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Sequential Probit Model for Infant Mortality Modelling in Turkey

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Abstract: This study analyzes the socioeconomic and demographic characteristics of infant mortality in Turkey using 1998 Turkish Demographic and Health Survey data, held by the Hacettepe Institute of Population Studies. A Sequential Probit model, assumed that decisions are made in a hierarchical manner, is used for analyzing this data. The effect of various demographic and socioeconomic characteristics on the probability of infant mortality is estimated via two stages sequential probit model for both correlated and uncorrelated error terms. The results of the analysis show that the correlation between the error terms, ρ, is significant. For this reason, it is needed to be examined two stages together.

Key words: Discrete choice, heteroscedasticity, infant mortality, sequential choice model, sequential probit model

INTRODUCTION

Infant mortality is determined by several characteristics associated with socioeconomic and demographic conditions. Conventional methods, such as multiple regression, used to investigate relationships between these factors and infant mortality, have been criticized by some authors[1-3].

Many studies on infant mortality characteristics have suggested different variables (for instance, level of education, employment and income etc.) indirectly affecting infant mortality[4-6]. However, hypotheses about indirect effect are not adequately represented by conventional methods. Sequential probit model is a more appropriate statistical technique for this type of situation. It allows for the hierarchical inclusion of dependent variables into a model and provides estimates of independent variables' marginal effects[7]. These make sequential probit model conceptually more sound for infant mortality characteristics' studies than, say, conventional methods.

This study presents the conceptual basis for the sequential probit model. Theoretical background and parameter estimation method are given. Also, the effect of various demographic and socioeconomic characteristics on the probability of infant mortality are estimated via two stages sequential probit model for both correlated and uncorrelated error terms. Then, estimates of parameters for the infant mortality data are given.

Sequential probit model: In many surveys, questions are asked sequentially. A sequential probit model consists in assuming that infant's age at death occurs about the three options in a sequential manner. For instance, a_0: Infant lives, a_1: Infant is died neonatal (died between 0-1 months) and a_2: Infant is died postneonatal (died between 1-12 months).

The mathematical structure in a sample for n∈Z can be examined. We consider a simple sequential model with two qualitative variables, Y_1 and Y_2, which are observed sequentially. This sequential model is illustrated in Fig. 1.

There are three possible outcomes: a_0, a_1 and a_2. If $y_1 = 0$, autcome a_0 is observed. Otherwise depending on the value of y_2, there are two additional outcomes: $a_1=\{y_1=1,\ y_2=0\}$ and $a_2=\{y_1=1,\ y_2=1\}$. A sample of n observations indexed by I was considered. The sequential model has a special feature: we only observe values of $y_{2,i}$ conditionally on the fact that $y_{1,i}=1$. Therefore, if it is denoted n_j the number of observations at stage j (1 and 2), the total number of observations for variable y_1 is n_1+n_2 and it is n_2 for y_2.

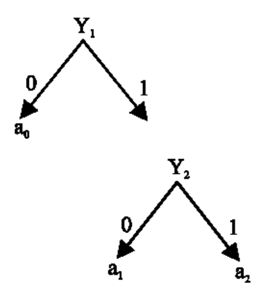

Fig. 1: Sequential probit model

For notational convenience, it is assumed that data have sorted according to the values of y_1 and y_2. In other

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words, the first n_1 observations correspond to outcome a_0 (y_1=0) and the next n_2 observations to outcome a_1 or a_2 depending on the value y_2. We associate with stage j (1 or 2) a latent variable $y^*_{j,i}$ such that

$$y_{j,i} = \begin{cases} 1 & y^*_{j,i} \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Continuous latent variables are modeled as follows:

$$y^*_{1,i} = x`_{1,i}\,\beta_1 + \varepsilon_{1,i} \qquad i=1,2,...,n$$
$$y^*_{2,i} = x`_{2,i}\,\beta_2 + \varepsilon_{2,i} \qquad i=n_1+1,..., n \quad (2)$$

where, $x_{1,i}$ and $x_{2,i}$ are vectors of explanatory variables of respective dimensions K_1x1 and K_2x1, β_1 and β_2 are vectors of parameters to be estimated of respective dimensions K_1x1 and K_2x1, $\varepsilon_{1,i}$ and $\varepsilon_{2,i}$ are vectors of error terms[8].

