Preliminary Draft

Earnings Inequality and the Changing Nature of Work: Evidences from Labour Force Survey Data of Bangladesh[1]

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Abstract

With structural changes in production coupled with technological progresses, there has been significant shift in modes of production as well as in patterns of employment over time. Such changed pattern is expected to have consequences on employment, resulting in significant changes in task composition and (even) destruction of certain types of jobs. Due to this changed employment, earnings of individual workers with differing skill level is expected to be adjusted as well leading to changes in income distribution across different skill groups. In this context, this research has attempted to understand the effects of factors like, structural transformation and technological change on labour market outcomes in the context of Bangladesh. The analysis has utilized different rounds of labour force survey data of Bangladesh (2005/06; 2010; 2016/17) and has combined it with occupation network data (O*NET) for the US for tracing the returns to different tasks over time. Our results reflect a number of important findings e.g.

(i)over time there has been an overall increase in educated work force leading to a corresponding increase in high skilled workers; (ii) in terms of real earnings, almost all education groups have experienced an increase and we also observe a sharp rise in education premium for those with tertiary education (iii) our regression based polarization tests do not provide evidence in favour of polarization in employment- our estimation however confirms earnings polarization; (iv) over the entire time period, on one hand we observe a fall in average routine intensity of tasks, on the other our results sugegest greater returns towards more skilled and lesser routine intensive works; (v) in case of earnings inequality, though not conclusive, we observe a fall in inequality over time, especially in the 2nd period of our analysis; (vi) Shapley decomposition shows that Inequality is mostly explained by within occupation differences where the dominance of between occupation differences have grown over time (vii) RIF decomposition technique reflects that it is primarily earning structure effect rather than characteristics effect that played the key role behind changes in inequality over time with routine task intensity of jobs along with education tend to explain differences in earnings for different earnings quintiles.

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Based on our findings, we can therefore conclude that we must prioritize our labour market policies towards better skill training programme targeting primarily those with low skill base. Given the relative fall in education premium over time, it is also extremely crucial to direct national policies towards market oriented education programmes. In this context, incorporating more market focused contents in secondary education curriculum in particular should be emphasized.

1. Introduction & Background

There is a growing body of literature that, with structural changes in production coupled with technological progresses, there has been significant shift in modes of production as well as in patterns of employment. Such changed pattern of production is expected to have consequences on employment with even destruction of certain types of jobs. With changed employment status (and maybe even with unemployment), earnings of individual labourers with differing skill level is expected to change as well, resulting in changes in income distribution across different skill groups. This skill biased technological change and shift in production process therefore is expected to raise income inequality (Berman et al. 2000). A recent stream of literature in this context argues that based on the task content of the work, the effect of structural transformation on earnings inequality would differ (Acemoglu and Restrepo 2017).[3] Besides, with globalized market and increased international trade, certain types of production and related tasks are being shifted from developed to developing countries. As Autor et al. (2015) argue, the effect of trade and technology on labour market and earnings should be understood together. Based on such argument, over time, as a result of a number of factors e.g. structural transformation, international trade, technology induced change in the production process and even with changed demand, task content of jobs is expected to change. This change is likely to differ across countries, based on their degree and pattern of structural change as well as the skill content of jobs. The pattern is expected to differ between the developed and developing countries in particular. Besides, the skill level of the workers along with their socio-demographic features can have important implications too.

Against this backdrop, this research attempts to understand the effect of changing nature of jobs on the labour market of Bangladesh. In particular, this study aims to explore the changes in the task content of jobs over time and the resulting impact of such changes on the earnings distribution of workers with differing skill level. The analysis has utilized different rounds of labour force survey data of Bangladesh and has combined it with occupation network data (O*NET) for tracing the returns to different tasks over time. In the face of ongoing structural transformation and automation on one hand and low skill content and unemployment on the other, this analysis is expected to provide important policy insights for the labour market strategies of Bangladesh. It contributes to the literature in a number of ways: firstly, it traces down the changes in key labour market statistics of Bangladesh over time. Secondly, it

[3] Here task content indicates the degree of cognitive skill embodied in work, routine nature of job etc.

examined different measures of the trend in income inequality over time while linking it with premiums in education and changes in skill contents of workers, it attempted to understand the link between changes in skill content and inequality in income. Thirdly, it has utilized a number of decomposition measures it tries to explore further into the trends of income inequality. In particular, with the help of Shapley decomposition analysis, it has measured the contributions of the changes in within-occupations inequality and between occupations inequality. On the other hand, the RIF decomposition tries to capture the pattern of inequality across quantiles when several factors (i.e. education, sex, RTI, etc.) are considered together.

The paper is organized as follows: section 2 offers a snapshot of overall economic profile of Bangladesh while section 3 provides a brief overview of relevant literature. Section 4 outlines about the sources of data and methodological issues of the paper with Section 5 provides the empirical findings of the research. Finally, section 6 summarizes and concludes.

2. A Brief Overview of Economic Profile of Bangladesh:

Bangladesh is a densely populated South Asian country that has just achieved the status of lower middle income country in 2015 and is aspiring to reach the least developed country status by 2024. Over the past decade or so, the country has been able to attain more than 6% annual growth rate on an average, accompanied by impressive progresses in a number of socio-economic indicators, e.g. fertility, child mortality, gender parity in primary education (Raihan & Bidisha, 2018) (Graph 1). Two of the major drivers of economic growth of Bangladesh are argued to be ready made garments (RMG) industry and remittances sent by international migrants. Remittances from international migrants stood at 16.42 billion USD during FY19 and have been playing a key role towards reduction of poverty and improving welfare of rural people in particular. On the other hand, the RMG sector accounts for more than 84% of total export of the country and currently it is the 2nd largest exporter after China. With 34 billion USD of export in FY19 and around 4 million employees, more than half of which is women (around 65 percent), it is aiming at accomplishing 100 billion USD benchmark by 2020 (EPB, 2020). Although primarily labour intensive, the industry is however slowly adopting capital intensive technologies and machineries, which is expected to have important implications towards its employability (Raihan & Bidisha, 2018).

Despite its success in accelerating GDP growth, one concern of Bangladesh is that of growing inequality in earnings as the Gini Index although has come down from 33.2 to 32.1 from 2005 to 2010, the trend has again started to revert with Gini in 2016 risen to 32.4 (Table 1).[4] Besides, despite of its tremendous growth experiences, it is often argued that the country has not been able to translate its growth in the labour market with low employment elasticity of growth rate in recent years (Table 2). The labour market is also highly informal with more than 85%

[4] We should however keep in mind that this trend in Gini index is based on Household Income and Expenditure Survey (2016) of Bangladesh which may differ from the findings of other surveys like that of Labour Force Survey used in our analysis.

workers employed in informal sector. This informality in employment is particularly crucial in terms of sustainability in earnings in the face of any economic shock or due to major shifts in skill biased production process. There also remains argument that with around 36% female labour force participation rate as opposed to 80% of that of males, there exist high degree of gender disparity in the labour market where the representation of the former in high skilled and high paid jobs is quite low as well (Table 3, Table 4). Furthermore, high degree of skill mismatch between the demand and supply side of the labour market has resulted in high rate of unemployment among the educated youths. With ongoing demographic transition, youth unemployment and youth NEET are obstructing the path towards reaping the benefits of demographic dividend. According to the Labour Force Survey data, as high as 29.9% of youths within the age group of 15 to 29 years are found to be not in any employment, education or training activities (NEET) with the rate being as high as 49% for the youth females (BBS, 2019). From the supply side, skill content of the workers is still quite low with as high as 30% labour force without any formal education (BBS, 2019). Although there is no specific empirical evidence, but whether there is any correlation between growing income inequality and types of employment is definitely a research question worth investigating.

On the other hand, in the context of its experience of structural transformation, over time although the share of agriculture in the GDP of Bangladesh has come down to around 15% with a corresponding increase in the share of industry to 32%, this structural shift has been quite disproportionate if we look at the labour market. For example, still 40% of the labour force with an overwhelming percentage of females (60%) are engaged in agriculture, where only around 20% of the employed are found to be in industry (Table 5). Another important feature of structure of production and employment of the country is, high share of service sector in GDP in comparison to industry's share and as high as 53% of GDP is originated from this sector with an employment share of around 39% (Ministry of Finance, 2019). The mode of structural transformation is therefore driven by service rather than industry and that has been reflected in both production as well as in employment structure. Slow pace of service sector led structural transformation can have implications towards distribution of earnings. In this regard, while discussing about the type of structural transformation in Bangladesh, Raihan & Khan (2019) emphasized about very low level of complexity in manufacturing sector and lack of diversification as key challenges for tackling inequality and attaining inclusive growth.

Being a labour abundant and capital scarce country, the production process as a whole is also strongly driven by labour intensive mode of production with relatively simple technology. However, for the last decade or so, in particular, there has been a moderate shift towards modern technology in the production process. With its fast growth momentum on one hand and the challenges of 4th industrial revolution on the other, it is expected that the country is increasingly moving towards more capital intensive mode of production. It is therefore important to understand whether and how changed occupational structure has contributed towards distribution in earnings.

3. Literature Review

Autor et al. (2003) studied the impact of adoption of changing technology (as represented by computerization) on task composition and the subsequent changes in the type of labor demanded across and within industries. Using pair representative data on job task requirements from the *Dictionary of Occupational Titles(DOT)* with samples of employed workers from the Census and Current Population Survey to form a consistent panel of industry and occupational task input over the four-decade period from 1960 to 1998, this paper found evidence that advent of computerization can substitute workers who perform routine cognitive and manual tasks and complement workers in non-routine problem solving and other complex tasks. These shifts in labor input favoring non-routine and against routine tasks were concentrated in rapidly computerizing industries. Moreover, these shifts were small and insignificant in the pre-computer decade of the 1960s, and accelerated in each subsequent decade, indicating that these changes were indeed caused by gradual and rapid adoption of computer based technology. This can give rise to job polarization in an economy where introduction to new a technology will cause to rise relative demand in highly paid skilled jobs (jobs requiring non-routine cognitive skills) and in low paid low skilled job (jobs requiring non-routine manual skills) and cause to fall in relative demand in the middle- jobs (jobs requiring routine manual and cognitive skills). This hypothesis was further explored by Goos et al (2007), who found evidence for job polarization in the United Kingdom. Bhorat et al. 2018 also found similar evidence in South Africa. They found that such a pattern has been present in the economy since 1975.

Autor and Dorn (2009) has tried to explain this in greater detail by pointing out a shift in employment of the mid-skilled workers who were involved in routine task-intensive work. They supported their analysis with 25 years data of the US labour market where they found a reduction in routine employment and resulting shift towards low skill, non-routine work. Alongside reduction of non-college workers with mid skill in high paying cities, diminishing urban wage premium for non-college workers, there has been a reduction in real wages for non-college workers. The author concluded that, in comparison to college educated workers, technology induced changes in the nature of work have not turned out as beneficial for non-college workers.

Some further exploration into this phenomenon was done by Firpo et al (2011). Using Current Population Survey (CPS) data and analyzing at occupation-level, they have argued that changes in the returns to occupational tasks have an impact on the changes in the wage distribution over the last decades, focusing on off shorability of tasks.

Acemoglu and Autor (2011) emphasized the importance of the interaction among skill of workers, content of the task they perform, growing technological change, shift in trading pattern etc. in explaining the changes in earnings and employment pattern in developed countries like the US. Their model is strongly based on the task content of work where tasks are the basic production units. The authors have assumed endogeneity in assigning skills to tasks and inferred that technological change may involve substitution of machines for some specific tasks that would have been performed by labour. They have utilized data of the US economy to support their model. In the similar line of analysis, Autor (2019) based on the data of the US argued that due to a number of factors, e.g. shifting of non-college workers from mid skill occupations into low wage occupations, reduction of non-college workers with mid skill in high paying cities, diminishing urban wage premium for non-college workers, there has been a reduction in real wages for non-college workers. The author concluded that, in comparison to college educated workers, technology induced changes in the nature of work have not turned out as beneficial for non-college workers.

Lewandowski et al. (2019) explored the phenomenon of the shift from manual and routine cognitive works to non-routine cognitive works using representative survey data (such as STEP, PIAAC, CULS etc.) Of 42 countries. They devised a measure of task content of jobs that are consistent with O*NET database based occupation-specific measures. They estimated the determinants of worker's RTI (Routine Task Intensity) as a function of technology (computer literacy), globalization, structural change and supply of skills, and decompose their role in accounting for the variation in RTI across countries. The study showed that computer skills and quality education is negatively associated with the level of RTI. Additionally, globalization (measured by sector foreign value-added share) causes an increase in RTI in poorer countries and the opposite scenario can be seen in richer countries. It also showed that technology and globalization have different impacts on different groups. Change in technology cause change in the RTI among workers in high skilled and non-off-shorable occupations whereas globalization does this among workers with low skill and off-shorable occupations.

Sebasian (2018) using various waves of Spanish Labour Force Surveys explored the evolution of job polarization between 1994 and 2014. This study firstly showed that there is a U-shaped relationship between employment share growth and job's percentile in the wage distribution. Secondly, the study explored the task content of the jobs using European Working Condition Survey and showed that changes in employment shares are negatively related to computerization. Finally, using information of past jobs, it provided evidence of displacement of middle-paid workers.

While exploring the implication of automation and AI on the demand for labor, wages and employment, Acemoglu and Restrepo (2018) devised a framework that deals with the dichotomy of displacement of labor involved in tasks where machines and AI replaces labor in tasks and increase in demand for labor in non-automated tasks due to the increase in productivity due to the introduction of automation. The study further argues that the counterbalancing effects of these two are not complete and it might result in a reduction in the share of labor in national income. So, they suggested that more powerful counterbalancing force will be creation of new labor-intensive tasks.

