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Analysis of Gender Disparity in Meghalaya by Various Types of Composite Indices

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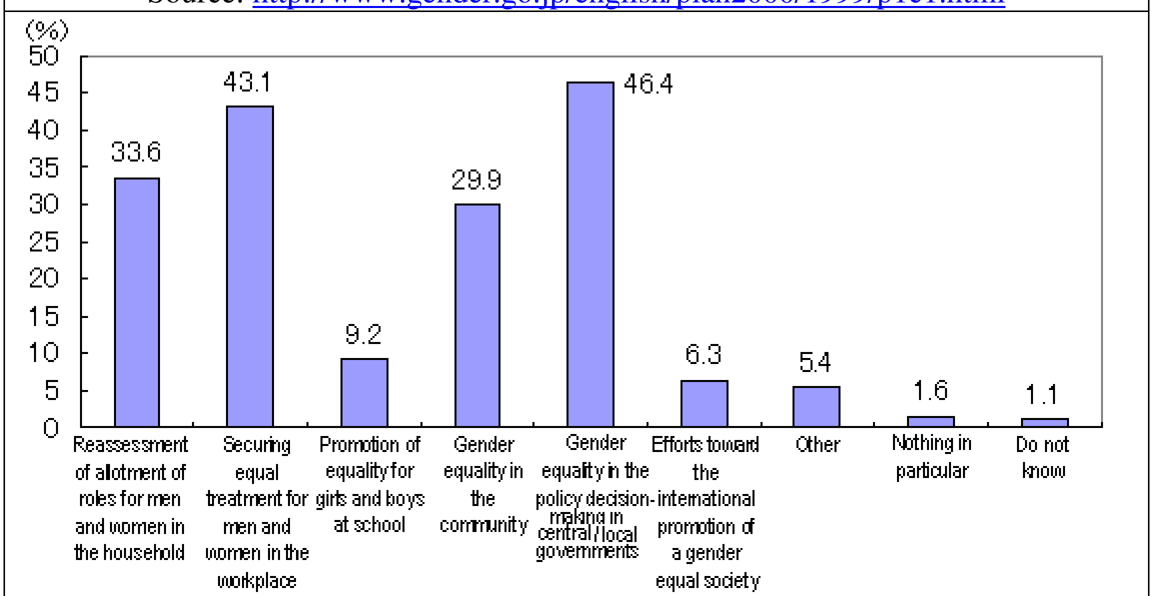
I. Introduction: Subjugation of women in certain spheres of life is very common in the patriarchal societies and it has a long history (see Davis, 1971; Firestone, 1972; Reed, 1975). Even in England that has a claim to incorporate the most of renaissance ideals in its social and intellectual fabric, people of repute (e.g. John Stuart Mill, the famous philosopher, economist, educationist, political scientist, etc. apart from being a member of the British Parliament) in the 19th century had to denounce the then practices leading to women's subjection at home and fight to form a public opinion against keeping the womenfolk as an underdog section. Mill, in the very first paragraph of his book wrote: "*… the principle which regulates the existing social relations between the two sexes – the legal subordination of one sex to the other – is wrong in itself, and now one of the chief hindrances to human improvement; and that it ought to be replaced by a principle of perfect equality, admitting no power or privilege on the one side, nor disability on the other*." In recent times, a survey conducted in 1998 in Japan targeting three thousand intellectuals nationwide asked the question, "In which area(s) does gender equality need to be realized in order to bring about a gender-equal society?" In response to this, the highest percentage, 46.4%, answered, "Gender equality in the policy decision-making processes of central and local governments," while the next highest percentage, 43.1%, answered, "Securing equal treatment for men and women in the workplace."

Fig.-1: Importance of Areas in which Gender Equality is Needed
Source: http://www.gender.go.jp/english/plan2000/1999/p1c1.html



In India, women have little social or economic independence. They are subjugated to men and discriminated against. In the greater part of India a girl, even as a foetus, suffers a chance of being discriminated. Cases of feticide are large in number when detected to be a female. After her birth, a girl child is often a second grade member of the family, usually dealt with roughly by the mother too. Getting rid of her by the family through early marriage is so common. In matters of education and health also she is given the last priority. Even then, if the sex ratio in India is only marginally unbalanced, the credit goes squarely to the stronger vitality and power of adaptation among the female sex. Their participation in economic activities outdoors is discouraged on the supply as well as the demand side. Working women of all segments of the Indian society face various forms of discrimination. Even professional women find discrimination to be prevalent; two-thirds of the women in a certain study felt that they had to work harder to receive the same benefits as comparably employed men (Liddle and Joshi, 1986). Perhaps, this is so for the Indian society is predominantly patriarchal.

II. The Case of Meghalaya: Meghalaya, a state in North East India, presents a case different than the rest of the country (except Kerala). A very large majority of population in the state belongs to three tribes, Garo, Jaintia and Khasi, well known for their being matrilineal and matrifocal. Most of them are Christian by religion although some have maintained their traditional tribal/indigenous religion.

In a matriarchal system of social organization the female is the real head of the family, and descent and inheritance are traced through the female line. Tracing of descent through the maternal line is a matrilineal system, which is only a subsystem within the larger framework of matrifocality/matriarchy (see Wikipedia: Matriarchy). Headship of a family is related with hierarchy: powers of decision-making, inheritance, benefaction and betrothal, ownership of economic resources, participation in activities relating to allocation, exchange and production, participation in socio-cultural activities, and so on. The effectiveness of headship may vary from being nominal to autocratic and dictatorial, without arousing strong feelings of disapproval and triggering off destabilizing reactions from other members in the organization. There could be various types of constraints on the decision-making powers of a head. Many of these constraints may be institutional (customs, mores, traditions and precedents) in nature. In reality matriarchy seldom exists, but matrifocality does.

It appears that matrifocality in Meghalaya has not crossed the boundaries of household when we notice that among the three Members of Parliament from the state all are men, and among sixty Members of the (7^{th}) Legislative Assembly of the state only three are women, one from the opposition and two from the ruling party. At the level of the local self-government a village head is a 'headman'. Then it is worth investigating if matrifocality has promoted literacy, economic participation and well being of the women.

III. The Present Study: In this paper we intend to investigate how women in Meghalaya perform vis-à-vis men in the socio-economic sphere. Our investigation is based on the data thrown up by the Census 2001. It may be noted that about 70 percent of people in Meghalaya are Christian, 13 percent are Hindu, 4 percent are Muslim and the rest belong to other religions (Table-1). Among those belonging to these 'other' religions, a little over 0.5 percent belongs to Sikhism, Buddhism and Jainism or those who have not stated their religion. About 11 percent people believe in various tribal religions. Most of the local people are Christian and most of the Christian are the local people. Thus, by studying the socio-economic status of the Christian segment of population we may infer as to the socio-economic status of the local people whose society is matrifocal. We may also reinforce our conclusions by examining the status of women in the 'others' religious category because this category includes mostly the non-Christian local people.

Table-1. Religion-wise Distribution of Population in Meghalaya (Census – 2001)

Religious Communities	Population (2001 Census)			Percentage-wise Distribution		
	Total	Male	Female	Population	Male	Female
All Religions	2318822	1176087	1142735	100.0000	100.0000	100.0000
Hindus	307822	168517	139305	13.2749	14.3286	12.1905
Muslims	99169	52455	46714	4.2767	4.4601	4.0879
Christians	1628986	812961	816025	70.2506	69.1242	71.4098
Sikhs	3110	1810	1300	0.1341	0.1539	0.1138
Buddhists	4703	2513	2190	0.2028	0.2137	0.1916
Jains	772	405	367	0.0333	0.0344	0.0321
Others	267245	133899	133346	11.5250	11.3851	11.6690
Religion not stated	7015	3527	3488	0.3025	0.2999	0.3052

Table-2: District-wise Distribution of Different Religious Communities of population in Meghalaya

Districts	WGaro	EGaro	SGaro	WKhasi	RiBhoi	EKhasi	Jaintia	Meghalaya
Population	518390	250582	100980	296049	192790	660923	299108	2318822
Hindu(%)	21.5143	5.6321	4.8326	1.9122	15.1030	19.5746	4.3964	13.2749
Muslims(%)	15.2343	1.5280	2.7401	0.0885	0.6774	1.4822	0.7476	4.2767
Christians(%)	54.5661	88.9497	89.6475	94.7640	79.7147	61.0172	65.2594	70.2506
All Others(%)	8.6854	3.8901	2.7798	3.2353	4.5049	17.9260	29.5967	12.1978

We envisage further that the place of habitation makes or mars the prospects of women in the socio-economic sphere. The place of habitation may be rural or urban on the one hand, and different districts on the other. Urban areas present different type of opportunities as well as constraints than do the rural areas. In the same vein, prospects in the West Khasi Hills district are surely different from those in Ri Bhoi or East Khasi Hills district. The three Garo districts differ significantly from Ri Bhoi and East Khasi Hills districts. Jaintia Hills district has an entirely different socio-economic atmosphere. The socio-economic landscape of different districts in the state have attracted the migratory population from other places differently, which has given rise to different proportions of various religious groups in the total population in those districts.

It may also be noted that different religions have different bearings on socio-economic and cultural prospects of women vis-à-vis men. Religion cuts across other cultural and residential forces and modifies them as much as is modified by the latter.

IV. Measures of Socio-Economic Characteristics: Although limited in coverage for the purpose at hand, the Census data may be used to present the socio-economic feature of population quantitatively. We choose the following measures gender-wise:

x_1=Proportion of Children (in 0-6 years' age group) in the total population [CHILD]
x_2=Literacy in the 6 plus years' population [LITER]
x_3=Workers in the 6 plus years' population [WORK]

x_4=Cultivators as a proportion to workers population [CULT]
x_5=Agricultural labourers as a proportion to workers population [AGRL]
x_6=Ratio of agricultural labourers to cultivators [AGLC]
x_7=Proportion of household industry workers to the workers population [HHIW]
x_8=Proportion of 'other workers' to the workers population [OTHW]
x_9=Ratio of non-workers to workers population [NWWR].

These nine measures are obtained for male and female populations separately. For example, we have $x_{1,M}$ defined as the proportion of male children (of 0-6 years age group) in the total male population and $x_{1,F}$ analogously. Thus we have eighteen measures in total: nine for male and their analogous nine for female population.

