IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

IMPACT OF DISTRIBUTIONAL ASYMMETRY IN LABOUR FORCE IN THE LEVELS OF WELL-BEING: A CASE STUDY

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Abstract: The situation in the labour market is such that one of the genders is dominating a given professional category. The phenomenon known as *occupational segregation* (by sex) is a persistent feature of labor markets all around the world. The present study seeks to look into the effect of this labour market heterogeneity (segregation) in terms of levels of living (well-being). It is observed that there is a negative relationship between segregation and levels of well-being. The higher is the intensity of segregation (i.e., the higher the asymmetry in the labour force), the higher is the deprivation in the levels of well-being (i.e., the higher the incidence of poverty).

JEL: C1, I3
Keywords: Segregation, Poverty, Vulnerability, Egalitarian Distribution

1. INTRODUCTION

It is a known fact that unequal access to jobs for male and female workers across various occupations takes place in almost all countries of the world. The situation in the labour market is such that one of the genders is dominating a given professional category. The phenomenon known as *occupational segregation*(by sex) in the literature is a persistent feature of labor markets all around the world. The present study seeks to look into the effect of this labour market heterogeneity (segregation) in terms of levels of living (well-being). To the best of our knowledge, no earlier attempt has been made in this regard. Without looking upon the issue as a problem at the first instance, we take a much broader perspective and begin by making an objective assessment of the situation. To be precise, how much the present distribution of the labour force is at a variance from the *egalitarian* distribution? Going by the holistic concept of economic well-being, an *egalitarian* society is supposed to be in a higher level of well-being in terms of equal opportunities and realizations for all. To the extent, the present distribution fails to achieve the egalitarian distribution; it suffers a potential welfare loss.

The present study distinctively finds out that the distributional heterogeneity across gender is a crucial factor determining the well-being of the society. The region with a higher distributional heterogeneity, i.e., having a higher departure from the ideal egalitarian distribution that is characterized by zero distributional heterogeneity (i.e., having an equal distribution of male and female workers across occupations) is found to have a higher incidence of poverty in the present period and also a higher chance of falling into the poverty in the future, as well.

The plan of the paper is as follows. Section 2 describes the methodology. Section 3 gives the data and results and finally Section 4 concludes.

2. METHODOLOGY

Construction of regions and estimation of regional poverty gap

Following the methodology proposed by (Chattopadhyay S. , 2014), regions are classified as A and B on the basis of some benchmark segregation score. A comprises of districts having segregation scores above the benchmark while B comprises of districts with segregation scores below the benchmark. The characterization as such links any subsequent economic analysis with the regions (viz., finding regional incidence of poverty) to the extent of segregation[1]. Incidences of poverty ($\mathrm{FGT}(\alpha)$) are next estimated separately for Region A and Region B[2]. The difference between the estimates, $\delta = \mathrm{FGT}(\alpha)^{\mathrm{A}} - \mathrm{FGT}(\alpha)^{\mathrm{B}}$ of poverty is next observed. It is then tested whether the difference, δ is significantly different from zero. This is implemented as follows:

1. $\mathrm{Variance}\big(\mathrm{FGT}(\alpha)\big) = \left(\frac{z}{\alpha!}\right)^2 \left[\frac{1}{N}\sum_{i=1}^{N}\left[\left(\frac{z-y_i}{z}\right)^{\alpha}\right]^2 - \left(\mathrm{FGT}(\alpha)\right)^2\right]$; z being the poverty line, y_i being the income of the i^{th} household , N being the number of households below the poverty line[3].
2. $\mathrm{Variance}(\mathrm{FGT}(\alpha)^{\mathrm{A}} - \mathrm{FGT}(\alpha)^{\mathrm{B}}) = \mathrm{Variance}(\mathrm{FGT}(\alpha)^{\mathrm{A}}) + \mathrm{Variance}(\mathrm{FGT}(\alpha)^{\mathrm{B}})$
3. The null hypothesisH_0:$\mathrm{FGT}(\alpha)^{\mathrm{A}} - \mathrm{FGT}(\alpha)^{\mathrm{B}} = 0$ is tested using the statistic:

$$t = \frac{\mathrm{FGT}(\alpha)^{\mathrm{A}} - \mathrm{FGT}(\alpha)^{\mathrm{B}}}{\sqrt{\mathrm{Variance}\big(\mathrm{FGT}(\alpha)\big)}}$$

"t" ratios corresponding to the test statistic are tested against theoretical values at the required level of significance. If the observed "t" value is greater than the theoretical value, we reject the null and accept the alternative hypothesis.

The above analysis is based on fixed set of poverty line. Poverty line can be allowed to vary between a range of values and a *stochastic dominance* approach to comparing levels of living between the Regions A and B can be implemented.

2.1.Formulating a regression set-up: static and dynamic poverty comparisons

Following (Chattopadhyay S. , 2011), a proper exploratory framework to assess the variations in the standard of living across the regions is set up as given below. The dependent variable here is the standard of living (incidence of poverty) and the explanatory variables are a set of potential socio-economic factors that are likely to influence consumption. The present approach uses *segregation score* (SEG) as one of the additional explanatory variables in the list of variables used in (Chattopadhyay S. , 2011)[4]. Incorporating SEG as an explanatory variable will help us assess the effect of labour market heterogeneity on the levels of well-being.

$$\left(\frac{y}{z}\right)_i^* = X_i\beta + \varepsilon_i \,;\, i = 1, 2, \ldots\ldots, n; var(\varepsilon_i) = \sigma^2 \qquad (1)$$

Here $\left(\frac{y}{z}\right)_i^* = ln\left(\frac{y}{z}\right)_i$; *y* being the household per capita total consumption expenditure, X being the set of explanatory variables, β being the coefficient vector and *z* being the poverty line.

$$\mathrm{prob}\left(\left(\frac{y}{z}\right)_i < 1\right) = \mathrm{prob}\left(\left(\frac{y}{z}\right)_i^* < 0\right) = \mathrm{prob}(X_i\beta + \varepsilon_i < 0)$$
$$= \mathrm{prob}(\varepsilon_i < -X_i\beta).$$

That is, $p_i = \Phi\left(\frac{-X_i\beta - E(\varepsilon_i)}{\sqrt{var(\varepsilon_i)}}\right)$; [Φ is the C.D.F of standard normal distribution]

[1] The higher the difference in the mean segregation scores between the groups, the better the categorization of the districts. This is however subject to the availability of finding adequate sample size in each group so as to run valid regression subsequently (for estimation of poverty).

