

## Modeling the Relationship Between Babies' Mortality and Prosperity Using Fully Latent Models

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**Abstract:** The researchers examined the relationship between babies' mortality and prosperity. The objective is to investigate the effect of prosperity factor which is constructed from three indicators: class 1, 2 and 3 of occupation on mortality factor which is also constructed from three indicators: infant, neonatal and stillbirth mortality ratio. The importance of the goal is followed from what Weeks stated: there are few things in the world more frightening and awesome than the responsibility for a newborn child-fragile and completely dependent on others for survival. Many methods have been used such as path analysis and more methods have been developed such as Structural Equation Modeling (SEM) which is the interested in this study. SEM is widely used in the social and behavioral sciences. We concluded that prosperity has significant effect on mortality. The data is collected from a census of 81 districts in Malaysia. This study was composed for a number of path-diagrams to create the management changing and health care especially for the babies in Malaysia or in all spots of the world.

**Key words:** Prosperity, pathways, infant, neonatal, stillbirth, mortality, healthy care, SEM, LISREL

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### INTRODUCTION

About >10,000 newborn babies died every day (Martines *et al.*, 2005). Every year, it was estimated that undernutrition contributes to the deaths of about 5.6 million children under the age of 5; 146 million children in the developing world were underweight and at increased risk of an early death (UNICEF, 2006). Most studies concerned with adults' mortality while in the study we were concerning about babies' mortality which were not very different in their causes. The higher the pay grade, the lower the death rate.

In general, countries with highest levels of income and education were those with enough money to provide the population with clean water, adequate sanitation, food and shelter and very importantly access to health care services that prevents diarrhea-an important cause of death among infants (Judge and Paterson, 2001; Morris *et al.*, 1996; Nordstrom *et al.*, 1993; Spencer, 2004; Weeks, 1992). The whole family is affected, of course by the social status of the household head; fertility surveys have consistently generated data showing an inverse relationship between infant and childhood mortality and the father's occupation (Weeks, 1992). In Britain occupation has continued to be widely used for the pragmatic reason that it is a potent predictor of a wide

range of health outcomes and study can contribute to the health of the population by its contribution to general prosperity which in turn wealth creation may improve the prospects for health (Blane *et al.*, 1996). Almost, poverty status is based on family income which is determined from the class of occupation or employment status. Income directly influences the availability of food, health care and housing (Aber and Bennett, 1997). Low income is associated with early neonatal (within 7 days of life) deaths (Luginaah *et al.*, 1999). The differential in infant mortality between social classes exists; infant death rates in classes IV-V between 50 and 65% higher than in classes I-II in England and Wales from 1975-1996 (Whitehead and Drever, 1999).

Infant mortality is a standard indicator of population health used through the world; rates of infant mortality can reflect levels of social and economic development, levels of care and the effectiveness of preventive programs, as well as post-birth services to both mothers and their children (Aron and Aron 2002; Burns 2005; Nordstrom *et al.*, 1993; Whitehead and Drever, 1999). Low Socioeconomic Status (SES) increases risk of stillbirth in Sweden; the researchers used an occupation as one of several indicators of SES (Stephansson *et al.*, 2001). Sudden infant death syndrome occurs in all social groups but is more prevalent in the socioeconomically deprived

groups; four components to present the socioeconomic status in five English health regions: unemployment, non-ownership of a car, non-ownership of a home and overcrowding (Fleming *et al.*, 2003). Characteristic was associated with women and children not receiving appropriate care was low income.

We cannot use standard regression modeling methods because the causal sequence implied by the pathways was complicated. As such, we followed Sobel (2000), Price *et al.* (2002) and Chandola *et al.* (2005) in using causal modeling technique to facilitate this analysis. Causal models are a family of statistical techniques through which pathways can be explicitly modeled and tested. More specifically, we used fully latent models as implemented in the software package: LInear Structural RELationships (LISREL). However, we have described earlier that the need to understand and quantify the effect of the pathways linking mortality and prosperity and how these could contribute to the debate on the prosperity role in reducing the babies' mortality ratio.