Among these (gender-wise groups of) nine measures, the first (x_1) relates to the growth rate of population. It also relates to consciousness regarding family planning and control of family size for socio-economic well-being. The second one (x_2) measures ability of the people to participate in a number of activities that an illiterate person cannot do. Literacy also opens various vistas to benefit from the civilization around oneself. The third measure (x_3) relates to readiness as well as participation in economic activities for one's well-being. The fourth measure (x_4) relates to an operational command over land, a major factor of production, especially in the rural areas. It is also related to the social status in the rural area. The fifth measure (x_5) is related to contribution of labour in agricultural activities. The sixth measure (x_6) is related to distribution of ownership of land resources. The seventh and the eighth measures (x_7 and x_8) relate to non-agricultural economic activities. These activities may be more remunerative than agriculture. The last measure (x_9) partly quantifies the dependency ratio. It also relates to the leisure class culture and values (Veblen, 1899).

V. Construction of A Composite Index: The set of nine measures enumerated above is obtained for all the seven districts in Meghalaya as well as for the state. In each district there are two sectors, urban and rural, and the population is distributed under four different of religious groups (Hindu, Muslim, Christian and 'others') there. This complex of data cannot give any comprehensive picture unless we make an index that obtains a single composite measure from those nine measures. However, before we construct a composite index, some introduction to the methodology is necessary.

VI. Analytic versus Synthetic Methods of Index Construction: It is pertinent to make a distinction between analytic and synthetic methods of index construction. Analytic methods assume that in the observed complex of data each variable is a mixture of influences or hues accountable to some latent, but more fundamental and deep-seated, factors. Speaking figuratively, each variable has a composite colour (so to say) that is only a mixture of basic colours in varying proportions. The proportion in which these factorial influences are composed varies from variable to variable. Therefore, they decompose the variations in data into some sort of manifestation or influence groups such that each group can be associated to a composite index, often mutually orthogonal to the other composite indices representing the other groups. Each composite index is sectarian by nature and construct. These methods include the principal components, maximum likelihood, communality R square, MINRES (minimum residual factor method of Harman and Jones, 1966), the principal axis and a number of other procedures of (factor) extraction. To streamline the factors, various methods of rotation are used, which effect to shedding off a little of explanatory power of the leading composite index. As a result, the variables that are non-conformal to the influence group that a particular composite index purports to represent are often poorly loaded and relegated to the other group or groups of influence. On the other hand, synthetic methods of index construction aim at representing every variable. They do not work on supposition that there could be other indices that would represent the residual variation in the data. They do not intend to analyze variation in data to form the distinct influence groups. In this category we may include MSAR (maximum sum of absolute correlation coefficients), MEFAR (maximum entropy-like function of absolute correlation coefficients) and MMAR (maxi-min absolute correlation coefficient). The choice of an appropriate method is contingent on the objective of exercise. If one wants several composite indices to construct (from the given data) then analytic methods are more appropriate. However, if the objective is to obtain a single composite index (and not to analyze the variations in data into a number of influence groups) one may prefer to use synthetic methods. It may be noted that if the variables are highly correlated with each other, the analytic and the synthetic methods yield very similar (leading) composite indices.

VII. Various Methods of Index Construction: There are numerous methods of constructing composite indices. We describe in details some major ones among them.

VII-A: The Principal Component Analysis: This methods decomposes the variance in multi-variable data (x_j, j=1, 2,…,m) into a number of components (I_k; i=1,2,…, k; $k \leq m$) such that the composite indices, which are linear combinations of variables (data), one for each component, maximizes the sum of squared correlation coefficients between itself and the variables, and those indices are pair-wise orthogonal among themselves. The number of components cannot exceed the number of variables in the data, but it could well be smaller. The first component absorbs the maximum variance in the data; the second component absorbs the maximum of the residual variance and so on. The principal component method is perhaps the most popular method of constructing composite indices.

VII-B: Factor Analysis: Factor Analysis is a multi-variate statistical method with a major objective of data reduction. It assumes that a few latent, fundamental and essential forces work in the hind side and manifest themselves into the empirically observed multivariate data on a complex of variables. These essential, but latent or unobservable forces are "factors". Thus, the relationship between these latent factors and the observed data on the variables is that of the "essence" and the "manifestations". Nevertheless, each individual variable that belongs to the complex of empirical data has 'noise', specificity or errors of its own. Using suitable statistical and mathematical methods it is possible to extract these essential factors and in turn, they can be given a conceptual and theoretical meaning. Thus, factor Analysis is a statistical method to extract the common, essential and latent variables that reflect themselves into a complex of empirically observed variables. These essential factors are very often much fewer in number than are their manifest variables. In this sense, factor analysis is a statistical method of reducing the dimensionality of data.

The method of factor Analysis may take a number of different forms based on the following assumptions and techniques used. These different approaches to factor analysis may conveniently be classified according to the following criteria.

1. Assumption regarding the relationship between the universe of variables and the sample variables drawn from the said universe: Latent factors may manifest themselves into innumerably many measurable variables, but in any particular empirical study, only a subset of the said universe of variables can be included in the analysis. That is to say that the sample over the variables is always a proper subset of the universe of variables.
2. Assumption regarding the relationship between the universe of individuals and the sample individuals drawn from the said universe**:** Empirical data on various variables (manifestations) are collected for a sample of individuals only.
3. Assumption regarding the composition of variables in terms its explicability by other variables (complimentary set) in the sample**:** It may be assumed that every variable included in the analysis can be (partly) explained by the complementary set of variables included in the analysis.
4. Inter-relationship among the latent factors: It may be assumed that the latent factors (essences, so to say) are orthogonal among themselves or, alternatively, they are correlated.
5. Optimization criterion**:** Factor Analysis has to depend on some optimization criterion, whether in terms of the minimization of some type of distance between the empirical data points and the inferred (estimated) points corresponding to them or maximization of the probability of occurrence of the data points. In measuring the distance different criteria might be used.
6. Identifiability of factors and reproducibility of the empirical inter-correlation matrix: On the one hand identifiability demands that the number of factors be as small as possible (parsimony) such that each factor can be given some conceptual or theoretical meaning. On the other hand it is also required that the original empirical inter-correlation matrix among the variables is reproducible in terms of the factor loadings. These two requirements often compete with each other.

VII-B(i). Methods to Extract Initial Factors from the Observed Correlation Matrix: The complex of the criteria mentioned above gives rise to several strategies of factor analysis to extract initial factors from the observed correlation matrix, R. The general method of extraction may be expressed symbolically as the solution of the eigen-equation (characteristic equation) in which $Det(R_x - \lambda I) = 0$ is solved for λ and from $R_xV = \lambda V$ the vector V is obtained. Then V is used to obtain initial factor loadings. The matrix R_x is a modified R, obtained from the variables included in the analysis. The real difference among the methods of extraction is in obtaining R_x from R. It depends on two major ideas: first, the communality, generality, image or similar to these; and the second the individuality, anti-image, uniqueness, residual or the like. The correlation matrix is decomposed into two parts, the common part and the uncommon part. The real issue is as to how one does the decomposition. Accordingly, we will see how R_x is defined differently in different methods of extraction (Kim and Mueller, 1978).

1. Alpha Factoring: In this method it is assumed that the variables included in the analysis are only the samples from a universe of innumerable variables that the latent factors may manifest themselves into. Accordingly, the initial factors are extracted and later necessary rotations are applied to them. In Alpha factoring, the key emphasis is not on the statistical inference but its objective is to draw inference for an understanding of the underlying essence that give rise to the manifestation as empirically observed. In Alpha factoring $R_x = H^{-1}(R-U^2)H^{-1}$, where U is the diagonal matrix made up of the elements that are square root of the unique component for each variable (unexplained by other variables and so uncommon or unique to the variable) and H is the matrix of the square root of communalities.

2. Image Factoring: Image analysis decomposes the variations in the variables into two parts, (i) image, and (ii) anti-image. The part of the variation of a variable that is predictable by a linear combination of all the other variables in the set (complimentary set) is called the image of the variable. It is the common part. On the other hand, the anti-image of the variable is the residual, which is the unique part of the variable. Here $R_x = (R-S^2)R^{-1}(R-S^2)$, where S is the diagonal matrix whose elements are the standard deviation of the residuals of each variable that could not be explained by other variables. This S is the matrix of anti-image standard deviations or $s_j = \text{sqrt}(\Sigma(e_{ij})^2/n)$ for variable j, in n observations.

3. Principal Axis Factoring: In this method an attempt is made to find out as many mutually orthogonal principal axes as needed. Each principal axis is obtained in such a manner that it minimizes the sum of distance between the observed points and the estimated points on the principal axis (distance measured by the length of the line *normal* to the principal axis and joining the observed point away from the principal axis and the expected point on the principal axis). This method uses the decomposition strategies of the principal components analysis as applied to the adjusted correlation matrix whose diagonal elements are replaced by corresponding estimates of communalities. These communalities are usually estimated by the highest absolute correlation in the corresponding row of a correlation matrix. In our general system here $R_x = R-h$, where h is a diagonal matrix of communalities. This method is gradually being replaced by the Least Squares factoring. In the Least Squares factoring, an attempt is made to minimize the residual correlation after extracting a given number of factors, and to assess the degree of fit between the reproduced correlation under the model and the observed correlations. Since the squared differences are minimized, the name follows. In the LS factoring the communalities are estimated at every iteration (not once for all as in the Principal Axis method) and a new R_x is found until the results are stable.

4. Maximum Likelihood Procedure for Initial Factoring: It is assumed that the observed data comprise a sample from a population where a k-common factor model exactly applies, and where the distribution of variables and the factors is a multivariate normal. The exact loadings on each variable are unknown and to be estimated. The objective of ML method is to find the underlying population parameters that would have the greatest likelihood of producing the observed correlation matrix. In our general framework, here $R_x = U^{-1}(R-U^2)U^{-1}$, where U is the square root of the unique variance estimated at each stage of iteration. The initial iteration begins with the principal component analysis. In contrast with the Least Squares method where the sum of squared discrepancies (between initial and reproduced correlations) is minimized, in case of maximum likelihood method the likelihood of reproducing the observed (that is, initial) correlations by the estimated loadings is maximized. Further, unlike of the LS method, assumption of normality of distribution is necessary for ML factoring.