4. Data & Methodology:

4.1 Sources of Data:

In our analysis we utilized 3 rounds of cross sections of the labour force survey (LFS) data, e.g. 2005/06 (hereafter 2005 for brevity), 2010 and 2016/17. These three rounds of the LFS contain basic information of socio-demographic characteristics of individuals, level of education, status in the labour market, earnings from employment as well as ISCO 4 digit level occupational classes. Although the three separate data are not of same ISCO classification, we converted data of all 3 waves to ISCO88 classification. Although the 2005 and 2010 data are cross section data, the 2016/17 data is a quarterly data converted to annual data while using annual weights of data.[5]

In terms of our sample of individuals, we considered those within the age range of 15 to 64 years and confined the sample to only those who worked for at least 1 hour for pay or profit or for households' pay or profit in the last seven days prior to the survey. The occupational categorization was made on the basis of the primary work of the individual. As for earnings data we included the weekly earning of the workers and converted the earnings data from monthly to weekly in case of the last wave of LFS (i.e. QLFS 2016/17).[6] In addition, we have considered weekly income of the wage employed and for the sake of comparability, we adjusted earnings data for inflation (wage changes has been done with respect to 2010).[7]

For the variables in our analysis, we have included a number of variables. For education, 4 categories have been considered: (i) no education; (ii) primary education; (iii) secondary education and (iv) tertiary education. As for skill level, we have considered ISCO classification where the 1 digit classification includes: (i) managers; (ii) professionals; (iii) technicians and associate professionals; (iv) clerical support workers; (v) services and sales workers; (vi) skilled agriculture, forestry and fishery; (vii) craft and related trade; (viii) plant and machine operators and assemblers and (ix) elementary occupations. In this analysis, we also considered a simplified categorization of skills: (i) low skill (elementary occupation and skilled agriculture/forestry/fishery; (ii) medium skill (clerical support workers, services and sales workers, craft and related trade workers, plant and machine operators/assemblers; (iii) high skill (managers, professionals, technicians and associate professionals).

In addition to country wise LFS data, we also used O*NET (occupational information network) data where the latter is the database developed by the US department of labour/employment and training administration and for almost thousands of occupations of the US economy, it contains standardized and occupation-specific information. In particular, a specific segment of it (O*NET content model) consists of information of required task content (related to knowledge, skill, abilities required to accomplish a certain task). The final data base of the study has been prepared by merging O*NET with LFS data so that each worker's occupation

[5]We should keep in mind that 2016/17 data though it is a rotating panel with one individual repeated twice, at the moment we have not corrected the standard errors.

[6] In order to ensure consistency across data sets, for 2005 data set we have conducted a detailed cleaning of data set.

[7] Earnings data is only available for the wage employed.

based on ISCO 4 digit level can further be decomposed into the associated tasks of those jobs. In this regard, following Autor et al. (2003), 5 different categories of tasks have been considered, (i) Cognitive: routine cognitive, non-routine cognitive and analytical, non-routine cognitive interpersonal (ii) Manual: routine manual, non-routine manual. The resulting data file therefore have disaggregated task based occupational classification of each individual. Given that the LFS dataset have earnings of the individual, combining these two information, it is possible to track the returns to different types of tasks. With different cross sections (2005/06, 2010 and 2016/17) spanning over a reasonably long time span, we tried to understand how (and whether) returns to such skills have changed over time. However, this approach is based on a strong assumption that, the task content of each occupation is same across different countries. In this regard, due to the differences in productivity, adoption of technology, level of education and skill of the workers, as argued by Lewandowski et al. (2019) and Lo Bello et al. (2019), there can be differences in skill sets utilized by different occupations. In this connection, as suggested by Hardy et al. (2016), we have constructed country specific task measures for Bangladesh.

The measures of task contents in connection with our survey data are consistent with those using ONET and we considered four different task contents as described below:

- Routine Manual: These include tasks of (i) operating vehicles, mechanized devices, or equipment; (ii) spending time using hands to handle, control or feel objects, tools or controls; (iii) manual dexterity; (iv) spatial orientation.
- Routine Cognitive: Tasks involving (i) importance of repeating the same tasks; (ii) importance of being exact or accurate; (iii) structured vs. unstructured work.
- Non-routine Cognitive Analytical: includes tasks which involve (i) analyzing data/information; (ii) thinking creatively; (iii) interpreting information for others.
- Non-routine Cognitive Interpersonal: Includes tasks like (i) establishing and maintaining personal relationships; (ii) guiding, directing and motivating subordinates; (iii) coaching/developing others.

We followed the literature (Goos et al. 2014, Autor and Dorn 2009) and combined these four measures of tasks into a composite index of routine task intensity (RTI). We used the following formula in this context:

$$RTI = \ln\left(\frac{r_{cognitive}+r_{manual}}{2}\right) - \ln\left(\frac{nr_{analytical}+nr_{personal}}{2}\right)$$

In this specification, unlike Autor and Dorn (2009, 2013) following Hardy et al. (2016), Lewandowski et al. (2017), Lewandowski et al. 2019, this definition has dropped non-routine manual tasks

4.2 Methodology:

4.2.1: Estimation Method for Education Premium:

In order to get better insights about the linkage between education and earnings and to understand the trend of education premium, we attempted to utilize a parametric method. We followed a regression analysis, under which we regressed log weekly earnings (y_{it}) in each dataset (t) separately by sex on a number of regressors, e.g. dummy variables for education categories (Edu_{it}); dummy variables for age categories (Age_{it}); dummies for country-specific geographic regions (Geo_{it}) etc. and obtained the following model:

$$y_{it} = \alpha_t + \beta_t' Edu_{it} + \gamma_t' Age_{it} + \delta_t' Geo_{it} + \theta_t' Pop_{it} + \varepsilon_{it} \qquad (1)$$

While following different versions of equation (1) we obtained education premium for different education groups.

4.2.2 Regression Method of Job Polarization:

In order of get better insights of the relationship between changes in employment and earning pattern based on skill level of the workers, it is often interesting to check whether there has been any polarization of employment and earnings over time. As a simple test of polarization, while following Goose and Manning (2007) and Sebastián 2018a we applied a regression based test of job and earnings polarization. The following equations have been estimated in this regard where a quadratic specification of log of mean earnings at 3 digit occupational classification has been applied:

$$\Delta \log(E_{i,t}) = \beta_0 + \beta_1 \log(y_{i,t-1}) + \beta_2 \log(y_{i,t-1})^2 \qquad (2)$$

$$\Delta \log(y_{i,t}) = \gamma_0 + \gamma_1 \log(y_{i,t-1}) + \gamma_2 \log(y_{i,t-1})^2 \qquad (3)$$

Here $\Delta\log(E_{i,t})$ is change in log of employment share of occupation i between survey wave (t-1) and t , $\Delta\log(y_{i,t})$ is change in log mean labour earnings in occupation i between survey wave (t-1) and t . As for the explanatory variables, $\log(y_{i,t-1})$ is the log of mean labour earnings in occupation i in survey wave (t-1) and $\log(y_{i,t-1})^2$ is its square. Both of these equations have been estimated by weighting each occupation i by its employment share at the initial survey wave to avoid any plausible biases. The sign and significance of the coefficient estimates in quadratic form can be used to test the presence of U-shaped relationship in employment (and earnings) and broad skill classes.

4.2.3 Methodological Background of RTI Analysis:

In order to examine the effect of evolution of routine task intensity (RTI) of occupations on changes in employment and earnings over time, while following Sebastian (2018a) we estimated the following equations where RTI_i measures the time-variant routine task intensity of occupation i:

$$\Delta \log(E_{i,t}) = \pi_0 + \pi_1(RTI_i) + \pi_2(RTI_i)^2 \quad (4)$$

$$\Delta \log(y_{i,t}) = \rho_0 + \rho_1(RTI_i) + \rho_2(RTI_i)^2 \quad (5)$$

4.2.4 Methodological Background of Decomposition:

From a methodological point of view, in addition to simple descriptive, this paper has attempted to understand the changes in wages (returns to skill) over time in greater detail and we attempted to assess how the task contents of occupations have changed the wage structure over the years. In this connection, we used a number of decomposition methods, e.g. Shapley Decomposition, RIF-decomposition

4.2.4.1: Shapley Decomposition:

While following Shorrocks (2013) we decomposed earnings inequality (measured most commonly by Gini index G) into two key components: (i) changes in within occupation inequality and (ii) changes in between occupation inequality. The 1st term reflects the fact that, if employment structure changes over time, with earnings differences between occupations remain constant, inequality can be affected. On the other hand, the 2nd term captures that, while the structure of employment remains constant, inequality can rise/fall if earnings gap between occupations changes.

If we remove within-occupation then assume y_b is the vector where earnings of individuals have been replaced by the average earnings in their occupation and y_w is a vector where between-occupation inequality have been removed as worker earnings are re-scaled to have same earnings on an average. In this set up, $G(y_b)$ and $[G-G(y_w)]$ are possible estimates of the contribution of between occupation inequality and $G(y_w)$ and $[G-G(y_b)]$ are possible estimates for the contribution within occupations. Shapley decomposition can be given by the following equation where the changes in Gini has been decomposed into the contribution of each of the components:

$$G = G_B + G_W$$

$$G_B = 0.5[G(Y_b) + G - G(Y_w)]$$

$$G_W = 0.5[G(Y_w) + G - G(Y_b)] \quad (6)$$

If this analysis is repeated, we can check the trend in inequality by the changes in the distributions of employment or the changes in earnings. Let ΔG_{be} is the change in inequality between occupations in a situation where occupational employment shares are kept constant in (t-1) and t time periods- thus the only component that varies across occupations is the mean earnings. Similarly, ΔG_{bm} is the change in inequality when the employment shares are allowed to change but mean earnings by occupations are held constant. In this set up, the Shapley index can be defined in the following manner:

$\Delta GB = \Delta G_{BE} + \Delta G_{BM}$
Where,
$\Delta G_{BE} = 0.5[\Delta G_{bm} + \Delta G_b - \Delta G_{be}]$ and
$\Delta G_{BM} = 0.5[\Delta G_{be} + \Delta G_b - \Delta G_{bm}]$

4.2.4.2: RIF Decomposition:

RIF-regression based decomposition method introduced by Firpo et al. (2009, 2011) which basically tries to explain the wage gap between two groups by decomposing it into two effects: composition effect (the part which is related to the differences in the observed characteristics of the groups) and earning structure effect (the part which is related to the differences in the returns of these characteristics of the groups). In contrast to the conventional decomposition analysis, this two groups can also be considered as two different time periods.

According to Firpo et al. (2009, 2011), for the cumulative distribution of wages F_Y, let us assume that the distribution statistic is v (F_Y*) (called distributional parameter in FFL-2011)*. Also let $F_{Y0|T=0}$ denote the cumulative distribution observed at period 0 and for period 1 it is $F_{Y1|T=1.}$ On the other hand, the counterfactual distribution can be denoted by $F_{Y0|T=1}$ (a situation when the workers in period 1 are paid under the same wage structure of period 0). Now, the overall change in v (F_Y) between these two periods can be written as-

$\Delta_0^v = v\big(F_{\mathrm{Y1|t1)}}\big) - v(F_{\mathrm{Y0|t0}})$
$= \big[v\big(F_{\mathrm{Y1|t1)}}\big) - v(F_{\mathrm{Y0|t1}})\big] + [v(\,F_{\mathrm{y0|t1}}) - v\,(F_{\mathrm{y0|t1}})$
$= \Delta_w^v + \Delta_c^v$

Here, Δ_w^v= Wage structure effect and Δ_c^v = Composition effect

A challenging part of this estimation is to find out the counterfactual wage distribution which uses the reweighting approach as applied by DiNardo et al (1996). In this method a reweighting factor is used to replace the marginal distribution of covariates X for workers in period 0 with the ones of period 1. The reweighting factor can be in the following manner:

$S(X) = \frac{\Pr(X|d_1=1)}{\Pr(X|d_1=0)}$

$$=\frac{\frac{\Pr(d_1=1|X)}{\Pr(d_1=1)}}{\frac{\Pr(d_1=0|X)}{\Pr(d_1=0)}} \tag{7}$$

The distributional statistic v (F_Y) can be calculated by Ŝ (X) (a value for each observation calculated using equation (7)). This method of Dinardo et al. however can only estimate the composition and wage structure effects but cannot decompose the contribution of each single variable. In this connection, FFL used RIF (re-centered influence function) regression where an influence function can capture how a distribution statistic changes due to a small change in the variable(s). For each value of y, the influence function IF (y; v; F_Y) gives a value for the changes occurring in y. The re-centered influence function (RIF) be defined as:

$$RIF\left(y;v;F_y\right) = v\left(F_y\right) + IF(y;v;F_y)$$

For detailed decomposition, FFL has showed that the coefficients from RIF regression can be used to do Oaxaca Blinder (OB) decomposition on the reweighted data. In this set up, total change can be expressed in the following manner:

Total change,
$\hat{\Delta}^v = \hat{\Delta}_w^v + \hat{\Delta}_c^v$
$= (\bar{X}_0 - \bar{X}_1)\hat{\beta}_0 + \bar{X}_1(\hat{\beta}_0 - \hat{\beta}_1)$ = Total earning structure + Total composition
While incorporating specification error, total composition effect can be expressed in the following manner:

Total composition, $\hat{\Delta}_{C,R}^v = (\bar{X}_{01} - \bar{X}_1)\hat{\beta}_0{}^v + \bar{X}_1\left(\hat{\beta}_{01}{}^v - \hat{\beta}_1{}^v\right) = \hat{\Delta}_{C,P}^v + \hat{\Delta}_{C,Se}^v$

Here, $\hat{\Delta}_{C,P}^v$= RIF composition effect and $\hat{\Delta}_{C,Se}^v$= RIF Specification error

Similarly, for the wage structure effect we get:

Total earning structure, $\hat{\Delta}_{W,R}^v = \bar{X}_1\left(\hat{\beta}_1{}^v - \hat{\beta}_{01}{}^v\right) + (\bar{X}_1 - \bar{X}_{01})\hat{\beta}_{01}{}^v = \hat{\Delta}_{W,P}^v + \hat{\Delta}_{W,Re}^v$

Here, $\hat{\Delta}_{W,P}^v$= RIF earnings structure effect and $\hat{\Delta}_{W,Re}^v$ = RIF reweighting error

5. Empirical Analysis:

Given the primary purpose of this research is to understand the linkage between employment and earnings inequality, we attempted to utilize a variety of graphs and tables to get better insights of the relationship. In addition, a number of estimation as well as decomposition techniques have been utilized to understand the research objectives of the study.

