

ECONOMETRICS ASSIGNMENT

ECON F241

Predictive behaviour of maternal health inputs and child mortality in West Bengal

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Motivation And Research Question

High child mortality in developing countries can be associated with the inadequate utilisation of maternal health care, a factor which is often overlooked. One of the major reasons for carrying out this research is to help design an effective health policy which is only possible with the use of relevant information about the efficiency of existing maternal healthcare and other related factors. Prenatal and postnatal care are essential for ensuring a safe delivery and promoting the health of both the mother and the newborn. We seek to explore the utilisation of these healthcare services among the different social groups and their impact on reducing child mortality rates.

The main question we seek to answer through the study is which variables and factors determine the demand for various maternal health inputs in West Bengal. The choice of prenatal care and the place of delivery are the first two health inputs we will determine as outcome variables. These two will form the basis for the analysis, and using these results we will determine the final outcome variable: child mortality. This would help the policymakers to identify the areas to focus on to pave the way for the formation of good quality human capital in the long run.

Data & Methodology

The research paper we are replicating uses data from the 2005-06 National Family Health Survey (NFHS-3). The survey was the third of its kind conducted, to explore the factors that affect women's preferences for prenatal care and their decision-making process regarding the place of delivery in West Bengal, India. The study also analyses how these factors, along with others, affect child mortality. The sample for the study consists of 1823 mothers who gave birth between 2001 and 2005 and were selected from the larger NFHS-3 dataset. We use various criteria to profile the women surveyed, such as religion, socioeconomic strata, and education level.

We replicated the paper using three probit regression models. The dependent variables in the model are binary. If the mother's child had died before the age of five (CM), if the mother gave birth in a hospital/institutional centre (HD), and if the mother used prenatal medical care services (PC). We aim to understand the factors contributing to child mortality, and we estimate the equations accordingly.

$$PC = \alpha_0 + \alpha_1 X_p + u_p + \varepsilon_p \quad (1)$$

$$HD = \beta_0 + \beta_1 X_h + u_h + \varepsilon_h \quad (2)$$

$$CM = \delta_0 + \delta_1 X_c + u_c + \varepsilon_c \quad (3)$$

p, h, and c subscripts denote prenatal care, hospital delivery, and child mortality. α_0 , β_0 , and δ_0 are the constant terms for those equations. α_1 , β_1 , and δ_1 represent the coefficients for the explanatory variables in these equations.

X_p , X_h , and X_c represent possible regressors that may have a significant influence on the demand for prenatal care, hospital delivery, and child mortality respectively. Therefore, the binary outcome variables are represented as

$$PC = \begin{cases} 1 & \text{if care is taken} \\ 0 & \text{if care is not taken} \end{cases} \quad (4)$$

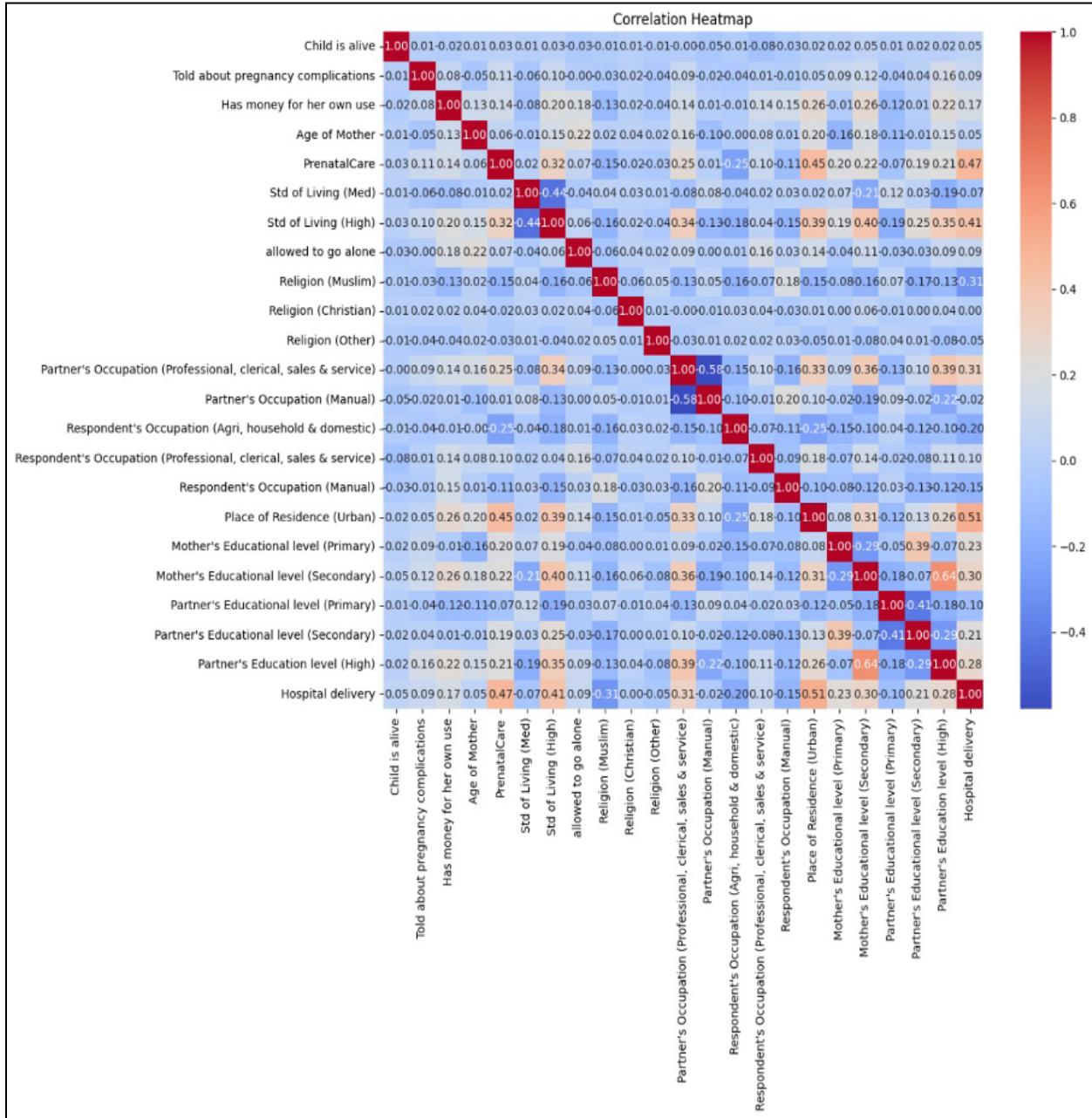
$$HD = \begin{cases} 1 & \text{if delivery is in hospital} \\ 0 & \text{if delivery is not in hospital} \end{cases} \quad (5)$$

