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ANALYSIS OF UNDER-FIVE MORTALITY OF MYANMAR USING ZERO-INFLATED REGRESSION MODELS

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ABSTRACT

Despite the reduction in the global under-five child mortality rate, there has been a considerable rate in the death of many children before their fifth birthday in Myanmar. Therefore, the causes of under-five mortality need to be investigated because it is a critical issue for the development of a country like Myanmar. This study attempted to analyze under-five mortality in Myanmar with an application of the various zero-inflated regression models. A sample of 3670 mothers with children aged 0-59 months was collected from the 2015-2016 Myanmar Demographic and Health Survey (MDHS) for the data analysis. As a result, the zero-inflated Poisson regression model was the most appropriate model among a variety of zero-inflated regression models to represent the under-five mortality in Myanmar. The results revealed that mothers' education, household size, childbirth order, and type of fuel for cooking significantly affected the under-five mortality in Myanmar. Among those, childbirth order and mother's education level were the most significant effects on under-five mortality. Therefore, concerned efforts should be made to improve mother's access to education and birth control. The simulation analysis also found that the zero-inflated Poisson model appeared to be unbiased because the average value of the estimate for each parameter was close to the respective estimated coefficient from the zero-inflated Poisson model. Hence, the Myanmar government should plan the respective programs and promote the infrastructures, health care services, well-being, and survival of a new generation of Myanmar children.

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LIST OF ABBREVIATIONS

AIC	Akaike's Information Criterion
AIDS	Acquired Immune Deficiency Syndrome
AMS	ASEAN Member States
ANC	Antenatal Care
ARI	Acute Respiratory Infections
ASEAN	Association of Southeast Asia Nations
BDHS	Bangladesh Demographic Health Survey
BIC	Bayesian Information Criterion
BNHS	Bhutan National Health Survey
CBO	Community-Based Organizations
COVID	Corona Virus Disease
CPR	Contraceptive Prevalence Rate
DHS	Demographic and Health Survey
EDHS	Ethiopia Demographic Health Survey
GDP	Gross Domestic Product
GLM	Generalized Linear Model
GMM	Generalized Method of Moment
HIV	Human Immunodeficiency Virus
HNB	Hurdle Negative Binomial
HP	Hurdle Poisson
ICS	Inter-censal Survey
IDHS	Indonesia Demographic and Health Survey
IM	Infant Mortality
IMR	Infant Mortality Rate
KDHS	Kenya Demographic and Health Survey
LB	Live Birth
LRT	Likelihood Ratio Test
MDGs	Millennium Development Goals
MDHS	Myanmar Demographic and Health Survey
MICS	Multiple Indicator Cluster Survey
MLE	Maximum Likelihood Estimator

MOH	Ministry of Health
MOHS	Ministry of Health and Support
NB	Negative Binomial
NGOs	Non-Government Organizations
NHIS	National Health Interview Survey
PNC	Postnatal Care
PR	Poisson Regression
SADHS	South African Demographic Health Survey
SCs	Scheduled Castes
SDGs	Substantial Development Goals
STs	Scheduled Tribes
SNNPR	Southern National, Nationalities and People's Region
TT	Tetanus Toxics
U5M	Under 5 Mortality
U5MR	Under 5 Mortality Rate
UN	United Nations
UNICEF	United Nations International Children's Emergency Fund
WHO	World Health Organization
ZI	Zero-Inflated
ZIGP	Zero-Inflated Generalized Poisson
ZINB	Zero-Inflated Negative Binomial
ZIP	Zero-Inflated Poisson

CHAPTER I
INTRODUCTION

Children are the future generation that can be considered important to all nations. The health and well-being of a nation's youngest citizens are critical indicators of its overall social and economic development. Under-five mortality rate which represents the death of a child within the first five years of life is also important for socioeconomic, health, environmental and national development with enhanced health equity and access. Moreover, substantial progress in recent decades has been made in reducing under-five mortality worldwide, due to advances in medical science, improved access to healthcare services, and effective public health initiatives. As an indicator of a society's overall health and well-being, under-five mortality encompasses the various factors such as socio-economic, demographic, health care and environmental factors. Therefore, it is necessary to conduct a critical investigation into under-five mortality with the reason of ensuring the growth of those children in their early ages. Additionally, one of the new targets set out in Sustainable Development Goals (SDGs) is that the under-five mortality rate is needed to reduce to 25 deaths per 1000 live births in all countries by 2030. In order to meet such target, the Myanmar must explore the major influencing factors of under-five mortality.

1.1 Rationale of the Study

Under-five mortality is one of the most significant global health indicators used to measure the health status of a country or a region. It is defined as the number of deaths that occur in children under the age of five years. According to the World Health Organization (WHO), in 2019, an estimated 5.2 million children under the age of five died worldwide, mostly from preventable causes. The under-five mortality rate varies widely across countries and regions.

Globally the under-five mortality rate dropped from 93 deaths per 1000 live births in 1990 to 41 in 2016. Progress in reducing under-five mortality has been accelerated from 2000 to 2016 compared with the 1990s. The annual reduction rate in under-five mortality has increased from 1.9 % in 1990-2000 to 4.0 percent in 2000-2016 (UNIGME, 2017). Moreover, under-five mortality has decreased during the period 2010-2021 compared with the 1990s by 2.7 %.

In low-income countries, the under-five mortality rate is much higher than in high-income countries. In Sub-Saharan Africa, which is one of the low-income countries, the under-five mortality rate was 76 deaths per 1,000 live births, however, it was just 5 deaths per 1,000 live births in high-income countries (UNIGME, 2022). According to the World Health Organization (WHO), the overall under-five mortality rate in the ASEAN region declined by 57% between 1990 and 2019, from an estimated 64 deaths per 1,000 live births to 28 deaths per 1,000 live births (WHO, 2019).

The world began working toward a new global development agenda, and new targets are set out in the Sustainable Development Goals (SDGs) by 2030. Reducing the under-five mortality rate to 25 deaths per 1000 live births in all countries by 2030 is imperative in achieving SDGs (UNIGME, 2022). All countries' urgent action is needed to accelerate reductions in under-five mortality to reach the SDGs targets on ending preventable child deaths by 2030. Out of 200 countries, 133 have already met the SDGs target on under-five mortality, and 13 countries are expected to meet the target by 2030. If current trends continue, 54 countries will not meet the SDGs target for under-five mortality (UNIGME, 2022).

Myanmar is a country located in Southeast Asia, with a population of approximately 51.14 million people (Department of Population, 2020). Like many developing countries, Myanmar has struggled with high rates of under-five mortality. According to the ASEAN statistical yearbooks (2022), the under-five mortality rate in Myanmar was 43.0 in 2013, which increased to 66.5 in 2014. Therefore, the various risk factors that influence under-five mortality in Myanmar were explored in this study.

Socioeconomic factors play a significant role to reduce under-five mortality rate. Poverty, lack of access to healthcare, and inadequate nutrition are major contributors to under-five mortality. Many families in Myanmar live in poverty and struggle to provide their children with the necessary resources for survival. The lack of access to healthcare facilities, particularly in rural areas also largely influenced the under-five mortality. Additionally, malnutrition is a significant problem in Myanmar with an estimated 32% of children under the age of five being underweight.

Furthermore, environmental factors also affect under-five mortality in Myanmar. Poor sanitation, inadequate water supply, and exposure to air pollution can all lead to disease and illness in young children. Many households in Myanmar lack access to clean water, which can lead to waterborne diseases such as diarrhea, which is a leading cause of under-five mortality (WHO, 2019).

In addition, maternal health is also a critical factor in under-five mortality in Myanmar. Poor maternal health can lead to complications during pregnancy and childbirth, which can ultimately lead to the death of the child. Myanmar has made significant progress in improving maternal health in recent years, but there is still much work to be done. Moreover, infectious diseases are a leading cause of under-five mortality in Myanmar. Malaria, tuberculosis, and HIV/AIDS are all prevalent in Myanmar and reflect under-five mortality. Although the Government of Myanmar tried to combat these diseases in recent years, there is still needed to achieve significant progress. And then, education is another important factor in under-five mortality in Myanmar. Women who are educated are more likely to seek healthcare for themselves and their children, which can reduce under-five mortality. Additionally, education can improve maternal health and reduce the risk of complications during pregnancy and childbirth. Therefore, this study tried to analyze the influencing factors of under-five mortality with an application to the various zero-inflated regression models.

1.2 Objectives of the Study

The main purpose of this study is to analyze under-five mortality in Myanmar using zero-inflated regression models.

The specific objectives of this study include:

(i) to examine the socio-economic, demographic, health care, and environmental factors which influence the under-five mortality,

(ii) to identify a suitable zero-inflated model for predicting under-five mortality and

(iii) to simulate the under-five mortality in Myanmar by using the chosen zero-inflated model.

1.3 Method of Study

The secondary data including socio-economic, demographic, health care, environmental characteristics of mothers and under-five mortality data were collected from the 2015-2016 Myanmar Demographic and Health Survey (MDHS). In this study, a descriptive analysis was carried out to examine the situation of under-five mortality based on the socio-economic, demographic, health care, and environmental status of mothers. Then, the zero-inflated regression models such as the zero-inflated Poisson regression model, zero-inflated negative binomial regression model, and hurdle models (hurdle Poisson and hurdle negative binomial) were employed to identify the suitable model to predict under-five mortality in Myanmar. Additionally, the simulation analysis was conducted for making sure of the significance and validity of the zero-inflated regression model.

1.4 Scope and Limitations of the Study

This study focused on under-five mortality of ever-married women aged 15-49 years who have ever born at least one child. The child's characteristics with his or her mother, socio-economic, demographic, health care, and environmental factors were analyzed. Some variables such as underweight births, complications during birth, and diseases including pneumonia, diarrhea, malaria, sepsis, and birth asphyxia with non-disease causes of death, and drowning are excluded in this study. Those variables are related to under-five mortality but have not been collected in 2015-2016 MDHS. This study only focused on the occurrence of death with child-related health issues, the occurrence of death due to mother-related health issues was not taken into account.

1.5 Organization of the Study

This study is composed of five chapters. Chapter I is the introduction which includes five sub-headings: rationale of the study, objectives of the study, method of study, scope and limitations of the study and organization of the study. Chapter II is the literature review which consists of reviewing count data and zero-inflated data, zero-inflated regression, socio-economic, demographic, and environmental factors of under-five mortality, and zero-inflated regression models applied to under-five mortality and theoretical as well as conceptual framework of under-five mortality and its related factors. Chapter III explains the methodology applied to assessing under-five mortality in Myanmar. Chapter IV presents the results of the data analysis. Chapter V is the conclusion of the study which describes the findings and discussions, recommendations, and needs for further research.

CHAPTER II
LITERATURE REVIEW

This chapter presents the situations of under-five mortality in various countries including Myanmar, the review of literature on factors related to under-five mortality, the usage of zero-inflated regression models, and the conceptual frameworks are also presented. The framework was built to analyze the factors related to under-five mortality in Myanmar.

2.1 Under-five Mortality

Under-five mortality is defined as the occurrence of a child dying between birth and the fifth birthday. Reducing under-five mortality has been the target of public health policies and may be the common indicator of the mortality level of a country. This mortality may represent a comprehensive indication of the socioeconomic, demographic, health care, and environmental status of the communities and countries. It also reflects the development status of the country and the quality of life. Under-five mortality is commonly used for monitoring and evaluating populations, health care programs, and public health policies of a nation.

2.1.1 Global Trend of Under-five Mortality

The global trend of under-five mortality has been on a steady decline over the past few decades. This trend directed towards a positive development and reflected significant improvements in maternal and child health, access to healthcare and education, and other factors that contribute to child well-being. However, there are still significant disparities in under-five mortality rates between different regions and countries and much work remains to be done to ensure that all children have the opportunity to grow and thrive. According to WHO (2006), there are huge differences in child mortality among low- and middle-income countries and the industrial world with Sub-Saharan Africa and Southeast Asia carrying the highest burden of under-five mortality. The highest rate of child mortality was still in Sub-Saharan Africa where 1 in 9 children dies before age 5, more than 16 times the average for developed regions (1 in 152) and Southern Asia (1 in 16) in 2011 (UNICEF, 2012).

The global under-five mortality rate dropped by 53%, from 91 deaths per 1,000 live births in 1990 to 43 in 2015. The annual rate of reduction in the under-five mortality rate has increased from 1.8% in 1990–2000 to 3.9 percent in 2000–2015. Especially promising, Sub-Saharan Africa, the region with the highest under-five mortality rate in the world, has also registered an acceleration in reducing under-five mortality. Its annual rate of reduction increased from 1.6% in the 1990s to 4.1% in 2000–2015. Of the 49 Sub-Saharan African countries, all but 5 had a higher annual rate of reduction in the 2000–2015 period as compared with the 1990s.

Also, 21 Sub-Saharan African countries have at least tripled their annual rates of reduction from the 1990s or reversed an increasing mortality trend in 2000– 2015 compared with the 1990s: Angola, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Congo, Côte d'Ivoire, Gabon, Kenya, Lesotho, Mauritania, Namibia, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, Swaziland, Zambia and Zimbabwe (UNIGME, 2015).

At a global rate of 17 deaths per 1,000 live births and approximately 6,700 neonatal deaths every day in 2019, the neonatal period (the first 28 days of life) is the most vulnerable time for the death of children under age 5. In comparison, the probability of death after the first month and before reaching age 1 was estimated at 11 deaths per 1,000, and the probability of dying after reaching age 1 and before reaching age 5 was estimated at 10 deaths per 1,000 in 2019. Within the neonatal period, the youngest lives are at even greater risk (UNIGME, 2020).

In 2019, the coronavirus pandemic reached every region of the world, with millions of infections globally and untold disruptions to nearly every aspect of daily life. While the extent and severity of the mortality impact of COVID-19 on children and youth were still unknown, the potential of a mortality crisis in 2020 threatened years of remarkable improvement in child and adolescent survival from 1990 to 2019. Globally, 70% of deaths among children and youth under 25 years of age occurred and among those children under 5 years of age represented for 5.2 million deaths. Among under-five mortality, 2.4 million (47%) occurred in the first month of life, 1.5 million (28%) at age 1–11 months, and 1.3 million (25%) at age 1−4 years in 2019 (WHO, 2020).

Achieving the SDGs target on under-five mortality on time would mean averting 11 million under-five deaths compared with the current situation. If current trends continue, roughly 52 million children under 5 years of age will die between 2019 - 2030, half of them will be newborns. Urgent efforts are needed in the countries that are falling behind, many of which are located in Sub-Saharan Africa and South Asia. Accelerating progress to achieve the SDGs target on neonatal mortality by 2030 in some 60 countries that are falling behind would save the lives of 5 million newborns from 2019 to 2030. Based on current trends, 26 million newborns would die between 2019 and 2030—about 80 percent of these deaths would occur in Sub-Saharan Africa and South Asia. According to UNICEF (2020), the problem of child mortality requires urgent attention from the health sector. If the conditions remain as such, approximately 60 million innocent children will die until 2030.

As the global under-five mortality rate declines, deaths are increasingly concentrated in the neonatal period. As a result of the different paces of decline among neonates and children aged 1-59 months, the share of neonatal deaths among all under-five deaths increased from 40% in 1990 to 47% in 2019 as can be seen in Figure (2.1) (UNIGME, 2020).

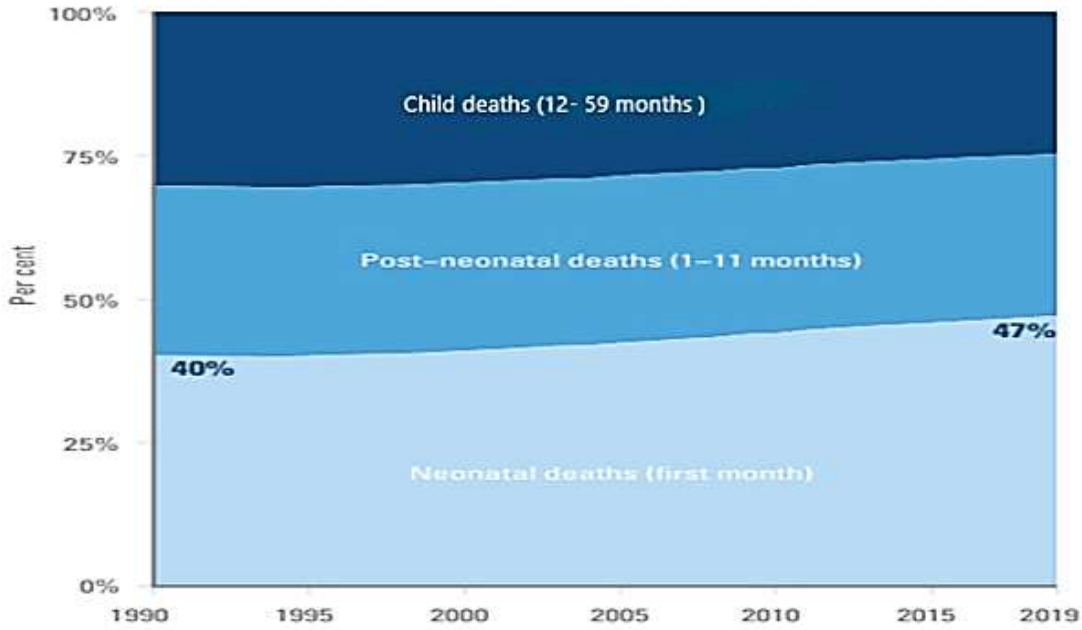

Figure (2.1) Distribution of Global Under-five Deaths by Age, during the Period from 1990-2019

Source: Level and Trend in Child Mortality, UNIGME Report (2020)

Lower under-five mortality is associated with a larger share of under-five deaths occurring in the neonatal period. The proportion of neonatal deaths accounted for 37% out of a total of under-five deaths is still relatively low in sub-Saharan Africa which remains the region with the highest under-five mortality rate. Both Europe and Northern America have the lowest under-five mortality rates among all the SDGs regions representing by 57% of all under-five deaths occurred during the neonatal period (UNIGME, 2020).

Almost everywhere in the world, a child born today has a better chance of surviving to age five than that in 1990. The under-five mortality rate was reduced from 93 deaths per 1,000 live births in 1990 to 38 deaths in 2019. One in every 11 children died before reaching their fifth birthday in 1990. By 2019, that number was reduced to 1 in 27. Nearly every major SDG regions has seen the under-five mortality rate decline by at least half since 1990. Moreover, 85 countries, including 34 low and lower-middle-income countries, cut their under-five mortality rate by at least two-thirds over the same period (UNIGME, 2020).

The global burden of under-five deaths dropped to 5.2 million in 2019 from 12.5 million in 1990 and 9.7 million in 2000. Despite this global progress, the geographic disparity in child survival persists. Children in sub-Saharan Africa continue to face the steepest odds of survival in the world, the under-five mortality rate is estimated at 76 deaths per 1,000 live births in 2019. That is equivalent to 1 child in 13 deaths before reaching age 5, which is 20 times higher than the rate of 1 in 264 in the region of Australia and New Zealand and 20 years behind the world average, which achieved a 1 in 13 rates by 1999. At the country level, the under-five mortality rates in 2019 ranged from 2 deaths per 1,000 live births to 117, and the risk of death before the fifth birthday for a child born in the highest-mortality country was about 70 times higher than in the lowest-mortality country. Sub-Saharan Africa is the region where all five countries with mortality rates above 100 deaths per 1,000 live births are located; and where 31 of the 37 'high-mortality' countries (with under-five mortality rates above 50 deaths per 1,000 live births) are found (UNIGME, 2020).

Children continue to face widely differing chances of survival based on where they are born. Globally, the under-five mortality fell to 38 deaths per 1,000 live births in 2021. This decline has been driven by various factors, including improvements in healthcare access, increased use of preventive interventions such as vaccinations, and increased education and awareness around child health and nutrition. By contrast, children born in sub-Saharan Africa are subject to the highest risk of childhood death in the world with a 2021 U5MR of 74 deaths per 1,000 live births, 15 times higher than the risk for children in Europe and Northern America and 19 times higher than in the region of Australia and New Zealand. Children born in poorer countries are more likely to die before reaching age 5. Children born in low-income countries, where the 2021 U5MR was 67 deaths per 1,000 live births, were 14 times more likely to die before reaching age 5 than children born in high-income countries, where the 2021 U5MR was just 5 deaths per 1,000 live births. At the country level, U5MRs in 2021 ranged from 2 deaths per 1,000 live births to 115 deaths per 1,000 live births, 67 times higher than in the lowest-mortality country. Within countries, there are also significant disparities in under-five mortality rates based on factors such as wealth, education, and geographic location (UNIGME, 2022).

Under-five mortality is alarming in developing countries. Around 29,000 under-five deaths happen 21 each minute, mostly from preventable causes. Around 70% of deaths are caused by diarrhea, preterm delivery pneumonia, neonatal infection, and lack of oxygen at birth. Poor sanitation, lack of safe water, and malnutrition are indirect risk factors contributing to half of the under-five deaths (UNICEF, 2016). Poor children are more prone to diseases as compared to their better-off peers (Victora et al., 2003). However, very little is known on the risk factors associated with all causes of mortality specifically in South Asian countries, and then to explore whether the associated risk factors are the same or different across the countries of South Asia.

Houwelling and Kunst (2009) explained about individual and community-level effects of under-five mortality in the Sub-Saharan area, which has the highest rate of mortality in the world. It has been found that with a 1% increase proportion of fully immunized children, the mortality rate decreased to 17.79% in half of the countries. Moreover, this study also found that mothers with secondary education made decrease in the rate of mortality.

Alhassan, Tuahiru and Abdulai (2016) studied the under-five mortality in the West Mamprusi district of Ghana, by using logistic regression analysis exploring the factors associated with under-five mortality. The result found that male deaths occurred more than female deaths with 52% for three years (2010-2012) while the majority (32.24%) of the deaths were caused by malaria. The study also found that among all the factors associated with under-five mortality and only one variable (Prematurity) showed a significant impact.

