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Race-based Educational, Occupational, and Industry Segregation and Wage Gaps in Trinidad and Tobago

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Abstract

As a result of its colonial history the labour market of Trinidad and Tobago is characterized by two majority racial groups of approximately equal number. During colonial times, these racial groups were highly segregated in terms of education, occupation, industry, and sector of work, and the institutionalized disparities in pay were large. This raises the question whether segregation and historical wage gaps still exist and are affected by the government in power. Using labour market survey data from 1999 to 2015, this study provides evidence of race-based educational, occupational, and industry segregation and wage gaps in Trinidad and Tobago's private and public sectors and their development. Despite its history, aggregate racial educational and occupational segregation is low. With 7%, measured in terms of the Karmel-Maclachlan index, it is even lower than respective gender-based segregation over the same period, and it has remained constant over the sample period. Furthermore, the findings suggest that most race-based occupational segregation is a result of prior educational segregation. In aggregate terms the racial wage gap was initially negligible but has been rising over time and shifting from initially favouring ATTs (citizens of Trinidad and Tobago of African origin) to favouring ITTs (citizens of Trinidad and Tobago of Indian origin). There is, however, considerable heterogeneity in segregation and wage gaps across educational attainment levels, occupations, industries, and sectors. Race-based wage gaps appear larger in the public sector, especially for women. Although we cannot control for all unobserved factors, there is also indicative evidence that the party in power affects the racial share of public sector workers and public sector wage gaps. Using quantile regression and decomposition techniques, this study also provides evidence of large heterogeneity in returns to education and a shift in the direction of the average wage gap from favouring ATTs to favouring ITTs along the entire wage distribution.

Keywords: Caribbean; educational segregation; occupational segregation; wage gaps; race

JEL Codes: J15; J24; J31; J71; N16

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1. Introduction

Trinidad and Tobago is a small island country in the Caribbean. Its two main racial groups are of African and Indian origin, henceforth ATTs ad ITTs, respectively. ATTs were brought to the country as slaves to work in sugar plantations during colonial times, while ITTs mainly came as indentured workers to perform equivalent activities after emancipation in 1838. There is an extensive anecdotal literature on how Trinidad and Tobago has faced a latent ethnic rivalry between these two major racial groups over political power and ethnic representation in government since gaining independence from the United Kingdom in 1962 (Bissessar and Gaffar Le Guerre, 2013; Premdas, 2007).

Today, agriculture and sugar plantations play a very limited role in Trinidad and Tobago's economy. In recent years, Trinidad and Tobago has become an oil-based economy with a national oil company and a in international comparison large public sector representing about 30 percent of the work force. Trinidad and Tobago is a multi-party republic with two dominant parties whose voter base is largely divided along racial lines. From independence until the 1990s, Trinidad and Tobago's government was supported by a largely ATT voter base. Since the 1990s, governments with ATT and ITT voter bases have been alternating. Because of the country's large public sector, the ethnic politics literature suggests a potential for clientelism in cases of race-based voting behaviour. Kanchan (2004), for example, argues this based on the Indian experience, and Robinson and Verdier (2013) provide a theoretical model linked specifically to public sector employment.

Debates regarding race-based labour market outcomes often flare up during the periods leading up to the country's general elections. These have largely been dominated by anecdotal assertions of discrimination. Apart from one snapshot study on race-based wage gaps in 1993 by Coppin and Olsen (1998), empirical evidence on these issues is non-existent. This study aims to provide empirical evidence of the evolution of race-based segregation and a widening wage gap over the 17-year period between 1999 and 2015.

This study conducts a multi-year empirical analysis (1999 to 2015) to fill this information lacuna. Specifically, it aims to answer the following five main questions: (i) What is the extent and evolution of race-based educational, occupational, and industry segregation in the public and private sectors? (ii) To what extent does educational segregation impact later occupational and industrial segregation? (iii) What is the extent and evolution of race-based wage gaps over time, what is driving them, and are they more prevalent in one sector than the other? (iv) Do wage gaps vary over the income distribution in different sectors and occupations over time? and (v) What are the drivers of these distributional differences?

The study employs the standard methodologies used in the segregation and wage gap literature. Segregation is based on variations of the Duncan-Duncan Dissimilarity Index, which defines segregation as the unequal distribution of two groups, here ATTs and ITTs, in educational attainment levels, occupations, and industries. Furthermore, this study estimates the impact of educational segregation on occupational segregation. Following the wage gap literature, income differentials are estimated based on a Mincer earnings equation and associated Oaxaca-Blinder decomposition analysis. To test for heterogeneity, these are estimated at different levels of aggregation, i.e., separating public and private sector employees. To determine if there are race-based differences along the wage distribution, this study estimates quantile regressions and uses decomposition techniques following Machado and Mata (2005), Melly (2005, 2006), and the RIF decomposition developed by Forpin, Fortan, and Lemieux (2009).

The contributions of this study are fivefold. First, to our knowledge, this is the first study to empirically analyse race-based educational, occupational, and industrial segregation and wage gaps in the public and private labour markets in Trinidad and Tobago over time. The period from 1999 to 2015 covers three administrations associated with variations in ruling parties (from UNC to a coalition UNC-PNM in 2001, from this joint coalition to only PNM in 2002, and from PNM to UNC in 2010). This may potentially affect segregation levels and wage differentials, as the voter base of PNM consists mainly of ATTs, whereas the UNC consists mainly of ITTs (Premdas, 1996). Thus, this study also adds to the literature on ethnic politics, for which Trinidad and Tobago is one of the classic examples (e.g., Brown, 1999; Horowitz, 1985; and Sriskandarajah, 2005). Second, it provides insights on the long-term labour market impact of historical marginalization of certain racial groups and whether efforts to implement anti-discrimination policies are reflected in the labour market. Third, this study focuses on the non-white racial groups—ATTs and ITTs—each representing roughly 40 percent of the population.[1] It does not include whites or others as a reference group as is typical in the literature on race-based segregation. It can thereby inform the literature on the extent to which earlier findings also hold between two non-white races over time. Fourth, the analysis adds to the literature on clientelism and race-based voting that has been largely theoretical and qualitative by providing an empirical, quantitative perspective. Fifth, this study contributes to the broader academic

[1] The remaining 20 percent of the working age population consist mainly of individuals who classify themselves as mixed (19 percent) and a small minority of white, Chinese, Syrian/Lebanese, and other races.

literature in terms of comprehensiveness. Specifically, it links the race-based segregation and wage gap analysis and conducts a detailed heterogeneity analysis for each part by educational attainment level, occupational category, industry, gender, and public versus private sector combined with a decomposition analysis over the wage distribution. This contrasts with the previous literature, where these issues are analysed separately.

The broader literature has mainly focused on segregation and wage gaps along gender lines. A relatively limited number of studies address racial segregation and wage discrimination. These mainly focus on whites versus blacks in Brazil (Garcia, Ñopo and Salardi, 2009; Lovel, 2000; Pinto, 2014; Salardi, 2012), South Africa (Gardin, 2014; Gradin, 2017), and the United States (Card and Krueger, 1993; Chandra, 2000; Hegewisch and Hartmann, 2014), and majority versus indigenous population comparisons or a combination thereof, as examined in a cross-country study by Atal, Ñopo and Winder (2009) on seven Latin American countries and on Bolivia, Ecuador, and Guatemala by Canelas and Salazar (2014). A study on Guatemala by Canelas and Gisselquist (2017) specifically distinguished between different indigenous groups. In terms of racial segregation, the literature finds evidence for higher race-based occupational segregation for men than for women and overall persistent but lower race- than gender-based occupational segregation (Hegewisch and Hartmann, 2014; Salardi, 2014). Concerning racial wage gaps, the findings of Garcia et al. (2009) stress their importance, as these are found to be more prevalent in the case of Brazil than the in the literature more frequently analysed gender gaps. Likewise, Atal et al. (2009) find gaps on the order of 37.8 percent in favour of whites or the majority group, whereas gender wage gaps only range around 10 percent. Similarly, Gallardo and Ñopo (2009) observe larger ethnic than gender wage gaps in Ecuador. Unlike gender wage gaps, race-based wage gaps and segregation are found to be mostly attributable to differences in characteristics and can thus be attributed to earlier educational segregation rather than to unexplained factors, such as discrimination (Atal et al., 2009; Canelas and Salazar, 2014; Garcia et al., 2009; Gardin, 2017; Pinto, 2014; Salardi, 2012).

The importance of educational attainment in explaining race-based wage gaps in the region is in line with survey results of the Latinobarómetro survey analysed by Chong and Ñopo (2008), who found that educational shortcomings were a more important reason for discrimination than just race. These results suggest that there is reason to expect also in Trinidad and Tobago a closing wage gap because, since independence, the existing education gap (with ITTs being less educated than ATTs) has been closing, with ITTs now more educated than their ATT peers. Educational and occupational segregation, however, does not necessarily need to be informative about the extent of wage gaps across groups; as Lovell (2002) observed, that Brazil has the lowest wage gaps in the region together with the largest educational gaps. In terms of heterogeneity of the racial wage gap, Atal et al. (2009) finds that especially single males, full-time workers, and those in rural areas are most affected by racial wage gaps and observed larger gaps for older workers at both extremes of educational attainment. Garcia et al. (2009) further conclude that racial wage gaps have persisted over time and exhibit large regional heterogeneity, whereas gender wage gaps are more homogeneous across regions and have decreased over time. Conclusions on the impact of unobservable factors that constitute the wage gap along the wage distribution and over time by Pinto (2014) and Atal et al. (2009), however, differ.

The paper proceeds as follows. Section 2 presents the data. Section 3 outlines the methodologies to estimate segregation and wage gaps. The results of the segregation and wage gap analysis are presented in Section 4. The last section concludes.

2. Data

This study is based on data from Trinidad and Tobago's Continuous Sample Survey of Population (CSSP), labour force survey for the 17-year period from 1999 to 2015. The CSSP is a quarterly stratified rotating panel survey and is geographically representative by administrative district. This study does not exploit the panel structure; rather, it uses the individual observations as repeated cross-sections. To avoid seasonality and selection bias from potentially non-random response frequencies and responding as occupied due to the rotational panel design, we use the individual-level panel to identify the first observation of an individual in any year in the household and only include the first observation.[2] Observations of individuals currently out of the labour force, unemployed, or without information on educational attainment and current occupational category are dropped. Further, this study includes only the two main ethnic groups, ATTs and ITTs. The ethnicity of an individual is determined according to the responses provided to a survey question regarding the individual's ethnicity.[3] Overall, this resulted in samples of

[2] We first sort the data by year and quarter, then we identify duplicates in terms of household ID, individual ID, cward (district), enumeration district, and gender and drop all but the first observations of repeated observations. As the survey does not seem to track moved household but instead surveys the newly moved household replacing the previous at that location using the same ID number, we assume that if a unique individual ID is linked to a different gender it must be a different individual and should thus not be dropped as duplicates. This reduces excessive dropping of duplicates.

[3] Various authors, such as Cornwell, Rivera, and Schmutte (2016). Schwartzman (2007), and Telles and Lim (1998), note income-related variation in racial classification in Brazil and observe with rising income a rising likelihood of individuals to be classified as white rather than non-white, which through this channel affects measures of racial wage gap. Such strategic race reporting cannot be controlled for in this study, given its repeated cross-sectional rather than panel structure over time. A phenomenon of individuals more likely to claim being ATT or ITT at top versus bottom income levels or belonging to another race and thereby dropping out of the sample is in this study, however, assumed to be non-existent in Trinidad and Tobago, as there is no evidence for such behavior.

approximately 6,000 and 4,000 individuals per year for the segregation and wage gap analysis, respectively, with a sample of almost double the size in 1999.

The samples for the segregation and wage gap analyses differ slightly. The former analysis includes all working individuals in the labour force between 15 and 75 years of age, while the latter analysis restricts the sample to the employed workforce, excluding self-employed individuals, as their wage structure might be very different. As Table A.2 shows, the self-employed represent a similar share of working ATTs and ITTs. Therefore, we do not expect any selection bias from this restriction. Moreover, the wage gap analysis narrows the age group to only those up to 65 years of age to avoid selection bias for individuals still employed beyond the general retirement age. Table A.1 in the Appendix provides a detailed sample breakdown by year.

The segregation and wage gap analyses require information on educational background, occupation and industry of all working and employed individuals, respectively. Information on educational attainment comprises a combination of schooling levels and additional trainings obtained. These have been aggregated into seven educational categories, listed in Table 1, which are comparable to the categories defined based on labour market surveys in other Caribbean countries. While educational quality likely matters this aspect cannot be controlled for within this educational categorization, either within or across countries. The CSSP provides four-digit level occupational information for employed persons based on categories, which are compatible with the International Standard Classification of Occupations (ISCO-1968) at the 1-digit code level. The subsequent analysis will use only the more aggregate 1-digit codes (see Table 2), due to the limited sample size of the more disaggregated information at the 5-digit training code and 4-digit occupational code level. This ensures comparability of categories over time and across other countries, which is the focus of this study. Besides, it avoids other biases due to too small samples in each further disaggregated occupational category. While firm-specific wage premiums have also been found to be a very important determinant of wage gaps (Card, Cardoso, and Kline, 2015), we cannot control for firm-specific wage premiums, as such firm information is not available. Regarding industries, this study uses a Trinidad and Tobago-specific industry classification rather than the 1-digit internationally comparable industry classification, as only this data is available for all the sample years (see Table 3).[4] [5]

[4] Due to limited sample size and their relatedness, the first and second original category "Sugar (cultivation and manufacturing)" and "Other agriculture, forestry, hunting and fishing," and third and fourth original industry categories "Petroleum and gas inc. prod., refining and service contr." and "Other mining and quarrying" are grouped together for this analysis. Those observations answering "not applicable" or "other" to the industry classification question are dropped from the wage gap analysis.

While the literature generally draws on log of hourly wages as a dependent variable to control for wage differentials due to part-time work, some studies, such as Canelas and Gisselquist (2017), which focus on the total earnings gap, have also used monthly income. Due to data availability and the overall income difference being of main interest, this study uses gross monthly income from wage employment of the main job as reported. We refrain from transforming monthly wages into hourly wages, as the data only contain working hour information in bins of multiple hours, so that a transformation into hourly wage based on the mean hours of the hour bin, would result in highly volatile wages. Instead of using hourly wages to control for part-time wages, some authors, such as Atal et al. (2009), have resorted to using monthly wage income for all those employees who reported having worked at least 35 hours a week. Given the importance of the variable of the share of ATT employees in a given occupation, this study refrains from introducing any such restrictions. Doing so may affect the actual racial composition in a respective occupation in the sample and thereby not allow to correctly control for its impact in the earnings equation. All labour income amounts are inflation-adjusted local currency values with the Consumer Price Index (CPI) based in 2014. To control for outliers in reported income, observations at the top and bottom 5 percent of the distribution of each occupation are excluded from the reported income sample but are included in the sample of observations for which missing wage income is imputed. An additional robustness check includes only those reported and imputed income values within three standard deviations from the mean reported income per occupation in the wage gap estimations.

Table 1: Seven Educational Categories

Category Number	Highest Education / Training
1	Primary or less
2	Primary education or less with training
3	Some incomplete secondary but no O'levels
4	Some incomplete secondary but no O'levels with training
5	Secondary completed with O' levels or A'levels
6	Secondary completed with O' levels or A'levels with training
7	University degree

Source: Authors' own categories based on categories existing in the various surveys.

[5] Using alternatively the first digit of the international comparable industry classification would mean losing samples from 2009, 2014, and 2015 so that in this study the length of the sample period is considered more important than the industry comparability.

Table 2: 9 1-digit Occupational Code Categories

Category Code	1-Digit Occupational Code
1	Legislators, Senior Officials and Managers
2	Professionals
3	Technicians and Associate Professionals
4	Clerks
5	Service Workers and Shop and Market Sales Workers
6	Skilled Agricultural and Fishery Workers
7	Craft and Related Workers
8	Plant and Machine Operators and Assemblers
9	Elementary Occupations

Source: Authors' own categories based on 1st digit of categories existing in the various surveys.

Table 3: Trinidad and Tobago-Specific Industry Classification

Category Code	Industry Category
1	Sugar and Other Agriculture Fishery and Forestry
2	Mining, Petroleum and Gas
3	Other Manufacturing (Ex. Sugar and Oil)
4	Electricity and Water
5	Construction
6	Wholesale and Retail Trade, Restaurants, and Hotels
7	Transport Storage and Communication
8	Financing, Insurance, Real Estate, and Business Services
9	Community, Social, and Personal Services

Source: Authors' own categories based on Trinidad and Tobago-specific industry classification (see footnote 1).

Another potential bias may arise from the non-response rate to the income question of wage employees. While there are a sizable number of employees especially among ATTs in the later years who do not report their income, when restricting the sample to employed respondents with information on education and occupation, response rates of on average 80 percent to the income question (see Figure A.1 in the Appendix) are of similar or even higher magnitude than in the often used US Current Population Survey (CPS) Census data discussed in Bollinger et al. (2018). Table A.3 in the Appendix shows sample statistics of characteristics among employees that do and do not respond to the wage questions. Generally, ATTs face a higher non-response rate concerning wages than ITTs. In line with findings by Bollinger et al. (2018), who find that non-response to the income question is more prevalent at the extreme ends of the income distribution, Table A.3 shows slightly higher non-response rates among university-educated respondents. As those with the highest levels of educational attainment enter occupations that are likely to be higher paid, this confirms Bollinger et al.'s (2018) findings. Nevertheless, we chose not to correct for non-response, as Bollinger et al. (2018) show that the common approach of reweighting the observations that respond to the income question by the inverse probability of responding has in most cases hardly any effect on the estimates. Therefore, we proceed with the analysis without correcting for non-response to the income question and estimate wage gaps only for the sub-sample that responds to the income question. Except in robustness checks, we do not impute incomes for those employees, who failed to report their income.

3. Methodology

3.1 Estimating Segregation Levels

To answer the first main research questions on the extent and evolution of race-based educational, occupational, and industry segregation in the public and private sector, this study uses standard race-based segregation indices for different educational attainment levels, occupational categories, and industries. Segregation occurs when a specific group is overrepresented in some occupations, industries, or educational status and underrepresented in others. This study estimates three alternative indices: the Duncan-Duncan Dissimilarity Index (DD) (Duncan and Duncan, 1955), the Karmel-Maclachlan Index (KM) (Karmel and Maclachlan, 1988), and the Gini index to measure educational, occupational, and industrial segregation, abbreviated as ES, OS, and IS, respectively. These measures are first calculated for the overall labour market and then separately by gender and for the public and private sectors. In terms of occupational segregation, the DD index estimates the proportion of ATTs that would have to change their occupation to achieve a racial balance among occupations. A drawback of this index is that redistributing ATT workers to remove all occupational segregation would lead to a different occupational structure of the working labour force. To overcome these problems, the KM index accounts for changes in occupation by ITTs and ATTs necessary to achieve a state without segregation, or equal occupational distributions for both racial groups, while maintaining the original occupational structure (Karmel and Maclachlan, 1988). The Gini index measures the inequality of the racial representation in different occupations (Silber, 2012).

3.2 Determining Impact of Educational Segregation on Occupational Segregation

Conditional on achieving a certain level of education, there are various possible labour market outcomes that subsequently affect the level of OS and IS in three ways, such that ES need not move in line with OS and or IS. This is the focus of the second research sub-question. For this part of the analysis, this study follows the methodology developed by Borghans and Groot

(1999), which was also applied in Sookram and Strobl (2009). ATTs and ITTs with educational attainment levels typical for their own racial group may work in similar occupations, thus compensating for their educational segregation by reintegrating (R). Alternatively, both racial groups can, after having attained the same level of education, take a job in similar occupations, which decreases (D) the OS, or take up a job in different occupations, which increases (I) the OS. Hence, one can formally write the relationship between ES and OS as follows:

$$\text{OS} = \text{ES} + \text{I} - \text{D} - \text{R} \tag{1}$$

The impact of ES on OS is thus driven by individuals not reintegrating and can be calculated as:

$$\text{Impact} = \left(1 - \frac{\text{R}}{\text{ES}}\right) * 100 \tag{2}$$

A lower impact value implies a lower effect of ES on OS and vice versa. This formula can be adapted to either express the aggregate impact of ES on OS or the specific impact of ES on OS in a given occupation.[6] In each step, OS can be replaced by IS to measure the impact of ES on IS.

3.3 Mean Wage Gap Analysis

3.3.1 Mean Wage Gap Calculation

The methodology to answer the third main research question concerning the existence and potential driving forces of a wage gap between ATTs and ITTs rests on a descriptive measure of the raw mean gap and the estimation of standard earnings equations in the form of a simple linear model of log wages and a set of control variables, $ln\, y = \beta x + \varepsilon$. Developed by Mincer (1974), this methodology allows us to test several hypotheses. First, we test H1: “There exists a wage difference between ATTs and ITTs.”

As a more descriptive measure, the mean wage gap in time t is determined as a percentage of ITTs’ mean wage with respect to the ATTs’ mean wage $\overline{\%WageGap}_t = \frac{\overline{(\text{income}_{\text{employees}})}_{tITT}}{\overline{(\text{income}_{\text{employees}})}_{tATT}}$. Hence, a gap >100 percent implies a gap in favour of ITTs, while a gap <100 percent stands for a wage gap in favour of ATTs. For the purpose of a heterogeneity analysis, the mean racial wage gap can, aside from as an aggregate in the same manner, be determined for each educational level, occupational category, industry, economic sector, and gender. This will

[6] See Borghans and Groot (1999) for more details on the methodology.

provide an answer concerning the existence, extent, heterogeneity, and potential driving forces of the mean racial wage gap.

To estimate the existence of a wage gap controlling for the individual's characteristics, we start our analysis by estimating separate earnings equations for each individual year and subsequently estimate an earnings equation over the whole period, including year fixed effects. In this analysis, log wage income is assumed to be a function of age, age squared, a measure of experience, gender, race, household location in urban versus rural area, public or private sector of employment, educational attainment, and industry. In addition, occupational category dummies or the share of ATT employees in an occupational category are included interchangeably in the individual year equations and both in the earnings equation with year fixed effects.[7] Given the concern about race-based discrimination unrelated to differences in endowments, we estimate earnings equations separated by race as follows:

(1a) $$\log(income\_employees)_{tr} = a + \beta_1 age_{tr} + \beta_2 age_{tr}^2 + \beta_3 male_{tr} + \beta_4 urban_{tr} + \beta_5 privatesec_{tr} + \beta_6 occup\_intens_{tr} + \sum_{educ\_cat=1}^{6} \beta_{educ\_cat} Dummy_{educ\_cat_{tr}} + \sum_{occup_{cat}=1}^{8} \beta_{occup\_cat} Dummy_{occup\_cat_{tr}} + \sum_{industry\_cat=1}^{8} \beta_{industry\_cat} Dummy_{industry\_cat_{tr}} + \varepsilon$$

Here, the subscripts t and r stand for the given year and ATT and ITT individuals, respectively. Differences in all or some of the coefficients between the earnings equations estimated for ATTs and ITTs suggest a difference in return to the respective characteristic based on race. To demonstrate the variation in the wage structure of the two races, the earnings equation is additionally estimated as a pooled model (1b), which assumes wage differences solely due to differences in characteristics rather than also in wage structure. Here, i identifies the individual observation irrespective of race.