[2] See Foster, Greer, & Thorbecke (1984) for FGT class of poverty indices.

[3] SeeDavidson & Duclos (1997) for the detailed methodology.

[4] The other explanatory variable introduced here is MGNREGA which is a dichotomous variable indicating whether having any MGNREGA Job Card or not.

$= \Phi\left(\frac{-X_i\beta}{\sigma}\right)$; [Assuming $var(\varepsilon_i)=\sigma^2$]

$= \Phi(X_i\beta^*)$. ; $\left[\beta^* = -\frac{\beta}{\sigma}\right]$ (2)

Here p_i gives the probability of being poor for the i^{th}household.
The regional incidence of poverty (H)is estimated as the sample average of $p_i{}'$ s.
Thus, H $=\frac{1}{n}\sum_{i=1}^{n}\Phi\left(X_i\hat{\beta}^*\right)$; n being the number of households in the Region.

Dynamic poverty Analysis: Modelling the probability of becoming Poor(v_{it})

The ex-ante probability of the incidence of poverty at any time$(t+1)p_i^{t+1}$ will depend on the expected future consumption level $(E_t y_i^{t+1})$ and also on the variability of the future consumption. To estimate $(E_t y_i^{t+1})$ from the cross-sectional dataset at time t, we need to make some restrictive assumptions regarding the stochastic process generating consumption (Chaudhuri S. , 2000). Assuming that the idiosyncratic shocks to consumption are identically and independently distributed over time for each household and the structure of the economy is relatively stable over time (so as to warrant a fixed β over time), we do away with any unobservable sources of persistence (arising for example, from serially correlated shocks or unobserved household-specific effects)over time in the consumption level of an individual household. This implies that the uncertainty in the future consumption solely stems from the uncertainty about the idiosyncratic shock,ε_i in Equation (1). Allowing for some parametric specifications for variance of ε_i,

$$\sigma^2{}_i = X_i\theta \tag{3}$$

β *and* θ are estimated using a three-stage generalized least square as described below.

1. Equation (1) is first estimated using OLS. Estimated residuals are used to estimate the following:

$$\hat{e}^2{}_i = X_i\theta + \eta_i \tag{4}$$

2. The predictions from this equation are used to transform the equation as follows:

$$\frac{\hat{e}^2{}_i}{X_i\hat{\theta}} = \left(\frac{X_i}{X_i\hat{\theta}}\right)\theta + \frac{\eta_i}{X_i\hat{\theta}} \tag{5}$$

3. This transformed equation is estimated using OLS to obtain an asymptotically efficient FGLS estimate, $\hat{\theta}_{FGLS}$. Note that $X_i\hat{\theta}_{FGLS}$ is a consistent estimate ofσ_i^2, the variance of the idiosyncratic component of household consumption.
4. The estimate $\hat{\sigma}_i = \sqrt{X_i\hat{\theta}_{FGLS}}$ is used to transform Equation (1) as follows:

$$\frac{\left(\frac{y}{z}\right)_i^*}{\hat{\sigma}_i} = \left(\frac{X_i}{\hat{\sigma}_i}\right)\beta + \frac{\varepsilon_i}{\hat{\sigma}_i} \tag{6}$$

OLS estimate of (5) yields consistent and asymptotically efficient estimate of β. Using the estimates $\hat{\beta}$ and $\hat{\theta}$ we are able to directly estimate for each household (i) the expected log consumption

$$\boxed{E|lny_i|X_i| = X_i\hat{\beta}} \tag{7}$$

and the variance of log consumption

$$\boxed{\hat{V}[lny_i|X_i] = \sigma_i^2 = X_i\hat{\theta}} \tag{8}$$

By assuming that the consumption is log normally distributed, we can use these estimates to form an estimate of the probability that a household with characteristics (X_i) will be poor at time (t+1).

$$v_{it} = \widehat{Pr}(y_{i,t+1} < z) = \Phi\left(\frac{\ln Z - X_i\hat{\beta}}{\sqrt{X_i\hat{\theta}}}\right) \tag{9}$$

The sample averages of the v_{it}'s would give the expected poverty of the group/region at time (t+1). $v_{it}^{'}s$ are aggregated to produce sample estimates of expected poverty at time (t+1). We classify the households into three categories:

1. Households with v_{it}'s less than or equal to Head Count Index (H).
2. Households with v_{it}'s greater than the head count index (H) but less than or equal to 0.5
3. Households with v_{it}'s> 0.5

Following Haughton& Khandker (2009), households under category 3 are assumed to be *highly vulnerable*. Those under category 2 are *moderately vulnerable* and the rest under category 1, are *not vulnerable*.

3. Data and Results

In this study we have used the household level or unit record data on employment and unemployment collected by the National Sample Survey Organization (NSSO)[5]. The present study has used the NSSO 68th round employment-unemployment data (pertaining to the period 2011-12) for the rural sector of State of West Bengal, an eastern state of India. The employment and unemployment indicators are measured in three different approaches, viz. *usual status (*US*)* with a reference period of one year, *current weekly status(*CWS*)* with a one-week reference period and *current daily status (*CDS*)* based on the daily activity pursued by individuals on each day of the reference week. For the workers in the usual status, information on the type of occupation in which they were engaged was collected using the 3-digit classification of National Classification of Occupation (NCO-2004). The occupation divisions of NCO-2004 are: Division 1: Legislators, senior officials and managers, Division 2: Professionals, Division 3: Technicians and associate professionals, Division 4: Clerks, Division 5: Service workers and shop & market sales workers, Division 6: Skilled agricultural and fishery workers, Division 7: Craft and related trades workers, Division 8: Plant and machine operators and assemblers, Division 9: Elementary occupations and Division X: Workers not classified by occupations. Each of the groups is subdivided into several groups.

