall findings, the results indicate that for BRICST countries, a 1% increase in GDP per capita (constant 2015 US$) leads to a 0.002% decrease in the NEET rate. These macroeconomic variables statistically significantly influence NEET rates.

When we investigated the results on a country basis in Brazil, a 1% increase in EDU (adjusted savings: education expenditure) raises the NEET rate by 3%, suggesting that increased education expenditure is associated with a higher NEET rate in Brazil.

For Russia, a 1% increase in EDU reduces the NEET rate by 2%, whereas a 1% increase in INF (Inflation) raises the NEET rate by 0.02%. Additionally, a 1% increase in WAGE (Wage and salaried workers, total % of employment) decreases the NEET rate by 0.59%. These results indicate that inflation contributes to a higher NEET rate, while increases in education expenditure and wage levels help reduce NEET rates in Russia.

According to test results in India, a 1% increase in GDP lowers the NEET rate by 0.008%, while a 1% increase in INF (Inflation) raises it by 0.42%. Furthermore, a 1% increase in WAGE raises the NEET rate by 1.2%.

China's results indicate that both GDP and EDU significantly impact NEET rates. A 1% increase in GDP reduces the NEET rate by 0.009%, while a 1% increase in EDU increases it by 9.8%. This pattern is similar to that observed in Brazil, where increased education expenditure is associated with a higher NEET rate.

In South Africa, a 1% increase in EDU raises the NEET rate by 0.003%, whereas a 1% increase in WAGE reduces the NEET rate by 0.11%. These findings suggest that while education expenditure may not effectively decrease youth inactivity, higher wages contribute to reducing NEET rates in South Africa.

In Türkiye, a 1% increase in EDU leads to a 7% decrease in the NEET rate. This indicates that in Türkiye, unlike in Brazil and China, education expenditure plays a significant role in reducing youth inactivity rates.

When evaluations are made according to the results obtained across the variables subject to the test results, many interesting situations are revealed. Overall, the findings highlight that the impact of macroeconomic factors on NEET rates varies across BRICST countries. While GDP growth generally contributes to reducing NEET rates, the effects of education expenditure differ significantly across countries, suggesting that the efficiency of education policies and labour market conditions play a crucial role in shaping youth employment and training outcomes. In this context, when we look at the variables with statistically significant results, it can be said that ensuring economic growth, increasing wages and salaries, and reducing inflation will influence reducing NEET rates. This result is compatible with Eurostat (2024) and Scarpetta et al. (2010. They found that GDP growth has a strong inverse correlation with NEET rates in developed economies, where economic expansion creates job opportunities for young people compatible with the results of India and China. Maynou et al. (2022) found similar results in their analysis of 274 European regions, highlighting that higher GDP reduces NEET rates, particularly in industries with strong labour demand. However, Bingöl (2020) found that in the Fragile Five (Brazil, India, Indonesia, South Africa, and Turkey), GDP growth alone was not enough to significantly reduce NEET rates, similar to the results of this study.

However, the structure of the countries should be considered for the EDU variable. For Brazil, China and South Africa, EDU has increased NEET. These countries are not countries with high per capita income. This situation can be interpreted as the high expenditure on education in these countries creating an element of pressure on low-income people. As the share of spending on education from the total income increases, savings cannot be realised and cannot be transferred to the fields that will create employment by converting them into investments. This result is consistent with Hu et al. (2023) and McQuaid et al. (2012), which found that higher education spending does not necessarily reduce NEET rates in economies where vocational and technical education is weak. This aligns with the findings in China and Brazil, where education spending appears ineffective in addressing youth inactivity. This implies that education spending in Brazil, China and South Africa may not effectively reduce NEET rates and could have unintended consequences. This situation shows that the high NEET rates in these countries are due to the lack of appropriate education. Therefore, it can be said that policymakers should consider the quality of education expenditures in these countries and their suitability for the country's needs. Simply increasing education budgets is not enough; the focus should be on improving the quality and relevance of education, ensuring that young people acquire skills employers demand.