5. Principal Component Analysis for Initial Extraction of Factors: In terms of eigenvalues and eigenvectors, an observed or initial correlation matrix, R, can always be decomposed as $R = R_1 + R_2 + \ldots + R_m$, where R_i matrix is an outer product of the i^{th} standardized eigenvector with itself, multiplied by the i^{th} eigenvalue. Conventionally eigenvalues are ordered according to magnitude and the first eigenvalue is the largest while the last is the smallest. Accordingly, R_1 reproduces larger part of R than do the subsequent R_s and that also in the order. Here we have $R_x = R$. Interestingly, the Principal Component method does not try to modify the matrix of inter-correlations in view of communalities, uniqueness, image, etc. In this sense, this method of initial factorization is quite different from others. However, due to its great power in decomposition of R matrix into orthogonal component matrices and finding out eigenvalues, it is often used at the initial level of many methods of extraction. As a matter of fact, the famous theorem of Cayley-Hamilton (that every continuous function of a matrix is a function of its eigenvalues and eigenvectors) makes the principal component method so powerful.

The initial factoring step usually determines the minimum number of factors that can adequately account for the observed correlations, and provides the estimates of the communalities for each variable. With these factors (say k in number) and estimated communalities, it is possible to carry out some transformation over the factors (by rotation performed on them in the k-plane) so that simpler and more easily interpretable factors can be obtained. The output of such an attempt is the rotated factors.

VII-B(ii). Rotation of Factors for Better Interpretation: To proceed for rotation, one must, first assert whether the factors would be correlated (non-orthogonal or oblique) or they are orthogonal (spherical) among themselves. If one visualizes that the factors need not be orthogonal, one may proceed to oblique rotation (OBLIMIN or PROMAX). In cases when there is a good reason to hold that factors are orthogonal, one may try with methods like VARIMAX, QUARTIMAX or EQUAMAX rotation. It is fair not to impose orthogonality on the factors from the very beginning and look into the pattern obtained after carrying out the oblique rotation. If the factors are orthogonal, such an evidence will be available in the results of the oblique rotation. Alternatively, rotation can be carried out to obtain a pattern that is close to a given target matrix (Kim and Mueller, 1978).

It is clear that an oblique solution is more general than an orthogonal rotation because it does not impose the restriction of orthogonality on the factors. Its supremacy over the orthogonal rotation methods lies in the fact that after carrying out the oblique rotation one may get the feel whether imposition of orthogonality relations on the factors from the very beginning could have been appropriate or not.

1. The Quartimax Rotation: Let us define $\mathbf{q}_i = [\Sigma_j (b_{ij})^4 - \{\Sigma_j (b_{ij})^2\}^2]/(k^2)$; where j =1, k ; i = 1, n. Further, let **q** be defined as the sum of $\mathbf{q}_{i.}$ That is $\mathbf{q} = \Sigma_i (q_i)$; i = 1,n. Here k is the number of initial factors and n is the number of observations in the data set. Since communalities $(h_i)^2 = \Sigma_j (b_{ij})^2$ are already fixed and k^2 = constant, **q** varies directly with $\Sigma_i\Sigma_j (b_{ij})^4$. Now axes are rotated in such a way that **q** is maximized and in that process old (initial) factor loadings are replaced by new factor loadings. This is called the Quartimax rotation. An application of quartimax criterion usually results in emphasizing the simplicity of interpretation of the variables at the expense of simplicity of interpretation of factors. In general, fewer common factors add to simplicity in interpretation of variables while fewer variables with large loadings on each factor facilitate the interpretation of the factors and their identification. The rotated factors obtained by this method are orthogonal among themselves.

2. The Varimax Rotation: Let us define $\mathbf{v}_j = [n\Sigma_i (b_{ij})^4 - \{\Sigma_i (b_{ij})^2\}^2]/(n^2)$; where j =1, k ; i = 1, n. Further, let **v** be defined as the sum of $\mathbf{v}_{j.}$ That is $\mathbf{v} = \Sigma_j (v_j)$; j = 1,k. Here k is the number of initial factors and n is the number of observations in the data set. Now, unlike in case of quartimax rotation, $\Sigma_j (b_{ij})^2$ are no longer fixed but they are variable due to summation being carried out over n individuals, the maximization of V is called the varimax method of rotation. This method of rotation concentrates on simplifying the interpretation of factors rather than the variables, as it was the case with the quartimax rotation method. The rotated factors obtained by varimax method are orthogonal among themselves.

3. The Equimax and the Biquartimax Rotation: A hybridization of quartimax and varimax rotation methods yields these methods. If one maximizes $\zeta = \alpha\mathbf{q} + \beta\mathbf{v}$, the compromise solution is obtained. Defining $\gamma = \beta/(\alpha+\beta)$, in special or limiting cases $\gamma = 0$ yields quartimax solution and $\gamma = 1$ yields varimax solution. In particular, maximization for $\gamma = k/2$ is called the Equimax solution and that for $\gamma = 0.5$ is called the biquartimax solution. The rotated factors obtained by this method are orthogonal among themselves.

4. Indirect Oblimin Rotation: This method of rotation tries to simplify loadings on <u>*Reference Axes*</u>. The indirect Oblimin criterion is given by:

$$B = \Sigma_j [\Sigma_p\{n\Sigma_i a_{ij}^2 a_{ip}^2 - \boldsymbol{\gamma}(\Sigma_i a_{ij}^2 \Sigma_i a_{ip}^2)\}]; \; p = 2, k; j = 1, k.$$

Iteratively, B is minimized. In the expression above, $\mathbf{a_{ij}}$ are projections of i^{th} factor on j^{th} reference axis usually normalized by h_i^2 (communality) and $\boldsymbol{\gamma}$ refers to the degree of obliqueness, which can be altered to obtain more or less oblique solution. For $\gamma = 0$ this rotation is called Quartimin solution, while for $\gamma = 1$ it is called Co-varimin solution. For $\gamma = 0.5$ it is called Biquartimin solution.

5. Direct Oblimin Rotation: This method of rotation tries to simplify loadings on <u>*primary factors*</u>. The direct Oblimin criterion is given by:

$$D = \Sigma_j [\Sigma_p\{\Sigma_i b_{ij}^2 b_{ip}^2 - \delta(\Sigma_i b_{ij}^2 \Sigma_i b_{ip}^2)/n\}];\ j,p = 1, k.$$

Iteratively, D is minimized. In the expression above, $\mathbf{b_{ij}}$ are factor loadings in a pattern matrix and δ refers to the degree of obliqueness, which can be altered to obtain more or less oblique solution. For a unifactoral factor pattern, $\delta = 0$ identifies the correct pattern.

6. Promax Rotation: Promax rotation is a variant of target matrix rotation, though in this case such a matrix is derived from the data itself and the analyst is not needed to supply any target matrix. The rationale behind the promax rotation is the observed fact that in practice the orthogonal solutions are not much different from oblique solutions. Therefore, if small loadings are reduced to near-zero loadings (that might be ignored), it is possible to construct a fairly good target matrix with much simpler structure. Having done that, one rotates the factors to be close to such an artificial target matrix.

VII-C. Synthetic or Inclusive Methods: The principal component and factor analytic methods aim at analysis of variance in the multi-variable data. Unless the variables are extremely highly correlated among themselves such that they might be summarized by a single component or factor, these methods have a tendency to decompose the data into two or more components or factors. Thus, the very nature of these methods is analytic. They tend to construct composite indices that are 'sectarian' or exclusive in some sense. The first component/factor absorbs the maximum conformal portion of variance in the data and relegates the non-conformal portion of variance to the other components or factors. Thus, if the data variables are weakly correlated among themselves, these methods produce numerous composite indices and in so doing each index has a tendency to exclude or weakly correlate itself with some variables.

Synthetic methods do not purport to decompose the multi-variable data into numerous components or factors. Their objective is to construct a single index that represents the data variables most effectively. Since there are no second or subsequent indices to be constructed, these methods include all variables such as to represent them in the best possible manner. The idea of rotation is not applicable here.

There could be various methods that have an inclusive approach to making indices. A simple averaging over variables is one of such methods. However, there are three other methods that have some mathematical justification. These are:

VII-C(i): MSAR or Max Sum of Absolute Correlation Coefficients: This method, as the name suggests, constructs the index as a weighted sum of variables such that $\sum_{j=1}^{m} |r(I, x_j)|;\ I = Xw$ is maximized. Here $r(I, x_j)$ is the coefficient of correlation between the index and the variable x_j. Suitable weights (w) are chosen mathematically to meet this objective. This method is an analog of the principal component as the latter maximizes $\sum_{j=1,}^{m} r^2(I,x_j)$ or equivalently $\sum_{j=1}^{m} |r(I,x_j)|^2$.

VII-C(ii). MEFAR or Max Entropy-like Function of Absolute Correlation Coefficients: This method obtains a composite index, $I = Xw$, by maximization of $\sum_{j=1}^{m} f\left(|r(I,x_j)|\right);\ f(.) = \sum_{j=1}^{m} b_j \ln(b_j) + B\ln(B);\ B = \sum_{j=1}^{m} |r(I,x_j)|;\ b_j = |r(I,x_j)|/B$. Weights (w) are chosen mathematically to this end.

VII-C(iii). MMAR or Maximin Correlation Coefficient: This method constructs a composite index such that $\min_j\left(|r(I,x_j)|\right)$ is maximized. Among all the inclusive methods, this is the most egalitarian one. It produces almost equal correlation of the composite index with all variables. It explains much less variation in X than the other methods do.

VIII. Computational Issues: For the principal component and factor analysis many software packages such as STATISTICA and SPSS are available. However, for construction of MSAR, MEFAR and MMAR indices one has to optimize the functions given above with weights (w) as the decision variables. They require non-linear optimization, not very simple on account of absolute functions and appearance of w_j; j=1,2,…,m indirectly in them. We have optimized the function by the Differential Evolution method. The FORTRAN program (Mishra, 2007-d) may be obtained from http://www1.webng.com/economics/make-indices.html or from the author. Its performance has been tested very well (see Mishra, 2007-a, b and c)

IX. Comparative Performance of Different Methods of Index Construction on Meghalaya Data: We have applied several of the methods described above to compare their performance on construction of composite indices from the two gender-specific sets of nine measures elaborated in section IV above. The loadings on different variables (correlation coefficients of the composite index with the data variables) and the explanatory power of the composite index (mean squared loading) for these methods are given in Table-3. We have gone in for orthogonal factor extraction only.