It may be noted that there is marked difference in the gender-wise distributions across the occupations[6]. The average male percentage is as high as 88% in contrast to average female percentage which is as low as 12%. The disparity in male/female distribution is reflected by plotting the cumulative proportion of female workers in the Y-axis against the cumulative proportion of male workers across the X-axis. As evident from Fig 1, the (x, y) combinations constitute a curve which is convex to the X-axis. Had there been no heterogeneity in the distribution of male and female workers, the curve would have coincided with the 45° line. The 45° line signifies an *'egalitarian distribution'*. The more the departure of the curve from the egalitarian line the greater the amount of segregation. The curve is the 'segregation curve' as outlined in the previous section. The Duncan (D), Hutchens (H) and Gini indices corresponding to Fig 1 turn out to be as high as 0.4748, 0.2251 and 0.65 respectively. A value of D of 0.47 implies that 47% of the male workers are to be

[5]The household level information in these surveys is collected using a multi-stage stratified sampling design technique. The sample weights (multipliers) are an integral part of the NSSO data sets. In the quinquennial rounds of survey, detailed information on place of residence, economic activities, social and demographic characteristics and household assets and expenditure were collected from diverse households covering different individuals at the all India level. The point of departure as regards the data sources of NSSO and Census is the information content. While basic demographic information about different population groups may be obtained from the Census data, NSSO data provides detailed information on several easily quantifiable welfare indicators. In view of the above, we have used the NSSO data in this study. The unique feature of the NSSO data is the information content on various demographic and socio-economic aspects viz. age, sex, social group, religion, educational level, various labour market characteristics in the form of 'labour force participation rate', 'principal activity status', 'subsidiary activity status', nature of employment and job as well as detailed information on item-wise and total consumption, wealth status in the form average level of land holdings (land possessed/land owned/land cultivated) are available at the person as well as the household level.

[6] The gender-wise distribution across the occupational categories is not shown here due to lack of space.

shifted to other professions to equalize the concentration of gender-ratios across occupations. This is a significantly high percentage pointing to the severity of the asymmetry in the rural work force.

We further look into the district-specific segregation scores (Duncan's, Hutchens and Gin indices) in order to look into the district specific occupational distribution structure (Table 1). It is observed that there are reasonable inter-state variations in the levels of segregation across the districts.Districts are next classified in terms of the estimated segregation scores as belonging to either Region A or to Region B as per the methodology mentioned in Section: 2.2. Percentiles corresponding to the district-level segregation scores (D) are given in Table 2.1 and 2.2. The benchmark is chosen to be the 50th percentile value. Selection of Regions under category A or B is made by noting the observed value of the district segregation score and then comparing it with the estimated benchmark. The categorization of districts is shown in Table2.3. $\text{FGT}(\alpha)$ estimates of poverty corresponding to α =0, 1 and 2 are found for each district (Tables 3, 4, 5) and also for each Region (Table 6). Monthly Per-capita Consumption Expenditure (MPCE) is taken as a proxy for income (y) and the poverty line (z) is taken to be Rs 783 per-capita per month[7]. Comparison of the values of the FGT indices with the segregation scores (Table 1) shows a high degree of positive association.

As regards the regional estimates of poverty, the values of FGT0 for Regions A and B come out to be 0.2822 and 0.2062. The regional difference (Table 7) between the estimates, $(\text{FGT}(0)^{\text{A}} - \text{FGT}(0)^{\text{B}})$ thus come out to be 0.0760 with an associated standard error of 0.0257. The't' value of 2.95 with a corresponding 'p' value of 0.0032 leads the rejection of the null hypothesis: H_0: $\text{FGT}(0)^{\text{A}} - \text{FGT}(0)^{\text{B}} = 0$
We accept the alternative hypothesis and thus infer that the $\text{FGT}(\alpha)$ measure corresponding to $\alpha = 0$ turns out to be significantly higher for Region A compared to that of Region B and the difference is highly statistically significant at 5% level of significance. It is evident from Table 7 that regional poverty gap in terms of FGT1 and FGT2 estimates is also significantly different from zero leading the rejection of the null hypothesis.

The FGT curves for Regions A and B corresponding to α =0, 1 and 2 are shown in Figure 2.1, 2.2 and 2.3. It is observed that the curve for Region A lies above that of Region B. This indicates higher levels of poverty in Region A compared to that in B. We thus conclude that all three measures of poverty, viz., Head Count, Poverty Gap and the Squared Poverty Gap are higher in the Region with a higher value of segregation score.

We classify the explanatory variables into five broad categories, viz. Demographic characteristics of the households, Educational Status, Wealth Status, Labour Market Characteristics and Government Aid[8].The extent of occupational heterogeneity as measured by the segregation scores is included as an additional variable (SEG) under labour market characteristics. It is believed that the higher the heterogeneity in the labour market, the higher the loss in social welfare from a reduced level of consumption.

Table 8 gives the results of the regression analysis. All the coefficients turn out to be highly statistically significant at 5% level of significance and have an associated 'p' value of less than 0.05. All the coefficients except PNSCH and SEG turn out to be positive. This is supported from theory. A possible explanation of the negative coefficient of PNSCH is that the income earned by joining the labour market is smaller than the gain in income made through increase in efficiency resulting from joining the educational institutions (Chattopadhyay S. , 2011). A negative coefficient of SEG implies that labour market heterogeneity leads to a decreased consumption level which in turn increases poverty. This observation is in line with the earlier findings that Region A has a higher incidence of poverty than Region B. Expectedly the variable MGNREGA has a positive impact on consumption.

The incidence of poverty for each household is found from Equation (2). The head count index of poverty turns out to be 0.25 for all the districts combined. It may be mentioned here that the appropriate sampling structure has been incorporated while implementing the analysis. District-level incidences of poverty are also found out from the sample averages of household level probabilities (Table 9). It is observed that there is plenty of variation in the incidences of poverty across the districts. Importantly, the regression-based estimates of poverty turn out to be close approximates to the direct income-based estimates of poverty (FGT0).

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[7] State-level poverty line has been used to estimate district-level poverty. It would be better to use district-level poverty line so as to get a more accurate picture using the methodology proposed in (Chattopadhyay S. , 2010) and (Coondoo, Majumder, & Chattopadhyay, 2011).

[8]The same set of variables has been used in the original papers by Chattopadhyay S. (2011) and Chattopadhyay S. (2014).

The probability of being poor in the next period, i.e., the ex ante probability of poverty at the household level(v_{it}) is obtained from Equation 9. $v_{it}^{'}s$ are aggregated to produce sample estimates of expected poverty at time (t+1). We classify the households into three categories:

4. Households with $v_{it}'s$ less than or equal to Head Count Index (H=0.25).
5. Households with $v_{it}'s$ greater than the head count index (H) but less than or equal to 0.5
6. Households with $v_{it}'s$> 0.5

Following Haughton& Khandker (2009), households under category 3 are assumed to be *highly vulnerable*. Those under category 2 are *moderately vulnerable* and the rest under category 1, are *not vulnerable*. Table 10 shows the district-specific frequency distribution of households vis-à-vis their status of vulnerability. Table 11 is a variant of Table 10 in percentage form. Tables 12 and 13 show respectively the region-specific frequency and percentage distribution of households vis-à-vis their status of vulnerability.