(1b) $$\log(income\_employees)_{ti} = a + \beta_1 age_{ti} + \beta_2 age_{ti}^2 + \beta_3 male_{ti} + \beta_4 urban_{ti} + \beta_5 privatesec_{ti} + \beta_6 occup\_intens_{it} + \beta_7 race_{ti} + \sum_{educ\_cat=1}^{6} \beta_{educ\_cat} Dummy_{educ\_cat_{ti}} + \sum_{occup\_cat=1}^{8} \beta_{occup\_cat} Dummy_{occup\_cat_{ti}} + \sum_{industry\_cat=1}^{8} \beta_{industry\_cat} Dummy_{industry\_cat_{ti}} + \varepsilon$$

In this pooled earnings equation (1b), the coefficient β_7 is of particular interest. A positive and significant coefficient β_7 implies that given its characteristics an ITT individual will earn more, whereas a negative significant coefficient would suggest the reverse. Whether positively or negatively significant, this would give support to H1 that there exists a race-based wage difference.

However, the reported income noted in the surveys is likely affected by selection bias into the labour market. Alternatively, mean real wages are hence predicted in an earnings equation, which corrects the income for selection bias of actually being an employee and not out

[7] Including both at the same time in the individual year equations leads to the omission of the share of ATT variable.

of the labour force, unemployed, or self-employed using a two-stage multinomial logit approach developed by Bourguignon et al. (2007). This builds on Lee (1983) and Dubbin and McFadden (1984), who expanded the general Heckman (1979) selection model for more than just binary categories.

In a first step, selection into wage employment is estimated by using a multinomial logit model expressed as (2) to control for selection bias from individual i of racial group r ={ATT, ITT} being in any of the four labour market status categories j:

$$\text{Where } j \in J = \begin{bmatrix} 1 \text{ if out of the labour force} \\ 2 \text{ if unemployed} \\ 3 \text{ if employed} \\ 4 \text{ if self-employed} \end{bmatrix}$$

(2) $$P_{irtj} = P(y_i = j) = \Pr(j|Z_i) = \frac{e^{Z_i\beta_j}}{\sum_{j=1}^{4} e^{Z_i\beta_j}} ,$$

whereby z_i is a vector of age, relationship to the household head, marital status, and a dummy variable for the individual being male. The selection correction is thus based on the assumption that the variables included in vector z_i are good estimators to explain selection into the labour market and further into wage employment. Subsequently, in the second stage the inverse mills ratios, m1, m2, m3, and m4, which are estimates of the multinomial logit function for each category j, are included into a weighted least square earnings equation regression model expressed as:[8]

(3) $$\log(income\_employees)_{tr} = a + \beta_1 age_{tr} + \beta_2 age_{tr}{}^2 + \beta_3 male_{tr} + \beta_4 urban_{tr} + \beta_5 privatesec_{tr} + \sum_{educ\_cat=1}^{6} \beta_{educ\_cat} Dummy\_educ\_cat_{tr} + \sum_{occup\_cat=1}^{8} \beta_{occup\_cat} Dummy\_occup\_cat_{tr} + \sum_{industry\_cat=1}^{8} \beta_{industry\_cat} Dummy\_industry\_cat_{tr} + \beta_6 m1_{tr} + \beta_7 m2_{tr} + \beta_8 m3_{tr} + \beta_9 m4_{tr} + \varepsilon$$

As in the standard OLS earnings equation, also this selection-corrected income earnings equation will be estimated, separated for each year t and each race r.[9]

The coefficients of this selection-corrected earnings equation subsequently allow for all those respondents with missing income the imputation of a selection-corrected income value based on the respondents' individual characteristics. In the following, the notation 'selection-corrected income' refers to the sample consisting of those individuals who reported their income, complemented by those individuals for whom income figures could be predicted based

[8] Here, instead of using an OLS model it is opted for a weighted least square model, which can take heteroscedasticity arising due to selection into consideration, as outlined in Bourguignon et al. (2007).
[9] The selection corrected earnings equation model has been estimated using the user written Stata command selmlog, developed by Bourguignon et al. (2007).

on the selection-corrected earnings equation estimates using a model including occupational dummies.[10]

Apart from the standard yearly earnings equations by race, we construct a pseudo-panel including all sample years. We then estimate a fixed effects model with year-fixed effects akin to (1b) to test our first hypothesis and several others.

This can be written as follows:

(4) $\log(income\_employees)_{it} = a + \beta_1 age_{it} + \beta_2 age_{it}^2 + \beta_3 male_{it} + \beta_4 urban_{it} + \beta_5 privatesec_{it} + \beta_6 share\ ATT\_occup_{it} + \beta_7 race_{it} + \beta_8 year + \sum_{educ\_cat=1}^{6} \beta_{educ\_cat} Dummy_{educ\_cat_{it}} + \sum_{occup_{cat}=1}^{8} \beta_{occup\_cat} Dummy_{occup\_cat_{it}} + \sum_{industry\_cat=1}^{8} \beta_{industry\_cat} Dummy_{industry\_cat_{it}} + \varepsilon$

A signification coefficient β_7 will hence provide support for H1 over the entire period, and the year-fixed effect ensures that the coefficient is not driven by the existence of a wage gap in a particular year. Second, we test whether H2: "The party in power at the national government affects the income level and the size and direction of the racial wage gap" using equation (5).

(5) $\log(income\_employees)_{it} = a + \beta_1 age_{it} + \beta_2 age_{it}^2 + \beta_3 male_{it} + \beta_4 urban_{it} + \beta_5 privatesec_{it} + \beta_6 share\ ATT\_occup_{it} + \beta_7 race_{it} + \beta_8 year + \beta_9 ATT\_government_{it} * race_{it} + \beta_{10} ATT\_government_{it} + \sum_{educ\_cat=1}^{6} \beta_{educ\_cat} Dummy_{educ\_cat_{it}} + \sum_{occup_{cat}=1}^{8} \beta_{occup\_cat} Dummy_{occup\_cat_{it}} + \sum_{industry\_cat=1}^{8} \beta_{industry\_cat} Dummy_{industry\_cat_{it}} + \varepsilon$

The variable $ATT\_government$ herein represents the government fixed effect, a dummy, which takes the value 1 if a PNM-led government with an ATT voter base is in power and 0 if a UNC government with an ITT voter base is in power. Government changes are accounted for in the first full calendar year that the new government has taken power. As the majority ATT-backed party wins the elections in 2002 and loses power to the majority ITT-backed opposition in the elections in 2010, the $ATT\_government$ dummy takes the value 1 for the years 2003-2011. Changing the period in a robustness check to just 2003-2010 does not change the significance of the findings. A significant coefficient β_9 thus implies that the government matters. A positive coefficient suggests that the wage and thus it is also likely that the gap in favour of ITTs increases with a PNM government, and a negative coefficient that the wage of ITTs and likely as a consequence the wage gap decreases with a PNM government. While the government has the power to engage in clientelism and change the racial composition of public sector employees, especially through short-term contracts, we hypothesize that H3: "There is no direct reason to believe that private-sector short-term contracting cycles follow the national

[10] While selection-corrected income levels could likewise be computed based on a model including the variable share of ATTs in an occupation, for simplicity here only the coefficients of the occupational dummy model are included.

government's electoral cycle and affect private sector racial wage gaps." Third, we therefore estimate model (6) separate for the public and private sector denoted by p.

(6) $$\log(income_{employees})_{itp} = a + \beta_1 age_{itp} + \beta_2 age_{itp}{}^2 + \beta_3 male_{itp} + \beta_4 urban_{itp} + \beta_6 share\ ATT\_occup_{itp} + \beta_7 race_{itp} + \beta_8 year + \beta_9 government_{itp} * ethnic_{itp} + \beta_{10} government_{itp} + \sum_{educ_{cat}=1}^{6} \beta_{educ_{cat}} Dummy_{educ_{cat itp}} + \sum_{occup_{cat}=1}^{8} \beta_{occup_{cat}} Dummy_{occup_{cat itp}} + \sum_{industry_{cat}=1}^{8} \beta_{industry_{cat}} Dummy_{industry_{cat itp}} + \varepsilon$$

Subsequently, we test for the equality of coefficients of the government-race fixed effect in the private and public-sector model and only expect the government-race fixed effect to become significant in the public-sector model. Furthermore, we hypothesize that discrimination can occur through quantity and quality of the jobs. Hence, we test, as a sub-hypothesis of H3, whether the share of public employment is differently affected depending on race during times of an ATT government, to provide evidence for the quantity effect. At first, we calculate the share of public employment of each race by year, providing us with 17 observations per race given the 17-year period studied. To increase the number of observations and also control for gender, age, and education, we estimate the share of public employment in each interacted gender, age, educational level, and year group, to have a separate share for each sub-group, for example, for women aged 15-24 with a university degree in 2009, and estimate equation (7):

(7) $$share\_public\_empl_{gtr} = a + \beta_1 ATT\_government_t + \beta_2 year_t + \beta y_{gtr} + \varepsilon\ ,$$

where the subscript g stands for the respective subgroup and $\beta\gamma_{gtr}$ represents a vector of control variables. We estimate (7) separate by race and compare the significance and sign of the coefficient β_1, whereby a more positive or a less negative coefficient of β_1 on an ATT sample hence provides support for H3. This would suggest that ATTs benefit from an ATT government in terms of probability of being employed in the public sector.

Regressing having an ATT government in power on the wage gap informs about discrimination based on quality of jobs, which is likely only or to a greater extent affecting the public sector. As the government in power is likely to only affect new short-term hires and largely for jobs at the lower half of the wage distribution, we hypothesize as H4, in line with H3, that having an ATT-backed government in power increases the wage gap in favour of ITTs in the public sector but not in the private sector, using a more direct model with the wage gap as the dependent variable. To estimate the mean effect without controls, we first estimate mean wages for each racial group in each year, as discussed above. Subsequently, we estimate mean wages for respective sub-groups. Based on these, we can calculate the wage gap for each sub-group as discussed for model (7) and estimate model (8):

(8) $\overline{wage\_gap}_{gtp} = a + \beta_1 ATT\_government_{tp} + \beta_2 year_t + \beta y_{gtp} + \varepsilon$

Observing a positive coefficient $\beta_1$would thus support H4, as a rising wage gap implies a gap in favor of ITTs.

3.3.2 Mean Wage Gap Decomposition

Apart from disaggregating the aggregate mean wage gap between ITTs and ATTs for various categories, this study uses the commonly used wage gap decomposition methodology of Oaxaca (1973) and Blinder (1973) to determine the drivers of the wage gap. This method distinguishes between the effect of characteristics, which is the explained part of the wage gap, and the effect of coefficients, which is the unexplained, wage structure part often interpreted as discrimination.

(9) $WageGap_t = \overline{\log(\imath ncome\_employees)}_{tI} - \overline{\log(\imath ncome\_employees)}_{tA} = \beta_{tITT}\ \underbrace{(\bar{x}'_{tI} - \bar{x}'_{tA})}_{\text{Effect of Chararacteristics}} + \underbrace{(\beta_{tI} - \beta_{tA})\bar{x}_{tA}{}'}_{\text{Effect of Coefficients}}$

For this decomposition this study refrains from using selection-corrected estimates; rather, it uses a sample of only those who reported income and this sample's standard earnings equation estimates. As pointed out by Neuman and Oaxaca (2004), using the former would create new biases through its assumptions regarding the model specification and the distribution. Moreover, decomposition analyses including selection-correction terms are highly susceptible to the way this term is accounted for, such as either as a separate factor, or taking varying weights on the endowment and discrimination part of the decomposition of the wage gap (Neuman and Oaxaca, 2004). General limitations of this popular decomposition technique, however, remain. These are its sensitivity to the choice of the base group and that it decomposes the wage gap solely at the mean, rather than over the distribution, as discussed in Oaxaca and Ransom (1999). To address the shortcomings regarding the sensitivity to the dummies' base category, this decomposition is as a robustness check also estimated using the specification with the share of ATTs in each occupation.

3.4 Wage Gap along Income Distribution - Estimation and Decomposition

As the wage gap and its determinants may well differ along the wage distribution and are the focus of the fourth main research sub-question, this study estimates earnings equations and decomposes the resulting wage gaps at every quantile.

3.4.1 Wage Gap along Distribution based on Mean Earnings Equation

First, the wage gap based on reported income estimated from the earnings equations separated by race is displayed at every percentile of the wage distribution. Second, the share of ATTs in an occupation is plotted over the wage distribution to show how certain racial dominance in an occupation may affect overall wages. Similarly, Banerjee (2014) observed, independent of gender, lower incomes for those employed in female-dominated occupations. Third, considering that selection into the labour force and also being employed differs along the income distribution, different selection-corrected income earnings equations are estimated for different income groups, as discussed below and presented as a robustness check.

3.4.2 Quantile Regressions – Quantile Earnings Equations

Since both the wage gap as an aggregate and the return to individual characteristics are likely to differ over the distribution, a quantile regression approach is applied to measure the differential impact of the variables in explaining the income and subsequently the wage gap over the income distribution. Using a standard quantile regression approach developed by Koenker and Bassett (1978), this study distinguishes between five different quantiles, at 10, 25, 50, 75, and 90 percent of the distribution, and estimates the earnings equation (10) at each quantile for each year, separated by race. First sorting the income values along the distribution and assuming income is distributed according to $P(Y < y) = F(y - x_{tR}\beta)$, the following objective function is minimized:

$$Q_N(\beta_q) = \sum_{i:y_i > x'_{itR}\beta}^{N} q|y_i - x'_{itR}\beta| + \sum_{i:y_i > x'_{itR}\beta}^{N} (1-q)|y_i - x'_{itR}\beta|$$

Herein, q, t, and r stand for the quantile, year, and race, respectively, and X represents the same vector of explanatory variables as in the mean earnings equation:[11]

$$(10)\ \log(income\_employees\_q_i)_{tr} = a + \beta_1 age_{tr} + \beta_2 age_{tr}{}^2 + \beta_3 male_{tr} + \beta_4 urban_{tr} + \beta_5 privatesec_{tr} + \sum_{educ\_cat=1}^{6} \beta_{educ\_cat} Dummy\_educ\_cat_{tr} + \sum_{occup_{cat}=1}^{8} \beta_{occup\_cat} Dummy\_occup\_cat_{tr} + \sum_{industry\_cat=1}^{8} \beta_{industry\_cat} Dummy\_industry\_cat_{tr} + \varepsilon$$

While there has long been a lack of consensus in the literature on how to control for selection over the distribution and in decompositions, recent papers by Arellano and Bonhomme (2017a, 2017b) suggest a promising new copula-based approach for selection correction over the distribution. Nevertheless, the quantile regression results and quantile regression decomposition techniques discussed in the remainder all rely on reported real income figures. Using the

[11] Quantile regressions are estimated using the stata command sqreg. For a more comprehensive explanation of the quantile regression methodology, see Koenker and Bassett (1978) and Cameron and Trivedi (2005).

selection-corrected predicted wage income for the estimation of the quantile regressions would potentially induce a new bias while correcting an earlier one, because the selection correction through the inverse mills ratio does not consider differences in selection over the wage distribution. Unfortunately, it cannot be determined whether the extent of the selection bias in reported income or the bias through differential selection at different parts along the income distribution outweighs the other, nor how selection correction should be weighted over effects on coefficients and characteristics. As a robustness check, selection-corrected earnings equations are calculated for incomes falling into five different income categories to analyse the differential return to characteristics among different income groups in case of differential selection (see Table A.4 in the Appendix).

3.4.3 Quantile Decomposition

While the quantile regression coefficients provide insights on the differential return of various characteristics over the income distribution, these are not informative about the importance of characteristics versus coefficients in explaining the observed wage gap, which is the focus of the second half of the fourth research sub-question. Therefore, this study applies two alternative decomposition techniques that expand the wage gap analysis beyond the mean gap: the Melly (2005, 2006) decomposition and the Firpo et al. (2009) re-centred influence function approach.

The Melly (2005, 2006) decomposition approach is related to the quantile decomposition methodology developed by Machado and Mata (2005), which is at the limit numerically identical. It extends the widely used Oaxaca (1973) and Blinder (1973) decomposition of mean wage gaps by looking at the effects of characteristics and coefficients across the distribution through the estimation of counterfactual distributions based on the other group's coefficients.[12] In a first step, the Melly (2006) decomposition requires the estimation of conditional distributions at each quantile based on the estimation of quantile regressions. Herein $F_A^{-1}(\theta)$ represents the wage distribution of ATTs at each quantile θ of the income Y and $F_I^{-1}(\theta)$, respectively, for ITTs. Through integrating over these conditional distributions, unconditional distributions can be obtained in a second step. By inverting these unconditional distributions, the counterfactual distributions can be obtained.

$$WageGap_{\theta t} = \overline{\log(income\_employees)}_{\theta tI} - \overline{\log\left(income_{employees}\right)}_{\theta tA} = \beta_{\theta tI}\ \underbrace{(\bar{x}'_{\theta tA} - \bar{x}'_{\theta tI})}_{\text{Effect of Chararacteristics}} + \underbrace{(\beta_{\theta tI} - \beta_{\theta tA})\bar{x}'_{\theta tA}}_{\text{Effect of Coefficients}}$$

[12] The Melly (2006) decomposition has been estimated using the stata command "rqdeco". For a more extensive explanation of the counterfactual quantile regression decomposition methodology, see Machado and Mata (2005) and Melly (2005, 2006).

Both decomposition techniques perform a simulation analysis to determine the counterfactual income distributions. This facilitates the identification of the extent of the race-based wage gaps at different points of the wage distribution that are attributable to differences in characteristics or differences in returns. While Machado and Mata's (2005) approach is performing simulations based on random draws with replacement to determine the counterfactual unconditional distributions, Melly's (2006) technique is computationally faster and based on non-parametric simulations by integrating over covariates of the conditional distribution to arrive at the counterfactual unconditional wage distribution. The limitation of both methodologies is that they still do not permit the calculation of each individual covariate's impact on the unconditional quantile wage distribution.

This limitation can, however, be overcome with the Re-centred Influence Function (RIF) Decomposition approach developed by Firpo et al. (2009). This approach disentangles the effect of each characteristic and coefficient as in the Oaxaca-Blinder decomposition, but at different points of the distribution rather than at the mean. Here we focus on the effect at the 10th, 50th, and 90th percentile. As in the Oaxaca-Blinder decomposition, however, this approach remains sensitive to the chosen base group. The RIF approach substitutes the dependent variable y, here log wages with the re-centred influence function $IF(y; Q_r)$ of the distributional measure of interest $f_Y(Q_r)$ at a particular quantile of the distribution, whereby $Rif(y; Q_r) = Q_r$ + $IF(Y; Q_r)$

$$Rif(y: Q_r) = Q_r + \frac{r - 1\{y \leq Q_r\}}{f_Y(Q_r)}$$

and by this approach estimates an unconditional quantile regression. The results of this decomposition highlight the importance of specific factors, such as age or education, in creating the wage gap for a specific section of the wage distribution.

4. Results

4.1 Racial Segregation Levels by Educational and Occupational Category and Industry

A number of features of race-based segregation stand out. There is no discernible increasing or decreasing trend in ES or in OS. There is, however, a small but significant decreasing trend in IS. This is largely driven by a steep significant decline in segregation in the sugar, other agriculture, and fishery industry and in the construction industry. Overall, ES, OS, and IS fluctuate around the same level of approximately 7 percent according to the KM index measure, and around 13 percent using the DD index (Table 4). The lower KM value implies that the rising number of ITTs constituting the working labour force lead to a smaller share of workers who must change their occupations to eradicate segregation.

Table 4: Aggregate Segregation Indices

	ES							OS							IS				
Year	D	KM-all	KM-Female	KM-Male	KM-Public	KM-Private	Gini	D	KM-all	KM-Female	KM-Male	KM-Public	KM-Private	Gini	D	KM-all	KM-Female	KM-Male	Gini
1999	15.48	7.73	5.74	8.83	7.13	7.74	19.20	11.97	5.98	4.06	7.85	7.44	5.53	16.97	17.80	8.89	8.47	9.14	21.74
2000	13.69	6.83	5.25	7.69	6.29	6.69	15.65	10.38	5.18	3.82	5.90	7.80	5.27	13.76	14.99	7.48	8.56	7.53	19.82
2001	12.63	6.30	4.34	7.44	5.06	6.71	16.31	11.37	5.68	7.05	6.85	7.79	6.16	17.24	13.28	6.63	5.75	7.60	17.19
2002	11.87	5.93	3.65	7.86	6.96	5.62	15.54	11.74	5.87	4.49	8.15	6.79	6.37	16.96	14.88	7.44	7.02	8.03	18.58
2003	11.45	5.72	4.16	6.95	6.36	5.99	14.38	12.33	6.16	5.66	7.16	8.57	6.17	15.83	18.14	9.07	11.10	7.52	21.20
2004	9.19	4.58	3.57	5.85	4.47	4.86	10.80	12.03	6.00	4.58	7.71	7.90	6.38	15.26	15.44	7.70	8.46	7.14	18.04
2005	13.55	6.77	5.79	7.43	5.41	6.69	15.66	10.33	5.16	5.19	6.06	7.39	5.54	15.51	16.63	8.31	10.80	7.02	19.90
2006	13.91	6.95	5.87	7.95	4.66	7.46	16.51	12.69	6.34	5.12	6.75	8.27	5.95	16.35	17.36	8.68	9.35	8.74	20.45
2007	12.84	6.40	6.12	7.15	5.79	6.99	17.69	12.69	6.33	6.03	7.25	8.12	6.28	16.29	13.20	6.58	7.37	6.35	15.17
2008	16.74	8.37	7.99	9.51	7.99	8.48	20.43	13.03	6.51	6.20	6.63	9.72	6.23	17.14	15.22	7.61	6.92	7.77	17.27
2009	13.52	6.75	6.46	7.37	5.77	8.11	16.43	13.61	6.80	6.47	7.64	8.33	6.89	18.33	14.68	7.33	6.85	7.76	15.97
2010	12.61	6.29	4.92	7.74	5.08	7.79	16.15	11.10	5.53	5.68	6.37	6.07	6.12	15.06	13.97	6.96	7.50	6.74	15.63
2011	10.75	5.38	5.77	6.46	5.01	6.31	14.42	14.92	7.46	9.05	7.17	7.50	7.83	19.37	12.97	6.49	8.53	6.18	16.24
2012	12.31	6.14	6.71	6.35	6.33	6.06	13.72	9.02	4.50	5.33	5.27	6.49	4.95	14.18	13.15	6.56	5.71	6.07	16.28
2013	14.55	7.27	7.26	7.86	9.44	7.08	17.70	11.50	5.74	5.63	5.93	7.65	5.10	15.97	11.10	5.55	6.18	5.04	14.42
2014	15.34	7.67	6.41	8.89	6.56	8.30	18.80	13.71	6.85	6.97	7.73	7.80	6.83	18.09	9.26	4.63	4.49	5.93	11.56
2015	15.82	7.80	8.95	7.64	7.64	8.00	18.58	12.66	6.25	5.80	7.36	8.16	6.20	17.94	10.73	5.29	5.65	5.25	12.93

Source: Authors' own calculations based on CSSP 1999-2015.
Note: All indices are in percentages. Bootstrapped standard errors with 1000 iterations: all indices are significant at 1%.