A perusal of Table-3 reveals that the analytic methods have uniformly undermined the one measure or the other. The PCA, the ML, the MINRES, the PA and the CRS all make composite indices that have very poor correlation with x_7 (proportion of household industry workers to total workers population of the two genders) uniformly, and with x_3 (workers as a proportion to total 6+ population for the two sexes) and x_9 (dependency) when factors are rotated. These variables are strongly related with economic involvement of the people and cannot be undermined.

The first two inclusive methods (the MSAR and the MEFAR) obtain absolute correlation between the composite index and the constituent variable about 0.3 at the lowest. The MMAR, a highly egalitarian method, obtains absolute correlation 0.5 at the minimum. Thus, the inclusive indices have represented every socio-economic measure of the population that we are concerned with in this study. The MSAR and the MEFAR loadings are almost same. We have chosen the MSAR results for further analysis.

Table-3: Loadings (Correlation of Composite index with the Constituent Variables) and Sum of Squared Correlation Coefficients (SSR) obtained by Different Methods of Weighted Linear Combination

Var	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	SSR	Explain
1. Principal Component (Max Sum of Squared Correlation Coefficients) or PCA											
Unrot	0.75910	-0.82716	0.33729	0.92046	0.61301	-0.30930	-0.04746	-0.97063	-0.35048	3.760068	0.417785
Vmax	0.49518	-0.59285	0.12309	0.91517	0.27826	-0.21082	0.03289	-0.84832	-0.13197	2.309374	0.256597
Bqmx	0.66832	-0.80229	0.12999	0.95450	0.44092	-0.22809	0.04324	-0.94143	-0.12868	3.169444	0.352160
Qrtmx	0.75489	-0.83126	0.12301	0.93905	0.54881	-0.21665	0.04367	-0.96900	-0.13205	3.464230	0.384914
Eqmx	0.75489	-0.83126	0.12301	0.93905	0.54881	-0.21665	0.04367	-0.96900	-0.13205	3.464230	0.384914
2. Max Likelihood (ML)											
Unrot	0.70468	-0.78337	0.26014	0.95283	0.56025	-0.30015	0.03793	-0.98398	-0.27192	3.533371	0.392597
Vmax	0.63945	-0.74635	0.13388	0.96583	0.31209	-0.43133	0.02242	-0.90115	-0.12425	3.028144	0.336460
Bqmx	0.67633	-0.76974	0.13946	0.96624	0.39724	-0.39636	0.02430	-0.93326	-0.13325	3.207213	0.356357
Qrtmx	0.70485	-0.78348	0.14283	0.95961	0.47076	-0.36105	0.02687	-0.95538	-0.14173	3.337423	0.370825
Eqmx	0.70485	-0.78348	0.14283	0.95961	0.47076	-0.36105	0.02687	-0.95538	-0.14173	3.337423	0.370825
3. MINRES											
Unrot	0.69358	-0.78171	0.35209	0.94161	0.58848	-0.28899	-0.04799	-0.97823	-0.35089	3.614904	0.401656
Vmax	0.64162	-0.75177	0.14453	0.97061	0.33123	-0.42834	0.02322	-0.91058	-0.11666	3.076291	0.341810
Bqmx	0.68388	-0.77343	0.14632	0.96990	0.42263	-0.38644	0.02559	-0.94451	-0.12748	3.264956	0.362773
Qrtmx	0.71371	-0.78501	0.14706	0.96164	0.49582	-0.34779	0.02847	-0.96554	-0.13678	3.390574	0.376730
Eqmx	0.71371	-0.78501	0.14706	0.96164	0.49582	-0.34779	0.02847	-0.96554	-0.13678	3.390575	0.376731
4. Principal Axis (PA)											
Unrot	0.73716	-0.79254	0.33482	0.93306	0.58970	-0.27268	-0.04040	-0.98131	-0.35049	3.663765	0.407085
Vmax	0.66331	-0.78284	0.13552	0.97177	0.42782	-0.37538	0.06769	-0.94582	-0.11919	3.252823	0.361425
Bqmx	0.73171	-0.80932	0.12842	0.94816	0.54239	-0.31037	0.06746	-0.97924	-0.12449	3.475369	0.386152
Qrtmx	0.75406	-0.81354	0.12976	0.93376	0.58306	-0.28222	0.06381	-0.98566	-0.13161	3.531718	0.392413
Eqmx	0.75406	-0.81354	0.12976	0.93376	0.58306	-0.28222	0.06381	-0.98566	-0.13161	3.531718	0.392413
5. Communality R Square (CRS)											
Unrot	0.71483	-0.79791	0.34235	0.92559	0.56579	-0.27160	-0.04096	-0.97321	-0.35476	3.590119	0.398902
Vmax	0.70110	-0.82115	0.12268	0.92864	0.53169	-0.30423	0.07559	-0.96931	-0.11047	3.375985	0.375109
Bqmx	0.73200	-0.82473	0.12231	0.91591	0.57410	-0.27225	0.06786	-0.97707	-0.12002	3.447246	0.383027
Qrtmx	0.74346	-0.82465	0.12707	0.90998	0.59072	-0.25877	0.06223	-0.97920	-0.12922	3.472326	0.385814
Eqmx	0.74346	-0.82465	0.12707	0.90998	0.59072	-0.25877	0.06223	-0.97920	-0.12922	3.472326	0.385814
6. Max Sum of Absolute Correlation Coefficients (MSAR)											
Unrot	0.66926	-0.71065	0.53704	0.87803	0.47793	-0.42233	-0.30373	-0.86599	-0.55900	3.573727	0.397081
7. Max Entropy-like Function of Absolute Correlation Coefficients (MEFAR)											
Unrot	0.67272	-0.71704	0.53235	0.88234	0.48289	-0.41827	-0.29190	-0.87225	-0.55367	3.589317	0.398813
8. Maximin Absolute Correlation (MMAR)											
Unrot	0.53634	-0.50039	0.50039	0.62378	0.50039	-0.50039	-0.50039	-0.65270	-0.50635	2.611132	0.290126

Note: The vectors of loadings are free to a multiplication by 1 or (-1). The Index also has to me multiplied by the same constant.

In Table-4 we present the values of the MSAR index for different districts, religious communities and areas (urban, rural) for the male and the female populations separately. These values are graphically represented in Fig.-2 through Fig.-4. The signs of loadings obtained by different measures indicate that we have indeed obtained the *composite index of exclusion from development or the Index of deprivation*. The index is positively correlated with the measures of population growth and dependence on agriculture as a means to livelihood (x_1, x_4 and x_5). It is correlated negatively with literacy and participation in non-agricultural activities of livelihood. As it happens so often, development is associated with concentration of resources in fewer hands as well as increase in the dependency ratio. We observe these tendencies here too as indicated by the loadings of x_6 and x_9.

However, many index values are negative while many others are positive. It is cumbersome to compare them. Hence we have rescaled them by a simple device such that they are transformed to $I^* = [I - \min(I)]/[\max(I) - \min(I)]$. With this transformation all the values fall in the [0, 1] range and thus are easily comprehensible. The values presented in Table-4 are such transformed values of the index, I^*.

Table-4: Values of Composite Index of Deprivation (I^*) obtained by MSAR Method

Total Population										
	Male Population					Female Population				
	All	Hindu	Muslim	Christian	Others	All	Hindu	Muslim	Christian	Others
Meghalaya	0.73223	0.50606	0.72556	0.76385	0.84165	0.71008	0.43122	0.43636	0.73368	0.79895
W_ Garo_Hills	0.75229	0.59595	0.82104	0.75762	0.97406	0.71280	0.49820	0.34399	0.75278	0.95304
East_Garo_Hills	0.78507	0.64153	0.62233	0.79089	0.97993	0.76145	0.55996	0.67421	0.76365	0.97961
South_Garo_Hills	0.77204	0.41647	0.69065	0.79895	0.93352	0.84020	0.46551	0.90062	0.84429	0.97835
West_Khasi_Hills	0.83594	0.60923	0.53997	0.83728	0.95636	0.84577	0.69564	0.84830	0.84303	0.97956
Ri_Bhoi	0.79241	0.57028	0.38112	0.84405	0.87265	0.80227	0.66292	0.38982	0.81950	0.88291
East_Khasi_Hills	0.56607	0.35610	0.25487	0.60619	0.70797	0.50654	0.08238	0.00000	0.53058	0.63210
Jaintia_Hills	0.84869	0.62883	0.60702	0.84309	0.90840	0.79085	0.77960	0.75299	0.76242	0.85116
Rural Population										
	Male Population					Female Population				
	All	Hindu	Muslim	Christian	Others	All	Hindu	Muslim	Christian	Others
Meghalaya	0.81056	0.61164	0.80095	0.82665	0.89027	0.78643	0.57959	0.46589	0.80093	0.84881
W_ Garo_Hills	0.79883	0.64237	0.82711	0.81268	0.97903	0.75772	0.54412	0.34690	0.81165	0.95574
East_Garo_Hills	0.82556	0.72566	0.68603	0.82452	0.98925	0.79791	0.63000	0.77628	0.79583	0.98637
South_Garo_Hills	0.80498	0.45489	0.71947	0.82464	0.93802	0.87169	0.59159	0.91466	0.87223	0.98362
West_Khasi_Hills	0.86449	0.62828	0.62847	0.86622	0.97947	0.87258	0.70312	0.99097	0.87034	1.00000
Ri_Bhoi	0.80140	0.57607	0.40853	0.85362	0.86820	0.81255	0.67555	0.42625	0.82996	0.88108
East_Khasi_Hills	0.72666	0.49658	0.42174	0.74461	0.77287	0.66656	0.34131	0.14405	0.67191	0.69968
Jaintia_Hills	0.88618	0.65760	0.64958	0.87625	0.95650	0.82961	0.81453	0.81538	0.79763	0.89825
Urban Population										
	Male Population					Female Population				
	All	Hindu	Muslim	Christian	Others	All	Hindu	Muslim	Christian	Others
Meghalaya	0.35315	0.32905	0.31802	0.37244	0.33764	0.25766	0.04073	0.19834	0.30707	0.21299
W_ Garo_Hills	0.35225	0.28745	0.42940	0.34270	0.40635	0.14884	0.01215	0.02915	0.18313	0.09670
East_Garo_Hills	0.50900	0.46631	0.51897	0.51958	0.50160	0.47389	0.33946	0.53498	0.49116	0.26702
South_Garo_Hills	0.41195	0.36713	0.47469	0.43824	0.43673	0.32960	0.12699	0.32352	0.36241	0.35971
West_Khasi_Hills	0.50423	0.43248	0.27412	0.50845	0.53490	0.53541	0.62898	0.37911	0.53469	0.51246
Ri_Bhoi	0.63473	0.43334	0.00899	0.67157	0.93636	0.62507	0.36711	0.55250	0.64099	0.90452
East_Khasi_Hills	0.28024	0.30377	0.29078	0.26270	0.29046	0.14014	0.03336	0.05748	0.17832	0.15965
Jaintia_Hills	0.34988	0.44497	0.35495	0.27841	0.37272	0.29596	0.31538	0.39409	0.29257	0.29777

X. Observations and Conclusion: First, we observe (Fig.-2) that women are much less deprived (vis-à-vis men) in the urban areas than in the rural areas. Secondly, the disparities in the extent of deprivation is gender-wise uniform in the Christian community as well as in the 'others' religious group (Fig.-3). Note that these communities mostly include the indigenous tribes: Garo, Jaintia, Khasi, etc having a matrifocal system. Among the Muslim community we find very large variance in the deprivation index. In the Hindu community also findings are inconclusive, although the variance is much less than in the Muslim community.

