The Returns to Education and the Wage Effect from Overeducation in Trinidad and Tobago: A Pseudo-Panel Approach

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Preliminary Draft March 2024

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Abstract

Having highly educated workers can be beneficial for organizations in terms of innovation and problem-solving capabilities, however when underpaid and underemployed, overeducated workers may experience feelings of frustration and stagnation as they are unable to fully utilize their skills and knowledge. This can result in high levels of job dissatisfaction and a high employee turnover rate. While the literature on returns to education and overeducation is extensive in developed countries, evidence from developing (and Caribbean) countries remains scarce. This study will aim to examine the returns to education and the overeducation of public sector workers in Trinidad and Tobago. By using the Ordinary Least Squares (OLS), Quantile Regression (QR), Recentred Influence Function (RIF) and a pseudo-panel approach to address the presence of Omitted Variable Bias (OMV), and Endogeneity, as well as CSSP data for 1991-2015, this study finds that the average returns to education in Trinidad and Tobago are 19.2% highlighting the downward bias from the OLS estimate of 11.5%. The average returns of overeducated workers although positive appear to be influenced by their year of birth, so the earnings of overeducated persons born between 1935-1942, and 1943-1950, were lower than workers born later on in 1975-1982, and 1983-1990.

Keywords Education Mismatch, Overeducation, Quantile Regression, Recentred Influence Function, Pseudo Panel, Public Sector

JEL Classification J01; J24; C21

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1. Introduction

Overeducation is a complex phenomenon that occurs when a worker's level of education is more than what is required for their job. Throughout the literature, this spectacle has been studied from a myriad of dimensions including the impact that it has on the labour market outcomes of university graduates, the integration of overeducated migrant workers, its gender differences, its methodological construct, as well as the scarring effects that it has on the wages of workers in the long-run (Passaretta et al., 2023; Chen& Hu, 2023; Eguia et al., 2023; Alattas, 2023). Overeducation, has been traditionally associated with adverse socio-economic consequences for the worker such as underemployment and an erosion in the quality of human capital, but also reduced earnings from higher wage penalties, diminished quality of life and job satisfaction from shortened intellectual stimulation, but worsened mental health outcomes (anxiety and depression) amongst overeducated young adults in countries like Korea and Kazakhstan (Toimbek, 2022; Rim & Kim, 2023).

Gaining employment in the public sector is often the preferred objective of most people because greater emphasis is placed on educational qualifications, rather than skills. As a result of this persons who wish to enter into public service, tend to acquire a higher level of education as this would assist them in not only becoming gainfully employed but also places them in a higher income bracket while increasing their access to job promotions (Alattas, 2023). This perception, unfortunately, encourages the growth of not only over-skilling in developing Latin American countries like Chile, Mexico, Peru, and Ecuador but also the influx of highly-educated persons into the public sector, whose surplus may not be met by the public sector due to diminishing job opportunities (Francisco Castro et al., 2023). The decline in public sector employment and generation of job opportunities in most countries like Kazakhstan implies that due to limited funds, highly-educated persons who are hired may not be sufficiently compensated for their educational credentials. Here in lies the problem of overeducation, where the imbalance in the labour market outcome encourages the underemployment and non-participation of highly educated workers, regardless of sector of employment. For this reason, the average returns to schooling of public sector workers in countries like Poland and Ukraine are often found to be below average, with workers earning less than persons employed in the private sector (Brintseva 2023).

Within the literature, the overeducation phenomenon has traditionally been a highly debatable topic in the European and North American region, having examined the potential risks of overeducation at the university level, as well as the mapping of overeducation across countries (Capsada-Munsech 2024; Choi et al., 2020). This phenomenon, however, has been rarely ever discussed by developing countries, particularly those in the Caribbean region like Trinidad and

Tobago where there is a virtual absence of empirical and applied research on the topic of educational mismatch. Such an absence as highlighted by Choi et al., (2020), may be due to developing country's inconsistent participation and nonparticipation in global surveys such as the Survey of Adult Skills (PIAAC), as well as the non-collection of data on overeducation in national surveys.

To close this gap, this study will aim to examine the returns to education and the overeducation of public sector workers in Trinidad and Tobago. This will be done by using the Ordinary Least Squares (OLS), Quantile Regression (QR), and Recentred Influence Function (RIF) methodology to examine not only the returns to education but also look at the distributive effects of education, the wage penalty from overeducation, as well as its disaggregation by gender, type of worker and geographic region. Further to this, this study also implements a pseudo-panel approach to address the presence of Omitted Variable Bias (OMV), and Endogeneity. A summary of the main findings of this article shows that:

(1) The average returns to education of public sector workers in Trinidad and Tobago have declined consistently from 7.8% to 5.5% between 1991-2015.
(2) The pseudo panel for a 1-year cohort indicates that the returns to education of private sector workers were notably higher at 19.2% than the 11.5% derived from the OLS sample for 1991-2015. This implies that the OLS estimate is downward biased and did not consider the problem of endogeneity.
(3) Using the unconditional quantile regression methodology to investigate the heterogeneity of the returns to education, it was found that if the proportion of public sector workers were to increase then this would cause their average returns to increase (positive shift). With the inclusion of the UPE1 (working experience and geographic location) covariates, the magnitude of their average earnings improved, but worsened with the inclusion of the UPE2 (industrial and occupational groupings) covariates, although the average returns to education remained positive.
(4) The average returns of overeducated workers for the entire birth cohort improved by 31.1%, but while improving across much of the wage distribution (0.10^{th}-0.60^{th}), steadily declined at the 0.90th decile. The average returns of overeducated workers although positive appears to be influenced by their year of birth, so the earnings of overeducated persons born between 1935-1942 (3.7%), and 1943-1950 (21.4%) were generally lower than those of overeducated workers born later on in 1975-1982 (30.6%), and 1983-1990 (31.7%).
(5) The average returns of women for both panels (24.6% for the 1-year cohort), were higher than that of men (20.4% for the 1-year cohort). The average returns to education of statutory board

workers were particularly higher (31.9%) than that of state enterprise workers (28.6%), and local government workers (20.8%) for the 1-year cohort. The average returns of public sector workers residing in the counties of Nariva-Mayaro (45.6%), St. Andrew, St. David, and Tobago (33.7%), displayed higher average returns to education than the other counties of Caroni (29.1%), St. George (24.9%), and Victoria (29.6%) for the 1-year cohort.

This article is structured as follows; section 2 provides a concise discussion on the overeducation of public sector workers in developing countries. In section 3, the data used, the sample selection, the construction of the pseudo panel dataset, and the descriptive statistics are discussed. In section 4, the Ordinary Least Squares (OLS), Quantile Regression (QR), the Recentred Influence Function (RIF), as well as the pseudo-panel approach to examining the returns to education and overeducation are explained. In section 5 the empirical results are presented, after which in section 6 the study is concluded.

2. Literature Review

An extensive literature has examined the causes of skill mismatch at the micro and macro levels. Macroeconomic dynamics may affect skill mismatch through short-run and long-run factors. Short-run factors are related to the business cycle (Liu et al., 2012) and the fact that mismatch tends to be procyclical. In the long run, mismatch can arise due to technology-driven structural changes in the economy that shift labor demand towards new skills and different fields of study (Mendes de Oliveira et al., 2000, Peng et al., 2016).

At the same time, changes in labor supply can also be a source of mismatch. In this respect, Figueiredo et al., (2017) as well as Cabus & Somers (2018), have shown that the recent increase in average educational attainment may have had an impact on the intensification of mismatch. From a skills supply perspective, academic attainment and field of study are key determinants of potential mismatch. Overeducation tends to be concentrated in certain fields of study (Ortiz & Kucel, 2008), with higher intensities in social sciences and humanities (Chevalier, 2003; Frenette, 2004). In these fields, the assessment of skills by employers is more complicated because it cannot rely on a specific definition of competences. Therefore, students tend to obtain additional qualifications to improve the signal of their skills in the labor market (Meliciani & Radicchia, 2016). The duration of studies can be an important determinant of vertical overeducation, especially in Italy (Caroleo & Pastore, 2018; Aina & Pastore, 2012). Moreover, in terms of the transferability of higher education, mismatches may also arise from the acquisition of educational qualifications abroad (Wiers et al., 2005).

Regarding the consequences of skill mismatch, a large body of research on developed countries has shown that overeducated workers suffer a wage penalty relative to individuals with similar levels of education but who are well matched (Sanchez-Sanchez & McGuinness, 2015; Caroleo & Pastore, 2018; Gaeta et al., 2017; Scicchitano et al., 2019). Other studies have examined the relationship between skill mismatch and job satisfaction (McGuinness & Sloane, 2011; McGuinness & Byrne, 2015; Mateos-Romero & Salinas-Jimenez, 2018). Overqualification affects job mobility (Verhaest & Omey, 2006), both between and within jobs. In this respect, young workers are more likely to be overqualified, but vertical mobility allows them to move to jobs that are more in line with their skills. This pattern is confirmed by Frei & Pouza-Souza (2012), while Verhaest et al., (2015) find a significant persistence of overeducation among Belgian graduates.

Despite the fact that most of the literature focuses on developed economies, the analysis of developing countries is somewhat incomplete. In fact, some reviews have been realized Hartog (2000), Leuven & Oosterbeek (2011), McGuinness (2006), and Sloane (2003), pay little or no attention to overeducation in low- and middle-income labor markets. This is largely because these countries do not have accurate and reliable data on educational or skill requirements for jobs (Mehta et al., 2011). It was highlighted that labor markets in developing countries are often unable to absorb the increased supply of skilled workers, leading to increased mismatch relative to developed countries (Battu & Bender, 2020).

Handel et al., (2016) demonstrate that overeducation is more frequent than undereducation in low- and middle-income countries. They claim that skills development alone may not be sufficient to create sustainable economic growth because highly skilled workers need to be fully utilized. Mehta et al., (2011) investigate four developing economies and find evidence of relevant overeducation in unskilled jobs in the Philippines and Mexico and little evidence of it in India and Thailand. Tran & Paweenawat (2023) show that the returns to education in the Vietnamese labor market have reduced since 2008, proving the oversupply of highly educated workers with an estimated wage penalty of 17%.

This is the first study employs a pseudo-panel approach to address omitted variables bias and the unconditional quantile regression to identify the heterogeneity of returns to education across the income distribution in Trinidad and Tobago.

3. Data & Descriptive Statistics

3.1 Data, Sample Selection and Pseudo Panel Data Construction

The survey data used in this article was that of the Continuous Sample Survey of Population (CSSP) for the period 1991-2015. Considered to be a Multi-Purpose Household Survey, its key objective was to collect and disseminate information on the Labor Force Characteristics of Trinidad and Tobago using a Stratified Cluster Sampling Methodology every quarter. The primary unit of analysis was that of households (household level) and individuals (person level), through which data was consistently collected on the housing facilities, economic activity, and demographic features.

For purposes of this article, using the CSSP dataset, to examine the presence of Overeducation and Wages in Public Sector Employment in Trinidad and Tobago, a sample of Public Sector workers who are employed as either Statutory Board workers, State Enterprise workers, or Local Government workers, was taken. The sample of workers comprised male and female persons who are employed on a full-time basis (30 hours or more per week), and who are considered to be a part of the economically active segment of Trinidad and Tobago's population (between the ages of 16 to 64). Based on these limits, a sample of 54,864 public sector workers was derived. Given that the state is a major source of employment for persons in Trinidad and Tobago, it was considered appropriate for a study of this nature as government jobs are generally more stable offering generous remuneration packages, as state enterprises are less likely to downsize or shut down and were more essential to the overall economic stability of the economy.