$$CM = \begin{cases} 0 & \text{if at least one child of less than 5 years age is dead} \\ 1 & \text{if no child of less than 5 years age is dead} \end{cases} \quad (6)$$

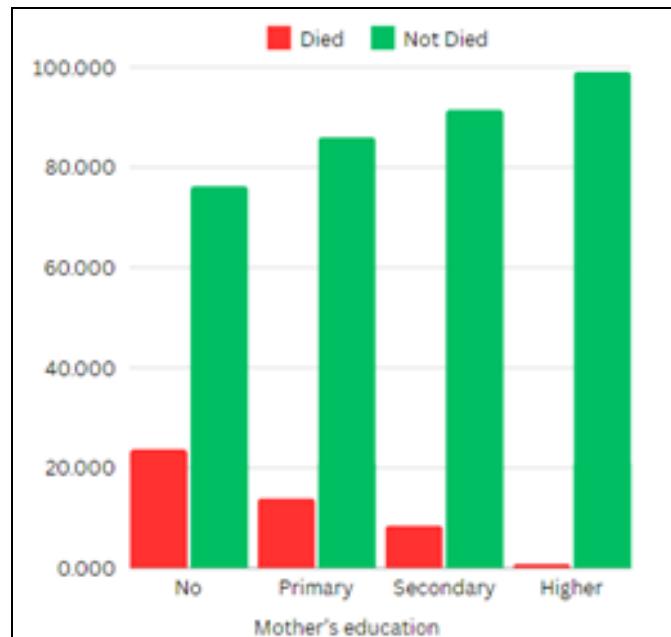
In the given paper, 1 was assigned at least one child of less than 5 years being dead while 0 was used for the opposite. However, in our analysis, we have used the child being dead as the base case while 1 is assigned to the cases where the child was alive.

Here u_i ($i = p, h, c$) is an error term that accounts for unobserved heterogeneity due to the mother. So $u_i \sim N(0, \sigma_i^2)$ where σ_i^2 is the variance of unobserved factors, if any. Again ε considers all other residual variation and follows $\varepsilon_i \sim \text{IID } N(0, 1)$ ($i=p, h, c$). Our study estimates three binary probit and equations (having a binary dependent variable) with the three outcome variables: PC, HD, and CM. These are assumed to be exogenous.