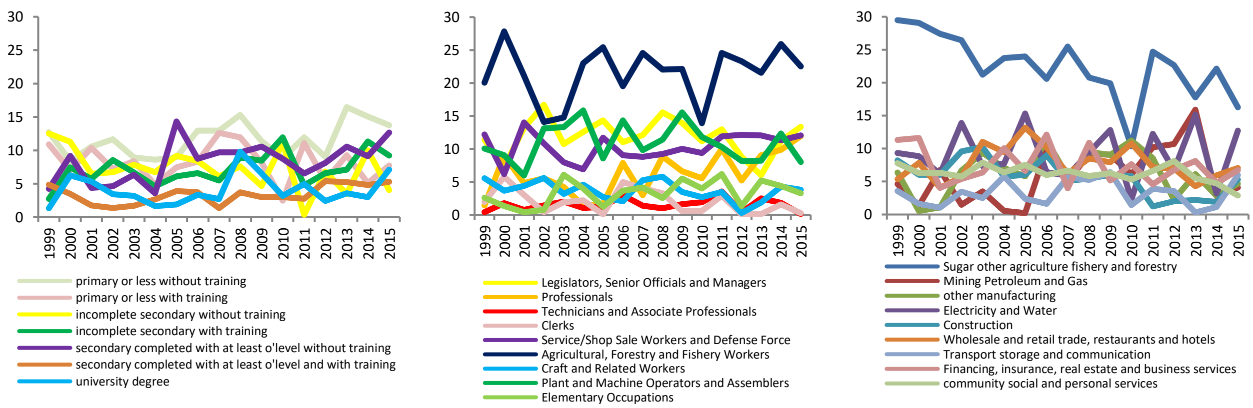
Race-based segregation measured separately by gender and by private versus public sector ES and IS levels do not vary much. OS, however, displays a small variation across subgroups, whereby male public sector employees face a relatively constant 2 percent more segregation than female employees and those with private sector jobs (Figure 1). Regardless of the subgroup, aggregate racial segregation is low and lower than gender-based ES and OS. ES along racial lines is 7 percent compared to 10 percent, and OS is 6 percent less than half of the 18 percent measured in terms of gender in Schimanski, Chagalj, and Ruprah (2018). The finding of less race-based than gender-based segregation is consistent with Salardi's (2014) findings for Brazil. To address the concern that aggregate segregation even within subgroups may average out heterogeneous segregation patterns across educational attainment levels, occupational categories, and industries, further analysis has been conducted, disaggregated by category. Figure 2 a) shows that educational segregation is slightly higher at lower than at higher educational levels. For the educational attainment levels of incomplete secondary with training as well as completed secondary with and without training, segregation has been significantly increasing, although from low levels.[13]

Figure 1: Evolution of Aggregate Occupational Segregation across Sub-Groups (KM Index)

Source: Authors' own calculations based on CSSP 1999-2015.
Note: All indices are in percentages. Bootstrapped standard errors with 1000 iterations: all indices are significant at 1%.

Figure 2: Heterogeneity in Segregation Levels (KM Index)

a) Educational category b) Occupational Category c) Industrial Sector



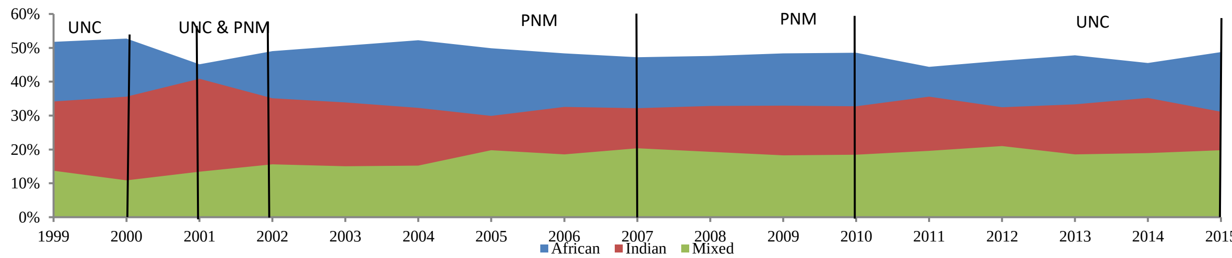
Source: Authors' own estimations based on CSSP 1999-2015.

Figures 2 b) and c) show that the dispersion between segregation levels in different occupations and industries is even stronger than for ES. In both, aggregate OS and ES segregation seems to be driven by much higher segregation levels in agricultural occupations and the agricultural industries where segregation levels average around 22 percent, with peaks reaching up to 30 percent, whereas segregation levels in the second most segregated other occupations and industries reach only 15 percent, and most others experience hardly any

[13] If larger samples were available, a segregation analysis at a more disaggregated level regarding specific educational subjects could provide useful insights on whether the extent and changes in educational and occupational segregation may just not be captured in the aggregated seven category level used here.

segregation. Within occupational categories, the Legislator, Senior Officials, and Manager, Plant and Machine Operators and Assemblers, and Service, Sales, and Shop Workers form a group of intermediate-level segregated occupations. These patterns can be understood as the lingering effects of the country's colonial past. Upon freedom, ATTs moved into urban areas and were replaced in the agriculture sector by ITTs.

Figure 3. Public Employment by Race



Source: Authors' estimations based on CSSP 1999-2015
Note: Based on wage gap sample, but robustness check based on full sample without duplicates shows same pattern.

The segregation levels for the agricultural occupations and industries need to be treated with caution, as sample sizes are much smaller. However, ITTs now also dominate Legislator, Senior Officials, and Managers, Plant and Machine Operator and Assembler occupations, while ATTs dominate the Service, Sales and Shop Worker occupations. In addition, there appear to be generational differences. Figure A.3 shows that over 30 percent of the female ITT youth between 15 and 24 years is working in occupations, such as Legislators, Senior Officials, Managers, Professional and Technicians and Associates, compared to just over 10 percent of ATTs in that age group. However, the difference is much smaller for the middle-aged generations. With respect to racial difference in occupations, Figure 3 displays slight movements in the shares of ATTs, ITTs, and mixed races working in the public sector around the time of general elections.[14]

The following section investigates whether educational segregation can explain the higher levels of occupational and industry segregation in these categories.

4.2 The Role of Educational Segregation in Occupational and Industry Segregation

As presented in the Methodology section 3.1, prior educational segregation can impact subsequent occupational and industry segregation. Tables 5 and 6 show that neither in the first

[14] Information on contract types (short-term versus permanent) would allow more detailed analysis but is not available.

nor in the last sample year, prior educational segregation drives neither racial occupational segregation nor industrial segregation. While the impact of ES on OS in the Crafts and Related Workers category was and remains high, educational segregation dropped in explaining occupational segregation in the Clerks and Plant and Machine Operators and Assemblers category. In contrast, educational segregation has become a more important determinant in explaining occupational segregation within the Legislators, Senior Officials and Managers and Professionals category. Only in the financial sector does ES seem to have a lasting high impact. In other sectors with initially relatively high impact of ES, the role has decreased over time or lost its significance. However, the impact of ES on OS and IS is highly volatile across years. Therefore, conclusions drawn from looking only at the first and last sample year should be treated with caution.

Table 5: Impact of Educational Segregation on Occupational Segregation by Occupational Category

Occupation	1999			2015		
	ES	OS	Impact (%)	ES	OS	Impact (%)
Legislators, senior officials and managers	7.21***	11.36***	49.61**	8.11***	13.34***	100***
Professionals	1.73	1.41	60.53	6.95***	11.95***	100***
Technicians and associate professionals	5.12***	0.41	50.67**	6.50***	0.14	41.62*
Clerks	5.74***	1.99	47.06**	7.51***	0.30	9.27
Service workers and shop and market sales workers	6.91***	12.2***	50.92***	7.45***	12.07***	61.11***
Skilled agricultural and fishery workers	11.1***	20.04***	69.58***	9.06***	22.51***	44.50
Ccraft and related workers	7.39***	5.56***	88.17***	7.73***	3.81**	88.27***
Plant and machine operators and assemblers	9.2***	10.06***	92.03***	8.27***	8.02***	53.78*
Elementary occupations	10.21***	2.59***	38.69***	8.90***	3.29**	30.70*

Source: Authors' own calculations based on CSSP 1999-2015.
Note: All indices are reported in percentages. Bootstrapped standard errors with 1000 iterations: ∗∗∗p < 1%, ∗∗p < 5%, ∗p < 10%

Table 6: Impact of Educational Segregation on Industrial Segregation by Industry Category

Occupation	1999			2015		
	ES	IS	Impact (%)	ES	IS	Impact (%)
Sugar other agriculture fishery and forestry	10.50***	29.49***	100.00	9.25***	16.27***	39.84
Mining, petroleum and gas	6.89***	4.63*	72.57**	7.31***	4.11	3.12
Other manufacturing	7.28***	6.37***	85.35***	7.64***	4.67*	35.81
Electricity and water	6.58***	9.35**	-13.41	7.32***	12.7**	51.84
Construction	8.65***	8.21***	46.56***	8.22***	5.31***	88.26***
Wholesale and retail trade, restaurants and hotels	8.2***	5.38***	65.81***	8.37***	7.04***	53.12**
Transport storage and communication	8.62***	3.54**	-21.19	8.03***	6.00**	36.54
Financing, insurance, real estate and business services	5.27***	11.33***	100.00***	7.11***	6.71***	85.79***
Community social and personal services	7.03***	7.78***	96.96***	7.46***	2.88***	32.14**

Source: Authors' own calculations based on CSSP 1999-2015.
Note: All indices are reported in percentages. Bootstrapped standard errors with 1000 iterations: ∗∗∗p < 1%, ∗∗p < 5%, ∗p < 10%

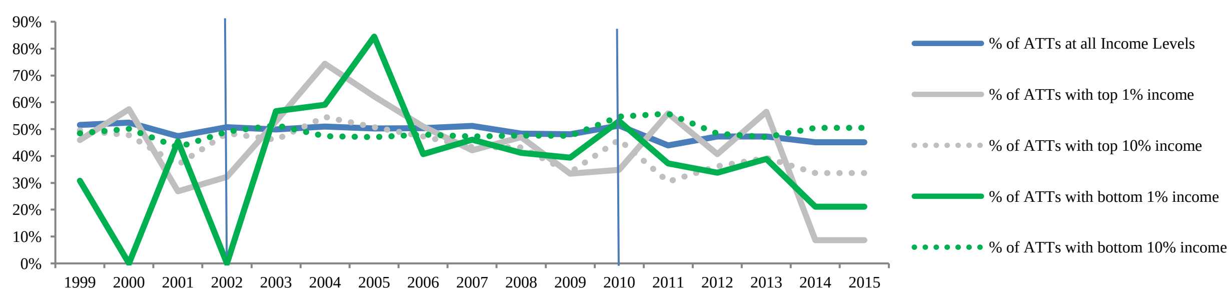
4.3 Mean Wage Gap Analysis

This section presents a wage gap analysis to provide insights on whether the segregation noted in section 4.2 is also reflected in the existence of race-based wage differentials. Sub-sections 4.3.1 to 4.3.4 present the findings regarding the third main research question on the existence, extent, drivers, and heterogeneity of a race-based wage gap. First, descriptive insights are provided and subsequently, the hypotheses put forward in section 3.3 are tested.

4.3.1 Descriptive Wage Statistics

We first analyse the differential representation of the two racial groups along the income distribution. Figure 4 presents the share of ATTs in different parts of the income distribution over the sample period. The shares should all be viewed relative to the blue line, which represents the average share of ATTs irrespective of income level among employees in a given year. The figure shows that even for the top and bottom 10 percent of earners, the racial composition fluctuates closely around the mean. For the top and bottom 1 percent of earners, the racial composition is somewhat noisier, fluctuating around the mean composition. It is noteworthy that the share of ATTs in top and bottom 1 percent move in parallel for most of the intermediate period, which coincides with the period of the largely ATT-supported PNM being in power in the national government. In the early and last years of the sample, ATTs are less represented at the 1 percent extremes of the income distribution. This indicates a more skewed income distribution and thus lower income inequality during periods of the UNC government with an ITT-dominated voter base.

Figure 4: Share of ATTs among all Employees and those with Top and Bottom 1 Percent (10 percent) Income



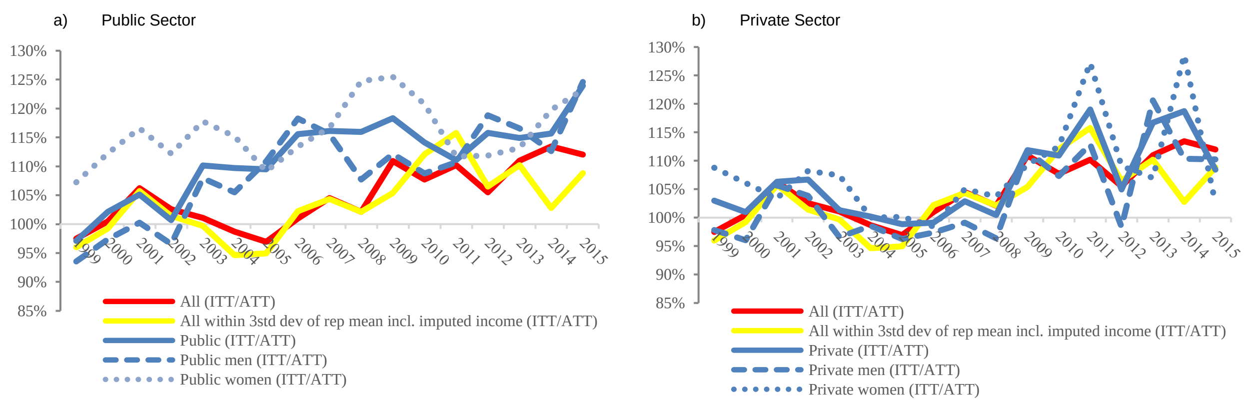
Source: Authors' own estimates based on CSSP 1999-2015.
Note: The real mean income in Trinidad and Tobago dollars is based on CPI-adjusted reported income for employees excluding top and bottom 5 percent incomes in a specific occupational category as outliers, but before dropping years and observations without occupation information. Top and bottom income shares are defined over the pooled income distribution.

Whether these coinciding movements are statistically significant and justifiable based on the employees' characteristics therefore needs further investigation. Except for during the last two years of the sample, there is thus no evidence for a general glass ceiling in terms of ATTs not reaching into the uppermost end of the wage distribution.

4.3.2 Mean Wage Gap

Mean wage gaps of real income over time as a ratio of ITTs over ATTs have been calculated using the sample of those individuals who reported to the income question (Figure 5). In addition, mean racial wage gaps have been calculated separately for those (i) working in the private versus public sector, (ii) having obtained different educational attainment levels (Figure 6a), working in different occupations (Figure 6b), and working in different industries (Figure 6c).

Figure 5: Aggregate Wage Gap Mean Income over Time by Ethnicity and Sector (ITTs/ ATTs)



Note: *All* refers to the real mean income racial wage gap, which is based on CPI adjusted reported income for those who reported income, excluding those observations as outliers that fall outside the 95 percent confidence interval of incomes within their respective occupational category. *Public* and *Private* restricts the sample to employees in the respective sector. *Public men*, *Public women*, *Private men* and *Private women* further restricts the sample on which the racial wage is calculated. *Public women* refers thus to the racial wage gap that women in the public sector face. *All within 3 standard deviations of the reported mean including imputed income* includes not only the individuals who report their income into the sample of the mean wage gap calculation but additionally imputes incomes for those employees who failed to report their income based on the coefficients from a selection-corrected income model, estimated following a two-stage multinomial logit model using a separate specification for each ethnic group including occupational dummies. In this sample, all those observations that fall above or below three standard deviations from the mean reported income are excluded as outliers, whereby the mean reported income in an occupational category is estimated after already excluding outliers at the top and bottom 5 percent of incomes in the respective occupational category. Observations are accordingly excluded as outliers irrespective of whether the income was reported or imputed.
Source: Authors' own estimations based on CSSP 1999-2015.

Considering the complete sample, Figure 5 illustrates a shift from a mean aggregate real racial wage gap initially in 1999 slightly favouring ATTs to a nine-year period of an almost non-existent wage gap that lasts until 2008. Thereupon the racial mean wage gap starts increasingly favouring ITTs until the mean gap reaches about 10 percent by the end of the sample period in 2015. This means that ITTs were earning 1.10 TTD for every 1 TTD an ATT earned in the post-2008 period. This shift and significant increase in the wage gap is robust to using only the sample of observations who report income, or complementing the sample with observations from employees who failed to report their income but for which income can be imputed. Unless we further restrict the sample including imputed incomes within a band of three standard deviations from the mean of the reported income by occupation, the aggregate mean wage gap including imputed incomes is much more volatile than that solely based on reported income.[15]

Comparing Figures 5 a) and b), we note a sizable heterogeneity between the public and private sectors. While in 1999 ATTs were in aggregate terms and in both sectors earning more than ITTs, in subsequent years the wage gap in the private sector has closely followed the movement of the aggregate gap. The wage gap among public sector employees widened in absolute terms and relative to the private sector in favour of ITTs starting in 2003, with a peak gap of around 20 percent in 2010 until converging with the pattern of the private sector in 2011 again. Figure 5a) further illustrates that the racial wage gap in the public sector is even larger when considering only female ATTs and ITTs and over the entire period favoured female ITT public sector employees. In comparison, the private sector racial wage gaps for men and women are much closer aligned, though racial wage gaps for private sector men seem continuously less pronounced and even fall below the overall aggregate wage gaps.

The finding that next to race, gender plays a major role in determining wage gaps is consistent with the larger gender-based wage gaps estimated by Schimanski, Chagalj, and Ruprah (2017). The large increase in ITTs' public sector salaries compared to ATTs' public sector salaries can potentially be explained by only highly paid longer-term contract ITTs left in the public sector during the time of the ATT-supported PNM government in the first decade of the new century. ATTs may have replaced lower-paid temporary contract employees, in line with the decrease in the elementary, crafts-related, and clerical positions held by ITTs. An additional explanation may be Trinidad and Tobago's energy boom, which largely benefited ITTs working in well-paid positions for state-owned enterprises that benefited from it, but lost them by 2010, shortly after the boom ended in 2008. A breakdown of the wage gap by occupation and industry is presented in Figure 6b) and c) and separated by sector in Figure A.2 in the Appendix. The latter displays high levels of volatility so that the overall public sector wage gap in favour of ITTs is likely to arise not only from a wage gap in a specific occupation or industry and will be analysed alongside the earnings equations in greater detail in the following section.

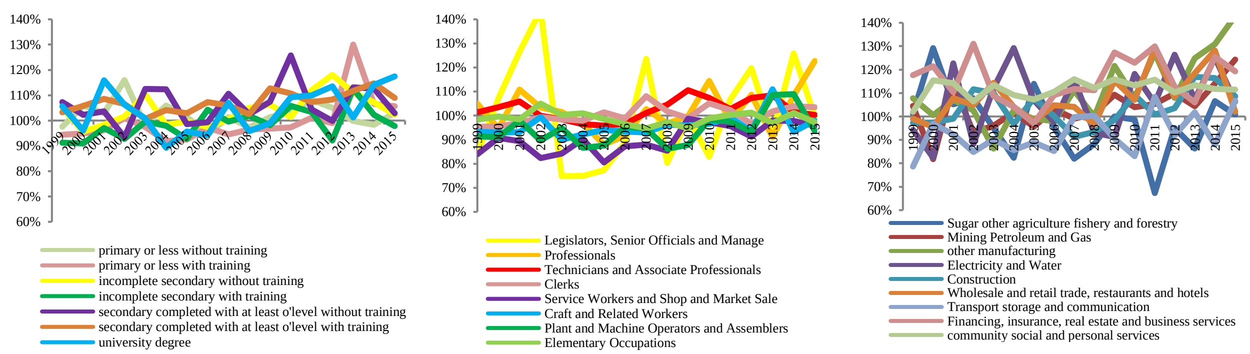
As in the case of segregation in Figures 2a)-c), Figures 6a)-c) display strong heterogeneity of the wage gap depending on the educational level, occupational category, or

[15] Therefore, this analysis proceeds using the reported income sample when presenting mean wage gaps, as Bollinger et al. (2018) find that neglecting the missing incomes hardly matters at the mean and that even imputing missing income figures, may provide biased estimates at the upper and lower end of the distribution.

industry. The graphs below display that ATTs with primary education or less and incomplete secondary but with additional training; the pink and green lines, respectively, in Figure 6a) were almost consistently earning more during the earlier years than their ITT peers, although the size of the gap is largely volatile, ranging mostly between ±10 percent, and is limited to at most ±20 percent. On the contrary, among those who obtained a university degree or completed secondary school and received additional training, ITTs consistently earned more. Over the years these relations do not seem to alter much, apart from some temporary shifts that could be considered noise.[16] These findings stress the importance of looking beyond mean wage gaps and demonstrate that the return to education differs by race and by education level.

Figure 6: Mean Real Wage Gaps by Race by Category (ITT/ATT)

a) Educational category b) Occupational Category c) Industrial Sector



Note: The real mean income wage gap is based on CPI adjusted reported income. The line of the wage gap of the occupational category Skilled Agricultural and Fishery Workers has been excluded in the graph, as this mean wage gap is very volatile over time due to the limited number of observations of individuals employed in this sector.
Source: Authors' own estimations based on CSSP 1999-2015.