Islam, Piyasa and Saikia (2021) explored the determinants of under-five child mortality with the evidence from Bangladesh multiple indicator cluster survey (MICS) 2019. The main aim of the study was to find out the socioeconomic and demographic determinants of under-five mortality in Bangladesh. The study showed that mothers' education, higher birth order, size of child at birth, and taking antenatal care had a significant effect on child mortality using the Cox proportional hazard model.

Ayele et al. (2022) expressed the determinants of under-five mortality in Ethiopia using the recent 2019 Ethiopian Demographic and Health Survey data through nested shared frailty survival analysis. This study aimed to investigate time to death and its associated factors among under-five children in Ethiopia. Semi-parametric nested shared frailty survival analysis was employed to identify factors affecting under-five mortality. Adjusted hazard ratio with 95% Confidence interval was reported and log-likelihood was used for model comparison. The results found that female and under-five children living in urban areas had a higher probability of survival than their counterparts. Additionally, also found that multiple births, breastfeeding within one hour after birth, preceding birth interval 18–23 months, under-five children younger than 18 months, and teenage pregnancy were statistically significant factors for under-five mortality.

2.1.2 Under-five Mortality in ASEAN Region

The Association of Southeast Asian Nations (ASEAN) region has made significant progress in reducing under-five mortality rates over the past few decades. However, there are still significant disparities in under-five mortality between different countries in the region, and much work remains to be done to ensure that all children have access to the resources and support they need to survive and thrive in their early years of life.

On average, the ASEAN Member States (AMS) have achieved a large reduction in child mortality and could meet the MDGs target to reduce the rate by 2/3. The target was quite ambitious in its effort to not just reduce the rate by half but by 2/3. There was a very large variation in the child mortality rate across ASEAN countries, from one to 56 of 1000 children born alive in 1990. While the rates have, in fact, been reduced over the years, the variation is still very high, from one to 29 out of 1000 children who have passed away before they reached their fourth birthday in 2015.

Even among ASEAN regions, Cambodia, Laos, Myanmar, and Vietnam had the highest under-five mortality rate and child mortality in 1990 but they have managed to significantly reduce the rate over the 25 years. Myanmar managed to cut the rate by two-thirds in 2010, but it could not maintain the low rate in 2015. The infant mortality rate and under-five mortality rate in Thailand were 3 and 4 per 1000 live births. In Myanmar, there were 33 and 43 per 1000 live births, and a child mortality rate of 10 per 1000 live births at that time (Secretariat, 2017).

Table (2.1) provided under-five mortality rates for various countries in the ASEAN region from 2005 to 2021.

Table (2.1) Under-Five Mortality Rate in the ASEAN Member States (2005-2021)

Country	Year																
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
Brunei Darussalam	9.5	9.2	9.5	9.5	8.2	7.2	10.0	10.3	9.7	8.7	10.0	10.4	11.5	10.6	9.9	9.2	-
Cambodia	83.0	-	-	-	-	54.0	43.0	40.0	45.2	35.0	39.6	36.9	34.1	31.4	28.0	25.9	-
Indonesia	45.0	-	-	-	-	42.0	32.0	40.0	-	-	26.3	26.4	32.0	-	-	-	-
Lao PDR	97.6	93.0	88.6	84.4	80.4	76.4	79.4	68.4	62.7	58.7	58.7	73.8	71.7	69.4	67.2	65.1	-
Malaysia	8.5	7.9	7.9	8.0	8.5	8.5	-	7.6	7.9	8.3	8.4	8.1	8.4	8.8	7.7	6.9	7.4
Myanmar	70.8	66.2	64.3	40.7	36.5	34.9	45.2	44.7	43.0	66.5	65.3	64.0	62.6	60.2	59.7	-	-
Philippines	34.0	32.0	-	-	-	-	25.0	-	-	-	31.0	27.1	27.0	-	-	-	-
Singapore	2.9	2.9	2.9	2.7	2.8	2.8	2.9	2.7	2.6	2.5	2.6	2.7	2.8	2.6	2.3	2.1	2.1
Thailand	10.8	10.4	10.0	9.9	9.8	9.8	9.0	9.0	8.7	8.8	8.6	8.8	8.2	8.4	7.9	7.0	-
Viet Nam	26.8	24.1	24.1	22.5	24.1	24.1	23.3	23.2	23.1	22.4	22.1	21.8	21.5	21.4	21.0	22.3	20.5

Source: ASEAN Statistical Yearbooks (2015, 2017, 2022)

According to Table (2.1), Brunei Darussalam has shown fluctuations in its under-five mortality rate over the years, ranging from 7.2 to 11.5 deaths per 1,000 live births. The data for 2021 is missing, making it essential to monitor trends in child mortality in the coming years. Cambodia has made significant progress in reducing under-five mortality rates, with the rate dropping from 83.0 deaths per 1,000 live births in 2005 to 25.9 deaths in 2020. The data for some years is missing, but the overall trend indicates improvements in child healthcare. Despite these improvements, Cambodia must continue its efforts to achieve the SDGs by 2030.

Indonesia's data is incomplete, with many years missing. However, the available data shows fluctuations, with the under-five mortality rate decreasing to 26.3 deaths per 1,000 live births in 2015. Lao PDR has experienced a consistent decline in under-five mortality rates, dropping from 97.6 deaths per 1,000 live births in 2005 to 65.1 deaths in 2020. This demonstrates positive progress in child survival, although the rate remains relatively high.

Malaysia has maintained a relatively low under-five mortality rate throughout the years, ranging from 6.9 to 8.8 deaths per 1,000 live births, showing a stable healthcare system for children. Myanmar has made significant strides in reducing child mortality, cutting the rate from 70.8 deaths per 1,000 live births in 2005 to 59.7 deaths in 2020. The data for 2021 is missing, requiring ongoing monitoring. The Philippines' data is incomplete, but there's evidence of fluctuations in the under-five mortality rate, with rates as low as 25.0 deaths per 1,000 live births in some years.

Singapore consistently maintains one of the lowest under-five mortality rates in the region, with rates ranging from 2.1 to 2.9 deaths per 1,000 live births during the period. Thailand has seen a consistent decline in child mortality, with rates dropping from 10.8 to 7.0 deaths per 1,000 live births in 2020. The data for 2021 is missing. Vietnam has made remarkable progress in reducing under-five mortality rates, with rates declining from 26.8 to 20.5 deaths per 1,000 live births in 2021. This consistent improvement reflects advancements in child healthcare.

Overall, the data highlights varying trends in under-five mortality rates across ASEAN countries, with some nations making substantial progress, while others continue to face challenges in ensuring the health and survival of children. The importance of ongoing efforts to meet SDGs for child health is evident in these disparities.

ASEAN statistical report (2021) on under-five mortality rate among ASEAN countries against SDGs showed that Myanmar is still one of the countries which did not achieve goals in 2020 as shown in Table (2.1) (ASEAN Secretariat, 2021). According to the ASEAN statistics report (2022), Brunei Darussalam, Malaysia, Singapore, and Viet Nam have successfully maintained the under-five mortality rate, but other countries are not available at the time of publication (Secretariat, 2017).

Myanmar's target numbers have exhibited fluctuations over the years, with some notable changes in the data. In the 2005, the target was relatively high at 70.8, but it decreased substantially by 2010 to only 34.9. However, in the subsequent years, there has been a gradual increase in Myanmar's target numbers, with a notable increased to 65 in 2015. This trend continued through 2018 and 2019, reaching 60 and 61, respectively. There is missing data for Myanmar in 2020 and 2021, making it challenging to assess the most recent developments accurately. To understand the reasons behind these fluctuations and the missing data, further context and information about the specific target being measured would be necessary. It is possible that changes in government policies, economic conditions, or international factors have contributed to these variations in Myanmar's target numbers.

To further reduce under-five mortality rates in the ASEAN region, efforts will need to focus on improving maternal and child health, increasing access to healthcare and education, and addressing the social determinants of health that contribute to disparities in health outcomes. This will require a coordinated effort between governments, healthcare providers, community organizations, and other stakeholders, as well as increased investment in healthcare infrastructure and workforce development (Secretariat, 2017).

By continuing to invest in maternal and child health, access to healthcare and education, and other factors that contribute to child well-being, it can continue to make progress toward a world where all children have the opportunity to grow and thrive (Secretariat, 2017).

2.1.3 Under-Five Mortality in Myanmar

Myanmar has abundant natural resources including land, water, forest, coal, mineral, and marine resources, and natural gas and petroleum. Great diversity exists between the regions due to the rugged terrain in the hilly north which makes communication extremely difficult. In the southern plains and swampy marshlands, there are numerous rivers and tributaries of these rivers that crisscross the land in many places, Mountain ranges of Myanmar create a different climatic condition, rain forest that makes regular rainfall for the rice farmers and acts as a natural barrier that protects the mainland from typhoons and hurricanes (MOH, 2014).

According to the 2019 Inter-censal Survey (ICS), the urban population constituted 28.8 percent (14740,228) of the total population. Yangon Region had the highest proportion (69.1%) of people living in urban areas followed by Mandalay Region and Kachin State (32.1%) each. The largest proportion of people living in rural areas was observed in Magway Region (86.3%) followed by Ayeyarwady Region (85.7%), Rakhine State, and Sagaing Region (83.3%) each (Department of Population, 2020)

In the 2019 ICS, data on births and deaths of children were collected from ever-married women aged 10 years and over. These were used to estimate fertility levels, trends, and differentials according to selected background characteristics. This was also used to estimate crude death rate, early age mortality, and life expectancy at birth. Table (2.2) shows the early-age, infant, child, and under-five mortality rates based on the 2019 ICS. The most recent estimate of under-five mortality twelve months before 2019 was 37.7 deaths per 1,000 live births: infant mortality at 30.9 and child mortality at 7.1 (Department of Population, 2020).

Myanmar has made progress in reducing under-five mortality rates over the past few decades, but the country still faces significant challenges in ensuring that all children have access to the resources and support they need to survive and thrive in their early years of life. Investing in the health and wellbeing of the children in Myanmar can be seen as an investment in the future development of Myanmar. Children under five years of age constituted about 11.67% of the total population of Myanmar, according to a report from the Central Statistical Organization in 2008.

Under-five mortality rate and the child mortality rate have declined from 130 and 32 per 1000 live births in 1990 to 35 and 8 in 2010. In 2015, under-five mortality and the child mortality rate were 52 and 13 deaths per 1000 live births. The child mortality rate gradually decreased from 32 deaths per 1000 live births in 1990 to 13 deaths per 1000 live births in 2015. According to the WHO, the under-five mortality rate in Myanmar declined from an estimated 112 deaths per 1,000 live births in 1990 to 44 deaths per 1,000 live births in 2019, that is, a 61% decrease. However, Myanmar still has one of the highest under-five mortality rates in the Southeast Asia region.

Early-age mortality rate and life expectancy at birth by sex, urban and rural areas of Myanmar, 2019 were described in Table (2.2). Life expectancy at birth shows the overall mortality level of a population. It summarizes the mortality pattern that prevails across all age groups – children and adolescents, adults, and the elderly. As shown in Table (2.2), the life expectancy at birth was 69.4 years for both sexes. It is worth noting that life expectancy at birth of females (73.3 years) is much higher than that of males (66.5 years). The life expectancy at birth for people in rural areas was 68.5 years compared to 71.9 years for people in urban areas (Department of Population, 2020).

Table (2.2) Early-age Mortality Rates and Life Expectancy at Birth by Sex, Urban and Rural Areas of Myanmar, 2019

Area and Sex	**Early-age mortality rate**			**Life expectancy at birth**
	Infant (0-11) months	**Child (12-59) months**	**Under-five (0-59) months**	
UNION	**30.9**	**7.0**	**37.7**	**69.4**
Urban	22.3	4.1	26.3	71.9
Rural	34.1	8.2	42.1	68.5
Male	39.4	9.1	48.2	66.5
Female	21.1	4.4	25.4	73.3

Source: Inter-censal Survey the Union Report, Department of Population, 2019

About 63% of the population aged 15 years and over were in the labour force. The proportions of males in the labour force were much higher than that of females for all age groups. The rates for both men and women were almost linear/flat from ages 25 to 49 years and started to decline after age 49. The rates fell rapidly after the age of 60 years for both men and women. The life expectancy at birth shows an increasing trend from 64.7 years in 2014 to 67 years in 2020 for both sexes. (Department of Population, 2020).

In general, females live longer than males with a life expectancy of 71.6 years and 62.6 years respectively in 2020. A closer look at urban and rural revealed that males lived in urban area have lower life expectancy at 62.2 years than males lived in urban area have lower life expectancy at 62.2 years than males in rural area at

63.1years, and the reverse is true for female population with the values at 73 years for urban and 71.2 years for rural residents in 2020 (MOHS, 2020).As the country is striving to attain its health objectives, positive trends in various health indicators are observed including life expectancy at birth.

Life expectancy at birth by States and Regions was displayed in Figure (2.2).

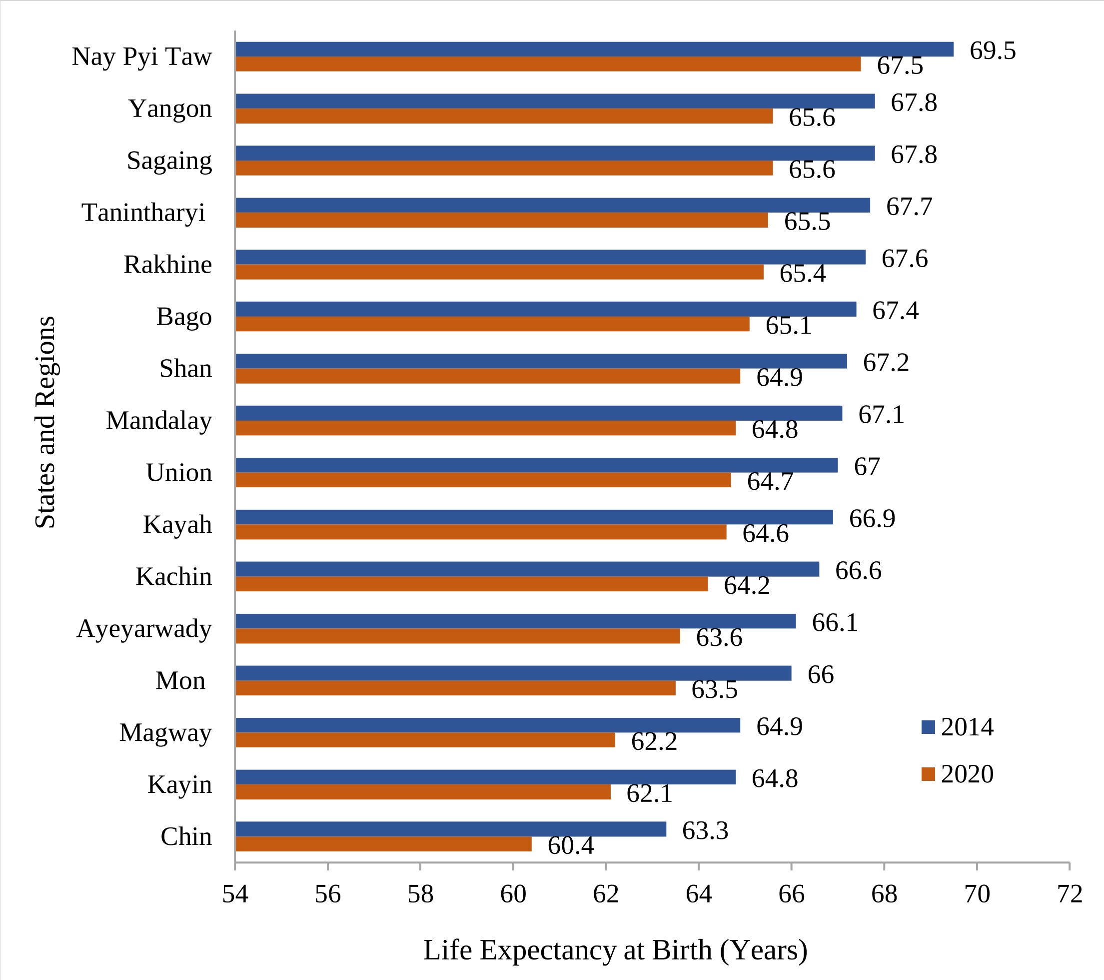

Figure (2.2) Life Expectancy at Birth by State and Region, 2014 & 2020

Source: Myanmar Health Statistics (2020)

There were several factors which contribute to the high under-five mortality rate in Myanmar. At sub-national level, life expectancy is observed at every state and region from 2014 to 2020. Among states and regions, the lowest life expectancy was seen in Chin state at 60.4 years in 2014 which increases to 63.3 years in 2020. The highest life expectancy was observed in Nay Pyi Taw territory at 67.5 years in 2014 and 69.5 years in 2020 (MOHS, 2020).

Limited access to healthcare, particularly in rural areas, is a significant barrier to improving child health outcomes. In addition, poverty, malnutrition, and inadequate water and sanitation infrastructure also contribute to the high under-five mortality rate. The leading cause of death among children under-five in Myanmar are pneumonia, diarrhea and neonatal conditions such as addressed through interventions such as improved access to healthcare, vaccinations, and promotion of good hygiene practices.

Despite these challenges, there have been positive developments in Myanmar's efforts to reduce under-five mortality rates. The government has prioritized maternal and child health, and there have been significant improvements in access to healthcare and immunization coverage. The percentage of children receiving the third dose of diphtheria-tetanus-pertussis (DTP3) vaccine increased from 45% in 2010 to 78% in 2019.

Efforts to reduce under-five mortality rate in Myanmar will need to focus on improving access to healthcare and addressing the social determinants of health that contribute to disparities in health outcomes. This will require a coordinated effort between the government, healthcare providers, community organizations, and other stakeholders, as well as increased investment in healthcare infrastructure and workforce development.

Myanmar has made significant strides in decreasing under-five mortality rates in recent decades, yet there is still substantial work ahead to guarantee that every child has access to the essential resources and assistance required for their well-being and survival during their formative years. Addressing the social determinants of health and improving access to healthcare will be critical in reducing under-five mortality rates in Myanmar. By continuing to invest in maternal and child health, access to healthcare, and other factors that contribute to child well-being, Myanmar can continue to make progress towards a world where all children have the opportunity to grow and thrive.

2.2 Overview of Myanmar's Healthcare Status

Myanmar's healthcare status evolves changing political and administrative status and the roles played by the key providers are also changing although the Ministry of Health remains the major provider of comprehensive health care. It has a pluralistic mix of the public and private systems both in the financing and provision. Health care is organized and provided by public and private providers. In implementing the objective of uplifting the health status of the entire nation, the

Ministry of Health is taking the responsibility of providing comprehensive health care services covering activities for promoting health, preventing diseases, providing effective treatment, and rehabilitation to raise the health status of the population (MOH, 2014).

According to the MOH (2014), the Department of Health, one of seven departments under the Ministry of Health plays a major role in providing comprehensive health care throughout the country including remote and hard-to-reach border areas. Some ministries are also providing health care for their employees and their families. They include Ministries of Defense, Railways, Mines, Industry, Energy, Home, and Transport. Ministry of Labour has set up three general hospitals, two in Yangon and the other in Mandalay to render services to those entitled under the social security scheme. Ministry of Industry is running a Myanmar Pharmaceutical Factory and producing medicines and therapeutic agents to meet the domestic needs. The private, for profit, sector is mainly providing ambulatory care though some providing institutional care has developed in Nay Pyi Taw, Yangon, Mandalay and some large cities in recent years. Funding and provision of care is fragmented. They are regulated in conformity with the provisions of the law relating to Private Health Care Services (MOH, 2014).

General Practitioners' Section of the Myanmar Medical Association with its branches in townships provides these practitioners the opportunities to update and exchange their knowledge and experiences by holding seminars, talks and symposia on currently emerging issues and updated diagnostic and therapeutic measures. The Medical Association and its branches also provide a link between them and their counterparts in the public sector so that private practitioners can also participate in public health care activities. The private, non-profit, run by Community-Based Organizations (CBOs) and Religious based society also provide ambulatory care though some providing institutional care and social health protection has developed in large cities and some townships. One unique and important feature of Myanmar's health system is the existence of traditional medicine along with allopathic medicine (MOH, 2014).

Traditional medicine has been in existence since time immemorial and except for its waning period during colonial administration when allopathic medical practices had been introduced and flourishing it is well accepted and utilized by the people throughout history. With the encouragement of the State scientific ways of assessing the efficacy of therapeutic agents, nurturing of famous and rare medicinal plants, exploring, sustaining and propagation of treatises and practices can be accomplished. There are a total of 14 traditional hospitals run by the State in the country. Traditional medical practitioners have been trained at an Institute of Traditional Medicine and with the establishment of a new University of Traditional Medicine conferring a bachelor's degree more competent practitioners can now be trained and utilized. As in the allopathic medicine there are quite a number of private traditional practitioners, and they are licensed and regulated in accordance with the provisions of related laws (MOH, 2014).

In line with the National Health Policy, NGOs such as Myanmar Maternal and Child Welfare Association, and Myanmar Red Cross Society are also taking some share of service provision and their roles are also becoming important as the need for collaboration in health becomes more prominent. Recognizing the growing importance of the need to involve all relevant sectors at all administrative levels and to mobilize the community more effectively in health activities health committees had been established in various administrative levels down to the wards and village tracts (MOH, 2014).

The Ministry of Health and Sport (MOH, 2014) is the main provider of providing preventive, promotive, curative, and rehabilitative services to the entire population. There are seven departments under the ministry of health and sports. Both public and private sectors act as primary healthcare service providers in both rural and urban areas (MOH, 2014).

The national population growth is steady at around 0.88% annual growth from 2014 to 2020 with a higher rate in an urban area (1.3%) than rural area (0.7%). At the sub-national level, Mon state and Magway Region are experiencing negative growth while most states and regions have a slight decline in growth rate from 2014 to 2020. The exceptions are with Yangon region where the growth rate remains constant, and the Ayeyarwady region where the growth rate remains slightly positive growth in 2014 to slightly negative growth in 2020 (MOHS, 2020).

According to the Myanmar Health Statistics (2020), the number of diarrhoea cases among under-five children who sought care from primary health facilities ranged from 3000 to over 28000 cases across states and regions. The highest caseload was seen in Sagaing Region and Rakhine State whereas the lowest caseload was reported from Nay Pyi Taw Territory and Shan (East) State. Among the diarrhoea cases, 93% received oral rehydration therapy with zinc sulphate, and the treatment coverage ranged from 82% to 99% across states and regions.