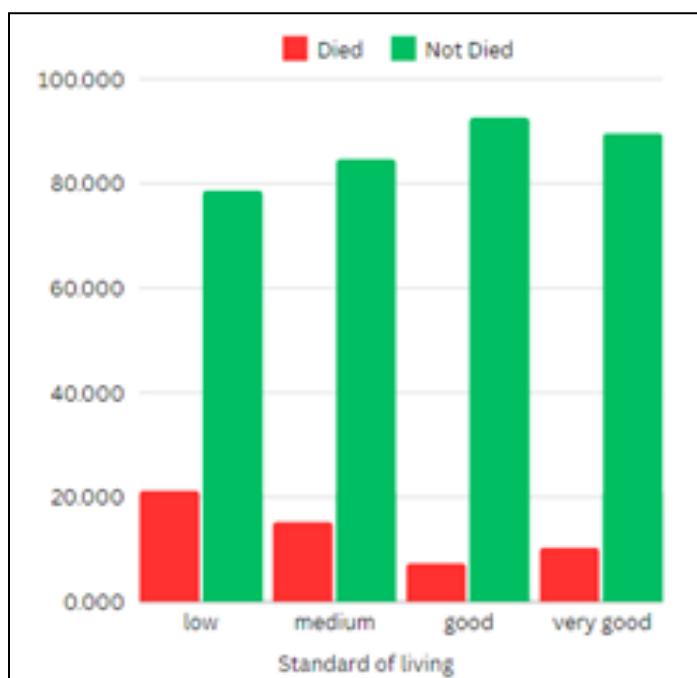
Descriptive Statistics



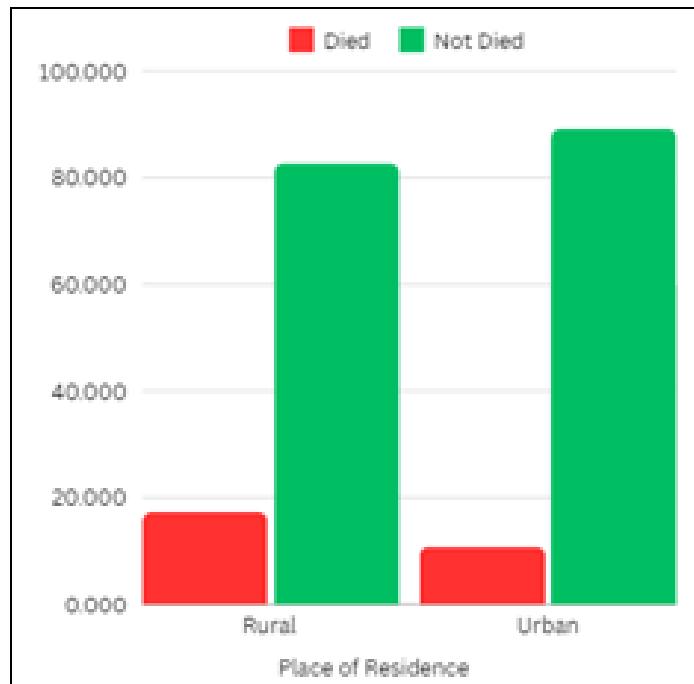
Correlation heatmap shows correlation between all combinations of the explanatory and dependent variables



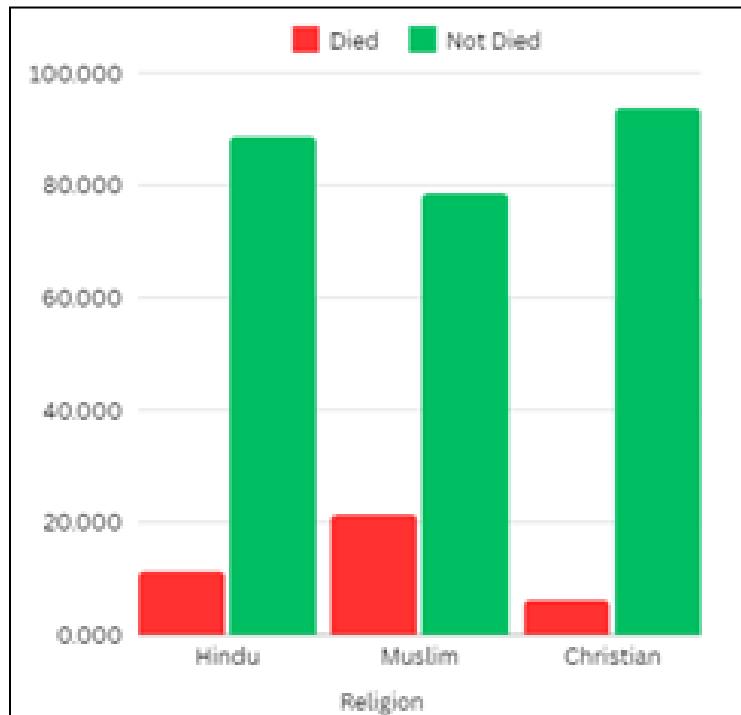
Higher the mother's education lower the child mortality rates



Child mortality rates decrease as standard of living increases



Those living in the rural areas have a higher child mortality rate.



Muslims exhibit unusually high rates of child mortality compared to Hindus and Christians

Regression analysis

Even though the research paper has dealt with both endogenous and exogenous models, we will only present the results and analysis of the exogenous models. We employed a probit regression analysis which is based on MLE(Maximum likelihood estimation). The signs of the coefficients have matched for most of the variables, however there is a difference in magnitude from the results in the research paper.

The discrepancy in results between the paper and our analysis is possibly because of other advanced techniques that the research paper employs to obtain results like Joint Estimation technique which is a Full Information Maximum Likelihood(FIML) Method, Conditional Mixed Process and accountancy for heterogeneity.