In this connection, we first tried to examine the distribution of workers in terms of basic education and occupational categories as well as pattern and trend of skill based occupational classification. In the next step, we tried to link this information of employment and education with earnings and tried to understand the pattern of education premium. Afterwards we attempted to explain earnings inequality over time while applying a number of methodologies. The next stage of this paper utilized regression based methods as discussed in Section 4 to test whether there has been polarization of employment and earnings over time. With a view to understand the changes in the task composition occupations and how the changes in task based skill composition of jobs influences earnings distribution over time, we also applied a number of regression techniques. Finally, decomposition analysis of inequality has been performed for analyzing the factors behind changes in inequality over time.

5.1 Distribution of Workers by Education and Skill Classes:

As shown in Table 6a, education based labour market profile of workers reflect low representation of both males and females in tertiary education (7% in 2016/17) where the latter's position is even worse- only 5.74% of women were in tertiary education in 2016/17. On the other hand, although the situation has improved over time, there is an overwhelming proportion of labour force without any schooling- in recent year (2016/17) the percentage was almost one-third of the total employed population (29.98%). Another quarter of workers are found to have primary education only (around 26.43%) (Table 6a). Overtime, there has however been a large decline (10.42% during the entire period) of those without any formal education with a steady increase of those with secondary education (6.24% increase).

In case of regular paid employees, as expected, the proportion of workers with tertiary education is much higher (19.94% in 2016/17) than the general workers and the proportion of paid employee without any education is found to be around 11.83% in recent year. The highest proportion of workers (paid employee) are those with secondary education (47.76%), followed by those with primary (20.47%) and tertiary education (19.94%) (Table 9a). Overtime, the proportion of paid employees with tertiary education has come down (3.77% decline in entire period) with a corresponding increase in the proportion of workers with primary education (3.25% increase).Therefore, for both paid employees as well as for the entire labour force, we observe a shift from low education towards secondary level of education.

Based on ISCO88 one digit level classification of skill groups, for recent years (2016/17), the highest proportion of workers are found to be in skilled agriculture, forestry and fishery (23.64%) with other prominent sectors that absorb workers are those of elementary occupations (19.95%) and craft and related trade workers (19.59%) (Table 7a). However, while looking at the changes that have occurred from 2005 to 2016/17, on one hand we can clearly observe a noteworthy increase in craft and trade workers (10.38% increase) whereas on the other there has been a reduction of those in skilled agriculture (8.61% reduction). In case of relatively high skilled occupations e.g. managerial jobs, professional occupations etc. we observe small changes over the entire time period. The changes in occupational classes have primarily taken place in the 2nd stage of our analysis, i.e. from 2010 to 2016/17 with inter occupational changes not being that strong in the 1st half of our analysis (2005- 2010). As for the paid employees, the largest group was that of craft and trades workers and almost one-third of the paid employees (29.14%) are found to be in such occupations. Among the paid employees, we however observe a systematic decline of those who are professionals in both of the time periods with a 10.08% decline over the entire time period (Table 10a).

In terms of basic skill level of workers (high, medium, low), the highest proportion of paid employees (60.68%) are found in mid skilled occupations, the proportion of which has increased by a large margin over the years (11.54% increase) with the proportion of low skilled workers on the contrary reduced by a large margin (15.12% decline). As for the individual time periods, we observe a fall in the proportion of those in mid skilled occupation with a corresponding fall in the two other groups, thereby indicating a polarization of jobs at two extremes of skill distribution at least in the 1st period (see Section 5.4 for job polarization). This trend has almost reverted in the 2nd period with an increase in the proportion of both medium and high skilled workers and a fall in those of low skilled (Table 8a). The structure of skill component of paid employees also reflects high concentration of mid skilled workers (60.58%), followed by high skilled (26.78%) workers (Table 11a).

A slightly greater detail as shown in relevant graphs also reflects an increase of those with medium skill. As shown in Graph 14, during the 1st phase of analysis (2005-2010): we observe an increase in the proportion of those who are (i) low skilled and have secondary education; (ii) low skilled and have tertiary education in particular and a decline in the proportion of those who are (i) mid skilled with tertiary education; (ii) mid skilled with secondary education; (iii) low skilled without any schooling. On the other hand, in the 2nd phase, we observe increase in the proportion of those with: (i) high skilled with tertiary education; (ii) mid skilled with secondary education; (iii) mid skilled with primary education and a decline in the proportion of those with: (i) low skilled with tertiary education; (ii) mid skilled with tertiary education; (iii) low skilled with secondary education; (iv) low skilled with primary education. Thus as a whole, we can say that, there has been an overall increase in the proportion of those with medium skill with low and mid-level education (primary and secondary education) as well as those with high skill and high education and a decline in the proportion of those with low skill with low and mid-level education (Graph 14).

Given the changes in skill based occupational distribution as in ISCO 1 digit level, it is worth investigating the changed pattern in occupational classes in greater detail with more disaggregation. In Graph 19a, employment share as in 2 digit ISCO occupational classification shows that, in the 1st half of our analysis (2005/06 to 2010), the largest increase has been registered for certain occupations within the category of elementary occupation (92) which in fact reverted in the 2nd half (2010 to 2016/17) with a decline in respective shares of that group. In the 2nd half, on the other hand, we observe increase in certain other categories of workers within skilled agriculture group (61) along with some other occupations within craft and related trade (73. 71) and few other mid skilled occupations. Combining the results of these two time periods, over the entire time frame of our analysis, we observe, sharp fall in certain low skilled occupations within elementary group (92) along with occupations under skilled agriculture class (61) with moderate increase in the shares of certain mid skilled occupations within craft and related trade (74, 73, 72), plant and machine operators (83). As for the high skilled occupations, some of the occupations (12, 33, 32, 34) have experienced a small to moderate increase in their respective shares (Graph 19a). As for the paid employees (Graph 19b), we do not observe any sharp fall in case of any occupational share (according to ISCO 2 digit classes) rather a moderate fall in the shares of certain mid skilled occupations (51, 41, 82) along with certain high skilled occupations (23). Some of the mid skilled occupations, on the other hand (particularly code 73) have experienced a sharp rise in its share with certain other high skilled occupations (13, 33) experiencing moderate rise in their respective shares.

5.2 Distribution of Earnings of Workers by Education and Skill Classes:

In terms of earnings of paid employees, the inflation adjusted data shows an overall increase in earnings for all education groups with the highest increase experienced by those at two extreme ends of distribution of education- those with tertiary education (5.52% increase) and those without any formal education (3.42% increase) (Table 12a). As for the earnings of paid employees, although there has been an overall increase in earnings, as expected those with tertiary education experienced the highest increase (5.65% increase) with those without any education experiencing slight decline in earnings in real term (Table 16a).

In order to get better insights about the linkage between education and earnings and to understand the trend of education premium, we attempted to utilize a parametric method in the next step. We followed a regression analysis, under which we regressed log weekly earnings (y_{it}) in each dataset (t) separately by sex on a number of regressors, e.g. dummy variables for education categories (Edu_{it}); dummy variables for age categories (Age_{it}); dummies for country-specific geographic regions (Geo_{it}) etc. and obtained the following equation:

$$y_{it} = \alpha_t + \beta_t' Edu_{it} + \gamma_t' Age_{it} + \delta_t' Geo_{it} + \theta_t' Pop_{it} + \varepsilon_{it}$$

As explained in Section 4....Here, in the first step we estimated the models controlling only for education (Graph 2a, 2b) and then in the next step added other controls (Graph 3a, 3b). In the third specification, we included occupation dummies (ISCO88 2 digit) and finally, we attempted to compare the coefficient estimates on the education categories (education premium) across survey waves separately by sex (Graph 4a, 4b).

As for the first two sets of graphs, we do not observe much differences and across the sexes the trend and pattern do not differ much either. As for the third set of graphs (Graph 4a, 4b) which are probably the most comprehensive ones incorporating the effects of other relevant covariates, we find significant effect of gender on returns to education. While considering the third set of graphs, it can be inferred that (i) for those holding a degree in tertiary education, education premium was highest and that too has increased consistently for both of the sexes; (ii) for those with secondary education, though we observe a consistent increment for females, as for males education premium only registered an increase in the 2nd half of our analysis; (iii) for those with primary education, for both males as well as for females, education premium declined in the 1st half but registered an increase in the 2nd half.

In terms of skill level of workers, while comparing the three waves of inflation adjusted mean weekly earnings for ISCO88 one digit occupation groups, we observe increase in real earnings for all occupational groups, with the largest increase being registered for those of managers (4.79%) and professionals (4.44%) (Table 14a). As for the paid employees, though the employees of most of the classes have experienced a rise, a number of mid skilled workers e.g. service and sales workers, craft and trade workers, skilled agriculture workers and those in elementary occupations experiences a small decline in their real earnings over time (Table 18a). A detailed analysis of ISCO 2 digit level classification over the entire time frame (2005-2016/17) for paid employees also shows that earnings of those involved in most of the high skilled occupation groups (12, 22, 21, 23, 24, 13, 31, 32, 33, 34) and those in some of the mid skilled jobs (42, 41, 51, 83) and those in low skilled elementary occupation belonging to occupation group 92 have experienced rise in earnings (Graph 20b). As for the entire workforce, as shown in Graph 20a, the highest rise in mean earnings was experienced by those of high skilled occupation groups (ISCO 2 digit classes of 12, 21, 13, 23, 24, 2233,) along with a number of low skilled occupational categories (92, 93, 91, 62) as well as and mid skilled occupational groups (74, 73, 72, 83, 81).

5.3 Distribution of Labour Earnings & Earnings Inequality:

In order to understand distribution of earnings, we utilized a number of tools. As for kernel density plot of earnings, we observe that, over time the distribution has somewhat shifted to the left, indicating a fall in real earnings over time. In addition, the kernel of 2016/17 has registered the highest variance in earnings (demeaned log labour earning of paid employee)[Graph5, 6]. The decile shares, on the other hand shows a pro-rich earnings distribution as for all three data points with the top deciles getting larger part of the distribution. Across the three data points, we do not observe any symmetric pattern though (Table 28).

Pro-rich distributional pattern is however not found in the inter-quartile ratio between the poorest and richest segments as well as between the middle income and poorest groups, as the ratios have consistently gone down over time for all of the workers (Table 29a; Graph 8). The trend for paid employees however reflects an increase in such ratios in the 1st period. Based on Gini indices, between 2005 and 2010, we do not observe much changes in earnings inequality but while comparing between 2010 and 2016/17 indices, we can see a decline in Gini of earning. Similar trend of declining inequality between 2010 and 2016/17 can be seen in case of variance of log earnings as well (Table 30a). The Lorenz curve of earnings for all the 3 datasets also show that, in terms of earnings inequality, there has not been much changes over time with the Lorenz curves lying very close to each other (Graphs 8, 7).

The growth incidence curves also do not reflect high inequality and atleast in the 2nd part of our analysis, we observe moderate growth in earnings in the bottom of the distribution (Graph 9). In the 1st half of our analysis, on the other hand, earnings growth was quite low across the entire distribution and those in the middle of the distribution mainly experienced average growth in earnings with in equal distributional pattern in both ends of the distribution.

5.3 Changes in Occupation Structure and Polarization of Employment and Earnings:

One of the key research interest of our study is to understand whether there has been any polarization of employment and earnings during our study period. As discussed in Section 5.1, our simple descriptive as in Table 11a indicate an opposite phenomenon of job polarization for the entire time period as the proportion of mid skilled workers increased moderately over time and that of low and high skilled workers declined marginally. The findings are however opposite in two of the time periods with the trend of 2nd period appeared to have dominated the overall trend. In case of polarization of earnings, though not conclusive for the entire time period, findings for the 2nd period are indicative of earnings polarization (Table 19a).

In order to get better insights of job and earnings polarization, while following Goose and Manning (2007) we applied a regression based test of job and earnings polarization as described in Section 3. As shown in Table 36a and Table 36b, in the 1st period of our analysis we find a negative coefficient of log of hourly wage with the square term of it being positive when we estimate log of change in employment share. The sign of the coefficient estimates however shows a completely opposite scenario when we consider the estimation result of the 2nd period. The results therefore indicates job polarization in Bangladesh with U shaped pattern between employment and earnings only in the 1st period of our analysis and over time we observe almost an opposite of job polarization. Given low (initial) skill base of the economy it is quite plausible that though in the 1st period of our analysis there has been a shift of workers towards two opposite extremes of the distribution, over time with greater accumulation of skill and/or due to the effect of off-shoring of jobs from developed countries, the proportion of mid skilled workers have increased. The trend is likely to continue in near future as well as the overall skill base of the workers is still at a low level with the high skilled workers comprising less than one-tenth (8.61% in 2016/17) of the work force.

When we conducted the analysis with log change in mean wage being the dependent variable we however find strong evidence of a U-shaped relationship and this result was consistently negative and significant in both of the time periods which is indicative of earnings polarization. Our regression based polarization tests therefore confirms earnings polarization in Bangladesh but not job polarization.

5.4 *Distributional Changes and Task Composition:*

Given that our prime research is to understand the plausible impact of changed nature of occupation due to change in production process/structural shift/technological change on inequality in earnings, at this stage we have attempted to decompose different occupational classes in greater detail by the task content embodied in each occupation while utilizing the information provided by O*NET dataset, In particular, while following Sebastian (2018a) we estimated the impact of routine task intensity (RTI) of O*NET in its quadratic form at 3-digit occupation classes as well as RTI at country level at 2-digit level on changes in employment and earnings while following the specification as described in Section 4.

Our OLS estimates of change in employment share reflects no statistically significant evidence of increase/decrease in routine task intensity over the entire time period and for both O*NET RTI measure and country specific RTI measure we got more or less similar findings (Table 34A). However, in case of estimation results of changes in earnings, we find that, in case of occupations with larger routine task content, there has been a negative change in earnings and the results become significant when country RTI measure is applied. Our results therefore are indicative of greater returns towards more skilled and lesser routine intensive works. Table 37 however shows that overtime, particularly during the 2nd stage of our analysis, there has been a fall in routine task content of occupations and that has been reflected in case of both O*NET and country-specific RTI measures.