In terms of morbidity rate, Chin, Kayah and Kachin States had more than 100 cases per 1000 under-five populations. The mortality rate was the highest in Chin, Shan (North) and Shan (South) States with over 100 deaths per 100,000 cases whereas Yangon Region and Shan (East) State did not report any deaths from diarrhoea among under-five children in 2019 (MOHS, 2020).

In addition, the number of pneumonia cases pursued health services from primary health facilities range from just below 1,000 to nearly 20,000 across states and regions in 2019. The case load was the lowest in Nay Pyi Taw Territory and Kayah State whereas it is the highest in Sagaing region and Rakhine State. In terms of morbidity rate, Chin, Shan (East) and Rakhine State had more than 60 cases per 1,000 under-five population whereas Nay Pyi Taw Territory and Mon State has less than 15 cases per 1,000 population. On average, 93% of pneumonia cases received antibiotic treatment and the treatment coverage ranged from 79% to 100 percent in states and regions (MOHS, 2020).

Furthermore, the findings from large scale sequential studies showed slight declining trends of stunting, underweight and wasting among under-five children from 2010 to 2018, however the under nutrition remains one of the public health problems for under-five children in Myanmar. In 2018, one in four of the under-five children was stunted and one in five was underweight. Children living in Chin State and Ayeyarwady Region have the higher probability of being stunted compared with those living in other states and regions.

According to MOH (2014), the general state of health care in Myanmar is poor. The government spends anywhere from 0.5% to 3% of the country's GDP on health care, consistently ranking among the lowest in the world. Although health care is nominally free, in reality, patients have to pay for medicine and treatment, even in public clinics and hospitals. Public hospitals lack many of the basic facilities and equipment (MOH, 2014).

The total health expenditure reveals that the total health expenditure increased from 3,048 to 4,814 billion kyats from the 2014 to 2018. The proportion of current health expenditure increased from 89.1% to 94.4% of total health expenditure during the same period. The current health expenditure per capita was estimated at 51,153 kyats for 2014 and at 85,231 kyats for 2018 in Myanmar. The per capita government current health expenditure was estimated at 155 kyats in 2000 which grew to 12,147 kyats in 2018. The Gross Domestic Product per capita in current prices increased from 1.26 to 1.8 million kyats through the year 2014 to 2018. Total current health expenditure as percentage of gross domestic product was ranging around 4.1 to 4.8% during the period of 2014 to 2018 along with the increasing amount of both GDP and total current health expenditure (MOHS, 2020).

2.3 Socio-Economic Factors Related to Under-Five Mortality

Mosley and Chen (1984) explained the under-five mortality in developing countries based on the results of socio-economic variables such as the education level of the mother, place of residence, region, economic status of the household, employment status of the mother, and religion. Age of mother at first birth is the demographic variable considered, and source of water supply and availability of toilet facility are considered among health and environmental variables. Mosley and Chen pointed out that the educational level of the father usually correlates strongly with occupation and therefore with household income. In many cases, the correlation between the health effect and the educational level of the father or other non-childbearing economically productive adult members in a household large occurs because of operations on the proximate determinants through the income effect.

Hobcraft, McDonald and Rutstein (1984) described the association of a mother's education and child survival. Furthermore, this study found that there was no threshold level of maternal education that needed to be reached before advantages in child survival began to accrue; even a small amount of education was usually associated with improved chances of child survival. However, some studies have shown that the association between mother's education and child survival were weaker in Sub-Saharan Africa than in Asia or particularly Latin America, where socioeconomic differentials were generally higher. However, Hobcraft (1993) attempted to explain this association. This study suggested that perhaps health infrastructures are weaker in Sub-Saharan Africa, thereby inhibiting the ability of more educated mothers to take advantage of their human capital in the health environment. Different researchers suggest pathways whereby a mother's education might enhance child survival.

Short et al. (2002) explored that work compatibility and work intensity reduce women's involvement in childcare in China. However, this study also pointed out that if women with intensive work demands provide less child – care, this does not necessarily hinder children's physical and psychological development. This is because in China, relatives or other members of the household assist in childcare. Alternative child caregivers such as grandmother can reduce a mother's burden greatly.

Machado and Hill (2005) showed that having a mother who lives in the highest developed community reduced the odds of neonatal deaths. The study concluded that community infrastructure may improve hygienic practices. Furthermore, interactions between friends and neighbours in the community may lead to changes in behavior regarding infant care, and in this case, better-off community may benefit from the overall level of community education.

Uddin, Hossain and Ullah (2009) attempted to examine the predictors of child mortality and identify the factors affecting child mortality and suggest viable strategies to increase health services and reduce child mortality in Bangladesh. In this study, cross-tabulation and multiple logistic techniques have been used to estimate the predictors of child mortality. The result showed that parents' education is the vital factor associated with child mortality risk but in logistic regression analysis, only the father's education has been found significant to reducing child mortality. The result also showed that the occupation of the father has a significant characteristic in cross-tabulation and multiple logistic analyzes, the mother's standard of living index, breastfeeding status, and birth order has a substantial impact on child mortality. Moreover, the finding also shows that in both analyzes maternal health care variables such as the timing of the first antenatal check and tetanus toxic (TT) during pregnancy has a momentous effect on child mortality.

Tibebu (2011) studied from the 2005 Ethiopia Demographic Health Survey (EDHS) risk factors and regional differentials in under-five mortality in Ethiopia by using the multilevel count model. This research found that the mother's education level, employment status of the mother, and economic status of the mother were found to be statistically significant with under-five mortality. These results also found that under-five child mortality differentials per mother among regions are significant.

Bereka, Habtewold and Nebi (2017) used data from 2000, 2005 and 2011 EDHS to identify and analyze socioeconomic, demographic, and environmental factors that may have a significant influence on under-five mortality in Ethiopia Somali regional state, astern Ethiopia by using Cox regression model. This study found that family size, preceding birth interval, birth order, type of birth, breast feeding status, source of drinking water, mother age at first birth, sex of a child (1996-2000), (2001-2005) and (2006-2011) respectively. This study suggested that family size, preceding birth interval, birth order, breastfeeding status and source of drinking water were significant.

Ko Ko et al. (2017) studied an ecological analysis of community-level socioeconomic factors of infant and under-five mortality by using the 2014 Myanmar Population and Housing Census data at the townships level. In this study, simple linear regression analysis and path analysis were applied to identify the effects of socio-economic determinants. The study showed that community providing safe water and sanitation supplies and electricity supplies in urban have more impact than promoting female education and employment.

Abate (2018) conducted the study to identify the main factors that affect under-five age mortality based on the major determinants of under-five mortality in Adigrat town. The data collection was done through primary data sources that were obtained from the respondents by interviewing women aged between 15-49 years and the town administrative office. A simple random sampling method who used for sample selection in this study. The result by the Poison regression model confirmed that there is an association between under-five mortality and father's education, family income, mother's age at first birth of the child, the health status of mother, breastfeeding status, and child vaccination adaptation. It also indicates that children born from working mothers have a higher risk of mortality than non-working mothers.

Bora, Raushan, and Lutz (2018) investigated the role of education in explaining the disparity in infant and under-five mortality rates between SCs/STs and the non-SC/ST population in India, with a particular emphasis on the impact of maternal education. The study utilized data from the National Family Health Survey (NFHS) for the years 1992–93, 1998–99, and 2005–06. Binary logistic regression analysis was employed to assess the association between infant mortality (IM) and under-five mortality (U5M) and factors such as maternal education and selected covariates. The study revealed that the infant mortality rate (IMR) among children born to illiterate mothers was approximately three times higher than that of children born to mothers with higher education across all caste groups. Similarly, the under-five mortality rate (U5MR) was five times higher among the ST population and three times higher among the SC population during the 14-year observation period (1992–2006). Moreover, the proportion of secondary and higher educated SC and ST mothers were comparatively lower than that among non-SC/ST mothers. The results of the regression analysis demonstrated that maternal education had a statistically significant impact on reducing IM and U5M. Additionally, several socio-economic covariates were identified as being associated with IM and U5M, including father's education, mother's age at first birth, mother's employment status, household wealth, exposure to media, and the socio-economic empowerment of mothers.

Vanthy et al. (2019) observed the determinants of children under-five mortality. This study aims to define persistent and emerging factors associated with under-five mortality in Cambodia using the Demographic and Health Surveys 2010 and 2014. The retrospective cohort life table of child births for the five years preceding the surveys, and multivariate Weibull regression. Longer childbirth interval (> 2 years), maternal antenatal care visit at last birth, and children being fully vaccinated were associated with lower under-five mortality but, older maternal age, and higher education level of the mother were associated with higher under-five mortality. The study concludes that Cambodia should continue the current child health interventions and suggests conducting a study on the association between mothers' education and under-five mortality.

Geremew et al. (2020) investigated factors influencing under-five mortality in Ethiopia using data from the EDHS 2016, including 11,023 weighted under-five children. They employed descriptive statistics and a multilevel negative binomial regression model in their analysis. The study revealed that the educational status of mothers, delivering at healthcare institutions, longer preceding birth intervals (24–35 and ≥48 months), and residing in Addis Ababa were associated with a reduced incidence of under-five mortality. Conversely, being a female household head, the mother's age at her first childbirth, employment status, multiple births, and childhood diarrhea were linked to a higher incidence of under-five mortality.

Woldeamanuel and Aga (2021) stated that count models analysis of factors associated with under-five mortality in Ethiopia using a retrospective cross-sectional study based on data obtained from the 2016 EDHS. Hurdle negative binomial (HNB) regression analysis was employed to determine the factors associated with under-five mortality. The results found that the age of mothers at first birth, the age of mothers at the time of under-five mortality occurred, number of household members, household access to electricity, region, education level of the mothers, sex of household head, wealth index, mother residing with husband/patterner at the time of under-five mortality occurred as factors associated with under-five mortality.

Nguyen-Phung (2023) obtained data from the Vietnam Demographic Health Survey from 1997 and 2002 to investigate the effect of maternal education on three child health indicators: neonatal, infant, and under-five mortality rates. This paper took advantage of the tuition fee introduction at the lower secondary school level in 1989 to create an exogenous negative shock of the educational environment for women. The results of this study initially revealed that women exposed to the introduction of tuition fees, on average, attained fewer years of schooling compared to their counterparts. These findings demonstrate that a one-year reduction in maternal education, resulting from this exogenous change, was associated with increased rates of neonatal, infant, and under-five mortality.

2.4 Demographic Factors Related to Under-Five Mortality

Chen, Huq and D'Souza (1981), Bhuiya and Streatfield (1991) and Arokiasamy (2002) pointed out that a number of studies have shown mortality differential by sex. Male mortality usually exceeds female mortality in the neonatal period, but this differential is reversed in the post-neonatal period. Higher female than male mortality continued through childhood.

Hobcraft, McDonald and Rutstein (1985) showed a clear excess of neonatal mortality for the first births and first-born children continued to be at a risk during the remainder of infancy. However, contrary to the general belief, there was no clear evidence of excess mortality for children of birth order four to six, nor even for those of order seven and higher, once the other factors in the regression model were controlled. This could suggest that mortality associated with births of high orders may be predominantly caused by other factors like birth intervals. However, it should be noted that the outcome of the first birth could be associated with the aged of mother rather than the order. Hobcraft (1991) concluded that delaying the first birth until a woman is at least 18 years of age might reduce the risk of death for first born children by up to 20 percent on average and up to 30 percent in a few countries.

Some studies like those conducted by Hobcraft, McDonald and Rutstein (1985), Rutstein (2000), and Machado and Hill (2005) have shown some association between the age of the mother at birth and child survival. Hobcraft, McDonald and Rutstein (1985) showed that mortality was clearly higher among children of teenage mothers. However, in their study there was nothing to suggest increased risks for children born to mothers at other ages, even those with mothers who were aged 35 or above after controlling for birth spacing. Mahmood (2002) observed that children of older women (30-39 years) were exposed to significantly higher neonatal and post neonatal mortality.

Zinabu, Alem and Abera (2012) examined the determinant of infant and child mortality in Ethiopia. The analysis was based on micro data from the 2011 EDHS. The findings of this paper study demonstrate that different factors such as mother's education status, place of residence, birth order number of children, preceding birth intervals, household size/ family size, source of drinking water, mother's marital status, types of birth occurred, and breast-feeding status have statistically significant impacts to determine infant and child mortality in Ethiopia.

Dendup, Zhao and Dema (2018) explored factors related to under-five mortality in Bhutan using data from the Bhutan National Health Survey (BNHS) 2012. Their study utilized multiple logistic regression analysis with a backward elimination approach to identify significant factors. Their findings suggest that a younger maternal age, a higher number of births, and being born in the central and eastern regions of Bhutan are associated with a higher risk of under-five mortality (U5M). Conversely, larger household sizes and access to electricity and safe sanitation are linked to lower U5M risk in Bhutan. To address this issue, the authors recommend scaling up initiatives that promote women's empowerment, health education, and maternal and child health strategies in rural areas

Tai, Htut and Swe (2019) investigated the impact of healthcare services on under-5 mortality among Myanmar's states and regions by examining relevant socioeconomic and demographic factors from the 2015-2016 MDHS. All factors examined in this study could affect the relationship between the use of health care and under-5 mortality in the multivariate analysis. The study found that the risk of child mortality was significantly higher for children of higher birth order; children who received health services had a reduced risk of childhood death compared with children who did not. In addition, the risk of child mortality was significantly reduced for children whose mothers accessed antenatal care at a government hospital, private hospital, or mobile clinic. The study results highlight the determinants of under-5 child mortality among Myanmar's states and regions.

Ekholuenetale et al. (2020) point out household factors associated with infant and under-five mortality in sub-Saharan African countries. They conducted a comprehensive analysis of secondary data sourced from the recent Demographic and Health Surveys (DHS) conducted in 35 countries in the region. The dataset included a substantial sample of 384,747 births that occurred between 2008 and 2017. Among their key findings were the highest infant mortality rates documented in Sierra Leone, Chad, and Nigeria, respectively. Moreover, the study revealed that total under-five mortality rates were most pronounced in Cameroon, Sierra Leone, and Chad, respectively. Furthermore, households with female household heads exhibited lower risk of under-five mortality compared to those with male household heads. Households with a larger number of children (3–5 and ≥6) also faced a higher risk of under-five mortality compared to those with 1–2 children ever born. Finally, under-five children born to mothers with a history of multiple unions had increased risk of mortality compared to those born to mothers from a single union.

Fenta, Fenta and Ayenew (2020) explored the best statistical model to estimate predictors of under-five mortality in Ethiopia using the 2016 Demographic and Health Survey. This study aimed to identify the best statistical model to estimate predictors of under-five mortality in Ethiopia. Various count models (Poisson, Negative Binomial, Zero-Inflated Poisson, Zero-Inflated Negative Binomial, Hurdle Poisson, and Hurdle Negative Binomial) were considered to identify risk factors associated with the death of under-five. The hurdle negative binomial model had the smallest AIC, Deviance and BI, suggesting the best goodness of fit. Besides, the predictive value and probabilities for many counts in the hurdle negative binomial model fitted the observed counts best. The result of hurdle negative binomial model showed that region, mother's age, educational level of the father, education level of the mother, father's occupation, family size, age of mother at first birth, vaccination of child, contraceptive use, birth order, preceding birth interval, twin children, place of delivery, antenatal visit predict under-five death in Ethiopia.

Jayathilaka et al. (2021) indicated socioeconomic and demographic characteristics associated with child mortality, the study was carried out based on data gathered from the micro-level national survey. Using the logit regression model through the stepwise technique, the study investigates the socio-economic and demographic characteristics associated with under-five mortality in Sri Lanka. According to the generated results, place of residence province-wise, household head's education level and source of drinking water have a negative effect on under-five mortality in Sri Lanka.

Gobebo (2021) explained that determinant factors of under-five mortality in Southern Nations, Nationalities and People's Region (SNNPR), Ethiopia. This study aimed to identify the determinant factors of under-five mortality in SNNPR. Data used for the study were drawn from the 2016 EDHS. A total of 1277 under-five children were included in the study by using multivariable logistic regression model. The study found that sex of a child, birth order, size of a child at birth, place of delivery, birth type, breastfeeding status, and family size were significant factors associated with under-five mortality in SNNPR, Ethiopia.

Kumar, Piyasa and Saikia (2022) described that an update on explaining the rural-urban gap in under-five mortality in India. Using the 2019-2021 NFHS data, this paper carried out a binary logistic regression analysis to examine the factors associated with under-five mortality. From 1992 - 93 to 2019–21, the annual decrease in rural and urban under-five mortality. This research showed that there was no disadvantage for the rural children due to their place of residence if they belong to economically well-off household or their mothers were educated.

2.5 Health Care Factors Related to Under-five Mortality

Maiga et al. (2015) explained that women's fertility history and cultural and socio-economic background were also significant factors in predicting use of modern contraception. Low modern contraceptive use is associated with higher birth risks and increased child mortality. This association is stronger in the Sahel, Est, and Sud-Ouest region. Even though all factors in high-risk births were associated with under-five mortality, it should be stressed that short birth spacing ranked as the highest risk in relation to mortality of children. Target sub-national differentials and leverage women's health system contacts to inform women about family planning opportunities may be effective in improving coverage, quality and equity of modern contraceptive use. Improving the demand satisfied for modern contraception may result in a reduction in the percentage of women experiencing high-risk births and may reduce child mortality.

Bedada (2017) examined determinants of under-five mortality in Ethiopia. The study utilizes the data extracted from the 2011 EDHS. Multivariate logistic analysis reflects that sex of the child, family size, education level of mother, age at first birth of mother, breast-feeding; using contraceptive method and region of child have significant influence on under-five child mortality in Ethiopia. The proximate determinants are found to have stronger influence on under-five mortality than the socioeconomic factors considered in the study do.

Ghimire et al. (2019) identified the common factors associated with under-five mortality. This study found that the most common factors associated with mortality across all age subgroups. This study also found that mothers with a previous death of a child, who did not receive tetanus toxics (TT) vaccines during pregnancy, and those who were nonusers of contraceptives were at greater risk of having neonatal, post-neonatal, infant, child, and under-five mortality.

Shukla et al. (2020) explored the effect of modern contraceptive use on IMR and U5MR in India using data from the 2015-2016 National Family Health Survey. Bivariate analysis and cox proportional hazard model are applied in the study. They found that use of reversible contraceptives prior to birth resulted in low childhood mortality rate. The use of reversible modern contraceptives prior to birth is protective against child mortality even among births with preceding birth interval of less than 24 months. This study provides evidence of dual benefit of contraceptive use. Such information is important for promoting evidence-based advocacy to expand use of family planning services.

Workie and Azene (2021) conducted a study to assess under-five child mortality and employed a Bayesian zero-inflated regression model. This study used data from the 2016 EDHS in a community-based cross-sectional study with a two-stage cluster sampling design. The analysis revealed that the mothers had not experienced under-five child deaths, while mothers had lost under-five children, and the data exhibited excess zeros. The Bayesian Negative Binomial–logit hurdle model showed that several factors were statistically associated with the number of non-zero under-five deaths in Ethiopia, including having twins, primary and secondary education, mother's age at first, using contraceptive methods, and antenatal visits during pregnancy. Furthermore, it highlights that factor such as mother's education, mother's age, birth order, type of birth, mother's age at first birth, contraceptive use, and antenatal visits during pregnancy are crucial determinants of under-five child mortality.

2.6 Environmental Factors Related to Under-Five Mortality

Environmental conditions have long been considered to have a significant influence on mortality. These include access to sanitation, source of drinking water, and source of energy.

The South African Demographic and Health Survey (SADHS) report of 1998 showed childhood mortality differentials caused by socio-economic, demographic, environmental and high-risk fertility behavior. For environmental factors, source of drinking water, sanitation, housing materials, and source of energy were investigated. Under-five mortality rates, more than doubled where the source of drinking water was other than piped water. Where poor sanitation existed child mortality rates are higher. The report also showed that there was a relationship between material used for the dwelling and source of energy with under-five mortality.

Ezzati and Kammen (2002) argued that to understand the health effects of exposure to indoor smoke so that appropriate interventions and policies can be designed and implemented is a complex phenomenon. Studies conducted by Anderson et al. (2002) and Wichmann and Voyi (2006) have shown a strong association with access to clean water, sanitation, clean source of energy and with infant and child mortality.

Alves and Belluzzo (2005) basing their study in Brazil found out that mortality rates are determined by hygiene at both the household and environment. In several studies, household's socioeconomic status has been considered in terms of their drinking water source, sanitation, source of cooking fuel and income level.

Wichmann and Voyi (2006) suggested that exposure to cooking and heating smoke from polluting fuels is significantly associated with 1-59 months mortality in South Africa, after controlling for mother's age at birth, water source, asset index and household overcrowding.

Fayehun (2010) found that there is a significant relationship between the environment of the household and child's survival in Sub-Saharan countries. Some of these differences in childhood mortality could be accounted and explained by levels environmental health hazards of households are exposed to. In addition, access to piped water, sanitation and availability of toilets have been found to reduce risks of mortality.

Sulaiman et al. (2017) examined the consequences of increased wood fuel consumption on health outcomes, specifically focusing on under-five and adult mortality in Sub-Saharan Africa, where wood usage for cooking and heating is rising. They employed Generalized Method of Moment (GMM) estimators to gauge the influence of wood fuel consumption on under-five and adult mortality in the region. The results unveiled a significant and positive impact of wood fuel consumption on both under-five and adult mortality. This implies that during the study period, the rise in wood fuel consumption corresponded to an increase in mortality among under-five children and adults. Furthermore, when examining the gender-specific effects, it became evident that the impact was more pronounced among female adults than male adults. This finding suggests that mortality resulting from wood smoke-related infections is higher among under-five children than adults and is also more prevalent among female adults than their male counterparts.