Here's our results from the exogenous model:

(i) Prenatal Care

Regression Coefficients using Probit:

```
> summary(PC_probit)

Call:
glm(formula = PC ~ Residence_urban + motherAge + ReligionMuslim +
    ReligionChristian + ReligionOther + LivingStdMed + LivingStdHigh +
    PartnerOcc_manual + PartnerOcc_agri_household_domes + PartnerOcc_prof_cler_sales_service +
    allowedtogo + hasmoneyforownuse + pregcomplication + MotherEduPrimary +
    MotherEduSecondary + PartnerEduPrimary + PartnerEduSecondary +
    PartnerEduHigh, family = binomial(link = "probit"), data = dataset)
```

```

Deviance Residuals:
    Min      1Q   Median     3Q     Max 
-2.8378 -0.8797  0.2744  0.7324  1.6954 

Coefficients:
                                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)                         0.363308  0.887205  0.409  0.682175    
Residence_urban                     1.123955  0.100548  11.178 < 2e-16 ***  
motherAge                           -0.004963  0.007364  -0.674  0.500372    
ReligionMuslim                      -0.147749  0.078506  -1.882  0.059835 .    
ReligionChristian                   -0.872827  0.456310  -1.913  0.055775 .    
ReligionOther                        -0.254471  0.741689  -0.343  0.731526    
LivingStdMed                        0.181288  0.086692  2.091  0.036512 *    
LivingStdHigh                       0.452841  0.122860  3.686  0.000228 ***  
PartnerOcc_manual                   -0.336601  0.455624  -0.739  0.460047    
PartnerOcc_agri_household_domes   -0.491545  0.455831  -1.078  0.280878    
PartnerOcc_prof_cler_sales_service -0.302234  0.458406  -0.659  0.509694    
allowedtogo                         0.077875  0.077342  1.007  0.313989    
hasmoneyforownuse                  0.003938  0.082278  0.048  0.961829    
pregcomplication                    0.197277  0.096016  2.055  0.039914 *    
MotherEduPrimary                    0.385689  0.091159  4.231  2.33e-05 ***  
MotherEduSecondary                  1.012926  0.307072  3.299  0.000971 ***  
PartnerEduPrimary                   0.182949  0.099956  1.830  0.067205 .    
PartnerEduSecondary                 0.264403  0.103837  2.546  0.010886 *    
PartnerEduHigh                      0.501460  0.248097  2.021  0.043257 *    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2089.6 on 1698 degrees of freedom
Residual deviance: 1522.2 on 1680 degrees of freedom
AIC: 1560.2

Number of Fisher Scoring iterations: 7

```

Observations:

- The increasing age of the woman has a negative relationship on the chance of the woman seeking out prenatal care. With an increase in age, confidence in their ability to avoid or tide over potential problems could increase, resulting in this relationship.
- Interestingly enough, being a Muslim/Christian woman reduces the chance of seeking out prenatal care compared to a Hindu woman, with being a Christian reducing the chance more. This could reflect the religious beliefs and culture that prioritise keeping these matters private.
- The standard of living has a positive marginal effect on the chances of women getting prenatal care. This could be because, with improvement in living standards,

one can easily access and afford good medical treatment and other necessary amenities. These results match those seen in the research paper.

- Women with primary education and with secondary education have higher chances of going for prenatal care, as compared to an uneducated woman, which could be attributed to greater knowledge about the available medical utilities and their benefits, which comes from exposure to education.
- There are some other predictor variables also included in the model but they are not significant and hence we ignore providing any interpretations for the same.

ii) Hospital Delivery-Regression Coefficients using Probit regression model:

```
> summary(HD_probit)

Call:
glm(formula = HD ~ Residence_urban + motherAge + ReligionMuslim +
    ReligionChristian + ReligionOther + LivingStdMed + LivingStdHigh +
    PartnerOcc_manual + PartnerOcc_agri_household_domes + PartnerOcc_prof_cler_sales_service +
    allowedtogo + hasmoneyforownuse + pregcomplication + MotherEduPrimary +
    MotherEduSecondary + PartnerEduPrimary + PartnerEduSecondary +
    PartnerEduHigh + PC, family = binomial(link = "probit"),
    data = dataset)

Deviance Residuals:
    Min      1Q   Median      3Q      Max 
-2.84653 -0.65289  0.05134  0.63590  2.65357 

Coefficients:
                                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)                         -0.53685   0.91278 -0.588  0.556430    
Residence_urban                      1.04502   0.09976 10.475 < 2e-16 ***
motherAge                            -0.01327   0.00779 -1.703  0.088599 .  
ReligionMuslim                        -0.67364   0.08287 -8.129 4.34e-16 ***
ReligionChristian                     -0.39161   0.51980 -0.753  0.451218    
ReligionOther                          -0.54669   0.77774 -0.703  0.482107    
LivingStdMed                          -0.04386   0.09144 -0.480  0.631458    
LivingStdHigh                         0.54585   0.12302  4.437 9.12e-06 ***
PartnerOcc_manual                     0.46723   0.43914  1.064  0.287347    
PartnerOcc_agri_household_domes     0.42261   0.44221  0.956  0.339231    
PartnerOcc_prof_cler_sales_service  0.57209   0.44049  1.299  0.194023    
allowedtogo                           0.10254   0.08062  1.272  0.203435    
hasmoneyforownuse                    -0.06167   0.08469 -0.728  0.466547    
pregcomplication                      0.05982   0.09593  0.624  0.532888    
MotherEduPrimary                      0.45125   0.09169  4.922 8.58e-07 *** 
MotherEduSecondary                     1.62524   0.43523  3.734  0.000188 *** 
PartnerEduPrimary                      0.15252   0.10597  1.439  0.150067    
PartnerEduSecondary                   0.18311   0.10633  1.722  0.085037 .  
PartnerEduHigh                         0.64686   0.26056  2.483  0.013045 *  
PC                                     0.62332   0.08782  7.098 1.27e-12 *** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2315.7 on 1698 degrees of freedom
Residual deviance: 1388.6 on 1679 degrees of freedom
AIC: 1428.6
```

Observations:

We have made interpretations for the coefficients which have at most a significance level of 10%.