We can write the model in matrix notations[9]. Let

$X_1 = (x`_{1,1},..., x`_{1,n})`$, $X_2 = (x`_{2,1},..., x`2,n_2)`$ [001], $\varepsilon_1 = (\varepsilon_{1,1},..., \varepsilon_{1,n})`$, $\varepsilon_2 = (\varepsilon_{2,1},..., \varepsilon 2,n_2)`$ [002], $y^*_1=(y^*_{1,1},...,y^*_{1,\ n})`$ and $y^*_2=(y^*_{2,1},...,y^*2, n_2)`$ [003].

Now, the latent model can be written as

$$y^* = X\beta + \varepsilon \quad (3)$$

where, $y^* = (y^{*`}_1, y^{*`}_2)`$, $\beta = (\beta`_1, \beta`_2)`$, $\varepsilon = (\varepsilon`_1,\varepsilon`_2)`$ and

$$X = \begin{bmatrix} X_1 & 0 \\ 0 & X_2 \end{bmatrix}_{(n_1+2n_2)x(K_1+K_2)}$$

$\varepsilon_i = (\varepsilon_{1,i},\varepsilon_{2,i})`$ values are assumed to be bivariate normal with mean (0,0)` and covariance $\Sigma = \begin{bmatrix} \sigma_{11} & \rho \\ \rho & \sigma_{22} \end{bmatrix}$ [004]. σ_{11} and σ_{22} terms in the covariance matrix denote the variances of error terms at each stage and ρ represents the covariance between the error terms.

Two remarks are made. First, it is noted that when Σ is diagonal, all latent variables are independent and the coefficients of the model can be estimated by two standard Probit regressions. Second, it is clear that multiplying each latent equation by a positive constant does not affect the qualitative variables y_1 or y_2. Hence, it is impossible to identify both location and scale parameters of these equations. Therefore, it is needed to impose three restrictions. We have restricted ($\sigma_{11} = \sigma_{22} = 1$) so that coefficients ρ have the natural interpretation of correlation coefficients[10].

The probabilities of the different options are written as follows[11]:

$$P(y_{1,i}=0) = P(\varepsilon_{1,i} \leq -x`_{1,i}\,\beta_1) = \Phi(-x`_{1,i}\,\beta_1)$$
$$P(y_{1,i}=1,\ y_{2,i}=0) = P(\varepsilon_{1,i} > -x`_{1,i}\,\beta_1,\ \varepsilon_{2,i} \leq -x`_{2,i}\,\beta_2,\ \rho) = \Phi_2(x`_{1,i}\,\beta_1, -x`_{2,i}\,\beta_2, \rho)$$
$$P(y_{1,i}=1,\ y_{2,i}=1) = P(\varepsilon_{1,i} > -x`_{1,i}\,\beta_1,\ \varepsilon_{2,i} > -x`_{2,i}\,\beta_2,\ \rho) = \Phi_2(x`_{1,i}\,\beta_1, -x`_{2,i}\,\beta_2, \rho\ [005]) \quad (4)$$

where, Φ and Φ_2 are cumulative distribution function (c.d.f.) of the univariate and bivariate standard normal distribution, respectively.