Gbadebo, Fagbamigbe and Adebowale (2018) pointed out that environmental factors as predictors of childhood mortality experience in Nigeria. This study used the 2013 Nigerian Demographic and Health Survey. The survey was a nationally representative sample of females of reproductive age (15-49 years). Data were analyzed using descriptive statistics, Chi-square, and Cox-Proportional hazard models. The hazard of child mortality was 28% higher among children who had no access to safe water and 31% higher for no access to improved toilet facilities. Children of mothers with no education were about 33%times more likely to die before age 5 than children whose mothers had secondary education. The richer the household from which a child comes, the lower the likelihood of death before age five. The hazard of child mortality was significantly higher among those who lived in houses made of unimproved roofs and walls, used unimproved cooking fuel, used mosquito nets regularly, and shared toilet facilities. Childhood mortality is still high in Nigeria and children from poor homes in rural areas, with limited access to improved sanitation, housing materials and safe water were the most affected.

Imo and Wet-Billings (2021) explored the impact of neighborhood poverty and the utilization of solid cooking fuels on under-five mortality in Nigeria. The study analyzed a weighted sample of 124,442 birth histories from women who used cooking fuels within their homes, sourced from the 2018 Nigeria Demographic and Health Survey. The research employed various methods, including frequency tables, Pearson's chi-squared test, and a multivariate analysis using a Cox proportional regression model. The findings demonstrated a significant association between under-five mortality risk and both high neighborhood poverty and the use of solid cooking fuels indoors. To mitigate harmful emissions and the associated child health risks, it is recommended that Nigerian government and non-governmental organizations launch strategic initiatives and awareness campaigns to educate and empower mothers about the importance of reducing the use of solid cooking fuels within their households.

Rana et al. (2021) found that association between household air pollution and neonatal, infant and under-five child mortality in Myanmar using a multilevel mixed-effects Poisson regression with robust variance. The study consisted of 3249 sample of under-five children in the households from the 2015-2016 MDHS. The risk of infant and under-five mortality but not neonatal mortality, were higher among children from households with solid fuel use compared to children from households using clean fuel. Additionally, children highly exposed to household air pollution had higher risks of mortality than unexposed children.

Prasetyoputra et al. (2022) investigated that socio-economic, demographic and environmental determinant of under-five mortality in Indonesia: insights from a national survey using the 2017 Indonesia Demographic and Health Survey (IDHS). This paper observed that under-five children living in a household with no access to improved sanitation and exposed to maternal smoking have a higher probability of dying. This study also found that maternal education protects under-five children from dying. However, under-five children whose mother is working are more likely to die. The results of this study provide evidence that addressing environmental issues, particularly increasing coverage of improved drinking water sources and sanitation facilities, and curtailing smoking prevalence among mothers, would potentially improve child survival.

Panda and Sarangi (2023) conducted a study in India to examine the socio-demographic and environmental risk factors associated with child mortality in the age group of 0-59 months. They used secondary data from the NFHS round 5 and employed a Cox regression model for statistical analysis. The research revealed that child mortality rates were higher when mothers were under 20 years old and had no education. Mortality rates were also higher in rural areas compared to urban areas. Children born as the sixth or higher birth order had a 2.0966 times higher risk of mortality, and male children were more susceptible to mortality than female children. Families with the richest wealth index had the lowest mortality. Additionally, the use of polluting cooking fuels and unimproved sanitation facilities increased the risk of under-five mortality by 1.1334 times and 1.0905 times, respectively.

2.7 Count Data and Zero-Inflated Data

Count data are the “realization of a nonnegative integer-valued random variable” (Cameron & Travedi, 1998) where, the response values take the form of discrete integers (Zorn ,1996). Count data models deal with the response (dependent) variable counts. It becomes popular in wide areas of interesting sciences, such as finance, marketing, health care, weather, and so on. In many of these areas of sciences one can see the important of modeling the related count variables. Counts are differing from dichotomized data and ordinal data. And unlike linear regression, count data regression model considers that the response variable takes only non-negative integer values. Characteristics of count data are (1) event counts are non-negative (lower bound is zero) (2) count are integers (3) a histogram will indicate a rapidly decreasing tail (4) distribution is not normal. Excess zeros in count data lead to a concept called “zero inflation”.

The term "zero inflation" is used to describe a data set that contains an excessive number of zeros, typically beyond the accommodation of a standard parametric distribution. Disregard zero-inflation can have two effects: firstly, the estimated parameters and standard errors may be biased and secondly, the excessive number of zeros led to over-dispersion. Therefore zero-inflation models were introduced to fix this problem. Ridout et al. (1998) introduced two resources of zeros in the data, the structural zeros and sampling zeros. The structural zeros are true zeros. The zeros due to design, survey and observer errors are called sampling zeros (false zeros). In analysis, the presence of a large number of zeros tends to violate the underlying distribution assumption and thus jeopardize the finding. Zero-inflated count data may not have equality of mean and variance. In such case over-dispersion (or under-dispersion) needs to be taken into account. Zero-inflated Poisson (ZIP) models were developed by Lambert (1992) to handle zero-inflated count data. Zero-inflated models combine two sources of zero outcomes which are called true zero and excess zeros. Greene (1994) has investigated zero-inflated models as modifications of the Poisson and the negative binomial models. This study also presented the test procedure to separate the zero inflation and over-dispersion.

The zeros can be classified as being either true zeros or sampling zeros. True zeros means that a zero data value indicates the absence of the object being measured. When true zeros lead to an excess of zeros, zero-inflated models such as the two-part (also known as conditional or hurdle models) or mixture models are recommended

(Lambert, 1992; Barry & Welsh, 2002). The negative binomial has also been advocated for modeling data sets with many zeros because of its ability to account for over-dispersion (Warton, 2005). However, Barry & Welsh (2002) and Warton (2005) demonstrated that the excess number of zeros often exceeds those expected under a negative binomial distribution.

For count data, there are two parts in the modeling approach, where the first part is a binary outcome model (i.e., Bernoulli), and the second part is a truncated count model (e.g. Poisson or negative binomial) (Cameron and Trivedi, 1998). This approach assumes that zeros arise from a single process with a set of covariates. One of its computational benefits is that it is possible to fit these models in two parts, for example, fitting zeros using a logistic regression separately from fitting non-zeros using a truncated Poisson (Barry and Welsh, 2002). Mixture models are combinations of probability distributions chosen for their ability to represent two or more real ecological processes. The ZIP mixture model used to model count data is a mixture of a point mass at zero and a Poisson distribution. With this approach, zeros may arise from one of two processes and their related covariates, a zero process from which only zero values are observed and a Poisson process in which non-zero and a proportion of the zero values, appropriate to the Poisson distribution are observed (Lambert, 1992).

The interpretation of mixture model parameters is less straightforward than the two-part model. For example, to get the true estimation of relative mean abundance from the ZIP, one must multiply the estimated relative mean number of individuals at a site by the probability that the relative mean number of individuals at a site is generated through a Poisson distribution. When there is zero inflation and over-dispersion caused by large counts of individuals, the use of a zero-inflated negative binomial (ZINB) mixture model has been shown to be appropriate (Barry and Welsh, 2002).

The count regression model is the preferred model of analysis. Since the response variable is the number of under-five death (count Y), classical Poisson regression is the most well-known method for modeling count data. However, its underlying assumption of equal dispersion (i.e., an equal mean and variance) limits its use in many real-world applications with over or under-dispersed data (i.e., the variance is larger than the mean or smaller than the mean). Excess variation may result in incorrect inferences about parameter estimates, standard errors, tests, and confidence intervals. Overdispersion frequently arises for various reasons. One is excessive zero counts or censoring. Over-dispersed count data are common in many areas which in turn, lead to the development of the statistical methodology for modeling over-dispersed data (Sellers & Shmueli, 2013).

Usman and Oyejola (2013) pointed out that models for count data in the presence of outliers and /or excess zero. The study focused on identifying models which can handle the impact of outliers and excess zero in count data. Datasets based on Poisson model were simulated for sample size 20, 50, and 100 and incorporated with outliers and zero. Maximum likelihood estimation method was employed in estimating the parameters. Model selection is based on dispersion index, AIC, BIC and log likelihood statistics, putting into consideration Poisson, Negative Binomial, Zero-inflated Poisson and Zero-inflated Negative Binomial models and results obtained indicates that ZINB is the best models for analyzing count data in the presence of outliers and/or excess zero.

Ismah, Kurnia and Sadik (2020) explained an analysis of overdispersed count data by Poisson models such as Poisson Regression, Zero-inflated Poisson Regression, Generalized Poisson Regression and Zero-inflated Generalized Poisson Regression of over-dispersion data. The data used in this research is Indonesian Demographic and Health Survey data in 2017. The results analysis of those four models show that over-dispersion case causes the usage of Poisson Regression model less appropriate, while Generalized Poisson model can be used for over-dispersion case. Thus, it can be concluded that in over-dispersion data with zero excess, Zero-inflated Generalized Poisson is less appropriate to be applied, because range of data is short.

2.8 Usage of Zero-Inflated Regression Models

Lambert (1992) discussed that zero-inflated Poisson (ZIP) regression is a model for count data with excess zeros. It assumes that with probability p the only possible observation is 0, and with probability 1- p, a Poisson random variable is observed. When manufacturing equipment is properly aligned, defects may be nearly impossible. But when it is misaligned, defects may occur according to a Poisson distribution. Both the probability p of the perfect, zero-defect state and the mean number of defects in the imperfect state may be dependent on covariates. In either case, ZIP regression models are easy to fit. The maximum likelihood estimators

(MLE's) are approximately normal in large samples, and confidence intervals can be constructed by inverting likelihood ratio test or using the approximate normality of the MLE's. Simulations suggest that the confidence intervals based on likelihood ratio tests are better, however. Finally, ZIP regression models are not only easy to interpret, but they can also lead to more refined data analysis. The count data may possess excess number of zeros and zero count may not occur in the same process as other positive counts and proposed zero- inflated Poisson (ZIP) model with an application to defects in manufacturing.

Zorn (1996) presented on two alternative specifications for estimating event count models in which the data generating process results in a larger number of zero counts than would be expected under standard distributional assumptions where he compared zero- altered Poisson model and zero- inflated Poisson model, using data on Congressional responses to Supreme Court decisions from 1979 to 1988. He shows that each of these models is a special case of a more general dual regime data generating process which results in extra- Poisson zero counts. Furthermore, because this data generating process can produce overdispersion, these models are also shown to be related to variance function negative binomial specifications. The underlying correspondence between these models leads to similar results in estimating and interpreting them in practice.

Poston and Mckibben (2003) expressed the estimation by using of Poisson regression, negative binomial regression, zero-inflated Poisson and zero-inflated negative binomial models to predict the average number of children ever born to women in the United States of America. The study showed that zero inflated Poisson and zero-inflated negative binomial models perform better than the Poisson and negative binomial models.

Famoye and Singh (2006) studied the generalized Poisson regression model has been used to model dispersed count data. It is a good competitor to the negative binomial regression model when the count data is over-dispersed. Zero inflated Poisson and zero inflated negative binomial regression models have been proposed for the situations where the data generating process results into too many zeros. They propose a zero inflated generalized Poisson (ZIGP) regression mode to model domestic violence data with too many zero. Estimation of the model parameters using the method of maximum likelihood is provided. A score test is presented to test whether the number of zeros is too large for the generalized Poisson model to adequately fit the domestic violence data.

Zulkifli, Ismail and Razali (2011) used data from ten insurance companies in Malaysia to model crime count data using ZIP) and ZINB regression models as an alternative for handling over-dispersion and zero-inflated phenomenon. Two different link functions are suggested in the fitting procedure of the zero-inflated regression model. The likelihood ratio and the Wald test show that the ZINB model is a better model compared ZIP, the ZIP for handing over-dispersion and zero-inflated theft insurance data.

Mouatassim and Ezzahid (2012) compared Poisson model to the zero-inflated model and applied to health insurance data set. Mouatassim, Ezzahid and Belasri (2012) analyzed operational risk to the zero-inflated data and assess the impact of ZIP distribution on the operational capital charge. The study concluded that the zero-inflated Poisson distribution is better fit than Poisson distribution for modeling operational risk frequency.

Peng (2013) studied count data models of analyzing injury data from the National Health Interview Survey (NHIS), where the author compared zero- inflated negative binomial regression model and logistic regression model. The results indicated that zero-inflated negative binomial regression model can explore injury proneness and predict the mean number of injuries in the injury-prone population. These goals cannot be achieved by logistic regression although it might fit the dichotomized data well.

Yang (2014) showed a comparison of different methods of zero-inflated data analysis and its application in health surveys, where this study aimed to evaluate the performance of Poisson regression, negative binomial regression, zero-inflated Poisson regression, zero-inflated negative binomial regression, zero-altered Poisson regression and zero-altered negative binomial regression model under different condition of zero-inflation and over-dispersion and to examine the amount of bias and poor fit resulting from fitting various models. Overall, this study suggested that zero-inflated negative binomial model and zero-altered negative binomial are fit if the data have both excessive zeros and skewness in the non-zero part.

Amir et al. (2015) used data from 2005 and 2009 cohort studies at medical record Hospital Putrajaya, Malaysia to examine the factors that are associated directly or indirectly in pneumonia patients among the children. This study found that the

ZINB regression can overcome over-dispersion, so it was better than the Poisson regression model.

Yang et al. (2017) studied a comparison of different methods of zero- inflated data analysis and an application in health surveys data, where it is indicated that the zero-altered or zero-inflated negative binomial model were preferred over ordinary least-squares regression with log- transformed outcome and Poisson model when data have excessive zero and over-dispersion.

Woldeamanuel and Aga (2021) described a count model analysis of factors associated with under-five mortality in Ethiopia. A retrospective cross-sectional study based on data obtained from the 2016 EDHS were used. The response variable was the total number of under-five children died per mother in her lifetime. Variables such as maternal socioeconomic and demographic characteristics, health, and environmental factors were considered as risk factors of under-five mortality. Hurdle negative binomial (HNB) regression analysis was employed to determine the factors associated with under-five mortality. Results. The data showed that 27.2% of women experienced under-five deaths. The study revealed the age of mother at first birth, the age of mother at the time of under-five mortality occurred, number of household members, household access to electricity, region, educational level of the mother, sex of household head, wealth index, mother residing with husband/partner at the time of under-five mortality occurred as factors associated with under-five mortality. Age of mother at first birth, access to electricity, primary education level of the mother and the richer wealth index were associated with reduced incidence of under-five mortality controlling for other variables in the model. Whereas older age of mother being a resident of the Benishangul-gumuz region, female household head were associated with an increased incidence of under-five mortality.

2.9 Zero-inflated Regression Models Applied to Under-Five Mortality

Mamun (2014) applied the data from the 2011 Bangladesh Demographic and Health Survey (BDHS) to examine the risk factors for under-five deaths in Bangladesh. This study used five models to analyze the social factors that contribute to a woman losing her child before the age of five. The traditional models did not distinguish between women who have lost children under the age of five and moms who have never lost children under the age of five. While zero-inflated models might distinguish between the two groups of women in terms of zero counts and positive counts of the number of their children under the age of five who died, with associated variables in the opposite slope of coefficients. Comparing the Hurdle model against the ZIP and ZINB models, it was the best at fitting the data among the three zero-inflated models.

Alam et al. (2014) also used data from the 2011 BDHS to explore the under-five mortality using negative binomial regression, a zero- inflated negative binomial regression and a hurdle regression model. This study found that zero-inflated negative binomial regression model fits the data best among these models. These results also identified respondent's age, respondent age at 1st birth, gap between 1st birth and marriage, number of family members, region, religion, respondent's education, husband's education, incidence of twins, source of water, and wealth index as significant predicators for the number of children's death in a family from the best-fitted model.

Yenew (2015) utilized data from the 2011 EDHS to identify determinants of under-five mortality in Ethiopia. In this study descriptive statistics and count regression models were used for data analysis using socio-economic, demographic and environmental related variables as explanatory variables and the number of under-five deaths per mother. The results found that mother's age at the first birth, breastfeeding status, wealth index, current mother working, region and mother's level of education has statistically significant on the number of under-five mortality in rural parts of Ethiopia. Similarly, mother's level of education, age of mother at the first birth, toilet facility and work/employment status of mothers were found to be statistically significant with the number of under-five deaths per mother in urban parts of Ethiopia. Also, region, age of mothers at the first birth, mother's level of education, breastfeeding status of mothers, wealth index and employment status of mothers were found to be statistically significant effect with the number of under-five mortality.

Fenta and Fenta (2020) explored a risk factors of child mortality in Ethiopia using the data from the 2016 EDHS data. A two-part random effects regression model was employed to identify the associated predictors of child mortality. The study found that 53.3% of mothers did not face any child death, while 46.7% lost at least one. Vaccinated child was currently using contraceptive who had antenatal care visit four or more times visit, fathers whose level of education is secondary or above, mothers who completed their primary school, mothers who have birth interval greater than 36 months where the age of the mother at first birth is greater than 16 years associated with the small number of child death. While multiple births associated with a higher number of child death. The variance components for the random effects showed significant variation of child mortality between enumeration areas.

Alito and Girmma (2021) presented that count regression modelling of under-five child mortality in SNNPRS, which is one of the nine regions of Ethiopia. The data used in this study was taken from the 2011 EDHS. The total number of mothers from SNNPRS included in the survey was 1614. In terms of AIC, Vuong's and likelihood-ratio test, ZINB regression model is better than other count models to predict the probability and determinants of the number of child death. The influences of some demographic, environmental and socioeconomic factors on child death were identified. The results show that among socioeconomic determinants: mother's educational level, household size, number of under-five children in household, mother's working status and wealth status of household are the most important determinants for child mortality. Other most important variables which were found to be statistically significant with under-five child mortality are current age of mother, mother age at first birth and type of toilet facility. Among variables included in zero-inflated part of count models, mother's educational level, mother's age at first birth, wealth index and mother's working status were found to be statistically significant factors for mothers who have not experienced under-five child mortality in her life time.

Yohannis, Fetene and Gebresilassie (2021) studied that identifying the determinants and associated factors of mortality under age five in Ethiopia using the data from the 2016 EDHS. In this study, count family models such as Poisson, negative binomial, zero-inflated Poisson and zero-inflated negative binomial regression were applied for analyzing the data. Each of these count models were compared with different statistical tests like log-likelihood ratio test, Akaike information criteria, mean absolute difference, Vuong test and observed versus predicted probability plot. This study found that, there were an overabundance zeros and broad heterogeneity in the nonzero outcomes. Zero-inflated negative binomial regression model was found to best fit the data, and from the regression model, age of mothers at first birth, mother's education level, place of residence and region were statistically significant factors of under-five mortality per mother.

Abera and Yohannis (2022) described determinants of under-five mortality in Tach- Armachiho District, North Gondar, Ethiopia. This study identified the determinants of under-five mortality among women in childbearing age group of Tach-Armachiho district using count regression models. In this study, Poisson regression, negative binomial, zero-inflated Poisson and zero-inflated negative binomial regression models were applied for data analysis. Each of these count models was compared by different statistical tests. So that, zero-inflated Poisson regression model was found to be the best fit for the collected data. Results of the zero-inflated Poisson regression model showed that education of husband, source of water, mother's occupation, kebele of mother, prenatal care, place of delivery, place of residence, wealth of household, average birth interval, and average breast feeding were found to be statistically significant determinants of under-five mortality. In this study, it was found that the factors like average birth interval and average breast feeding were found to be statistically significant factors in both groups (not always zero category and always zero category) with under-five child death whereas education of husband, source of water, place of delivery, mother occupation and wealth index of the household have significant effect on under-five mortality under not always zero group. Place of residence, kebele of mother and prenatal care have a significant effect on under-five mortality in Tach-Armachiho district on inflated group.

Argawu and Mekebo (2022) attempted to identify the risk factors for under-five mortality in Ethiopia using the 2019 Ethiopian Mini Demographic and Health Survey data. The best model that fits the data well was selected using selection criterion like AIC, BIC. Zero-inflated Poisson model was found to fit the data well. The study found that mother's age, marital status of mother, age of mother at first birth, place of delivery, place of residence, time to get drinking water, number of children at home, birth order, type of birth were statistically significant determinants for under-five mortality in Ethiopia.

2.10 Mosely-Chen Model

Studies have used several different conceptual frameworks to analyze the impact of different factors on child survival. Mosley and Chen (1984) proposed an analytical framework for the study of the determinants of child survival in developing countries. The authors considered both social and biological variables and integrated research methods employed by social and medical scientists. The framework was based on the premise that socio-economic determinants of child mortality operate through a common set of biological and proximate mechanisms to influence child mortality.

Traditionally, social science research on child mortality has focused on the association between socioeconomic status and levels and patterns of mortality in populations Figure (2.3 A). Correlation between mortality and socioeconomic characteristics is used to generate causal inferences about the mortality determinants. Income and maternal education are two commonly measured correlates of child mortality in developing country populations.

Medical research focuses primarily on the biological processes of diseases, less frequently on mortality. The differing assumptions and methods are classified in Figure (2.3 B). Studies of the cause of death attribute mortality to specific disease processes. Clinical trials assess the therapeutic effect of a particular medical technology. Field intervention studies measure the effectiveness of personal preventive measures on levels of morbidity and mortality in a population. Epidemiological studies may define mechanisms of disease transmission in the environment. The connection between environmental contamination and disease. Nutrition research focuses on breastfeeding, dietary practices, and food availability as they relate to nutritional status.