- As can be seen from the coefficients and a very low level of significance, the probability of choosing hospital delivery rises significantly in the urbanities.
- It can also be observed that Muslim women have a significantly lower chance of going for hospital delivery which could be attributed to their religious and cultural orientation of not exposing their private lives.
- As expected, mothers with high primary and secondary education have a higher probability of opting for hospital delivery. This could be due to the increased freedom to go outdoors that they get upon receiving education, making them better placed to seek medical help whenever necessary.
- Women whose partners have higher education have higher chances of seeking hospital delivery. A husband's education can influence his understanding of healthcare options and the importance of professional medical assistance during childbirth.
- The women who took prenatal care have a higher probability of going for hospital delivery which may be due to their increased awareness about the importance of seeking medical help.

iii) Child Mortality

Regression Coefficients using Probit:

```
> summary(CM_probit)

Call:
glm(formula = CM ~ Residence_urban + motherAge + ReligionMuslim +
    ReligionChristian + ReligionOther + LivingStdMed + LivingStdHigh +
    PartnerOcc_manual + PartnerOcc_agri_household_domes + PartnerOcc_prof_cler_sales_service +
    allowedtogo + hasmoneyforownuse + pregcomplication + MotherEduPrimary +
    MotherEduSecondary + PartnerEduPrimary + PartnerEduSecondary +
    PartnerEduHigh + PC + HD, family = binomial(link = "probit"),
    data = dataset)
```

```

Deviance Residuals:
    Min      1Q  Median      3Q     Max 
-3.1889  0.1317  0.2062  0.2659  0.4792 

Coefficients:
                                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)                         8.725642 399.489722  0.022   0.9826    
Residence_urban                     0.041564  0.176032  0.236   0.8133    
motherAge                           0.010070  0.013356  0.754   0.4509    
ReligionMuslim                      0.036079  0.148733  0.243   0.8083    
ReligionChristian                   3.561009 267.149477  0.013   0.9894    
ReligionOther                        -3.505870 312.471446 -0.011   0.9910    
LivingStdMed                        0.084027  0.166893  0.503   0.6146    
LivingStdHigh                       -0.022626  0.211926 -0.107   0.9150    
PartnerOcc_manual                   -3.872555 248.904616 -0.016   0.9876    
PartnerOcc_agri_household_domes   -3.293294 248.904653 -0.013   0.9894    
PartnerOcc_prof_cler_sales_service -3.939752 248.904633 -0.016   0.9874    
allowedtogo                         -0.201937  0.139652 -1.446   0.1482    
hasmoneyforownuse                  -0.089259  0.141525 -0.631   0.5282    
pregcomplication                    0.011938  0.169301  0.071   0.9438    
MotherEduPrimary                    0.162232  0.176021  0.922   0.3567    
MotherEduSecondary                 0.904039  0.462136  1.956   0.0504 .  
PartnerEduPrimary                   0.174985  0.193382  0.905   0.3655    
PartnerEduSecondary                0.093670  0.192224  0.487   0.6261    
PartnerEduHigh                      -0.091740  0.358412 -0.256   0.7980    
PC                                  0.007611  0.167366  0.045   0.9637    
HD                                  0.284823  0.177341  1.606   0.1083    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 415.60  on 1698  degrees of freedom
Residual deviance: 388.65  on 1678  degrees of freedom
AIC: 430.65

```

We find that almost all of the coefficients except one are insignificant even for a 10% significance level, thus implying the results of this regression analysis irrelevant.

Regression for Child Mortality in Python

In addition to the above models fitted to the data in R using the base *glm* method, we also ran regression in python for the same dataset. However, the python implementation using the *scikit-learn* library allowed for an increase in the number of iterations that helped mitigate the problems of multicollinearity and allowed the model to converge to a solution. When regression was run on the same dataset, we found the standard errors to be significantly smaller than those estimated using R.

The dataset was split into training and testing data (80:20) and the model was evaluated on the testing data after being fit to the training data.

Results of Regression:

	Coefficients	Variance	Standard Error
Told about pregnancy complications	0.099568	0.000000e+00	0.000000e+00
Has money for her own use	0.352558	7.888609e-31	8.881784e-16
Age of Mother	-0.004847	1.925930e-32	1.387779e-16
PrenatalCare	0.259869	1.925930e-34	1.387779e-17
Std of Living (Med)	0.171103	4.930381e-32	2.220446e-16
Std of Living (High)	-0.032883	3.774823e-32	1.942890e-16
allowed to go alone	-0.127457	9.321501e-32	3.053113e-16
Religion (Muslim)	0.155934	9.984021e-31	9.992007e-16
Religion (Christian)	0.161070	4.930381e-32	2.220446e-16
Religion (Other)	0.923511	3.081488e-31	5.551115e-16
Partner's Occupation (Agri, household & domestic)	0.738264	7.703720e-34	2.775558e-17
Partner's Occupation (Professional, clerical, sales & service)	0.034288	1.509929e-31	3.885781e-16
Partner's Occupation (Manual)	-0.022556	3.081488e-31	5.551115e-16
Respondent's Occupation (Agri, household & domestic)	-0.057470	3.774823e-32	1.942890e-16
Respondent's Occupation (Professional, clerical, sales & service)	-0.814085	1.232595e-32	1.110223e-16
Respondent's Occupation (Manual)	0.043057	7.523164e-35	8.673617e-18
Place of Residence (Urban)	0.226933	2.773339e-32	1.665335e-16
Mother's Educational level (Primary)	0.110362	1.109336e-31	3.330669e-16
Mother's Educational level (Secondary)	1.092972	4.437343e-31	6.661338e-16
Partner's Educational level (Primary)	-0.017117	7.703720e-34	2.775558e-17
Partner's Educational level (Secondary)	0.110994	6.039716e-31	7.771561e-16
Partner's Education level (High)	0.186758	7.888609e-31	8.881784e-16
Hospital delivery	0.193484	6.933348e-33	8.326673e-17
Intercept	1.140000	0.000000e+00	0.000000e+00

