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The Relationship Between Mortality, Prosperity and Amenities in Malaysia Using Hybrid Models

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Abstract: This study examines the relationship between babies' mortality, prosperity and amenities. Our objective is to investigate some factors (Prosperity and Amenities), which are related to infant, neonatal and stillbirth mortality. The importance of our goal or our purpose is followed from what Weeks[9] 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. We concluded that prosperity and amenities do not have significant effect on babies' mortality. The goal of causal modeling is to test whether the pattern of correlations among the variables fits the variables, which affect the babies' mortality. Causal modeling is widely used in the social and behavioral sciences. Many methods have been used such as *path analysis* and more methods have been developed such as *hybrid model*, which is our interested in this study. We examined the goodness of fit for models assumed. This study is composed for a number of path-diagrams to create a picture of babies' health in Malaysia. The data is collected from census of 80 districts in Malaysia-1990.

Key words: Prosperity, amenities, pathways, infant mortality, neonatal mortality, stillbirth mortality, hybrid models, lisrel

INTRODUCTION

More than 10,000 newborn babies die every day[1]. Every year, it is estimated that undernutrition contributes to the deaths of about 5.6 million children under the age of five; 146 million children in the developing world are underweight and at increased risk of an early death[2]. Most studies concerned with adults' mortality while in our study we are concerning about babies' mortality which are not very different in their causes. The higher the pay grade, the lower the death rate; within each pay grade, those who owned a car had lower death rates than those without a car. In general, countries with highest levels of income and education are 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[3-11].

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[11]. 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 work 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[12]. Almost, poverty status is based on family income, which is determined from the class of occupation or employment status. Low income is associated with early neonatal deaths (within 7 days of life)[13]. Infants who died in Gambia because of sickness, premature at birth or prolonged illness were very few taken for treatment since difficulties with transportation[14]. 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[15].

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[8,9,15-17]. Low Socioeconomic Status (SES) increases risk of stillbirth in Sweden; the authors used occupation as one of several indicators of SES[18]. 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[19]. Characteristics were associated with women and children not receiving appropriate care are low income and limited or no access to transportation[20].

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We cannot use standard regression modeling methods because the causal sequence implied by the pathways is complicated. As such, we follow (Sobel; Price *et al.* and Chandola *et al.*)[21-23] and use 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 hybrid models as implemented in the software package: Linear Structural RELationships-LISREL8.7[24]. However, the above illustration demonstrates the need to understand and quantify the effect of the pathways linking mortality, prosperity and amenities; and how these could contribute to the debate on the role prosperity and amenities 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 at 1990. Our indicators (observed variables) represent the percentage value in each district, which they were (N = 80) districts. We must construct, on the basis of prior conceptual or statistical analyses *indicators* of the latents. More precisely, we structured the following construct (Latent) variables with some indicators:

Mortality: Mortality has three indicators: Standardized Infant Mortality Rate (SIMR), standardized Neonatal mortality rate (SNMR) and Standardized Stillbirth Mortality Rate (SSMR). Infant mortality indicates the number of deaths under one year of age. Neonatal mortality refers to the number of deaths within 28 days after birth. Stillbirth mortality occurs after 24 weeks of gestation[25]. Standardization is a set of procedures for controlling the effects of external factors. Standardized Mortality Rate (SMR) allows comparison of the causes of death between population groups[4]. It is calculated as follows:

$$SMR_i = O_i / \hat{O}_i, \qquad \text{for } i = 1,2,...,80, \text{ and } \hat{O}_i = SM + E_i$$

$$\text{where}: O_i = \text{observed deaths}; \hat{O}_i = \text{expected deaths};$$

$$\text{and } SM = \left(\sum_{i=1}^{80} O_i\right) \Big/ \left(\sum_{i=1}^{80} E_i\right)$$

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: i.e., level of economic development, represents the type of occupation status, which is grouped to two classes starting from top to bottom in the income and social level: Class-1 includes professional, technical related, administrative and managerial workers. Class-2 includes clerical and related, sales and service workers. 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[26]. Low levels of occupational security often accompany poverty status and poverty can induce serious health risks including mortality[5].