On the other hand, the racial wage gap in terms of occupations seems to be generally smaller than in terms of education apart from the agricultural and legislator, senior officials and manager occupations, which depict very large volatility. The racial wage gap more clearly initially favours ATTs, who work in service and shop and market sales occupations, or are crafts and related workers or plant and machine operators and assemblers. These same occupations show, however, a very small but statistically significant increasing wage gap over time moving in favour of ITTs. In line with the broader policy concern regarding the latent ethnic rivalry

[16] While the time trends of the wage gaps for the educational categories primary or less with trainings, incomplete secondary with and without training and completed secondary with training are found to be positive statistically significant, thus increasing in favour of ITTs in these categories, the coefficients are very small: 0.0139***, 0.00908***, 0.00620**, 0.00521*, respectively, and potentially a result of noise and the small sample size. Therefore, wage gaps for educational attainment levels are nevertheless considered largely constant.

discussed in Premdas (2007), the high volatility of the wage gap for those in the Legislators, Senior Officials and Managers category favours either group at a given time in line with the electoral cycles. An analysis of whether the size of the occupation-based racial wage gaps differs among public sector versus private sector employees suggested only minor differences but greater overall volatility (see Appendix Figure A.4).

Industry-specific wage gaps are small. Over the 17-year sample period there is, however, a significant decreasing trend in wage gaps in the sugar and other agricultural industries. Other manufacturing and wholesale industry employees display a very small but increasing wage gap. Wage gap levels do not coincide with segregation and over- versus underrepresentation of a specific racial group in an industry category. While ITTs were overrepresented in jobs in the sugar and agricultural industry, the wage gap in this and the transport, storage, and communications sector favours ATTs. Those employed in the finance, insurance, and real estate business services as well as in the community and social personal services sector experience a continuous wage gap in favour of ITTs.

4.3.2 Mean Earnings Equation

Following the more descriptive analysis of the racial representation along the wage distribution and the mean wage gap, this section presents the results of the mean wage earnings equations and discusses the hypotheses tested. Earnings equations are estimated in a pooled model, as well as separately for ITTs and ATTs following the specifications discussed in Section 3.3. Reported income values are predicted, first using OLS and then correcting for selection into participation in the labour market and specifically into employment. Due to space limitations, only the results for 2015 are presented in Table 7.

Comparing the coefficients across model types clearly indicates the impact of selection bias of the reported income. Including the inverse mill ratios, m_1-m_4 in the table, to correct for selection into being employed changes the coefficients considerably in level though not in direction. As a robustness check, the coefficients of the selection-corrected earnings equations for ATTs and ITTs have therefore been used to impute incomes for all employed individuals who did not report their income to measure mean wage gaps. This did not change the findings in mean wage gaps, except for displaying higher volatility.

Table 7: Earnings Equations – Race

	Selection Correction Model -Multinomial Logit 2015			Standard Model- OLS 2015		
VARIABLES	Pooled Model Log Wage Income	African Origin Log Wage Income	Indian Origin Log Wage Income	Pooled Model Log Wage Income	African Origin Log Wage Income	Indian Origin Log Wage Income
D_primary or less with training	0.119*	0.0614	0.101	0.0612**	0.0752*	0.0560
	(0.0644)	(0.0749)	(0.0978)	(0.0300)	(0.0429)	(0.0450)
D_incomplete secondary without training	0.0549	0.0565	0.00674	0.0475	0.0854*	0.0155
	(0.0618)	(0.0842)	(0.0858)	(0.0292)	(0.0436)	(0.0393)
D_incomplete secondary with training	0.127**	0.0844	-0.0169	0.102***	0.150***	0.0308
	(0.0600)	(0.0764)	(0.0795)	(0.0290)	(0.0416)	(0.0421)
D_secondary completed with at least o'level without training	0.168***	0.180**	0.0782	0.159***	0.195***	0.132***
	(0.0592)	(0.0772)	(0.0798)	(0.0288)	(0.0435)	(0.0390)
D_secondary completed with at least o'level and with training	0.323***	0.303***	0.203**	0.273***	0.304***	0.252***
	(0.0573)	(0.0728)	(0.0815)	(0.0269)	(0.0401)	(0.0374)
D_university degree	0.484***	0.646***	0.409***	0.442***	0.494***	0.399***
	(0.0786)	(0.112)	(0.111)	(0.0387)	(0.0569)	(0.0538)
Age	0.0329	-0.0335	0.0532	0.0273***	0.0240***	0.0323***
	(0.0349)	(0.0743)	(0.0382)	(0.00393)	(0.00511)	(0.00631)
age2	-0.000480	0.000275	-0.000531	-0.000273***	-0.000224***	-0.000347***
	(0.000480)	(0.000725)	(0.000601)	(5.00e-05)	(6.44e-05)	(8.10e-05)
D_Professionals	0.211**	-0.0218	0.221	0.125**	0.0153	0.178**
	(0.106)	(0.151)	(0.143)	(0.0525)	(0.0781)	(0.0700)
D_Technicians and Associate Professionals	-0.104	-0.105	-0.136	-0.172***	-0.165**	-0.183***
	(0.0890)	(0.123)	(0.124)	(0.0448)	(0.0671)	(0.0596)
D_Clerks	-0.385***	-0.375***	-0.277**	-0.484***	-0.497***	-0.465***
	(0.0986)	(0.133)	(0.128)	(0.0436)	(0.0649)	(0.0589)
D_Service/Shop Sale Workers	-0.359***	-0.291**	-0.282**	-0.466***	-0.462***	-0.472***
	(0.0970)	(0.138)	(0.139)	(0.0441)	(0.0663)	(0.0595)
D_Agricultural, Forestry and Fishery Workers	-0.635***	-0.363	-0.884***	-0.663***	-0.470***	-0.733***
	(0.224)	(0.293)	(0.273)	(0.115)	(0.159)	(0.140)
D_Craft and Related Workers	-0.431***	-0.342**	-0.389***	-0.513***	-0.512***	-0.485***
	(0.0971)	(0.147)	(0.122)	(0.0453)	(0.0684)	(0.0605)
D_Plant and Machine Operators and Assemblers	-0.337***	-0.284*	-0.298**	-0.409***	-0.377***	-0.402***
	(0.0957)	(0.157)	(0.122)	(0.0468)	(0.0715)	(0.0617)
D_Elementary Occupations	-0.679***	-0.597***	-0.616***	-0.760***	-0.749***	-0.758***
	(0.0954)	(0.148)	(0.129)	(0.0446)	(0.0672)	(0.0597)
Percentage Share of African Origin TTs in Occupation	0	0	0	-	-	-
	(0)	(0)	(0)			
D_urban	0.0436	-0.0570	0.0442	0.0342	0.0173	0.0463
	(0.0450)	(0.0545)	(0.0653)	(0.0223)	(0.0285)	(0.0374)
D_privatesec	-0.176***	-0.201***	-0.164**	-0.212***	-0.196***	-0.239***
	(0.0363)	(0.0466)	(0.0687)	(0.0171)	(0.0225)	(0.0279)
D_Mining Petroleum and Gas Industry	0.331***	0.364***	0.334***	0.345***	0.367***	0.303***
	(0.0840)	(0.127)	(0.106)	(0.0516)	(0.0787)	(0.0645)
D_Manufacturing Industry	0.169**	0.0853	0.273***	0.176***	0.120	0.203***
	(0.0785)	(0.120)	(0.0968)	(0.0495)	(0.0763)	(0.0609)
D_Electricity Gas and Water Industry	0.318***	0.430***	0.228	0.301***	0.388***	0.199**
	(0.0992)	(0.135)	(0.157)	(0.0595)	(0.0808)	(0.0927)
D_Construction	0.167**	0.103	0.126	0.128***	0.176**	0.0806
	(0.0745)	(0.118)	(0.0879)	(0.0462)	(0.0702)	(0.0578)
D_Wholesale and Retail Trade and Restuarants and Hotels	-0.0102	0.0661	0.00888	0.0201	0.0795	-0.0319
	(0.0735)	(0.115)	(0.0884)	(0.0467)	(0.0717)	(0.0576)
D_Transport Storage and Cummunication Industry	0.155*	0.227	0.129	0.148***	0.231***	0.0735
	(0.0880)	(0.146)	(0.115)	(0.0544)	(0.0861)	(0.0654)
D_Financing Insurance and Real Estate Industry	0.230***	0.138	0.179*	0.195***	0.230***	0.174***
	(0.0814)	(0.121)	(0.104)	(0.0488)	(0.0736)	(0.0623)
D_Community Social and Personal Services Industry	0.0561	0.0953	0.0749	0.0511	0.115	-0.0159
	(0.0734)	(0.114)	(0.0916)	(0.0455)	(0.0700)	(0.0550)
D_Indian	0.0149			0.0141		
	(0.0271)			(0.0129)		
D_male	0.139	0.123	-0.0309	0.189***	0.190***	0.193***
	(0.187)	(0.281)	(0.732)	(0.0151)	(0.0208)	(0.0219)
_m1	-0.0388	1.181	5.965			
	(4.083)	(5.934)	(7.111)			
_m2	1.150	8.189	3.209			
	(5.103)	(11.24)	(5.732)			
_m3	0.632	0.576	3.711			
	(3.872)	(5.438)	(4.655)			
_m4	-0.0601	0.699	3.207			
	(4.618)	(6.632)	(6.295)			
Constant	7.892***	10.13***	8.387***	8.054***	8.010***	8.076***
	(1.091)	(2.522)	(1.431)	(0.0987)	(0.143)	(0.142)
Observations	.	.	.	2,448	1,337	1,111
R-squared				0.646	0.586	0.703

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: The dependent variable "ln_inc_catconst3" is the logarithm of income at constant prices of individuals working in category 3 which was defined in section 3.2.2.1.1 as being employed. Selection Corrected Model standard errors are based on 1000 bootstraps and the selection parameters have been calculated using 100 iterations. Reported Income earnings equations have been estimated using heteroscedasticity robust standard errors.

Source: Authors' own calculations based on CSSP 1999-2015.

Table 8: Fixed Effect Model over all Years using a Selection-correction Model

Dependent Variable: Log_reported Income	(1) All	(2) ITT	(3) ATT	(4) All with year trend	(5) All with ATT_gov	(6) All with ATT_gov*ITT	(7) Private Sector	(8) Public Sector
Dummy_ATT_government					0.0486***	0.0510***	0.0657***	0.0362***
					(0.00536)	(0.00510)	(0.00856)	(0.00626)
Dummy_ITT*Dummy_ATT_government						-0.00643	-0.0215**	0.00894
						(0.00923)	(0.00896)	(0.00888)
Dummy_ITT	-0.0219*			-0.0228***	-0.0325**	-0.0248**	-0.0959***	0.0218***
	(0.0129)			(0.00489)	(0.0147)	(0.0126)	(0.0276)	(0.00818)
Dummy_Educ_primary or less with training	0.0556***	0.0424***	0.0509*	0.0616***	0.0693***	0.0613***	0.0537***	0.0126
	(0.0115)	(0.0161)	(0.0280)	(0.00972)	(0.0107)	(0.0133)	(0.0137)	(0.0126)
Dummy_Educ_incomplete secondary without training	0.0509***	0.0815***	0.0459*	0.0594***	0.0423***	0.0397***	0.0693***	-0.0392**
	(0.0109)	(0.0140)	(0.0277)	(0.0116)	(0.00752)	(0.0142)	(0.0154)	(0.0168)
Dummy_Educ_incomplete secondary with training	0.0943***	0.0883***	0.110***	0.108***	0.0988***	0.0904***	0.0910***	0.0220**
	(0.0109)	(0.0188)	(0.0315)	(0.00661)	(0.0135)	(0.00721)	(0.00965)	(0.00981)
Dummy_Educ_secondary completed with at least o'level without training	0.152***	0.129***	0.139***	0.156***	0.131***	0.125***	0.121***	0.0581***
	(0.0133)	(0.0287)	(0.0350)	(0.0113)	(0.0129)	(0.00900)	(0.0110)	(0.0122)
Dummy_Educ_secondary completed with at least o'level and with training	0.261***	0.288***	0.244***	0.271***	0.251***	0.247***	0.227***	0.162***
	(0.0106)	(0.0155)	(0.0262)	(0.00989)	(0.0139)	(0.00722)	(0.0102)	(0.0122)
Dummy_Educ_university degree	0.445***	0.469***	0.418***	0.452***	0.399***	0.401***	0.440***	0.228***
	(0.0109)	(0.0540)	(0.0565)	(0.0129)	(0.0169)	(0.00998)	(0.0363)	(0.0182)
Age	0.0286***	0.0289***	0.0426***	0.0270***	0.0263***	0.0257***	0.0220***	0.0319***
	(0.00178)	(0.00653)	(0.00625)	(0.00172)	(0.00269)	(0.00152)	(0.00279)	(0.00241)
age2	- 0.000295***	- 0.000280**	- 0.000487***	-0.000277***	-0.000283***	-0.000271***	-0.000335***	- 0.000262***
	(2.23e-05)	(0.000114)	(0.000109)	(2.74e-05)	(2.69e-05)	(3.23e-05)	(2.79e-05)	(3.83e-05)
Dummy_Occupation_Professionals	0.101***	-0.0141	0.119*	0.128***	0.158***	0.146***	0.177***	0.0278
	(0.0115)	(0.0567)	(0.0678)	(0.0205)	(0.0205)	(0.0461)	(0.0525)	(0.0249)
Dummy_Occupation_Technicians and Associate Professionals	-0.203***	-0.241***	-0.164***	-0.129***	-0.121***	-0.125***	-0.141***	-0.228***
	(0.0268)	(0.0624)	(0.0263)	(0.0177)	(0.0257)	(0.0298)	(0.0256)	(0.0273)
Dummy_Occupation_Clerks	-0.515***	-0.529***	-0.454***	-0.428***	-0.417***	-0.426***	-0.400***	-0.579***
	(0.0321)	(0.0582)	(0.0397)	(0.0206)	(0.0320)	(0.0327)	(0.0281)	(0.0280)
Dummy_Occupation_Service/Shop Sale Workers and Defense Force	-0.677***	-0.590***	-0.557***	-0.533***	-0.530***	-0.533***	-0.601***	-0.425***
	(0.0475)	(0.0827)	(0.0571)	(0.0141)	(0.0648)	(0.0339)	(0.0326)	(0.0376)
Dummy_Occupation_Agricultural, Forestry and Fishery Workers	-0.678***	-0.796***	-0.616***	-0.718***	-0.777***	-0.774***	-0.752***	-0.830***
	(0.0416)	(0.0918)	(0.0989)	(0.0288)	(0.0489)	(0.0510)	(0.0544)	(0.0277)
Dummy_Occupation_Craft and Related Workers	-0.616***	-0.592***	-0.551***	-0.511***	-0.509***	-0.510***	-0.508***	-0.604***
	(0.0439)	(0.0638)	(0.0342)	(0.0141)	(0.0477)	(0.0337)	(0.0243)	(0.0316)
Dummy_Occupation_Plant and Machine Operators and Assemblers	-0.522***	-0.538***	-0.460***	-0.500***	-0.517***	-0.516***	-0.476***	-0.646***
	(0.0190)	(0.0475)	(0.0320)	(0.0274)	(0.0156)	(0.0242)	(0.0176)	(0.0270)
Dummy_Occupation_Elementary Occupations	-0.906***	-0.869***	-0.826***	-0.794***	-0.792***	-0.797***	-0.754***	-0.886***
	(0.0344)	(0.0713)	(0.0407)	(0.0173)	(0.0511)	(0.0377)	(0.0231)	(0.0313)
Share of ATTs	0.299	-0.106	0.156	-0.327***	-0.441	-0.413***	-0.227	-0.616***
	(0.197)	(0.172)	(0.215)	(0.0768)	(0.299)	(0.103)	(0.159)	(0.0961)
Dummy_urban	0.0273***	0.0364	0.0142	0.0250***	0.0361***	0.0368***	0.0424**	0.0166*
	(0.00905)	(0.0233)	(0.0153)	(0.00748)	(0.0106)	(0.00816)	(0.0192)	(0.00937)
Dummy_privatesector	-0.254***	-0.230***	-0.213***	-0.245***	-0.247***	-0.246***		
	(0.00587)	(0.0203)	(0.0180)	(0.00739)	(0.0115)	(0.00681)		
Dummy_Industry_Mining Petroleum and Gas	0.300***	0.265***	0.352***	0.296***	0.265***	0.265***	0.343***	0.230***
	(0.0189)	(0.0164)	(0.0409)	(0.00859)	(0.0206)	(0.00923)	(0.0386)	(0.0132)
Dummy_Industry_other manufacturing	0.125***	0.152***	0.137***	0.128***	0.109***	0.110***	0.180***	0.0330
	(0.0208)	(0.0364)	(0.0340)	(0.0107)	(0.0107)	(0.00691)	(0.0267)	(0.0290)
Dummy_Industry_Electricity and Water	0.237***	0.222***	0.298***	0.255***	0.229***	0.221***	0.285***	0.218***
	(0.0221)	(0.0228)	(0.0280)	(0.0131)	(0.0167)	(0.0141)	(0.0561)	(0.0127)
Dummy_Industry_Construction	0.0998***	0.117***	0.102***	0.108***	0.0716***	0.0714***	0.186***	-0.101***
	(0.0185)	(0.0250)	(0.0370)	(0.00924)	(0.0192)	(0.00853)	(0.0246)	(0.0106)
Dummy_Industry_Wholesale and retail trade, restaurants and hotels	0.0107	0.00572	0.0111	0.0137	-0.00692	-0.0127*	0.0748***	-0.188***
	(0.0233)	(0.0299)	(0.0358)	(0.00894)	(0.0139)	(0.00685)	(0.0273)	(0.0472)
Dummy_Industry_Transport storage and communication	0.195***	0.147***	0.214***	0.180***	0.154***	0.153***	0.203***	0.115***
	(0.0161)	(0.0101)	(0.0446)	(0.0154)	(0.0130)	(0.0108)	(0.0240)	(0.0132)
Dummy_Industry_Financing, insurance, real estate and business services	0.214***	0.169***	0.181***	0.209***	0.191***	0.186***	0.232***	-0.0859***
	(0.0276)	(0.0259)	(0.0446)	(0.0146)	(0.0203)	(0.0280)	(0.0261)	(0.0217)
Dummy_Industry_community social and personal services	0.0467**	0.0450*	0.0589*	0.0435***	0.0206*	0.0201**	-0.0184	0.0331***
	(0.0213)	(0.0258)	(0.0342)	(0.0108)	(0.0112)	(0.00845)	(0.0195)	(0.00811)
male	0.0940***	0.107	0.108***	0.0743***	0.0668***	0.0583**	0.224***	0.0793***
	(0.0112)	(0.213)	(0.0218)	(0.0142)	(0.0243)	(0.0232)	(0.0679)	(0.0124)
Year FE	x	x	x					
Year trend				-0.0106***				
				(0.000524)				
_m1	0.809**	1.844*	2.537**	1.072***	1.086**	1.173**	1.745***	0.650***
	(0.401)	(0.989)	(1.166)	(0.296)	(0.424)	(0.476)	(0.509)	(0.133)
_m2	0.767	2.714***	1.822	1.128***	1.167***	1.302**	4.056***	0.479***
	(0.500)	(0.885)	(1.366)	(0.348)	(0.413)	(0.621)	(1.200)	(0.132)
_m3	0.487**	0.990	2.505*	0.623***	0.647***	0.647***	1.415***	0.155*
	(0.195)	(0.778)	(1.344)	(0.147)	(0.156)	(0.191)	(0.319)	(0.0880)
_m4	0.0303	1.155	1.436	0.192	0.0784	0.167	1.827**	
	(0.405)	(0.981)	(1.340)	(0.253)	(0.347)	(0.471)	(0.726)	
Constant	8.380***	8.961***	8.214***	29.95***	8.778***	8.832***	9.085***	8.802***
	(0.211)	(0.283)	(0.366)	(1.172)	(0.183)	(0.235)	(0.318)	(0.0621)

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' own calculations based on CSSP 1999-2015.

Note: Selection Corrected Model standard errors are based on 10 bootstraps and the selection parameters have been calculated using 100 iterations.

Comparing the coefficients of the pooled versus the race-separated earnings equations reveals clear differences. It suggests distinct returns to their respective characteristics and thus differences in the wage structure of ITTs and ATTs, particularly for educational and occupational categories, relative to the omitted base category primary or less without training and legislators, senior officials and managers, respectively. However, the wage differences appear not necessarily related to differential endowments, as the coefficient of the race dummy in the pooled models does not provide any support for H1 the existence of a racial wage difference when controlling for other characteristics in 2015 because the coefficient is insignificant in the OLS as well as the selection-corrected model. Nevertheless, we find some support for the hypothesis in other years. In the standard earnings equation, we observe a negative significant coefficient in the years 1999, 2001, 2006, and 2008, but a positive significant coefficient in 2010, 2011, 2013, and 2014. This is in line with the descriptive wage gaps, suggesting an initial wage benefit from being an ATT. In later years, however, being an ITT results in a wage premium. Using the selection-corrected earnings equation, we only observe a positive significant race coefficient in 2013 and a negative significant coefficient in 1999. Using a pooled model with year fixed effects does not provide a conclusive answer, as the coefficient for race is negative and significant in the selection-correcting earnings equation (see Table 8 column (1)), but it is insignificant in the standard OLS model (see Table 9 column (1)).

Next, this study jointly tests H2, whether the government matters for the wage level, and the size and direction of the wage gap, and H3 whether the government matters more or only for the public sector. When pooling over both races and all years, results suggest, in both the selection-corrected and OLS model, (Table 8 columns (7) and (8) and Table 9 columns (5) and (6)), that ITT wages in the private sector are relatively lower with an ATT government in power, despite a general increase in wages under an ATT government, whereas counter our expectation no significant effect is observed in the public sector. However, when splitting the sample and estimating earnings equations separately by race and sector, we observe a different situation.