It may be noted that number of households (%) under Category 3 (5 %) and Category 2 (41%) are higher for Region A compared to that in B (31% and 1% respectively). This implies households in Region A suffer a greater risk of falling into poverty in the future as compared to those in Region B. The present analysis observes that the extent of segregation in the labour market is a potential factor that reduces per-capita consumption. The higher is the amount of segregation in the labour market, the higher is the incidence of poverty. It has also been found that the predicted future incidence of poverty, i.e., the vulnerability is also higher for the group which has a higher level of segregation. Thus one can conclude that the asymmetry in the labour market leads to a decrease in the level of consumption not in the current period but also in the future.

4. Conclusion

The paper has sought to quantify the (economic) effect of asymmetry in the labour force from a perfectly egalitarian distribution, i.e., the distribution characterized by equal proportion of male and female workers across occupations. Using survey data of an Indian state, the extent of asymmetry, i.e the departure of the present distribution of the labour force from the *ideal*(egalitarian)distribution has been captured in terms of occupational segregation scores. The paper finds out that there is a direct correspondence between segregation scores and the incidence of poverty. The higher the intensity of segregation, the higher the asymmetry in the labour force, the higher the deprivation in the levels of well-being, i.e., the higher the incidence of poverty not only in the present period but also in the future, i.e., the region with higher value of segregation scores is more vulnerable to poverty in the future. The gist of the analysis is that the intensity of segregation has a detrimental impact on the levels of well-being.

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District Code	District Name	Duncan Index	Gini Index	Hutchens Index
1	Darjiling	0.592	0.738	0.407
2	Jalpaiguri	0.490	0.636	0.258
3	Koch Bihar	0.650	0.795	0.445
4	Uttar Dinajpur	0.655	0.805	0.437
5	DakshinDinajpur	0.669	0.812	0.481
6	Maldah	0.633	0.818	0.442
7	Murshidabad	0.805	0.898	0.526
8	Birbhum	0.641	0.817	0.462
9	Barddhaman	0.609	0.777	0.373
10	Nadia	0.566	0.738	0.316
11	North Twenty Four Parganas	0.458	0.640	0.274
12	Hugli	0.642	0.753	0.400
13	Bankura	0.727	0.842	0.551
14	Puruliya	0.583	0.740	0.385
15	PaschimMidnapur	0.593	0.735	0.351
16	Haora	0.555	0.695	0.347
18	South Twenty Four Parganas	0.533	0.701	0.331
19	PurbaMidnapur	0.668	0.827	0.419

Table 1: District-wise Segregation Scores

Table 2.1 Summary Statistics of Duncan Index (From Table 1)				
	Percentiles	Smallest		
1%	0.458	0.458		
5%	0.458	0.49		
10%	0.49	0.533	Obs	18
25%	0.566	0.555	Sum of Wgt.	18
50% (Benchmark)	**0.621**		Mean	0.6149
		Largest	Std. Dev.	0.0819
75%	0.655	0.668		
90%	0.727	0.669	Variance	0.0067
95%	0.805	0.727	Skewness	0.2178
99%	0.805	0.805	Kurtosis	3.3241

Table 2.2 Summary Statistics of Hutchens Index (From Table 1)

	Percentiles	Smallest		
1%	0.258	0.258		
5%	0.258	0.274		
10%	0.274	0.316	Obs	18
25%	0.347	0.331	Sum of Wgt.	18
50% (Benchmark)	**0.4035**		**Mean**	**0.400278**
		Largest	Std. Dev.	0.079952
75%	0.445	0.462		
90%	0.526	0.481	Variance	0.006392
95%	0.551	0.526	Skewness	0.032113
99%	0.551	0.551	Kurtosis	2.414336

Table 2.3 Categorization of Regions Based on Benchmark Segregation Score

Composition of Region A			
District Code	Freq.	Percent	Cum.
3	530	7.44	7.44
4	623	8.74	16.18
5	383	5.37	21.55
6	841	11.8	33.36
7	1,265	17.75	51.11
8	688	9.65	60.76
12	924	12.97	73.73
13	745	10.45	84.18
19	1,127	15.82	100
Total	7,126	100	
Composition of Region B			
district	Freq.	Percent	Cum.
1	272	3.34	3.34
2	821	10.08	13.42
9	1,232	15.13	28.56
10	881	10.82	39.38
11	1,063	13.06	52.43
14	651	8	60.43
15	1,261	15.49	75.92
16	520	6.39	82.3
18	1,441	17.7	100
Total	8,142	100	

Table 3 District-wise Estimates of FGT0

District Code	District Name	Estimate	Standard Error	Lower Bound	Upper Bound

1	Darjiling	0.2342	0.0817	0.0741	0.3944
2	Jalpaiguri	0.3515	0.0605	0.2330	0.4700
3	Kochbihar	0.3333	0.0767	0.1829	0.4836
4	Uttar Dinajpur	0.4377	0.0763	0.2880	0.5873
5	DakshinDinajpur	0.2241	0.0694	0.0880	0.3602
6	Maldah	0.3685	0.0796	0.2124	0.5245
7	Murshidabad	0.2741	0.0465	0.1829	0.3653
8	Birbhum	0.2617	0.0544	0.1551	0.3683
9	Barddhaman	0.2331	0.0454	0.1441	0.3222
10	Nadia	0.2194	0.0507	0.1199	0.3188
11	North Twenty Four Parganas	0.1176	0.0337	0.0516	0.1837
12	Hugli	0.2932	0.0561	0.1833	0.4031
13	Bankura	0.1417	0.0378	0.0675	0.2159
14	Puruliya	0.3156	0.0491	0.2194	0.4119
15	PaschimMidnapur	0.2699	0.0439	0.1839	0.3559
16	Haora	0.1704	0.0511	0.0702	0.2705
18	South Twenty Four Parganas	0.1102	0.0291	0.0531	0.1674
19	PurbaMidnapur	0.2417	0.0458	0.1518	0.3316
State		0.2416	0.0127	0.2166	0.2666