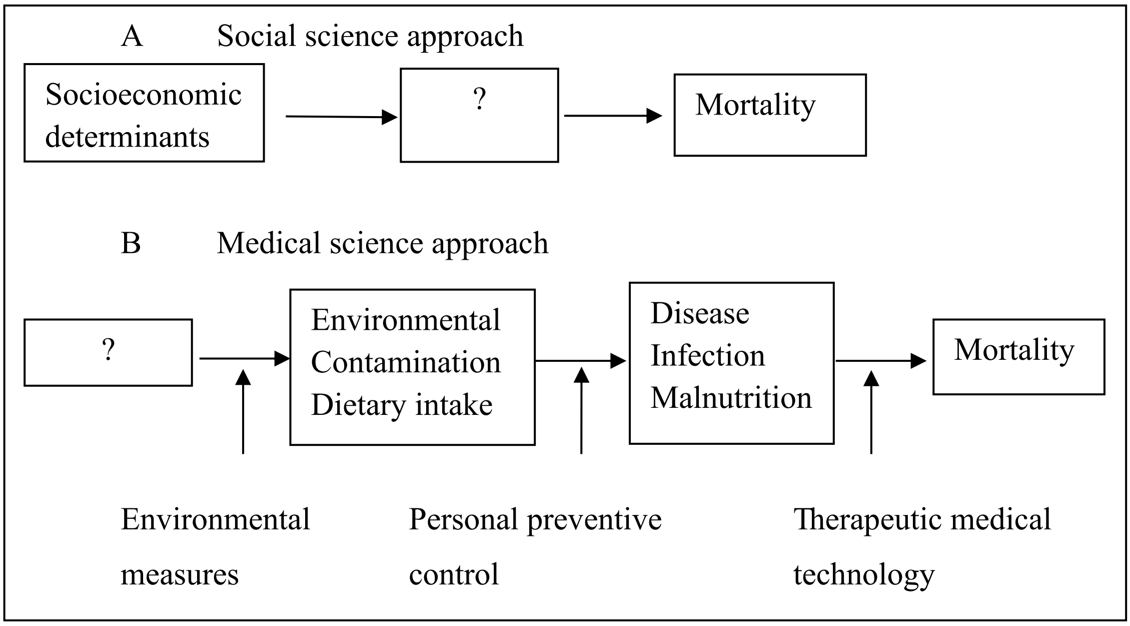

Figure (2.3) Conceptual Models of Social Science and Medical Science Approaches to Research on Child Survival

Source: Mosley & Chen (1984)

Mosley and Chen note that the problem raised by mortality analysis is far more complex because a child's death is the ultimate consequence of a cumulative series of biological insults rather than the outcome of a single biological event. The development of a conceptual framework for the study of child survival requires both a definition of the proximate determinants of mortality and a redefinition of the independent and dependent variables.

A framework identifies five proximate determinants of child health and survival: (1) maternal factors, (2) environmental contamination, (3) nutrient deficiency, (4) injury, and (5) personal illness control. Individual, household, and community-level socio-economic characteristics influence child health and survival through each of these sets of intervening variables. Though not based explicitly on a theoretical model of household behavior, the framework specifies the following variables to be causally prior to the proximate determinants: individual factors, such as maternal education; household factors, such as income and family composition; institutional factors, including community infrastructure and health programs; ecological factors, such as rainfall, temperature, seasonality, and altitude; and cultural factors, such as traditions, norms, and values.

2.11 Conceptual Framework of the Study

This study is based on Mosley and Chen's framework. It is used for social and medical science approaches to research on child survival in developing countries. Although there are many factors that affect under-five mortality, this study only considered variables available from the 2015-2016 MDHS. A number of previous studies pointed out the socioeconomic, demographic, health care, and environmental factors which have influenced on under-five mortality. Accordingly, the conceptual framework of this study which depicts how under-five mortality is affected by socio-economic, demographic, health care, and environmental factors is developed and described in Figure (2.4).

The measurement variables for each of the influencing factors of under-five mortality contained in the conceptual framework are also obtained from the literature. In more detail, the measurable variables for socioeconomic factors include the mother's education level, and household wealth index. The measurement variables for demographic factors are state and region, the place of residence, household size, marital status, mothers age at birth, and childbirth order. The measurement variables for health care factors consist of place of delivery, and contraceptive methods. The measurement variables for an environmental factor include access to safe water, access to a safe toilet, and sources of fuel for cooking are obtained from the literature.

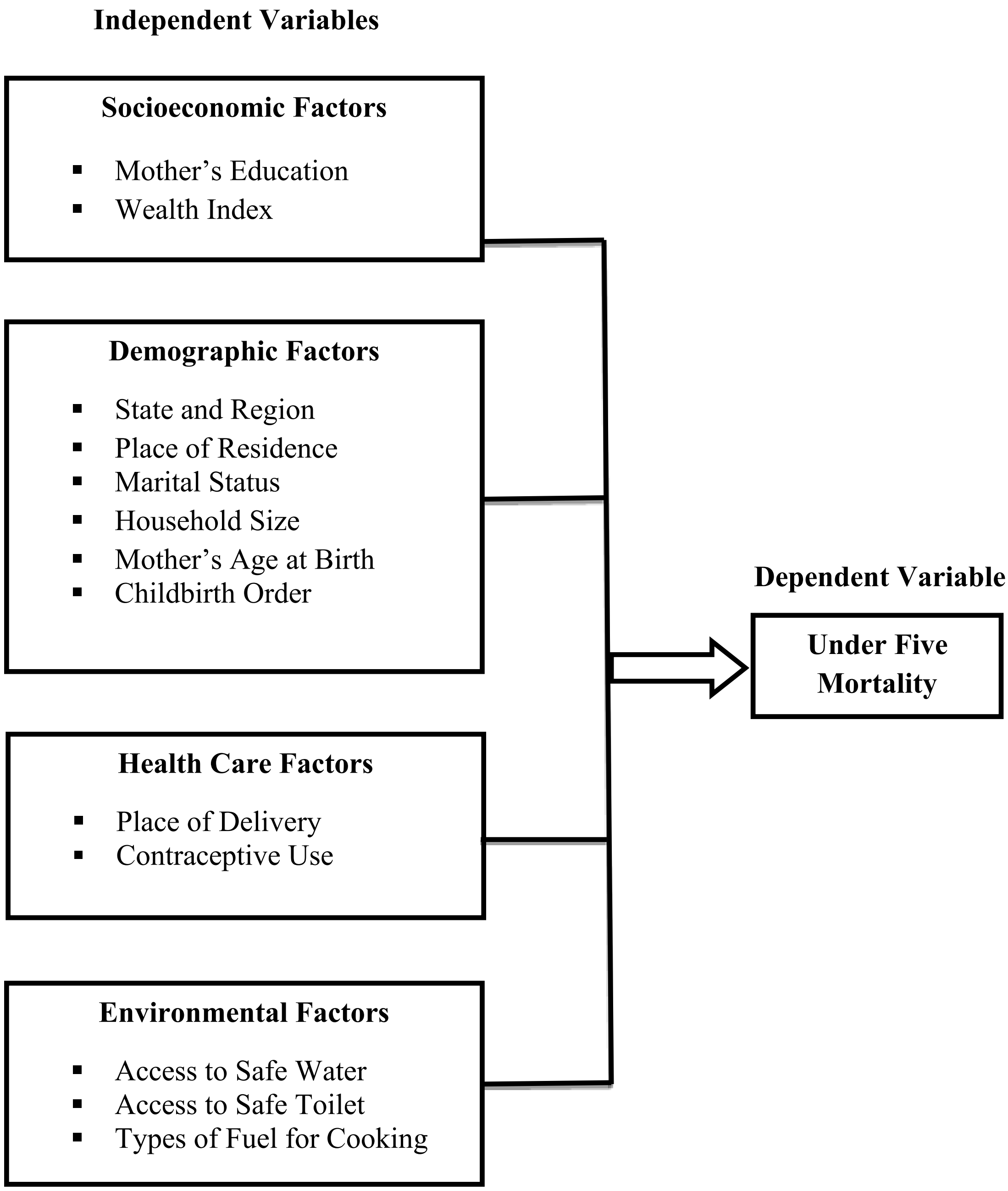

Figure (2.4) Conceptual Framework of the Study

Source: Own Compilation

CHAPTER III
RESEARCH METHODOLOGY

In this chapter, source of data, variables used in this study, the explanation of how three regression models such as zero-inflated Poisson (ZIP) regression, zero-inflated negative binomial (ZINB) regression, and the hurdle or alter regression which are applied to zero-inflated count data in the assessment of under-five mortality in Myanmar are presented.

3.1 Source of Data

In this study, the national population-based cross-sectional survey of the 2015-2016 MDHS was used to get the required data. Out of 13,260 households selected for the MDHS, 12,780 houses were occupied, out of which 12,500 were interviewed yielding a 98% response rate (MDHS and MOHS, 2017). In the interviewed households, 13,454 women were found to be eligible being in the targeted age range (15-49 years), out of which, 12,885 were interviewed resulting in a 96% response rate. The survey provided information about 12885 children ever born to interviewed women and 4,815 children who were born in the past five years, both including dead children.

The MDHS is a nationwide survey that employed a two-stage cluster sampling method stratifying all fifteen states and divisions (provinces) of Myanmar. The sample size and sampling method were adjusted to enable the representativeness of the estimates of key indicators at the national level and all fifteen states and divisions (MDHS and MOHS, 2017). The sample selection of the survey represented the country's population since the master sampling frame was taken from the National Population Census conducted in 2014. The master frame consisted of all households countrywide and internally displaced populations living in temporary settlements. The first stage of sampling selected 442 clusters or communities from a master sampling frame of 4000 primary sampling units generated by the National Population Census.

At the second stage of sampling, a fixed number of 30 households was selected from each of the identified clusters resulting in 13,260 households (MOHS, 2017).

With this distribution of interviews, some regions/states are overrepresented, and some regions/states are underrepresented. The unweighted distribution of women does not accurately represent the population. In order to get statistics that are representative of Myanmar with different sizes of states and regions, the distribution of the number of women included in the sample needs to be weighted (or mathematically adjusted) so that the sample proportionally and actually represents the whole country of Myanmar. For example, women from a small state, like Kayah, should only contribute a small number to the national total. Women from a large region, like Yangon, the number should contribute much more. With sampling and weighting, it is possible to interview enough women to provide reliable statistics at national and regional/state levels. Therefore, the analysis was based on weighted samples of 3670 women aged 15-49.

3.2 Variables Used in the Study

Detailed working definitions, descriptions, and coding of the dependent and independent variables related to under-five mortality are presented in this section.

3.2.1 Working Definitions of the Variables

The working definition of the dependent variable (under-five mortality) and a number of independent variables considered for the data analysis are defined as according to the 2015-2016 MDHS.

The dependent variable (Y_i) is the number of deaths of children whose age is 0-59 months (under-five mortality) that each mother has experienced under the study period. Thus, (Y_i) takes on values 0, 1, 2, … where 'i' denotes the individual mother.

(i) Socio-economic Variables

The socio-economic variables are considered as the independent variables. These variables include the mother's education level, and wealth index as defined below.

Mother's Education Level: It measures the highest education level of mothers. In this study, the four categories (no education, primary, secondary, and higher) are used.

Wealth Index: Households are given scores based on the number and kinds of consumer goods they own, ranging from a television to a bicycle or car, plus housing characteristics such as the source of drinking water, toilet facilities, and flooring materials. In the 2015-2016 MDHS, the resulting wealth quantiles are described as poorest, poorer, middle, richer, and richest. However, the wealth quantiles are recategorized into three indexes: poor (poorest and poorer), middle, and rich (richer and richest) in this study.

(ii) Demographic Variables

The demographic variables such as state and region, place of residence, household size, marital status, mother's age at birth, and childbirth order are presented as follows.

State and Region: The entire nation of Myanmar is divided into states and regions. There are 15 in all, consisting of 7 states and 8 regions. These include the following: Kachin, Kayah, Kayin, Chin, Sagaing, Tanintharyi, Bago, Magway, Mandalay, Mon, Rakhine, Yangon, Shan, Ayeyarwaddy, and Nay Pyi Taw.

Place of Residence: The place of residence represents the household's location. It is categorized as urban, and rural areas.

Household Size: It is the total number of persons in a household and is categorized as 2-3 persons, 4-5 persons, and more than 5 persons.

Marital Status: The marital status is the civil marriage of everyone in relation to the marriage laws or customs of the country. There are categorized as married, others such as widowed, divorced, and separated/no longer living together.

Mother's Age at Birth: Mother's age at birth refers to the age of a mother at the time of giving birth of the dead child, which is divided into three categories: below 20 years, 20-29 years, and 30-45 years.

Childbirth Order: Birth order is a categorical variable with a child's position in birth order. It is divided into three categories: First child, 2^{nd} and 3^{rd}, and 4^{th} and above.

(iii) Health Care Variables

Health care variables such as place of delivery and contraceptive use are presented as follows.

Place of Delivery: The place where the birth of a child was delivered. It is categorized as home, public sector, and private sector.

Contraceptive Use: The methods used by mothers to limit or space the number of children. This is classified into two categories which are no and yes.

(iv) Environmental Variables

Environmental variables such as access to safe water, access to safe toilets, and types of fuel for cooking are presented as follows.

Access to Safe Water: It is the household's access to improved (safe) water. It is divided into two categories: improved and unimproved. Improved water includes piped water, public taps, standpipes, tube wells, boreholes, protected dug wells and springs, rainwater, and bottled water. Unprotected well, surface from spring, unprotected spring, river/dam/lake/pond/stream/canal/irrigation channel/tanker truck, cart with small tanks is regarded as unimproved water sources.

Access to the Safe Toilet: It is the household's access to an improve (safe) toilet. It is divided into two categories: improved and unimproved. Improved toilet facility includes any non-shared toilet of the following types: flush/pour flush toilets to piped sewer systems, septic tanks, and pit latrines; ventilated improved pit latrines; pit latrines with slabs; and composting toilets. Unimproved toilet facility includes pit latrine without slab/open pit, no facility/bush/field, bucket toilet, hanging toilet/latrine, and others.

Types of Fuel for Cooking: It is the household's use of types of cooking fuel. It is divided into clean fuels, wood and coal and others fuel**.** Clean fuels include liquefied petroleum gas, electricity, natural gas, and biogas. Wood and coal include coal/lignite, charcoal, and wood. Others include straw/shrub/grass, agricultural crops, and animal dung.

3.2.2 Description and Coding of the Variables

Description of variables representing the socio-economic, demographic, health care, and environmental factors and their coding are described in the following tables.

Table (3.1) presents the coding and description of socio-economic variables.

Table (3.1) Description and Coding of Socio-economic Variables

No.	Description of Variables	Coding
1	Mother's Education Level	1 = No education 2 = Primary 3 = Secondary 4 = Higher
2	Wealth Index	1 = Poor 2 = Middle 3 = Rich

The demographic variables and their coding are shown in the Table (3.2).

Table (3.2) Description and Coding of Demographic Variables

No.	Description of Variables	Coding
1	State and Region	1 = Kachin 2 = Kayah 3 = Kayin 4 = Chin 5 = Sagaing 6 = Taninthayi 7 = Bago 8 = Magway 9 = Mandalay 10 = Mon 11 = Rakhine 12 = Yangon 13 = Shan 14 = Ayeyarwaddy 15 = Nay Pyi Taw
2	Place of Residence	1 = Urban 2 = Rural
3	Household Size	1= 2 -3 2 = 4 – 5 3 = More than 5

Table (3.2) Description and Coding of Demographic Variables (Continued)

No.	Description of Variables	Coding
4	Marital Status	1 = Married 2 = Others (Widowed, Divorced, Separated/No Longer Living Together)
5	Mother's Age at Birth	1 = Below 20 2 = 20-29 3 = 30-45
6	Childbirth Order	1 = First birth 2 = Second and third 3 = Fourth and above

The description and coding of healthcare variables are presented in the Table (3.3).

Table (3.3) Description and Coding of Health Care Variables

No.	Description of Variables	Coding
1	Place of Delivery	1 = Private institution 2 = Public institution
2	Contraceptive Use	1 = No 2 = Yes

Table (3.4) expresses the description and coding of environmental variables.

Table (3.4) Description and Coding of Environmental Variables

No.	Description of Variables	Coding
1	Access to Improved Source of Water	1 = Improved 2 = Unimproved
2	Access to Improved Sanitation Facilities	1 = Improved 2 = Unimproved
3	Types of Cooking Fuels	1 = Clean Fuels 2 = Wood and Coal 3 = Others

3.3 Count Models

Non-negative integer-valued numbers are called count data. Count (or frequency) responses such as number of heart attacks, number of days of alcohol drinking, number of suicide attempts, and number of children of deaths. Count models are widely used for dependent variable counting numbers like (0, 1, 2, 3, and so on). Most of the data are concentrated on a few small discrete values.

The estimated Y value will be

$$\hat{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p$$

The foundation for the development of count models is the Poisson distribution. Most of the count data models belong to Generalized Linear Models (Hilbe, 2014).

All the count models have a basic structure,

$$\ln(\lambda) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p \tag{3.1}$$

To isolate the predicted mean count on the left side of the above equation, taking exponential on both sides of the equation

$$\lambda = e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p}$$

The above expressions are important in defining the terms used in the count models. Hilbe (2014) stated the important feature of the linear relationship model using the natural log of the count data which guarantees that the predicted values will be positive, that is, $\lambda > 0$. The several models for handling count data include Poisson model, negative binomial model, zero-inflated Poisson, zero-inflated negative binomial, and hurdle models.

Count regression models were developed using the integer outcome variables. These models can be employed to examine occurrence and frequency of occurrence. The most popular model for count data is the Poisson model, which is based on the property that the mean and variance of the dependent variable are assumed to be equal (Hoffman, 2004). However, this is not always the case, as the variance sometimes exceeds the mean. This is referred to as over-dispersion (Molla and Muniswamy, 2012). Overdispersion can be modeled using a negative binomial regression model, but more models accounting for overdispersion exist. When the sample variance is larger (or smaller) than the sample mean, the data is said to exhibit over-dispersion (or under-dispersion). In order to overcome the problem of over-dispersion or under-dispersion, hurdle regression models were used. Further, the response variable can be observed to show excess zero counts, against what is expected, on the basis of Poisson or negative binomial distribution.

3.3.1 Poisson Regression Model

The Poisson distribution was developed to model discrete counts and because it is like linear regression in many respects, it is relatively easy to interpret. This distribution becomes increasingly positively skewed as the mean of the dependent variable decrease (Long and Freese, 2006), reflecting a common property of count data. Generally, count data are considered realizations of the Poisson model (Agresti, 2002). The Poisson model represents the de facto model for handling count data and this model is completely described by one parameter, λ. The Poisson model, in general, is a flexible model that can accommodate a myriad of count data situations. While the Poisson model is flexible, in practice count data often are not realization from this model. The apparent simplicity of Poisson comes with two restrictive assumptions (Sturman, 1999).

First, the variance and mean of the count variable are assumed to be equal. However, the variance is usually much greater than the mean which is called over-dispersion (Cameron and Trivedi, 1986) and therefore Poisson model though widely used to handle count data may not be well suited to handle some types of count outcomes. Another restrictive assumption of Poisson model is that occurrences of the event are assumed to be independent of each other. This assumption is also frequently violated (Jaquess and Finney, 1994). The Poisson probability model is appropriate for events that occur randomly over time and/or space. The probability function for Y is given by

$$Pr(\mathrm{Y} = y) = \frac{\mathrm{e}^{-\lambda}\lambda^{y}}{\mathrm{y}!} \quad ; \; y = 0,1,2, \ldots \tag{3.2}$$

where λ is the average number of times an event occurs, y is the number of times an event occurs, and e is the Euler's constant. The random variable Y is the count response, and the natural number (parameter) λ is also called the rate or intensity parameter. The constant value of the distribution is E(Y) = λ, and the variance is V(Y) = λ.

The Poisson regression model is widely used to model count data. If the form of the Poisson distribution for the observed value 'i' is $Y_i \sim \text{Poisson}(\lambda_i)$, Equation (3.2) can be rewritten as follows.

$$Pr(Y = y_i) = \frac{e^{-\lambda_i} \lambda_i^{y_i}}{y_i!} \;;\quad y_i = 0,1,2,\dots;\; \lambda_i > 0;\; i = 1,2,\dots,n \tag{3.3}$$

where y_i is the number of child deaths the i[th] mother in a given time with a mean parameter λ_i. Therefore, the Poisson regression for the observed value 'i' can be expressed as follows.

$$\left.\begin{array}{l} \ln(\lambda_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_p X_{pi} \\ \text{where } \Pr(Y = y_i) = \frac{e^{-\lambda_i} \lambda_i^{y_i}}{y_i!} \;;\; y_i = 0,1,2,\dots \end{array}\right\} ,\; i = 1, 2,\dots,n \tag{3.4}$$

The relationship between y_i and i[th] row vector of **X**, $\mathbf{X_i}$ linked by $g(\lambda_i)$ is

$$\ln(\lambda_i) = \boldsymbol{X}_i' \boldsymbol{\beta}$$

The following assumptions must be satisfied for Poisson regression.

(i) The response variable is a count per unit of time or space, described by a Poisson distribution.

(ii) The observations must be independent of one another.

(iii) The mean of a Poisson random variable must be equal to its variance.

(iii) The log of mean rate $\ln(\lambda_i)$, must be a linear function of x.

In Poisson regression, the maximum likelihood estimation (MLE) method is commonly used to estimate the unknown regression coefficients $\boldsymbol{\beta} = [\beta_0, \beta_1, \dots, \beta_p]'$ that define the relationship between the predictor variables and the expected counts of the dependent variable. Given a random sample of independent observations $Y_1, Y_2, \dots, Y_n$, where each Y_i represents the count of occurrences of an event for the i[th] observation, the likelihood function for the Poisson regression model can be formulated as follows:

$$\begin{aligned} L(\boldsymbol{\beta}) &= \prod_{i=1}^{n} P(Y_i = y_i) \\ &= \prod_{i=1}^{n} \frac{e^{-\lambda_i} (\lambda_i)^{y_i}}{y_i!} \end{aligned} \tag{3.5}$$

It takes the logarithm of both sides, the log-likelihood value obtained is as follows.

$$\begin{aligned} \ell(\boldsymbol{\beta}) &= \sum_{i=1}^{n} [y_i \ln(\lambda_i) - \lambda_i - \ln(y_i!)] \\ &= \sum_{i=1}^{n} [y_i(\mathbf{X}_i'\boldsymbol{\beta}) - \exp(\mathbf{X}_i'\boldsymbol{\beta}) - \ln(y_i!)] \end{aligned} \tag{3.6}$$

where $\mathbf{X}$ be an $n \times (p+1)$ matrix of explanatory variables and $\boldsymbol{\beta}$ is a $(p+1)\times 1$ dimensional column vector of unknown parameters to be estimated. Differentiating Equation (3.6) with respect to the parameter vector β give the parameter estimates.
The mean and variance of Poisson distribution is given as

$$E(Y_i) = \mathrm{Var}(Y_i) = \lambda_i$$

3.3.2 Negative Binomial Regression Model

The negative binomial regression model is more flexible than the Poisson model and is frequently used to study count data with over-dispersion (Hilbe, 2011, Hoffman, 2004, Lawless, 1987). In fact, the negative binomial regression model is in many ways equivalent to the Poisson regression model because the negative binomial model could be viewed as a Poisson-gamma mixture model (Hilbe, 2011). However, the difference is that the negative binomial regression model has a free dispersion parameter. In other words, the Poisson regression model can be considered as a negative binomial regression model with an ancillary or heterogeneity parameter value of zero (Hilbe, 2011, Lord and Mannering, 2010).