**MATERIALS AND METHODS**

**Data:** The data are collected from the National census report which is a census conducted in Malaysia which they were (N = 81) districts. We must construct on the basis of prior conceptual or statistical analyses the indicators of the latents. The data are transformed to normal distribution which is the assumption of SEM technique. More precisely, we structured the following construct or latent factors with their indicators:

**Mortality latent factor:** Mortality has three indicators: Standardized Infant Mortality Ratio (SIMR), Standardized Neonatal Mortality Ratio (SNMR) and Standardized Stillbirth Mortality Ratio (SSMR). Infant mortality indicates the number of deaths under 1 year of age. Neonatal mortality refers to the number of deaths within 28 days after birth. Stillbirth mortality occurs after 24 weeks of gestation (Hansell and Aylin, 2000; Lawn *et al.*, 2005). Standardization is a set of procedures for controlling the effects of external factors. Standardized Mortality Ratio (SMR) allows comparison of the causes of death between population groups. It is calculated as follows:

$$SMR_i = \frac{O_i}{\hat{O}_i}$$

and

$$\hat{O}_i = SM + E_i,$$

for

$$i = 1, 2, \dots, 81$$

Where:

$O_i$  = Observed deaths

$\hat{O}_i$  = Expected deaths

$$SM = \frac{\sum_{i=1}^{81} O_i}{\sum_{i=1}^{81} E_i}$$

$E_i$  represents the number of live births for infants, also  $E_i$  represents the number of live births for neonatals while  $E_i$  represents the number of live births plus the number of stillbirths for stillbirths.

**Prosperity latent factor:** Prosperity means the level of economic development, represents the type of occupation status which is grouped of three classes starting from top to bottom in the income and social level (education): class 1 includes professional, administrative and managerial workers; class 2 includes clerical workers and class 3 includes sales and service workers. These classes are measured in percentages. The babies of fathers in semi-routine occupations had infant mortality rates over 2.5 times higher than those of babies whose fathers were in higher professional occupations (National Statistics, 2003). Low levels of occupational security often accompany poverty status and poverty can induce serious health risks including mortality (Aber and Bennett, 1997).

**Analysis**

**Fully latent model:** Fully latent model or SEM is an extension of standard regression models through which multivariate outcomes and latent factors can be modeled. SEM is more appropriate for this application than alternative causal modeling techniques because it permits specification of measurement models. Fully latent model needs two types of models: the measurement model (outer model) which connects the manifest variables to the latent variables and the structural model (inner model) which connects latent variables between them.

The causal variables are called exogenous variables  $\xi$  and the effect variable is called the endogenous variable,  $\eta$ . Unexplained variation is referred to as disturbance. The aim is to test the synthesized model of relations between the latent variables. The structural equation model:  $\eta = B\eta + \Gamma\xi + \zeta$ . Vectors  $\eta$  and  $\xi$  are not observed; instead vectors  $y$  and  $x$  are observed such that Measurement model for  $y$ :  $y = \Lambda_y\eta + \varepsilon$  and measurement model for  $x$ :  $x = \Lambda_x\xi + \delta$ . Where,  $y$  is a  $P \times 1$  vector of observed response or outcome variables. The  $x$  is a  $q \times 1$  vector of predictors, covariates or input variables where  $p = q = 3$ . The  $\eta$  is an  $m \times 1$  random vector of latent