Amenities: We have two variables, car and telephone; which are combined into a single latent variable, amenities for modeling purposes. The availability of certain foods can be restricted in more remote areas[27]. For example, fresh fruit and vegetables, or their variety, may simply not be available. Availability of fresh fruit and vegetables is important for the maintenance of health; it mentioned to several services-one of them is the telephone, which is important for a number of reasons: either to provide health services or other infrastructure to contribute to a safe and convenient environment; as a means of enhancing communication and access to information; or to provide emergency services in time of crisis. Public transport is either limited or not available in rural and especially remote areas, so access to a car is important for accessing goods and services (including health services, education and work). People can not take their children to vaccinate them because they said that, it is too far and too expensive to go to the nearest health center[28].

Analysis

Hybrid models: Hybrid models-a Structural Equation Modeling (SEM)-are an extension of standard regression models through which multivariate outcomes and latent variables can be modeled. Hybrid models are more appropriate for this application than alternative causal modeling technique because they permit specification of "measurement models". Hybrid 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. Slight to moderate departures from normality can be handled by the Maximum Likelihood (ML)[29]. In our observed variables, we have slight departures from normality. The causal variables are called exogenous variables ξ and the effect variable is called the endogenous variable η. 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: $\eta = B\eta + \Gamma\xi + \xi$. Vectors η and ξ are not observed; instead vectors y and x are observed, such that:

Measurement model for y: y and measurement model for x: $x = \Lambda_x \xi + \zeta$.

Y is a p ×1 vector of observed response or outcome variables. x is a q ×1 vector of predictors, covariates, or input variables. η is an m ×1 random vector of latent dependent, or endogenous variables. ξ is an n × 1 random vector of latent independent, or exogenous variables. ε is a p × 1 vector of measurement errors in y. δ is a q × 1 vector of measurement errors in x. Λ_y is a p × m matrix of coefficients of the regression of x on η; it is also called factor loadings. Λ_x is a p × m matrix of coefficients of the regression of y on η. These coefficients relate the indicators to the underlying factors. Γ is an m × n matrix of coefficients of the ξ-variables in the structural relationship. The elements of Γ represent direct causal effects of ξ variables on η variables. B is an m × m matrix of coefficients of the η-variables in the structural relationship. B has zeros in the diagonal and (I-B) is required to be non-singular. The elements of B represent direct causal effects of η-variables on each other. ξ is an m × 1 vector of random disturbances.

The random components in the LISREL model are assumed to satisfy the following minimal assumptions: $\varepsilon$is uncorrelated with η. δ is uncorrelated with ξ. ζ is uncorrelated with ξ. ζ and δ are mutually uncorrelated. The n × n covariance matrix of ξ is Φ. The m × m, Ψ matrix contains the estimated values for the variances of the disturbances in the *equations*. The values reported under p × p matrix Θ_ε and q × q matrix Θ_δ are the variances of errors in the *indicators* of the latent endogenous and exogenous variables respectively. These assumptions imply the following form for the covariance matrix of the observed variables:

$$S = \begin{pmatrix} S_{yy} & S_{yx} \\ S_{xy} & S_{xx} \end{pmatrix} = \begin{pmatrix} ?_y A(GFG' + ?)A'?'_y + T_\varepsilon & ?_y AGF?'_x \\ ?_x FG'A'?'_y & ?_x F?'_x + T_\delta \end{pmatrix},$$

$$\text{where: } ? = (? - ?)^{-1}$$

$$\text{Whene } ? = O \text{ then } S = \begin{pmatrix} ?_y(GFG' + ?)?'_y + T_\varepsilon & ?_y GF?'_x \\ ?_x FG'?'_y & ?_x F?'_x + T_\delta \end{pmatrix}$$

The model is identified if we have two or more factors and each factor has at least two indicators[30,31].

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 is reality in some countries but what about Malaysia? Do amenities influence mortality?

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. The possibility exists that other models may provide an equally good or better fit to the data[32]. Accordingly, we identified and tested three alternative structural models based on a series of plausible alternative hypotheses.

Model-1 and model-2: Assume that model-1 represents our preferred model for the corroborative relations among variables y_1 y_2 y_3 x_1 x_2 and x_3. Figure 1 shows three x-variables as indicators of one latent ξ variable. There are three y-variables as indicators of one latent η_1 variable. The two latents are connected in a single-headed arrow. Figure-1 displays the results of the analysis to test the model-1 and The values along the paths represent unstandardized path coefficients.