The negative binomial distribution looks like the Poisson distribution, except that it has a longer, fatter tail to the extent the variance exceeds the mean. Depending on the degree of overdispersion, the negative binomial model could capture more zeros than the Poisson model (Hilbe, 2011). Nevertheless, the model may be insufficient with respect to empirical applications bearing zero values in the data. Zero-inflated models provide a way of modeling the excessive proportion of zero values by allowing overdispersion. When the number of zeros is large, it provides a good fit than Poisson or negative binomial model (Lambert, 1992). However, these models are not suitable for under-dispersion. A flexible alternative that captures both over and under-dispersion is the hurdle model (Gurmu, 1998).

Negative binomial regression is a type of generalized linear model in which the dependent variable Y is a count of the number of times an event occurs. A convenient parametrization of the negative binomial distribution is given by Hilbe (2011):

The negative binomial distribution is given by

$$P(\mathrm{Y}=y)=\frac{\Gamma\left(y+\frac{1}{\alpha}\right)}{y!\Gamma\left(\frac{1}{\alpha}\right)}(1+\alpha\lambda)^{\frac{-1}{\alpha}}\left(1+\frac{1}{\alpha\lambda}\right)^{y} \quad ; \; y\geq 0 \; and \; \alpha>0 \tag{3.7}$$

where $\lambda > 0$ is the mean of Y and $\alpha > 0$ is the heterogeneity parameter. Hilbe (2014) derives this parametrization as a Poisson-gamma mixture. where, α shows the level of overdispersion and $\Gamma(.)$ is the gamma function. If $\alpha = 0$, NB regression model will reduce to Poisson regression model. Often data will show over-dispersion (variance > mean) or under-dispersion (variance < mean). With over-dispersed data could use the negative binomial regression model. λ_i. If the form of the negative binomial distribution for the observed value 'i' is $\mathrm{Y_i} \sim$ negative binomal(λ_i), Equation (3.7) can be rewritten as follows.

$$P(\mathrm{Y}_i=\mathrm{y_i})=\frac{\Gamma\left(y_i+\frac{1}{\alpha}\right)}{y_i!\,\Gamma\left(\frac{1}{\alpha}\right)}(1+\alpha\lambda_i)^{\frac{-1}{\alpha}}\left(1+\frac{1}{\alpha\lambda_i}\right)^{y_i} \quad ; \; y_i \; \geq 0 \; and \; \alpha>0$$

Therefore, the negative binomial regression for the observed value 'i' can be expressed as follows.

$$\ln(\lambda_\mathrm{i})=\beta_0+\beta_1\mathrm{X_{1i}}+\beta_2\mathrm{X_{2i}}+\cdots+\beta_\mathrm{p}\mathrm{X_{pi}} \tag{3.8}$$

where $P(\mathrm{Y}_i=\mathrm{y_i})=\frac{\Gamma\left(y_i+\frac{1}{\alpha}\right)}{y_i!\,\Gamma\left(\frac{1}{\alpha}\right)}(1+\alpha\lambda_i)^{\frac{-1}{\alpha}}\left(1+\frac{1}{\alpha\lambda_i}\right)^{y_i} \; ; \; y_i \; \geq 0 \; and \; \alpha>0$

The relationship between y_i and $\mathrm{i^{th}}$ row vector of X, $\mathrm{X_i}$ linked by $g(\lambda_i)$ is

$$\ln(\lambda_i)=\boldsymbol{X}_i'\boldsymbol{\beta}$$

Negative binomial regression is a popular generalization of Poisson regression because it loosens the highly restrictive assumption that the variance is equal to the mean made by the Poisson model. The traditional negative binomial regression model is based on the Poisson-gamma mixture distribution. This model is popular because it models the Poisson heterogeneity with a gamma distribution. The basic assumption for Poisson regression is as follows: when the mean equals the variance, it indicates equidispersion; when the variance is less than the mean, it indicates underdispersion; and when the variance is greater than the mean, it indicates overdispersion. To overcome the overdispersion problem, one alternative is to use negative binomial regression. It is a special regression of Poisson regression that occurs overdispersion.

Given a random sample of n objects, Equation (3.8) observes for subject i the dependent variable Y_i and the predicator variables $X_{1i}, X_{2i}, \dots, X_{pi}$. Utilizing vector and matrix notation, $\boldsymbol{\beta} = [\beta_0, \beta_1, \dots, \beta_p]'$ and the predictor data into the design matrix **X**.

A random sample of independent observations $Y_1, Y_2, \dots, Y_n$, where each Y_i represents the count of occurrences of an event for the i^{th} observation, the likelihood function for the negative binomial regression model can be formulated as follows:

$$L(\boldsymbol{\beta}, \boldsymbol{\alpha}) = \prod_{i=1}^{n} P(Y_i = y_i)$$

$$= \prod_{i=1}^{n} \frac{\Gamma\left(y_i + \frac{1}{\alpha}\right)}{y_i!\,\Gamma\left(\frac{1}{\alpha}\right)} (1 + \alpha\lambda_i)^{\frac{-1}{\alpha}} \left(1 + \frac{1}{\alpha\lambda_i}\right)^{y_i} \tag{3.9}$$

It takes the logarithm of both sides, the log-likelihood value obtained is as follows.

$$\ell(\boldsymbol{\beta}, \boldsymbol{\alpha}) = \sum_{i=1}^{n} \Bigg[y_i \ln\alpha + y_i\lambda_i - \left(y_i + \frac{1}{\alpha}\right)\ln(1 + \alpha\lambda_i) + \ln\Gamma\left(y_i + \frac{1}{\alpha}\right)$$
$$- ln\Gamma(y_i + 1) - ln\Gamma\left(\frac{1}{\alpha}\right)\Bigg]$$
$$= \sum_{i=1}^{n} \Bigg[y_i \ln\alpha + y_i e^{\mathbf{X}_i'\boldsymbol{\beta}} - \left(y_i + \frac{1}{\alpha}\right)\ln\left(1 + \alpha e^{\mathbf{X}_i'\boldsymbol{\beta}}\right) + \ln\Gamma\left(y_i + \frac{1}{\alpha}\right)$$
$$- ln\Gamma(y_i + 1) - ln\Gamma\left(\frac{1}{\alpha}\right)\Bigg] \tag{3.10}$$

Differentiating Equation (3.10) with respect to the parameter vector $\boldsymbol{\beta}$, to get the estimates.

The mean and variance are given by

$$E(Y_i) = \lambda_i = \exp(\mathbf{X}_i'\boldsymbol{\beta})$$

and

$$Var\,(Y_i) = \lambda_i(1 + \alpha\lambda_i).$$

where, $\mathbf{X}_i'$ is 1×p row vector of covariate, p is the number of covariates in the model and $\boldsymbol{\beta}$ is the corresponding p×1 column vector of unknown regression parameters.

3.3.3 Zero-Inflated Models

Zero-inflated Models refer to models that are designed to accommodate excess zeros in count data. In some case, excess zeros exist in count data and considered as a result of over-dispersion. In such case, the NB model might not be appropriate if the over-dispersion is caused by an excessive number of zeros in the outcome. In this result of over-dispersion. In such cases, the NB model might not be appropriate if the over-dispersion is caused by an excessive number of zeros in the outcome. In these cases, alternative models such as zero-inflated models are recommended (Lambert, 1992). These models assume that there are two latent classes of observations: those who can only have a 0 count (probability 1 for a zero), and those who have a positive probability for any count. Let y_i be a nonnegative integer-valued random variable and suppose $y_i = 0$ is observed with a frequency significantly higher than can be modeled by the usual model. Thus, the zero-inflated regression model is defined as:

$$P(Y_i = y_i) = \begin{cases} w_i + (1 - w_i)\, P(Y_i = 0; \lambda_i) & ; \quad y_i = 0 \\ (1 - w_i)\, P(Y_i; \lambda_i) & ; \quad y_i = 1,2,\ldots \end{cases} \tag{3.11}$$

where, $P(Y_i)$ follows either the Poisson or the negative binomial distribution and $0 \le w_i \le 1$.

The mean and variance of the zero-inflated distribution ZI $P(Y_i; \lambda_i)$ distribution is given by

$$E_{zi}P(Y_i; w, \lambda) = (1 - w)E(Y_i; \lambda)$$

and

$$\begin{aligned} V_{zi}P(Y_i; w, \theta) &= (1 - w)[E^2(Y_i; \lambda)] - [(1 - w)E(Y_i; \lambda)]^2 \\ &= (1 - w)\{V(Y_i; \lambda) + wE^2(Y_i; \lambda)\} \end{aligned}$$

Zero-inflated regression provides to handle excessive number of zeros. Zero-inflated regression also considers two data generating processes. However, instead of assuming all zero counts from a single generating process, zero-inflated regression assumes zero counts come from two different sources. Specifically, a zero count may come from the always-zero group (mothers who are never born) or the not always-zero group (mothers who may not be dead her child). Zero-inflated regression is also a two-part model. In this study, used the two zero inflated models. These are Zero-inflated Poisson (ZIP) and Zero-inflated negative binomial regression models.

Zero-Inflated Poisson Regression Model (ZIP)

The zero-inflated Poisson regression model is used for modeling count data that show over-dispersion and zero counts (excess zeros). The ZIP model, introduced by (Lambert,1992), allows for covariates for both the binary and Poisson parts of the model and it has been commonly used to model count data with excess zeros (Hur et al., 2002). The zero-inflated Poisson regression studies the relationship between dependent and independent variables when there are many zeros value in the dependent variable, where the relationship is the mixture between Poisson model and Logistic model. Specifically, if Y_i is the number of under-five mortality per mothers are independent random variables having a zero-inflated Poisson distribution, the zeros are assumed to arise in two ways corresponding to distinct underlying sources.

The first source occurs with probability w_i and produces only zeros (mothers who are never born), while the second source occurs with probability $1 - w_i$ and leads to a standard Poisson count with mean λ and hence a chance of further zeros (mothers who may not be dead her child). In general, the zeros from the first source are called structural zeros (with true zeros) that distributed according to Poisson distribution. The Zero-inflated Poisson regression model is

$$P(Y_i = y_i) = \begin{cases} w_i + (1 - w_i)e^{-\lambda_i} & ; \quad y_i = 0 \\ (1 - w_i)\dfrac{e^{-\lambda_i}\lambda_i{}^{y_i}}{y_i!} & ; \quad y_i = 1,2, \dots \end{cases} \tag{3.12}$$

where $Y_i \sim ZIP\ (\lambda_i, w_i)\ and\ \ 0 \leq w_i \leq 1$. The first part of the equation above is the zero parts of the model and the second part is the non-zero count's part of the model. The two components together constitute the zero-inflated model. The parameters λ_i and w_i can be obtained by using the link functions,

$\ln(\lambda_i) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \cdots + \beta_p X_{ip} = \mathbf{X}_\mathbf{i}'\boldsymbol{\beta}$ and

$$\begin{aligned} \mathrm{logit}(\pi_i) &= \gamma_0 + \gamma_1 Z_{i1} + \gamma_2 Z_{i2} + \gamma_3 Z_{i3} + \cdots + \gamma_q Z_{iq} \\ &= \ln\left(\frac{w_i}{1-w_i}\right) \\ &= \boldsymbol{Z}_i'\boldsymbol{\gamma} \qquad ; \ i = 1,2, \dots, n \end{aligned}$$

where, $\mathbf{X}_\mathbf{i}'\ and\ \mathbf{Z}_\mathbf{i}'$ are covariate matrices and $\boldsymbol{\beta}, \boldsymbol{\gamma}$ are the (p +1) ×1 and (q +1) ×1 unknown parameter vectors $\boldsymbol{\beta} = (\beta_1, \beta_2, \dots, \beta_p)$ and $\boldsymbol{\gamma} = (\gamma_1, \gamma_2, \dots, \gamma_q)$ respectively.

The likelihood function of ZIP model is

$$L(\boldsymbol{\beta},\boldsymbol{\gamma}) = \prod_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{P}(\mathrm{Y_i} = \mathrm{y_i})$$

$$= \prod_{\mathrm{i}=1}^{\mathrm{n}} \left[w_i + (1-w_i)e^{-\lambda_i}\right] \prod_{\mathrm{i}=1}^{\mathrm{n}} \left[(1-w_i)\frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!}\right] \tag{3.13}$$

The log-likelihood function of ZIP model is

$$\ell(\boldsymbol{\beta},\boldsymbol{\gamma}) = \sum_{y_i=0}^{n} ln\left[w_i + (1-w_i)e^{-\lambda_i}\right] \sum_{y_i\neq 0}^{n} [\ln(1-w_i) - \lambda_i + y_i ln\lambda_i - \ln(y_i!)]$$

$$= \sum_{y_i=0}^{n} \ln\left(exp(\boldsymbol{Z_i'\gamma}) + \exp\left(-exp(\boldsymbol{X_i'\beta})\right)\right) + \sum_{y_i\neq 0}^{n} [y_i\boldsymbol{X_i'\beta} - \exp(\boldsymbol{X_i'\beta})$$

$$- \ln(y!)] - \textstyle\sum_{y_i\neq 0}^{n} \ln(1+\exp(\boldsymbol{Z_i'\gamma})) \tag{3.14}$$

The parameters of this model can be estimated using maximum likelihood estimation. The mean and variance of ZIP are given by

$$E(Y_i) = (1-w_i)\lambda_i$$

and

$$V(Y_i) = E(Y_i)(1+w_i\lambda_i).$$

Indicating that the marginal distribution of y_i exhibits over-dispersion, if $w_i > 0$. It is clear that this reduces to the standard Poisson model when $w_i = 0$.

Zero-Inflated Negative Binomial Regression Model (ZINB)

Zero-inflated negative binomial models have been described as an extended version of the negative binomial regression models for excess zero count data (Greene, 1994). Zero-inflated negative binomial (ZINB) regression is one of the methods used in troubleshooting over-dispersion due to excessive zero values in the response variable (excess zero). This model provides a way of modeling the excess number of zeros in addition to allow for count data that are skewed and over-dispersion. The over-dispersed data are characterized by "excess zeros", excess large outcomes or both ZINB model therefore accounts for "excess zeros" and extra heterogeneity in a positive outcome. This regression model was given by

$$P(Y_i = y_i) = \begin{cases} w_i + (1-w_i)(1+\alpha\lambda_I)^{\frac{-1}{\alpha}} & ; \quad y_i = 0 \\ (1-w_i)\frac{\Gamma\left(y_i+\frac{1}{\alpha}\right)}{y_i!\Gamma\left(\frac{1}{\alpha}\right)}(1+\alpha\lambda_i)^{\frac{-1}{\alpha}})\left(1+\frac{1}{\alpha\lambda_i}\right)^{-y_i} & ; \quad y_i > 0 \end{cases} \tag{3.15}$$

where $0 \leq w_i \leq 1, \lambda_i \geq 0,\ \alpha$: dispersion coefficient and $\Gamma(.)$: gamma function. If both $\alpha\ and\ w_i = 0$, then ZINB reduces to Poisson. The parameter λ_i is expressed as: $\lambda_i = \exp(\mathbf{X_i}'\boldsymbol{\beta})$ where, $\boldsymbol{\beta}\ is\ the\ (p+1) \times 1$ vector of unknown parameters associated with the known covariate vector $\mathbf{X_i'} = \left(1, \mathrm{X_{i1}}, \ldots, \mathrm{X_{ip}}\right)$, p is the number of covariates not including the intercept. The parameter w_i is often referred as the zero-inflation factor, which is the probability of zero count from the binary process. The response variable is defined as $\mathrm{Y_i} \sim NB(\lambda_i, \alpha)$. The value of $\lambda_i\ (i = 1,2, \ldots, n)$ is defined as the Equation (3.15).

$$\lambda_i = \exp\left(\boldsymbol{X_i'\beta}\right)$$

$$w_i = \frac{\exp\left(\boldsymbol{X_i'\gamma}\right)}{1 + \exp\left(\boldsymbol{X_i'\gamma}\right)}$$

$$1 - w_i = \frac{1}{1 + \exp\left(\boldsymbol{X_i'\gamma}\right)} \tag{3.16}$$

Hence the ZINB regression model is obtained as written in the Equation (3.16). The model for discrete data that follows the negative binomial distribution is in the first part of Equation (3.16) and the model for zero excess is in the second part of the Equation (3.16) below.

$$\ln(\lambda_i) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \cdots + \beta_p X_{ip} = \mathbf{X_i'\beta} \text{ and}$$

$$\begin{aligned} \mathrm{logit}(\pi_i) &= \gamma_0 + \gamma_1 Z_{i1} + \gamma_2 Z_{i2} + \gamma_3 Z_{i3} + \cdots + \gamma_q Z_{iq} \\ &= \ln\left(\frac{w_i}{1 - w_i}\right) \\ &= \boldsymbol{Z_i'\gamma},\ \ i = 1,2, \ldots, n \end{aligned} \tag{3.17}$$

where, $\boldsymbol{\gamma}$ is the (q+1) ×1 vector of zero-inflated coefficients to be estimated which is associated with the known zero-inflation covariates vector z_i and q is the number of the covariates in the model. From Equation (3.17), it can be seen that $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are parameters of the ZINB model. In order to find the value of the ZINB parameter, maximum likelihood estimation (MLE) method was used.

The likelihood function of ZINB model is

$$L(\boldsymbol{\beta},\boldsymbol{\gamma}) = \prod_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{P}(\mathrm{Y_i} = \mathrm{y_i})$$

$$= \prod_{\mathrm{i=1}}^{\mathrm{n}} \left[w_i + (1-w_i)(1+\alpha\lambda_I)^{\frac{-1}{\alpha}}\right] \prod_{i=1}^{n} \left[(1-w_i)\frac{\Gamma\left(y_i+\frac{1}{\alpha}\right)}{y_i!\Gamma\left(\frac{1}{\alpha}\right)}(1+\alpha\lambda_i)^{\frac{-1}{\alpha}}\right)\left(1+\frac{1}{\alpha\lambda_i}\right)^{-y_i}\right] \quad (3.18)$$

Then, the log-likelihood function of ZINB model can be obtained as the following:

$$\ell(\boldsymbol{\beta},\boldsymbol{\gamma}) = \sum_{i=1}^{n} \ln\left[\frac{e^{\mathbf{X}_i'\boldsymbol{\gamma}}}{1+e^{\mathbf{X}_i'\boldsymbol{\gamma}}} + \left(\frac{1}{1+e^{\mathbf{X}_i'\boldsymbol{\gamma}}}\right)\left(1+\alpha e^{\mathbf{X}_i'\boldsymbol{\beta}_I}\right)^{\frac{-1}{\alpha}}\right] + \sum_{i=1}^{n} \ln\left[\frac{1}{1+e^{\mathbf{X}_i'\boldsymbol{\gamma}}}\frac{\Gamma\left(y_i+\frac{1}{\alpha}\right)}{y_i!\Gamma\left(\frac{1}{\alpha}\right)}\left(1+\quad \alpha(e^{\mathbf{X}_i'\boldsymbol{\beta}}\right)^{\frac{-1}{\alpha}}\left(\frac{1}{1+e^{X_i'\gamma}}\right)\left(1+\alpha e^{\mathbf{X}_i'\boldsymbol{\beta}_I}\right)^{-y_i}\right] \quad (3.19)$$

In this case, the mean and variance of the Y_i are

$$E(Y_i) = (1-w_i)\lambda_i$$

and

$$Var\ (Y_i) = (1-w_i)\lambda_i(1+w_i\lambda_i+\alpha\lambda_i)$$

The parameters of this model can be estimated using maximum likelihood estimation.

3.3.4 Hurdle Models

Hurdle models are also called zero-altered model. Hurdle model known as a two-part model, where the first part is a binomial distribution determining if a count is zero or positive and second is a truncated count model. In zero-inflated models assumed that count data consist of two types of data subgroup, the first subgroup is a set of only zeros count (false zeros), and the second subgroup is a set of count variables (with true zeros). While hurdle model does not discriminate between the types of zeros; they are simply zeros. The basic idea for the hurdle models is the outcomes are treated as absence and presence zeros data. This means that the outcomes are divided into two groups, the first includes all zeros, the second includes non-zero count. The binomial distribution is used to model the absence and presence and a Poisson or negative binomial distribution for the counts. To measure a non-zero count should be modified the distribution and exclude the possibility of a zero observation, and this is called a zero-truncated distribution.