dependent or endogenous variables, where  $m = 1$ .  $\xi$  is an  $n \times 1$  random vector of latent independent or exogenous variables, where  $n = 1$ . The  $\varepsilon$  is a  $p \times 1$  vector of measurement errors in  $y$ . The  $\delta$  is a  $q \times 1$  vector of measurement errors in  $x$ . The  $\Lambda_y$  is a  $p \times m$  matrix of coefficients of the regression of  $y$  on  $\eta$ ; it is also called factor loadings. The unstandardized factor loadings are interpreted as regression coefficients that indicate expected change in the indicator given a 1-point increase in the factor (Kline, 1998).  $\Lambda_x$  is a  $q \times n$  matrix of coefficients of the regression of  $x$  on  $\xi$ . These coefficients relate the indicators to the underlying factors.  $\Gamma$  is an  $m \times n$  matrix of coefficients of the  $\xi$ -variables in the structural relationship. The elements of  $\Gamma$  represent direct causal effects of  $\xi$  variables on  $\eta$  variables.  $B$  is an  $m \times m$  matrix of coefficients of the  $\eta$ -variables in the structural relationship.  $B$  has zeros on the diagonal and  $(1-B)$  is required to be non-singular. The elements of  $B$  represent direct causal effects of  $\eta$  variables on each other where in this study there is no  $B$  since we have only one endogenous variable.  $\zeta$  is an  $m \times 1$  vector of random disturbances.

The random components in the LISREL model are assumed to satisfy the following minimal assumptions:  $\varepsilon$  is uncorrelated with  $\eta$ .  $\delta$  is uncorrelated with  $\xi$ .  $\zeta$  is uncorrelated with  $\xi$ .  $\zeta$ ,  $\varepsilon$  and  $\delta$  are mutually uncorrelated. The  $n \times n$  covariance matrix of  $\xi$  is  $\Phi$ . The  $m \times m$ ,  $\Psi$  matrix contains the estimated values for the variances of the disturbances in the equations. The values reported under  $p \times p$  matrix  $\Theta_\varepsilon$  and  $q \times q$  matrix  $\Theta_\delta$  are the variances of errors in the indicators of the latent endogenous and exogenous variables, respectively. The model is identified because we have at least two indicators for each factor.

**Parameter estimation:** Parameter estimation is performed by ML estimation. The unknown parameters of the model are estimated so as to make the variances and covariances that are reproduced from the model in some sense close to the observed data. Obviously, a good model would allow very close approximation to the data. Covariance matrix,

$S$  has used in the analysis. This model was designed specifically to answer such questions as: is the link between mortality and prosperity myth or reality? From the previous studies, this link was reality in some countries but what about Malaysia?

**Path diagrams:** A popular way to conceptualize a model is using a path diagram which is a schematic drawing of the system (model) to be estimated. There are a few simple rules that assist in creating these diagrams: ovals represent latent variables. Indicators are represented by rectangles. Directional and Non-directional relations are indicated using a single-headed arrow and a double-headed arrow, respectively.

**Model 1 and model 2:** Assume that model 1 represents the preferred model for the corroborative relations among variables,  $y_1$ - $y_3$  and  $x_1$ - $x_3$ . Figure 1 shows three  $x$ -variables as indicators of one latent  $\xi$  variable. There are three  $y$ -variables as indicators of one latent  $\eta$  variable. The two latents are connected in a single-headed arrow. The matrix,  $B = 0$ . Figure 1 displays the results of the analysis to test model 1 and the values along the paths represent the path coefficients. The indicators of the factors are as follows:

- $y_1$  = Transformed Standardized Infant Mortality Ratio (TSIMR)
- $y_2$  = Transformed Standardized Neonatal Mortality Ratio (TSNMR)
- $y_3$  = Transformed Standardized Stillbirth Mortality Ratio (TSSMR)
- $x_1$  = Transformed Class 1 of occupation (TCLASS1)
- $x_2$  = Transformed Class 2 of occupation (TCLASS2)
- $x_3$  = Transformed Class 3 of occupation (TCLASS3)

We see from Fig. 1 that factor loading of TSNMR ( $\lambda_{21}^{(y)} = 0.18$ ) which is close to TSSMR ( $\lambda_{31}^{(y)} = 0.13$ ). Model 2 which was explained in Fig 2, showed the same relationship as in model 1 but with the following constrained: the factor loadings of TSNMR and TSSMR