Within this sample, apart from the type of worker, the hours worked, the age, and the sex of the worker mentioned earlier, there was a wide range of variables included as control variables that highlighted the individual features, and educational and economic background of the worker. The first group of variables which reflect the individual characteristics of the worker included the birth year[3], i.e., calculated using the workers' age and the year of the data collection, the birth cohort, i.e., where each cohort was defined as Cohort 1 (workers born between 1935-1942), Cohort 2 (workers born between 1943-1950), Cohort 3 (workers born between 1951-1958), Cohort 4 (workers born between 1959-1966), Cohort 5 (workers born between 1967-1974), Cohort 6 (workers born between 1975-1982), and Cohort 7 (workers born between 1983-1990). The marital status of the worker as reflected by the survey included persons who were never married, married but living alone, had a partner but living alone, married, and in common-law relationships. The major ethnic groups comprised workers who were of either African, Indian, or Mixed heritage. The geographic location of workers was indicated by their county of residence, i.e., Caroni, Nariva-Mayaro, St. Andrew/St. David/Tobago, St. George, St. Patrick, and Victoria.

The second group of variables mirrored the educational background (main independent variables under scrutiny) of the worker, which in the case of this article included the Years of Schooling, i.e., the number of years of educational instruction that the worker attained, as well as if

[3] Birth Year = Year of Data Collection - Age

the worker was considered to be either overeducation, undereducated, or matched. Using the Realized Matches (RM) method which measures the vertical mismatch of education, public sector workers were considered to be overeducated (undereducated) if their actual education attained (years of schooling) was above (below) one standard deviation from the mean years of schooling required by their occupation, and matched if their years of schooling was appropriate for their specific occupation (Ege & Erdil, 2023; Baktash, 2023). For purposes of this article, this method was used because of the ease at which it can be used by micro-level datasets, like that of the CSSP dataset to measure educational mismatch, where information on worker's educational attainment and occupation is present (Mc. Guinness et al., 2018). Although the RM technique is widely used in the educational mismatch literature, its most notable downside is that it doesn't incorporate any information on the actual skill requirements of the workers' actual jobs and is often calculated using broad occupational groupings which may obscure the variation in the type and level of qualifications needed across different jobs within the same occupational group (Verhaest & Omey, 2010).

The third group of variables highlighted the economic background of the worker and included their labour market characteristics. The income of the worker was highlighted by their hourly wage rate, annual income, and real wage rate (dependent variable). Where in the case of the latter was deflated using an annual deflation series from 1991 to 2015 which incorporates the Consumer Price Index (CPI). The working experience of the worker was captured by their potential working experience,[4] which is often used as a proxy for their actual working experience as this information was not collected by the CSSP dataset (Zveglich et al., 2019). The occupational groupings depicted in this survey included workers who were employed in the areas of the Defence Force; Legislators, Senior Officials, Managers; Professionals; Technicians, Associate Professionals; Clerks; Service workers, Shop Sale workers; Agriculture, Forestry and Fisheries; Craft and Related workers; Plant, Machine Operators and Assemblers; and Elementary Occupations, while the industrial grouping of workers included the areas of Agriculture, Hunting, Forestry and Fishing; Mining and Quarrying; Manufacturing; Electricity, Gas and Water; Construction; Wholesale and Retail Trade, Restaurants and Hotels; Transport Storage and Communication; Financing, Insurance and Real Estate; and Community Social and Personal Services.

Apart from the sample data used in this article, a pseudo panel dataset of the variables highlighted was constructed. To do this, after identifying the birth year of workers, and establishing the birth cohort, the sample of workers consisted of 54, 864 workers ages 16-64, or who were born between 1935-1990. This new sample was then redesigned into a pseudo-panel dataset which

[4] Potential Working Experience = Years of Schooling - 5

consisted of 56 birth cohorts and 7 birth cohort waves. Where each cohort has a range of 8 years, with 1,612 to 12,760 observations in each. Since the number of observations in each cohort is fairly large, it is likely to produce more accurate estimates of the mean cohort. As a result of this construction, Verbeek (1993), explains that both the measurement error variances and the variation within the cohorts are likely to be small, even though the variation between the cohorts is large. Typically, in the construction of pseudo panel data, the cohorts are defined based on variables in the sample that do not vary over time, and that are observed for all workers in the sample, so in the case of the CSSP dataset, these variables included the age, birth year, sex, potential working experience, ethnicity, marital status, geographic location, as well as workers occupational and industrial groupings. Further to this, as the number of observations in each cell of the pseudo-panel dataset declines as the returns to education of different aspects of the dataset such as the gender, the geographic location, and the type of public sector worker are investigated, each cell in the pseudo panel was then constructed to include 1 and 2-year cohorts similar to that demonstrated by Tran & Paweenawat (2023) to increase the number of observations in each cell.

3.2 Descriptive Statistics

A detailed investigation into the descriptive statistics of selected variables contained with the sample dataset being used for this article shown in Table 1 indicated that the years of schooling attained by public sector workers increased from an average of 11.74 years in 1991 to, 13.41 years by the end of 2015. A similar upward trend in the hourly wage rate (growing from TT$18.61 in 1991, to TT$48.90 in 2015), and annual income (growing from TT$36,771.70 in 1991, to TT$$96,624.22 in 2015), was observed.

Although the composition of male public-sector workers declined from 68% in 1991 to 52% in 2015, which implies that the participation of females in public-sector employment was growing, the overall age of public-sector workers was found to be older over time, as reflected by their average age of 36.74 years in 1991, to 41.19 years in 2015. Concerning the marital status of public sector workers, the percentage of persons who were never married (growing from 28% in 1991 to 36% in 2015) and married but living alone (growing from 6% in 1991 to 8% in 2015) appears to have grown over time, persons who had either a partner but living alone, or in a common law union, were both somewhat consistent at 4%, and 10% respectively throughout the 1991-2015 timeframe. While the majority of public sector workers were found to be married, the opposite trend was observed, where the percentage of married workers declined from 50% in 1991, to 42% in 2015.

As expected from a culturally diverse country like Trinidad and Tobago, the multiplicity of ethnicities is also reflected in its workers. In the case of the public sector, the three main ethnicities of workers are those who have an African, Indian, and Mixed heritage. Workers of an African heritage employed in the public sector have traditionally dominated the labour force, as its ethnic construct ranged between 50% to 55% from 1991-2015. During the same time frame, there has been a growing prominence of workers of an Indian heritage, with its composition growing from 32% in 1991, to 36% in 2015, and to a lesser extent workers of a Mixed heritage which fluctuated between 12% to 17%.

Given that a great majority of public sector offices are concentrated within the City of Port-of-Spain found in Northern Trinidad, it is not surprising that the majority of public sector workers reside in St. George County, however, over time the composition of workers from these areas declined significantly from 44% in 1991 to 20% in 2015. Such a decline may be a result of the increased growth in the demand for public sector workers residing in Central Trinidad (Caroni-growing from 14% in 1991 to 17% in 2015), Eastern Trinidad & Tobago (St, Andrew, St. David, Tobago-growing from 9% in 1991 to 23% in 2015), and Southern Trinidad (St. Patrick-growing from 11% in 1991 to 18% in 2015, and Victoria-slight decline from 20% in 1991 to 19% in 2015). As expected, historically the smallest percentage of workers employed within the public sector were found to be living in Southwestern Trinidad (Nariva-Mayaro- ranging between 1% to 4%) which was the furthest distance away from the more urbanized city and town areas.

Table 1 Summary Statistics

Variables	1991		1994		1997		2000		2003		2006		2009		2012		2015	
	Mean	**SD.**	**Mean**	**SD.**	**Mean**	**SD.**	**Mean**	**SD.**	**Mean**	**SD.**	**Mean**	**SD.**	**Mean**	**SD.**	**Mean**	**SD.**	**Mean**	**SD.**
Years of Schooling	11.74	2.41	11.97	2.38	12.06	2.49	12.19	2.36	12.35	2.34	12.55	2.37	12.69	2.49	13.03	2.65	13.41	2.70
Hourly Wage	$18.61	43.35	$16.58	8.50	$19.07	13.04	$21.85	13.07	$25.76	15.77	$29.60	18.54	$37.40	21.84	$42.34	23.34	$48.90	26.72
Annual Income	$36,771.70	85,650.56	$32,756.55	16,799.28	$37,681.66	25,757.33	$43,179.52	25,830.53	$50,909.28	31,158.99	$58,490.23	36,630.83	$73,899.76	43,150.96	$83,663.47	46,112.52	$96,624.22	52,790.10
Male	0.68	0.47	0.62	0.49	0.64	0.48	0.62	0.49	0.59	0.49	0.55	0.50	0.53	0.50	0.51	0.50	0.52	0.50
Age	36.74	9.17	37.77	9.62	39.19	9.73	39.28	10.12	39.48	10.96	38.89	11.18	39.23	11.31	39.48	10.93	41.19	10.40
Ethnic Group																		
African	0.53	0.50	0.54	0.50	0.55	0.50	0.53	0.50	0.51	0.50	0.52	0.50	0.51	0.50	0.50	0.50	0.50	0.50
Indian	0.32	0.47	0.32	0.47	0.32	0.47	0.34	0.47	0.32	0.47	0.31	0.46	0.33	0.47	0.32	0.47	0.36	0.48
Mixed	0.14	0.35	0.13	0.33	0.13	0.33	0.12	0.33	0.16	0.37	0.17	0.37	0.16	0.37	0.17	0.38	0.14	0.34
Marital Status																		
Never Married	0.28	0.45	0.28	0.45	0.28	0.45	0.30	0.46	0.32	0.47	0.36	0.48	0.37	0.48	0.36	0.48	0.36	0.48
Married Living Alone	0.06	0.24	0.08	0.26	0.08	0.27	0.08	0.27	0.08	0.27	0.07	0.26	0.08	0.27	0.08	0.28	0.08	0.27
Had Partner Living Alone	0.04	0.20	0.02	0.14	0.03	0.18	0.04	0.19	0.04	0.20	0.04	0.20	0.04	0.19	0.04	0.20	0.04	0.19
Married	0.50	0.50	0.50	0.50	0.50	0.50	0.48	0.50	0.46	0.50	0.42	0.49	0.40	0.49	0.42	0.49	0.42	0.49
Common Law Union	0.11	0.32	0.12	0.33	0.10	0.30	0.10	0.30	0.10	0.30	0.10	0.31	0.11	0.32	0.10	0.30	0.10	0.30
Geographic Location																		
Caroni	0.14	0.35	0.14	0.35	0.15	0.36	0.17	0.38	0.16	0.37	0.13	0.33	0.13	0.34	0.14	0.35	0.17	0.38
Nariva-Mayaro	0.02	0.15	0.01	0.10	0.02	0.13	0.02	0.15	0.01	0.12	0.04	0.19	0.02	0.15	0.03	0.17	0.03	0.17
St. Andrew, St. David, Tobago	0.09	0.28	0.11	0.32	0.13	0.34	0.13	0.34	0.13	0.33	0.15	0.36	0.21	0.41	0.32	0.47	0.23	0.42
St. George	0.44	0.50	0.44	0.50	0.43	0.50	0.37	0.48	0.40	0.49	0.33	0.47	0.26	0.44	0.18	0.38	0.20	0.40
St. Patrick	0.11	0.31	0.09	0.29	0.09	0.28	0.10	0.30	0.11	0.31	0.16	0.36	0.17	0.37	0.15	0.36	0.18	0.38
Victoria	0.20	0.40	0.20	0.40	0.18	0.39	0.21	0.41	0.19	0.39	0.19	0.39	0.20	0.40	0.18	0.38	0.19	0.40
Observations	1,502		2,192		2,461		1,658		2,448		2,648		2,219		2,154		2,139	