The hurdle model is

$$P(Y) = \begin{cases} f_1(0) & ; y = 0 \\ \frac{1-f_1(0)}{1-f_2(0)} f_2(y) & ; y > 0 \end{cases} \tag{3.20}$$

where f_1: $\mathrm{f}_{\mathrm{binomial}}$

f_2: $f_{Poission\ or\ Negative\ binomial}$

Hurdle Poisson Regression Model (HP)

Hurdle Poisson regression model is also called zero-altered Poisson. The probability of measuring zero observation in the first part of hurdle structure is modeled with a binomial distribution, where w_i is the probability that y_i = 0. The response variable for the positive counts (truncated zero) with Poisson probability mass function

$$P(\mathrm{Y}_i; \lambda_i \,|y_i = 0) = e^{-\lambda}$$

and

$$P(\mathrm{Y}_i; \lambda_i \,|y_i > 0) = 1 - P(\mathrm{Y}_i; \lambda_i \,|y_i = 0)$$

Therefore,

$$P(\mathrm{Y}_i; \lambda_i \,|y_i > 0) = 1 - e^{-\lambda}$$

Furthermore, let the probability of observing $y_i = 0$ in the first part of hurdle model (zero count) as follows:

$$P(\mathrm{Y}_i = 0) = f_1 = (0) = w_i$$

where, the probability of observing $(y_i = 0)$ in the second part of hurdle model (positive counts) as follows

$$P(\mathrm{Y}_i; \lambda_i \,|y_i > 0) = f_2(y) = \frac{\lambda_i^{y_i} e^{-\lambda_i}}{y_i!}$$

This is a hurdle model

$$P(Y_i = y_i) = \begin{cases} w_i & ; \quad y_i = 0 \\ (1 - w_i) \frac{\lambda_i^{y_i} e^{-\lambda_i}}{(1-e^{-\lambda_i}) y_i!} & ; \quad y_i > 0 \end{cases} \tag{3.21}$$

By assumptions of GLM, $\lambda_i = e^{\mathrm{X}_i'\beta_i}$, where $\mathbf{X}_i'$ are knows independent variables, Lambert (1992) suggested the functional form for modeling the parameter w_i as logistic function, which is given by

$$Log\left(\frac{w_i}{1 - w_i}\right) = \boldsymbol{z}_i'\boldsymbol{\gamma}_i$$

and therefore

$$w_i = \frac{e^{\mathbf{z}_\mathbf{i}'\boldsymbol{\gamma}_\mathbf{i}}}{1 + e^{\mathbf{z}_\mathbf{i}'\boldsymbol{\gamma}_\mathbf{i}}} > 0$$

where $\boldsymbol{Z_i} = (1, z_{i1}, z_{i2}, \dots, z_{iq})$ is the ith row of covariate matrix $\mathbf{Z}$ and $\boldsymbol{\gamma} = (\gamma_1, \gamma_2, \dots, \gamma_q)$ are unknown q-dimensional column vector of parameters. While the effect of covariates z_i on strictly positive. Count data are modeled through Poisson regression:

$$\ln(\lambda_i) = \mathbf{X}_\mathbf{i}'\boldsymbol{\beta}$$

where $\mathbf{X_i} = 1, X_{i1}, X_{i2}, \dots, X_{iq})$ is the ith row of row of covariate matrix $\mathbf{X}$ and $\boldsymbol{\beta} = (\beta_1, \beta_2, \dots, \beta_p)$ are unknown p-dimensional column vector of parameters.

$$L(\boldsymbol{\beta}, \boldsymbol{\gamma}) = \prod_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{P}(\mathrm{Y_i} = \mathrm{y_i})$$

$$L(\boldsymbol{\beta}, \boldsymbol{\gamma}) = \prod_{\mathrm{i}=1}^{\mathrm{n}} [w_i] \prod_{i=1}^{n} \left[(1 - w_i) \frac{\lambda_i^{y_i} e^{-\lambda_i}}{(1 - e^{-\lambda_i}) y_i!}\right] \quad (3.22)$$

The log likelihood function of two components as below:

$$\ell(\boldsymbol{\beta}, \boldsymbol{\gamma}) = \sum_{\mathrm{i}=1}^{\mathrm{n}} \ln(w_i) + \sum_{i=1}^{n} \ln(1 - w_i) - \lambda_i + y_i \ln(\lambda_i) - \ln\left(1 - e^{-\lambda_i}\right) - \ln(y_i!)$$

Then, the log-likelihood function of HP model can be obtained as the following:

$$\ell(\boldsymbol{\beta}, \boldsymbol{\gamma}) = \sum_{\mathrm{i}=1}^{\mathrm{n}} \ln\left[\frac{\exp(\mathbf{Z}_\mathbf{i}'\boldsymbol{\gamma})}{1 + \exp(\mathbf{Z}_\mathbf{i}'\boldsymbol{\gamma})}\right] + \sum_{i=1}^{n} \ln\left[\frac{1}{\exp(\boldsymbol{Z}_i'\boldsymbol{\gamma})}\right] - \exp(\mathbf{X}_\mathbf{i}'\boldsymbol{\beta}) + y_i \mathbf{X}_\mathbf{i}'\boldsymbol{\beta} - \ln[(1 - \exp(-\exp(\mathbf{X}_\mathbf{i}'\boldsymbol{\beta})))] - \ln(y_i!) \quad (3.23)$$

Differentiating Equation (3.23) with respect to the parameter vector **β**, to get the estimates.

The mean and variance for hurdle are

$$E(Y_i) = \frac{1 - w_i}{1 - e^{-\mu}} \lambda_i$$

and

$$Var(Y_i) = \frac{1 - w_i}{1 - e^{-\mu}} (\lambda_i + \lambda_i^2) - \left(\frac{1 - w_i}{1 - e^{-\mu}} \lambda_i\right)^2$$

Hurdle Negative Binomial Regression Model (HNB)

The same procedure can be easily generalized to “hurdle negative binomial regression” model. This model is also called zero-altered negative binomial. The probability of measuring zero observation in the first part of hurdle structure is modeled with a binomial distribution, where w_i is the probability that $Y_i = 0$. The response variable for the positive count (truncated at zero) with negative binomial probability mass function,

$$P(\mathrm{Y}_i; \lambda_i | y_i = 0) = \left(\frac{1}{1+\alpha\lambda_i}\right)^{\frac{1}{\alpha}}$$

and

$$P(\mathrm{Y}_i; \lambda_i \, | y_i > 0) = 1 - P(\mathrm{Y}_i; \lambda_i \, | y_i = 0)$$

Therefore,

$$P(\mathrm{Y}_i; \lambda_i \, | y_i > 0) = 1 - \left(\frac{1}{1+\alpha\lambda_i}\right)^{\frac{1}{\alpha}}$$

Furthermore, let the probability of observing $y_i = 0$ in the first part of hurdle model (zero count) as follows

$$P(\mathrm{Y}_i = 0) = f_i = (0) = w_i$$

where, the probability of observing $(y_i = 0)$ in the second part of hurdle model (positive counts) as follows

$$P(\mathrm{Y}_i; \lambda_i \, | y_i > 0) = f_2(y) = \frac{\Gamma\left(y_i + \frac{1}{\alpha}\right)}{\Gamma\left(\frac{1}{\alpha}\right)\Gamma(y_i+1)} \left(\frac{1}{1+\alpha\lambda_i}\right)^{\frac{1}{\alpha}} \left(\frac{\alpha_i\lambda_i}{1+\alpha_i\lambda_i}\right)^{y_i}$$

$$P(Y_i = y_i) = \begin{cases} w_i & ; \; y_i = 0 \\ \dfrac{(1-w_i)\frac{\Gamma\left(y_i+\frac{1}{\alpha}\right)}{\Gamma\left(\frac{1}{\alpha}\right)\Gamma(y_i+1)}\left(\frac{1}{1+\alpha\lambda_i}\right)^{\frac{1}{\alpha}}\left(\frac{\alpha_i\lambda_i}{1+\alpha_i\lambda_i}\right)^{y_i}}{\left(1-\left(\frac{1}{1+\alpha_i\lambda_i}\right)^{\frac{1}{\alpha}}\right)} & ; \; y_i > 0 \end{cases} \tag{3.24}$$

By assumptions of GLM, $\lambda_i = e^{\mathbf{x}_i'\boldsymbol{\beta}_i}$, where $\mathbf{X}_i'$ are knows independent variables, Lambert (1992) suggested the functional form for modeling the parameter w_i as logistic function, which is given by

$$Log\left(\frac{w_i}{1-w_i}\right) = \boldsymbol{z}_i'\boldsymbol{\gamma}_i$$

and therefore

$$w_i = \frac{e^{\boldsymbol{z}_i'\boldsymbol{\gamma}_i}}{1+e^{\boldsymbol{z}_i'\boldsymbol{\gamma}_i}} > 0$$

where $\boldsymbol{Z_i} = (1, z_{i1}, z_{i2}, \dots, z_{iq})$ is the ith row of covariate matrix $\mathbf{Z}$ and $\boldsymbol{\gamma} = (\gamma_1, \gamma_2, \dots, \gamma_q)$ are unknown q-dimensional column vector of parameters.

$$L(\boldsymbol{\beta}, \boldsymbol{\gamma}) = \prod_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{P(Y_i = y_i)}$$

$$= \prod_{\mathrm{i=1}}^{\mathrm{n}} [w_i] \prod_{i=1}^{n} \left[(1 - \mathrm{w_i}) \frac{\Gamma\left(\mathrm{y_i} + \frac{1}{\alpha}\right)}{\Gamma\left(\frac{1}{\alpha}\right)\Gamma(\mathrm{y_i}+1)} \left(\frac{1}{1+\alpha\lambda_i}\right)^{\frac{1}{\alpha}} \left(\frac{\alpha_i\lambda_i}{1+\alpha_i\lambda_i}\right)^{\mathrm{y_i}} \left(1 - \left(\frac{1}{1+\alpha_i\lambda_i}\right)^{\frac{1}{\alpha}}\right) \right] \quad (3.25)$$

The log likelihood function of two components as below:

$$\ell(\boldsymbol{\beta}, \boldsymbol{\gamma}) = \sum_{\mathrm{i=1}}^{\mathrm{n}} \ln(w_i) \sum_{i=1}^{n} \left[\ln(1 - w_i) - \frac{1}{\alpha} \ln\big(1 - (1 + \alpha\lambda_i)\big) - y_i \ln\left(1 + \frac{1}{\alpha\lambda_i}\right) - \frac{1}{\alpha}\ln(\alpha\lambda_i + 1) + \ln\left(\frac{\Gamma\left(y_i + \frac{1}{\alpha}\right)}{\Gamma\left(\frac{1}{\alpha}\right)}\right) \right] \quad (3.26)$$

Then, the log-likelihood function of HNB model can be obtained as the following:

$$\ell(\boldsymbol{\beta}, \boldsymbol{\gamma}) = \sum_{\mathrm{i=1}}^{\mathrm{n}} \ln\left[\frac{\exp(\mathbf{Z}_i'\boldsymbol{\gamma})}{1+\exp(\mathbf{Z}_i'\boldsymbol{\gamma})}\right] + \sum_{i=1}^{n} \left\{ \ln\left[\frac{1}{\exp(\boldsymbol{Z}_i'\boldsymbol{\gamma})}\right] - \frac{1}{\alpha}\mathrm{In}\Big(1 - \big(1 + \alpha(\exp(\mathbf{X}_i'\boldsymbol{\beta}))\big)\Big) + y_i \ln\left(1 + \frac{\mathbf{1}}{\boldsymbol{\alpha}(\mathbf{exp}(\mathbf{X}_i'\boldsymbol{\beta}))}\right) - \frac{1}{\alpha}\ln(\alpha(\exp(\mathbf{X}_i'\boldsymbol{\beta})) + 1) - \ln\left(\frac{\Gamma\left(y_i + \frac{1}{\alpha}\right)}{\Gamma\left(\frac{1}{\alpha}\right)}\right) \right\} \quad (3.27)$$

Differentiating Equation (3.27) with respect to the parameter vector $\boldsymbol{\beta}$, to get the estimates.

The mean and variance for HNB are

$$E(Y_i) = \frac{1-w_i}{1-P_0}\lambda_i$$

and

$$Var(Y_i) = \frac{1-w_i}{1-P_0}(\lambda_i^2 + \lambda_i + \alpha\lambda_i^2) - \left(\frac{1-w_i}{1-P_0}\lambda_i\right)^2$$

where $P_0 = \left(\dfrac{1}{1 + \alpha_i\lambda_i}\right)^{\frac{1}{\alpha}}$.

3.4 Over-dispersed (Extra-) Poisson Model

It is possible to account for overdispersion with respect to the Poisson model by introducing a dispersion parameter α into the relationship between the variance and the mean:

$$Var\ (\mathrm{Y_i}) = \alpha\mu$$

If $\alpha = 1$ then the variance equals the mean that obtain the Poisson model. If $\alpha > 1$ then the model has over-dispersion relative to Poisson. If $\alpha < 1$ then model have under-dispersion, but this is relatively rare. There are three ways of dealing about overdispersion:

1. Deviance, $D(y, \hat{\mu})$, is given by

$$D(y, \hat{\mu}) = 2\sum_{i=1}^{n}\left\{y_i ln\left(\frac{y_i}{\hat{\mu}_i}\right) - (y_i - \hat{\mu}_i)\right\}$$

where y is the number of events, n is the number of observations and $\hat{\mu}_i$ is the fitted Poisson mean.

2. Pearson chi-square test, χ^2 is also given by

$$\chi^2 = \sum_{i=1}^{n}\frac{(y_i - \hat{\mu}_i)^2}{\hat{\mu}_i}$$

Over-dispersion may be a result of higher occurrence of zero counts and subject heterogeneity. Deviance and Pearson Chi-Square divided by the degrees of freedom are used to detect over dispersion or under-dispersion in the Poisson regression. Values greater than one indicate overdispersion, that is the true variance is bigger than the mean, whereas values smaller than one indicate under- dispersion, that is the true variance is smaller than the mean.

3. Another way of checking the presence of over dispersion is a likelihood ratio test the hypotheses:

$$H_0: \alpha = 0\ vs \quad H_1: \alpha > 0.$$

Test statistic:

$$G^2 = -2\ln\left[\frac{L_0}{L_1}\right] = -2\{lnL_0 - lnL_1\}$$

where $\ln L_0$ and $\ln L_1$ are the maximized log-likelihood of models under the null and alternative hypothesis, respectively.

If P-value of $LRT_\alpha < \alpha$ (level of significance), which is an indicated of over-dispersion is present: negative binomial is preferred.

If P-value of $LRT_{\alpha} > \alpha$ (level of significance), Poisson regression is preferred.
The negative binomial regression model is more appropriate for over-dispersed data because it relaxes the constraints of mean and variance.

For this study LRT will be used to compare the Poisson with the negative binomial and zero-inflated Poisson with zero- inflated negative binomial as well as hurdle Poisson with hurdle negative binomial since Poisson is nested on negative binomial and zero-inflated Poisson is nested on zero-inflated negative binomial. However, this will not be used to compare Poisson or negative binomial with the zero-inflated Poisson and negative binomial as long as these models are not nested one on the other.

3.5 Selecting of a Zero-Inflated Count Models

Figure (3.1) presents a flow chart that could be used to assist in selecting one of the previously described models.

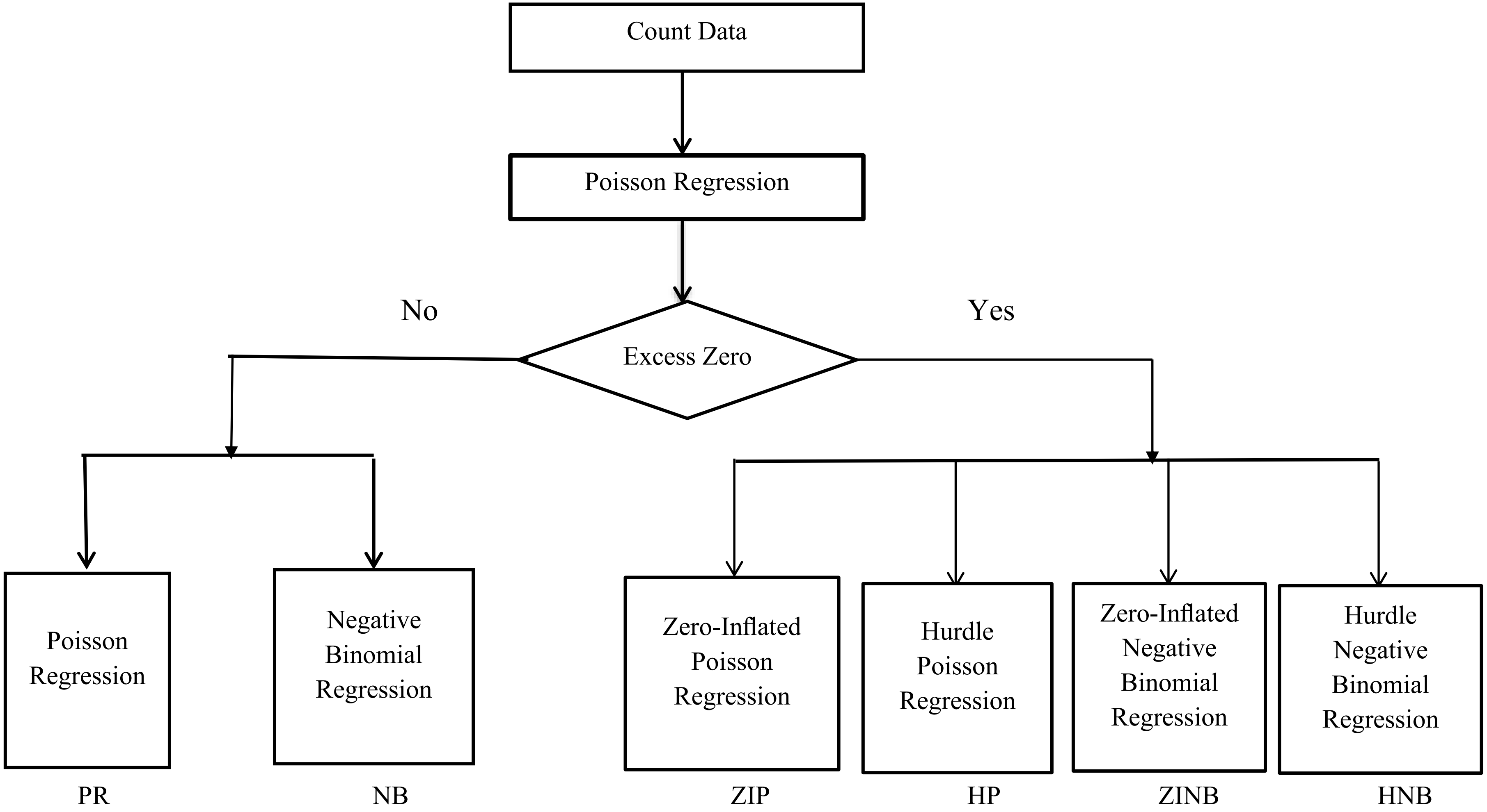

Figure (3.1) Flow Chart for the Best Model Selection

Source: Own Complication

As shown in Figure (3.1), Poisson regression is fundamental to the modeling of count data. It was the first model specifically used to model count and it still stands at the base of the many types of count models available to analysis. Having data with an excessive number of zero counts is another problem for many count models. Typically, analysis uses either a two-part hurdle model or zero-inflated models such as zero-inflated Poisson and zero-inflated negative binomial. Two types of models are commonly used to handle excess zeros: hurdle models and zero-inflated models. A hurdle model is an appropriate model to use when the count response variable has either fewer or greater zero counts than are expected based on the distributional assumptions of the model. A zero-inflated model is a mixture model that may also be referred to as a type of finite mixture model. A zero-inflated model is used when there are excessive zero count in the data. The frequently used models for zero-inflated count data are zero-inflated regression Poisson (ZIP), zero-inflated regression negative binomial, hurdle Poisson regression, and hurdle negative binomial regression models (Hilbe, 2014).

3.6 Model Selection Criteria

If there are a number of models to be compared in order to select the best model which fits the data by using the Akaike information criteria (AIC) and Bayesian information criteria (BIC).

3.6.1 Akaike Information Criteria (AIC)

One of the most regularly used measure is AIC. For comparison of non-nested models based on maximum likelihood, several authors beginning with Akaike in 1973 have proposed model selection criteria based on the fitted log-likelihood function. The AIC penalized a model with larger number of parameters and is defined as

$$AIC = -2 \ln L + 2k$$

where lnL is the maximized log likelihood function for the estimated model and -lnL offer summary information on how much discrepancy exists between the model and the data, where k is the number of parameters in the model (Konishi and Kitagawa, 2008). A relatively small value of AIC is preferred for the fitted model (Ismail and Zamani, 2013).

3.6.2 Bayesian Information Criteria (BIC)

Unlike, the Akaike information criteria the Bayesian information matric (BIC) takes into account the size of the data under considered. It is given by

$$BIC = -2\ InL + k\ ln(n)$$

where lnL is the maximum log likelihood function of the data given the model that will compare with the other models, n is the sample size of the data and k is the number of parameters in the model including the intercept. The good model is the one which has the minimum BIC value (Konishi and Kitagawa, 2008).

3.7 Simulation Analysis

The simulation study is carried out to investigate the behavior of the zero-inflated (ZI) models. The proposed approach is evaluated in simulation studies and applied to zero-inflated data arising from under-five mortality. The following pseudo code was used for simulation purpose.

1. Determine the sample size for the data to be simulated.
2. Simulate the independent variables to be used in modeling. This was achieved by assuming that the independent variables follow uniform distribution.
3. Generate random numbers in the sample for the purpose of defining characteristics of dataset.
4. Set the number of simulations. In this case the data sets were simulated 100 times.

Lambert (1992) discussed the ZI regression model and likelihood function of the model with the estimation techniques. This study performed a simulation experiment to understand the asymptotic results of the parameter estimation along with the properties of MLE's behavior of confidence interval and tests. The author performed the experiment for 2000 times on finite sample of size (n) of 25, 50, 100 with one covariate **x** taken from a uniformly spaced values between 0 and 1. Lambert assigned the two sets of parameters, $\gamma = (-1.5, 2)\ and\ \beta = (1.5, 2)$. The response variable generated y by first drawing a uniform (0,1) random vector U of length n and then assigning $y_i = 0\ if\ U_i \geq\ p_i$, otherwise $y_i \sim\ Poisson\ (\lambda_i)$.

Muoka, Ngesa and Waititu (2016) pointed out that statistical models for count data may take a number of forms depending on the context of use. In this study, statistical simulation technique was used to compare the performance of count data models. Count data sets with different proportion of zero were simulated. Akaike Information Criterion (AIC) was used in the simulation study to compare how well a number of count data models fit the simulated datasets. From the results of the study, it was concluded that negative binomial model fits better to over-dispersed data which has below 0.3 proportion of zeros and that hurdle model performs better in data with 0.3 and above proportion of zero.