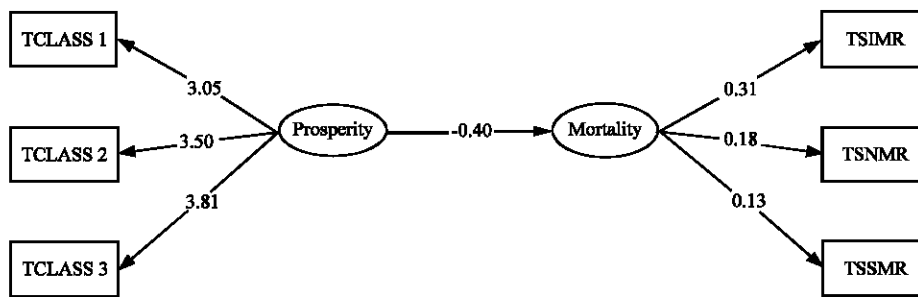


Fig. 1: Path diagram shows the results of fitted model 1

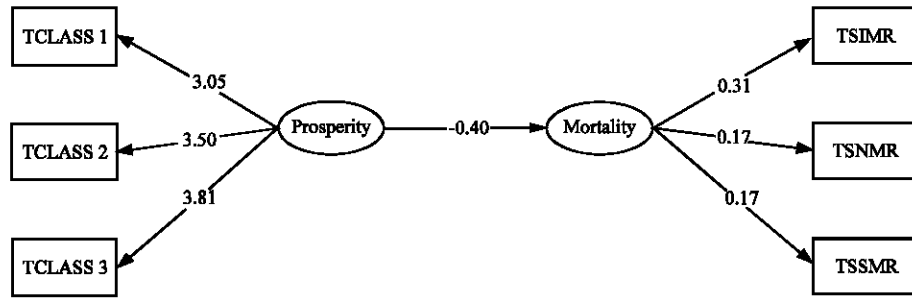


Fig. 2: Path diagram shows the results of fitted model 2

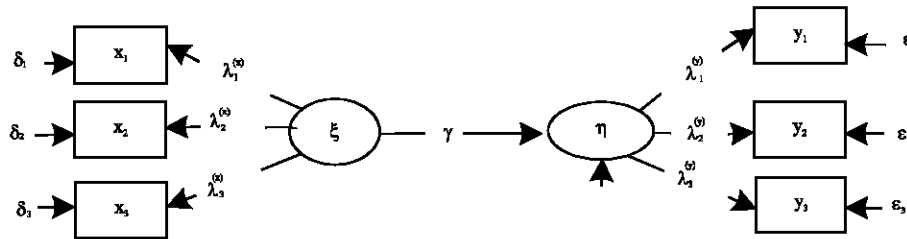


Fig. 3: Conceptualized path diagram for models 1 and 2 including all variables and parameters

are equal ( $\lambda_{21}^{(\theta)} = \lambda_{31}^{(\theta)}$ ). The resulted model was more significant because it was more parsimonious. Figure 3 explained all observed and unobserved variables, error terms and parameter terms. The necessary condition as stated by Bollen (1989) for model identification is:  $t \leq 1/2(p+q)(p+q+1)$ , where  $t$  is the number of parameters required to be estimated,  $p$  and  $q$  is the number of  $y$ -variables and  $x$ -variables, respectively.

**Fit indexes:** Perhaps the most basic fit index is the likelihood ratio which is sometimes called  $\chi^2$  in the SEM literature. The value of the  $\chi^2$  statistic reflects the sample size and the value of the ML fitting function. The fitting function is the statistical criterion that ML attempts to minimize and is analogous to the least squares criterion of regression. Values of indexes that indicate absolute or relative proportions of the observed covariances explained by the model such as the Goodness-of-Fit Index (GFI), the Adjusted Goodness-of-Fit Index (AGFI) and Normed Fit Index (NFI) should be  $>0.90$  (Bollen, 1989; Dillon and Goldstein, 1984). Comparative Fit Index (CFI) indicates the proportion in the improvement of the overall fit of the researcher's model relative to a null model like NFI but may be less affected by sample size. CFI should be  $>0.90$  (Kline, 1998; Hu and Bentler, 1999) endorsed stricter standards, pushing CFI to about 0.95. Another widely used index is the Standardized Root Mean squared Residual (SRMR) which is a standardized summary of the average covariance residuals. Covariance residuals are the differences between the observed and model-implied covariances. A favorable value of the SRMR is  $<0.10$