The regression analysis have been supplemented by detailed graphical representation while following AD2013 and FFL2011 approaches to task composition of O*NET RTI index, survey RTI index and country-specific RTI index across skill percentiles (ranked by 2005 occupational mean wage) as in Graph 27a, 27b. Though not confirmative, but the graphical analysis reflects that, for paid employees in particular, a decline in the share of routine manual tasks with an almost unchanged pattern of routine cognitive tasks. On the other hand, as expected there has been an overall increase in non-routine cognitive tasks and non-routine cognitive: interpersonal tasks (Graph 27b). Graph 24 also revealed that, in comparison to the O*NET RTI, the country-specific RTI and survey RTI are sort of linear. Additionally, the RTI index is negative for O*NET after 58 skill percentile (ranked by 2005 occupational mean wage) where as it is after 68 percentile for the country specific one. So for the country-specific case, it takes more skill percentage (ranked by occupational mean wage) to have negative task content measures (RTI index).(Graph 24)

In the next stage, we attempted to study the relationship of changes in employment and in earnings on task composition of occupations while using AD2013 and FFL2011 approaches to task composition. In Graph25b we can see the pattern of changes in employment share of paid employees across ISCO 2 digit occupation groups over 2005-2010, 2010-2016/17 and 2005-2016/17 periods. If we look at the change in employment share during 2005-10 period, we can see a decrease in the share of employment in service and sales workers (51) and increase in elementary occupations (92) and machine operators (82). The following period (2010-2016/17) is characterized by an increase in those in personal and protective service workers (51) and fall in plant and machine operators (82) and in agricultural labors (92). During this entire period, we can see employment shares of some low skilled workers (82, 93, 74) as well as some high skilled (23) and mid skilled workers (41, 51) has fallen whereas the proportion of some of high skilled (12, 33) as well as low skilled (81, 71, 72, 73) has gone up (Graph 25b). So, considering the entire time period it is apparent that employment shares of the jobs involving less routine tasks have decreased. If we look at the change in log of real earnings across 2-digit occupational groups for paid employees, as in Graph 26a, across all occupational groups we can observe a fall in real earnings, with the largest fall registered for those in ISCO 2 digit groups of senior officials (11), Office clerks(41), building and machinery related workers (71, 72) and sales and services elementary occupations (91).

5.5 Decomposition Analysis:

As discussed in Section 4, in addition to knowing the pattern of inequality over time, we apply appropriate decomposition techniques to identify the factors that are acting as key drivers of inequality. We decompose the earnings inequality as measured by Gini index between the two sub-periods 2005 to 2010 and 2010-2016/17 as well as over the entire period of analysis 2005-2016/17 using Shapley decomposition and RIF decomposition.

5.5.1 Shapley Decomposition:

After looking at the detailed classification of employment based on different occupational classes, we attempted to examine earnings inequality while applying a number of decomposition techniques. In the context of income inequality, decomposition techniques have been commonly used to distinguish the "between-group" effect due to differences in average incomes across subgroups, from the "within-group" effect due to inequality within the population subgroups. Despite their widespread use, their reliability has been questioned with regard to intuitiveness and accuracy of interpretation of several components. Furthermore, these procedures are also criticized as they are applicable only to a number of limited types of inequality indices.

Shapley decomposition technique in this connection has addressed these limitations (Shorrocks, 2012). In broader terms, Shapley decomposition method considers the marginal effect of eliminating each of the contributory factors in a sequence, and then assigns each factor the average of its marginal contributions in all possible elimination sequences. This procedure yields an exact additive decomposition of the considered inequality index into desired number of contributions- this is formally referred as the Shapley Value. Following Chantreuil and Trannoy (1997), we apply Shapley decomposition method to decompose Gini inequality into "within-occupations" and "between-occupations" (as measured by two digit ISCO-88 codes) inequality. Focusing on these two channels to inequality allows us to distinguish two different types of effects. On one hand, changes in the structure of employment may affect inequality trends. For example, if middle-income occupations decrease in size relative to other groups, while the earnings differences between occupations remain stable, overall inequality will rise. on the other hand, changes in the earnings gap between occupations may also affect the overall distribution of earnings. For example, if income grow faster in high-paying occupations than in low-paying occupations, while the structure of employment remains unchanged, this will result in an increase in overall earnings inequality as well.

In this paper, we are interested in the role of tasks performed by workers in their respective jobs in explaining observed trend in inequality. There is a growing number of literature focusing on the fact that differences between occupations do not account for the entire differentials in skill requirements and productivity but can also be influenced by other job characteristics, such as working conditions, sectoral differences (e.g., wage differentials between public and private sector workers), and the type of tasks being performed. If changes in the rewards of certain occupations help explain the trends in earnings inequality, this would be reflected in the gap in average earnings between occupations. On the other hand, if inequality changes are explained by other factors not related to the characteristics of occupations, this would be reflected in within-occupation inequality, driving the overall earnings inequality patterns.

	Actual			**Shares Constant**			**Means Constant**		
	2005	**2010**	**2016/17**	**2005**	**2010**	**2016/17**	**2005**	**2010**	**2016/17**
1 Overall Gini	0.3677	0.3698	0.3198	0.3677	0.3571	0.3092	0.3677	0.3915	0.3004
Shapley Decomposition									
2 Between-occupations	0.1491	0.0975	0.1615	0.1491	0.0999	0.152	0.1491	0.1343	0.1373
% Ratio	41	26	51	41	28	49	41	34	46
3 Within-occupations	0.2186	0.2723	0.1583	0.2186	0.2572	0.1572	0.2186	0.2572	0.1631
% Ratio	59	74	49	59	72	51	59	66	54

From Table ...., we can infer that differences of average earnings across occupations (between-occupation differences) could explain almost half (41%) of overall earnings inequality in 2005. However, over time this share has fallen significantly, with differences within occupations accounted for almost three-fourths of the overall earnings inequality (74%) in 2010. While keeping in mind the changes in employment shares of different skill groups, we can infer that factors other than earnings and job characteristics must have driven the trend in inequality during the 1st sub-period. During the 2ndsub-period of our study, inequality have fallen significantly and between-occupations effect have become important once again, explaining more than half of the total earnings inequality (51%). During 2010-2016/17, share of employment in mid skilled occupations have increased significantly, with a strong decline in the share of low skilled jobs and a moderate increase in high skilled jobs. In terms of earnings, during this time period, though high skilled workers have experienced the highest increase in average earnings, since the share of high skilled workers is quite low (around 8%), the trend in inequality is most likely to be driven by changes in mid skilled occupations. Other factors such as education, information asymmetry between workers and employers etc. might have also played an important role in increasing frictions in the labor market. Therefore, within-occupation factors not directly related to changes in average earnings continues to play a significant role in explaining overall inequality.

We further decompose the decline in inequality between occupations into the contribution of changes in mean earnings (holding occupation shares constant with 2005 as the reference period) and in occupation shares (holding mean earnings constant with 2005 being the reference period). The first contribution reflects the change in inequality that is associated with changes in the returns to job characteristics (e.g., skills and tasks) on the labour market, while the second reflects the effect on inequality of changes in the employment composition (e.g., movements of workers towards higher skilled and less routine occupations). Notably, in case of "means constant" case, we find that the explanatory share of within-occupations effect has become even stronger in 2016/17.

In table...., the results of isolating the effect of RTI, i.e. the extent to which the degree of routinization of occupations is associated with this decline in earnings inequality between occupations have been portrayed through the concentration index. This index measures the extent to which average earnings of occupations tend to systematically increase with lesser routine intensity of jobs. As reflected in Table....., the role of RTI and average earnings of occupations in explaining inequality are quite similar, explaining about 72 to 90 per cent of between-occupations inequality. This finding is even more pronounced in the first and the last survey waves of the analysis. The somewhat weaker relationship in 2010 can perhaps be explained by the argument that average earnings were less relevant in explaining inequality in that year.

	Actual			**Shares Constant**			**Means Constant**		
	2005	**2010**	**2016/17**	**2005**	**2010**	**2016/17**	**2005**	**2010**	**2016/17**
Gini between occupations	0.2215	0.1584	0.2239	0.2215	0.1612	0.2117	0.2215	0.2103	0.1949
Concentration Index									
RTI (Country specific)	0.1959	0.114	0.2004	0.1959	0.1253	0.1928	0.1959	0.1758	0.1713
% Ratio	88	72	90	88	78	91	88	84	88
RTI (O*NET)	0.1072	0.1128	0.1611	0.1072	0.1085	0.1413	0.1072	0.0999	0.1048
% Ratio	48	71	72	48	67	67	48	48	54

Furthermore, while comparing the corresponding figures of Country RTI with those of O*NET RTI, we observe that the two occupation rankings are significantly different in the first wave (2005) as indicated by the corresponding concentration ratios (varying between 88 per cent using the country-specific measure, and 48 per cent using O*NET). However, while the country-specific measure suggests that the relationship between RTI and average earnings in explaining between-occupations inequality have become weaker over the first sub- period, we observe an increase in rank correlation between earnings and O*NET RTI measure. However, during the second sub-period as well as the entire period, the correlation unambiguously increases according to both measures (to a ratio of 90 and 72 per cent respectively), indicating that over time the relationship between routine intensity of occupations and average earnings has gradually become strong.

5.4.2 RIF Decomposition:

Though Shapley decomposition technique is useful to explain earnings inequality through between and within occupation components, it does not shed light on the contribution of individual factors on inequality. In this connection, as discussed in Section 4, RIF-regression decomposition technique helps us to explore the role of routine task content in the trend of inequality and helps us to isolate its impact. This method also helps us to disentangle whether the effect is channeled through the characteristics of employment (composition effect) or the returns to these characteristics of the employment (structure effect). In addition, another notable feature of RIF decomposition is that, it allows us to explore a non-monotonic relationship between RTI and inequality (reference/clarification).

In this analysis, RIF decomposition was applied in order to decompose log of changes in earnings over time across different quantiles. The results reflect that earnings structure effect primarily dominates the total change in earnings in both of the sub-periods across the entire distribution (See Figure: 1. Our RIF decomposition analysis shows that the changes in demographic characters like age, gender, level of education of the workforce or the change in the composition of routine task content of the occupations do not explain the trend in earning inequality in Bangladesh. This has been witnessed during both the sub-periods of 2005-2010 and 2010-2016/17 where the composition effect of educational attainment was found to be dis-equalizing whereas the effect of RTI (i.e. structure of employment) was equalizing. According to our analysis, it is the earnings structure effect which explains the trend in inequality during both of the two sub-periods. For these two sub-periods, earnings structure effect of education was found to be equalizing for both the country specific and O*NET RTI measures where for the first sub-period the effect was found to be much stronger than that of the later. Country specific RTI measure shows earning structure effect of RTI having a de-equalizing effect in the first sub-period but an equalizing effect in the second period. If we use ONET measure then the effects are equalizing for both of the sub periods. For both of the sub-periods, the growth of education premium was inequality reducing where as for the changes in routine versus non-routine tasks, it was inequality reducing if measured by O*NET and for the country specific measures it is rather inequality inducing during the first sub-period but inequality reducing for the second period.

Therefore, from RIF analysis, we can deduce that, for the first sub-period (2005-2010) the detailed decomposition of earnings structure effect (country-specific measure) suggest us a 'pro-rich' profile of the change in RTI whereas the effect of education is not entirely pro-rich for the first sub-period as the effects are found to be negative for the upper most percentiles of the distribution. For the second sub-period, on the other hand, we can observe a pro-poor feature of the RTI. During this time period, education accounts for decreasing inequality for most part of the upper tail of the distribution (See Figure: 2)

Table-1: Gini Decomposition

	RTI (country-specific)			RTI O*NET		
	2005-2016/17	**2005-2010**	**2010-2016/17**	**2005-2016/17**	**2005-2010**	**2010-2016/17**
Distribution						
Final F	0.0497***	0.0539***	0.0497	0.0497***	0.0539***	0.0497***
	0.0014	0.05	0.0005***	0.0013	0.0001	0.0005
Initial I	0.0563***	0.0563***	0.0539	0.0563***	0.0563***	0.0539***
	0.0008	0.06	0.0002***	0.0008	0.003	0.0002
Total Change F-I	-0.0066***	-0.0023	-0.0042***	-0.0066***	-0.0023	-0.0042
	0.0021	-0.002	0.0003	0.002	0.003	0.0003
Reweighting Decomposition						
Counterfactual C	0.0573***	0.058***	0.054	0.0568	0.0582	0.0542
	0.002	0.06	0.0002***	0.0015***	0.0017***	0.00014***
Total Composition C-I	0.001	0.0018	0.0001**	0.0005	0.002	0.0003
	0.0013	0.00176	0.00004	0.0008	0.0012	0.00005***
Total Earnings Structure	-0.0076**	-0.0041	-0.0043***	-0.0071**	-0.0043***	-0.0045***
	0.003	-0.004	0.0003	0.003	0.002	0.0004
RIF Aggregate Decomposition						
RIF Composition	0.0013*	0.0012	0.0006***	0.0009	0.0016*	0.0008***
	0.0007	0.0008	0.0001	0.0006	0.0009	0.00012
RIF Specification Error	-0.0002	0.0005*	-0.0005***	-0.0004	0.0004	-0.0005***
	0.0006	0.0003	0.00015	0.0002	0.0003	0.00017
RIF Earnings Structure	-0.0074**	-0.0041***	-0.0043***	-0.0072**	-0.0044***	-0.0045***
	0.0032	0.002	0.00041	0.003	0.0015	0.0004
RIF Reweighting Error	-0.0002	0	0	0.0002	0.0001	-0.0001
	0.0002	0.0001	0.00006	0.00004***	0.00005**	0.00008
RIF Composition						
age	0	0	0	0	0	0
	0.0002	0.0003	0.00006	0.0002	0.0002	0.00005
sex	0.0019***	0.0011***	0.0002***	0.0019***	0.0012***	0.0003***
	0.0007	0.0004	0.00002	0.0006	0.0002	0.00002
education	-0.0004*	0.0003	0.0006***	-0.0006***	0.0003	0.0008***
	0.0003	0.0005	0.00007	0.0002	0.0005	0.00004
religion	0	0	0	-0.0001	0	0
	0.0001	0.00010	0.00013	0.00013	0.00010	0.000010
RTI	-0.0001	-0.0002	-0.0002***	-0.0003***	0.0001	-0.0002***
	0.0001	0.0004	0.00001	0.00002	0.0001	0.00007
explained	0.0013*	0.0012	0.0006***	0.0009	0.0016*	0.0008***
	0.0007	0.0008	0.00011	0.00056	0.0009	0.00012
RIF Earnings Structure						
age	0.002	0	0.002***	0.003*	0.001	0.002***
	0.0020	0.0018	0.0005	0.0017	0.0016	0.0005
sex	0	-0.002**	0.002***	0	-0.002***	0.002**
	0.0021	0.0011	0.0007	0.0017	0.0007	0.0007
education	-0.012***	-0.009***	-0.002**	-0.009***	-0.01***	-0.0003
	0.00007	0.003	0.0007	0.0005	0.002	0.0002
religion	-0.00001	-0.0002	0.0004	-0.00009	-0.0003***	0.0004
	0.0008	0.00008***	0.0003	0.0007	0.00004	0.0004
RTI	-0.002**	0.003	-0.004***	-0.002***	-0.002***	-0.0003
	0.001	0.004	0.0004	0.0005	0.00004	0.0003
Constant	0.005***	0.004*	-0.002***	0.002	0.009***	-0.008***
	0.0009	0.0022	0.0004	0.0012	0.0013	0.0008
unexplained	-0.007**	-0.004***	-0.004***	-0.007**	-0.004***	-0.004***
	0.0032	0.0016	0.0004	0.003	0.0015	0.0004