For Russia and Türkiye, education expenditure is found to have a significant role in reducing NEET rates, and it is imperative to reinforce investments in education, vocational training, and targeted skill development programs. Policy efforts should focus on expanding access to quality education and designing industry-relevant training initiatives to enhance youth employability. Under all provisions, given the observed correlation between increased education expenditure and higher NEET rates, policymakers should prioritise strengthening the quality and relevance of educational programs. Governments should revise and modernise curricula, integrate more vocational and technical training, and collaborate with industries to ensure education aligns with employment opportunities. For Russia, the study indicates that (INF) has a statistically significant positive impact on NEET rates in Russia, meaning rising inflation contributes to youth inactivity. Also, implementing monetary policies to stabilise inflation and maintain purchasing power and introducing targeted subsidies for youth job seekers to mitigate the impact of rising living costs may bring up novel solutions to decrease NEET rates. The study suggests that an increase in (WAGE) reduces NEET rates in Russia. To address the challenges of youth unemployment and reduce NEET rates in Russia, the government should introduce youth wage subsidies for employers who hire first-time job seekers. These subsidies would incentivise businesses to take on inexperienced young workers by offsetting part of their wages, making them more attractive hires.

India exhibits the most pronounced influence of economic factors on NEET rates, indicating a strong association between macroeconomic conditions and youth labour market dynamics. This is evidenced by the significant impact of GDP, inflation (INF), and wage and salary employment (WAGE) variables on NEET rates. As previously discussed, the relationship indicates that an increase in GDP is associated with a decline in NEET rates, suggesting that economic growth contributes to improved youth labour market outcomes. A particularly intriguing finding emerges in the case of India. Empirical evidence suggests that an increase in the proportion of wage and salary workers corresponds to a rise in NEET rates, an unexpected outcome that warrants further examination. This observation raises the possibility that many young individuals are engaged in informal or unregistered employment. Another pillar may suggest that rising wages may not necessarily translate into lower youth inactivity rates in India. Suppose rising NEET rates accompany the expansion of wages and salaried employment. In that case, it may suggest that young individuals are increasingly disengaged from formal employment opportunities due to the prevalence of low-wage labour conditions. In this context, implementing compensatory wage policies that ensure fair and sustainable earnings may effectively reduce NEET rates in India by fostering greater labour market participation among young individuals. Also, in India, given that GDP growth exhibits a limited influence on reducing NEET rates, policy measures should emphasise the creation of sustainable employment opportunities and the implementation of effective inflation control mechanisms. Addressing structural barriers to youth employment and fostering a conducive economic environment will be essential in mitigating NEET prevalence.

In China, economic growth reduces youth inactivity, likely by increasing employment opportunities and improving labour market conditions. While economic expansion contributes to lower NEET rates, its impact is relatively small. This indicates that GDP alone is insufficient to reduce youth inactivity significantly and that additional labour market and education reforms are needed. For example, improving vocational and technical education might be a good option to overcome the problem. As the study mentioned, higher education expenditures are paradoxically associated with increased youth inactivity. This suggests structural inefficiencies in the education system and labour market mismatches that must be addressed. To effectively reduce NEET rates, China should focus on aligning education with job market needs, expanding vocational training, and implementing targeted employment policies to facilitate the transition from school to work.

In South Africa, it has been concluded that an increase in the concentration of wage and salaried workers in the labour market reduces NEET rates. This finding aligns with the existing literature, as such a trend is generally interpreted as indicating that young individuals classified as NEET are being integrated into employment in the country. The significant role of wage growth in lowering NEET rates underscores the need for strategic labour market reforms, wage policy adjustments, and job creation initiatives. Efforts should be directed towards promoting inclusive employment strategies and strengthening institutional frameworks to facilitate youth labour market integration.

Future studies can expand the analysis by adding foreign direct investments (FDI) and gross fixed capital formations (GFCF) to the dataset and separating country samples according to income groups. Thus, the factors affecting NEET rates can be revealed in more detail with an econometric analysis with more detailed macroeconomic indicators.

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