(Kline, 1998). Another measure based on statistical information theory is the Akaike Information Criterion (AIC). It is a comparative measure between models with different numbers of latents. AIC values closer to zero indicate better fit and greater parsimony (Bollen, 1989; Hair *et al.*, 1998).

Bollen's incremental fit-index values were examined as these are least biased due to non-normality of variables and they were all  $>0.95$ . The Parsimonious Goodness-of-Fit Index (PGFI) modifies the GFI differently from the AGFI where the AGFI's adjustment of the GFI was based on the degrees of freedom in the estimated and null models, the PGFI is based on the parsimony of the estimated model (Hair *et al.*, 1998). The value varies between 0 and 1 with higher values indicating greater model parsimony. The Non-Normed Fit Index (NNFI) includes a correction for model complexity much like the AGFI; a recommended value is 0.90 or greater.

Values of the NNFI can fall outside of the range 0-1 (Kline, 1998). The Root Mean Square Error of Approximation (RMSEA) value below 0.08 indicates a good fitting model (Hair *et al.*, 1998; Hu and Bentler, 1999) pushes RMSEA values to smaller 0.06 and they considered it  $>0.10$  is poor fit. RMSEA is a measure to assess how well a given model approximates the true model (Hox and Bechger, 1998).

## RESULTS AND DISCUSSION

Every application of SEM should provide at least the following information: a clear and complete specification

**Table 1: Explains the Pearson correlation matrix, mean, and standard deviation (SD)**

Variables	$y_1$	$y_2$	$y_3$	$x_1$	$x_2$	$x_3$	Mean±SD
SIMR, $y_1$	1.00						1.07±0.29
SNMR, $y_2$	0.67**	1.00					1.03±0.28
SSMR, $y_3$	0.35**	0.25*	1.00				1.05±0.39
CLASS1 $x_1$	-0.40**	-0.16	-0.12	1.00			10.07±3.30
CLASS2 $x_2$	-0.35**	-0.13	-0.25*	0.88**	1.00		6.82±3.84
CLASS3 $x_3$	-0.28*	-0.12	-0.11	0.66**	0.68**	1.00	18.36±4.98

SIMR, SNMR and SSMR are the standardized (infant, neonatal and stillbirth) mortality ratio respectively; CLASS1, CLASS2 AND CLASS3 are the percentages of occupation; \*\*Correlation is significant at the 0.01 level (2-tailed); \*Correlation is significant at the 0.05 level (2-tailed)

of models and variables including a clear listing of indicators of each latent factor; a clear statement of the type of data analyzed with presentation of the sample correlation or covariance matrix; specification of the software and method of estimation and complete results (Raykov *et al.*, 1991; MacCallum and Austin, 2000; Boomsma, 2000).

Table 1 showed the Pearson correlation matrix, mean and Standard Deviation (SD). As with even the simplest models, it is essential to establish how well the model fits the observed data. The simplest gauge of how well the model fits the data would be to inspect the residual matrix (Field, 2000). The acceptable range is one in 20 residuals exceeding  $\pm 2.58$  strictly by chance, i.e., 0.005% of the normalized residuals (Hair *et al.*, 1998). All the models result residuals in the acceptable range and all models have a high number of residuals close to zero, indicating high correspondence between elements of the implied covariances matrix and the actual covariance matrix.