Overall, in the East Khasi Hills and the West Garo Hills districts the women are in a better position than the men. In the East Garo Hills, with a few exceptions, women are better off in general. In the West Khasi Hills and Ri Bhoi districts, on the contrary, women are either deprived, or more or less at par with the men. In the Jaintia Hills and the South Garo Hills districts a mixed picture emerges.

Returning to our main query whether matrifocal system in the developing societies favours women and helps achieve growth with gender equality, we find that indeed it does so. The tribes of Meghalaya whose societies are organized on matrifocal principles have obtained much greater gender equality than the societies (e.g. Hindu and Muslim) that are organized on the patriarchal principles. In the impetus of development equality is achieved better. An entangled question, however, remains unanswered: "Is it Christianity that promotes gender equality?" Our study has given some indication that *matrifocality in the environment of prospects of development*, not Christianity, has contributed to gender equality, for if it had been so, the non-Christian "others" category would not have exhibited gender equality so clearly and the West Khasi Hills district would not have performed so dismal. Yet, one must remember that identification of the "others" religious category with the local indigenous tribes has some obvious problems.

Fig.-2: Gender-Specific Index (MSAR Method) of Deprivation in Meghalaya
[According to Habitation – Total, Rural and Urban]

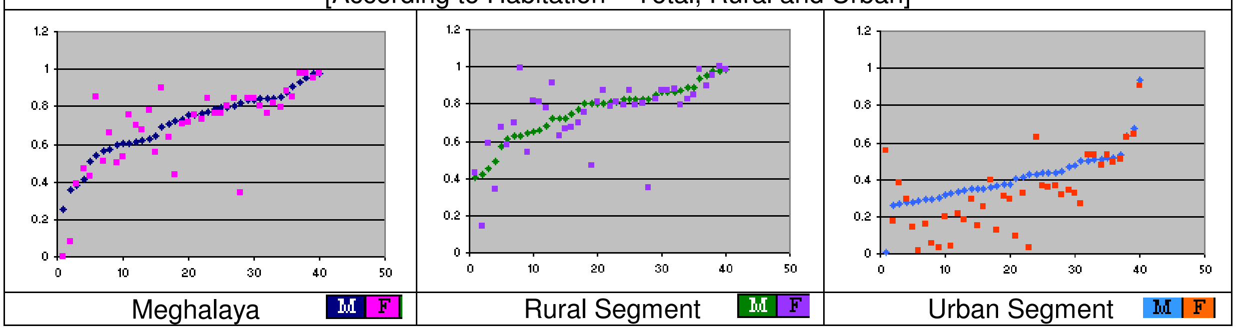


Fig.-3: Gender-Specific Index (MSAR Method) of Deprivation in Meghalaya
[According to Religion – All, Hindu, Muslim, Christian and Others]

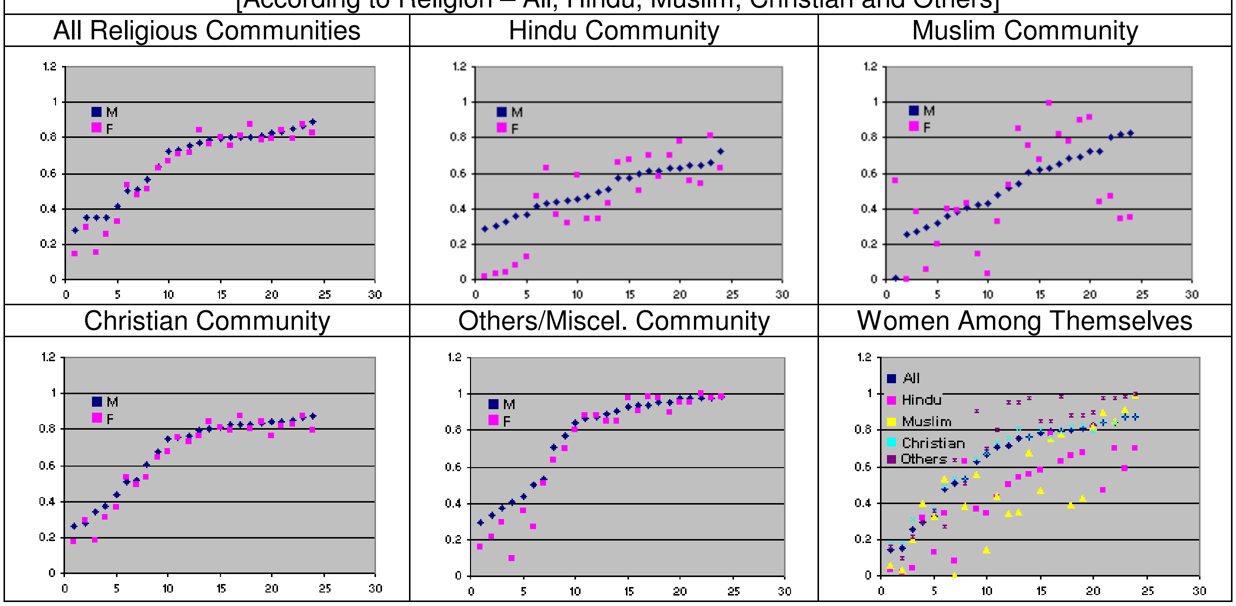
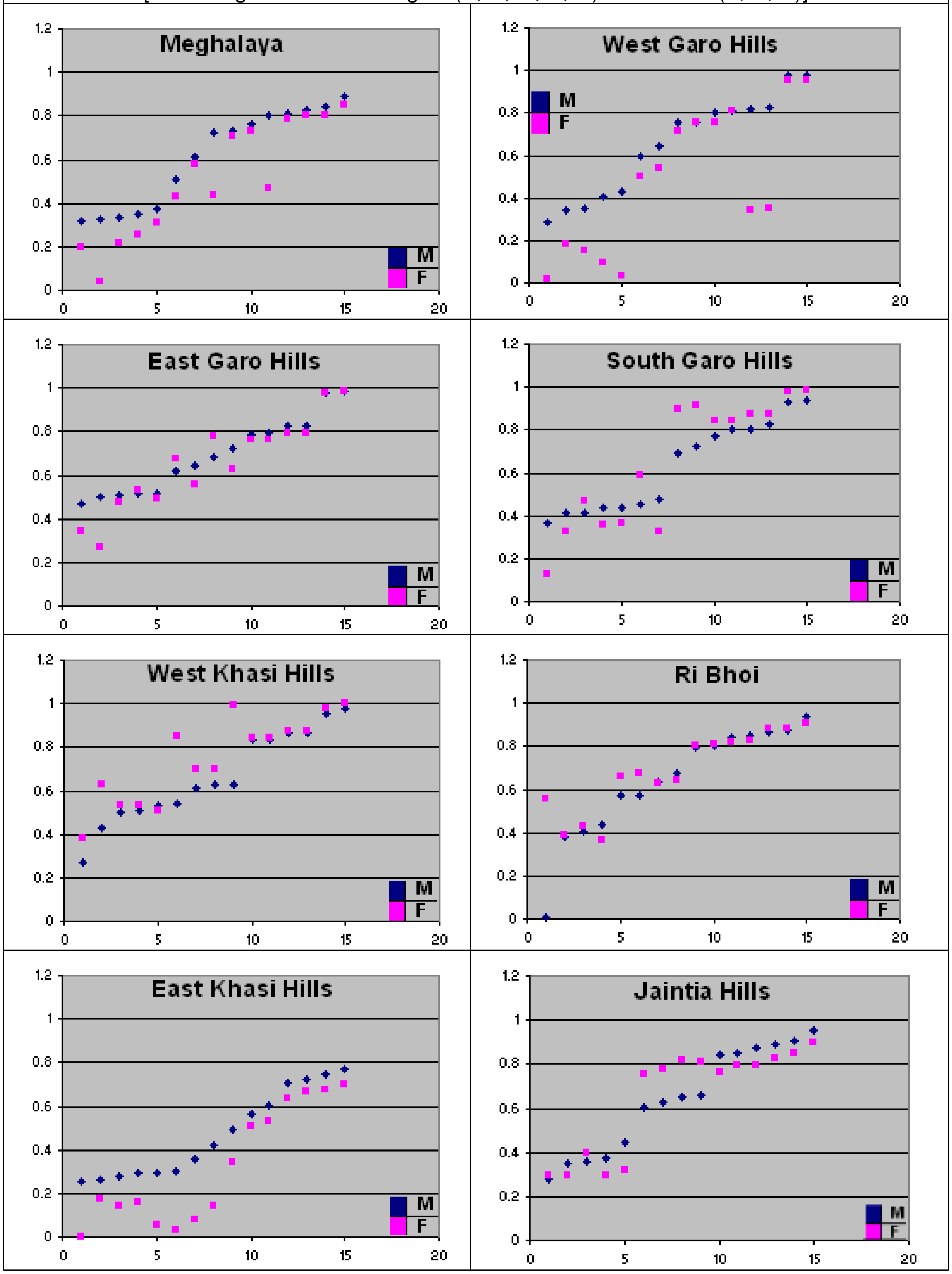