If we assumed that ε_1 and ε_2 are independent, then Eq.(4) can be written as follows[12].

$$P(y_{1,i}=1,\ y_{2,i}=0) = P(\varepsilon_{1,i} > -x`_{1,i}\,\beta_1).\ P(\varepsilon_{2,i} \leq -x`_{2,i}\,\beta_2) = \Phi(x`_{1,i}\,\beta_1).\Phi(-x`_{2,i}\,\beta_2)$$

$$P(y_{1,i}=1,\ y_{2,i}=1) = P(\varepsilon_{1,i} > -x`_{1,i}\,\beta_1).\ P(\varepsilon_{2,i} > -x`_{2,i}\,\beta_2) = \Phi(x`_{1,i}\,\beta_1).\Phi(x`_{2,i}\,\beta_2) \quad (5)$$

Using the probabilities given above, likelihood function of the sequential probit model is

$$L(\beta_1,\beta_2,\rho) = \prod_{i=1}^{n} P_{00,i}^{(1-y_{1,i})}.P_{10,i}^{y_{1,i}(1-y_{2,i})}.P_{11,i}^{y_{1,i}\cdot y_{2,i}}\ [006] \quad (6)$$

Taking the natural logarithm of likelihood function $L(\beta_1, \beta_2, \rho)$, we obtain[13].

$$L(\beta_1,\beta_2,\rho) = \sum_{i=1}^{n}\Big\{(1-y_{1,i})\ln P_{00,i} + y_{1,i}(1-y_{2,i}) .\ln P_{10,i} + y_{1,i}.y_{2,i}.\ln P_{11,i}\Big\}\ [007] \quad (7)$$

If the error terms are independent (ρ = 0), natural logarithm of likelihood function becomes[14].

$$n\,L(\beta_1,\beta_2,) = \sum_{i=1}^{n}\Big\{(1-y_{1,i}).\ln\Phi(-x'_{1,i}\beta) + y_{1,i}(1-y_{2,i}) .\ln\big[\Phi(x'_{1,i}\beta) - \Phi(x'_{1,i}\beta_1).\Phi(x'_{2,i}\beta_2)\big]\ [008] + y_{1,i}.y_{2,i}.\ln[\Phi(x'_{1,i}\beta_1).\Phi(x'_{2,i}\beta_2)]\Big\} \quad (8)$$

It is easy to numerically implement the sequential probit procedure when the error terms are uncorrelated. But ignoring the selection rules causes biases[12]. The natural logarithm of maximum likelihood function with correlated error terms is as follows:

$$n L(\beta_1,\beta_2,\rho) = \sum_{i=1}^{n} \Big\{ (1-y_{1,i}).\ln\Phi(-x'_{1,i}\beta) + y_{1,i}(1-y_{2,i}$$

$$.\ln\big[\Phi(x'_{1,i}\beta) - \Phi_2(x'_{1,i}\beta_1, x'_{2,i}\beta_2,\rho)\big][009]$$

$$+ y_{1,i}.y_{2,i}.\ln\Phi_2(x'_{1,i}\beta_1, x'_{2,i}\beta_2,\rho)\Big\} \qquad (9)$$

The estimators of sequential Probit model is derived by maximizing likelihood function given in Eq.(8) and (9) for uncorrelated and correlated error terms, respectively.

Application: At the first stage of this study, the factors affecting the mortality and survival of infants born between 1993-1998 in Turkey were examined. At the next stage of the sequential process, we investigated the factors that affect the infant's age at death. The data used in the study obtained from the answers of the married women, between 15-49 years, who join the 1998 Turkish Demographic and Health Survey (TDHS-98) held by the Hacettepe Institute of Population Studies[15]. In the sequential process, data of 3480 infants and 133 infants have been used at the first and second stage, respectively. The variables used in this study are given in Table 1.

Table 2 describes the mean, standard deviation and p values of the parameters estimated by two independent Probit models in which the correlation coefficient ρ is assumed to be equal to zero (uncorrelated error terms).

Likelihood ratio test is used to test the hypothesis H_0: all the parameters of the model is equal to zero (see Table 2). The null hypothesis is rejected with α =0.01 significance level.

According to Table 2, dependent variable (infant's being alive or death) is affected by woman's age at birth, woman's total children ever born, infant's birth order number, duration of breastfeeding and place of delivery. At the second stage equation of the model, infant's age at death is affected by place of delivery, delivery by caesarian section, age of woman at first birth and duration of breasfeeding. If the significant coefficients at the first and second stage equations are positive, this means that the associated independent variable increases the probability of the occurence of relevant dependent variable. While negative signs mean that it decreases the probability of occurence of relevant dependent variable.