4. Methodology

4.1 Quantile Regression

Based on the nature of the dataset used in this article, it provides an opportunity to use not only Ordinary Least Squares (OLS), and Quantile Regression (QR), as the primary means of analysis, but also the Recentred Influence Functions (RIF) to examine the impact that Education, and Overeducation has on the wages of Public Sector workers in Trinidad and Tobago. The Mincerian earnings equation, which looks at wages as a function of schooling and working experience, is often used in the labour economics literature to quantify the financial benefits of the workers' additional years of schooling (Mincer, 1974). The use of the technique has several benefits in that, not only does it provide a greater understanding of the Cost-Benefit-Analysis (CBA) of investing in education, but its outcome has a noteworthy impact on labour market policies as it can influence the strategies used to fund educational opportunities, as well as anti-discrimination legislation (Heckman et al., 2003). When the mincerian earnings function is adapted to examine the impact that the years of education have on the wages of public sector workers using OLS and QR, it is specified as:

$$\ln Y_i = \propto + \beta_1 E_i + \beta_2 C_i + u_i + \varepsilon_i \qquad (1)$$

$$\ln Y_i = \propto + \beta_1 OE_i + \beta_2 C_i + u_i + \varepsilon_i \qquad (2)$$

$$\ln Y_i = C_i \beta_\tau + \varepsilon_{\tau i}, \tau(lnY_i|C_i) = Y_i \beta_\tau \qquad (3)$$

Where for the ith public sector worker, Y_i is the natural logarithm of the real hourly wage rate, E_i is the years of schooling, OE_i refers to if the worker is considered to be overeducated, C_i is the control variables discussed earlier, u_i is the unobserved individual heterogeneity, and finally ε_i is the error term, β_τ is the unknown vector of parameters (constant), τ *is* the sample quantile, $\tau(lnY_i|C_i)$ is the conditional quantile *(τ)* of the workers' hourly wage rate $(lnY_i|C_i)$ given the vectors of control variables.

Although the mincerian earnings function is an important tool to gain an understanding of the relationship between education, working experience and wages, it is not without limitations. The two primary limitations of using this method are that of Omitted Variable Bias (OVB) and that of Endogeneity. In the case of the former, OVB tends to occur because the mincerian earnings function only includes education, and working experience as its main explanatory variables, however, in reality, there may be several factors that influence the wages of public sector workers such as their family background, nationality, political constraints and discrimination that may not be captured by the CSSP dataset (Patrinos, 2016; Freeman, 1987). By not considering these factors, the education and working experience estimates produced by the mincerian earnings function may be biased.

In the case of the latter problem of unobserved endogeneity, the education and working experience of public sector workers are not randomly assigned and are based on their individual preferences. This implies that the connection between the workers' education, working experience, and wage may be influenced by unobserved factors that influence education and wages such as their financial literacy, motivation, household income, natural ability, assortive mating, i.e., the tendency of highly educated persons to marry other highly educated persons, inheritance, and health outcomes, that can all contribute to biased estimates being produced (Peng et al., 2023).

4.2 Pseudo-Panel Data Approach

Given the limitations of the mincerian earnings function, equation (1) was adjusted to construct a panel dataset, which considers the time component t, as specified below:

$$\ln Y_{it} = \propto \ + \beta_1 E_{it} + \beta_2 C_{it} + u_{it} + \varepsilon_{it} \tag{4}$$

To address the problem of unobserved endogeneity, Deaton (1985) proposed that in the absence of a genuine panel dataset, a pseudo panel dataset be used, as it is based on using repeated cross-sections to group public sector workers into fixed cohorts where workers in each cohort share the same characteristic features as birth year. If these cohorts of workers meet these conditions and are considered to be stable over time, then the mean of each variable within each cohort is taken, and then considered to be an observation (Guillerm, 2015; Guillerm, 2017). Thus, in the case of this article, the pseudo panel dataset was constructed using the birth year to control for specific cohort effects c. Thus, using this requirement, equation (4) was re-specified as:

$$\ln \overline{Y_{ct}} = \propto \ + \ \beta_1 \bar{E}_{ct} \ + \ \beta_2 \bar{C}_{ct} + \bar{u}_{ct} + \bar{\varepsilon}_{ct} \tag{5}$$

Where for the c cohort of public sector workers at time t, $\ln \overline{Y_{ct}}$ is the mean of the natural logarithm of the real hourly wage rate, $\bar{E}_{ct}$ is the mean years of schooling, $\bar{C}_{ct}$ is the mean of the control variables discussed earlier, $\bar{u}_{ct}$ is the mean of fixed effects of workers in cohort c, and finally $\bar{\varepsilon}_{ct}$ is the mean of the error term. The fixed effects model based on the repeated cross-sections was included as a test of robustness to address the measurement error which is another limitation of the mincerian earnings function (Neugebauer 2015).

By using the pseudo panel data approach although it addresses the problem of unobserved endogeneity, it is not likely to eliminate the issue as expected, because some unobserved variables like natural ability, assortive mating and even health outcomes are more likely to be determined at the individual level, and not the cohort level (Kemelbayeva, 2020). However, by using the cohort approach it is expected that workers from a similar generation based on their characteristic features will have experienced similar socio-economic conditions and potentially have similar labour market outcomes.

4.3 Recentred Influence Function

To investigate the heterogeneity of the returns to education across the wage distribution the unconditional quantile regression method proposed by Firpo et al., (2009) is used to examine the distributional changes with marginal variations in the workers' education, because it can capture the fluctuations in the workers' education as reflected by their years of schooling, on the unconditional distribution of their wage. To implement this technique, a regression of the Recentred Influence Function (RIF) of the unconditional distributional statistic on the workers' education is estimated across the wage distribution from the 10th to the 90th decile to capture any partial effects (shifts) resulting from any wage variation.

Further to this, the technique aims to investigate the impact that changes in the distribution of covariates (C) may have on the wages (Y) of public sector workers by estimating a simple regression where the wage is replaced with its transformed version, i.e., the recentred influence function. For this study, three vectors of covariates will be considered, i.e., UE which includes only the biographical information of public sector workers (gender, ethnicity, and marital status), UPE1 which includes the working experience and geographic location (potential working experience, and county of residence), and UPE2 which considers the workers industrial and occupational groupings. The labour distribution function of public sector workers (F), given a distributional statistic such as the mean or quantile v(F), can be specified as:

$$\mathrm{F(y) = s_1F_1(y) + s_2F_2(y)} \tag{6}$$

where y is the gross labour income, i.e., the outcome variable, F_1 (F_2) is the income distribution among public sector workers, and s_1 (s_2) is the share of workers in that subgroup on the total sample. To estimate the impact that any marginal variations in the distribution of the variables, may have on v(F), following the technique of Choe & Van Kerm (2018), the Unconditional Effect (UE) is specified as:

$$\mathrm{UE(v(F), 2) = \int RIF(y; v, F)d(\, GY_1{}^{F,t,2} - F)(y)} \tag{7}$$

where $\mathrm{GY_1{}^{F,t,2}}$ is the gross income distribution after the marginal substitution of public sector workers. Since the size of the UE is determined by the difference in the conditional distribution of the workers and the control variables (C), it often permits small partial effects which can be specified as:

$$\mathrm{IF}(y; v, F) = \lim_{t \downarrow 0} \frac{v\big((1-t)F + t\Delta_y\big) - v(F)}{t} \quad (8)$$

Since the UE can be estimated using OLS, when the RIF of v(F) is used, it can now be specified as:

$$\mathrm{RIF}(y; v, F) = v(F) + \mathrm{IF}(y; v, F) \quad (9)$$

When estimated, the RIF can be used to estimate the Unconditional Partial Effects (UPE) of the returns to education of public sector workers on these distributional features of the quantile regression, which considers the different characteristic features of the workers. Since these differences may lead to potential biases on policy influences, the RIF is regressed through an OLS model. The effect is the UPE, which according to Chernozhukov et al., (2013) is also known as the "counterfactual effect", or "policy effect" that when adapted from the corollary (1) of Firpo et al., (2009) can be specified as:

$$\mathrm{UPE}(v(F), k) = \left(\int_{\Omega_z} E[\,\mathrm{IF}(y; v, F)|C = k, Z = z) - E[\mathrm{IF}(y; v, F)|C = 1, Z = z]\, f_Z(z)dz\right) \times t \quad (10)$$

here Ω_z denotes a set of employees given the covariates vector Z.

5. Empirical Results & Discussion

5.1 Returns to Education

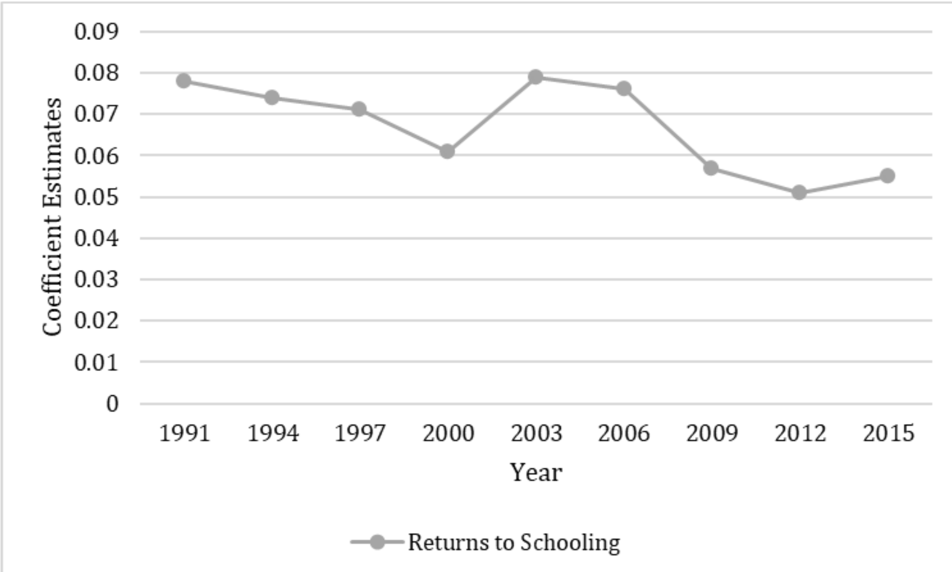
Based on the OLS estimation of equation (1) above, the returns to education of public sector workers from 1991-2015 were presented in Table 2 and illustrated by Figure 1. A close examination of the estimates shown reveals that as time progressed, the average returns to education of public sector workers in Trinidad and Tobago as reflected by their years of schooling, declined consistently between 1991-2000 from 7.8% to 6.1%, after which it increased to 7.9% in 2003. This growth was short-lived as soon after the average returns of public sector workers began to erode to 5.1% in 2012, and 5.5% in 2015. Interestingly enough, the gender of the worker, i.e., if he was male, had a much more significant impact on their returns, than their potential working experience. In fact, throughout the timeframe, the potential working experience of public sector workers appears to count for less, declining from 1.3% in 1991, to 0.6% in 2015, meanwhile, if the gender of the worker was male, then this had a consistent influence over the returns of public sector workers in the range of 13.4% to 20.3%.