Table 9: Fixed Effect Model over all Years using a Standard OLS Model

Dependent Variable: Log_reported Income	(3) All	(4) All	(5) Public	(6) Private	(7) ITT Public	(8) ATT Public	(9) ITT Private	(10) ATT Private	(11) ITT Public	(12) ATT Public	(13) ITT Private	(14) ATT Private
Dummy_ATT_government		-0.0921***	-0.161***	-0.0528***	-0.174***	-0.139***	-0.0439***	-0.0982***	0.0667***	0.0315***	0.0503***	0.0705***
		(0.00963)	(0.0147)	(0.0121)	(0.0212)	(0.0187)	(0.0150)	(0.0169)	(0.0136)	(0.0113)	(0.00854)	(0.00835)
Dummy_ITT*Dummy_ATT_government		-0.00986	0.0114	-0.0229***								
		(0.00642)	(0.0103)	(0.00780)								
Dummy_ITT	-0.000970	0.00329	0.0108	-0.00367								
	(0.00343)	(0.00493)	(0.00783)	(0.00598)								
Dummy_Educ_primary or less with training	0.0546***	0.0546***	0.0154	0.0584***	-0.0125	0.0216	0.0388***	0.0713***				
	(0.00671)	(0.00671)	(0.0113)	(0.00785)	(0.0184)	(0.0146)	(0.0108)	(0.0116)				
Dummy_Educ_incomplete secondary without training	0.0601***	0.0601***	-0.000422	0.0647***	-0.0122	0.0102	0.0658***	0.0633***				
	(0.00710)	(0.00710)	(0.0146)	(0.00774)	(0.0229)	(0.0184)	(0.00986)	(0.0124)				
Dummy_Educ_incomplete secondary with training	0.103***	0.104***	0.0575***	0.0953***	0.0515***	0.0569***	0.0753***	0.109***				
	(0.00689)	(0.00689)	(0.0124)	(0.00787)	(0.0187)	(0.0163)	(0.0107)	(0.0117)				
Dummy_Educ_secondary completed with at least o'level without training	0.148***	0.148***	0.115***	0.140***	0.115***	0.118***	0.144***	0.134***				
	(0.00752)	(0.00752)	(0.0135)	(0.00863)	(0.0198)	(0.0188)	(0.0112)	(0.0135)				
Dummy_Educ_secondary completed with at least o'level and with training	0.270***	0.270***	0.214***	0.234***	0.229***	0.202***	0.247***	0.221***				
	(0.00672)	(0.00672)	(0.0117)	(0.00787)	(0.0177)	(0.0156)	(0.0109)	(0.0115)				
Dummy_Educ_university degree	0.440***	0.440***	0.327***	0.476***	0.324***	0.331***	0.482***	0.467***				
	(0.0124)	(0.0124)	(0.0165)	(0.0188)	(0.0245)	(0.0223)	(0.0240)	(0.0302)				
Age	0.0324***	0.0324***	0.0347***	0.0309***	0.0304***	0.0380***	0.0331***	0.0287***				
	(0.000993)	(0.000993)	(0.00189)	(0.00114)	(0.00294)	(0.00246)	(0.00162)	(0.00161)				
age2	-0.000323***	-0.000323***	-0.000341***	-0.000309***	-0.000294***	-0.000375***	-0.000336***	-0.000282***				
	(1.31e-05)	(1.31e-05)	(2.38e-05)	(1.53e-05)	(3.70e-05)	(3.10e-05)	(2.20e-05)	(2.15e-05)				
Dummy_Occupation_Professionals	0.0942***	0.0941***	0.0112	0.193***	0.120**	-0.100***	0.155***	0.259***				
	(0.0188)	(0.0188)	(0.0319)	(0.0254)	(0.0502)	(0.0381)	(0.0324)	(0.0417)				
Dummy_Occupation_Technicians and Associate Professionals	-0.191***	-0.191***	-0.269***	-0.158***	-0.176***	-0.351***	-0.170***	-0.135***				
	(0.0170)	(0.0170)	(0.0318)	(0.0201)	(0.0500)	(0.0382)	(0.0256)	(0.0323)				
Dummy_Occupation_Clerks	-0.490***	-0.490***	-0.610***	-0.427***	-0.508***	-0.698***	-0.441***	-0.398***				
	(0.0174)	(0.0174)	(0.0329)	(0.0203)	(0.0514)	(0.0399)	(0.0260)	(0.0323)				
Dummy_Occupation_Service/Shop Sale Workers and Defense Force	-0.594***	-0.594***	-0.470***	-0.633***	-0.323***	-0.588***	-0.656***	-0.601***				
	(0.0220)	(0.0220)	(0.0396)	(0.0257)	(0.0620)	(0.0487)	(0.0339)	(0.0398)				
Dummy_Occupation_Agricultural, Forestry and Fishery Workers	-0.688***	-0.688***	-0.646***	-0.684***	-0.597***	-0.712***	-0.728***	-0.602***				
	(0.0334)	(0.0334)	(0.0499)	(0.0409)	(0.0774)	(0.0612)	(0.0501)	(0.0687)				
Dummy_Occupation_Craft and Related Workers	-0.576***	-0.576***	-0.618***	-0.544***	-0.478***	-0.735***	-0.556***	-0.511***				
	(0.0200)	(0.0200)	(0.0372)	(0.0232)	(0.0584)	(0.0453)	(0.0300)	(0.0365)				
Dummy_Occupation_Plant and Machine Operators and Assemblers	-0.477***	-0.477***	-0.570***	-0.444***	-0.501***	-0.624***	-0.468***	-0.398***				
	(0.0154)	(0.0154)	(0.0308)	(0.0176)	(0.0475)	(0.0378)	(0.0218)	(0.0292)				
Dummy_Occupation_Elementary Occupations	-0.853***	-0.853***	-0.899***	-0.791***	-0.771***	-1.007***	-0.812***	-0.755***				
	(0.0193)	(0.0193)	(0.0360)	(0.0225)	(0.0559)	(0.0442)	(0.0292)	(0.0353)				
Share of ATT	0.138*	0.138*	0.00799	0.103	-0.301	0.270	0.0494	0.217				
	(0.0816)	(0.0816)	(0.137)	(0.0966)	(0.209)	(0.177)	(0.131)	(0.143)				
Dummy_urban	0.0227***	0.0226***	0.00188	0.0377***	0.0185	-0.00607	0.0523***	0.0263***				
	(0.00573)	(0.00573)	(0.00877)	(0.00696)	(0.0159)	(0.0106)	(0.0112)	(0.00889)				
Dummy_privatesector	-0.234***	-0.233***										
	(0.00455)	(0.00455)										
Dummy_Industry_Mining Petroleum and Gas	0.300***	0.301***	0.271***	0.375***	0.258***	0.263***	0.334***	0.438***				
	(0.0117)	(0.0117)	(0.0158)	(0.0168)	(0.0203)	(0.0284)	(0.0203)	(0.0315)				
Dummy_Industry_other manufacturing	0.125***	0.125***	0.0870***	0.184***	0.0688	0.0708	0.185***	0.188***				
	(0.0101)	(0.0101)	(0.0317)	(0.0140)	(0.0504)	(0.0432)	(0.0165)	(0.0272)				
Dummy_Industry_Electricity and Water	0.253***	0.253***	0.260***	0.318***	0.261***	0.242***	0.249***	0.443***				
	(0.0153)	(0.0153)	(0.0167)	(0.0444)	(0.0256)	(0.0270)	(0.0567)	(0.0595)				
Dummy_Industry_Construction	0.107***	0.107***	-0.0757***	0.213***	-0.0787***	-0.0944***	0.198***	0.240***				
	(0.00938)	(0.00939)	(0.0126)	(0.0137)	(0.0169)	(0.0239)	(0.0161)	(0.0269)				
Dummy_Industry_Wholesale and retail trade, restaurants and hotels	-0.000579	-0.000170	-0.137***	0.0815***	-0.0597	-0.184***	0.0663***	0.112***				
	(0.00991)	(0.00992)	(0.0512)	(0.0137)	(0.112)	(0.0514)	(0.0164)	(0.0267)				
Dummy_Industry_Transport storage and communication	0.163***	0.163***	0.150***	0.222***	0.137***	0.136***	0.199***	0.263***				
	(0.0113)	(0.0113)	(0.0158)	(0.0161)	(0.0238)	(0.0267)	(0.0191)	(0.0306)				
Dummy_Industry_Financing, insurance, real estate and business services	0.178***	0.178***	-0.0468**	0.274***	-0.0512	-0.0669**	0.263***	0.298***				
	(0.0105)	(0.0105)	(0.0196)	(0.0145)	(0.0341)	(0.0294)	(0.0179)	(0.0273)				
Dummy_Industry_community social and personal services	0.0403***	0.0407***	0.0604***	0.00819	0.0639***	0.0373	-0.00173	0.0310				
	(0.00892)	(0.00893)	(0.0113)	(0.0138)	(0.0140)	(0.0229)	(0.0168)	(0.0266)				
Dummy_Male	0.198***	0.198***	0.127***	0.189***	0.111***	0.140***	0.203***	0.174***				
	(0.00411)	(0.00411)	(0.00654)	(0.00513)	(0.0103)	(0.00851)	(0.00732)	(0.00718)				
Year FE	x	x	x	x	x	x	x	x				
Constant	8.142***	8.140***	8.351***	7.858***	8.511***	8.252***	7.858***	7.793***	8.841***	8.744***	8.413***	8.363***
	(0.0422)	(0.0422)	(0.0740)	(0.0496)	(0.113)	(0.0973)	(0.0662)	(0.0755)	(0.0101)	(0.00834)	(0.00665)	(0.00631)
Observations	50,128	50,128	17,386	32,742	7,168	10,218	17,013	15,729	7,168	10,218	17,013	15,729
R-squared	0.630	0.630	0.666	0.571	0.695	0.640	0.599	0.541	0.004	0.001	0.003	0.006

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' own calculations based on CSSP 1999-2015.

Table 10: Wage Gap Effects of Ethnic Government

	Grouping by year and sector					Grouping by year, sector and educational category				Grouping by year, gender and sector			
Dependent Variable: Racial Wage Gap (ITT/ATT)	(1) All	(2) Private Sector	(3) Private Sector	(4) Public Sector	(5) Public Sector	(2) Private Sector	(3) Private Sector	(4) Public Sector	(5) Public Sector	(2) Private Sector	(3) Private Sector	(4) Public Sector	(5) Public Sector
Dummy_ATT government	0.00222	-0.00243	-0.00243	0.00687*	0.00687***	-0.00236	-0.00236	0.00435**	0.00435*	-0.00162	-0.00162	0.00541**	0.00541*
	(0.00269)	(0.00322)	(0.00245)	(0.00346)	(0.00175)	(0.00155)	(0.00163)	(0.00219)	(0.00220)	(0.00234)	(0.00240)	(0.00213)	(0.00278)
Year Trend			0.000862***		0.00112***	0.000730***	0.000730***	0.000290	0.000290	0.000770***	0.000770***	0.000832***	0.000832***
			(0.000240)		(0.000177)	(0.000154)	(0.000160)	(0.000222)	(0.000223)	(0.000262)	(0.000263)	(0.000210)	(0.000286)
Dummy_Male										-0.00403*		-0.0102***	
Educational Category FE						x		x					
Constant	1.008***	1.007***	-0.723	1.009***	-1.231***	-0.458	-0.458	0.419	0.422	-0.539	-0.541	-0.654	-0.659
	(0.00191)	(0.00219)	(0.480)	(0.00323)	(0.356)	(0.308)	(0.322)	(0.444)	(0.446)	(0.523)	(0.528)	(0.421)	(0.576)
Observations	34	17	17	17	17	119	119	119	119	34	34	34	34
R-squared	0.021	0.036	0.471	0.222	0.785	0.275	0.155	0.108	0.045	0.318	0.250	0.593	0.284

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' own calculations based on CSSP 1999-2015.

Table 11: Share of Public Employment affected by Ethnic Government

	Grouping by race of government, year and race					Grouping by race of government, year, race, educational category, age group and gender		Grouping by race of government, year, race and gender	
Dependent Variable: Share of Public Sector Workers	(1) All	(2) ITT	(3) ITT	(4) ATT	(5) ATT	(6) ITT	(7) ATT	(8) ITT	(9) ATT
Dummy_ATT government	-0.0257***	-0.0442***	-0.0442***	-0.00713	-0.00713	-0.0189*	9.32e-05	-0.0238**	-0.0185*
	(0.00861)	(0.00889)	(0.00859)	(0.00827)	(0.0167)	(0.00972)	(0.00968)	(0.00967)	(0.0109)
Year Trend	0.00283***	-0.000139		0.00579***		-0.00474***	0.00204**	8.17e-05	0.00303**
	(0.000877)	(0.000906)		(0.000843)		(0.001000)	(0.000993)	(0.000985)	(0.00111)
Dummy_ITT	-0.102***								
	(0.00859)								
Dummy_Male						-0.00651	0.0130	-0.0397***	-0.0320***
						(0.00984)	(0.00966)	(0.00965)	(0.0108)
Educational Category FE						x	x		
Age Group FE						x	x		
Constant	-5.265***	0.597	0.319***	-11.23***	0.401***	9.573***	-3.902*	0.301	-5.558**
	(1.760)	(1.818)	(0.00625)	(1.691)	(0.0122)	(2.006)	(1.993)	(1.976)	(2.220)
Observations	34	17	17	17	17	956	1,094	34	34
R-squared	0.842	0.639	0.638	0.774	0.012	0.636	0.558	0.434	0.389

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' own calculations based on CSSP 1999-2015.

Table 9 shows that when only looking at mean outcomes without controls, incomes for ITTs working in the public sector (column (11)) rise more than incomes of ATTs (column (12)) when there is an ATT government in power, as the coefficient for ATT government is larger for ITTs. This could be regarded as indicative evidence that the mean income of ATTs is lowered by worse-paid ATTs joining the public sector relative to low-paid ITTs and supports the clientelism argument for jobs at the lower end of the income distribution. Respectively, columns (13) and (14) show that for those ATTs and ITTs remaining in the private sector, the mean income changes reversely though to a smaller extent, which may be related to lower-paid ATTs joining the public sector that would not otherwise be participating in the labour market if there were not an ATT government in power. However, when controlling for other demographic characteristics, the respective coefficients in columns (7)-(10) suggest the reverse—that working in the public sector while an ATT government is in power reduces ITTs' mean income more than ATTs' mean income. This may suggest that there may not only be selective racial hiring taking place but also that the return on ATTs' characteristic is higher than on ITTs' when there is an ATT government. These outcomes, however, should be viewed with caution and need further investigation, as controlling for selection into the labour market as in Table 8 columns (6) and (8) leads in both cases to an insignificant coefficient of the interaction of being ITT while an ATT government is in power, meaning that income is not significantly affected in such a case, either overall or only considering the public sector.

Next, we look at the impact of the government in power on the wage gap. Table 10 presents further support for H3 that the government in power affects the wage gap in the public sector to a greater extent than in the private sector. In all specifications, irrespective of using a specification without controls or controlling for education age group, gender and a year trend, the wage gap in the public sector significantly rises by about 0.05 to 0.07 percent during the period that the largely ATT-backed government is in power, while the wage gap in the private sector is not significantly affected. The differential impact, however, declines when including more controls. This lends more further support to the earlier discussed point that additional lower-wage ATTs joining the public sector affects the mean wage gap, whereas controlling for their characteristics, such as through educational category fixed effects, reduces the size of the change in the wage gap. While these findings provide some indicative evidence that the party in power at the national government affects the race-based public sector wage gap, the coefficients are very small. Moreover, even though this study controls for selection into employment in some of the model variations, there may be other unobserved factors that we did not control for that may bias the current results. Thus, these results should be treated with caution but could motivate future research.

In further support of these findings, the results in Table 11 show that the share of ITT public sector workers is significantly more reduced than for ATTs when an ATT government is in power. This confirms the quantity effect hypothesized and is in line with the descriptive observations from Figure 3. However, here also, the reductions are relatively small, ranging between about 2-4.5 percent. Moreover, since the effect here also declines when controlling for more other factors, the quantity effect on the share of public employees appears to work only through a specific demographic group and not to be generalizable.

4.3.4 Mean Wage Gap Decomposition

Following the Oaxaca (1973) and Blinder (1973) decomposition methodology, the observed mean wage gaps can be attributed to differences in endowments, explained factors and coefficients, unexplained factors across ethnicities, at the mean based on separate earnings equations for ATTs and ITTs. The variable *difference* in the Oaxaca Blinder decomposition in Table 12 below constitutes the wage gap. The first two columns present the decomposition using a specification based on the share of ATTs in each occupation for 1999 and 2015, respectively, while the third and fourth display the decomposition based on occupational dummies. The wage gap decomposition uses real reported income earnings equations separated by ethnicities. While the estimated wage gaps do not vary by specification, the impact of endowments and coefficients on wage gaps do differ by specification. The decompositions for 2015 measure the differential importance of the effects of the coefficients versus the endowments. Irrespective of the specification, the wage gaps are, however, driven by the endowments with the coefficients, especially in the specification with the share of ATTs in each occupation, enhancing the effect.

According to the specification with the share of ATTs in each occupation, in 1999 the ATT-favouring initial wage gap was mainly driven by differential endowments among the ethnic groups, while the coefficients slightly dampened this effect. Using, however, a specification with occupational category dummies, the unexplained effect of the coefficients is driving the wage gap, with the differential endowments enhancing the effect. The fact that these two specifications, despite relatively similar earnings equation specifications, lead to such different results with opposing interpretations for policy conclusions underlines the limitations of this decomposition methodology raised in the literature. In this respect, Oaxaca & Ransom (1999) raise the choice of the reference group with regard to a group of dummies as a major concern and limitation of the Oaxaca (1973) and Blinder (1973) decomposition methodology and is thus likely to be also affecting this study's Oaxaca-Blinder decomposition results.

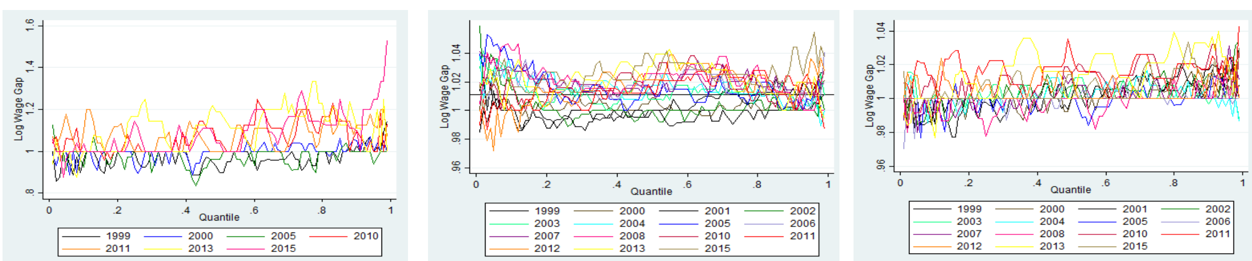
Table 12: Oaxaca Decomposition by Race for 1999 and 2015

	Specification with the share of ATTs in each occupation		occupational dummy specification	
VARIABLES	1999	2015	1999	2015
Difference	-0.0344***	0.0785***	-0.0344***	0.0785***
	(0.00247)	(0.00165)	(0.00247)	(0.00165)
Endowments	-0.0441***	0.0409***	-0.0167***	0.0581***
	(0.00202)	(0.00128)	(0.00215)	(0.00137)
Coefficients	0.00673***	0.0346***	-0.0262***	0.00932***
	(0.00178)	(0.00118)	(0.00161)	(0.00108)
Interaction	0.00291**	0.00299***	0.00852***	0.0110***
	(0.00115)	(0.000710)	(0.00112)	(0.000688)
Observations	5,803	2,448	5,803	2,448

Robust standard errors in parentheses:*** p<0.01, ** p<0.05, * p<0.1
Source: Authors' own estimations using CSSP 1999-2015.
Note: TT Racial Oaxaca decomposition using race separated earnings equations based on reported income and sample weights.

Figure 7: Log Wage Gap (ITT/ATT) across Races over Log Wage Distribution of Selected Years

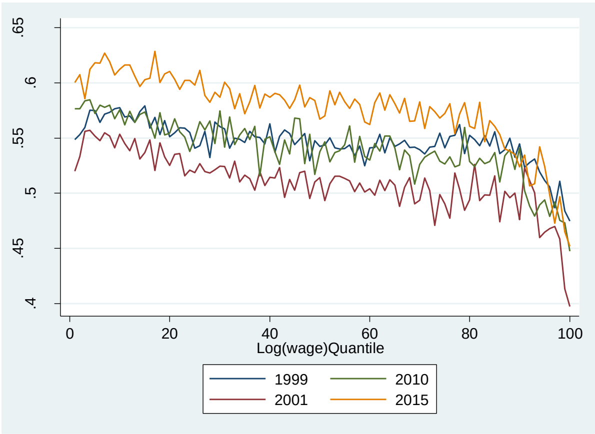
a) All employees b) Only Public Sector c) Only Private Sector



Source: Authors' own calculations based on CSSP 1999-2015.
Note: This graph only plots the mean log wage gap (ITT/ATT) or reported income at each quantile over the log wage distribution

Figure 7 reveals whether the wage gap varies over the wage distribution. Figure 7a shows that there is a marked difference in terms of the size of the wage gap over the wage distribution and that the direction of the wage gap changes by income level and over time. Specifically, one observes a shift from a mostly ATT-favoured wage gap except for the uppermost percentile of the distribution in 1999 to 2006 and subsequently increasingly ITT-favoured wage gaps at all but the lowest parts of the income distribution, as illustrated by the orange and yellow line. Over time the wage gap has moved more in favour of the ITTs as their relatively higher wages have shifted from the 80th percentile in 1999 to the 20th percentile by 2015. Given the earlier observation of seemingly more pronounced segregation and a larger wage gap along racial lines in the public sector, Figures 7 b-c depict the log wage differential over all sample years separated by sector. Comparing both figures shows that most of the wage gap changes in levels and direction in recent years and at the upper end of the wage distribution favouring ITTs seem to be driven by the public sector, whereas the private sector wage structure drives the ATT-favouring wage gap at the bottom end of the distribution. A minimum wage was introduced in 1998. Hence, the observation of a small but existing wage gap at the bottom could either point at non-compliance regarding the minimum wage or be an indicator of weak data quality, resulting in too much noise at the extremes of the income distribution.

Figure 8: Share of African Origin Trinbagonians over Log Mean Wage Distribution, Selected Years



Source: Authors' own calculations based on CSSP 1999-2015 reported income separately by race.
Note: This graph only plots the mean percentage share of ATTs in the occupation over the mean log wage distribution.

Figure 8 plots the share of ATTs in an occupation over the wage distribution and illustrates lower shares of ATTs above the 80th percentile of the wage distribution. While the exact point of the income distribution from whereon one observes a decline in the share of ATTs in the occupations slightly varies over the years, there appears to be a continuous negative pressure on the share of ATTs in the occupations of those earning the highest wages. This provides information on whether a certain racial dominance in an occupation may have a detrimental effect on wages regardless of race, as Banerjee (2014) observed independent of gender for female-dominated occupations. These results should be interpreted with caution, as wages vary only over an around 10 percent difference in share of ATTs, ranging from 48 percent to at most 60 percent, which could potentially be a result of surveys not being weighted by occupations.

4.2 Distributional Wage Gap Analysis and Decompositions

The preceding analysis dealt with the mean wage gap. This section considers mean wage differentials and their determinants at different points of the wage distribution.

4.4.1 Quantile Regression Estimation

Table 13 presents the quantile earnings equation regression results in columns (1)-(5) compared to the standard OLS earnings equation estimates in column (6). It shows that a coefficient of a particular explanatory variable takes very different importance in predicting the income at different parts of the distribution. The following sections therefore further decompose the importance of differential characteristics versus wage structure at the different parts over the income distribution.