Table 4 District-wise Estimates of FGT1

District Code	District Name	Estimate	Standard Error	Lower Bound	Upper Bound
1	Darjiling	0.0392	0.0172	0.0055	0.0730
2	Jalpaiguri	0.0531	0.0123	0.0290	0.0772
3	Kochbihar	0.0381	0.0097	0.0191	0.0571
4	Uttar Dinajpur	0.1073	0.0252	0.0579	0.1567
5	DakshinDinajpur	0.0264	0.0119	0.0031	0.0496
6	Maldah	0.0671	0.0146	0.0384	0.0958
7	Murshidabad	0.0518	0.0115	0.0292	0.0743
8	Birbhum	0.0452	0.0127	0.0204	0.0701
9	Barddhaman	0.0317	0.0074	0.0171	0.0462
10	Nadia	0.0239	0.0056	0.0129	0.0348
11	North Twenty Four Parganas	0.0283	0.0097	0.0094	0.0473
12	Hugli	0.0456	0.0098	0.0264	0.0649
13	Bankura	0.0217	0.0073	0.0073	0.0360
14	Puruliya	0.0528	0.0101	0.0330	0.0726
15	PaschimMidnapur	0.0584	0.0123	0.0343	0.0825
16	Haora	0.0255	0.0081	0.0097	0.0413
18	South Twenty Four Parganas	0.0129	0.0041	0.0048	0.0209
19	PurbaMidnapur	0.0504	0.0151	0.0208	0.0800
State		0.0413	0.0028	0.0358	0.0467

Table 5 District-wise Estimates of FGT2

District Code	District Name	Estimate	Standard Error	Lower Bound	Upper Bound
1	Darjiling	0.0092	0.0047	-0.0001	0.0185
2	Jalpaiguri	0.0107	0.0030	0.0048	0.0166
3	Kochbihar	0.0058	0.0019	0.0021	0.0095
4	Uttar Dinajpur	0.0348	0.0104	0.0144	0.0552

5	DakshinDinajpur	0.0054	0.0032	-0.0010	0.0117
6	Maldah	0.0167	0.0047	0.0076	0.0259
7	Murshidabad	0.0141	0.0040	0.0062	0.0220
8	Birbhum	0.0114	0.0045	0.0025	0.0203
9	Barddhaman	0.0065	0.0019	0.0028	0.0101
10	Nadia	0.0047	0.0016	0.0016	0.0078
11	North Twenty Four Parganas	0.0091	0.0045	0.0002	0.0180
12	Hugli	0.0091	0.0021	0.0050	0.0133
13	Bankura	0.0049	0.0018	0.0013	0.0085
14	Puruliya	0.0125	0.0029	0.0069	0.0181
15	PaschimMidnapur	0.0193	0.0050	0.0095	0.0291
16	Haora	0.0047	0.0016	0.0016	0.0078
18	South Twenty Four Parganas	0.0027	0.0011	0.0006	0.0048
19	PurbaMidnapur	0.0180	0.0073	0.0038	0.0323
State		0.0108	0.0010	0.0088	0.0128

Table 6 Regional Estimate of FGT(α)

Region	Estimate	STE	LB	UB
Regional Estimate of FGT0				
Region	Estimate	STE	LB	UB
A	0.2822	0.0205	0.2419	0.3225
B	0.2062	0.0155	0.1758	0.2365
State	0.2416	0.0127	0.2166	0.2666
Regional Estimate of FGT1				
Region	Estimate	STE	LB	UB
A	0.0506	0.0048	0.0413	0.0599
B	0.0331	0.0031	0.0271	0.0392
State	0.0413	0.0028	0.0358	0.0467
Regional Estimate of FGT2				
Region	Estimate	STE	LB	UB
A	0.01359	0.0018	0.01007	0.01711
B	0.00834	0.00111	0.00617	0.01052
State	0.01079	0.00103	0.00877	0.01281

Table 7 Difference between Regional FGT Estimates

	FGT0	Std. Error	t	P>t	95% Conf. Interval	
Region A	0.2822	0.0205	13.7332	0	0.2418756	0.322478
Region B	0.2062	0.0155	13.3109	0	0.1757784	0.236527
Diff.	0.0760	0.0257	2.95466	0.0032	-0.1264716	-0.02558
	FGT1	Std. Error	t	P>t	95% Conf. Interval	
Region A	0.050589	0.004755	10.63887	0	0.0412622	0.059916
Region B	0.033127	0.003098	10.69174	0	0.0270507	0.039204
Diff.	0.017462	0.005676	3.076663	0.0021	0.0063341	0.028589
	FGT2	Std. Error	t	P>t	95% Conf. Interval	
Region A	0.013588	0.001796	7.56424	0	0.0100649	0.017112

Region B	0.008344	0.001109	7.524256	0	0.0061694	0.010519
Diff.	0.005244	0.002111	2.484013	0.0131	0.0011049	0.009383

Table 8 Estimation of Consumption Equation

Explanatory Factors	Coefficient	Standard Error	t ratio	P>t	95% Conf. Interval	
1-DEPRAT	0.1304	0.0534	2.4400	0.0150	0.0258	0.2351
D_FEMH	0.0791	0.0338	2.3400	0.0190	0.0128	0.1454
PSECEDU	0.2139	0.0710	3.0100	0.0030	0.0748	0.3531
PTERTEDU	0.4000	0.0784	5.1000	0.0000	0.2462	0.5538
GENEDU	0.0325	0.0061	5.3300	0.0000	0.0206	0.0445
PLAND	0.0006	0.0001	6.7400	0.0000	0.0004	0.0008
POWNAC	0.5534	0.0747	7.4000	0.0000	0.4069	0.7000
PNSCH	-0.2417	0.0733	-3.3000	0.0010	-0.3854	-0.0980
PDOM	0.4206	0.0798	5.2700	0.0000	0.2642	0.5770
PDOMO	0.1847	0.0726	2.5400	0.0110	0.0422	0.3271
PEMP	0.2962	0.0630	4.7000	0.0000	0.1727	0.4197
MGNREGA	0.1107	0.0196	5.6500	0.0000	0.0723	0.1491
SEG	**-0.3743**	0.1099	-3.4100	0.0010	-0.5898	-0.1589
D_GOVAID	0.9273	0.1370	6.7700	0.0000	0.6587	1.1959
Constant	-0.1118	0.0905	-1.2300	0.2170	-0.2892	0.0657

Table 9 Regression-based Estimates of Poverty

District Code	District Name	Incidence of Poverty	
		(Unweighted)	(Weighted)
1	Darjiling	0.1390	0.1655
2	Jalpaiguri	0.1498	0.1926
3	Koch Bihar	0.2096	0.2661
4	Uttar Dinajpur	0.3058	0.3468
5	DakshinDinajpur	0.2159	0.2756
6	Maldah	0.2481	0.3089
7	Murshidabad	0.2891	0.3338
8	Birbhum	0.2325	0.3091
9	Barddhaman	0.1795	0.2294
10	Nadia	0.1865	0.2240
11	North Twenty Four Parganas	0.1763	0.1986
12	Hugli	0.1848	0.2443
13	Bankura	0.1912	0.2336
14	Puruliya	0.1779	0.2019
15	PaschimMidnapur	0.1676	0.2147
16	Haora	0.1736	0.1990
18	South Twenty Four Parganas	0.1781	0.1994
19	PurbaMidnapur	0.2050	0.2633
State-level Incidence of Poverty		**0.2005**	**0.2448**