The heightened returns of workers in 1991 may be linked to the settlement of arrears concerning the salaries and wages owed to public servants and statutory bodies of approximately TT$903mn, as well as the issuing of redeemable units in the National Investment Company (Trinidad and Tobago House of Representatives, 1991). In addition to this, the development of remedial and special needs programmes, the construction of sixth-form colleges, work-study programmes, adult education and community college programmes, expansion of university and technical/vocational skills programmes, may have all contributed to the returns of public sector workers being higher in 1991, as there was greater access to educational and training opportunities (ROTT, 1988; ROTT, 1990).

Meanwhile, the higher returns to schooling experienced by public sector workers in 2003, may be reflective of not only the TT$907.3mn worth of investment made in various public sector investment projects throughout Trinidad and Tobago across all sectors, but that of TT$181.9mn directed towards education and training in 2003, as well as earlier investments made in 2002, which led to the construction and upgrading of several educational institutions/special education institutes, (through IDB funded programmes like the Secondary Education Modernization Programme (SEMP) and the World Bank-assisted Fourth Basic Education Programme), as well as educational reforms (curriculum development, professional development, testing and evaluation, teaching and learning strategies) (MPD, 2002).

Regardless of these educational and training initiatives, the failure of the state to sustain investment in the educational sector, together with the economic downturn of the 1983-1993 and 2008 global economic crises which preceded the 2009-2015 economic recession may have contributed to the overall decline in the earnings of workers throughout 1991-2015. During these periods not only were the levels of inflation and unemployment high, but the reduction in the educational support services implies that the quality of graduates entering into the labour force exhibited low levels of achievement at the secondary school level, and a high failure rate at regional examinations (Alleyne et al., 1984). As a result, graduates are ill-prepared to enter the world of work, as their academic preparation may not be sufficient for occupations higher than clerical positions (ROTT, 1990).

Fig. 1 The Returns to Education



Source: Own compilation based on model estimation for the years specified.

Table 2 The Returns to Education

Variables	1991	1994	1997	2000	2003	2006	2009	2012	2015
Years of Schooling	0.078 *****	0.074 *****	0.071 *****	0.061 *****	0.079 *****	0.076 *****	0.057 *****	0.051 *****	0.055 *****
	-(0.008)	-(0.006)	-(0.006)	-(0.006)	-(0.005)	-(0.006)	-(0.006)	-(0.005)	-(0.005)
Male	0.134 *****	0.135 *****	0.141 *****	0.131 *****	0.121 *****	0.146 *****	0.203 *****	0.173 *****	0.136 *****
	-(0.029)	-(0.02)	-(0.017)	-(0.02)	-(0.018)	-(0.019)	-(0.019)	-(0.018)	-(0.019)
Potential Working Experience	0.013 *****	0.017 *****	0.015 *****	0.011 *****	0.012 *****	0.010 *****	0.008 *****	0.008 *****	0.006 *****
	-(0.002)	-(0.001)	-(0.001)	-(0.001)	-(0.001)	-(0.001)	-(0.001)	-(0.001)	-(0.001)
Observations	1,502	2,192	2,461	1,658	2,448	2,648	2,219	2,154	2,139

The dependent variable is the real wage rate (Lnwage), Robust standard errors are shown in parenthesis,
*****p<0.001****p<0.005 *** p<0.01, ** p<0.05, * p<0.1 are the respective levels of significance.

Further estimation of equation (5) to examine the average returns of public sector workers using the pseudo panel data approach shown in Table 3 below, when summarized shows that the returns to education of workers from the pooled sample, i.e., 1991-2015 to be 11.5% using the OLS technique. The pseudo panel for a 1-year cohort indicates that the returns to education of public sector workers were notably higher at 19.2%. As a test of robustness, the pseudo-panel for a 2-year cohort shows similarly elevated returns to education of 36.2%. These results imply that the returns to education estimates derived by the OLS procedure are downward biased, as it did not consider the problems of endogeneity as discussed earlier.

As a test of robustness, the fixed effects specifications for the returns to education were included, and the results are summarized in Table 4. With the inclusion of the fixed effects, the average returns to education of public sector workers were found to be much smaller (12.9% for the 1-year cohort, and 13.2% for the 2-year cohort) than the estimates shown in table 3. Unlike that of Table 3, if the worker was male, it had a positive impact on their average returns (8.2% for the 1-year cohort, and 5% for the 2-year cohort), while their potential working experience also had a positive impact (5.1% for the 1-year cohort, and 5% for the 2-year cohort).

Korwatanasakul (2022), explains that since developing countries experience similar developmental challenges associated with periods of economic downturn, their returns to education are also underestimated. The results of Table 3 may also be indicative of ability bias, as the parents of children who exhibit above-average abilities and cognition may be more inclined to encourage their child to pursue higher educational opportunities, than the parents of under-achieving children. Such actions and the social inequality created, unfortunately, encourage the growth of educational inequality within households, which when examined in terms of intergenerational educational mobility also leads to a downward bias in the returns to education (Dendir, 2023).

At the intergenerational level, the downward bias can stem from the fact that the older generations of both parents and children may have had low levels of schooling. Further to this, Antman et al., (2023) explain that the downward bias of estimates can also be related to ethic attrition created by either assortive mating or the selective marriages of persons into families with a more elevated socio-economic background.

Table 3 The Returns to Education (Pseudo Panel Data Estimation)

Variables	Individual Data OLS	Pseudo-Panel 1 Year Cohort (Mean)	Pseudo-Panel 2-Year Cohort (Mean)
Years of Schooling	0.115 *****	0.192 *****	0.362 *****
	(0.001)	(0.000)	(0.000)
Male	0.092 *****	-0.014	-0.491 *****
	(0.005)	(0.764)	(0.000)
Potential Working Experience	0.017 *****	0.046 *****	0.035 *****
	(0.000)	(0.000)	(0.000)
Individual Observations	54,864	54,864	54,864
Number of Groups		56	28
Cohort Year Observations		1400	700
Observations per cohort			
Maximum		88	188
Minimum		1,882	3,548

The dependent variable is the real wage rate (Lnwage), Robust standard errors are shown in parenthesis, *****p<0.001****p<0.005 *** p<0.01, ** p<0.05, * p<0.1 are the respective levels of significance.

Table 4 The Returns to Education, specifications with Fixed Effects (FE) (Pseudo Panel Data Estimation)

Variables	Pseudo Panel 1 Year cohort (Mean)	Pseudo Panel 2 Year cohort (Mean)
Years of Schooling	0.129 *****	0.132 *****
	(0.013)	(0.002)
Male	0.082 ***	0.055 *****
	(0.045)	(0.007)
Potential Working Experience	0.051 *****	0.050 *****
	(0.001)	(0.000)
Individual Observations	54,864	54,864
Number of Groups	56	28
Cohort Year Observations	1400	700
Observations per cohort		
Maximum	88	188
Minimum	1,883	3,548

The dependent variable is the real wage rate (Lnwage), Robust standard errors are shown in parenthesis, *****p<0.001****p<0.005 *** p<0.01, ** p<0.05, * p<0.1 are the respective levels of significance.

5.2 The Distributive Effects of Education

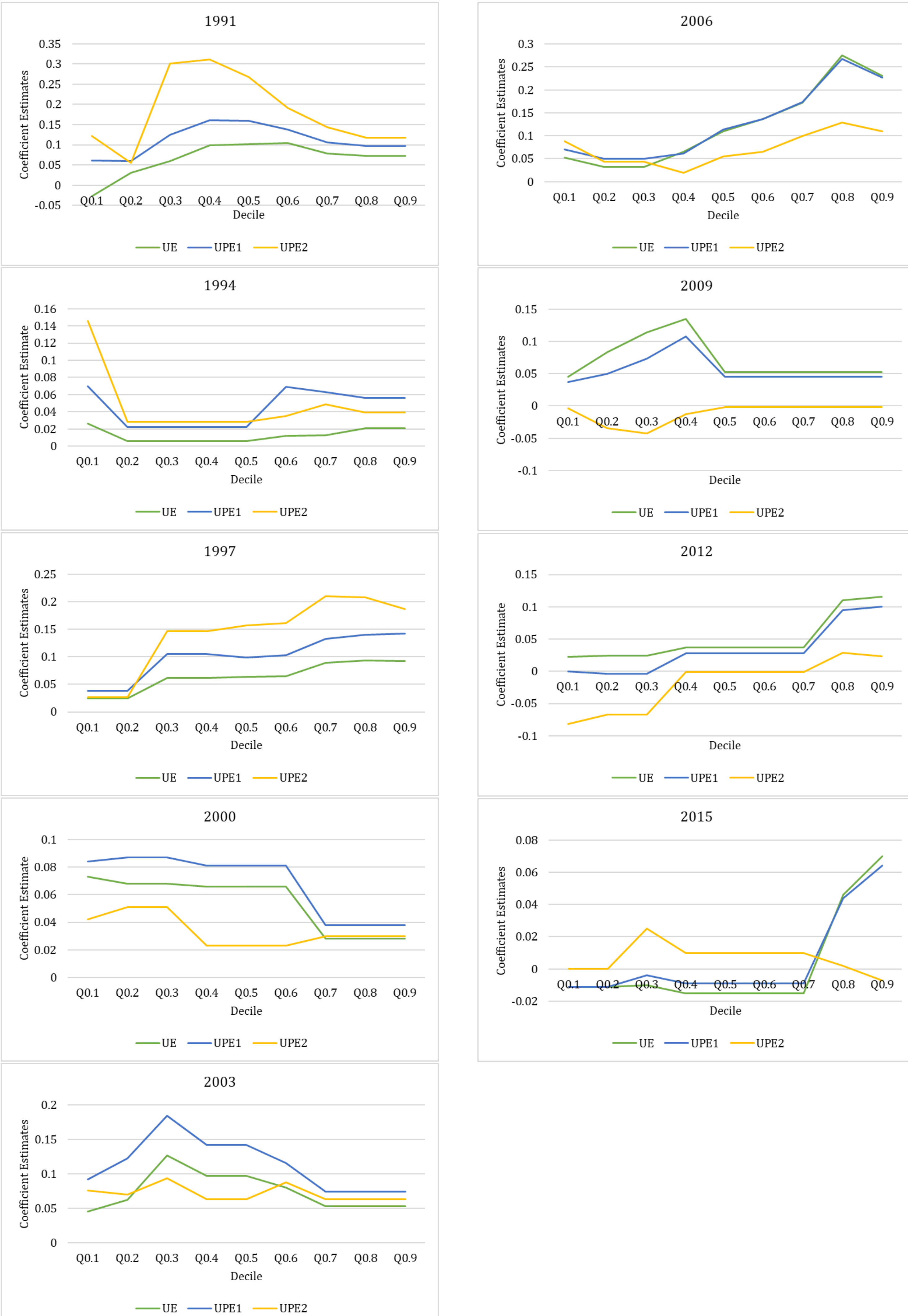
The summary results of the estimation of equation (10) used to investigate the heterogeneity of the returns to education across the wage distribution of the unconditional quantile regression method are presented in Table 5 and graphically illustrated in Figure 4. According to the estimates summarized in Table 5, regardless of the year, if the proportion of public sector workers were to increase then would cause the average returns to education of workers to increase (creating a positive shift). The inclusion of the UPE1 (working experience and geographic location) covariate led to considerable growth in the magnitude of workers' earnings, particularly in 2006 (15.5%), and 2003 (14.5%). With the inclusion of UPE2 (industrial and occupational groupings), although the average returns to education remained positive and significant, the magnitude by which their earnings improved declined considerably.