Table 13: TT Racial Quantile Regression Earnings Equation 2015 ITTs

VARIABLES	(1) q10	(2) q25	(3) q50	(4) q75	(5) q90	(6) OLS- mean wage earnings model
D_primary or less with training	0.120*	0.0381	-0.0150	0.105	0.136	0.0561
	(0.0702)	(0.0630)	(0.0685)	(0.0640)	(0.0841)	(0.0452)
D_incomplete secondary without training	0.0120	0.0232	0.0189	0.0689*	-0.0183	0.0148
	(0.0546)	(0.0573)	(0.0528)	(0.0387)	(0.0713)	(0.0394)
D_incomplete secondary with training	0.0525	-0.000538	0.00231	0.00378	0.154	0.0308
	(0.0545)	(0.0600)	(0.0526)	(0.0555)	(0.107)	(0.0422)
D_secondary completed with at least o'level without training	0.130**	0.111*	0.124**	0.150***	0.132	0.131***
	(0.0574)	(0.0603)	(0.0505)	(0.0407)	(0.0866)	(0.0392)
D_secondary completed with at least o'level and with training	0.216***	0.230***	0.224***	0.288***	0.298***	0.252***
	(0.0632)	(0.0511)	(0.0526)	(0.0432)	(0.0802)	(0.0375)
D_university degree	0.338***	0.339***	0.420***	0.424***	0.470***	0.401***
	(0.0867)	(0.0718)	(0.0790)	(0.0702)	(0.101)	(0.0539)
Age	0.0395***	0.0380***	0.0421***	0.0218**	0.0182**	0.0319***
	(0.0114)	(0.00899)	(0.00833)	(0.00873)	(0.00913)	(0.00630)
age2	-0.000464***	-0.000431***	-0.000466***	-0.000215**	-0.000182	-0.000342***
	(0.000146)	(0.000119)	(0.000107)	(0.000108)	(0.000114)	(8.08e-05)
D_Professionals	0.393***	0.260***	0.131	0.103	0.0764	0.176**
	(0.104)	(0.0793)	(0.0884)	(0.130)	(0.120)	(0.0700)
D_Technicians and Associate Professionals	-0.0627	-0.0450	-0.149*	-0.339***	-0.423***	-0.184***
	(0.0839)	(0.0837)	(0.0859)	(0.112)	(0.101)	(0.0596)
D_Clerks	-0.200**	-0.321***	-0.474***	-0.638***	-0.733***	-0.467***
	(0.0862)	(0.0713)	(0.0944)	(0.112)	(0.100)	(0.0589)
D_Service/Shop Sale Workers	-0.340***	-0.332***	-0.484***	-0.633***	-0.686***	-0.478***
	(0.0902)	(0.0734)	(0.102)	(0.120)	(0.107)	(0.0595)
D_Agricultural, Forestry and Fishery Workers	-0.837***	-0.941***	-0.773***	-0.711***	-0.633***	-0.732***
	(0.157)	(0.177)	(0.261)	(0.252)	(0.188)	(0.140)
D_Craft and Related Workers	-0.318***	-0.306***	-0.452***	-0.663***	-0.848***	-0.486***
	(0.0879)	(0.0733)	(0.0985)	(0.110)	(0.104)	(0.0605)
D_Plant and Machine Operators and Assemblers	-0.275***	-0.252***	-0.392***	-0.598***	-0.614***	-0.404***
	(0.0951)	(0.0820)	(0.0983)	(0.109)	(0.103)	(0.0617)
D_Elementary Occupations	-0.652***	-0.667***	-0.691***	-0.892***	-0.953***	-0.759***
	(0.0917)	(0.0778)	(0.103)	(0.115)	(0.109)	(0.0597)
Percentage Share of African Origin TTs in Occupation	-	-	-	-	-	-
D_urban	0.0689	0.0582	0.0506	0.0767	0.0511	0.0476
	(0.0771)	(0.0595)	(0.0610)	(0.0507)	(0.0618)	(0.0375)
D_privatesec	-0.174***	-0.289***	-0.251***	-0.282***	-0.236***	-0.241***
	(0.0588)	(0.0355)	(0.0340)	(0.0421)	(0.0691)	(0.0279)
D_Mining, Petroleum and Gas Industry	0.152	0.208*	0.316***	0.369***	0.456***	0.303***
	(0.116)	(0.109)	(0.0764)	(0.117)	(0.127)	(0.0641)
D_other Manufacturing Industry	0.0235	0.0779	0.216***	0.299***	0.339***	0.206***
	(0.105)	(0.103)	(0.0755)	(0.101)	(0.117)	(0.0605)
D_Electricity and Water Industry	-0.00361	-0.0374	0.261**	0.381***	0.362***	0.196**
	(0.153)	(0.166)	(0.125)	(0.122)	(0.129)	(0.0927)
D_Construction	-0.0326	-0.0502	0.106	0.211**	0.183	0.0818
	(0.111)	(0.0984)	(0.0700)	(0.0984)	(0.119)	(0.0574)
D_Wholesale and Retail Trade and Restuarants and Hotels	-0.143	-0.157	0.0154	0.0543	0.0591	-0.0308
	(0.105)	(0.102)	(0.0795)	(0.0930)	(0.114)	(0.0572)
D_Transport Storage and Cummunication Industry	-0.00532	-0.0718	0.0621	0.133	0.206	0.0730
	(0.113)	(0.111)	(0.0832)	(0.123)	(0.155)	(0.0650)
D_Financing, insurance, real estate and business services	0.0589	0.0438	0.202**	0.309***	0.268**	0.177***
	(0.105)	(0.0961)	(0.0857)	(0.0991)	(0.116)	(0.0619)
D_Community Social and Personal Services Industry	-0.156	-0.175*	0.00403	0.1000	0.0948	-0.0155
	(0.0980)	(0.0997)	(0.0707)	(0.0882)	(0.0973)	(0.0546)
D_male	0.202***	0.190***	0.204***	0.226***	0.241***	0.193***
	(0.0335)	(0.0319)	(0.0300)	(0.0370)	(0.0449)	(0.0220)
Constant	7.557***	7.870***	7.857***	8.486***	8.761***	8.084***
	(0.261)	(0.193)	(0.164)	(0.226)	(0.266)	(0.141)
Observations	1,111	1,111	1,111	1,111	1,111	1,111
R-squared						0.704

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' own calculations based on CSSP 1999-2015.

Note: 1) Quantile Regression column (1)-(5) bootstrapped standard errors with 100 replications, column (6) OLS with robust standard errors 2) D_ refers to Dummy variable. Results for other years are available from the authors.

4.4.2 Quantile Decompositions

For the quantile decomposition, two approaches are used: First the Machado & Mata (2005) and the Melly (2006) decompositions, which are numerically equal at the limits, and second the Rif decomposition developed by Forpin et al. (2009). The calculations are presented in Table 14 and Figure 9, respectively. While the gap and importance of the characteristics and coefficients measured using the two approaches differ, one tendency is shared: the wage gap has widened and moved in favour of ITTs over time and over the income distribution.

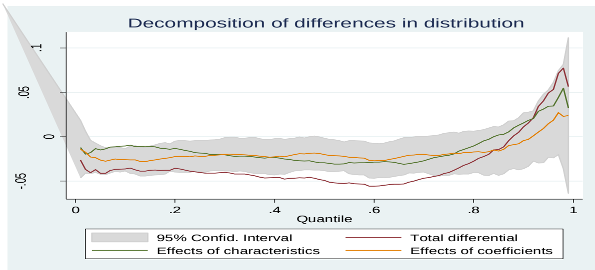
Table 14: Aggregate Quantile Decomposition Results

	Model with share of ATT in Occupation Variable						*Model with Occupational Category Dummies*					
	1999			*2015*			*1999*			*2015*		
	0.1	*0.5*	*0.9*	*0.1*	*0.5*	*0.9*	*0.1*	*0.5*	*0.9*	*0.1*	*0.5*	*0.9*
Melly (2006) Decomposition												
Raw Difference	-0.0314	-0.0534	0.0002	0.0230	0.0579	0.1707	0.0132	0.0092	0.0152	0.0188	0.0523	0.1783
s.e.	0.0141	0.0099	0.0154	0.0186	0.0110	0.0181	0.0050	0.0000	0.5460	0.0163	0.0119	0.0201
Characteristics	-0.0326	-0.0549	-0.0202	-0.0075	0.0243	0.1035	0.0129	0.0112	0.0144	0.0115	0.0425	0.1312
s.e.	0.0135	0.0068	0.0102	0.0157	0.0196	0.0202	0.3150	0.0090	0.3130	0.0204	2.2000	0.0302
Coefficients	0.0012	0.0015	0.0204	0.0305	0.0336	0.0672	0.0109	0.0111	0.0139	0.0072	0.0097	0.0471
s.e.	0.0116	0.0095	0.0149	0.0207	0.0174	0.0322	0.0160	0.0590	0.7250	0.0168	0.5300	0.0291
RIF - OLS Decomposition Forpin Fortan Lemieux (2009)												
Explained	-0.0033	-0.0293	0.0347	0.0143	0.0207	0.0958	0.0071	0.0091	0.7800	0.0322	0.0346	0.1123
se	0.0084	0.0118	0.0181	0.0115	0.0118	0.0201	0.0091	0.7800	0.4370	0.0131	0.0128	0.0218
Unexplained	0.0426	0.0035	0.0442	-0.0024	0.0623	0.1035	0.0582	0.0141	4.1300	-0.0203	0.0485	0.0870
se	0.0144	0.0123	0.0168	0.0210	0.0145	0.0245	0.0141	4.1300	0.0000	0.0200	0.0136	0.0233
Total Gap	0.0653	0.0584	0.0397	0.0119	0.0830	0.1993	0.0653	0.0584	0.0397	0.0119	0.0830	0.1993
se	0.0165	0.0164	0.0220	0.0239	0.0187	0.0308	0.0166	0.0165	0.0220	0.0240	0.0188	0.0309

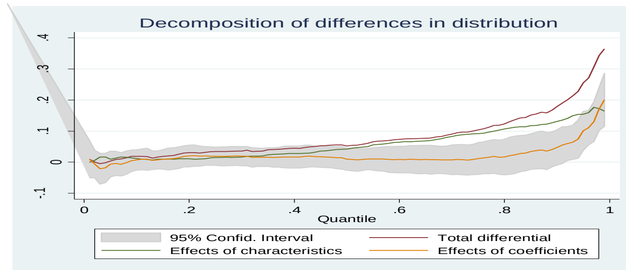
Source: Authors' own estimations based on CSSP 1999-2015.
Note: Melly (2006) estimated using Stata command rqdeco based on race separated specification and real reported income. Bootstrapped standard errors with 10 replications. RIF - OLS Decomposition Forpin Fortan Lemieux (2009) using Stata command rifreg based on race-separated specification and real reported income.

Figure 9: Melly (2006) Decomposition of Difference in Distribution

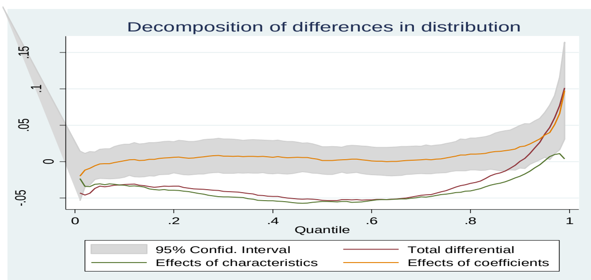
a) 1999 including occupational category dummies



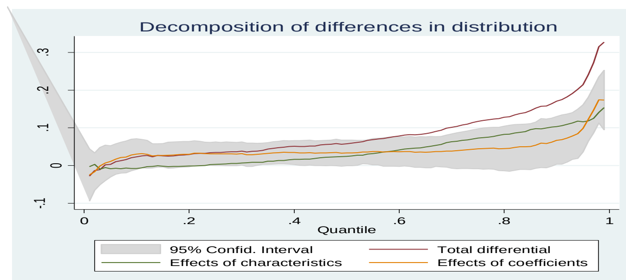
b) 2015 including occupational category dummies



c) 1999 including share of ATT in occupation



d) 2015 including share of ATT in occupation



Source: Authors' own calculations based on CSSP 1999-2015.
Note: Based on 10 bootstraps

Source: Authors' own calculations based on CSSP 1999-2015.
Note: Based on 10 bootstraps

Table 15a: RIF Decomposition Results

	*Share of ATT in Occupation **Specification***											
	1999						2015					
	0.1		0.5		0.9		0.1		0.5		0.9	
	Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.
	explained											
D_primary or less with training	0.02	0.0035	0.018	0.0029	-0.0105	0.0022	-0.0058	0.0034	-0.0069	0.0024	0.0009	0.0014
D_incomplete secondary without training	-0.0056	0.0022	-0.0057	0.0016	0.0078	0.0017	0.0005	0.0025	0.0026	0.0015	0.0014	0.0012
D_incomplete secondary with training	0.0012	0.0026	0.0011	0.0026	-0.0009	0.0021	-0.0155	0.0052	-0.0121	0.0035	-0.0046	0.0023
D_secondary completed with at least o'level without training	-0.001	0.0023	-0.0011	0.0025	0.0007	0.0017	0.011	0.005	0.0076	0.0034	0.0032	0.0018
D_secondary completed with at least o'level and with training	0.0134	0.0053	0.0167	0.0065	-0.0164	0.0064	-0.0271	0.0088	-0.0271	0.0082	-0.0191	0.0062
D_university degree	-0.0012	0.002	-0.0021	0.0037	0.0068	0.0118	0.024	0.0064	0.0329	0.0075	0.0672	0.0154
Age	0.0491	0.0124	0.0639	0.0139	-0.0357	0.0093	0.0034	0.0111	0.0045	0.0139	0.0031	0.0102
age2	-0.041	0.0109	-0.0463	0.0107	0.0158	0.0068	0.0008	0.0095	0.0011	0.0119	0.0005	0.0066
Share of ATTs	-0.015	0.0023	-0.0175	0.0026	0.0225	0.0035	0.023	0.0044	0.0266	0.0045	0.043	0.0081
D_Professionals												
D_Technicians and Associate Professionals												
D_Clerks												
D_Service/Shop Sale Workers												
D_Agricultural, Forestry and Fishery Workers												
D_Craft and Related Workers												
D_Plant and Machine Operators and Assemblers												
D_Elementary Occupations												
D_urban	0.0018	0.001	0.0032	0.0011	0.0009	0.0013	-0.0024	0.0014	-0.0015	0.001	-0.0017	0.0018
D_privatesec	0.0228	0.0042	0.0285	0.005	-0.0047	0.0017	-0.0171	0.0048	-0.016	0.0036	-0.0121	0.004
D_Mining, Petroleum and Gas Industry	-0.003	0.0013	-0.0044	0.0018	0.0081	0.0032	0.0046	0.0045	0.0045	0.004	0.0061	0.0056
D_Manufacturing Industry	-0.0131	0.0033	-0.0096	0.0025	0.0065	0.0019	0.0183	0.0076	0.0097	0.0037	0.0073	0.0033
D_Electricity Gas and Water Industry	0.0005	0.0004	0.0012	0.0009	-0.001	0.0009	-0.0028	0.0026	-0.0027	0.0023	-0.0028	0.0027
D_Construction	0.0108	0.0033	0.0079	0.0024	-0.0026	0.0011	-0.0192	0.0092	-0.0111	0.0046	-0.0063	0.0034
D_Wholesale and Retail Trade and Restuarants and Hotels	-0.0031	0.0024	-0.0013	0.0011	0.0022	0.0017	0.0168	0.0088	0.0085	0.0041	0.0082	0.0042
D_Transport Storage and Cummunication Industry	-0.003	0.0016	-0.0031	0.0016	0.0011	0.0008	0.0055	0.0045	0.0038	0.003	0.0025	0.0022
D_Financing Insurance and Real Estate Industry	0.0092	0.0028	0.0089	0.0027	-0.0047	0.0017	-0.0091	0.0074	-0.0067	0.0052	-0.003	0.0026
D_Community Social and Personal Services Industry	0.001	0.0044	0.0152	0.0038	-0.0171	0.0034	-0.0103	0.008	-0.0094	0.0059	-0.005	0.0037
D_male	-0.021	0.0031	-0.0186	0.0026	0.0168	0.003	0.0156	0.0044	0.0124	0.0033	0.0071	0.0029
Total	0.0227	0.0084	0.0549	0.0106	-0.0046	0.0142	0.0143	0.0115	0.0207	0.0118	0.0958	0.0201
	unexplained											
D_primary or less with training	0.0093	0.009	0.0033	0.0073	-0.0059	0.0065	0.0058	0.0106	-0.0023	0.0058	0.0076	0.0053
D_incomplete secondary without training	0.0008	0.0065	-0.0014	0.004	0.0019	0.0034	0.0099	0.0142	-0.0091	0.0064	-0.0053	0.0062
D_incomplete secondary with training	0.0189	0.0092	0.0004	0.0067	0.0003	0.0067	-0.0138	0.0147	-0.0125	0.0081	-0.0028	0.0083
D_secondary completed with at least o'level without training	-0.001	0.0056	-0.0046	0.0043	0.0042	0.0044	0.0055	0.015	0.0057	0.0079	-0.0013	0.0083
D_secondary completed with at least o'level and with training	-0.0033	0.0167	-0.0293	0.0118	0.0347	0.0181	-0.0177	0.0365	-0.0022	0.0182	-0.0274	0.0253
D_university degree	0.0007	0.0024	-0.0038	0.0022	0.0192	0.0055	-0.0081	0.0135	-0.0091	0.0077	-0.0174	0.0172
Age	-0.3825	0.3216	-0.5097	0.2325	0.4866	0.2509	-0.0272	0.516	0.5425	0.3251	-0.3399	0.4842
age2	0.1478	0.1592	0.2468	0.119	-0.2134	0.1311	-0.0029	0.2624	-0.2909	0.1657	0.0821	0.2623
Share of ATTs	0.076	0.1194	0.4438	0.1302	0.1893	0.1752	0.274	0.1568	-0.0624	0.1458	0.2418	0.3067
D_Professionals												
D_Technicians and Associate Professionals												
D_Clerks												
D_Service/Shop Sale Workers												
D_Agricultural, Forestry and Fishery Workers												
D_Craft and Related Workers												
D_Plant and Machine Operators and Assemblers												
D_Elementary Occupations												
D_urban	0.003	0.0043	-0.0024	0.004	-0.0137	0.0057	0.0057	0.0041	0.0064	0.004	0.0082	0.0071
D_privatesec	-0.0066	0.0263	0.1341	0.0216	0.0527	0.0259	-0.032	0.0402	-0.0905	0.0237	-0.0381	0.0358
D_Mining, Petroleum and Gas Industry	0.0011	0.0036	0.0016	0.0028	0.0094	0.0054	-0.0021	0.0133	0.0037	0.0055	-0.009	0.0095
D_Manufacturing Industry	-0.0053	0.0132	-0.0194	0.009	0.0069	0.0091	0.005	0.0202	0.0176	0.0084	0.015	0.0097
D_Electricity Gas and Water Industry	-0.0001	0.0013	-0.0018	0.0013	0.0039	0.0031	-0.0013	0.005	-0.0012	0.0022	0.0034	0.005
D_Construction	-0.0032	0.0144	-0.0131	0.01	0.0075	0.0085	-0.0109	0.0441	0.0185	0.0167	0.0034	0.0181
D_Wholesale and Retail Trade and Restuarants and Hotels	0.0149	0.0169	-0.014	0.0105	0.0007	0.0104	-0.0136	0.0408	0.0148	0.0157	-0.0065	0.0178
D_Transport Storage and Cummunication Industry	-0.0006	0.0045	0.0009	0.0037	-0.0109	0.0045	-0.0029	0.0103	0	0.0047	-0.0023	0.0063
D_Financing Insurance and Real Estate Industry	0.003	0.0084	-0.0237	0.0067	0.0124	0.0081	-0.006	0.0224	0.0121	0.0091	-0.0044	0.011
D_Community Social and Personal Services Industry	0.0134	0.0295	-0.0028	0.0194	-0.0025	0.02	-0.0501	0.0935	-0.0044	0.0348	0.0027	0.0378
D_male	0.0062	0.0209	-0.0062	0.0165	0.0024	0.0247	0.0307	0.0276	-0.0025	0.0169	-0.047	0.029
_cons	0.15	0.2241	-0.1952	0.1928	-0.5416	0.2272	-0.1503	0.3912	-0.0719	0.2451	0.2409	0.412
Total	0.0426	0.0144	0.0035	0.0123	0.0442	0.0168	-0.0024	0.021	0.0623	0.0145	0.1035	0.0245

Source: Authors' own estimations based on CSSP 1999 and 2015.