Table 10 District-wise Household Vulnerability Status (No)

District Code	Status of Vulnerability			Total
	1	2	3	
1	46	13	0	59
2	132	47	1	180
3	65	47	5	117
4	43	61	21	125
5	51	37	1	89
6	82	83	14	179
7	128	135	17	280
8	78	69	10	157
9	196	83	2	281
10	146	77	1	224
11	161	90	4	255
12	141	79	4	224
13	124	60	8	192
14	112	42	5	159
15	184	70	4	258
16	86	41	1	128
18	205	111	1	317
19	158	90	5	253
Total	2,138	1,235	104	3,477

Table 11 District-wise Household Vulnerability Status (%)

District Code	Status of Vulnerability			Total
	1	2	3	
1	78	22	0	100
2	73	26	1	100
3	56	40	4	100
4	34	49	17	100
5	57	42	1	100
6	46	46	8	100
7	46	48	6	100
8	50	44	6	100
9	70	30	1	100
10	65	34	0	100
11	63	35	2	100
12	63	35	2	100
13	65	31	4	100
14	70	26	3	100
15	71	27	2	100
16	67	32	1	100
18	65	35	0	100

19	62	36	2	100
Total	61	36	3	100

Table 12 Region-wise Household Vulnerability Status (No)

Region	Status of Vulnerability			Total
	1	**2**	**3**	
A	870	**661**	**85**	1616
B	1,268	**574**	**19**	1861
Total	2,138	1235	104	3477

Table 13 Region-wise Household Vulnerability Status (%)

Region	Status of Vulnerability			Total
	1	**2**	**3**	
A	54	**41**	**5**	100
B	68	**31**	**1**	100
Total	61	36	3	100

Figure 1: State-level Segregation Curve

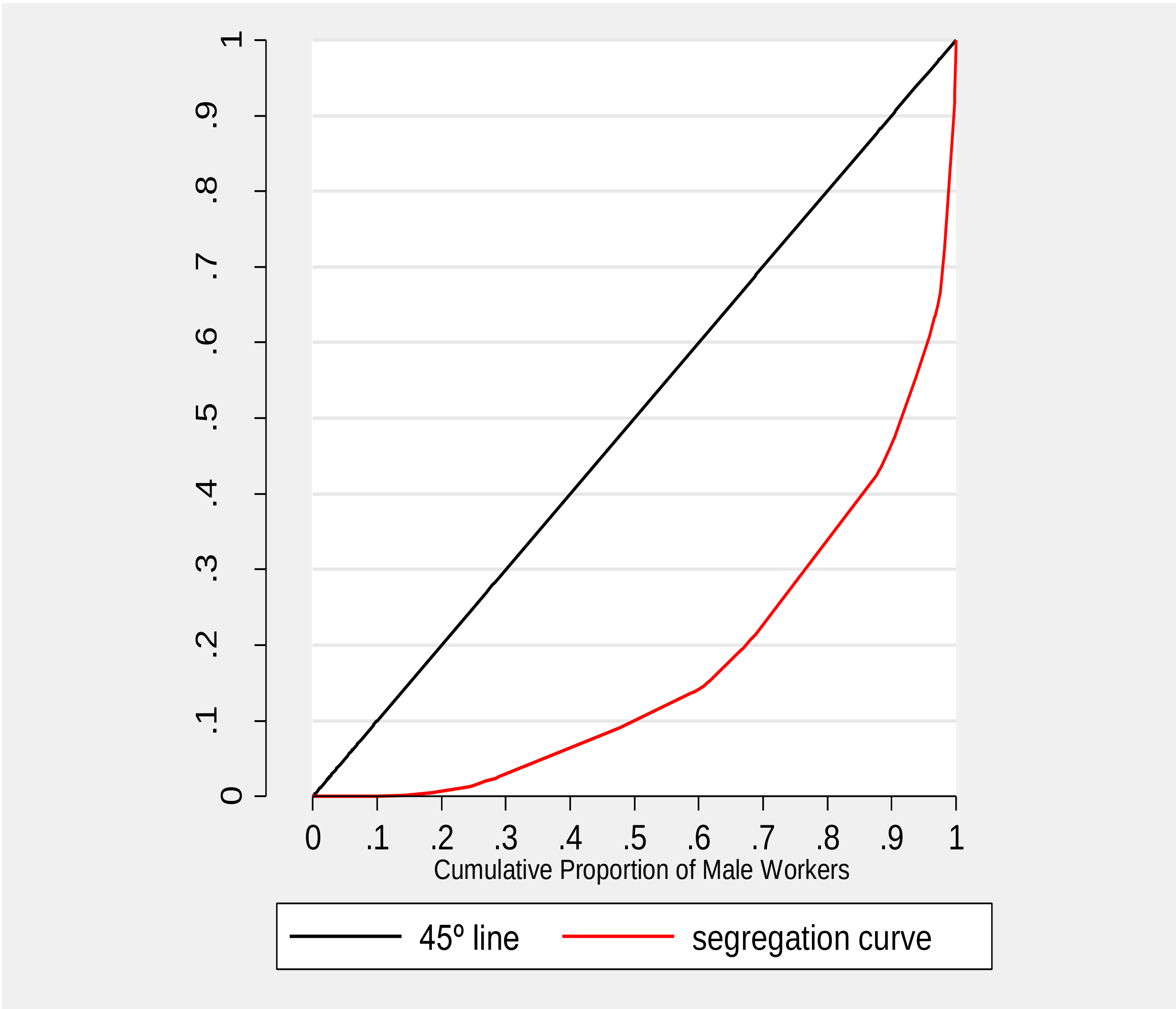

Figure 2.1 FGT Curves ($\alpha = 0$)