Confusion Matrix:

```
▶ dataframe = [[ "CONFUSION MATRIX", "Actual 1", "Actual 0"], [ "Predicted 1", "0", "10"], [ "Predicted 0", "0", "330"]]
ddf=pd.DataFrame(dataframe)
ddf
```

	0	1	2	
0	CONFUSION MATRIX	Actual 1	Actual 0	
1		Predicted 1	0	10
2		Predicted 0	0	330

Next steps: [Generate code with ddf](#) [View recommended plots](#)

Testing Parameters:

The model was tested on the following statistics and the following results were obtained:

1. Accuracy

- This is defined as the ratio of correct predictions to the total number of predictions made by the model.
- Accuracy = $(\text{True positives} + \text{True negatives}) / \text{Total number of predictions}$
- Accuracy provides a straightforward measure of how often the classifier is correct. However, it can be misleading when dealing with imbalanced datasets, where one class is much more frequent than the other, as in our case where more children are alive than not.

2. Precision

- The ratio of true positive predictions to the total number of positive predictions of the model.
- Precision = $\text{True positives} / (\text{True positives} + \text{False positives})$
- It measures the accuracy of positive predictions.

3. Recall

- The ratio of true positive predictions to the total number of positives in the dataset.
- Recall = $\text{True positives} / (\text{True positives} + \text{False negatives})$
- Also known as sensitivity, it describes the model's ability to identify all positive instances.

4. F1 Score

- The harmonic mean of precision and recall.
- $\text{F1 Score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$
- It captures the effects of both precision and recall.
- It reaches its best value at 1 and worst at 0.
- A good testing parameter when the classes are imbalanced, as in our child mortality case.
- An F1 score of 0.95 indicates that it is an extremely accurate model.

Observations:

- Hospital delivery decreases the probability of child mortality as they are under the supervision of trained medical professionals.
- Prenatal care has also been found to decrease the chances of child mortality as it involves preparing expectant mothers for childbirth and provides guidance on postnatal care for both the mother and the newborn.
- Mother's age has also been found to be negatively correlated with child mortality, as early motherhood can be associated with poor maternal health outcomes that feed through to the child's health.
- Muslim and Christian mothers are less likely to be exposed to the hazards of child mortality as compared to the Hindu mothers.
- Neither educational attainment of mothers nor their partners have any significant impact on child mortality in our analysis.

Fitting Heteroskedastic Probit Models

We experimented with the FIML method mentioned in the paper using the *Rchoice* library's *hetprob* model, which gave us the following results:

```

> summary(PC_hetprobit)
-----
Maximum Likelihood estimation of Heteroskedastic Binary model
Newton-Raphson maximisation, 150 iterations
Return code 4: Iteration limit exceeded (iterlim)
Log-Likelihood: -738.1734
37 free parameters

Estimates for the mean:
                                         Estimate Std. error z value Pr(> z)
(Intercept)                      204.2309      Inf     0     1
Residence_urban                  134.5497      Inf     0     1
motherAge                         -1.5896      Inf     0     1
ReligionMuslim                   -18.0943      Inf     0     1
ReligionChristian                 -67.3986      Inf     0     1
ReligionOther                      28.7712      Inf     0     1
LivingStdMed                      26.6144      Inf     0     1
LivingStdHigh                     139.0882      Inf     0     1
PartnerOcc_manual                -242.4457      Inf     0     1
PartnerOcc_agri_household_domes  -264.3272      Inf     0     1
PartnerOcc_prof_cler_sales_service -205.1539      Inf     0     1
allowedtogo                       5.8608      Inf     0     1
hasmoneyforownuse                -13.7476      Inf     0     1
pregcomplication                  85.1678      Inf     0     1
MotherEduPrimary                  32.5068      Inf     0     1
MotherEduSecondary                 511.5171      Inf     0     1
PartnerEduPrimary                  26.2376      Inf     0     1
PartnerEduSecondary                 41.6307      Inf     0     1
PartnerEduHigh                     317.4911      Inf     0     1

Estimates for lnsigma:
                                         Estimate Std. error z value Pr(> z)
het.Residence_urban                -0.431290      Inf     0     1
het.motherAge                      -0.011666      Inf     0     1
het.ReligionMuslim                  0.080828      Inf     0     1
het.ReligionChristian                -11.328076      Inf     0     1
het.ReligionOther                   6.328911      Inf     0     1
het.LivingStdMed                   0.258998      Inf     0     1
het.LivingStdHigh                  0.510398      Inf     0     1
het.PartnerOcc_manual              -0.912248      Inf     0     1
het.PartnerOcc_agri_household_domes -1.024129      Inf     0     1
het.PartnerOcc_prof_cler_sales_service -0.566309      Inf     0     1
het.allowedtogo                    -0.264512      Inf     0     1
het.hasmoneyforownuse              -0.189452      Inf     0     1
het.pregcomplication                0.592656      Inf     0     1
het.MotherEduPrimary                -0.325605      Inf     0     1
het.MotherEduSecondary               0.032723      Inf     0     1
het.PartnerEduPrimary                -0.023049      Inf     0     1
het.PartnerEduSecondary               0.092577      Inf     0     1
het.PartnerEduHigh                  0.506593      Inf     0     1

LR test of lnsigma = 0: chisq 45.85 with 18 df. Prob > chisq = 3e-04
-----
```