Using the quantile regression, as the primary distributional statistic, if the proportion of public sector workers were to increase, then generally speaking this would produce either a rise (upward shift)/ fall (downward shift) in the returns to education, with the inclusion of the different category of UE covariates, i.e., UPE1 (working experience and geographic location) and UPE2 (industrial and occupational groupings). As the initial point of departure, the UE estimates reflect only the returns to education of workers with only their biographical information (gender, ethnicity, and marital status). When UPE1 were considered, this led to a positive shift in the earnings of workers in the years 1991, 1994, 1997, 2000, and 2003, a negative shift in 2009, 2012, and very slight changes in their earnings in 2006 and 2015. A visual examination of Figure 4 reveals that regardless of the type of shift experienced by public sector workers, the trends exhibited by UE and UPE1 are somewhat comparable. As a result of this, for both groups of covariates workers although the shift has led to either an increase or decrease in their earnings, tend to experience different wage penalties based on their position on the wage distribution.

The years in which public sector workers benefitted from a positive shift in their earnings (1991, 1994, 1997, 2000, and 2003) at UPE1, had mixed outcomes in terms of their wage penalties. Even though public sector workers benefit from the shift, the highest wage penalties were found in the middle deciles (0.40^{th}-1991, 0.60^{th}-1994), highest decile (0.90^{th}-1997), and the lowest deciles (0.20^{th}-2000, and 0.30^{th}- 2003). An examination of the estimates in Table 5, showed that the shift led to an overall higher wage penalty for most of the distribution when compared to the UE estimates. For the years in which public sector workers suffered a negative shift in their earnings (2009, 2012), the largest wage penalties were found in the middle decile (0.40^{th} – 2009), and the highest decile (0.90^{th}- 2012). The negative shift led to an overall decline in the wage penalty for most of the distribution, as the UE estimates have a higher wage penalty across the distribution. For the years in which workers experienced a minuscule shift in their earnings (2006 and 2015), their largest wage penalties were found at the highest decile (0.90th- 2006 and 2015), but it led to an overall higher wage penalty for most of the distribution.

With the inclusion of the UPE2 vector of covariates as a check of robustness, Figure 4 shows there were again both positive (1991, 1994, 1997, 2015), and negative shifts (2000, 2003, 2006, 2009, 2012) in the earnings of public sector workers. For the years in which workers benefitted from a positive shift in their earnings, the highest wage penalties were found at the lower deciles (0.40th-1991, 0.10th- 1994, and 0.30th-2015), and the higher deciles (0.70th- 1997), the shift itself led to an overall higher wage penalty across most of the wage distribution. In comparison the workers who suffered from a negative shift in their earnings, the highest wage penalties were exhibited at both the lower (0.30th-2000 and 2003), and higher deciles (0.80th-2006, 0.50th-0.90th-2009, 0.80th-2012), where the shift led to an overall lower wage penalty for most of the wage distribution.

Fig. 2 The Returns to Education-Unconditional Quantile Regression (UQR)-UE, UPE1, UPE2



Source: Own compilation based on model estimation for the years specified.

Table 5 The Returns to Education-Unconditional Quantile Regression (UQR)-UE, UPE1, UPE2

Variable	Mean	Q0.10	Q0.2	Q0.3	Q0.4	Q0.5	Q0.6	Q0.7	Q0.8	Q0.9
1991 UE	0.106*****	-0.027	0.03	0.059	0.099	0.101*	0.104**	0.078**	0.072***	0.072***
	(0.005)	-(0.032)	-(0.041)	-(0.058)	-(0.069)	-(0.056)	-(0.052)	-(0.033)	-(0.027)	-(0.027)
UPE1	0.129*****	0.061	0.059	0.125	0.161*	0.159**	0.137**	0.106***	0.097****	0.097****
	(0.006)	-(0.065)	-(0.045)	-(0.079)	-(0.086)	-(0.07)	-(0.056)	-(0.038)	-(0.031)	-(0.031)
UPE2	0.078*****	0.122	0.055	0.302	0.311*	0.268*	0.192**	0.143**	0.117**	0.117**
	(0.008)	-(0.136)	-(0.049)	-(0.196)	-(0.186)	-(0.144)	-(0.097)	-(0.062)	-(0.049)	-(0.049)
1994 UE	0.110*****	0.026	0.006	0.006	0.006	0.006	0.012	0.013	0.021	0.021
	(0.004)	-(0.019)	-(0.006)	-(0.006)	-(0.006)	-(0.006)	-(0.024)	-(0.02)	-(0.015)	-(0.015)
UPE1	0.135*****	0.07	0.022	0.022	0.022	0.022	0.069**	0.063**	0.056****	0.056****
	(0.004)	-(0.05)	-(0.015)	-(0.015)	-(0.015)	-(0.015)	-(0.031)	-(0.026)	-(0.019)	-(0.019)
UPE2	0.074*****	0.146	0.028	0.028	0.028	0.028	0.035	0.049	0.039	0.039
	(0.006)	-(0.117)	-(0.039)	-(0.039)	-(0.039)	-(0.039)	-(0.062)	-(0.055)	-(0.037)	-(0.037)
1997 UE	0.110*****	0.024	0.024	0.062**	0.062**	0.064***	0.065***	0.089*****	0.093*****	0.092*****
	(0.004)	-(0.024)	-(0.024)	-(0.031)	-(0.031)	-(0.024)	-(0.024)	-(0.026)	-(0.026)	-(0.026)
UPE1	0.135*****	0.038	0.038	0.105**	0.105**	0.099****	0.103****	0.133*****	0.140*****	0.142*****
	(0.004)	-(0.038)	-(0.038)	-(0.044)	-(0.044)	-(0.033)	-(0.033)	-(0.036)	-(0.035)	-(0.035)
UPE2	0.071*****	0.027	0.027	0.147**	0.147**	0.157***	0.161***	0.210*****	0.208*****	0.187****
	(0.006)	-(0.027)	-(0.027)	-(0.073)	-(0.073)	-(0.059)	-(0.058)	-(0.061)	-(0.059)	-(0.06)
2000 UE	0.110*****	0.073	0.068	0.068	0.066*	0.066*	0.066*	0.028**	0.028**	0.028**
	(0.005)	-(0.073)	-(0.049)	-(0.049)	-(0.036)	-(0.036)	-(0.036)	-(0.012)	-(0.012)	-(0.012)
UPE1	0.127*****	0.084	0.087	0.087	0.081*	0.081*	0.081*	0.038***	0.038***	0.038***
	(0.005)	-(0.084)	-(0.056)	-(0.056)	-(0.043)	-(0.043)	-(0.043)	-(0.014)	-(0.014)	-(0.014)
UPE2	0.061*****	0.042	0.051	0.051	0.023	0.023	0.023	0.03	0.03	0.03
	(0.006)	-(0.043)	-(0.054)	-(0.054)	-(0.061)	-(0.061)	-(0.061)	-(0.021)	-(0.021)	-(0.021)
2003 UE	0.124*****	0.045	0.062	0.127*	0.097**	0.097**	0.080****	0.053****	0.053****	0.053****
	(0.004)	-(0.049)	-(0.041)	-(0.065)	-(0.042)	-(0.042)	-(0.026)	-(0.016)	-(0.016)	-(0.016)
UPE1	0.145*****	0.092	0.123*	0.185**	0.142***	0.142***	0.116*****	0.074*****	0.074*****	0.074*****
	(0.005)	-(0.079)	-(0.071)	-(0.079)	-(0.052)	-(0.052)	-(0.034)	-(0.02)	-(0.02)	-(0.02)
UPE2	0.079*****	0.076	0.07	0.094	0.063	0.063	0.088**	0.063**	0.063**	0.063**
	(0.005)	-(0.107)	-(0.077)	-(0.082)	-(0.053)	-(0.053)	-(0.038)	-(0.025)	-(0.025)	-(0.025)
2006 UE	0.138*****	0.052	0.032	0.032	0.065**	0.110***	0.136****	0.172****	0.275*****	0.231*****
	(0.004)	-(0.041)	-(0.023)	-(0.023)	-(0.032)	-(0.04)	-(0.046)	-(0.053)	-(0.075)	-(0.061)
UPE1	0.155*****	0.07	0.050*	0.050*	0.062	0.114**	0.137**	0.174****	0.268****	0.227*****
	(0.004)	-(0.051)	-(0.03)	-(0.03)	-(0.038)	-(0.048)	-(0.053)	-(0.06)	-(0.083)	-(0.067)
UPE2	0.076*****	0.088	0.044	0.044	0.02	0.055	0.065	0.099	0.129	0.11
	(0.006)	-(0.068)	-(0.038)	-(0.038)	-(0.059)	-(0.066)	-(0.071)	-(0.077)	-(0.107)	-(0.087)
2009 UE	0.125*****	0.045	0.083*	0.114**	0.135**	0.052***	0.052***	0.052***	0.052***	0.052***
	(0.005)	-(0.035)	-(0.045)	-(0.054)	-(0.056)	-(0.019)	-(0.019)	-(0.019)	-(0.019)	-(0.019)
UPE1	0.134*****	0.037	0.05	0.073*	0.108**	0.045***	0.045***	0.045***	0.045***	0.045***
	(0.005)	-(0.029)	-(0.036)	-(0.042)	-(0.048)	-(0.017)	-(0.017)	-(0.017)	-(0.017)	-(0.017)
UPE2	0.057*****	-0.004	-0.034	-0.043	-0.013	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.006)	-(0.022)	-(0.051)	-(0.059)	-(0.059)	-(0.019)	-(0.019)	-(0.019)	-(0.019)	-(0.019)
2012 UE	0.109*****	0.022	0.024	0.024	0.037**	0.037**	0.037**	0.037**	0.110*****	0.116*****
	(0.004)	-(0.022)	-(0.015)	-(0.015)	-(0.016)	-(0.016)	-(0.016)	-(0.016)	-(0.033)	-(0.032)
UPE1	0.113*****	0	-0.004	-0.004	0.028*	0.028*	0.028*	0.028*	0.095***	0.100****
	(0.004)	-(0.007)	-(0.007)	-(0.007)	-(0.016)	-(0.016)	-(0.016)	-(0.016)	-(0.034)	-(0.034)
UPE2	0.051*****	-0.082	-0.067	-0.067	-0.001	-0.001	-0.001	-0.001	0.029	0.023
	(0.005)	-(0.082)	-(0.044)	-(0.044)	-(0.029)	-(0.029)	-(0.029)	-(0.029)	-(0.049)	-(0.048)

2015 UE	0.106 *****	-0.011	-0.011	-0.01	-0.015	-0.015	-0.015	-0.015	0.046	0.070 *
	(0.004)	-(0.011)	-(0.011)	-(0.025)	-(0.023)	-(0.023)	-(0.023)	-(0.023)	-(0.036)	-(0.038)
UPE1	0.113 *****	-0.011	-0.011	-0.004	-0.009	-0.009	-0.009	-0.009	0.044	0.064 *
	(0.004)	-(0.011)	-(0.011)	-(0.026)	-(0.023)	-(0.023)	-(0.023)	-(0.023)	-(0.033)	-(0.035)
UPE2	0.055 *****	0	0	0.025	0.01	0.01	0.01	0.01	0.002	-0.007
	(0.005)	-(0.001)	-(0.001)	-(0.035)	-(0.032)	-(0.032)	-(0.032)	-(0.032)	-(0.04)	-(0.041)

The dependent variable is the real wage rate (Lnwage), Robust standard errors are shown in parenthesis,
*****p<0.001****p<0.005 *** p<0.01, ** p<0.05, * p<0.1 are the respective levels of significance.