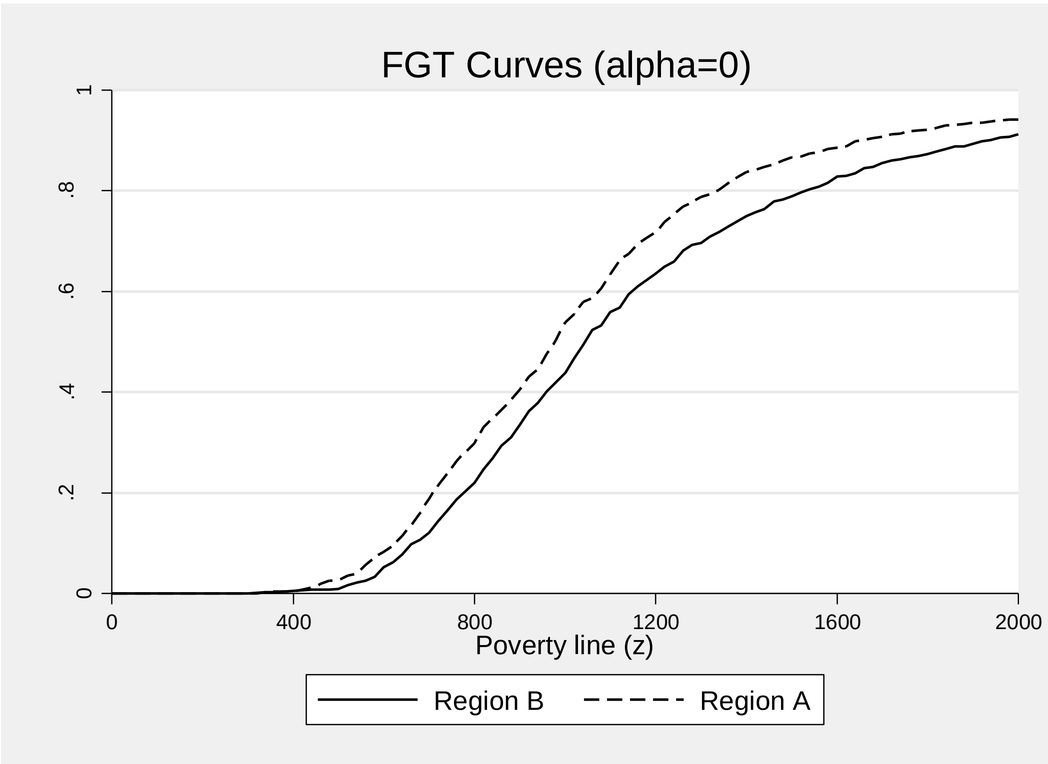

Figure 1.2 FGT Curves ($\alpha = 1$)

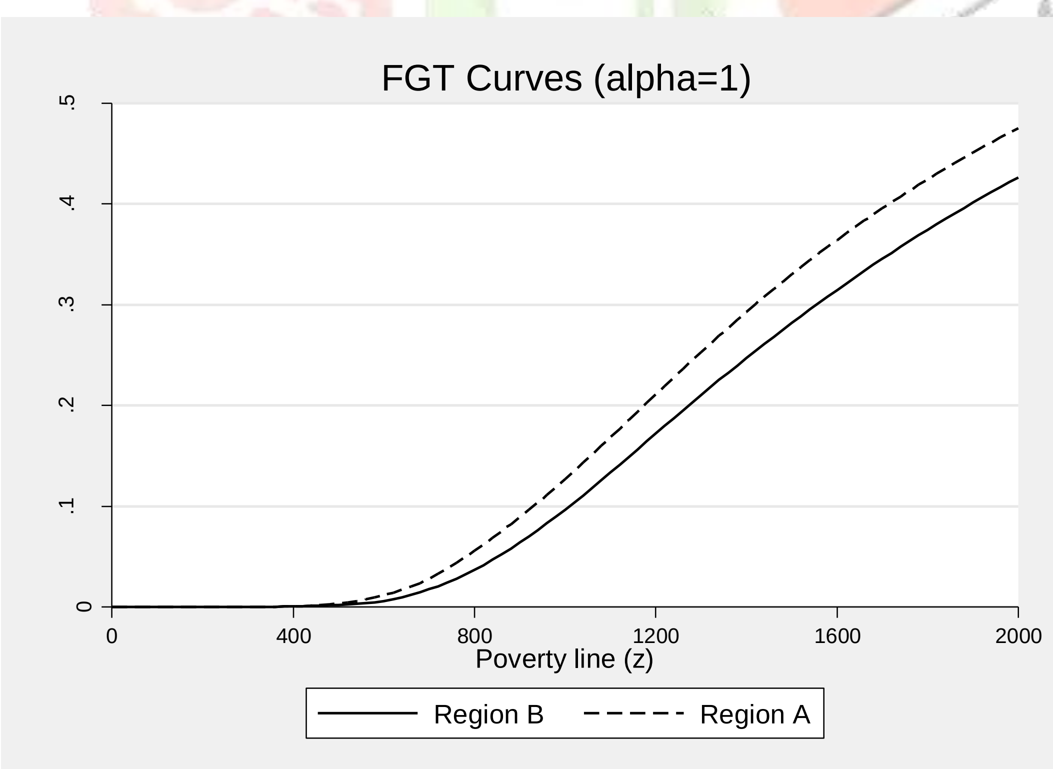

Figure 2.3 FGT Curves ($\alpha = 2$)