The effect of independent variables on the dependent variable can be seen from the sign of the coefficients. To determine the magnitude of those effects, marginal effects can be calculated. Table 3 shows the marginal effects of the independent variables.

According to Table 3, effect of the woman's total children ever born is about 2.29% and positive. In other words, this percent indicates that increase of one unit in this variable causes an increase on the probability of infant's death. Marginal effect of infant's birth order number indicates that decrease of one unit in this variable causes a decrease on the probability of infant's death. According to the magnitude of percent, infant's birth order number is effective by about 1.97% in decreasing the probability of infant's death. Duration of breastfeeding is the most effective negative variable on the probability of infant's death. So, if the woman breastfeeds her infant, the probability of infant's death decreases 8.32%.

Table 1: The definition of variables

Variable	Type of variable	Levels of variable	Variable code	Stage
Infant's being alive or death	Dependent,	0:alive, 1:death	IA/D	
Woman's age at birth	Independent	15-49	WAB	
Infant's birth order number	Independent	1, ..., 16	BORD	
Woman's total children ever born	Independent	1, ..., 16	TBORN	
Duration of breastfeeding	Independent	0:Never breastfeed, 1:Breastfeed	DURBR	1
Woman's highest education level	Independent	0:No education, 1:Primary, 2:Secondary, 3:Higher	EDUC	
Place of delivery	Independent	1:Home, 2:Public sector, 3:Private sector, 4:Other	PLACE	
Infant's age at death	Dependent	0:Prenatal (0-1month) 1:Postneonatal (1-12month)	IAD	
Duration of breastfeeding	Independent	0, ..., 12	DURBR	
Place of delivery	Independent	1:Home, 2:Public sector 3:Private sector 4:Other	PLACE	2
Delivery by caesarian section	Independent	0:Normal, 1:Caesarian	CAES	
Age of woman at first birth	Independent	11, ..., 32	FSTAGE	

Table 2: The estimation results of sequential Probit model for ρ=0

Variable	Coefficient	Standard error	p value
First stage			
WAB	-0.0170	0.0076	0.0247
TBORN	0.4527	0.0678	0.0000
BORD	-0.3895	0.0693	0.0000
DURBR	-1.6481	0.1157	0.0000
PLACE	-0.1241	0.0756	0.1007
Heteroscedasticity			
EDUC	-0.0571	0.0404	0.1578
Second stage			
PLACE	-0.3963	0.2177	0.0687
CAES	0.9016	0.5149	0.0799
FSTAGE	-0.0422	0.0189	0.0255
Heteroscedasticity			
DURBR	1.0842	0.2590	0.0000
	First Stage		Second Stage
Log of likelihood function	-420.0612		-30.5434
χ^2	286.5003		120.4055
Degrees of freedom	5		4
Heteroscedasticity Test	1.998		4.9993

Table 3: The marginal effects of independent variables for ρ=0

Variable	Coefficient	Standard error	p value
First stage			
WAB	-0.0009	0.0004	0.0550
TBORN	0.0229	0.0064	0.0003
BORD	-0.0197	0.0061	0.0011
DURBR	-0.0832	0.0231	0.0003
PLACE	-0.0063	0.0038	0.0961
Heteroscedasticity			
EDUC	-0.0056	0.0028	0.0281
Second stage			
PLACE	-0.3241	0.1939	0.0945
CAES	0.7373	0.4084	0.0711
FSTAGE	-0.0348	0.0163	0.0339
Heteroscedasticity			
DURBR	0.8338	0.3041	0.0061

Table 4: Parameter estimates of sequential probit model for $\rho \neq 0$

Variable	Coefficient	Standard error	p value
First stage			
WAB	-0.0139	0.0067	0.0380
TBORN	0.3984	0.0677	0.0000
BORD	-0.3512	0.0681	0.0000
DURBR	-1.6381	0.1125	0.0000
PLACE	-0.1249	0.0699	0.0738
Heteroscedasticity			
EDUC	-0.0671	0.0335	0.0453
Second stage			
PLACE	-0.9097	0.3747	0.0152
CAES	1.1342	0.5103	0.0262
FSTAGE	-0.0244	0.0303	0.4209
Heteroscedasticity			
DURBR	0.5616	0.4319	0.1934
$\hat{\rho}$	0.6389	0.1871	0.0006

Similarly, it can be said that place of delivery, woman's age at birth and woman's highest education level decrease the probability of infant's death.