Table 15b: RIF Decomposition Results

	Occupational Category Dummy Specification											
	1999						2015					
	0.1		0.5		0.9		0.1		0.5		0.9	
	Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.
explained												
D_primary or less with training	0.0119	0.0031	0.0056	0.0021	-0.0044	0.0018	-0.0017	0.0031	-0.0031	0.0017	0.002	0.0014
D_incomplete secondary without training	-0.0029	0.002	-0.0018	0.0013	0.0042	0.0012	-0.0007	0.0024	0.0016	0.0012	0.0011	0.0011
D_incomplete secondary with training	0.0007	0.0015	0.0004	0.0009	-0.0004	0.001	-0.0076	0.0041	-0.0045	0.0022	-0.0014	0.002
D_secondary completed with at least o'level without training	-0.0005	0.0012	-0.0004	0.001	0.0003	0.0008	0.0059	0.0033	0.004	0.002	0.0018	0.0014
D_secondary completed with at least o'level and with training	0.0071	0.003	0.0069	0.0028	-0.0066	0.0027	-0.0139	0.0057	-0.0141	0.0046	-0.0102	0.0039
D_university degree	-0.0006	0.0011	-0.0008	0.0014	0.0032	0.0055	0.013	0.0048	0.0158	0.0042	0.034	0.0093
Age	0.0449	0.0116	0.0571	0.0125	-0.0227	0.0071	0.0035	0.0113	0.0041	0.0126	0.0024	0.0082
age2	-0.0382	0.0104	-0.0425	0.0099	0.0086	0.0058	0.0009	0.0098	0.001	0.0111	0.0004	0.0052
Share of ATTs												
D_Professionals	0.0002	0.0003	0.0008	0.0006	0.0019	0.0017	-0.0032	0.0014	-0.004	0.0019	0.0206	0.0078
D_Technicians and Associate Professionals	-0.0002	0.0004	0.0008	0.0008	-0.0048	0.0039	-0.0002	0.0005	-0.0011	0.0012	-0.0057	0.0056
D_Clerks	-0.0002	0.0006	0.0007	0.0018	-0.0046	0.0114	0.0001	0.0007	-0.0011	0.005	-0.0025	0.0113
D_Service/Shop Sale Workers	-0.0121	0.0028	-0.0354	0.0054	0.0935	0.0149	0.0124	0.004	0.0196	0.0058	0.0342	0.0113
D_Agricultural, Forestry and Fishery Workers	0.0011	0.0009	0.0024	0.0011	-0.0053	0.0022	-0.0024	0.0022	-0.003	0.0016	-0.0054	0.0026
D_Craft and Related Workers	-0.0058	0.0021	-0.0124	0.0041	0.0375	0.0123	0.0027	0.002	0.0068	0.0045	0.0187	0.0122
D_Plant and Machine Operators and Assemblers	0.0002	0.0012	0.0132	0.003	-0.0476	0.0099	-0.0011	0.0011	-0.0083	0.0032	-0.0255	0.0093
D_Elementary Occupations	0.0122	0.0043	0.0236	0.008	-0.0427	0.015	0.023	0.008	0.0306	0.0103	0.0419	0.015
D_urban	0.0014	0.001	0.0026	0.0009	0.0013	0.0013	-0.0018	0.0012	-0.0012	0.0009	-0.0021	0.0018
D_privatesec	0.021	0.0039	0.0273	0.0048	-0.0045	0.0017	-0.0184	0.0049	-0.0176	0.0038	-0.0084	0.0036
D_Mining, Petroleum and Gas Industry	-0.0019	0.001	-0.0029	0.0012	0.0069	0.0028	0.0019	0.0027	0.0023	0.0022	0.0046	0.0042
D_Manufacturing Industry	-0.0091	0.0028	-0.005	0.0019	0.0058	0.0017	0.0092	0.0067	0.0023	0.0023	0.0031	0.0022
D_Electricity Gas and Water Industry	0.0001	0.0002	0.0007	0.0006	-0.0013	0.0011	-0.0009	0.0016	-0.0013	0.0012	-0.0017	0.0018
D_Construction	0.0084	0.0027	0.0043	0.0017	-0.002	0.0009	-0.0093	0.0082	-0.0028	0.0027	0.0001	0.0018
D_Wholesale and Retail Trade and Restuarants and Hotels	-0.0015	0.0014	0.0005	0.0006	0.0013	0.001	0.0076	0.007	-0.0003	0.0021	-0.0024	0.002
D_Transport Storage and Cummunication Industry	-0.0014	0.0009	-0.0014	0.0009	0.0011	0.0008	0.0022	0.0028	0.0013	0.0013	0.001	0.0012
D_Financing Insurance and Real Estate Industry	0.0054	0.002	0.0046	0.0016	-0.0029	0.0013	-0.0049	0.0049	-0.0029	0.0025	0.0013	0.0015
D_Community Social and Personal Services Industry	-0.0077	0.0046	0.0033	0.0033	-0.0048	0.0025	-0.0023	0.0063	-0.0025	0.0025	0.002	0.0019
D_male	-0.0252	0.0035	-0.0227	0.0029	0.0158	0.003	0.0183	0.005	0.013	0.0034	0.0085	0.0032
Total	0.0071	0.0091	0.0294	0.0113	0.0268	0.0158	0.0322	0.0131	0.0346	0.0128	0.1123	0.0218
unexplained												
D_primary or less with training	0.0105	0.0094	0.0111	0.0072	-0.0087	0.006	0.0037	0.0105	-0.0051	0.0056	0.0059	0.0049
D_incomplete secondary without training	0.0016	0.0064	0.0012	0.0039	-0.0003	0.0031	0.0097	0.0139	-0.0085	0.006	0.001	0.0058
D_incomplete secondary with training	0.0206	0.0096	0.0109	0.0068	-0.0034	0.0063	-0.0181	0.0148	-0.0162	0.0081	0.003	0.0083
D_secondary completed with at least o'level without training	0.0014	0.006	0.0022	0.0042	-0.0046	0.0042	0.0023	0.015	0.0015	0.0076	0.0029	0.008
D_secondary completed with at least o'level and with training	0.0029	0.019	0.0077	0.0139	-0.0001	0.0156	-0.01	0.0377	-0.0143	0.0193	-0.0139	0.0242
D_university degree	0.0018	0.0032	0.0052	0.0035	-0.0036	0.0103	-0.0047	0.0138	-0.0115	0.0086	-0.0211	0.0197
Age	-0.2224	0.3125	-0.2251	0.2205	0.1842	0.2258	-0.0484	0.4991	0.4609	0.3091	-0.4744	0.4588
age2	0.0794	0.1545	0.1312	0.1128	-0.0802	0.1184	0.0081	0.2528	-0.252	0.1572	0.175	0.2484
Share of ATTs	-0.0002	0.0016	0.0042	0.0026	0.0129	0.0082	0.0019	0.0025	-0.0005	0.0032	0.0113	0.0143
D_Professionals	0.0028	0.0053	0.0143	0.0092	-0.0029	0.0297	0.0035	0.006	0.0048	0.009	0.0152	0.0307
D_Technicians and Associate Professionals	-0.0064	0.0066	0.037	0.0111	-0.0161	0.0319	0.0025	0.0074	-0.0044	0.0103	0.0407	0.0277
D_Clerks	0.0047	0.0086	0.0544	0.0117	-0.026	0.0338	0.0019	0.0117	-0.0023	0.012	0.0391	0.0346
D_Service/Shop Sale Workers	0.0021	0.0009	0.001	0.0007	-0.0004	0.0009	-0.0028	0.0017	-0.0012	0.001	0.0014	0.001
D_Agricultural, Forestry and Fishery Workers	0.0039	0.0091	0.0448	0.0129	-0.0181	0.0359	0.0232	0.0098	-0.0106	0.0116	0.0407	0.0305
D_Craft and Related Workers	-0.0012	0.0042	0.0195	0.007	-0.0201	0.0191	0.0032	0.0049	-0.0006	0.0072	0.0166	0.0185
D_Plant and Machine Operators and Assemblers	0.0148	0.0161	0.0921	0.0194	-0.0313	0.0559	0.0152	0.0186	-0.0199	0.0164	0.0611	0.0453
D_Elementary Occupations	0.0037	0.0041	-0.0014	0.0036	-0.0138	0.0055	0.0019	0.0039	0.0029	0.0037	0.0031	0.0065
D_urban	-0.009	0.0249	0.1328	0.0205	0.0435	0.025	-0.026	0.0386	-0.0658	0.0221	0.0124	0.0336
D_privatesec	0.0021	0.0039	0.0015	0.0028	0.0082	0.0049	-0.0135	0.0149	-0.0026	0.0056	-0.0129	0.0083
D_Mining, Petroleum and Gas Industry	0.0028	0.014	-0.0164	0.0091	0.0124	0.0078	-0.0141	0.0228	0.0052	0.0085	0.0072	0.0077
D_Manufacturing Industry	0.0007	0.0013	-0.0015	0.0013	0.0042	0.0028	-0.0056	0.0058	-0.0029	0.0025	0.0041	0.0044
D_Electricity Gas and Water Industry	0.0022	0.0152	-0.0132	0.0103	0.0125	0.0072	-0.0544	0.0506	0.0012	0.0175	0.0024	0.0128
D_Construction	0.0242	0.0178	-0.0099	0.011	0.0122	0.009	-0.0426	0.0468	-0.0103	0.0163	-0.0069	0.0135
D_Wholesale and Retail Trade and Restuarants and Hotels	0.0024	0.0049	0.0007	0.0039	-0.0054	0.004	-0.0117	0.012	-0.0057	0.0049	-0.0004	0.0055
D_Transport Storage and Cummunication Industry	0.0076	0.0088	-0.0213	0.0066	0.0169	0.0068	-0.0229	0.0253	-0.0004	0.0092	-0.0018	0.0088
D_Financing Insurance and Real Estate Industry	0.026	0.031	0.005	0.0197	0.0047	0.0163	-0.1204	0.1066	-0.04	0.036	0.018	0.0261
D_Community Social and Personal Services Industry	-0.0143	0.0223	-0.0259	0.0153	0.0182	0.0246	0.0271	0.0287	0.0056	0.0163	-0.0449	0.0299
D_male	0.0936	0.211	-0.2328	0.161	-0.082	0.2631	0.2707	0.4037	0.0414	0.2013	0.2027	0.3191
_cons	0.0582	0.0141	0.029	0.0118	0.0128	0.0151	-0.0203	0.02	0.0485	0.0136	0.087	0.0233
Total	0.0428	0.0144	0.0027	0.0123	0.0445	0.0168	0.0623	0.0144	0.0623	0.0144	0.1036	0.0245

Source: Authors' own estimations based on CSSP 1999 and 2015.

The Melly (2006) decomposition graphs (Figure 9) illustrate the wage gap decomposed into explained, unexplained, and predicted gap graphically for the first and last sample year, 1999 and 2015, and each for both specifications (occupational category dummies and the share of ATTs in an occupation). Generally, the wage gap has widened in favour of ITTs whereby the coefficients play an increasingly larger role. By contrast, the initial wage gap at the lower end of the distribution favouring ATTs in 1999 was mainly driven by the characteristics. Considering the case with the share of ATTs in an occupation, the characteristics have shifted from favouring the ITTs above the 90^{th} quantile in 1999 to favouring them from the 30^{th} quantile onward in 2015. When considering the specification with occupational dummies, the existence of a wage gap can be explained over the whole distribution by the characteristics that favour ITTs, though being additionally widened through additional returns to these characteristics. These results are line with the catch-up of ITTs in terms of educational attainment displayed in Figure A.4 in the Appendix.

Regardless of whether one uses a model that includes the share of ATTs in an occupation or occupational category dummies income, one can observe for 1999 that the dark red line, representing the total differential, crosses the zero/no wage gap line at the 90^{th} percentile of the wage distribution. This means that at the 90^{th} percentile the wage gap changes from a wage gap favouring the ATT population to one that is advantageous for the ITTs. Specifically, until about the median of the wage distribution, the wage gap is widening in favour of the ATTs; thereafter, the gap is closing until it reverses in favour of ITTs. In the figure of the occupational category dummies specification, one additionally observes a decrease at the very top of the wage distribution again, but as this is not visible in the specification with the share of ATTs wage gaps, this might be a result of noise at the extreme end of the wage distribution. As the green and red lines move largely overlapping in the specification with the share of ATTs in each occupation, the observed total differential in wages can be equally attributed to differences in characteristics, such as education level and occupation, and differences in coefficients, which determine the return on the respective characteristics in the labour market. In the specification with occupational category dummies, the wage gap seems driven by the characteristics up until the 90^{th} percentile and is, once the gap reverses, driven by the coefficients. In 2015, however, the wage differential at the lower end of the distribution is driven by differences in coefficients, while at the upper half of the distribution it is determined by differences in characteristics in both specifications. The direction of the effects is, however, more pronounced in the specification including the share of ATTs in an occupation.

The RIF decomposition has the advantage that it does not just decompose the wage gap at each quantile into the extent that it is driven by explained or unexplained factors, but further disaggregates into the effect of each specific characteristic and its coefficient. As the characteristics emerged as the main driver of the wage gap and the shift in the wage gap in the previous Melly type decompositions, the RIF decomposition in Table 15 presents the effect of each of the characteristics and coefficients in the aggregate driving force of the characteristics and coefficients. Considering only the first and last sample year the age and gender and some industry coefficients stand out as the main drivers in both specifications. While age has a wage gap reducing effect at lower income levels it increases wage gaps for the top 10% of the income distribution. Besides, being male has in 2015 a wage gap increasing effect especially for the lowest earners. These findings should be treated with caution, as the effect of coefficients is highly volatile between years and displays large standard errors and the results do not allow inference on statistical significance.

5 Conclusions

Trinidad and Tobago inherited colonial, state-enforced race-based educational, occupational and industrial segregation and wage gaps when it became independent in 1962. Even though these were abolished upon independence and racial background does generally no longer play a major role in today's society anymore, racial discrimination allegations become more frequent around the time of general elections. Such claims are, however, based on anecdotes. This study is a first attempt to estimate the existence, extent, and driving forces of post-independence, race-based educational, occupational, and industry segregation and wage gaps among the two major racial groups: Indian (ITT) and African (ATT)-origin Trinbagonians to provide evidence whether the claims are grounded on facts. The segregation and wage—mean and distribution—gap analysis is based on labour market survey data from 1999 to 2015.

Generally, aggregate race-based educational and occupational segregation is found to be low, both at a level of 7 percent. The levels of racial segregation found are lower than the gender-based educational and occupational segregation levels of 9.6 percent and 18.4 percent documented by Schimanski, Chagalj, and Ruprah (2018). These estimates are found to have remained largely constant over the past 17 years. However, race-based industrial segregation has slightly but significantly declined over time from around 7 percent to around 5 percent, driven by large reductions in agricultural and construction sector segregation.

Regarding the existence of a race-based wage gap, we observe that also the aggregate race-based wage gaps are small and likewise smaller than the mean gap by gender. ITTs earn on average just under 1.048 TTD for every 1 TTD an ATT earns, while irrespective of race men earn on average 1.10 TTD for every 1 TTD a woman earns, as estimated in Schimanski, Chagalj, and Ruprah (2017). However, interestingly we do not observe a sole reduction or rise in the racial wage gap, but rather a shift in the mean wage gap. In 1999 the wage gap favoured ATTs, but then shifted over time to more recently favouring ITTs. Moreover, public sector wage gaps are observed to be slightly larger than private sector wage gaps. This appears to be especially so for women and during the time of the ATT-favouring PNM party being in office at the national government, which is a period also characterized by increases in the share of ATTs in public sector employment and the oil boom. We also observe a shift in terms of the drivers of the mean wage gap, from predominantly a result of distinctive characteristics, such as education, to increasingly an unexplained different return to those characteristics. While we control for selection into employment, there remains a potential bias from unobserved factor and endogeneity that we cannot control for. Hence, more research is needed to provide further evidence on these findings.

Departing from the mean wage gap and taking a more detailed look at the wage gap over the wage income distribution demonstrates that the tipping of the direction of the wage gap holds over the entire distribution but not to the same extent. It rather exhibits a wage gap favouring ATTs at the lower end of the income distribution and favouring ITTs at the upper end of the distribution, with an increasingly larger range of the income distribution facing wage gaps in favour of ITTs. Moreover, the results suggest that Trinbagonians at the upper end of wage distribution work in occupations with slightly lower shares of ATTs.

While this is the first empirical study on racial segregation and wage gaps in Trinidad and Tobago over time, it only provides insights about the wage gap situation amongst employees. Hence, more research is needed on this aspect, as this analysis cannot inform about the situation of the labour market as a whole. Race groups may be working with different levels of returns in self-employment, which may either reinforce or offset the small race differentials observed amongst formal sector employees. The evidence on the absence of extensive aggregate racial segregation and mean wage gaps, but the existence of notable wage gaps in the public sector and at specific quantiles of the wage distribution and a potential small moderating effect of the national government in power, emphasises the importance of looking beyond the mean. Moreover, the increasing importance of race-based gaps due to unexplained factors and the diminishing importance of characteristics plausibly related to labour productivity, raise concerns about potential future rising discrimination. Given the noted heterogeneity, but the limited sample size of subsamples when disaggregating into specific demographic groups, this study suggests the need for larger datasets that allow a disentanglement of all factors determining segregation and wage gaps.

6 References

Arellano, M., and Bonhomme, S. 2017a. Sample Selection in Quantile Regression: A Survey. CEMFI Working Paper No. 1702.

_____. 2017b. Quantile selection models with an application to understanding changes in wage inequality*. Econometrica, 85*(1): 1-28.

Atal, J. P., Ñopo, H. R., and Winder, N. 2009*. New Century, Old Disparities: Gender and Ethnic Wage Gaps in Latin America.* Inter-American Development Bank Working Paper, IDB-WP-109. Washington, DC: Inter-American Development Bank.

Banerjee, B. 2014. Occupational segregation and gender differentials in earnings in Macedonia. *IZA Journal of European Labor Studies*, *3*(1): 4.

Borghans, L., and Groot, L. 1999. Educational presorting and occupational segregation. *Labour Economics*, *6*(3): 375-95.

Bissessar A. M. and Gaffar Le Guerre, J. (2013). *Trinidad and Tobago and Guyana. Race and Politics in Two Plural Societies.* Plymouth, United Kingdom: Lexington Books

Blinder, A. 1973. Wage Discrimination: Reduced Form and Structural Differences. *Journal of Human Resources,* 7(4): 436-55.

Bollinger, C. R., Hirsch, B. T., Hokayem, C. M. and Ziliak, J. P. 2018. Trouble in the Tails? What We Know about Earnings Nonresponse Thirty Years after Lillard, Smith, and Welch. *Journal of Political Economy* **(**forthcoming**).**

Bourguignon, F., Fournier, M., and Gurgand, M. 2007. Selection Bias Corrections Based on the Multinomial Logit Model: Monte Carlo Comparisons. *Journal of Economic Surveys*, *21*(1): 174-205.

Brown, D. R. 1999. Ethnic Politics and Public Sector Management in Trinidad and Guyana. *Public Administration and Development*, *19*(4): 367.

Canelas, C., and Gisselquist, R. M. 2017. Human Capital, Labour Market Outcomes, and Horizontal Inequality in Guatemala (No. 2017/91). UNU-WIDER Working Paper. Helsinki, Finland: World Institute for Development Economic Research.

Canelas, C., and Salazar, S. 2014. Gender and Ethnic Inequalities in LAC Countries. *IZA Journal of Labor & Development*, *3*(1): 18.

Cameron, A. C., and Trivedi, P. K. 2005. *Microeconometrics: Methods and Applications*. Cambridge, United Kingdom: Cambridge University Press.

Card, D., Cardoso, A. R., and Kline, P. 2015. Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women. *The Quarterly Journal of Economics*, *131*(2): 633-86.

Card, D., and Krueger, A. B. 1993. Trends in Relative Black-white Earnings Revisited. *The American Economic Review*, *83*(2): 85-91.

Chandra, A. 2000. Labor-market Dropouts and the Racial Wage Gap: 1940-1990. *The American Economic Review*, *90*(2): 333-338.

Chandra, K. 2007. *Why Ethnic Parties Succeed: Patronage and Ethnic Head Counts in India*. Cambridge, United Kingdom: Cambridge University Press.

Chong, A., & Ñopo, H. 2008. The Mystery of Discrimination in Latin America. *Economía*, *8*(2): 79-107.

Coppin, A., and Olsen, R. N. 1998. Earnings and Ethnicity in Trinidad and Tobago. *The Journal of Development Studies*, *34*(3): 116-34.

Cornwell, C., Rivera, J., and Schmutte, I. M. 2017. Wage Discrimination When Identity Is Subjective Evidence from Changes in Employer-Reported Race. *Journal of Human Resources*, *52*(3): 719-55.

Duncan, O. D., and Duncan, B. 1955. A Methodological Analysis of Segregation Indexes. *American Sociological Review*, *20*(2): 210-217.

Firpo, S., Fortin, N. M. and Lemieux, T. 2009. Unconditional Quantile Regressions. *Econometrica 77*(3): 953-973.

Garcia, M. L., Ñopo, H., & Salardi, P. 2009. Gender and Racial Wage Gaps in Brazil 1996-2006: Evidence using a Matching Comparisons Approach. Inter-American Development Bank Working Paper, No. 681 RG-N3338. Washington, DC: Inter-American Development Bank.

Gradín, C. 2014. Race and Income Distribution: Evidence from the USA, Brazil and South Africa. *Review of Development Economics*, *18*(1): 73-92.

_____. 2017. Occupational Segregation by Race in South Africa after Apartheid. UNU-WIDER Working Paper No. 073. Helsinki, Finland: World Institute for Development Economic Research.

Hegewisch, A. and Hartmann, H. 2014. *Occupational Segregation and the Gender Wage Gap: A Job Half Done. Occupational Segregation and the Gender Wage Gap: A Job Half Done.* Washington, DC: Institute for Women's Policy Research.

Horowitz, D. L. 1985. *Ethnic Groups in Conflict*. Oakland, CA: University of California Press.

Karmel, T., & Maclachlan, M. 1988. Occupational Sex Segregation—Increasing or Decreasing? *Economic Record*, *64*(3): 187-195.

Koenker, R., & Bassett Jr, G. 1978. Regression Quantiles. *Econometrica: Journal of the Econometric Society*, *46*(1): 33-50.

Lovell, P. A. 2000. Race, Gender and Regional Labor Market Inequalities in Brazil. *Review of Social Economy*, *58*(3): 277-93.

Machado, J. A., and Mata, J. 2005. Counterfactual Decomposition of Changes in Wage Distributions using Quantile Regression. *Journal of Applied Econometrics*, *20*(4): 445-65.

Mincer, J. 1974. *Schooling, Experience, and Earnings.* Human Behavior & Social Institutions No. 2. Cambridge, MA: National Bureau of Economic Research (NBER) Books. New York, NY: Cambridge University Press.

Melly, B. 2005. Decomposition of Differences in distribution using quantile regression. *Labour Economics*, *12*(4), 577-90.

_____. 2006. *Estimation of counterfactual distributions using quantile regression*. mimeo, Swiss Institute for International Economics and Applied Economic Research (SIAW). St. Gallen, Switzerland: University of St. Gallen.

Neuman, S., and Oaxaca, R. L. 2004. Wage decompositions with selectivity-corrected wage equations: A methodological note. *The Journal of Economic Inequality*, *2*(1): 3-10.

Oaxaca, R. 1973. Male-female Wage Differentials in Urban Labor Markets. *International Economic Review*, *14*(3): 693-709.

Oaxaca, R. L., & Ransom, M. R. 1999. Identification in Detailed Wage Decompositions. *Review of Economics and Statistics*, *81*(1): 154-57.

Pinto, M. F. 2014. *Tres décadas de brechas salariales por raza en Brasil. Un análisis más allá de la media. [in Spanish: Three decades of racial wage gaps in Brazil. An analysis beyond the mean.]* (Master's Thesis) Working Paper, 169. Centro de Estudios Distributivos, Laborales y Sociales. La Plata, Argentina: Universidad de la Plata: ISSN 1853-0168

Premdas, R. R. 1996. *Ethnicity and Elections in the Caribbean: A Radical Realignment of Power in Trinidad and the Threat of Communal Strife*. Working Paper 224. Notre Dame, IN: Helen Kellogg Institute for International Studies.

Premdas R. 2007. Trinidad and Tobago. Ethnicity, Inequality and Public Sector Governance. Palgrave Macmillan

Robinson, J. A., & Verdier, T. 2013. The Political Economy of Clientelism. *The Scandinavian Journal of Economics*, *115*(2): 260-91.