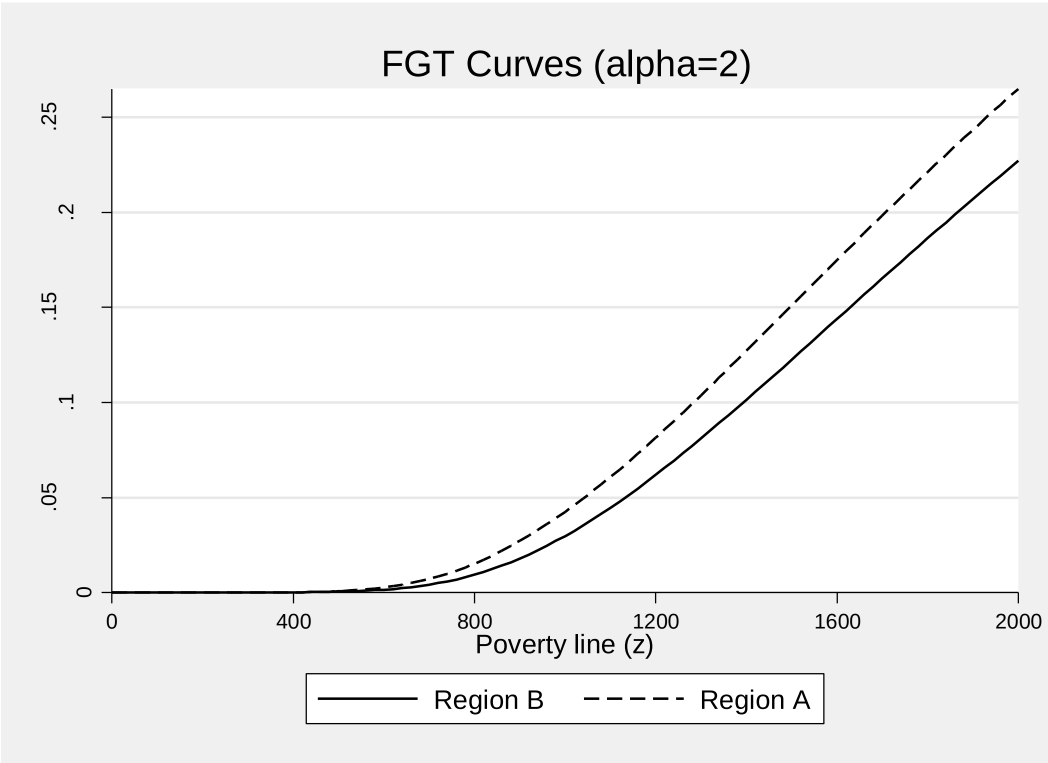

Figure 2.4

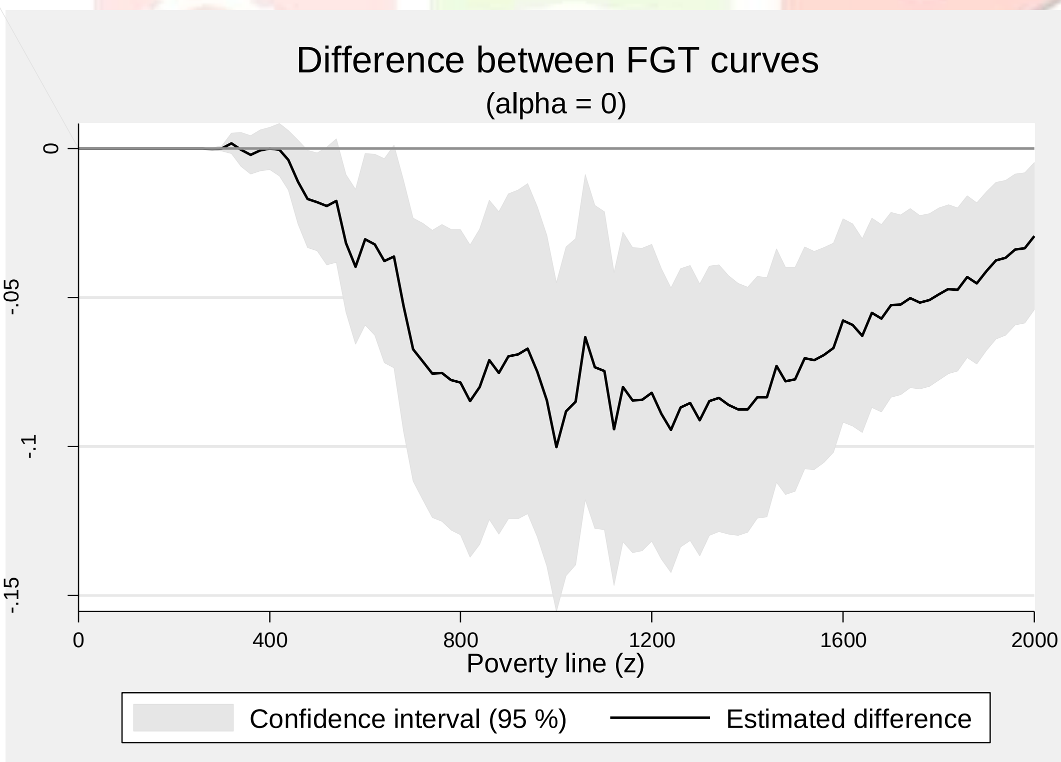

Figure 2.5

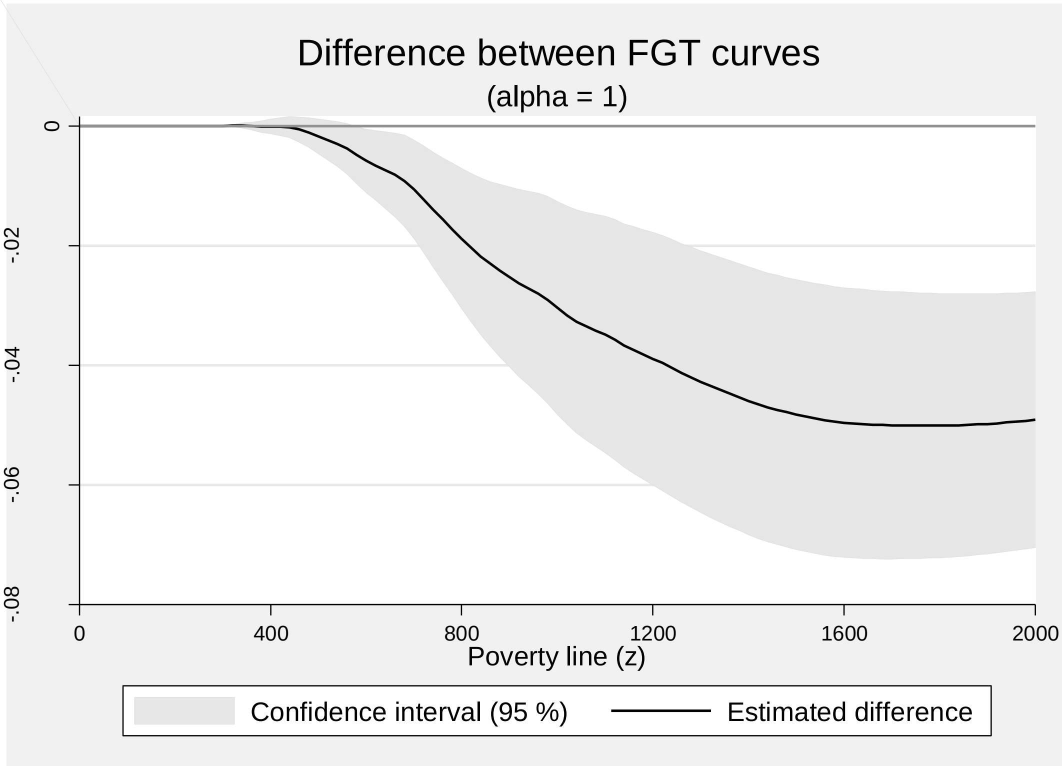

Figure 2.6