Source: Authors' calculation based on LFS-2005, LFS-2010, QLFS-2016/17, *** p<0.01, ** p<0.05, * p<0.1

Figure-1: RIF Decomposition (Country Specific)

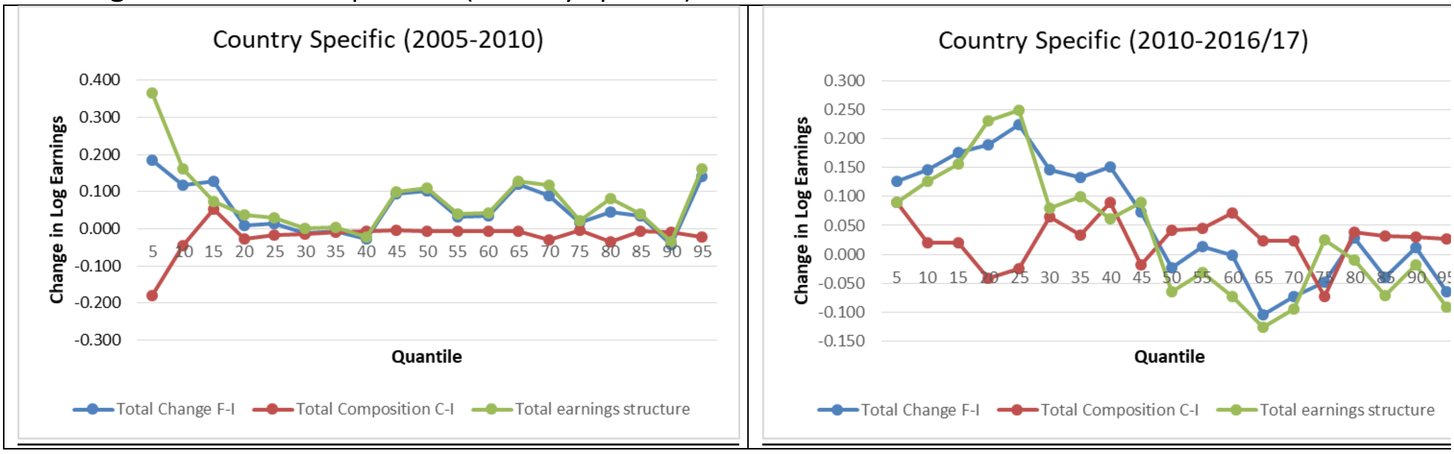
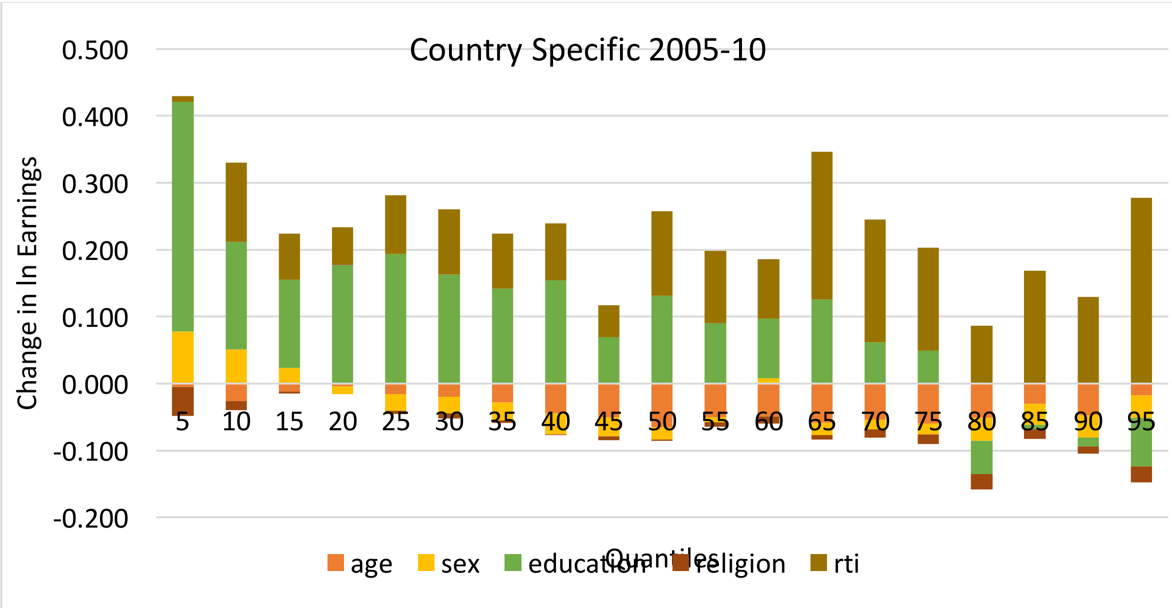
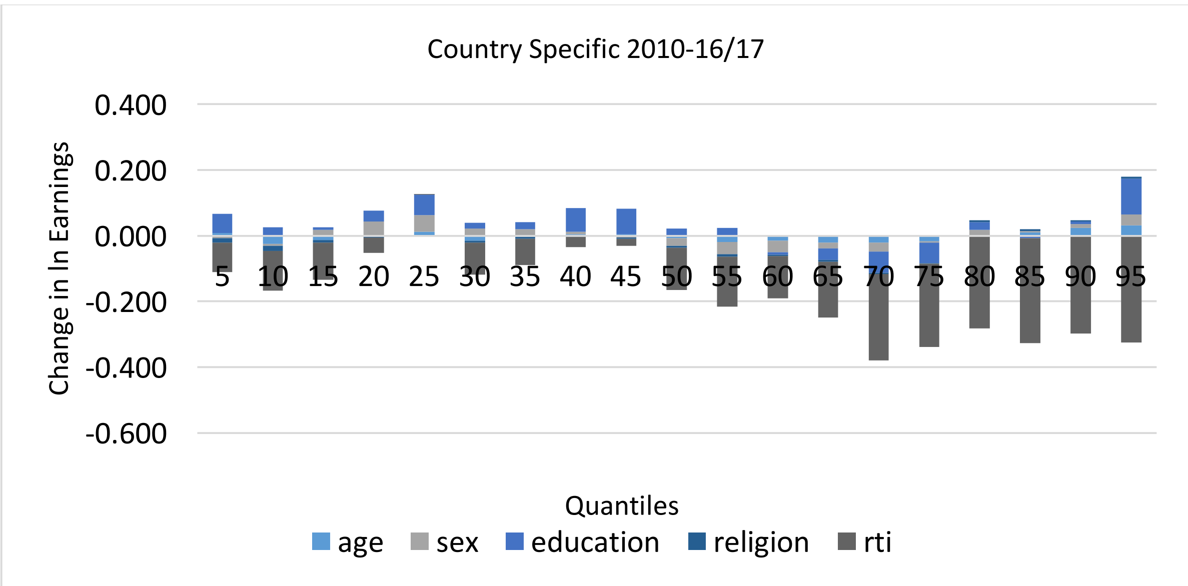


Figure: 2 Detailed RIF Decomposition of Earnings Structure





6. Summary of Results & Recommendations:

While utilizing three cross sections of nationally representative survey data of Bangladesh, this paper has applied a number of quantitative tools to understand the way structural change in production along with technological innovation have affected employment in occupations with different skill content and as a consequence have altered earnings distribution over time. Our analysis has revealed a number of findings as follows:

- Education based labour market profile of workers reflect very low representation of both males and females in tertiary education where the latter's position is even worse. The highest proportion of workers are those with secondary education, followed by those without any schooling as well those with primary education. Overtime, there has been an increase in all education groups with a large reduction of the proportion of those without any schooling. As for the paid employees, the proportion of tertiary educated is though much higher, in the 1st part of our analysis, there has been a decline in this group of workers which however reverted in the 2nd part. Thus, it appears that over time there has been an overall increase in educated work force leading to a corresponding increase in high skilled workers.

- In terms of skill component of the workers, it is the mid skilled workers who comprises almost half of the workforce with a high proportion of the low skilled in the work force. We however observe a large fall in the proportion of low skilled workforce in the 2nd period of our analysis with an increase in the proportion of mid skilled workers. As for the paid employees, we observe similar trend too.

- For all education groups, we observe increase in real earnings with those with tertiary education experiencing the highest increment. As for the paid employees, as expected those without any schooling experiencing a fall in real earning along with those in primary education as well. As for education premium: for those holding a degree in tertiary education, education premium was highest and that too has increased consistently for both of the sexes; for those with secondary education, though we observe a consistent increment for females, as for males education premium only registered an increase in the 2nd half of our analysis; and for those with primary education, education premium declined in the 1st half but registered an increase in the 2nd half. In terms of skill level, the highest increase in real earnings has been experienced by those of high skilled occupation, especially those of managers and professionals.

- Our regression based polarization tests reflects polarization in employment in the 1st stage but not in the 2nd period of our analysis- therefore for the entire time period we do not observe polarization in employment. Our estimation however confirms earnings polarization.

- According to our regression analysis of change in employment share reflects no statistically significant evidence of increase/decrease in routine task intensity (RTI) over the entire time period and for both O*NET RTI measure and country specific RTI measure we got more or less similar findings. However, on an average our descriptive suggest almost no change in average RTI during the 1st period of our analysis but a fall in average RTI in the 2nd period. As for the earning based regression specific RTI analysis, we find that, in case of occupations with larger routine task content, there has been a negative change in earnings and the results become significant when country RTI measure is applied. Our results therefore sugegests greater returns towards more skilled and lesser routine intensive works.

- In case of analysis of earnings inequality, we have adopted a number of techniques and though not highly consistent and conclusive, there has been a fall in inequality over time, especially in the 2nd period of our analysis.

- In order to understand the factors behind inequality in earnings, a number of decomposition techniques mainly those of Shapley and RIF decomposition have been applied. Shapley decomposition in this regard shows that Inequality is mostly explained by within occupation differences. However the dominance of between occupation differences have grown over time, specially in the recent years. According to RIF decomposition, it can be inferred that it is primarily earning structure effect rather than characteristics effect that played the key role behind changes in inequality over time, In addition, further analysis of earnings structure decomposition reflects that RTI along with education explain differences in earnings for different earnings quintiles. In particular, for the 1st period, RTI had a pro-rich effect while education had a pro-poor earnings, whereas in the 2nd period, RTI had a pro-poor effect on inequality.

While summing up the results, we can deduce that on one hand, in terms skill content of the workers, there has been a shift towards educated and better skilled workers with increase in returns to education, while on the other there has also been a gradual movement towards jobs with lesser routine tasks. We also observe that, although there has been increase in real labour earnings across the board for all education and broad skill classes, this has not been translated into growing inequality as we have observed decline in earnings inequality especially in recent years.

Against this backdrop of our analysis, we must therefore prioritize our labour market policies towards better skill training programme targeting primarily those with low skill base. Given the rise in education premium over time, it is also extremely crucial to direct national policies towards market oriented education programmes. The need to reorient education programmes catering to the necessities of the labour market is even more pertinent in light of the results of our detailed RTI decomposition analysis.

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Appendix

Tables: **Table 1: GINI Index**

Year	GINI index(HH Income)
2005	46.7
2010	45.8
2016	48.3

Table 2: Employment Elasticity of Growth

Sector	1995-96 to 1999-00	1999-00 to 2005-06	2005-06 to 2009-10	2009-10 to 2017-18
Agriculture	0.73	0.82	0.71	-0.09
Manufacturing	0.26	0.78	0.87	0.65
Construction	0.27	0.63	2.22	0.55
Services	0.21	0.69	0.27	0.40
GDP	0.54	0.59	0.55	0.25

Source: SANEM (2019); Sample households survey by SANEM for the GED, Planning Commission and ADB-ILO report (2016)

Table 3: Trend of Labour Force Participation Rate (%)

	1999/00	2005-06	2010	2013	2015-16	2016-17
All	54.9	58.5	59.3	57.1	58.5	58.2
Male	84.2	86.8	82.5	81.7	81.9	80.5
Female	23.9	29.2	36	33.5	35.6	36.3

Source: Labour Force Surveys, different years and Raihan&Bidisha (2018).