We see from Fig. 1 that factor loading of SNMR ($\lambda^{(y)}_{21} = .17$), which is close to SSMR ($\lambda^{(y)}_{31} = .12$). Model-2, which is explained in Fig. 2 represents the same relationship in model-1 but with constrained: the factor loadings of SNMR and SSMR are equal ($\lambda^{(y)}_{21} = \lambda^{(y)}_{31}$). The resulted model is more significant because it is more parsimonious. Figure. 3 explains all observed and unobserved variables, error terms and parameter terms.

Model-3: Model-3 represents the corroborative relations among variables y_1 y_2 y_3 x_1 x_2 x_3 and x_4. Figure 4 shows two x-variables, x_1 and x_2 as indicators of latent ξ_1 variable and two x-variables, x_3 and x_4 as indicators of latent ξ_2 variable. There are three y-variables as indicators of one latent η variable.

Typically in SEM, exogenous constructs are allowed to covary freely. Parameter labeled with ϕ_{21} represents this covariance. This covariance comes from common

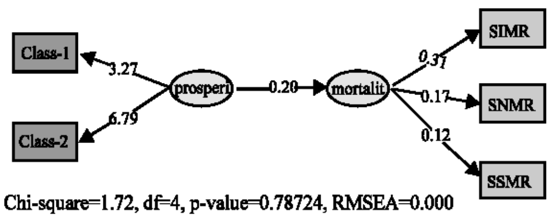

Fig. 1: Path diagram explained the relationship between prosperity and mortality

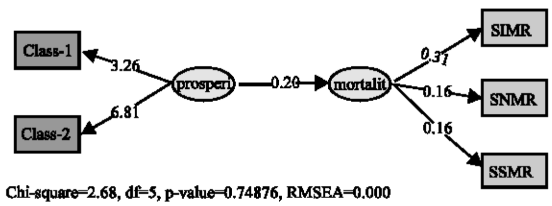

Fig. 2: Path diagram explained the relationship between prosperity and mortality after putting the constraint ($\lambda^{(y)}_{21}$, $\lambda^{(y)}_{31}$).

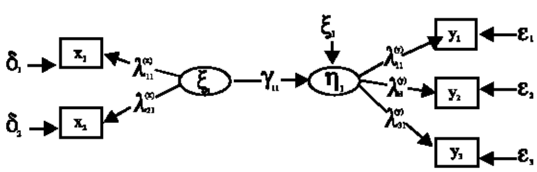

Fig. 3: Conceptualize path-diagram for model-1 and model-2 represents all variables

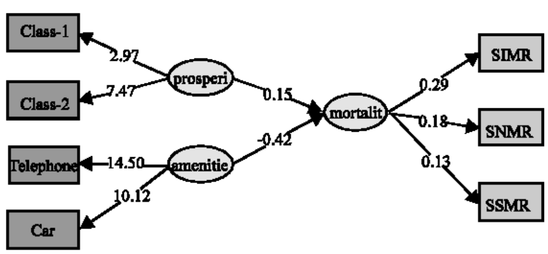

Fig. 4: Path diagram demonstrates the relationship between prosperity, amenities and mortality

predictors of the exogenous constructs which lie outside the model under consideration. The necessary condition[30] for model identification is:

$$t \le \frac{1}{2}(p+q)(p+q+1)$$

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 x^2 in the SEM literature. The value of the x^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 greater than .90[30,33].

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 greater than .90[31,34] endorsed stricter standards, pushing CFI to about .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 less than .10[31]. 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[30-33].

Bollen's incremental fit-index values were examined as these are least biased due to non-normality of variables and they were all above .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[33]. 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 .90 or greater[33]. Values of the NNFI can fall outside of the range 0-1[31]. The Root Mean Square Error of Approximation (RMSEA) value below .08 indicates a good fitting model[24,34] pushes RMSEA values to smaller .06 and they considered it greater than .10 is poor fit. RMSEA is a measure to assess how well a given model approximates the true model[35].