Fig.-4: Gender-Specific Index (MSAR Method) of Deprivation in Meghalaya
[According to District – Religion (A, H, M, C, O) and Sector (T, R, U)]



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Appendix

DISTRICT-SECTOR-RELIGION-WISE INDICATORS OF SOCIO-ECONOMIC INCLUSION IN MEGHALAYA-2001 (MALE)											
DIST	SEC	REL	CHILD	LITER	WORK	CULT	AGRL	AGLC	HHIW	OTHW	NWWR
MGH	T	ALL	0.20170	0.65427	0.60550	0.44859	0.15988	0.35640	0.01646	0.37508	1.06879
		HIN	0.13221	0.76573	0.64393	0.17487	0.08973	0.51315	0.02188	0.71352	0.78955
		MUS	0.20244	0.49173	0.61347	0.28973	0.23043	0.79532	0.02357	0.45626	1.04383
		CHR	0.21410	0.67242	0.58829	0.51950	0.16487	0.31735	0.01509	0.30053	1.16294
		OTH	0.21287	0.46572	0.65061	0.49251	0.19996	0.40601	0.01401	0.29352	0.95269
	R	ALL	0.21434	0.59240	0.62914	0.53752	0.18623	0.34646	0.01668	0.25958	1.02309
		HIN	0.15061	0.66753	0.66236	0.28984	0.14589	0.50334	0.02786	0.53641	0.77747
		MUS	0.21805	0.44008	0.60079	0.34872	0.27683	0.79384	0.01884	0.35560	1.12862
		CHR	0.22248	0.62442	0.61758	0.59269	0.18123	0.30578	0.01512	0.21096	1.08254
		OTH	0.21939	0.41306	0.67238	0.53604	0.21544	0.40191	0.01422	0.23430	0.90526
	U	ALL	0.14944	0.89050	0.51524	0.03395	0.03700	1.09008	0.01546	0.91359	1.28184
		HIN	0.10599	0.89869	0.61899	0.00830	0.00837	1.00940	0.01321	0.97012	0.80707
		MUS	0.10546	0.77221	0.68229	0.00766	0.00856	1.11765	0.04618	0.93760	0.63843
		CHR	0.17278	0.89483	0.45253	0.05667	0.06136	1.08287	0.01493	0.86704	1.67139
		OTH	0.15852	0.87251	0.48242	0.02376	0.03330	1.40136	0.01180	0.93115	1.46339
WGH	T	ALL	0.19566	0.57030	0.59423	0.50749	0.14805	0.29172	0.02083	0.32364	1.09221
		HIN	0.15035	0.65152	0.60363	0.31474	0.12898	0.40980	0.03054	0.52574	0.94977
		MUS	0.22500	0.41274	0.57890	0.35128	0.29926	0.85190	0.01609	0.33337	1.22893
		CHR	0.20447	0.63316	0.57607	0.58022	0.12389	0.21353	0.01866	0.27723	1.18207
		OTH	0.20406	0.22308	0.71066	0.80885	0.10082	0.12465	0.01601	0.07431	0.76791
	R	ALL	0.20245	0.52517	0.61150	0.56007	0.16307	0.29116	0.02201	0.25485	1.05042
		HIN	0.15771	0.60228	0.60457	0.37954	0.15499	0.40838	0.03528	0.43019	0.96379
		MUS	0.22635	0.40782	0.57763	0.35659	0.30383	0.85203	0.01617	0.32341	1.23769
		CHR	0.21189	0.58658	0.60705	0.64322	0.13673	0.21257	0.01949	0.20056	1.09019
		OTH	0.20487	0.21697	0.71112	0.81558	0.10168	0.12467	0.01607	0.06667	0.76856
	U	ALL	0.14325	0.89474	0.47009	0.01587	0.00756	0.47668	0.00978	0.96679	1.48294
		HIN	0.11324	0.88721	0.59918	0.00176	0.00333	1.88889	0.00764	0.98727	0.88208
		MUS	0.10619	0.78960	0.67574	0.00366	0.00000	0.00000	0.01099	0.98535	0.65568
		CHR	0.15889	0.90114	0.39781	0.02710	0.01123	0.41436	0.01138	0.95030	1.98862
		OTH	0.10497	0.88889	0.66049	0.01869	0.00000	0.00000	0.00935	0.97196	0.69159
EGH	T	ALL	0.20370	0.66148	0.60247	0.65619	0.11338	0.17279	0.01568	0.21475	1.08444
		HIN	0.15055	0.76661	0.66758	0.41701	0.10179	0.24409	0.01559	0.46561	0.76341
		MUS	0.17313	0.57342	0.72083	0.23703	0.05267	0.22222	0.02943	0.68087	0.67777
		CHR	0.20756	0.67128	0.59105	0.67683	0.11662	0.17231	0.01566	0.19089	1.13505
		OTH	0.21201	0.29756	0.70166	0.83894	0.09789	0.11669	0.00960	0.05356	0.80864
	R	ALL	0.20716	0.62961	0.61473	0.72642	0.11268	0.15511	0.01456	0.14634	1.05176
		HIN	0.15399	0.71144	0.67299	0.56911	0.10614	0.18649	0.00917	0.31559	0.75635
		MUS	0.17209	0.58315	0.72360	0.43478	0.06522	0.15000	0.03416	0.46584	0.66925
		CHR	0.20998	0.64240	0.60611	0.73273	0.11463	0.15644	0.01497	0.13767	1.08839
		OTH	0.21238	0.28685	0.70124	0.85358	0.09660	0.11317	0.00830	0.04151	0.81057
	U	ALL	0.18320	0.84503	0.53183	0.18858	0.11808	0.62616	0.02317	0.67017	1.30203
		HIN	0.14423	0.86681	0.65776	0.13434	0.09371	0.69756	0.02752	0.74443	0.77654
		MUS	0.17415	0.56382	0.71809	0.04019	0.04019	1.00000	0.02473	0.89490	0.68624
		CHR	0.19111	0.86258	0.49129	0.21994	0.13290	0.60427	0.02137	0.62578	1.51633
		OTH	0.19388	0.81013	0.72152	0.15789	0.15789	1.00000	0.07018	0.61404	0.71930
SGH	T	ALL	0.20799	0.61520	0.64314	0.55026	0.11468	0.20841	0.01974	0.31531	0.96320
		HIN	0.09853	0.83188	0.78359	0.09129	0.05422	0.59391	0.04124	0.81325	0.41566
		MUS	0.12955	0.59745	0.80439	0.41674	0.10485	0.25159	0.02467	0.45374	0.42819
		CHR	0.21780	0.61008	0.62500	0.59741	0.12089	0.20236	0.01778	0.26392	1.04550
		OTH	0.21599	0.26834	0.67621	0.66138	0.11772	0.17800	0.00926	0.21164	0.88624
	R	ALL	0.21214	0.59019	0.64822	0.60003	0.12430	0.20716	0.01983	0.25584	0.95807
		HIN	0.09415	0.78191	0.80452	0.13186	0.07697	0.58376	0.04217	0.74900	0.37216
		MUS	0.14014	0.61392	0.79114	0.47200	0.11900	0.25212	0.02400	0.38500	0.47000
		CHR	0.22016	0.58946	0.63307	0.63709	0.12812	0.20111	0.01841	0.21637	1.02557
		OTH	0.21696	0.26354	0.67599	0.66756	0.11883	0.17800	0.00935	0.20427	0.88919
	U	ALL	0.16536	0.85803	0.59386	0.02277	0.01270	0.55769	0.01883	0.94571	1.01751
		HIN	0.10746	0.93534	0.74025	0.00000	0.00301	0.00000	0.03916	0.95783	0.51355
		MUS	0.02649	0.45578	0.91837	0.00741	0.00000	0.00000	0.02963	0.96296	0.11852
		CHR	0.18861	0.85458	0.52937	0.03451	0.01827	0.52941	0.00880	0.93843	1.32815
		OTH	0.09091	0.80000	0.70000	0.00000	0.00000	0.00000	0.00000	1.00000	0.57143