5.3 Overeducation

To examine the impact that overeducation has on the earnings of public sector workers in Trinidad and Tobago, equation (2) was estimated using both the OLS and QR methodologies. The results of this procedure are summarized in Table 6 and illustrated in Figure 3.

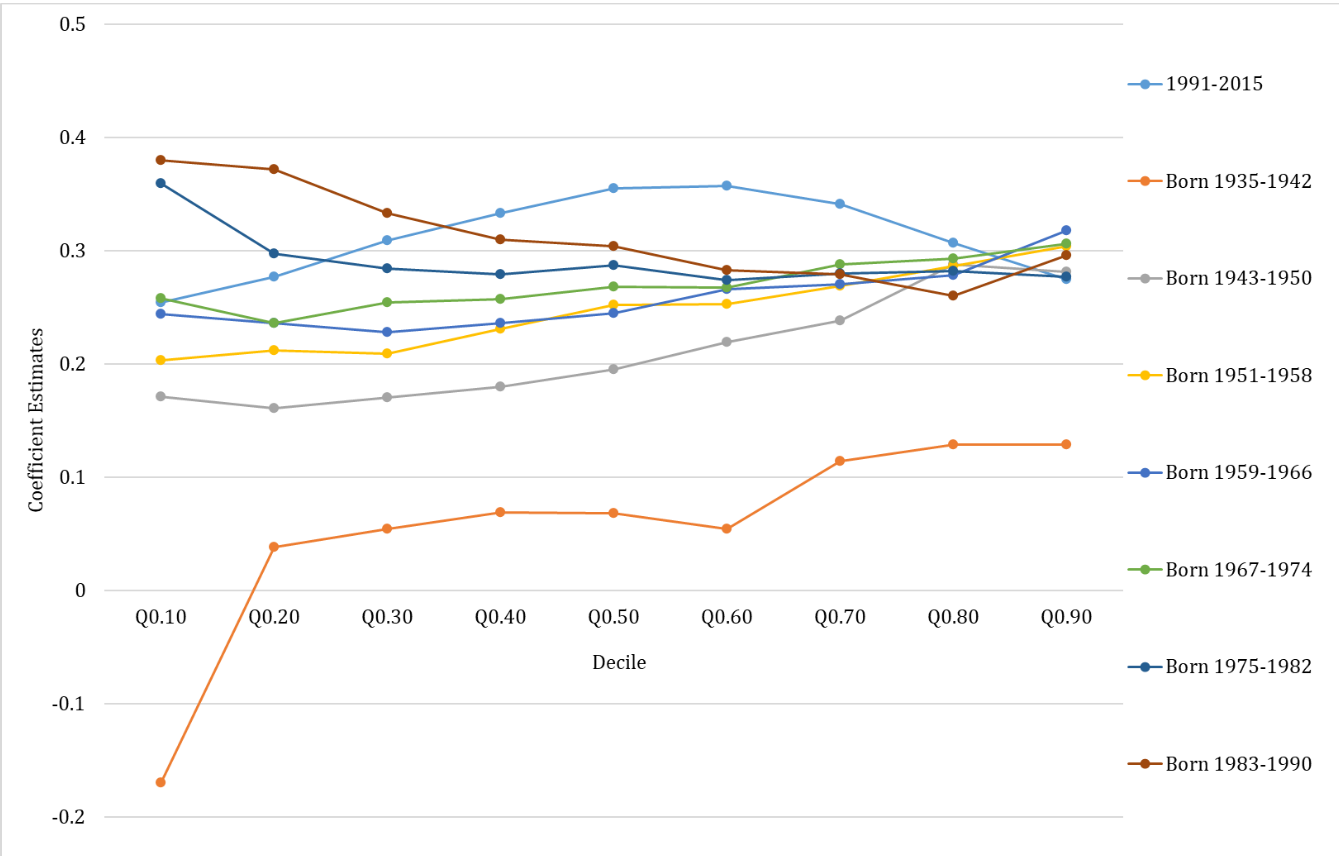
Based on these results, it was found that the average returns of overeducated public sector workers for the entire birth cohort improved by 31.1%. However, their earnings while improving across much of the wage distribution from 25.4% to 35.7% over the 0.10^{th} – 0.60^{th} deciles, steadily declined to 27.5% at the 0.90^{th} decile. The average returns of overeducated workers although positive appears to be influenced by their year of birth, so the earnings of overeducated persons born between 1935-1942 (3.7%), and 1943-1950 (21.4%) were generally lower than those of overeducated workers born later on in 1975-1982 (30.6%), and 1983-1990 (31.7%).

A closer analysis of the QR estimates finds that first the cohorts of overeducated workers with the overall lowest earnings across the wage distribution were born in 1935-1942, 1943-1950, 1951-1958, and 1959-1966, when compared to persons born in 1967-1974, 1975-1982, and 1983-1990.

Second, the returns of overeducated workers born in 1935-1942 (from -17% to 12.9%,) 1943-1950 (from 17.1% to 28.1%), 1951-1958 (from 20.3% to 30.4%), 1959-1966 (from 24.4% to 31.8%), and 1967-1974 (from 25.8% to 30.6%), appears to exhibit an overall increase over the entire wage distribution (0.10^{th}-0.90^{th}). As a result, they experienced their highest earnings at the higher deciles (0.70^{th}-0.90^{th}) and lower returns at the lower deciles (0.10^{th}-0.30^{th}) of the wage distribution).

Third, the earnings of overeducated public sector workers born in 1975-1982 (from 35.9% to 27.7%), and 1983-1990 (from 38% to 29,6%) appear to have declined over the entire wage distribution. Unlike the much older cohorts of overeducated workers, these groups of younger workers benefitted from higher earnings at the lower deciles (0.10^{th}), and lower earnings at the higher deciles (0.90^{th}).

Fig. 3 Wage Effects from Overeducation by Birth Cohort



Source: Own compilation based on model estimation for the birth cohort specified.

Table 6 Wage Effects from Overeducation by Birth Cohort-Quantile Regression (QR)

Variables	OLS	Q0.10	Q0.20	Q0.30	Q0.40	Q0.50	Q0.60	Q0.70	Q0.80	Q0.90
All Cohorts	0.311	0.254	0.277	0.309	0.333	0.355	0.357	0.341	0.307	0.275
Overeducation	*****	*****	*****	*****	*****	*****	*****	*****	*****	*****
	-(0.006)	-(0.01)	-(0.009)	-(0.008)	-(0.009)	-(0.008)	-(0.008)	-(0.009)	-(0.008)	-(0.008)
Born 1935-1942:	0.037	-0.17	0.038	0.054	0.069	0.068	0.054	0.114	0.129	0.129
Overeducation					*			**	**	***
	-(0.044)	-(0.108)	-(0.092)	-(0.056)	-(0.039)	-(0.044)	-(0.044)	-(0.058)	-(0.058)	-(0.05)
Born 1943-1950:	0.214	0.171	0.161	0.170	0.180	0.195	0.219	0.238	0.288	0.281
Overeducation	*****	*****	*****	*****	*****	*****	*****	*****	*****	*****
	-(0.021)	-(0.037)	-(0.027)	-(0.02)	-(0.025)	-(0.024)	-(0.023)	-(0.027)	-(0.029)	-(0.037)
Born 1951-1958:	0.259	0.203	0.212	0.209	0.231	0.252	0.253	0.269	0.286	0.304
Overeducation	*****	*****	*****	*****	*****	*****	*****	*****	*****	*****
	-(0.013)	-(0.021)	-(0.015)	-(0.016)	-(0.015)	-(0.015)	-(0.015)	-(0.018)	-(0.016)	-(0.019)
Born 1959-1966:	0.264	0.244	0.236	0.228	0.236	0.245	0.266	0.270	0.278	0.318
Overeducation	*****	*****	*****	*****	*****	*****	*****	*****	*****	*****
	-(0.011)	-(0.019)	-(0.014)	-(0.013)	-(0.014)	-(0.012)	-(0.013)	-(0.012)	-(0.016)	-(0.019)
Born 1967-1974:	0.263	0.258	0.236	0.254	0.257	0.268	0.267	0.288	0.293	0.306
Overeducation	*****	*****	*****	*****	*****	*****	*****	*****	*****	*****
	-(0.012)	-(0.022)	-(0.017)	-(0.014)	-(0.014)	-(0.012)	-(0.014)	-(0.013)	-(0.013)	-(0.016)
Born 1975-1982:	0.306	0.359	0.297	0.284	0.279	0.287	0.274	0.280	0.282	0.277
Overeducation	*****	*****	*****	*****	*****	*****	*****	*****	*****	*****
	-(0.012)	-(0.025)	-(0.015)	-(0.017)	-(0.013)	-(0.013)	-(0.013)	-(0.012)	-(0.013)	-(0.02)
Born 1983-1990:	0.317	0.380	0.372	0.333	0.310	0.304	0.283	0.279	0.260	0.296
Overeducation	*****	*****	*****	*****	*****	*****	*****	*****	*****	*****
	-(0.016)	-(0.031)	-(0.023)	-(0.019)	-(0.021)	-(0.017)	-(0.016)	-(0.018)	-(0.017)	-(0.019)

The dependent variable is the real wage rate (Lnwage), Robust standard errors are shown in parenthesis, *****p<0.001****p<0.005 *** p<0.01, ** p<0.05, * p<0.1 are the respective levels of significance.

5.4 Disaggregation of the Returns to Education

Apart from overall Returns to Education discussed earlier in section a, equation (5) was also estimated using the pseudo panel approach to examine the average returns of overeducated public sector workers based on their gender, type of public sector employment, and geographic region of residence. The summary of the results is presented in Tables 7, 8, and 9, where in addition to the pseudo-panel for a 1-year cohort, a pseudo-panel for a 2-year cohort was also included as a test of robustness to consider the presence of endogeneity.

According to Table 7, while men and women both exhibited positive average returns to education, the average returns of women for both panels (24.6% for the 1-year cohort, and 40% for the 2-year cohort), was higher than that of men (20.4% for the 1-year cohort, and 39.4% for the 2-year cohort). Notwithstanding these findings, the potential working experience had a greater impact on the average earnings of men than that of women employed in the public sector. This result was also consistent with other similar studies which examined the returns to education of workers in Vietnam (Tran & Paweenawat 2023).

When the type of public sector worker is taken into consideration, the summary of the results shown in Table 8, reveals that regardless of the type of worker, their average returns to education increased between the 1-year to the 2-year cohort. The average returns to education of statutory board workers were particularly higher (31.9%) than that of state enterprise workers (28.6%), and local government workers (20.8%) for the 1-year cohort. The 2-year cohort presented a different outcome, as the average returns to education of state enterprise workers (38.8%) was now higher than both local government workers (38.3%), and statutory board workers (36.5%). The potential working experience of the worker appears to have a positive impact on the average returns to workers while if the worker is male has a negative impact.

Finally, as expected when the 2-year cohort is included in Table 9 which summarizes the returns to education of public sector workers by their geographic location, their average returns were again higher than that of the 1-year cohort. For the 1-year cohort, public sector workers residing in the counties of Nariva-Mayaro (45.6%), St. Andrew, St. David, and Tobago (33.7%), displayed higher average returns to education than the other counties of Caroni (29.1%), St. George (24.9%), and Victoria (29.6%). Regardless of location, the potential working experience of the worker had a similar impact on their average earnings, however, if the worker was male had a greater negative impact on their average earnings if they resided in the St. Patrick and Victoria counties. A similar outcome was observed for the 2-year cohort where again the highest average returns to education were found by public sector workers who lived in the Nariva-Mayaro (51.7%) and the St. Andrew, St. David and Tobago (51.5%) counties. The workers' potential working experience had an average impact of between 3.6% to 4% on their average returns to education regardless of location, while if the worker was male had its greatest negative impact on earnings if residing in the area of Nariva-Mayaro.