RESULTS

Every application of SEM should provide at least the following information: a clear and complete specification of models and variables, including a clear listing of the indicators of each latent; a clear statement of the type of

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

Variable	y_1	y	y_3	x_1	x_2	x_3	x_4	x_5	Mean	SD
SIMR, y_1	1.00								1.07	.29
SNMR, y_2	.67	1.00							1.03	.28
SSMR, y_3	.36	.25	1.00						1.05	.39
CLASS-1, x_2	-.20	-.03	-.05	1.00					10.08	3.32
CLASS-2, x_3	-.18	-.05	-.06	.82	1.00				25.19	8.14
TELEPHON, x_4	-.35	-.09	-.27	.65	.70	-.73	1.00		23.65	16.03
CAR, x_5	-.30	-.08	-.28	.76	.77	-.81	.91	1.00	27.10	10.11

Table-2: Comparison between all propositional models using fit indices

Goodness-of-fit measure	Model-1	Model-2	Model-3
Absolute-Fit measures			
x^2-statistic(p-value)	1.72 (.79)	2.68(.75)	18.79(.06)
GFI	.99	.99	.94
SRMR	.03	.05	.06
RMSEA	.000	.000	.095
Incremental-Fit measures			
CFI	1.00	1.00	.97
AGFI	.97	.96	.84
NFI	.98	.98	.94
NNFI	1.06	1.05	.95
Parsimonious-Fit measures			
PGFI	0.26	.33	.37
AIC	23.72	22.68	52.79

x^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

data analyzed, with presentation of the sample correlation or covariance matrix; specification of the software and method of estimation; and complete results[24]. Table 1 shows 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[17]. The acceptable range is one in 20 residuals exceeding ±2.58 strictly by chance, i.e., .05 percent of the normalized residuals[33]. All 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-value>.05) was considered significant and it is recommended as the minimum accepted for the propose model[33]. Model-1 results (x^2 = 1.72) with degrees freedom (d.f = 4) and significant (p-value = .79). This propose model is acceptable (or adequate) in interpreting the relationship between prosperity and babies' mortality. Model-2 with equality constraint results (x^2 = 2.68, d.f = 5) and significant (p-value = .75). Model-2 is acceptable in interpreting the same relationship. In these nested models, However, we have slightly difference between model-1 and model-2; they are both plausible and we don't have significant difference between two values of x^2. It is obvious to prefer model-2 because it is more parsimonious in the estimated parameters. Also PGFI for model-2 (.33) is higher than PGFI for model-1 (.26). Model-3 shows (x^2 = 18.79, d.f = 11) and significant (p-value = .06). Given two non-nested models, compared with model-3 (AIC = 52.79), model-2 with (AIC = 22.68) is better than model-3 because its AIC value is less than AIC value of model-3.

Parameter's effect is significant at .05 level (two-tailed) if its absolute value exceeds 1.96. In all models, we don't have corroborative relationship between prosperity, amenities and mortality. $\hat{y}$-values and their t-values are as follows: for model-1 ($\hat{y}_{11}$ = -.20, t = -1.89); for model-2 ($\hat{y}_{11}$ = -.20, t = -1.86); and for model-3 ($\hat{y}_{11}$ = .15, t =.67; $\hat{y}_{12}$ -.42, t = 1.89). T-value is the ratio of each estimate to its standard error [$\hat{\theta}_1 / \hat{S}(\hat{\theta}_1)$]. From a SEM viewpoint, we provide in Table 2 the most fit indexes, allowing a detailed consideration of model fit.

DISCUSSION

We have focused on non-medical factors and their contribution to the rates of mortality. Although, the positive relationship between prosperity and mortality is not significant; it means probably that most workers have worked in low level of occupation because the mean of percentage of class-2 is more than double of class-1. Children who live in poverty encounter more hurdles to a healthy development and 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[36].

The use of hybrid models for prosperity, amenities 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 (x^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[30,31,33].

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 is important to note that we do not claim to establish the fundamental true cause of how prosperity and amenities affect babies' mortality despite the causal analysis tag. Rather, we have taken the most widely believed theories on how prosperity and amenities relate 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[32]. 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 conclusions drawn about good-fitting models. From Table 2 we can consider model-1 and model-2 are good fit and model-3 is acceptable 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 is low income, which is coming from low class of prosperity or may be one of the parents doesn't work. Almost, mother is not working, that's why mothers have been encouraged or adviced to work, not only to increase their income but also to gain some feeling in responsibility as well as general information. The main aim of the study presented here was to answer the following question: Could these factors have been responsible for the corroborating mortality in Malaysia at (1990). Prosperity and amenities have not substantial effects on mortality. The structures we have reported here as well as the strength of causal path-ways may vary depending on the specific nature and circumstances of the population under study.

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