A ( $p > 0.05$ ) was considered significant and it is recommended as the minimum accepted for the proposed model (Hair *et al.*, 1998). Model 1 resulted ( $\chi^2 = 13.77$ ) and significant ( $p = 0.09$ ). This proposed model was acceptable or adequate in interpreting the relationship between prosperity and babies' mortality. Model 2 with equality constraint resulted ( $\chi^2 = 14.88$ ) and significant ( $p = 0.09$ ). Model 2 was acceptable in interpreting the same relationship.

In these nested models, however we have slightly difference between model 1 and 2; they were both plausible and we did not have significant difference between two values of  $\chi^2$ . It was obvious to prefer model 2 because it was more parsimonious in the estimated parameters. Also PGFI from model 2 was found (0.40) which somewhat higher than PGFI of model 1 (0.36). Parameter effect is significant at the 0.05 significance level (two-tailed) if its absolute value exceeds 1.96.  $\hat{\gamma}$ -values and their t-values were found as follows: for model 1 ( $\hat{\gamma} = -0.40$ ,  $t = -3.97$ ); for model 2 ( $\hat{\gamma} = -0.40$ ,  $t = 3.96$ ). The t-value is the ratio of each estimate to its standard error ( $\hat{\theta}/\hat{s}(\hat{\theta})$ ). From a SEM viewpoint, we provided in Table 2 most fit indexes, allowing a detailed consideration of model fit. We focused on non-medical factor and its contribution to the ratios of mortality. Children who

**Table 2: Comparison between propositional models using fit indices**

Goodness-of-fit measure	Model 1	Model 2
<b>Absolute-fit measures</b>		
$\chi^2$ -statistic(p-value)	13.77(0.09)	14.88(0.09)
GFI	0.950	0.940
SRMR	0.045	0.047
RMSEA	0.088	0.085
<b>Incremental-fit measures</b>		
CFI	0.970	0.970
AGFI	0.870	0.870
NFI	0.940	0.940
NNFI	0.950	0.960
<b>Parsimonious-fit measures</b>		
PGFI	0.360	0.400
AIC	38.980	38.260

$\chi^2$ -statistic = Likelihood-Ratio Chi-Square Statistic, GFI = Goodness-of-Fit Index, SRMR = Standardized Root Mean Square Residual, RMSEA = Root Mean Square Error of Approximation, CFI = Comparative fit index, AGFI = Adjusted Goodness-of-Fit Index, NFI = Normed Fit Index, NNFI = Non-Normed Fit Index (an old name for the NNFI is the Tucker-Lewis Index TLI), PGFI = Parsimonious Goodness-of-Fit Index, AIC = Akaike Information Criterion

live in poverty encounter more hurdles to a healthy development and they are at an elevated risk for a wide range of negative health outcomes; low income families live downwind, downstream and downhill from sources of environmental contaminants (Canadian Institute of Child Health, 2001).

The use of SEM for prosperity and mortality enable better measures for these concepts by potentially reducing biases inherent in single item measures. The existence of a number of theoretically justifiable equivalent models in some cases could be seen as a limitation of SEM. SEM, through the assessment of fit indexes, provides the possibility to extend and refine models to arrive at improved models that are theoretically justified.

We observed a wide variety of measures of fit being used as well as a range of criteria for determining what constitutes good fit. However, there is no agreement regarding the absolute acceptable levels of fit or benchmarks for individual measures. Thus, researchers typically look for a consensus across several measures to assess the acceptability of the fit of a model and only one fit measure ( $\chi^2$ -statistic) has an associated statistical test of significance. However, this is not necessarily a problem and is not unique to SEM. For each measure there is a range of acceptable values (Bollen, 1989; Hair *et al.*, 1998;

Hosseinpour *et al.*, 2005). SEM has several characteristics which allow the results of SEM modeling to be more informative for many fields, compared to the more traditionally applied multiple regression and path analysis techniques. First, SEM allows a range of relations between variables to be recognized in the analysis compared to multiple regression analysis and those relations can be recursive or non-recursive. Thus, SEM provides the researcher with an opportunity to adopt a more holistic approach to model building.