Salardi P. 2012. Chapter 6 in: *An Analysis of Pay and Occupational Differences by Gender and Race in Brazil - 1987 to 2006*. (submitted for Doctoral Dissertation, University of Sussex). Retrieved from: http://sro.sussex.ac.uk/45204/1/Salardi%2C_Paola.pdf

_____. 2014. The Evolution of Gender and Racial Occupational Segregation across Formal and Non-formal Labor Markets in Brazil, 1987 to 2006. *Review of Income and Wealth*, *62*(S1): 1-22.

Silber, J. 2012. Measuring Segregation: Basic Concepts and Extensions to Other Domains. CEPS INSEAD Working Papers (No. 2012-20). Fontainbleu, France: INSEAD.

Schimanski, C., Chagalj, C. and Ruprah, I. 2018. Gender-based Educational and Occupational Segregation in the Caribbean. Inter-American Development Bank Working Paper No.931. Washington, DC: Inter-American Development Bank.

_____. 2017. Are There Sticky Floors and Glass Ceilings in the Caribbean? - Returns to Education and Gender Pay Gaps over the Wage Distribution in the Caribbean. Unpublished Manuscript.

Schwartzman, L. F. 2007. Does Money Whiten? Intergenerational Changes in Racial Classification in Brazil. *American Sociological Review*, *72*(6): 940-963.

Sookram, S., and Strobl, E. 2009. The Role of Educational Choice in Occupational Gender Segregation: Evidence from Trinidad and Tobago. *Economics of Education Review*, *28*(1): 1-10.

Sriskandarajah, D. 2005. Development, Inequality and Ethnic Accommodation: Clues from Malaysia, Mauritius and Trinidad and Tobago. *Oxford Development Studies*, *33*(1): 63-79.

Telles, E. E. and Lim, N. (1998). Does It Matter Who Answers the Race Question? Racial Classification and Income Inequality in Brazil. *Demography*, *35*(4): 465-74.

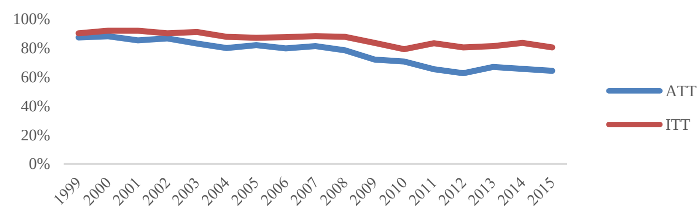
7 Appendix

Table A.1: Sample Overview

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total
Segregation sample	9466	3634	5767	5006	4784	4587	5347	5272	5112	5116	4897	3477	3242	5747	4657	4596	4648	85355
Wage gap sample																		
Reported income	5803	2264	3550	3160	2929	2661	3254	3204	3160	3103	2771	1912	1794	3095	2522	2498	2448	50128
Rep.+ imputed inc.	7468	2900	4496	3994	3829	3705	4299	4258	4156	4153	3953	2785	2597	4638	3664	3618	3688	68201
Rep.+ imputed income within 3sd from rep. mean inc.	7446	2869	4489	3953	3822	3665	4291	4250	4155	4140	3950	2781	2595	4630	3660	3613	3684	67993

Source: Authors' own estimations based on CSSP 1999-2015.
Note: See data section for description of each sample.

Figure A.1: Response Rate to Income Question



Source: Authors' own estimations based on CSSP 1999-2015.
Note: The rates are conditional of responding to survey and being in wage employment and providing information regarding education and occupation.

Table A.2 Average Labor Market Activity Share by Race (average 1999-2015)

	Ethnic Group		
Activity	ATT	ITT	Total
Economically Inactive	27.05 %	36.13 %	31.66 %
Unemployed	5.83 %	3.98 %	4.89 %
Employed	55.80 %	46.57 %	51.11 %
Self-Employed/Employer	11.32 %	13.33 %	12.34 %
Total	100 %	100 %	100 %

Source: Authors' own estimations based on CSSP 1999-2015.
Note: The rates are conditional of responding to survey and being in wage employment and providing information regarding education and occupation.

Table A.3 Comparison of Characteristics Non-Respondent and Respondent to Income Question Sample (average 1999-2015)

		Male	Female	Rural	Urban	Age 15-24	Age 25-34	Age 35-44	Age 45-54	Age 55-65
Response to Income Question	No	52.8 %	47.2 %	91.3 %	8.7 %	17.3 %	30.6 %	23.0 %	19.8 %	9.4 %
	Yes	58.3 %	41.8 %	91.0 %	9.0 %	18.6 %	29.6 %	24.6 %	19.4 %	7.7 %
		Legislators/Officers/ Managers	Professionals	Technicians/ Associate Professionals	Clerks	Service/Sales Workers	Agriculture/ Fishery/ Forestry	Crafts and Related Trades	Plant and Machine Operators/ Assemblers	Elementary Occupations
Response to Income Question	No	5.0 %	6.5 %	14.1 %	14.7 %	19.9 %	0.5 %	11.6 %	6.6 %	21.1 %
	Yes	3.0 %	4.4 %	13.3 %	14.0 %	16.7 %	0.5 %	15.3 %	8.6 %	24.2 %
		primary or less without training	primary or less with training	incomplete secondary without training	incomplete secondary with training	secondary completed with at least o'level without training	secondary completed with at least o'level and with training	university degree		
Response to Income Question	No	9.3 %	10.3 %	9.9 %	15.5 %	8.2 %	34.0 %	12.9 %		
	Yes	12.6 %	12.1 %	9.8 %	14.4 %	9.5 %	33.7 %	8.0 %		

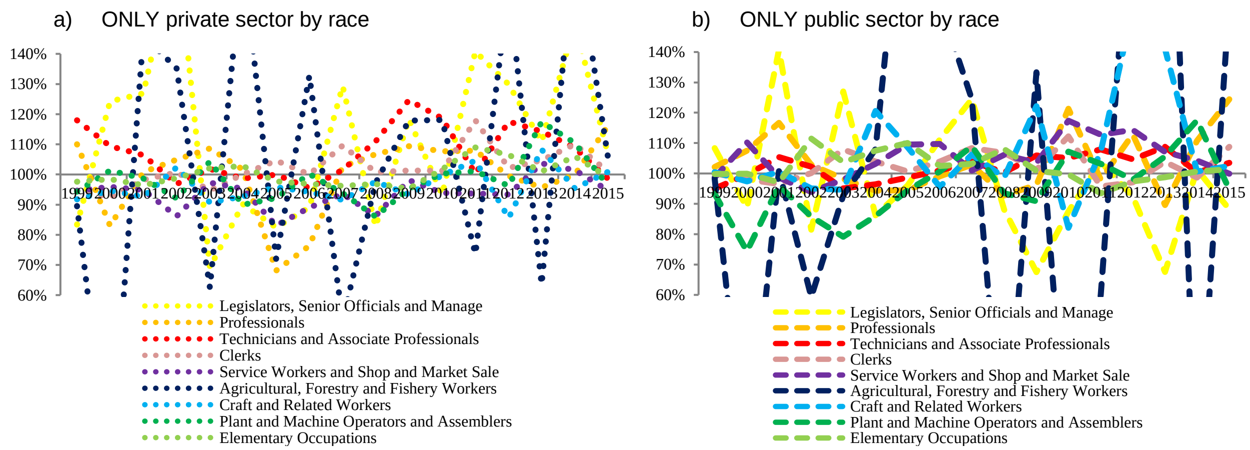
Source: Authors' own estimations based on CSSP 1999-2015.
Note: The response rates to the income questionnaire conditional of responding to survey and being in wage employment and providing information regarding education and occupation.

Table A.4: Distribution-specific Selection-corrected Earnings Equations ITT 2015

Dependent Variable: Reported income 2015 ITT VARIABLES	q0-q10	q10-q25	q25-q50	q50-q75	q75-q90	q90-q100	all
D_primary or less with training	-0.0276	-0.102	-0.00301	-0.0247	0	0.101	0.101
	(0.121)	(0.0782)	(0.0469)	(0.116)	(0.0615)	(0.0675)	(0.0978)
D_incomplete secondary without training	-0.0780	-0.0803*	-0.00998	-0.0205	0	0.00674	0.00674
	(22.69)	(0.0425)	(0.0208)	(0.116)	(0)	(0.0798)	(0.0858)
D_incomplete secondary with training	0.0204	-0.109*	-0.0241	0.0130	-0.0861	-0.0169	-0.0169
	(22.68)	(0.0558)	(0.0259)	(0.114)	(0.106)	(0.0719)	(0.0795)
D_secondary completed with at least o'level without training	0.0572	-0.106**	0.0243	-0.0262	0.127*	0.0782	0.0782
	(22.57)	(0.0522)	(0.0431)	(0.102)	(0.0748)	(0.0775)	(0.0798)
D_secondary completed with at least o'level and with training	-0.0760	-0.127**	-0.0135	0.000622	0.0373	0.203**	0.203**
	(22.61)	(0.0574)	(0.0255)	(0.0956)	(0.0749)	(0.0885)	(0.0815)
D_university degree	-0.123	0	-0.00306	0.0185	0.0626	0.409***	0.409***
	(22.44)	(0.0713)	(0.0474)	(0.0875)	(0.0733)	(0.153)	(0.111)
Age	0.0479	0.0267	-0.0171	0.0271	0.000465	0.0532	0.0532
	(0.418)	(0.0259)	(0.0147)	(0.163)	(0.0184)	(0.0336)	(0.0382)
age2	-0.000248	-0.000589	0.000322	-0.000259	-2.75e-05	-0.000531	-0.000531
	(0.00471)	(0.000534)	(0.000233)	(0.00152)	(0.000577)	(0.000423)	(0.000601)
D_Professionals	0	0	0	0.102	0.0328	0.221	0.221
	(0)	(0)	(0)	(0.177)	(0.0407)	(0.162)	(0.143)
D_Technicians and Associate Professionals	0	-0.162*	-0.0128	-0.0273	0.0191	-0.136	-0.136
	(0)	(0.0837)	(0.0553)	(0.129)	(0.0511)	(0.112)	(0.124)
D_Clerks	0	-0.229***	-0.0726	-0.0791	-0.0790	-0.277*	-0.277**
	(22.44)	(0.0691)	(0.0657)	(0.146)	(0.102)	(0.158)	(0.128)
D_Service/Shop Sale Workers and Defense Force	-0.248	-0.214***	-0.00448	-0.0461	0.0279	-0.282*	-0.282**
	(22.47)	(0.0804)	(0.0572)	(0.113)	(0.0402)	(0.159)	(0.139)
D_Agricultural, Forestry and Fishery Workers	-0.301	0	0	0	0	-0.884***	-0.884***
	(0.231)	(0.113)	(0)	(0)	(0.0620)	(0.259)	(0.273)
D_Craft and Related Workers	-0.163	-0.257***	-0.0596	-0.0617	0.0176	-0.389**	-0.389***
	(22.53)	(0.0793)	(0.0605)	(0.115)	(0.0650)	(0.169)	(0.122)
D_Plant and Machine Operators and Assemblers	0	-0.160**	-0.0415	-0.0802	0.0776*	-0.298	-0.298**
	(0)	(0.0746)	(0.0539)	(0.130)	(0.0444)	(0.188)	(0.122)
D_Elementary Occupations	-0.184	-0.271***	-0.0612	-0.146	0	-0.616***	-0.616***
	(22.60)	(0.0843)	(0.0568)	(0.159)	(0)	(0.199)	(0.129)
Percentage Share of African Origin TTs in Occupation	0	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)
D_urban	0	0.0595**	0.0449***	0.0343	0.0462	0.0442	0.0442
	(0.0421)	(0.0250)	(0.0114)	(0.0493)	(0.0657)	(0.0746)	(0.0653)
D_privatesec	0.0835	-0.0355	-0.00528	0.0677	0.0302	-0.164***	-0.164**
	(0.281)	(0.0456)	(0.0162)	(0.0473)	(0.0519)	(0.0595)	(0.0687)
D_Mining and Quarrying Industry	0	0.143	0.0273	-0.125	0.0243	0.334***	0.334***
	(0)	(0.105)	(0.0889)	(0.135)	(0.105)	(0.0846)	(0.106)
D_Manufacturing Industry	0.156	0.134*	0.0545	-0.0880	0.00578	0.273***	0.273***
	(0.0996)	(0.0704)	(0.0642)	(0.125)	(0.139)	(0.0380)	(0.0968)
D_Electricity Gas and Water Industry	0	0.218*	0.0800	0	-0.0272	0.228*	0.228
	(0)	(0.120)	(0.0549)	(0.177)	(0.0678)	(0.131)	(0.157)
D_Construction	0.0490	0.189***	0.0635	-0.186	-0.0540	0.126*	0.126
	(0.359)	(0.0709)	(0.0590)	(0.132)	(0.107)	(0.0692)	(0.0879)
D_Wholesale and Retail Trade and Restuarants and Hotels	0.0547	0.132**	0.00780	-0.171	0	0.00888	0.00888
	(0.198)	(0.0617)	(0.0593)	(0.126)	(0)	(0.0441)	(0.0884)
D_Transport Storage and Cummunication Industry	0	-0.0545	0.0138	-0.164	0.0300	0.129***	0.129
	(0)	(0.0874)	(0.0667)	(0.103)	(0.0690)	(0.0438)	(0.115)
D_Financing Insurance and Real Estate Industry	0	0.129**	0.0327	-0.153	-0.0480	0.179	0.179*
	(0.108)	(0.0581)	(0.0640)	(0.131)	(0.113)	(0.110)	(0.104)
D_Community Social and Personal Services Industry	-0.0987	0.182**	0.0496	-0.106	-0.0118	0.0749*	0.0749
	(0.240)	(0.0799)	(0.0574)	(0.138)	(0.0919)	(0.0396)	(0.0916)
ethnic (D_Indian)	-0.129	0.235	-0.0396	0.0350	-0.0104	-0.0309	-0.0309
	(0.646)	(1.317)	(0.0810)	(1.380)	(1.282)	(0.309)	(0.732)
D_male	11.65	-0.853	0.417	0.555	-0.459	5.965	5.965
	(93.98)	(9.675)	(2.979)	(14.83)	(6.771)	(5.007)	(7.111)
_m1	12.11	-0.340	-0.215	0.621	-0.767	3.209	3.209
	(92.95)	(7.759)	(3.125)	(30.54)	(9.260)	(3.251)	(5.732)
_m2	8.316	0.895	0.0117	0.0650	-0.0653	3.711*	3.711
	(98.83)	(6.554)	(2.848)	(5.155)	(5.433)	(2.054)	(4.655)
_m3	13.96	0.270	-0.146	1.012	-0.925	3.207	3.207
	(128.2)	(8.319)	(3.635)	(5.458)	(8.060)	(3.611)	(6.295)
Constant	10.35	7.621***	8.685***	8.646	8.726***	8.726***	8.387***
	(16.32)	(1.802)	(0.597)	(6.406)	(1.982)	(1.982)	(1.431)
Observations	.	.	.	.	.	.	.

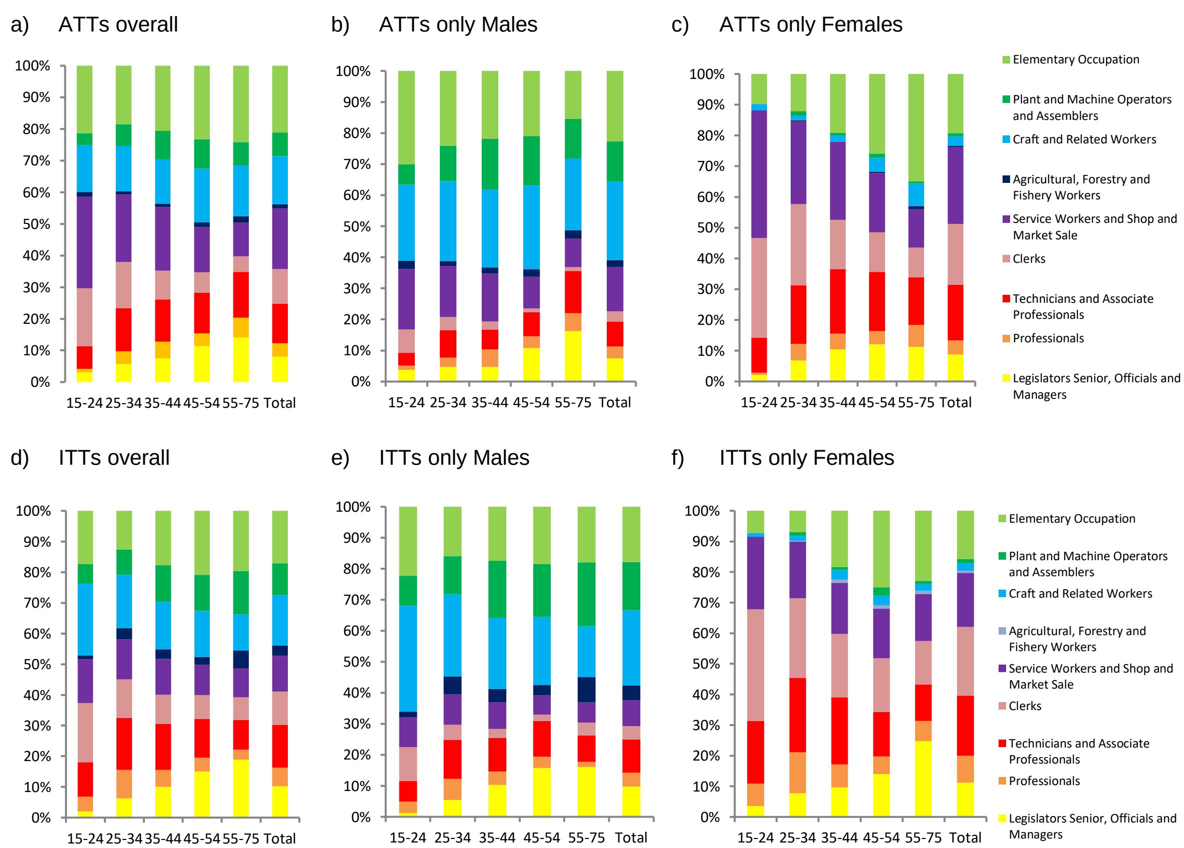
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Note: These are not quantile regression results, but TT race-separated selection-corrected earnings equations for different quantile groups of the reported wage distribution for ITTs in 2015.
Source: Authors' own estimations based on CSSP 1999-2015.

Figure A.2: Mean Wage Gap by Occupational Category and Sector (ITT/ATT)



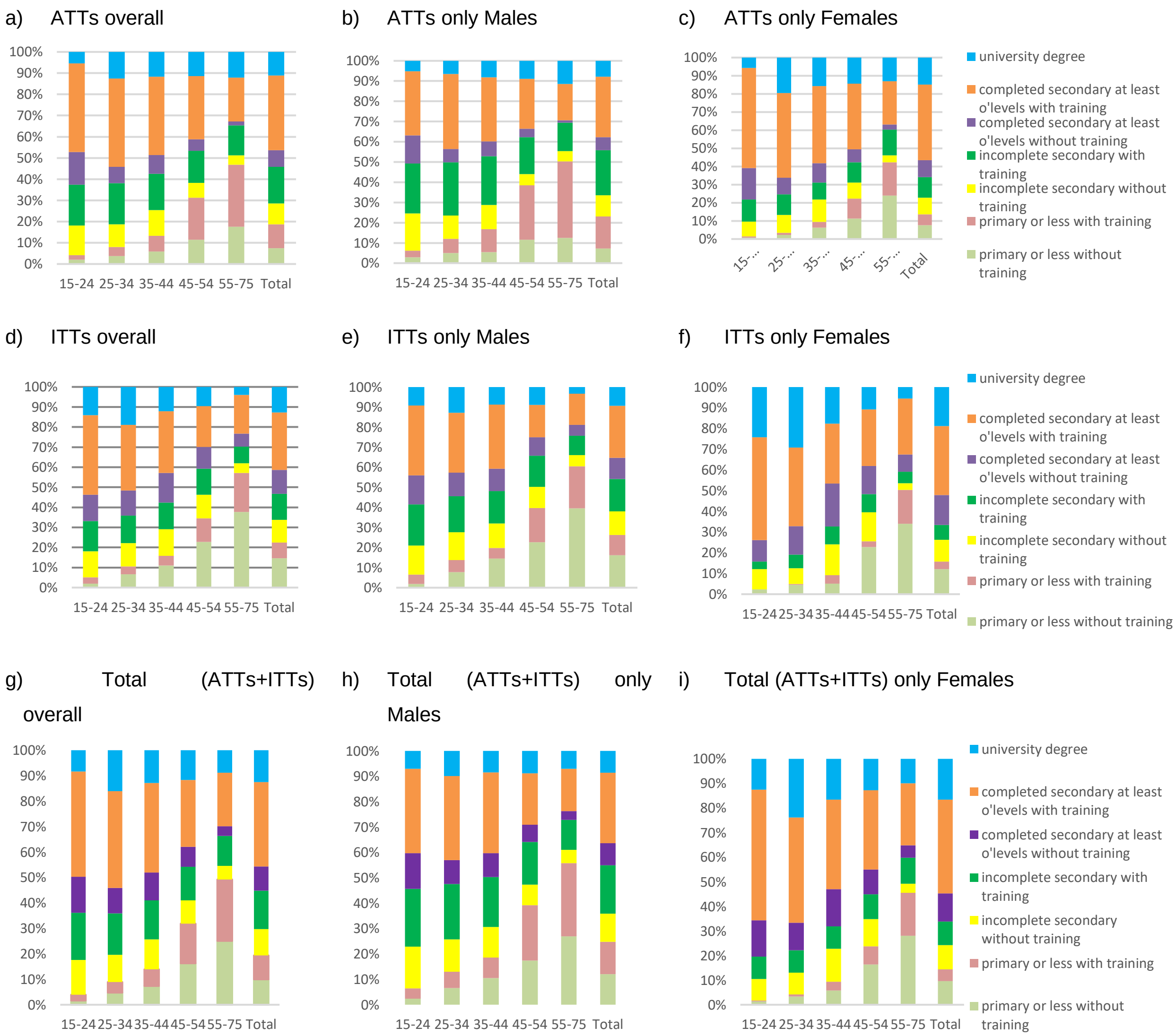
Source: Authors' own estimations based on CSSP 1999-2015.
Note: Wage Gap by occupation in % based on the reported income sample.

Figure A.3: Occupation by Age and Race Aggregated and Separated by Gender



Source: Authors' calculations based on CSSP 2014.

Figure A.4. Education Category by Race, Gender, and Age (2014)



Source: Authors' calculations based on CSSP 1999-2014.