Table 7 Returns to Education by Gender (Pseudo Panel Data Estimation)

Variable	**Men**		**Women**	
	Pseudo-Panel 1-Year Cohort (Mean)	**Pseudo-Panel 2-Year Cohort (Mean)**	**Pseudo-Panel 1-Year Cohort (Mean)**	**Pseudo-Panel 2-Year Cohort (Mean)**
Years of Schooling	0.204 ******	0.394 *****	0.246 *****	0.400 *****
	(0.012)	(0.002)	(0.013)	(0.000)
Potential Working Experience	0.045 *****	0.032 *****	0.043 *****	0.030 *****
	(0.001)	(0.000)	(0.001)	(0.000)
Individual Observations	31,756	31,756	23,108	23,108
Number of Groups	56	28	56	28
Cohort Year Observations	1400	700	1400	700
Observations per cohort				
Maximum	60	132	28	56
Minimum	1,153	2,202	730	1,346

The dependent variable is the real wage rate (Lnwage), Robust standard errors are shown in parenthesis, *****p<0.001****p<0.005 *** p<0.01, ** p<0.05, * p<0.1 are the respective levels of significance.

Table 8 The Returns to Education by Type of Public Sector Worker (Pseudo Panel Data Estimation)

Variable	**Statutory Board**		**State Enterprises**		**Local Government**	
	Pseudo-Panel 1-Year Cohort (Mean)	**Pseudo-Panel 2-Year Cohort (Mean)**	**Pseudo-Panel 1-Year Cohort (Mean)**	**Pseudo-Panel 2-Year Cohort (Mean)**	**Pseudo-Panel 1-Year Cohort (Mean)**	**Pseudo-Panel 2-Year Cohort (Mean)**
Years of Schooling	0.319 *****	0.365 *****	0.286 *****	0.388 *****	0.208 *****	0.383 *****
	(0.015)	(0.005)	(0.014)	(0.005)	(0.011)	(0.002)
Male	-0.222 *****	-0.331 *****	-0.161 *****	-0.408 *****	-0.035	-0.384 *****
	(0.061)	(0.026)	(0.051)	(0.000)	(0.049)	(0.011)
Potential Working Experience	0.037 *****	0.031 *****	0.041 *****	0.032 *****	0.045 *****	0.031 *****
	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Individual Observations	6,524	6,524	9,314	9,314	39,026	39,026
Number of Groups	56	28	56	28	56	28
Cohort Year Observations	1400	700	1400	700	1400	700
Observations per cohort						
Maximum	4	13	17	38	66	135
Minimum	219	428	374	664	1,290	2,492

The dependent variable is the real wage rate (Lnwage), Robust standard errors are shown in parenthesis,
*****p<0.001****p<0.005 *** p<0.01, ** p<0.05, * p<0.1 are the respective levels of significance.

Table 9 The Returns to Education by Geographic Location (Pseudo Panel Data Estimation)

Variables	Caroni	Nariva-Mayaro	St. Andrew, St. David, Tobago	St. George	St. Patrick	Victoria
Pseudo-Panel 1-Year Cohort (Mean)						
Years of Schooling	0.291 *****	0.456 *****	0.337 *****	0.249 *****	0.293 *****	0.296 *****
	(0.000)	(0.025)	(0.018)	(0.015)	(0.019)	(0.018)
Male	-0.206 ***	-0.352 *****	-0.270 *****	-0.123 ***	-0.181 ***	-0.195 *****
	(0.010)	(0.122)	(0.074)	(0.061)	(0.073)	(0.065)
Potential Working Experience	0.047 *****	0.047 *****	0.048 *****	0.047 *****	0.048 *****	0.048 *****
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Individual Observations	7,975	1,297	9,166	18,929	6,794	10,703
Number of Groups	56	56	56	56	56	56
Cohort Year Observations	1400	1400	1400	1400	1400	1400
Observations per cohort						
Maximum	8	1	7	43	8	13
Minimum	287	55	317	646	277	386
Pseudo-Panel 2-Year Cohort (Mean)						
Years of Schooling	0.503 *****	0.517 *****	0.515 *****	0.489 *****	0.507 *****	0.507 *****
	(0.005)	(0.013)	(0.005)	(0.003)	(0.006)	(0.005)
Male	-0.654 *****	-0.440 *****	-0.631 *****	-0.638 *****	-0.589 *****	-0.669 *****
	(0.0283)	(0.069)	(0.025)	(0.018)	(0.030)	(0.024)
Potential Working Experience	0.037 *****	0.039 *****	0.040 *****	0.036 *****	0.040 *****	0.039 *****
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Individual Observations	7,975	1,297	9,166	18.929	6,794	10,703
Number of Groups	28	28	28	28	28	28
Cohort Year Observations	700	700	700	700	700	700
Observations per cohort						
Maximum	17	1	21	94	18	37
Minimum	537	93	600	1,266	490	729

The dependent variable is the real wage rate (Lnwage), Robust standard errors are shown in parenthesis,
*****p<0.001****p<0.005 *** p<0.01, ** p<0.05, * p<0.1 are the respective levels of significance.

6. Conclusion

This article estimates the rate of returns to education in Trinidad and Tobago the distributive effects of education on wages, and the wage effect from the incidence of overeducation in the labor market during 1991–2015. We employ a pseudo-panel approach to address omitted variables bias and the unconditional quantile regression to identify the heterogeneity of returns to education across the income distribution.

The results provide some insights into education policies in Trinidad and Tobago. To meet the demand for highly educated workers, the returns to education estimated in this study have been highly significant, indicating that education should always be one of the key priorities in the economic growth policy of the government. However, the average returns to education of public sector workers in Trinidad and Tobago have reduced consistently from 7.8% to 5.5% between 1991-2015, due to the excess supply of highly educated workers. Using the pseudo-panel approach to address the unobservable characteristics and potential selectivity bias, the returns to education of private sector workers were clearly higher at 19.2% than the 11.5% derived from the OLS sample for 1991-2015. This implies that the OLS estimate is downward biased and did not consider the problem of endogeneity.

Using the unconditional quantile regression methodology to study the heterogeneity of the returns to education, it was found that if the proportion of public sector workers were to raise then this would cause their average returns to increase (positive shift). The average returns of overeducated workers, while positive, appear to be higher for younger cohorts than for older cohorts. Moreover, while improving across much of the wage distribution (0.10^{th} - 0.60^{th}), the average returns of overeducated clearly declined at the highest deciles.

While our findings are specific to Trinidad and Tobago, they have useful policy implications for other countries that are attempting to reform their human capital systems. The growth of the high-skill workforce can lead to overeducation problems if labour demand is concentrated in less technologically intensive sectors that cannot absorb the number of graduates that the university system turns out every year (Basso, 2019; Brunetti et al., 2020). Previous evidence has shown that structural characteristics play a key role in creating overeducation, thus showing that both demand-side and supply- side policies are needed (Esposito & Scicchitano, 2022; 2023).

From the demand point of view, the specialization in traditional and low-skilled jobs push tertiary-educated workers towards these sectors and firms, thus fostering overeducation. Therefore, to avoid the risk of unemployment due to deskilling, firms need to select and allocate workers efficiently and create enough high-skilled jobs in innovative high-tech and knowledge-intensive sectors. On-the-job training policies aimed at reducing skill obsolescence are also relevant, especially in more technologically intensive sectors. Improving human capital through on-the-job training helps firms to make fuller and more efficient use of their skills. This in turn has a positive impact on their productivity, creating a virtuous circle. It is hoped that an industrial system is capable of rewarding merit and allowing those who deserve it to move up.

In terms of skills supply, there is a need to refocus education policy in Trinidad and Tobago to reduce the problem of over-education and to promote the matching of supply and demand in the labour market. These educational services can provide young people with appropriate skills to help them enter the labour market in a short period of time. However, our analysis focused on the issue of vertical mismatch, where the level of skills or education is more or less than the level of skills or education required to perform a job. Therefore, we cannot discuss in detail which type of education is more in demand in the labor market. A further analysis of the horizontal education-job mismatch could be carried out, where the research concerns the mismatch of the type of education rather than the level of education appropriate for a job.

In addition, improving the quality of educational services, which would provide the necessary skills that are in demand in the labor market, would contribute to reducing overeducation among youth. Although our empirical analysis did not explicitly control for the quality of education, most analytical reports indicate that the shortage of skilled labor is one of the most important issues for private sector development. Bearing in mind the findings of this paper, it provides an interesting starting point to begin the educational mismatch discussion for Trinidad and Tobago, as further research can be done in areas to explore the horizontal mismatch, the role of personality traits, as well as the intensity of educational mismatch for the main revenue earners for Trinidad and Tobago and Caribbean islands such as the energy and manufacturing sectors.

Funding This work received no funding.

Declarations:

Conflict of Interest: No potential conflict of interest was reported by the author(s).

References

1. Aina, C. & Pastore, F. (2012). Delayed Graduation and Overeducation: A Test of the Human Capital Model versus the Screening Hypothesis, *IZA discussion paper,* 6413.
2. Alattas, H. (2023). Overeducation in Arab Labour Markets; Different Measures, Different Outcomes. *European Journal of Sustainable Development,* 12(1): 91. https://doi.org/10.14207/ejsd.2023.v12n1p91
3. Alleyne, P., Demas, W., & Warner, E. (1984). Republic of Trinidad and Tobago. The Imperatives of Adjustment: Draft Development Plan 1983-1986: Report of the Task Force appointed by Cabinet to formulate a multi-sectoral development plan for the Republic of Trinidad and Tobago. Port-of-Spain: Government Printry.

4. Antman, F. M., Duncan, B., & Trejo, S. J. (2023). Hispanic Americans in the Labor Market: Patterns over Time and across Generations. *Journal of Economic Perspectives,* 37(1):169-198. https://doi.org/10.1257/jep.37.1.169
5. Baktash, M. B. (2023). Overeducation, Performance Pay and Wages: Evidence from Germany, GLO Discussion Paper, 1327, Global Labor Organization (GLO), Essen. http://hdl.handle.net/10419/276272
6. Basso, G. (2019). The evolution of the occupational structure in Italy in the last decade. Questioni di Economia e Finanza (Occasional Papers) 478, Bank of Italy, Economic Research and International Relations Area.
7. Battu, H., & Bender, K. (2020). Chapter 20-Educational Mismatch in developing countries: A Review of the existing evidence, In the Economics of Education: A Comprehensive Review, edited by Steve Bradley and Colin Green. Amsterdam, Netherlands: Elsevier Ltd.
8. Brintseva, O. (2023). The Returns to Education and Role of Overeducation: An Empirical Analysis Using Panel Data from Ukraine. *Social Sciences Research Network,* 1-20. https://dx.doi.org/10.2139/ssrn.4627990
9. Brunetti, I., Intraligi, V., Ricci, A., & Cirillo, V., (2020). Low-skill jobs and routine tasks specialization: New insights from Italian provinces. Papers Regional Sci. 99 (6), 1561–1581. https://doi.org/10.1111/pirs.12538
10. Cabus, S., & Somers, M. (2018) Mismatch between education and the labour market in the Netherlands: is it a reality or a myth? The employers' perspective, *Studies in Higher Education,* 43(11): 1854-1867.
11. Capsada-Munsech, Q. (2024). Do secondary education systems influence the overeducation risk of university graduates? A cross-national analysis by field of study and social background. *International Journal of Comparative Sociology,* 65(1). https://doi.org/10.1177/00207152241228148
12. Caroleo, F.E., & Pastore, F. (2018). Overeducation at a Glance. Determinants and Wage Effects of the Educational Mismatch Based on AlmaLaurea Data. *Social Indicators Research,*137(3): 999-1032.
13. Chen, L., & Hu, J. (2023). Overeducation and Social Integration Among Highly Educated Migrant Workers in China. *Social Indicators Research*, 170: 25-49. https://doi.org/10.1007/s11205-023-03145-2
14. Chernozhukov, V., Fernández-Val, I., & Melly, B. (2013). Inference on counterfactual distributions. *Econometrica,* 81(6), 2205–2268. https://doi.org/10.3982/ECTA10582