Table 4: Trend of Labour Force Participation Rate (%) – Type of Employment

	2005		**2010**		**2016/17**	
Types	Male	Female	Male	Female	Male	Female
Wage employment	40.0	23.9	46.1	18.5	42.6	31.2
Self-employment	50.4	16.0	47.7	25.3	52.5	39.2
Unpaid family worker	9.7	60.1	7.1	56.3	4.2	29.1

*Source:*Labour Force Surveys, different years and Raihan&Bidisha (2018)

Table-5: Trend of sectorwise labour force participation

	1999-00	**2005-06**	**2010**	**2013**	**2015-16**	**2016-17**
Agriculture	51.3	48	47.5	45.1	42.7	40.6
Male	52.2	41.8	40.1	41.7	34	32.2
Female	47.6	68.1	64.8	53.5	63.1	59.7
Industry	13.1	14.5	17.7	20.8	20.5	20.4
Male	11.3	15.1	19.6	19.6	22.3	22
Female	20	12.5	13.3	23.7	16.1	16.8
Manufacturing	9.5	11	12.4	16.4	14.4	14.4
Male	7.4	10.8	12.7	13.9	14.2	14
Female	17.9	11.5	11.7	22.5	14.9	15.4
Service	35.6	37.4	35.3	34.1	36.9	39
Male	36.4	43	41.1	38.7	43.7	45.8
Female	32.2	19.3	21.8	22.8	20.8	23.5

Source: Various rounds of LFS, Raihan and Bidisha (2018)

Table- 6a: Distribution of Workers by Gender and Level of Education

Highest level of education completed	Male			Female			Total		
	2005	2010	2016/17	2005	2010	2016/17	2005	2010	2016/17
No schooling	36.98	39.75	28.22	51.64	40.79	35.68	40.4	40.07	29.98
Primary	24.5	23.29	27.35	23.35	23.07	23.44	24.23	23.22	26.43
Secondary	32.94	32.2	37.05	21.89	33.98	35.14	30.36	32.75	36.6
Tertiary	5.58	4.76	7.39	3.13	2.15	5.74	5.01	3.96	7

Table- 7a: Distribution of Workers by Gender and Occupation

ISCO-88 (1-digit)	Male			Female			Total		
	2005	2010	2016/17	2005	2010	2016/17	2005	2010	2016/17
1 Managers	0.58	1.49	2.23	0.2	0.58	0.82	0.49	1.21	1.9
2 Professionals	3.28	3.22	2.48	3.2	2.14	2.83	3.26	2.89	2.56
3 Technicians and Associate Professionals	1.62	1.85	3.76	1.45	1.05	6.72	1.58	1.6	4.46
4 Clerical Support Workers	2.47	2.47	1.99	1.36	0.64	1.14	2.21	1.9	1.79
5 Services and Sales Workers	23.13	21.07	20.47	6.29	10.11	6.51	19.2	17.7	17.18
6 Skilled Agricultural, Forestry and Fishery workers	22.82	16.31	19.85	63.18	64.92	35.97	32.25	31.25	23.64
7 Craft and Related Trade Workers	9.5	9.82	17.72	8.26	7.8	25.67	9.21	9.2	19.59
8 Plant and Machine Operators and Assemblers	5.78	6.49	10.61	3.84	4.78	3.46	5.33	5.97	8.93
9 Elementary Occupations	30.82	37.28	20.9	12.2	7.99	16.88	26.47	28.28	19.95

Table- 8a: Distribution of Workers by Gender and Occupation

skill	Male			Female			Total		
	2005	2010	2016/17	2005	2010	2016/17	2005	2010	2016/17
High	5.48	6.56	8.46	4.86	3.77	10.37	5.33	5.7	8.91
Medium	40.88	39.85	50.79	19.76	23.32	36.78	35.95	34.77	47.49
Low	53.64	53.59	40.75	75.38	72.91	52.85	58.72	59.53	43.6

Table 12a Real Mean Earnings by Gender and Level of Education

Highest class passed	Male			Female			Total		
	2005	2010	2016/17	2005	2010	2016/17	2005	2010	2016/17
No Schooling	938	1234	1371	842	1313	1243	922	1244	1335
Primary	1215	1417	1481	1184	1372	1450	1211	1413	1475
Secondary	1664	1887	1997	1629	1554	1968	1660	1850	1991
Tertiary	2377	3769	4440	2432	2552	3858	2387	3612	4310
Total	1342	1611	1981	1276	1468	1821	1332	1594	1943

Table 13aEducation Premium in mean weekly earnings (Ratio) (All workers)

Highest class passed	Male			Female			Total		
	2005	2010	2016/17	2005	2010	2016/17	2005	2010	2016/17
No Schooling	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Primary	1.30	1.15	1.08	1.41	1.04	1.17	1.31	1.14	1.10
Secondary	1.77	1.53	1.46	1.93	1.18	1.58	1.80	1.49	1.49
Tertiary	2.53	3.05	3.24	2.89	1.94	3.10	2.59	2.90	3.23
Total	1.43	1.31	1.44	1.52	1.12	1.47	1.44	1.28	1.46

Table 14a Real Mean Weekly Earnings by Gender and Occupation

ISCO-88 (1-digit)	Male			Female			Total		
	2005	2010	2016/17	2005	2010	2016/17	2005	2010	2016/17
1 Managers	3126	3647	5204	2223	2402	4918	3093	3562	5173
2 Professionals	2469	2682	3997	2375	2044	3735	2445	2536	3925
3 Technicians and Associate Professionals	2165	2578	3209	2015	2034	2996	2129	2489	3124
4 Clerical Support Workers	2115	2549	2588	1922	2258	2292	2085	2522	2541
5 Services and Sales Workers	1809	1972	1876	1147	1655	1689	1707	1947	1844
6 Skilled Agricultural, Forestry and Fishery Workers	971	1598	1304	823	1167	1352	966	1486	1309
7 Craft and Related Trade workers	1414	1391	1686	1003	1592	1566	1356	1422	1652
8 Plant and Machine Operators and Assemblers	1468	1716	1994	1274	1243	1860	1418	1604	1975
9 Elementary Occupations	901	1205	1326	823	1254	1135	892	1208	1282
Total	1342	1611	1981	1276	1468	1821	1332	1594	1943

Table 15a Real Mean Weekly Earnings by Gender and Skill Level

skill	Male			Female			Total		
	2005	2010	2016/17	2005	2010	2016/17	2005	2010	2016/17
High	2399	2843	4035	2265	2065	3372	2366	2701	3841
Medium	1643	1793	1861	1232	1498	1655	1572	1753	1814
Low	910	1258	1324	823	1214	1143	901	1254	1284
Total	1342	1611	1981	1276	1468	1821	1332	1594	1943

Table 29a: Inter-quantile ratios (All Workers)

	2005/06	2010	2016/17
ln(q90)-(q10)	1.83	1.54	1.20
ln(q90)-(q50)	0.98	0.85	0.80
ln(q50)-(q10)	0.85	0.69	0.41

Table 30a: Summary Indices (All Workers)

	2005	2010	2016/17
Var	0.512	0.397	0.309
Gini LN	0.057	0.049	0.039
Gini	0.378	0.370	0.320

Table-34b Corr. between Country Specific RTI and changes in employment and earnings, 2005–2016/17(All)

Country Specific RTI	Log Change in Employment Share			Change in log (mean) earnings		
VARIABLES	2005-2010	2010-2016/17	2005-2016/17	2005-2010	2010-2016/17	2005-2016/17
Country Specific*RTI (t-1)	0.645	-0.546	0.344	0.018	-0.678***	-0.463
	(1.106)	(1.063)	(0.651)	(0.170)	(0.184)	(0.299)
Sq. Country Specific *RTI (t-1)	-1.142	0.007	-0.494	0.189	0.374**	0.317
	(1.475)	(1.117)	(0.537)	(0.207)	(0.159)	(0.334)
Constant	-0.215	-0.174	-0.164	-0.015	0.365***	0.342***
	(0.192)	(0.243)	(0.225)	(0.045)	(0.051)	(0.049)
Observations	108	106	106	107	102	103
Adj. R-squared	0.0473	0.0191	0.00741	0.170	0.378	0.0285

Note: Robust standard errors in parentheses, ** p<0.01, ** p<0.05, * p<0.1

Table 36a: Correlation coefficients between change in log employment share and change in log oflabour earnings (All)

	Log Change in Employment Share			Change in log (mean) earnings		
VARIABLES	2005-2010	2010-2016/17	2005-2016/17	2005-2010	2010-2016/17	2005-2016/17
(log) mean weekly earnings (t-1)	-50.423**	68.937**	9.835	-4.341**	-9.571**	-12.373***
	(24.492)	(27.764)	(8.569)	(1.820)	(3.915)	(2.985)
Sq. (log) mean weekly earnings (t-1)	3.469**	-4.595**	-0.678	0.269**	0.664**	0.844***
	(1.700)	(1.874)	(0.602)	(0.129)	(0.266)	(0.209)
Constant	181.820**	-258.256**	-35.858	17.362***	34.591**	45.393***
	(87.631)	(102.524)	(30.414)	(6.416)	(14.371)	(10.591)
Observations	107	105	106	107	102	103
Adj. R-squared	0.268	0.232	0.00961	0.716	0.101	0.592

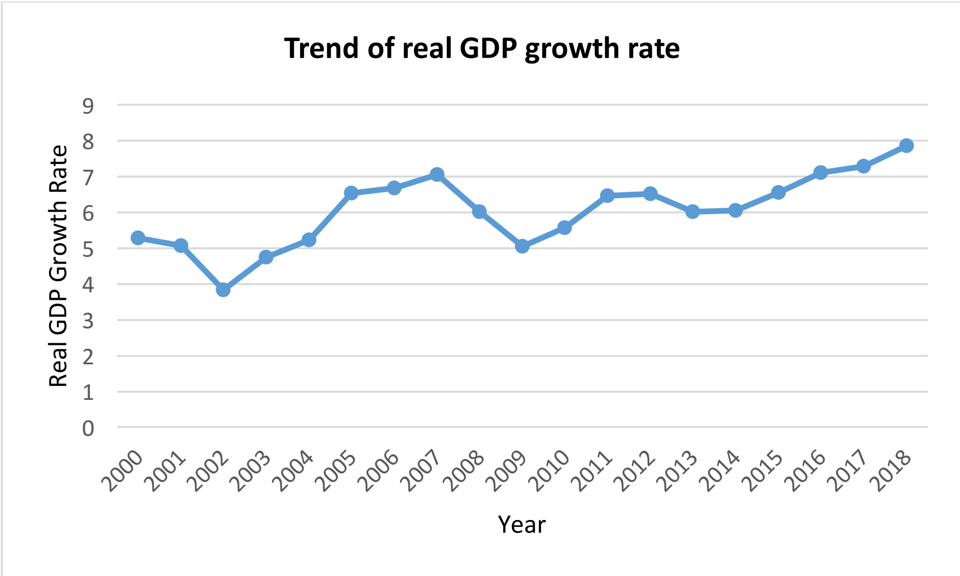
Note: Robust standard errors in parentheses, ** p<0.01, ** p<0.05, * p<0.1

Table 37: Average routine-task intensity (RTI), 2005 – 2016/17

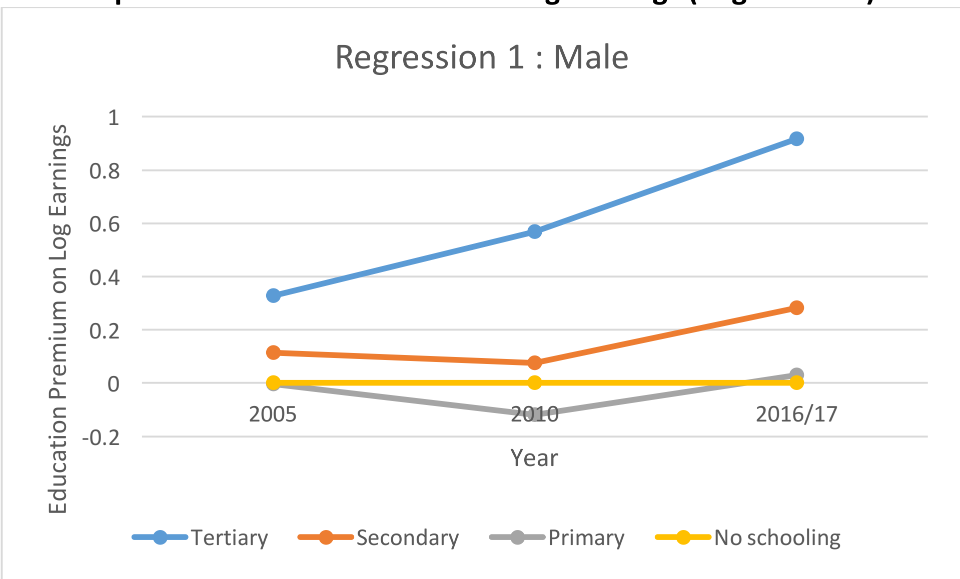
RTI measure	**All workers**			**Paid employees**		
	2005	**2010**	**2016/17**	**2005**	**2010**	**2016/17**
Country-specific	0.85	0.86	0.67	0.36	0.42	0.31
O*NET	0.28	0.43	0.29	0.18	0.33	0.11

Graphs:

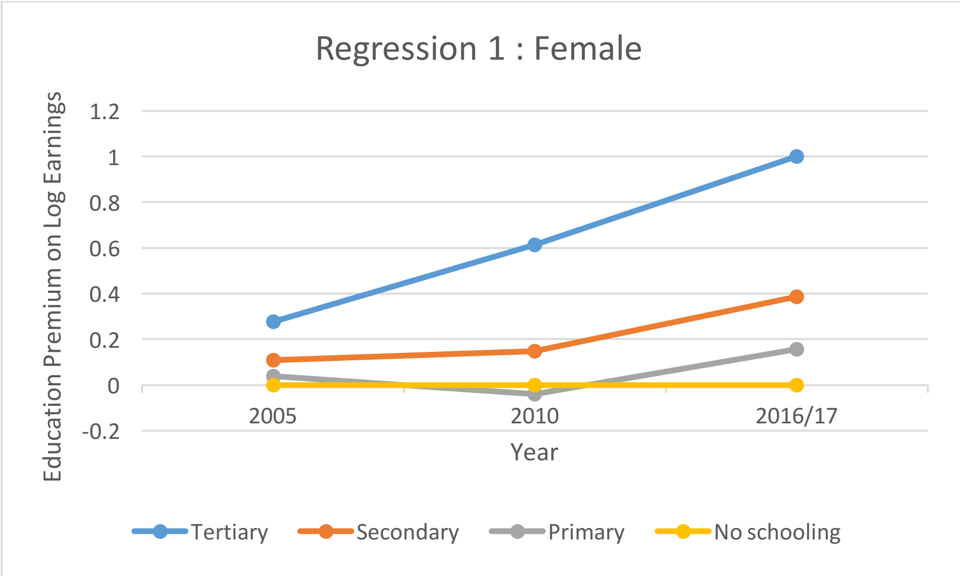
Graph 1: Trend of real GDP growth rate



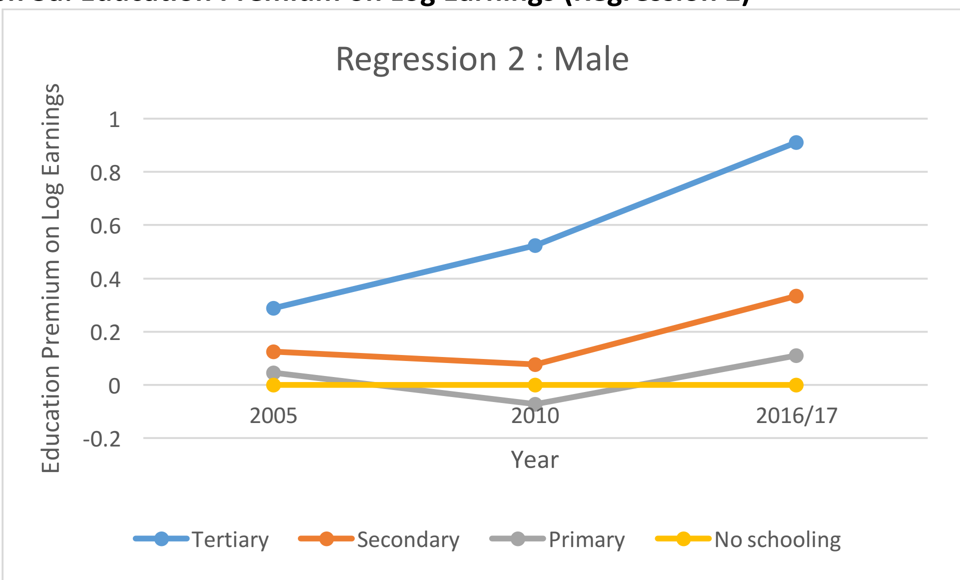
Graph 2a: Education Premium on Log Earnings (Regression 1)