At the second stage, infant's age at death is positively affected by about 83.38% on the duration of breastfeeding. Delivery by caesarian section has also positive effect by about 73.73%. So, if the infant is born by caesarian section, infant's living time increases. On the other hand, place of delivery and age of woman at first birth have negative effects on infant's age at death. That is, it can be said that this effect decreases the probability of infant's death.

By using Table 3, the probability of third infant's death is calculated for a woman whose demographic characteristics are given below:

- gave her third birth at 26 years old,
- has 3 children,
- graduted primary school,
- gave birth at public sector,
- breastfeeded her infant.

$P(y_{1,i}=1) = 0.4562$

In addition, by using Table 3, the probability of third infant's death at postneonatal period is calculated for the same woman whose demographic characteristics are given below:

- gave her first birth at 18 years old,
- gave birth in a regular way.

$$P(y_{2,i}=1, y_{1,i}=1)=P(y_{2,i}=1).P(y_{1,i}=1) = (0.3300).(0.4562) = 0.1505$$

The parameter estimates, standard error and p values for the sequential Probit model with correlated error terms are given in Table 4.

According to Table 4, dependent variable (infant's being alive or death) is affected by woman's age at birth, woman's total children ever born, infant's birth order number, duration of breastfeeding and place of delivery. On the other hand, the independent variable which affects related dependent variable and causes heteroscedasticity is woman's highest education level. Therefore, it is calculated in the variance equation part.

At the second stage equation of the model, infant's age at death is affected by place of delivery and delivery by caesarian section.

At the both of stages, the significant positive coefficients show that the associated independent variable increases the probability of the occurrence of relevant dependent variable. While the significant negative coefficients denote decrease at the probability of occurrence of the relevant dependent variable.

It can be seen easily from Table 4, the hypothesis (H_0:ρ=0) about the correlation between the error terms is statistically significant at α=0.01 significance level. For this reason, it is needed to be considered two stages together. Otherwise, ignoring the potential correlation between error terms can create both bias and inefficiency.

Table 5: The marginal effects of independent variables for $\rho \neq 0$

Variable	X_1 effect	X_2 effect	Z_1 effect	Z_2 effect	(Total effect) coefficient	Standard error	p value
WAB	0.0037	0.0000	0.0000	0.0000	0.0037	0.0024	0.1250
TBORN	-0.1068	0.0000	0.0000	0.0000	-0.1068	0.0492	0.0301
BORD	0.0942	0.0000	0.0000	0.0000	0.0942	0.0440	0.0324
DURBR	0.4391	0.0000	0.0000	0.2709	0.7100	0.1562	0.0000
PLACE	0.0335	-0.2322	0.0000	0.0000	-0.1987	0.0949	0.0363
CAES	0.0000	0.2895	0.0000	0.0000	0.2895	0.1504	0.0542
FSTAGE	0.0000	-0.0062	0.0000	0.0000	-0.0062	0.0098	0.5249
EDUC	0.0000	0.0000	0.0344	0.0000	0.0344	0.0186	0.0641

At both stages, the effect of independent variables on the dependent variable can be seen from the sign of the coefficients. To determine the magnitude of those effects, marginal effects can be calculated. The marginal effects showing the independent variable's effects individually are given in Table 5.

In Table 5, effect of X_1 shows the effects of independent variables in the first stage, effect of X_2 shows the effects of independent variables in the second stage, effect of Z_1 shows the effects of independent variables that cause heteroscedasticity in the first stage, effect of Z_2 shows the effects of independent variables that cause heteroscedasticity in the second stage. Total effect is the sum of those effects.