WKH	T	ALL	0.23339	0.66494	0.60477	0.57387	0.22768	0.39675	0.01533	0.18312	1.15695
		HIN	0.15897	0.68883	0.70601	0.20688	0.14392	0.69565	0.01640	0.63280	0.68413
		MUS	0.08383	0.72549	0.83007	0.20472	0.15748	0.76923	0.03150	0.60630	0.31496
		CHR	0.23626	0.67409	0.59763	0.58423	0.22665	0.38795	0.01533	0.17379	1.19091
		OTH	0.20511	0.40373	0.71965	0.59748	0.30743	0.51455	0.01397	0.08112	0.74813
	R	ALL	0.23387	0.64284	0.61782	0.62378	0.22604	0.36238	0.01470	0.13549	1.11269
		HIN	0.16379	0.67260	0.70134	0.22562	0.15465	0.68542	0.01673	0.60300	0.70514
		MUS	0.10606	0.70339	0.83898	0.26263	0.19192	0.73077	0.02020	0.52525	0.33333
		CHR	0.23664	0.65252	0.61096	0.63570	0.22497	0.35390	0.01468	0.12465	1.14417
		OTH	0.20775	0.37265	0.73160	0.63459	0.29563	0.46586	0.01359	0.05619	0.72530
	U	ALL	0.22979	0.83263	0.50577	0.11144	0.24290	2.17966	0.02120	0.62447	1.56705
		HIN	0.09649	0.88350	0.76214	0.00000	0.02548	0.00000	0.01274	0.96178	0.45223
		MUS	0.00000	0.80000	0.80000	0.00000	0.03571	0.00000	0.07143	0.89286	0.25000
		CHR	0.23346	0.83475	0.49840	0.11443	0.24199	2.11475	0.02126	0.62232	1.61748
		OTH	0.17633	0.72958	0.59437	0.11848	0.45972	3.88000	0.01896	0.40284	1.04265
RBH	T	ALL	0.21724	0.68809	0.66165	0.53319	0.16942	0.31775	0.01621	0.28117	0.93081
		HIN	0.14479	0.76642	0.69704	0.27193	0.09567	0.35182	0.02680	0.60560	0.67753
		MUS	0.15405	0.75772	0.72994	0.05497	0.10359	1.88462	0.06131	0.78013	0.61945
		CHR	0.23397	0.67731	0.65039	0.59843	0.18887	0.31560	0.01328	0.19943	1.00714
		OTH	0.20485	0.54737	0.69668	0.64056	0.17097	0.26691	0.01153	0.17694	0.80517
	R	ALL	0.21767	0.68219	0.66870	0.55171	0.16512	0.29930	0.01615	0.26702	0.91151
		HIN	0.14506	0.76899	0.70673	0.28554	0.09256	0.32417	0.02747	0.59442	0.65504
		MUS	0.16304	0.75881	0.73655	0.06297	0.10579	1.68000	0.06045	0.77078	0.62217
		CHR	0.23420	0.66933	0.65755	0.61761	0.18441	0.29859	0.01313	0.18485	0.98589
		OTH	0.20347	0.54856	0.69482	0.64930	0.15883	0.24462	0.01144	0.18043	0.80686
	U	ALL	0.21137	0.76821	0.56588	0.23582	0.23847	1.01125	0.01725	0.50846	1.24080
		HIN	0.14163	0.73617	0.58296	0.07776	0.13997	1.80000	0.01711	0.76516	0.99844
		MUS	0.10656	0.75229	0.69725	0.01316	0.09211	7.00000	0.06579	0.82895	0.60526
		CHR	0.23074	0.79073	0.54867	0.27171	0.26471	0.97423	0.01587	0.44771	1.36928
		OTH	0.22628	0.52830	0.72642	0.50649	0.35714	0.70513	0.01299	0.12338	0.77922
EKH	T	ALL	0.17512	0.77283	0.58840	0.20458	0.12445	0.60833	0.01271	0.65826	1.06033
		HIN	0.11103	0.87277	0.64025	0.02790	0.03350	1.20070	0.01325	0.92535	0.75696
		MUS	0.09988	0.81876	0.67822	0.00722	0.01333	1.84615	0.04972	0.92972	0.63806
		CHR	0.19333	0.77494	0.54845	0.25881	0.15610	0.60316	0.01136	0.57374	1.26030
		OTH	0.20024	0.62742	0.64028	0.31115	0.16994	0.54617	0.01147	0.50744	0.95284
	R	ALL	0.20727	0.66780	0.63784	0.33568	0.20252	0.60331	0.01105	0.45075	0.97769
		HIN	0.13824	0.76889	0.71145	0.09750	0.11683	1.19835	0.01408	0.77159	0.63105
		MUS	0.13761	0.84043	0.73582	0.05060	0.10602	2.09524	0.00964	0.83373	0.57590
		CHR	0.21621	0.68862	0.61068	0.37127	0.22221	0.59853	0.01026	0.39626	1.08924
		OTH	0.21104	0.57260	0.67488	0.36039	0.19571	0.54304	0.01159	0.43232	0.87811
	U	ALL	0.13036	0.90611	0.52565	0.00270	0.00424	1.56977	0.01527	0.97780	1.18759
		HIN	0.10178	0.90663	0.61704	0.00174	0.00218	1.25000	0.01293	0.98315	0.80429
		MUS	0.09517	0.81619	0.67137	0.00157	0.00126	0.80000	0.05495	0.94223	0.64615
		CHR	0.15236	0.91789	0.44540	0.00344	0.00598	1.73626	0.01385	0.97673	1.64872
		OTH	0.14814	0.87227	0.48578	0.00562	0.01007	1.79167	0.01077	0.97354	1.41653
JH	T	ALL	0.22546	0.50082	0.61905	0.49881	0.24399	0.48913	0.01798	0.23923	1.08561
		HIN	0.15062	0.58354	0.75835	0.17176	0.28653	1.66819	0.03055	0.51116	0.55249
		MUS	0.15280	0.69179	0.75699	0.22931	0.20134	0.87805	0.03915	0.53020	0.55928
		CHR	0.22765	0.54094	0.60696	0.54757	0.20974	0.38304	0.01629	0.22640	1.13318
		OTH	0.23651	0.38726	0.61316	0.48393	0.31134	0.64335	0.01766	0.18707	1.13610
	R	ALL	0.22982	0.46149	0.63637	0.53120	0.25977	0.48903	0.01862	0.19041	1.04031
		HIN	0.15445	0.55743	0.76214	0.19008	0.31796	1.67277	0.03349	0.45846	0.55176
		MUS	0.16461	0.65911	0.78719	0.25657	0.22528	0.87805	0.04380	0.47434	0.52065
		CHR	0.23130	0.50720	0.62469	0.57841	0.22139	0.38275	0.01679	0.18341	1.08247
		OTH	0.24200	0.33119	0.63279	0.51849	0.33377	0.64373	0.01810	0.12964	1.08483
	U	ALL	0.17656	0.91364	0.43716	0.00385	0.00272	0.70588	0.00816	0.98527	1.77798
		HIN	0.11616	0.80857	0.72571	0.00591	0.00197	0.33333	0.00394	0.98819	0.55906
		MUS	0.07263	0.89157	0.57229	0.00000	0.00000	0.00000	0.00000	1.00000	0.88421
		CHR	0.18327	0.92703	0.40409	0.00206	0.00370	1.80000	0.00740	0.98684	2.03003
		OTH	0.18089	0.91260	0.42924	0.00652	0.00145	0.22222	0.01159	0.98043	1.84420

DISTRICT-SECTOR-RELIGION-WISE INDICATORS OF SOCIO-ECONOMIC INCLUSION IN MEGHALAYA-2001 (FEMALE)

DIST	SEC	REL	CHILD	LITER	WORK	CULT	AGRL	AGLC	HHIW	OTHW	NWWR
MGH	T	ALL	0.20194	0.59607	0.44043	0.52780	0.20118	0.38117	0.02955	0.24148	1.84507
		HIN	0.15351	0.60274	0.26435	0.33171	0.22382	0.67476	0.07455	0.36992	3.46891
		MUS	0.22235	0.35222	0.15129	0.33188	0.27566	0.83059	0.08825	0.30422	7.49964
		CHR	0.20744	0.63323	0.47323	0.55623	0.19145	0.34419	0.02455	0.22776	1.66618
		OTH	0.21124	0.45228	0.53096	0.50209	0.23280	0.46366	0.02619	0.23893	1.38775
	R	ALL	0.21530	0.53243	0.49218	0.58943	0.21850	0.37070	0.03081	0.16126	1.58922
		HIN	0.17430	0.45617	0.35383	0.42176	0.27770	0.65843	0.08370	0.21684	2.42280
		MUS	0.22979	0.30653	0.15026	0.36989	0.30648	0.82859	0.09686	0.22677	7.64085
		CHR	0.21861	0.58066	0.51761	0.61923	0.20600	0.33268	0.02568	0.14908	1.47248
		OTH	0.21977	0.40170	0.56566	0.53574	0.24625	0.45964	0.02705	0.19096	1.26580
	U	ALL	0.14746	0.83499	0.24614	0.06514	0.07118	1.09265	0.02006	0.84362	3.76552
		HIN	0.12337	0.80291	0.14214	0.02555	0.04065	1.59116	0.04347	0.89033	7.02541
		MUS	0.15856	0.71112	0.15943	0.05046	0.04740	0.93939	0.02446	0.87768	6.45413
		CHR	0.15673	0.85422	0.28670	0.07813	0.08102	1.03700	0.01600	0.82485	3.13622
		OTH	0.14426	0.81415	0.28270	0.02028	0.04029	1.98718	0.01378	0.92566	3.13361
WGH	T	ALL	0.19408	0.44122	0.40127	0.59922	0.18812	0.31394	0.04816	0.16450	2.09222
		HIN	0.15792	0.45568	0.31771	0.38422	0.29032	0.75559	0.10558	0.21989	2.73777
		MUS	0.22957	0.29066	0.12121	0.29266	0.34074	1.16429	0.12285	0.24375	9.70845
		CHR	0.19829	0.52709	0.46632	0.63701	0.16248	0.25506	0.03130	0.16921	1.67485
		OTH	0.19302	0.12099	0.66206	0.78108	0.13293	0.17018	0.03112	0.05488	0.87171
	R	ALL	0.19992	0.38931	0.43204	0.63062	0.19722	0.31274	0.04909	0.12308	1.89297
		HIN	0.16154	0.40304	0.35309	0.40758	0.30793	0.75550	0.10870	0.17580	2.37777
		MUS	0.23011	0.28683	0.12126	0.29488	0.34332	1.16429	0.12321	0.23859	9.71157
		CHR	0.20615	0.46749	0.51542	0.67913	0.17194	0.25318	0.03173	0.11720	1.44398
		OTH	0.19313	0.11651	0.66531	0.78203	0.13302	0.17009	0.03108	0.05387	0.86284
	U	ALL	0.14816	0.82444	0.17409	0.02390	0.02133	0.89216	0.03117	0.92360	5.74315
		HIN	0.13717	0.74920	0.12044	0.00242	0.00242	1.00000	0.05455	0.94061	8.62303
		MUS	0.15468	0.77021	0.11489	0.00000	0.00000	0.00000	0.07407	0.92593	9.29630
		CHR	0.15216	0.85484	0.19634	0.02913	0.02589	0.88889	0.02501	0.91998	5.00736
		OTH	0.17518	0.84071	0.14159	0.06250	0.06250	1.00000	0.06250	0.81250	7.56250
EGH	T	ALL	0.20482	0.54885	0.51935	0.70634	0.13086	0.18526	0.04408	0.11872	1.42143
		HIN	0.16212	0.58866	0.49424	0.54494	0.19857	0.36439	0.11207	0.14442	1.41482
		MUS	0.19483	0.42270	0.43241	0.39551	0.12090	0.30568	0.02245	0.46114	1.87219
		CHR	0.20719	0.56504	0.51550	0.71226	0.12928	0.18150	0.04166	0.11680	1.44680
		OTH	0.21105	0.16771	0.67294	0.83929	0.09084	0.10823	0.02096	0.04891	0.88354
	R	ALL	0.20837	0.50914	0.55013	0.74960	0.12096	0.16137	0.04284	0.08660	1.29622
		HIN	0.16421	0.52459	0.55897	0.65650	0.16150	0.24600	0.10850	0.07350	1.14050
		MUS	0.20438	0.44801	0.48012	0.62739	0.14331	0.22843	0.02866	0.20064	1.61783
		CHR	0.21022	0.52629	0.54397	0.74902	0.12094	0.16147	0.04120	0.08884	1.32763
		OTH	0.21165	0.16055	0.67757	0.84700	0.08670	0.10236	0.01962	0.04668	0.87211
	U	ALL	0.18342	0.78084	0.33958	0.29697	0.22453	0.75606	0.05577	0.42272	2.60630
		HIN	0.15794	0.71587	0.36570	0.20637	0.31108	1.50735	0.12291	0.35964	2.24734
		MUS	0.18549	0.39854	0.38686	0.12075	0.09434	0.78125	0.01509	0.76981	2.17358
		CHR	0.18711	0.81422	0.33243	0.32549	0.21699	0.66667	0.04657	0.41095	2.70061
		OTH	0.17500	0.57576	0.40909	0.11111	0.48148	4.33333	0.14815	0.25926	1.96296
SGH	T	ALL	0.21434	0.48020	0.55507	0.68802	0.13991	0.20335	0.01943	0.15264	1.29307
		HIN	0.18630	0.59529	0.27946	0.30843	0.25783	0.83594	0.07952	0.35422	3.39759
		MUS	0.20593	0.41648	0.60879	0.73285	0.14982	0.20443	0.01083	0.10650	1.06859
		CHR	0.21575	0.48697	0.56347	0.69246	0.13729	0.19826	0.01876	0.15149	1.26296
		OTH	0.21289	0.15823	0.61638	0.75522	0.13582	0.17984	0.00896	0.10000	1.06119
	R	ALL	0.21688	0.44891	0.57868	0.72070	0.14618	0.20283	0.01994	0.11318	1.20663
		HIN	0.19861	0.45326	0.37717	0.36888	0.30259	0.82031	0.08934	0.23919	2.30836
		MUS	0.20882	0.40614	0.62002	0.74495	0.15229	0.20443	0.01101	0.09174	1.03853
		CHR	0.21770	0.45984	0.58184	0.72523	0.14347	0.19783	0.01930	0.11199	1.19697
		OTH	0.21392	0.15098	0.62255	0.75599	0.13623	0.18020	0.00898	0.09880	1.04341
	U	ALL	0.18612	0.81547	0.30207	0.01714	0.01109	0.64706	0.00907	0.96270	3.06754
		HIN	0.16544	0.82655	0.12035	0.00000	0.02941	0.00000	0.02941	0.94118	8.95588
		MUS	0.11429	0.70968	0.29032	0.00000	0.00000	0.00000	0.00000	1.00000	2.88889
		CHR	0.19141	0.81488	0.34144	0.01752	0.00986	0.56250	0.00767	0.96495	2.62212
		OTH	0.12500	0.71429	0.14286	0.50000	0.00000	0.00000	0.00000	0.50000	7.00000