Upon trying to run the heteroskedastic FIML estimation for prenatal care regression, we found that the gradient descent/parameter optimization algorithm failed to converge to a solution within the given number of iterations (150), hence implying that either it needs more time or a better cost function to be defined.

```

> summary(HD_hetprobit)
-----
Maximum Likelihood estimation of Heteroskedastic Binary model
Newton-Raphson maximisation, 37 iterations
Return code 8: successive function values within relative tolerance limit (reltol)
Log-Likelihood: -687.0315
39 free parameters

Estimates for the mean:
                                         Estimate Std. error z value Pr(> z)
(Intercept)                      -5.507979  38.023011 -0.1449  0.8848
Residence_urban                  6.156865  22.883942  0.2690  0.7879
motherAge                         -0.083575  0.313777 -0.2664  0.7900
ReligionMuslim                   -3.917980  14.560090 -0.2691  0.7879
ReligionChristian                -3.198065  12.505621 -0.2557  0.7982
ReligionOther                     -1.224263  32.092939 -0.0381  0.9696
LivingStdMed                      -0.107129  0.704376 -0.1521  0.8791
LivingStdHigh                     2.118348  7.912542  0.2677  0.7889
PartnerOcc_manual                 2.732324  10.550089  0.2590  0.7956
PartnerOcc_agri_household_domes  2.454446  9.572107  0.2564  0.7976
PartnerOcc_prof_cler_sales_service 3.104787 11.886136  0.2612  0.7939
allowedtogo                      0.642595  2.440601  0.2633  0.7923
hasmoneyforownuse                -0.407079  1.594172 -0.2554  0.7984
pregcomplication                 0.425732  1.706407  0.2495  0.8030
MotherEduPrimary                 2.441317  9.082984  0.2688  0.7881
MotherEduSecondary               8.501223  32.468342  0.2618  0.7935
PartnerEduPrimary                0.886717  3.360702  0.2638  0.7919
PartnerEduSecondary              1.222736  4.586203  0.2666  0.7898
PartnerEduHigh                   2.777889 10.514071  0.2642  0.7916
PC                                4.294969 15.965934  0.2690  0.7879

Estimates for lnsigma:
                                         Estimate Std. error z value Pr(> z)
het.Residence_urban                  0.1631007  0.2418564  0.6744  0.5001
het.motherAge                        0.0056706  0.0093157  0.6087  0.5427
het.ReligionMuslim                  -0.1756349  0.1219257 -1.4405  0.1497
het.ReligionChristian                0.2620197  0.6396841  0.4096  0.6821
het.ReligionOther                   2.0756746  3.7409950  0.5548  0.5790
het.LivingStdMed                   -0.1934202  0.1233569 -1.5680  0.1169
het.LivingStdHigh                  -0.3874176  0.1730806 -2.2384  0.0252 *
het.PartnerOcc_manual              -0.1292968  0.4814531 -0.2686  0.7883
het.PartnerOcc_agri_household_domes -0.1630966  0.4893118 -0.3333  0.7389
het.PartnerOcc_prof_cler_sales_service -0.2317119  0.4815038 -0.4812  0.6304
het.allowedtogo                    -0.0211007  0.0990935 -0.2129  0.8314
het.hasmoneyforownuse              -0.0756735  0.1039308 -0.7281  0.4665
het.pregcomplication               0.0660567  0.1343210  0.4918  0.6229
het.MotherEduPrimary               0.1241329  0.1355303  0.9159  0.3597
het.MotherEduSecondary             0.0438570  0.7992200  0.0549  0.9562
het.PartnerEduPrimary              0.0810085  0.1536429  0.5273  0.5980
het.PartnerEduSecondary            -0.0444436  0.1558770 -0.2851  0.7756
het.PartnerEduHigh                 -0.1277447  0.4064286 -0.3143  0.7533
het.PC                             -0.2789938  0.1949925 -1.4308  0.1525
---
Signif. codes:  0 '****' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

LR test of lnigma = 0: chi2 14.59 with 19 df. Prob > chi2 =  0.7486
-----
```