As with multiple regression and path analysis, the level of prediction and explanation can still be assessed and hypotheses can be tested through the assessment of the significance of path coefficients. However, the judicious use of a range of measures of fit can provide the researcher with a basis for evaluating the overall model. Second, the ability to account for the effects of estimated measurement error of latent variables is a major difference between SEM and both path analysis and multiple regression analysis.

Finally with regards to methodology, it was important to note that we did not claim to establish the fundamental true cause of how prosperity affects babies' mortality despite the causal analysis tag. Rather, we had taken the most widely believed theories on how prosperity relates to mortality.

### CONCLUSION

With respect to model fit, researchers do not seem adequately sensitive to the fundamental reality that there is no true model and all models are wrong to some degree, even in the population and that the best one can hope for is to identify a parsimonious, substantively meaningful model that fits observed data adequately well (MacCallum and Austin, 2000). Given this perspective, it is clear that a finding of good fit does not imply that a model is correct or true but only plausible.

These facts must temper conclusion drawn about good-fitting models. From the results, we can consider model 1 and 2 are acceptable or adequate fit. Infant deaths occur in families living below the poverty line or living in other stressful circumstances. In our point of view, mostly the cause of poor nutrition and poverty was low income which was coming from low class of prosperity or may be one of the parents did not work. Almost, mother was not working that is why mothers had been encouraged or advised to work, not only to increase their income but also to gain some feeling in responsibility as well as general information. Prosperity was found to have negative substantial effect on mortality. The structures we

had reported here as well as the strength of causal pathways may vary depending on the specific nature and circumstances of the population under study.

### REFERENCES

- Aber, J.L. and N.G. Bennett, 1997. The effects of poverty on child health and development. *Annu. Rev. Public Health*, 18: 463-483.
- Aron, A. and E.N. Aron, 2002. *Statistics for the Behavioral and Social Sciences: A Brief Course*. Prentice Hall, New Jersey, USA., pp: 330.
- Blane, D., E. Brunner and R. Wilkinson, 1996. *Health and Social Organization*. Routledge, London.
- Bollen, K.A., 1989. *Structural Equations with Latent Variables*. John Wiley and Sons, New York, ISBN: 0-471-01171-1.
- Boomsma, A., 2000. Reporting analysis of covariance structures. *Structural Equation Modeling*, 7: 461-483.
- Burns, P.G., 2005. Reducing infant mortality rates using the perinatal periods of risk model. *Public Health Nurs.*, 22: 2-7.
- Canadian Institute of Child Health, 2001. *The Health of Canadas Children: A pocket Guide*. 3rd Edn., Canadian Institute of Child Health, Ottawa, Ontario, pp: 1-36.
- Chandola, T., P. Clarke, J.N. Morris and D. Blane, 2005. Pathways between education and health: A causal modeling approach. *J. R. S at. Soc.: Series A*, 169: 337-359.
- Dillon, W.R. and M. Goldstein, 1984. *Multivariate Analysis: Methods and Applications*. John Wiley and Sons, New York, ISBN: 978-0-471-08317-7, pp: 608.
- Field, A., 2000. *Structural equation modelling*. 19. <http://www.statisticshell.com/sem.pdf>.
- Fleming, P.J., P.S. Blair, M.W. Platt, J. Tripp and I.J. Smith, 2003. Sudden infant death syndrome and social deprivation: Assessing epidemiological factors after post-matching for deprivation. *Paediatr. Perinat. Epidemiol.*, 17: 272-280.
- Hair, J.F., R.L. Tatham, R.E. Anderson and W. Black, 1998. *Multivariate Data Analysis*. 5th Edn., Prentice Hall International, Englewood Cliffs, New Jersey, London, ISBN-13: 978-0138948580, pp: 169-215.
- Hansell, A. and P. Aylin, 2000. *Routine Data and Health Impact Assessment-a Review of Epidemiological Studies of Socio-Economic Influence on Health and Evaluation of Outcome Indicators Derived from Routine Health Data for Health Impact Assessment*. Department of Epidemiology and Public Health, Imperial College School of Medicine, St Mary's, Norfolk Place, London pp: 256.