WKH	T	ALL	0.23502	0.63655	0.53282	0.63525	0.24014	0.37802	0.01582	0.10880	1.45342
		HIN	0.19734	0.43037	0.33384	0.34789	0.32831	0.94372	0.01807	0.30572	2.73193
		MUS	0.28421	0.48529	0.50000	0.29412	0.35294	1.20000	0.00000	0.35294	1.79412
		CHR	0.23551	0.64798	0.53278	0.63838	0.23727	0.37167	0.01594	0.10840	1.45519
		OTH	0.23960	0.40260	0.65179	0.64671	0.28526	0.44109	0.01224	0.05578	1.01769
	R	ALL	0.23657	0.61154	0.55669	0.67558	0.23398	0.34634	0.01639	0.07405	1.35297
		HIN	0.19428	0.41547	0.33863	0.36150	0.32551	0.90043	0.01878	0.29421	2.66510
		MUS	0.31646	0.35185	0.48148	0.38462	0.46154	1.20000	0.00000	0.15385	2.03846
		CHR	0.23718	0.62359	0.55728	0.67927	0.23141	0.34067	0.01650	0.07282	1.35237
		OTH	0.24095	0.37067	0.67440	0.68378	0.26731	0.39093	0.01308	0.03584	0.95351
	U	ALL	0.22343	0.82058	0.35712	0.17252	0.31078	1.80146	0.00925	0.50746	2.60580
		HIN	0.25000	0.70588	0.24510	0.00000	0.40000	0.00000	0.00000	0.60000	4.44000
		MUS	0.12500	1.00000	0.57143	0.00000	0.00000	0.00000	0.00000	1.00000	1.00000
		CHR	0.22323	0.82411	0.35581	0.17597	0.30353	1.72491	0.00959	0.51090	2.61819
		OTH	0.22651	0.70717	0.43614	0.10000	0.55000	5.50000	0.00000	0.35000	1.96429
RBH	T	ALL	0.22435	0.62427	0.52369	0.61173	0.20393	0.33338	0.02097	0.16337	1.46184
		HIN	0.17697	0.56689	0.39297	0.53690	0.15494	0.28858	0.02615	0.28201	2.09189
		MUS	0.23704	0.61165	0.20388	0.11905	0.34524	2.90000	0.03571	0.50000	5.42857
		CHR	0.23227	0.64388	0.54602	0.61789	0.21109	0.34163	0.02034	0.15068	1.38552
		OTH	0.22171	0.45567	0.58184	0.69206	0.18274	0.26405	0.01971	0.10549	1.20831
	R	ALL	0.22574	0.61715	0.53728	0.62580	0.20038	0.32020	0.02165	0.15216	1.40388
		HIN	0.17889	0.56302	0.40994	0.55124	0.14891	0.27013	0.02613	0.27372	1.97083
		MUS	0.25270	0.60405	0.21098	0.13699	0.31507	2.30000	0.04110	0.50685	5.34247
		CHR	0.23358	0.63610	0.55934	0.63199	0.20842	0.32978	0.02108	0.13852	1.33270
		OTH	0.22069	0.45193	0.58241	0.70522	0.17238	0.24443	0.02077	0.10163	1.20326
	U	ALL	0.20548	0.71826	0.34424	0.32157	0.27718	0.86195	0.00683	0.39442	2.65623
		HIN	0.15303	0.61355	0.18821	0.16000	0.31333	1.95833	0.02667	0.50000	5.27333
		MUS	0.14286	0.65152	0.16667	0.00000	0.54545	0.00000	0.00000	0.45455	6.00000
		CHR	0.21446	0.74785	0.36828	0.33200	0.26533	0.79920	0.00533	0.39733	2.45667
		OTH	0.23982	0.52381	0.57143	0.44792	0.37500	0.83721	0.00000	0.17708	1.30208
EKH	T	ALL	0.17338	0.74839	0.34983	0.28641	0.15736	0.54942	0.02259	0.53364	2.45805
		HIN	0.13384	0.76841	0.15089	0.04561	0.08586	1.88270	0.04507	0.82346	6.65160
		MUS	0.15748	0.76651	0.10807	0.01972	0.02817	1.42857	0.04789	0.90423	9.98310
		CHR	0.17703	0.77123	0.37791	0.29281	0.16379	0.55938	0.01780	0.52560	2.21534
		OTH	0.20018	0.64221	0.47510	0.35318	0.16478	0.46656	0.02858	0.45346	1.63163
	R	ALL	0.20647	0.66913	0.44776	0.40194	0.21883	0.54444	0.02504	0.35419	1.81440
		HIN	0.19461	0.56677	0.21480	0.14676	0.28259	1.92547	0.07384	0.49681	4.78031
		MUS	0.20253	0.69206	0.18095	0.10526	0.17544	1.66667	0.12281	0.59649	5.92982
		CHR	0.20420	0.70474	0.44333	0.41577	0.23032	0.55396	0.02025	0.33366	1.83445
		OTH	0.21579	0.59924	0.52609	0.39937	0.18524	0.46383	0.03037	0.38502	1.42387
	U	ALL	0.12814	0.84699	0.22800	0.00415	0.00717	1.72807	0.01662	0.97207	4.03066
		HIN	0.11653	0.82077	0.13429	0.00360	0.00416	1.15789	0.03313	0.95911	7.42873
		MUS	0.15240	0.77441	0.10034	0.00336	0.00000	0.00000	0.03356	0.96309	10.75839
		CHR	0.13303	0.87002	0.28070	0.00424	0.00766	1.80488	0.01206	0.97603	3.10923
		OTH	0.13218	0.81133	0.27439	0.00462	0.01040	2.25000	0.01502	0.96995	3.19954
JH	T	ALL	0.22527	0.53666	0.47584	0.43506	0.34104	0.78389	0.02483	0.19906	1.71264
		HIN	0.22420	0.40967	0.38327	0.31874	0.44623	1.40000	0.01674	0.21829	2.36317
		MUS	0.25297	0.66614	0.46423	0.37329	0.29110	0.77982	0.01370	0.32192	1.88356
		CHR	0.22247	0.59688	0.46894	0.45789	0.30203	0.65960	0.02587	0.21421	1.74262
		OTH	0.23100	0.41581	0.50219	0.39931	0.41316	1.03469	0.02361	0.16392	1.58944
	R	ALL	0.23118	0.50199	0.49499	0.46070	0.36125	0.78414	0.02591	0.15215	1.62769
		HIN	0.22476	0.37619	0.40349	0.33491	0.46888	1.40000	0.01691	0.17930	2.19689
		MUS	0.26462	0.63447	0.48485	0.42578	0.33203	0.77982	0.01563	0.22656	1.80469
		CHR	0.22814	0.56759	0.48562	0.48481	0.31985	0.65976	0.02708	0.16826	1.66785
		OTH	0.23807	0.36734	0.52700	0.42275	0.43760	1.03515	0.02446	0.11519	1.49043
	U	ALL	0.16225	0.87583	0.28837	0.00453	0.00162	0.35714	0.00679	0.98706	3.13944
		HIN	0.21888	0.72494	0.19280	0.00000	0.00000	0.00000	0.01333	0.98667	5.64000
		MUS	0.18548	0.83168	0.35644	0.00000	0.00000	0.00000	0.00000	1.00000	2.44444
		CHR	0.15892	0.89843	0.29716	0.00498	0.00199	0.40000	0.00547	0.98756	3.00100
		OTH	0.16122	0.84993	0.27994	0.00412	0.00103	0.25000	0.00928	0.98557	3.25876