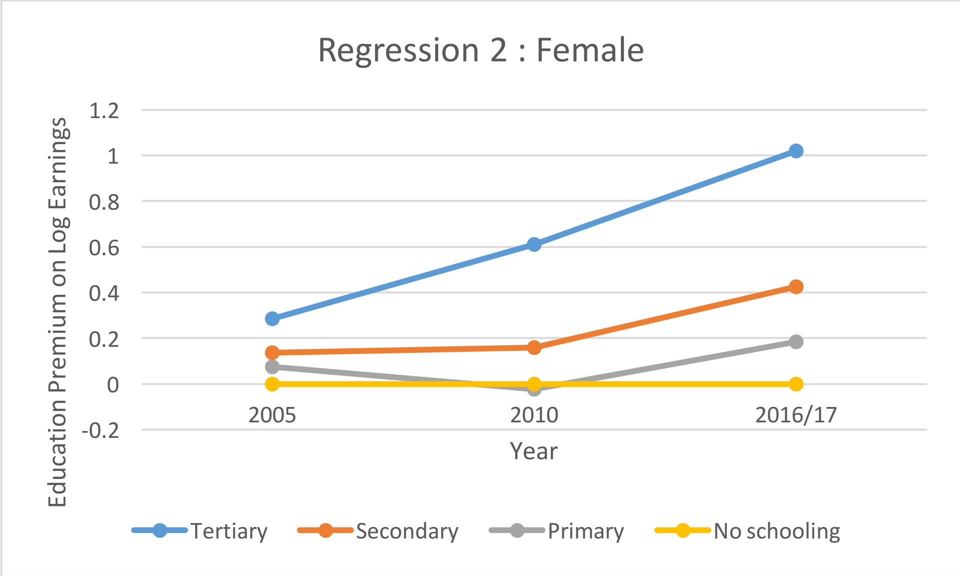
Graph 2b: Education Premium on Log Earnings (Regression 1)



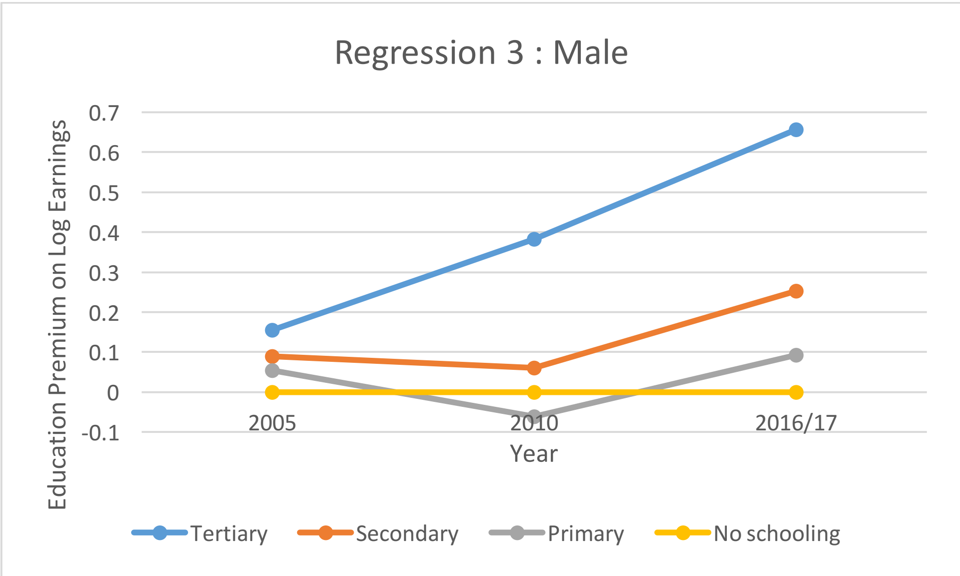
Graph 3a: Education Premium on Log Earnings (Regression 2)



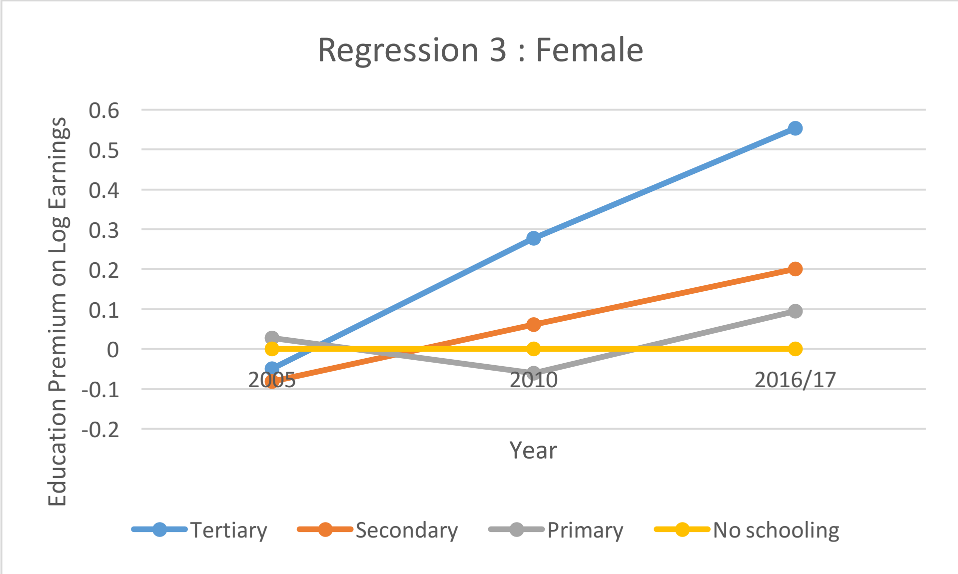
Graph 3a: Education Premium on Log Earnings (Regression 2)



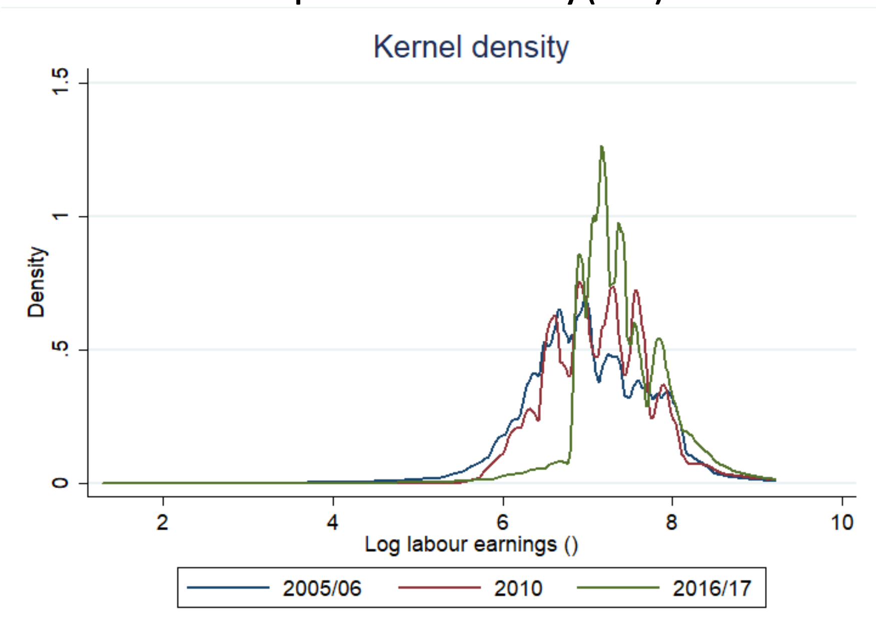
Graph 4a: Education Premium on Log Earnings (Regression 3)



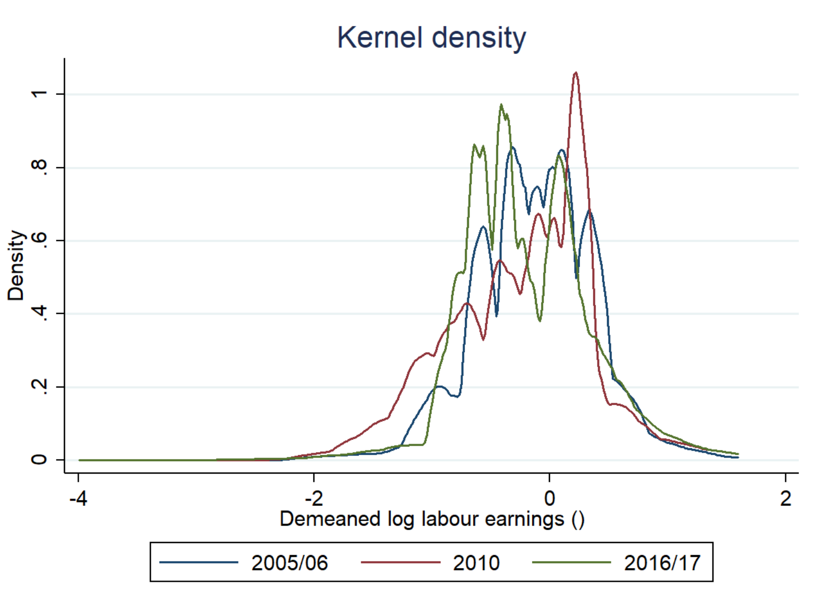
Graph 4b: Education Premium on Log Earnings (Regression 3)



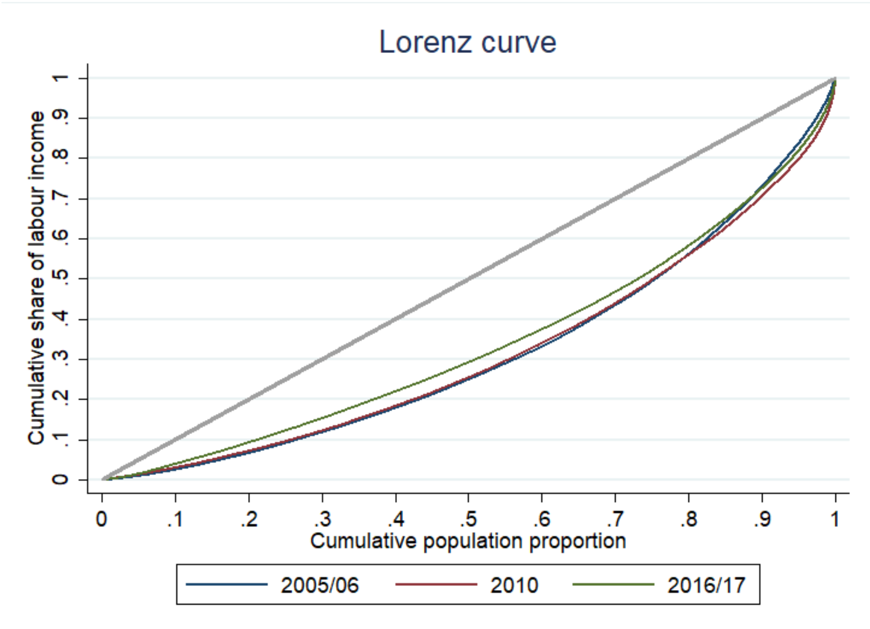
Graph 5b: Kernal Density (Paid)



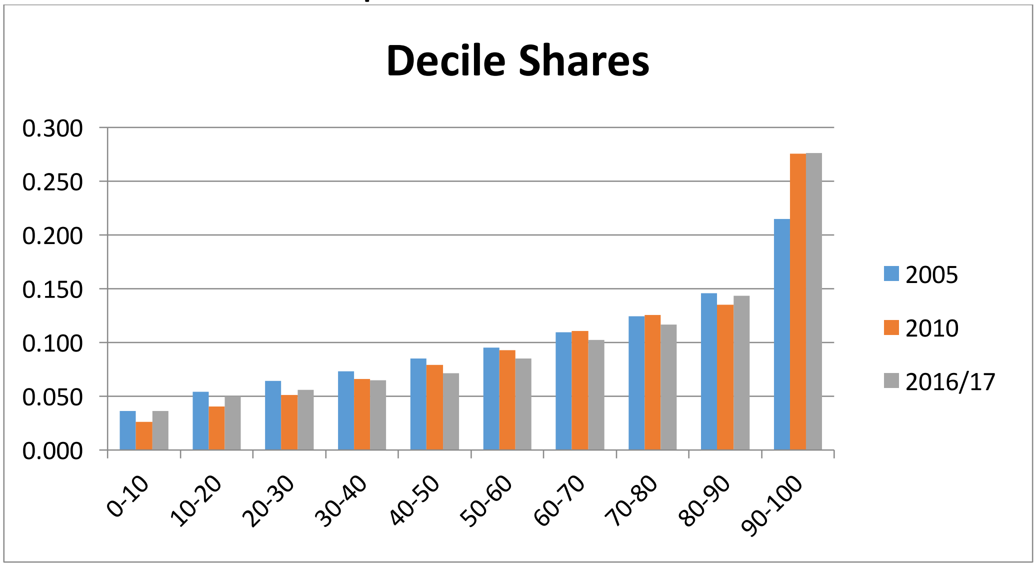
Graph 6b: Kernal Density Demeaned (Paid)