For the hospital delivery regression, the gradient descent/parameter algorithm did converge to a solution, however, it was not a good solution as almost all of the parameters were insignificant.

```

> summary(CM_hetprobit)
-----
Maximum Likelihood estimation of Heteroskedastic Binary model
Newton-Raphson maximisation, 20 iterations
Return code 8: successive function values within relative tolerance limit (reltol)
Log-Likelihood: -173.415
41 free parameters

Estimates for the mean:
                                         Estimate Std. error z value Pr(> z)
(Intercept)                      35.5040352      Inf     0     1
Residence_urban                 -0.0134284      Inf     0     1
motherAge                         0.0043998      Inf     0     1
ReligionMuslim                     0.0959795      Inf     0     1
ReligionChristian                  1.1799594      Inf     0     1
ReligionOther                      -0.3607819      Inf     0     1
LivingStdMed                       0.4870012      Inf     0     1
LivingStdHigh                      -0.1910931      Inf     0     1
PartnerOcc_manual                -14.5015445      Inf     0     1
PartnerOcc_agri_household_domes   -14.3002125      Inf     0     1
PartnerOcc_prof_cler_sales_service -14.4850352      Inf     0     1
allowedtogo                        0.0466532      Inf     0     1
hasmoneyforownuse                  0.0113836      Inf     0     1
pregcomplication                   5.6040421      Inf     0     1
MotherEduPrimary                  -0.0379434      Inf     0     1
MotherEduSecondary                 8.2432228      Inf     0     1
PartnerEduPrimary                  0.0592515      Inf     0     1
PartnerEduSecondary                 0.0599556      Inf     0     1
PartnerEduHigh                      0.2437306      Inf     0     1
PC                                -0.0311669      Inf     0     1
HD                                -0.4900659      Inf     0     1

Estimates for lnsigma:
                                         Estimate Std. error z value Pr(> z)
het.Residence_urban                -0.0142233      Inf     0     1
het.motherAge                       0.0044770      Inf     0     1
het.ReligionMuslim                  0.2232000      Inf     0     1
het.ReligionChristian                 -1.7204262      Inf     0     1
het.ReligionOther                    -0.1251462      Inf     0     1
het.LivingStdMed                     0.5742606      Inf     0     1
het.LivingStdHigh                   -1.0365715      Inf     0     1
het.PartnerOcc_manual               -0.9293199      Inf     0     1
het.PartnerOcc_agri_household_domes  -1.0438437      Inf     0     1
het.PartnerOcc_prof_cler_sales_service -0.7811381      Inf     0     1
het.allowedtogo                      0.3121671      Inf     0     1
het.hasmoneyforownuse                0.0971718      Inf     0     1
het.pregcomplication                  2.1015729      Inf     0     1
het.MotherEduPrimary                 -0.2404814      Inf     0     1
het.MotherEduSecondary                 1.5014126      Inf     0     1
het.PartnerEduPrimary                 0.0041494      Inf     0     1
het.PartnerEduSecondary                -0.0385602      Inf     0     1
het.PartnerEduHigh                      0.6870922      Inf     0     1
het.PC                                -0.1355109      Inf     0     1
het.HD                                -0.8667732      Inf     0     1

LR test of lnsigma = 0: chi2 41.82 with 20 df. Prob > chi2 = 0.0029
-----
```

For the child mortality heteroskedastic model, the function returned code 8, implying successful convergence within tolerance limits. However, we still see that this is not the case as the std errors are shown to be infinite. As in the prenatal care model, a better cost function needs to be defined to approach a solution. However, compared to the prenatal care model, this one achieved convergence to a solution within 20 iterations, further implying that the algorithm (Newton-Raphson) cannot find a satisfactory solution given its cost function.

CONCLUSION

The conclusions that we have reached from our analysis are comparable to those in the original research paper in spite of the different techniques that we have used to run our regression.

We looked into the important socio-economic and socio-demographic factors that possibly impact the demand for maternal inputs - prenatal health care and hospital delivery for the child. The results are promising and not too far removed from one's expectations.

Our results show that urban women tend to have a higher demand for maternal inputs as compared to rural women. Also the chances of seeking out prenatal care and an institutionalised child delivery increases when the woman in question is educated and comes from a more well to do family.

Our results also include the effects that the age of the woman and the birth order of the child may have on them seeking out maternal inputs.

On the other hand, child mortality generally decreases in women who receive prenatal care and opt for hospital delivery. There are other characteristics that reduce the likelihood of child mortality, such as a higher standard of living and a greater education for women.

In summary, it's evident that maternal inputs such as prenatal care and leveraging institutional support for child labour play crucial roles in significantly reducing child mortality rates. The findings of this study underscore the importance of these factors and cannot be overlooked. Therefore, it's imperative for the government to proactively formulate policies aimed at stimulating demand for maternal inputs, ultimately leading to a decline in child mortality rates.

A few policies that the government can implement to promote women's education could be to enact laws that require compulsory education for girls up to a certain age, providing scholarships and grants specifically targeted towards women and invest in infrastructure development especially in areas where access to education for girls is limited.. The government could also institutionalise laws such that families are forced to resort to the institutional child delivery mechanism rather

than relying on traditional methods, as it would go a long way in reducing child mortality.