15. Chevalier, A. (2003). Measuring over-education. *Economica,* 70(279), 509–531. https://doi.org/10.1111/1468-0335.t01-1-00296.
16. Choe, C., & Van Kerm, P. (2018). Foreign Workers and Wage Distribution: What Does the Influence Function Reveal. *Econometrics,* 6(41):1-26. http://dx.doi.org/10.3390/econometrics6030041
17. Choi, A., Guio, J., & Escardibul, J. O. (2020). The challenge of mapping overeducation and overskilling across countries: a critical approach using PIAAC. Compare: A Journal of Comparative and International Education, 50(2), 237-256.
18. Deaton, A. (1985). Panel data from time series of cross-sections. *Journal of Econometrics*, 30(1-2):109-126. https://www.princeton.edu/~erp/ERParchives/archivepdfs/M317.pdf
19. Dendir, S. (2023). Intergenerational educational mobility in Sub-Saharan Africa. *World Development Sustainability*, 2(100072):1-13. https://doi.org/10.1016/j.wds.2023.100072
20. Ege, A. A., & Erdil, E. (2023). A Review of Empirical Research on Vertical Mismatch and Field of Study Mismatch in Turkey and Additional Evidence from their Overlapping Mismatch. *Ankara Üniversitesi SBF Dergisi,* 78(4), 761-783. 10.33630/ausbf.1161828
21. Eguía, B., Rodríguez González, C., & Serrano, F. (2023). Overeducation and scarring effects on the wages of young graduates. *International Journal of Manpower*, 44(4): 755-771. https://doi.org/10.1108/ijm-02-2022-0075
22. Esposito P., & Scicchitano, S. (2023). Drivers of skill mismatch among Italian graduates: the role of personality traits. *Applied Economics*, 55(40): 4642-4663.
23. Esposito, P., & Scicchitano, S. (2022). Educational mismatch and labour market transitions in Italy: Is there an unemployment trap? *Structural Change and Economic Dynamics*, 61: 138-155.
24. Fortin, N., Firpo, S., & Lemieux, T. (2009). Unconditional Quantile Regressions. *Econometrica,* 77(3):953-973. http://dx.doi.org/10.3982/ECTA6822
25. Francisco Castro, J., Ortega, L., Yamada, G., & Mata, D. (2023). Overeducation and Overskilling in Latin America: evidence from PIAAC. *Comparative Education,* 1-19. https://doi.org/10.1080/03050068.2023.2244263
26. Freeman, R. B. (1987). How Do Public Sector Wages and Employment Respond to Economic Conditions? New York: National Bureau of Economic Research (NBER). http://www.nber.org/chapters/c7154
27. Frei C., A., & Sousa-Poza, (2012). Overqualification: permanent or transitory? *Applied Economics*, 44(14), 1837-1847.

28. Gaeta, G.L., Lavadera, G.L., & Pastore, F. (2017). Much Ado about Nothing? The Wage Penalty of Holding a PhD Degree but Not a PhD Job Position. Skill Mismatch in Labor Markets. *Research in Labor Economics,* 243-277. http://dx.doi.org/10.1108/S0147-912120170000045007
29. Guillerm, M. (2015). Les méthodes de pseudo-panel. Documents de Travail de l'Insee - INSEE Working Papers m2015-02, Institut National de la Statistique et des Etudes Economique.
30. Guillerm, M. (2017). Pseudo-panel methods and an example of application to Household Wealth data, *Economics and Statistics*, 491-492.
31. Handel, M.J., Valerio, A., & Sanchez. P. M. (2016). *Accounting for Mismatch in Low- and Middle-Income Countries, Directions in Development.* Washington, DC: World Bank.
32. Hartog, J. (2000). Over-education and earnings: Where are we, where should we go? *Economics of Education Review*, 19 (131e147).
33. Heckman, J. J., Lochner, L. J., & Todd, P. E. (2003). Fifty Years of Mincer Earnings Regressions. New York: National Bureau of Economic Research (NBER).
34. Kemelbayeva, S. (2020). Returns to schooling in Kazakhstan: an update using a pseudo-panel approach. *Eurasian Economic Review,* 10: 437-487. https://doi.org/10.1007/s40822-020-00148-z
35. Korwatanasakul, U. (2022). Returns to Schooling in Thailand: Evidence from the 1978 Compulsory Schooling Law. *The Developing Economies*, 61(1):3-35. https://doi.org/10.1111/deve.12341
36. Leuven, E., & Oosterbeek, H. (2011). Overeducation and mismatch in the labor market. In E. A. Hanushek, S. Machin, and L. Woessmann (Eds.), Handbook of the economics of education, 4: 283e326.
37. Mateos-Romero L, & Salinas-Jiménez, M. M. (2018). Labor mismatches: Effects on wages and on job satisfaction in 17 OECD countries. *Social Indicators Research*, 140(1):369–391
38. Mc. Guinness, S., Pouliakas, K., & Redmond, P. (2018). Skills Mismatch: Concepts, Measurement and Policy Approaches. *Journal of Economic Surveys,* 32(4): 985-1015. https://doi.org/10.1111/joes.12254
39. McGuinness S., & Sloane P.J. (2011). Labour market mismatch among UK graduates: An analysis using REFLEX data. *Economics of Education Review*, 30: 130-145.
40. McGuinness, S. & Byrne, D. (2015). Born abroad and educated here: examining the impacts of education and skill mismatch among immigrant graduates in europe. *IZA Journal of Migration,* (4).

41. Mehta, A., Felipe, J., Quising, P., & Camingue, S. (2011). Overeducation in developing economies: How can we test for it, and what does it mean? *Economics of Education Review*, 30: 1334–1347.
42. Meliciani, V., & Radicchia, D. (2016). Informal networks, spatial mobility and overeducation in the Italian labour market. Annals of Regional Science, 56(2), 513–535. https://doi.org/10.1007/s00168-016-0752-y
43. Mendes de Oliveira, M., Santos, M., & Kiker, B. (2000). The Role of Human Capital and Technological Change in Overeducation. *Economics of Education Review,* 19: 199-206.
44. Mincer, J. (1974). Schooling, Experience and Earnings. New York: National Bureau of Economic Research (NBER).
45. Ministry of Planning and Development (MPD). (2002). Public Sector Investment Programme 2003. Port-of-Spain: Republic of Trinidad and Tobago. https://www.finance.gov.tt/wp-content/uploads/2013/11/pub18.pdf
46. Neugebauer, M. (2015). The Introduction of bachelor's degrees and the Under-representation of Students from Low Social Origin in Higher Education in Germany: A Pseudo-Panel Approach. *European Sociological Review*, 31(5): 591-602. https://doi.org/10.1093/esr/jcv061
47. Ortiz L., A. Kucel. (2008). Do Fields of Study Matter for Over-education?The Cases of Spain and Germany. *International Journal of Comparative Sociology*, 49(4-5): 305-327.
48. Passaretta, G., Sauer, P., Schwabe, U., & Wessling, K. (2023). The role of overeducation and horizontal mismatch for gender inequalities in labor income of higher education graduates in Europe. *Research in Comparative and International Education*, 18: 123-146. https://doi.org/10.1177/17454999231158042
49. Patrinos, H. (2016). Estimating the return to schooling using the Mincer equation. The IZA World of Labor, 278-278. https://doi.org/10.15185/izawol.278
50. Peng, J., Li, J., Ma, L., & Lv, Z. (2023). The Contribution of Work Experience on Earnings Inequality of Migrant Workers: Decompositions Based on the Quantile Regression Equation. *Research on World Agricultural Economy*, 4(1): 73-82. http://dx.doi.org/10.36956/rwae.v4i1.819
51. Peng, L. Zhang, S., & Gu, J. (2016) Evaluating the competency mismatch between Master of Engineering graduates and industry needs in China, *Studies in Higher Education,* 41:3, 445-461,

52. Republic of Trinidad and Tobago (ROTT). (1988). Restructuring for Economic Independence: Draft Medium-Term Programme 1989-1991. Port-of-Spain: National Planning Commission.
53. Republic of Trinidad and Tobago (ROTT). (1990). Restructuring for Economic Independence. Draft Medium Term Macro Planning Framework 1989-1995. Port-of-Spain: National Planning Commission.
54. Rim, H., & Kim, J. (2023). Status Inconsistency, Gender, and Health in Korean Young Adults: Separating Educational and Skill Mismatch. *Social Indicators Research,* 170: 1141–1153. https://doi.org/10.1007/s11205-023-03243-1
55. Sanchez-Sanchez, N., & S. McGuiness. (2015). Decomposing the impacts of overeducation and overskilling on earnings and job satisfaction: An analysis using REFLEX data. *Education Economics,* 23: 419–432.
56. Scicchitano, S., Biagetti, M., & Chirumbolo, A. (2020). More insecure and less paid? The effect of perceived job insecurity on wage distribution, *Applied Economics,* 52(18):1998-2013.
57. Toimbek, D. (2022). Building human capital in Kazakhstan: Information-processing skills and socio-economic outcomes of the population. *Journal of Adult and Continuing Education,* 29: 683 - 702. https://doi.org/10.1177/14779714221145861
58. Tran, D. B., & Paweenawat, S. W. (2023). The returns to education and wage penalty from overeducation: New evidence from Vietnam. *Bulletin of Economic Research*, 75(4), 1267-1290. https://doi.org/10.1111/boer.12409
59. Trinidad and Tobago House of Representatives. (1991). 31st Sitting-5th Session-3rd Republican Parliament. In Hansard, May 31st, 1991, 693-704. https://www.ttparliament.org/wp-content/uploads/2022/01/hh19910531.pdf
60. Verbeek, M. J. C. M. (1993). Pseudo Panel Data. *Reprint Series/CentER for Economic Research*, 122: 303-314. https://pure.uvt.nl/ws/files/1180185/VM5613003.pdf
61. Verhaest, D. & Omey, E. (2010). The determinants of overeducation: Different measures, different outcomes? *International Journal of Manpower,* 31(6): 608–625. https://doi.org/10.1108/01437721011073337
62. Verhaest, D., & Omey, E. (2006). The Impact of Over-education and its Measurement. *Social Indicators Research,* 77:419-448.
63. Verhaest, D., Schatteman T., & Van Trier, W. (2015). Overeducation in the Early Career of Secondary Education Graduates: An Analysis Using Sequence Techniques. *Young,* 23(4):336-356.

64. Wiers-Jenssen, J., & Try, S. (2005). Labour market outcomes of higher education undertaken abroad. *Studies in Higher Education*, 30(6):681-705,
65. Zveglich, J. E., Rodgers, Y., & Laviña, E. (2019). Expected work experience: a new human capital measure. *Asian Development Bank Economics*, 570. http://dx.doi.org/10.22617/WPS190005-2