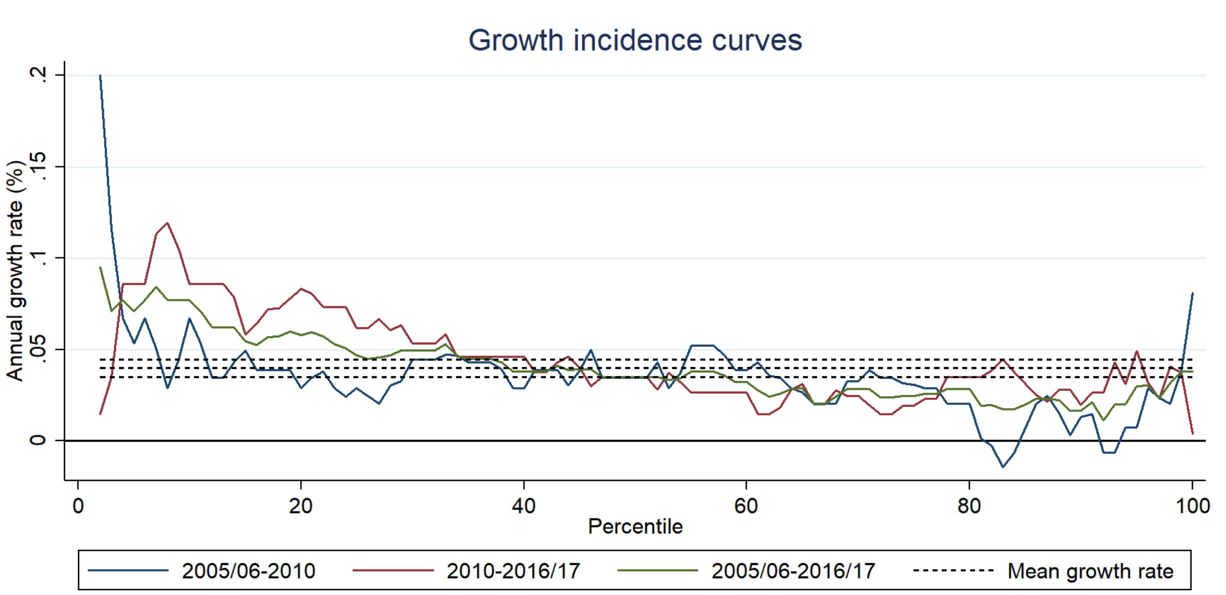
Graph 7a: Lorenz Curve (All)



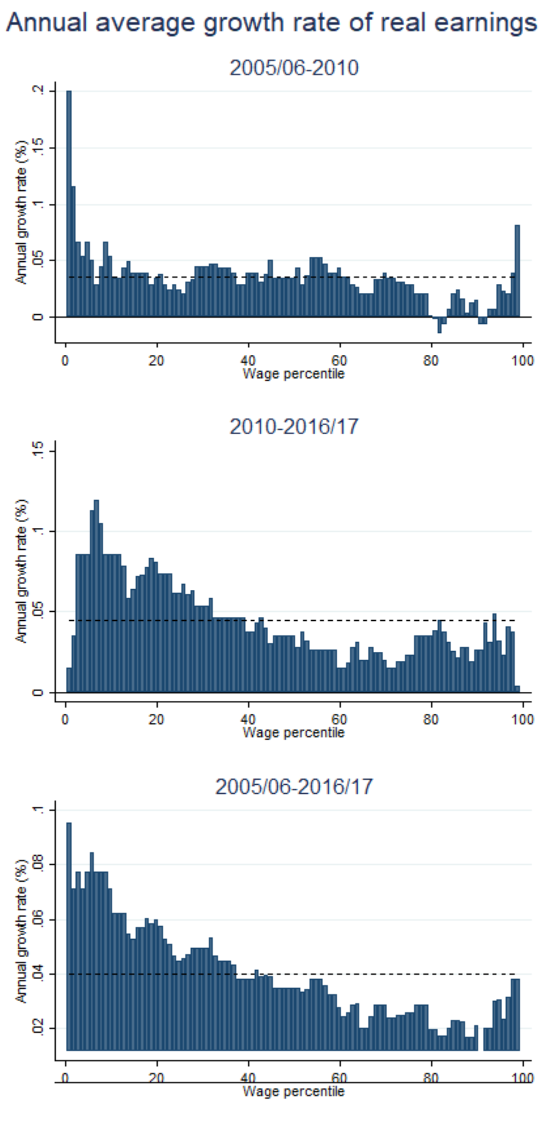
Graph 8: Decile Shares



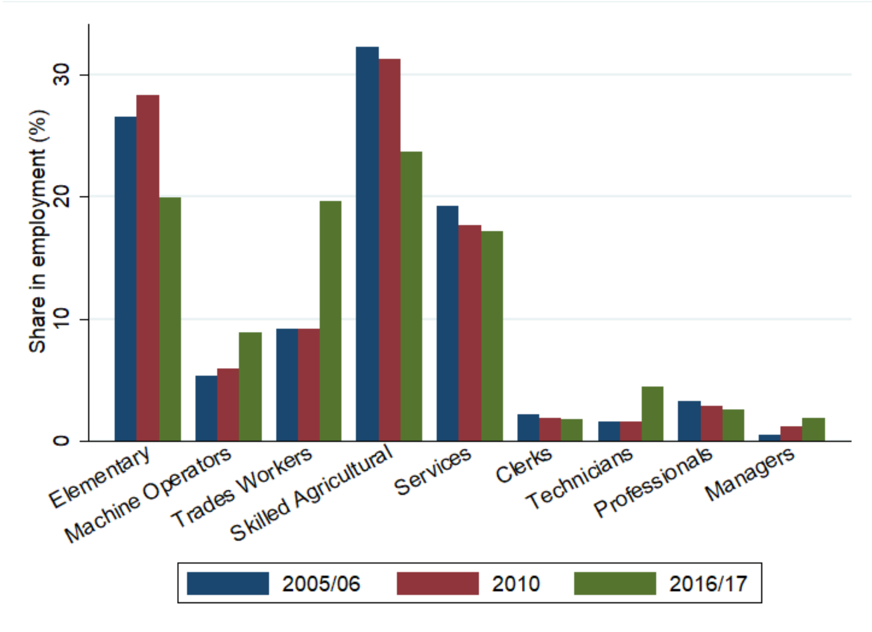
Graph 9a: Growth Incidence Curves (All)



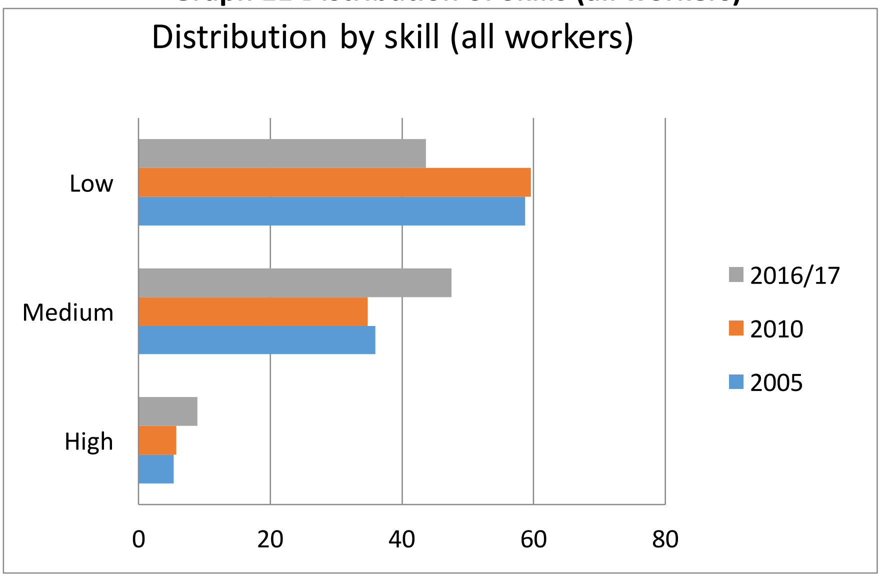
Graph 9b: Growth Incidence Curves-Bar (All)



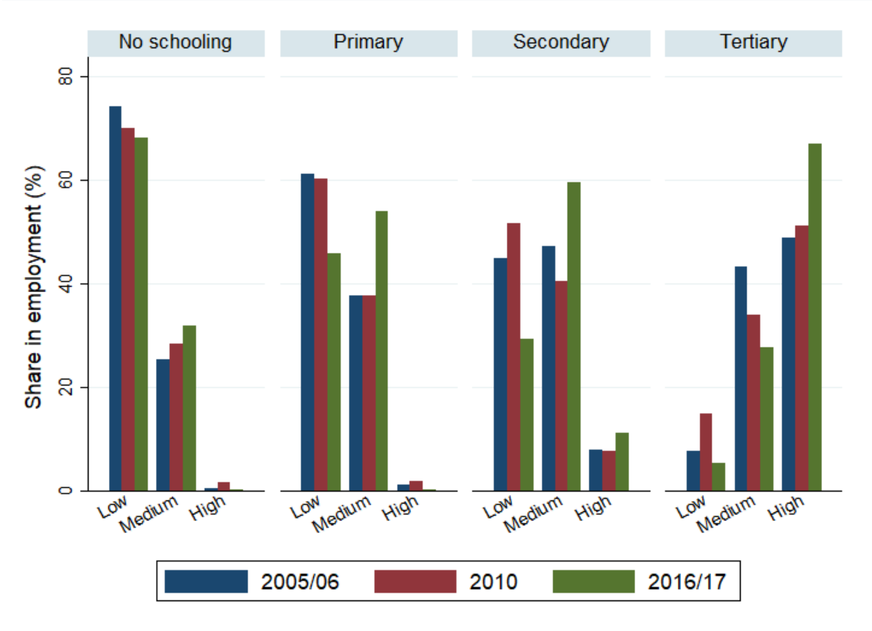
Graph 10 Employment Shares



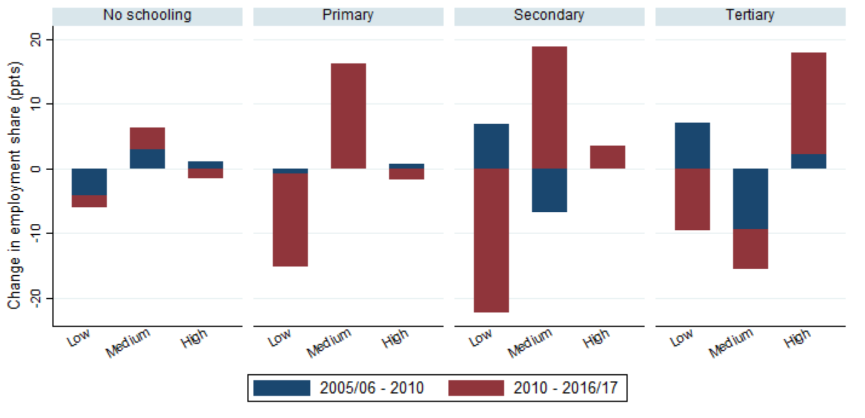
Graph 11 Distribution of Skills (all workers)



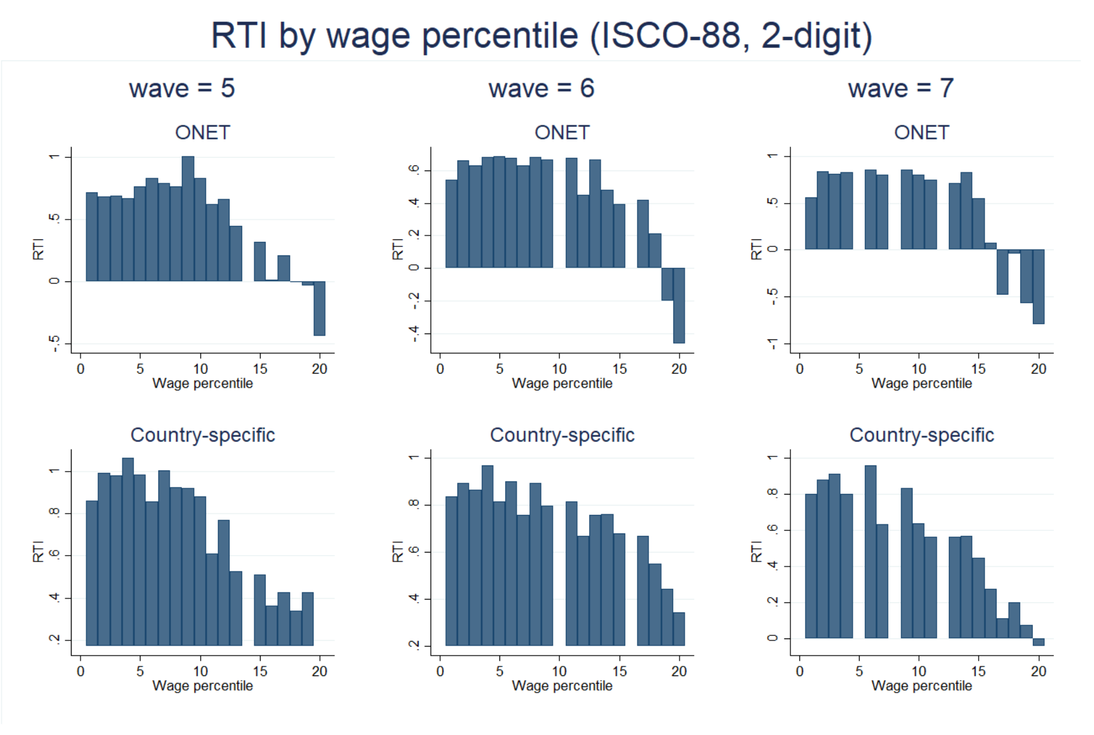
Graph 13 Education wise Employment share (all workers)



Graph 14 Skill and Education wise change in employment share (all workers)



Graph 28a Routine-task-intensity by earnings percentile, 2005/06 – 2016/17 (all)



Graph 28b Routine-task-intensity by earnings percentile, 2005/06 – 2016/17 (Paid)