- Hosseinpour, A.R., K. Mohammad, R. Majdzadeh, M. Naghavi and F. Abolhassani *et al.*, 2005. Socioeconomic inequality in infant mortality in Iran and across its provinces. *Bull. World Health Organ.*, 83: 837-844.
- Hox, J.J. and T.M. Bechger, 1998. An introduction to structural equation modeling. *Family Sci. Rev.*, 11: 354-373.
- Hu, L. and P.M. Bentler, 1999. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Struct. Eq. Model.*, 6: 1-55.
- Judge, K. and I. Paterson, 2001. Poverty, income inequality and health. Treasury Working Paper, pp: 1-64. <http://ideas.repec.org/p/nzt/nztwps/01-29.html>.
- Kline, R.B., 1998. Principles and Practice of Structural Equation Modeling. Guilford Press, New York, ISBN-10: 1572303379, pp: 354.
- Lawn, J., K. Shibuya and J. Lawn, 2005. No cry at birth: Global estimates of intrapartum stillbirths and intrapartum-related neonatal deaths. *Bull. World Health Organ.*, 83: 409-417.
- Luginaah, I.N., K.S. Lee, T.J. Abernathy, D. Sheehan and G. Webster, 1999. Trends and variations in perinatal mortality and low birthweight: The contribution of socio-economic factors. *Can. J. Public Health*, 90: 377-381.
- MacCallum, R.C. and J.T. Austin, 2000. Applications of structural equations modeling in psychological research. *Ann. Rev. Psychol.*, 51: 201-226.
- Martines, J., V.K. Paul, Z.A. Bhutta, M. Koblinsky and A. Soucat *et al.*, 2005. Neonatal survival: A call for action. *Lancet*, 365: 1189-1197.
- Morris, J.N., D.B. Blane and I.R. White, 1996. Levels of mortality, education, and social conditions in the 107 local education authority areas of England. *J. Epidemiol. Community Health*, 50: 15-17.
- National Statistics, 2003. In brief: Population estimates for England and Wales. *Health Statistics Quarterly*, No.20: 1-69.
- Nordstrom, M.L., S. Cnattingius and B. Haglund, 1993. Social differences in swedish infant mortality by cause of death, 1983 to 1986. *Am. J. Public Health*, 83: 26-30.
- Price, R.H., J.N. Choi and A.D. Vinokur, 2002. Links in the chain of adversity following job loss of personal control lead to depression, impaired functioning and poor health. *J. Occup. Health Psychol.*, 7: 302-312.
- Raykov, T., A. Tomer and J.R. Nesselroade, 1991. Reporting structural equation modeling results in psychology and aging: Some proposed guidelines. *Psychol. Aging*, 6: 499-503.
- Sobel, M.E., 2000. Causal inference in the social sciences. *J. Am. Stat. Assoc.*, 95: 647-651.
- Spencer, N., 2004. The effect of income inequality and macro-level social policy on infant mortality and low birth weight in developed countries-a preliminary systematic review. *Care Health Dev.*, 30: 699-709.
- Stephansson, O., P.W. Dickman, A.L. Johansson and S. Cnattingius, 2001. The influence of socioeconomic status on stillbirth risk Sweden. *Int. J. Epidemiol.*, 30: 1296-1301.
- UNICEF, 2006. Progress for children. A Report Card on Nutrition, <http://www.unicef.org/progressforchildren/2006n4/>.
- Weeks, J.R., 1992. Population: An Introduction to Concepts and Issues. 5th Edn., Wadsworth Publishing Company, Belmont California, ISBN: 0534173462.
- Whitehead, M. and F. Drever, 1999. Narrowing social inequalities in health? Analysis of trends in mortality among babies of lone mothers. *Br. Med. J.*, 318: 908-912.