It can be seen easily from Table 5, woman's total children ever born, infant's birth order number, duration of breastfeeding, place of delivery, delivery by caesarian section and woman's highest education level are the significant variables according to magnitude of percentage of total effect which are affecting infant's death at postneonatal period when it is known that infant is died (y_1=1).

Duration of breastfeeding is the most effective positive variable on the probability of infant's death at postneonatal period and the probability is 71%. That is, it delays the infant's death. The effect of duration of breastfeeding is 43.91% on probability of infant's death and when it is known that infant is died (y_1=1), this effect is 27.09% on probability of infant's death at postneonatal period.

According to the magnitude of percent of total effect, delivery by caesarian section is second order. When y_1=1, this effect is positive and 28.95% on probability of infant's death at postneonatal period.

For y_1=1, the effect of place of delivery is 3.35% and positive, 23.22% and negative at the first and second stage on probability of infant's death at postneonatal period, respectively. Also, total effect of place of delivery is 19.87% and negative.

Similarly for y_1=1, woman's total children ever born decreases the probability of infant's death at postneonatal period and it has affected 10.68%.

Infant's birth order number has positive effect by about 9.42%.

Woman's highest education level has also positive effect by about 3.44%.

The probability of third infant's death at postneonatal period is calculated for a woman whose demographic characteristics are given below by using Table 5:

- gave her first birth at 18 years old
- gave her third birth at 26 years old
- has 3 children
- graduated from the primary school
- gave birth at public sector
- gave birth in a regular way
- breastfeeded her infant.

$$P(y_{2,i}=1, y_{1,i}=1) = \Phi_2(x_{1,i}\hat{\beta}_1, x_{2,i}\hat{\beta}_2, \hat{\rho})\,[0010]$$

$$= \Phi_2(0.5027, -0.4644, 0.6389) = 0.2981$$

The above probability is 15.05% and 29.81% for the uncorrelated and correlated error terms, respectively.

Although ρ is significantly different from zero, if it is assumed ρ = 0, consistent but asymptotically inefficient estimates for all parameters can be obtained.

RESULTS AND DISCUSSION

In this study, the two stages sequential probit model to analyze infant mortality for two different situations, namely, correlated and uncorrelated error terms, is applied.

At the first stage of the model, the factors affecting the infant's being alive or death are examined. In the next stage of sequential process, the factors that affect the infant's age at death are investigated.

In both of the situation with correlated and uncorrelated error terms, infant's being alive or death is affected negatively by woman's age at birth, infant's birth order number, duration of breastfeeding, place of delivery and positively by woman's total children ever born. This means that the related independent variables decrease the probability of the infant's being death. Also, infant's age at death is affected negatively by place of delivery, age of woman and positively by delivery by caesarian section. In other words, it denotes that the related independent variables increase at the probability of infant's postneonatal death.

It is important to remind the reader, however, that some of the socioeconomic and demographic variables, namely, woman's highest education level and duration of breastfeeding, cause heteroscedasticity. For this reason, assumption violation is corrected and consistent parameter estimates are obtained.

The findings of this study show that the correlation coefficient, ρ, is statistically significant (P = 0.64). That is, it is related infant's age at death and infant's being alive or death. This shows that it is the correct way to examine those two stages together.

Considering two stages together, it is clear that there are significant differences among the variables on the probability of infant's death at postneonatal period. Duration of breastfeeding is the most effective positive variable on that. Thus, it can be interpreted as period of breastfeeding increases, the probability of postneonatal death decreases.

Delivery by caesarian section is second order effective variable. It can be concluded that the probability of infant's neonatal death decreases when woman receives medical care.

Furthermore, the other five socioeconomic or demographic variables are less effective in order to explain the probability of postneonatal death.

In sum, the expectation about the coefficient signs and magnitudes are supported with the parameter estimates.

It is hoped that the findings of this study will guide to policy planners to achieve the goals of Turkey's development plan. As discussed here, while the planners and policy makers deal with infant mortality, they should also consider infant's age at death.

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