Fitrian, Chrisdiana and Efendi (2019) studied that simulation on the zero-inflated negative binomial (ZINB) to model over dispersed, Poisson distributed data in the 2016 Maternal Mortality Rate data in Bojonegoro District. The study aims at examining the relationship of zero excess and overdispersion assumption violation and using simulation to determine which condition that is usually best for data with overdispersion. This study concluded that an event of overdispersion is always accompanied by the event of zero excess, but not vice versa. From the simulation process, several things can be obtained that the value of $\lambda, p\ and\ n$ then the dispersion coefficient gets larger and then overdispersion caused by excess zero can be well modeled with the ZINB regression as evidenced by the average value of τ less than 1 in all generation conditions.

Bekalo and Kebede (2021) described zero-inflated models for count data as an application to number of antenatal care service visits from the 2016 EDHS. In the simulation experiment, it was found that zero-inflated Poisson, zero-inflated negative binomial and hurdle regression models were better fitted zero-inflated data than the classical models Poisson, negative binominal. Each of these zero-inflated models were compared using Vuong's test and hurdle models were better fitted the data which was characterized by excess zeros and high variability in the non-zero outcome than any other zero-inflated models.

CHAPTER IV
DATA ANALYSIS

In order to examine the overall picture of the data, the distribution of the number of under-five mortality per mother and the cross tabulation by explanatory variables are displayed in this section. Then, zero count and positive counts are separated for building the zero- inflated regression models. After that, there is also a test for association between under-five mortality and its related factors. Additionally, this chapter involves selecting the fitted model for estimating under-five mortality and evaluating parameters estimated for the model through simulation.

4.1 Number of Mothers by Factor of Under-Five Mortality

Table (4.1) shows the distribution of under-five mortality per mother in Myanmar based on information from 3670 ever married women surveyed in the MDHS. It is observed that among the 3670 ever married women, a total of 187 (5.1%) experienced the under-five mortality (their children died at 0-59 months) whereas 3483 (94.9%) of women have never experienced under-five mortality of their children. It is also found that 102 (2.78%) of women experiencing under-five mortality lost only one child, 56 (1.53%) lost two children, 22 (0.6%) lost three children, 2 (0.05%) lost four children, 3 (0.08%) lost five children, 1 (0.03%) lost six children, no women lost seven children and there was only one woman (0.03%) who lost eight children which is the highest number of all.

Table (4.1) Distribution of Under-Five Mortality

Number of Under-five Deaths Per Mother	Mothers	
	Number	Percent
0	3483	94.9046
1	102	2.7794
2	56	1.5259
3	22	0.5995
4	2	0.0545
5	3	0.0817
6	1	0.0272
7	0	0.0000
8	1	0.0272
Total	3670	100

Source: Myanmar Demographic and Health Survey (2015-2016)

Furthermore, the statistics for under-five mortality are as follows: the highest number of under-five deaths recorded was 8, and the mean under-five mortality rate was calculated to be 0.0877, with a corresponding variance of 0.1995. In this situation, the mode was not used because of the number of under-five deaths to see whether there are any major violations of the assumptions on which the basic Poisson model is based. This means that the variance is greater than the mean, and it suggests a case of over- dispersion. Moreover, the data have excess zero and thus one might expect that the Poisson model would not be appropriate to predict the number of child deaths.

Further screening in Figure (4.1) shows that the distribution of the number of under-five mortality has a rapidly decreasing and highly skewed to the right. This is an indication that the data could be fitted better by count data models which take into account excess zeros.

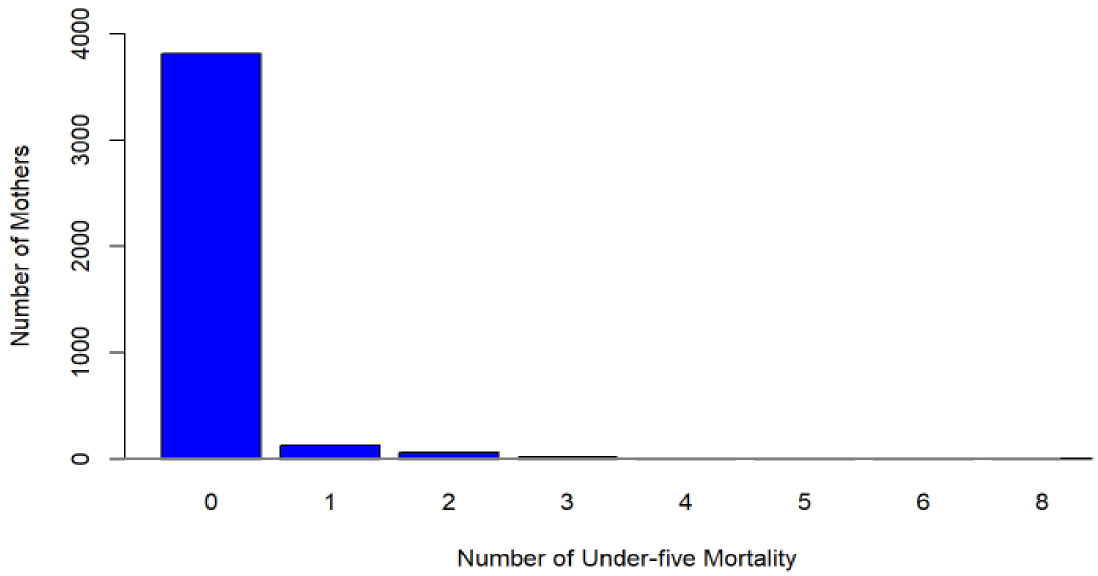

Figure (4.1) Bar Chart of the Number of Under-five Mortality

Source: Myanmar Demographic and Health Survey (2015-2016)

Moreover, some of the socioeconomic, demographic, health and environmental factors are summarized in this section. Summary statistics of the socio-economic factors such as mother's education and household wealth index are described in Table (4.2).

Table (4.2) Number of Mothers by Socio-economic Factors

Variables	Categories	Number of Mothers			
		Rural	Urban	Total	Percent
Mother's education level	No education	526	46	572	15.59
	Primary	1432	211	1643	44.77
	Secondary	710	430	1140	31.06
	Higher	108	207	315	8.58
	Total	**2776**	**894**	**3670**	**100**
Household wealth index	Poor	1667	133	1800	49.05
	Middle	545	91	636	17.33
	Rich	564	670	1234	33.62
	Total	**2776**	**894**	**3670**	**100**

Source: Myanmar Demographic and Health Survey (2015-2016)

From Table (4.2), it is observed that (15.59%) of the mothers are not educated, (44.77%) of mothers are in primary education, (31.06%) of mothers are in secondary education and (8.58%) of mothers are in higher education. It is also found that the household wealth index of mothers, poorest and poorer are recategorized into poor and it constitutes the highest proportion by (49.05%), middle (17.33%), and richer and richest are compiled as rich group and it is (33.62%).

Table (4.3) Number of Mothers by Demographic Factors

Variables	Categories	Number of Mothers			
		Rural	Urban	Total	Percent
States and Regions	Kayah	20	7	27	0.74
	Kachin	109	34	143	3.90
	Kayin	98	19	117	3.19
	Chin	38	9	47	1.28
	Sagaing	332	79	411	11.20
	Taninthayi	95	13	108	2.94
	Bago	247	74	321	8.75
	Magway	226	33	259	7.06
	Mandalay	280	109	389	10.60
	Mon	97	28	125	3.41
	Rakhine	229	25	254	6.92
	Yangon	130	270	400	10.90
	Shan	411	109	520	14.17
	Ayeyarwaddy	400	70	470	12.81
	Nay Pyi Taw	63	16	79	2.15
	Total	**2776**	**894**	**3670**	**100**
Household Size	2-3	331	116	447	12.18
	4-5	1252	315	1567	42.70
	More than 5	1193	463	1656	45.12
	Total	**2776**	**894**	**3670**	**100**
Marital Status	Married	2642	858	3500	95.37
	Others (W, D, S)*	134	36	170	4.63
	Total	**2776**	**894**	**3670**	**100**
Mother's age at the birth (Years)	Below 20	294	92	386	10.52
	20 -29	1518	474	1992	54.27
	30-45	964	328	1292	35.21
	Total	**2776**	**894**	**3670**	**100**
Childbirth order	First birth	1052	433	1485	40.46
	Second and Third	1222	377	1599	43.57
	Fourth and above	502	84	586	15.97
	Total	**2776**	**894**	**3670**	**100**

Source: Myanmar Demographic and Health Survey (2015-2016)

Note: * W: widowed, D: divorced, S: separated/no longer living together

Besides, the result shows the percent distribution of the demographic factors such as state and region, place of residence, household size, marital status, mother's age at birth, and childbirth order for the marriage women are presented in Table (4.4). Furthermore, in accordance with the highest number of mothers lived in Shan State (14.17%) and the lowest, in Kayah State (0.74%).

As shown in Table (4.3), (45.12%) of mothers are from households with more than 5 members while (42.70%) of mothers are from households with four to five members. Additionally, (12.18%) of mothers are from households with two to three people. Moreover, a big difference is observed in the marital status of mothers as the percentage of married mothers (95.37%) is higher than that of others such as widowed, divorced and separated/no longer living together (4.63%).

According to the mother's age at birth, aged below 20 years when they deliver their born child is (10.52%) whereas aged 20-29 years when they deliver their born child is (54.27%). In addition, 30-45 years of mother's age at birth when they deliver their born child is (35.21%).

Mothers from urban areas are (24.36%) while mothers from rural areas are (75.64%) respectively. Nearly half of the mothers (43.57%) had their birth order 2nd (second) and 3rd (third), (40.46%) had their birth order of 1st and (15.97%) had their bird order of 4th and above respectively.

Table (4.4) Number of Mothers by Health Care Factors

Variables	Categories	Number of Mothers			
		Rural	**Urban**	**Total**	**Percent**
Place of delivery	Private institution	2042	419	2461	67.06
	Public institution	734	475	1209	32.94
	Total	**2776**	**894**	**3670**	**100**
Contraceptive use	No	1173	282	1455	39.65
	Yes	1603	612	2215	60.35
	Total	**2776**	**894**	**3670**	**100**

Source: Myanmar Demographic and Health Survey (2015-2016)

Regarding the place of delivery, it is observed that mothers delivered at institutions such as private hospitals, clinics, and health facilities is (67.06%) and those institutions like the public hospitals, clinics, and health facilities is (32.94%).

With respect to contraceptive use, (39.65%) of mothers did not use any type of contraceptive method and the remaining (60.35%) used one of the contraceptive methods at the time of the interview.

Table (4.5) Number of Mothers by Environmental Factors

Variables	Categories	Number of Mothers			
		Rural	**Urban**	**Total**	**Percent**
Access to safe water	Improved	2095	790	2885	78.61
	Unimproved	681	104	785	21.39
	Total	**2776**	**894**	**3670**	**100**
Access to safe toilet	Improved	1266	645	1911	52.07
	Unimproved	1510	249	1759	47.93
	Total	**2776**	**894**	**3670**	**100**
Types of fuel for cooking	Clean Fuels	217	468	685	18.67
	Wood and Coal	2418	397	2815	76.70
	Others	141	29	170	4.63
	Total	**2776**	**894**	**3670**	**100**

Source: Myanmar Demographic and Health Survey (2015-2016)

Table (4.5) also shows the percent distribution of mothers who were accessing to safe drinking water, safe toilets, and types of fuel for cooking. Most of the families (78.62%) accessed safe drinking water while (21.38 %) did not. The most common improved toilet facilities were (52.06%), while unimproved toilet facilities were (47.94%). The results also indicates that most households (78.50 %) used wood and coal. There was (5.91%) of household use of electricity in rural areas whereas (12.75%) of household use of electricity in urban areas. Furthermore, there were (65.89%) of household use of wood and coal in rural areas whereas (10.82%) of household use of wood and coal in urban. It was found that the use of wood and coal was more common in rural households than in urban households.

In addition, some of the socioeconomic, demographic, health and environmental related variables on the under-five mortality are summarized in Appendix Table (A-1). It is considered only those women who gave at least one live birth in their reproductive age.

Appendix Table (A-1) presents summary statistics of the independent variables that directly influence the risk of under-five mortality. The variables which are included in the study are mothers' educational level, household wealth index, state and region, place of residence, household size, marital status, mother age at birth, childbirth order, place of delivery, contraceptive use, access to safe water, access to safe toilet and types of fuels for cooking.

The total number of women considered in this study was 3670 of which 187 of them experienced under-five mortality. There was a difference in the number of under-five mortality that has been observed between women with no education and those with education. Women with some education exhibited lower mean number of under-five mortality than those with no education. Regarding the mean number of under-five mortality per mother, (0.2133), (0.0779), (0.0439) and (0.0534) were observed for no education, primary, secondary, and higher education level of mother respectively. In this case, the maximum standard deviation occurred from no education, and it was (0.7224).

Among the women included in the study, it is revealed that the mean number of under-five mortality for women's living in household with poor and middle wealth index were (0.1233), and (0.0675), higher as compared with a women's living in rich household wealth index (0.0422). Because a women's living in household with rich and middle wealth index experienced to have less mean number of under-five mortality as compared with women is living in household with poor wealth index.

Tanintharyi Region, Chin State and Shan State had the highest mean number of under-five mortality per mother, and they were (0.2129), (0.1702), and (0.1673) respectively. Generally, the average number (0.0973) of under-five mortality occurred in rural areas with the standard deviation of (0.4674) while the average number (0.0525) of mortality happened in urban areas and the standard deviation is (0.3284). Of the total number of under-five mortality per women, a smaller number of under-five deaths occurred in urban areas compared to rural under-five mortality.

It is also observed that the mean number of under-five mortality was higher number of household size of 2 and 3 (0.1457) and the smallest mean number of under-five mortality occurred for household with more than 5 member (0.0761). Moreover, mother's age at birth was observed that young mothers (below 20 years) had the lowest mean number of under-five mortality (0.0518) and the mother's age at birth (30-45 years) had the highest mean number of under-five mortality (0.1293).

The results in Appendix Table (A-1) also show that married mothers have a higher mean number of under-five mortality (0.0869) as compared to other mothers such as widowed, divorced and separated (0.0765). Besides, the highest mean number of under-five mortality was observed for children of birth order of four and above (0.2747) while the lowest mean number of under-five mortality was observed of first birth order (0.0377).

Among the women included in the study, the mean number of under-five deaths for children who were delivered at home (0.1140) is higher than that for those delivered at public and private hospitals (0.0490 and 0.0264 respectively). In the same way, the mean number of under-five deaths with respect to contraceptive use was (0.1196), of which (0.1196) mothers did not use any type of contraceptive method, and the remaining (0.0646) used one of the contraceptive methods.

It is also found that the highest mean number of under-five mortality occurred with families who used unimproved water (0.1299) as compared with families who used improved water (0.0745). Similarly, the mean number of under-five mortality (0.1092) occurred in household unimproved toilet facility and the mean number of under-five mortality (0.1092) happened in improved toilet facility user households. With regards to type of fuels for cooking, the higher mean number of under-five mortality occurred, the mothers who used clean fuels (0.0731) and wood and cool (0.0892) and as compared to mothers who use others fuel such as straw/shrub/ grass, agricultural crops and animal dung (0.0936).

4.2 Separation for Zero Counts and Positive Counts in Modeling

From the policy making viewpoint, it is important to study why some mothers experienced under-five mortality of their children while some mothers never experienced such events. The causes of under-five mortality may also be influenced by socioeconomic, demographic, health care and environmental factors.

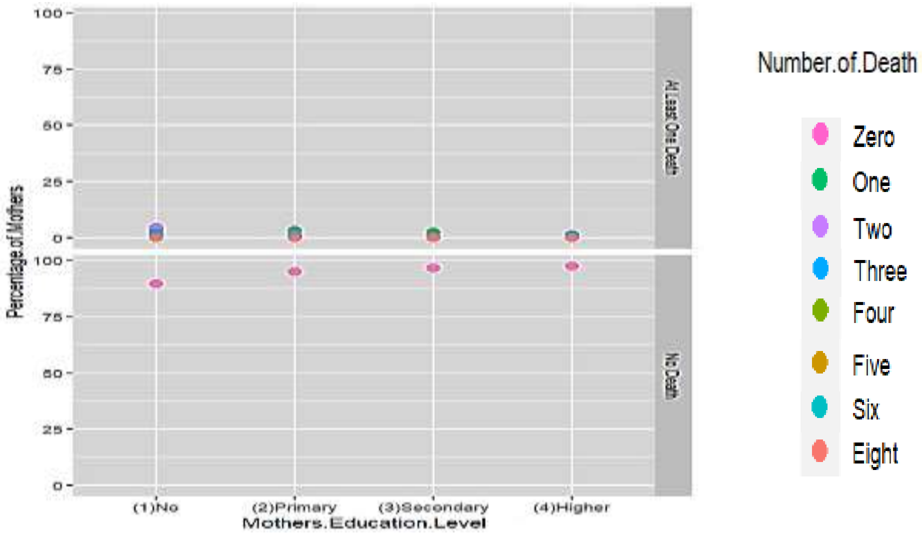

Figure (4.2) Percentage of Mothers Experiencing Under-five Mortality by Mothers' Level of Education

Source: Calculated from Appendix Table (A-1)

A mother's level of education may have effects on experiencing under-five mortality as shown in Figure (4.2). According to Figure (4.2), the results found that (10.31%) of mothers with no education have experienced under-five mortality while (2.54%) of mothers with higher education have experienced under-five mortality. This finding was also motivational to employ zero-inflated count data models where factors affecting zero counts can be modeled separately.

Wealth index is another factor which has substantial effects on under-five mortality. As described in Figure (4.3), (2.6%) of rich mothers have experienced under-five mortality while (6.89%) of poor mothers have experienced under-five mortality. Therefore, women who were from rich households had lower experience of under-five mortality than the women who were from poor households. Again, the slope for the percentage of women who had no experience under-five mortality shows a trend with opposite slope of women who had at least one experience of under-five mortality.

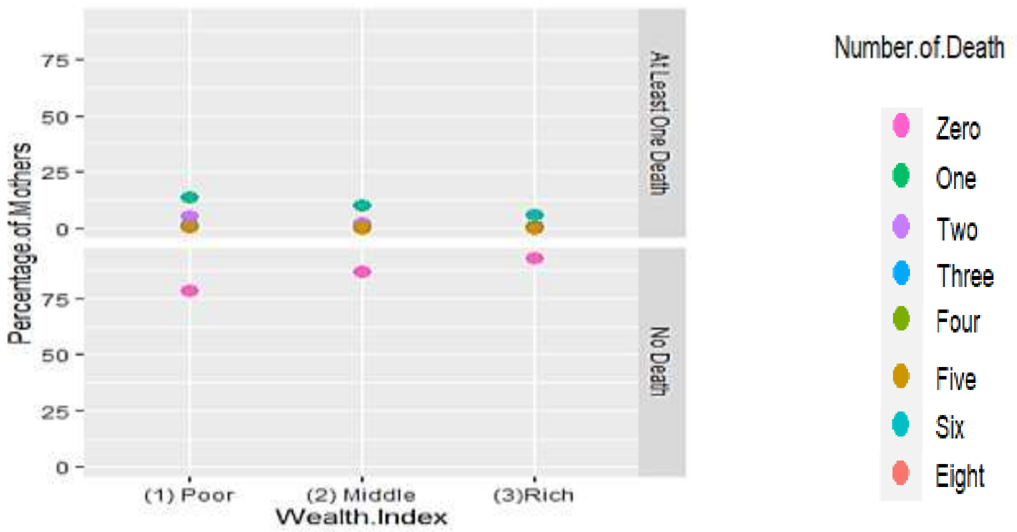

Figure (4.3) Percentage of Mothers Experiencing Under-five Mortality by Wealth Index

Source: Calculated from Appendix Table (A-1)

Figure (4.4) shows women from Chin State accounted for the lower proportion (88%) of experiencing no under-five mortality, whereas percentage of women with the experience of no under-five in Yangon Region is higher (97%) compared to women from other states and regions.

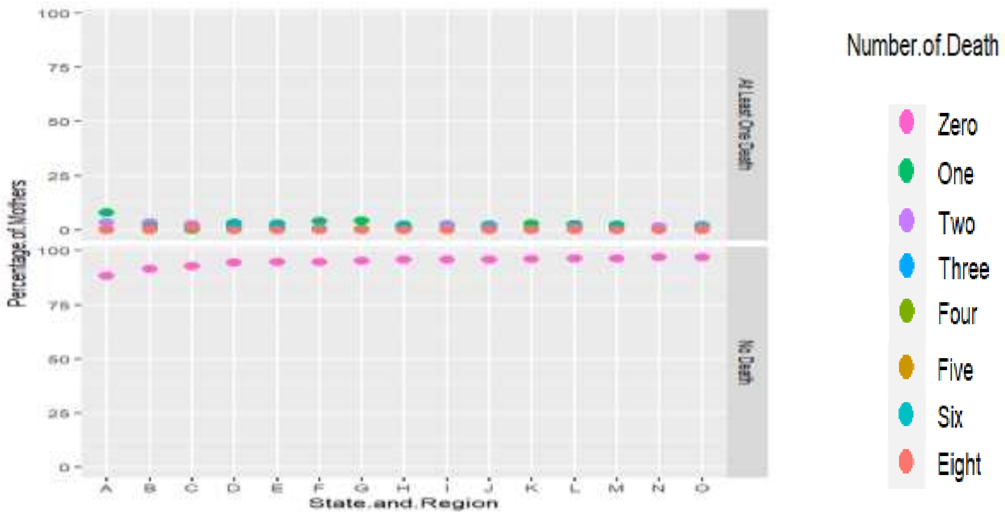

Figure (4.4) Percentage of Mothers Experiencing Under-five Mortality by State and Region

Source: Calculated from Appendix Table (A-1)

Note: A: Chin State, B: Shan State, C: Taninthayi Region, D: Kayin State, E: Mandalay Region, F: Ayeyarwaddy Region, G: Nay Pyi Taw Region, H: Sagaing Region, I: Bago Region, J: Magway Region, , K: Kachin State, L:Mon State, M: Rakine State, N: Kayah State, O: Yangon Region

According to Figure (4.5), mother's place of residence may have effects on the degree of experiencing under-five mortality. The results found that around (5.70%) of rural mothers have experienced under-five mortality while (3.24%) of mothers from urban areas have experienced under-five mortality.

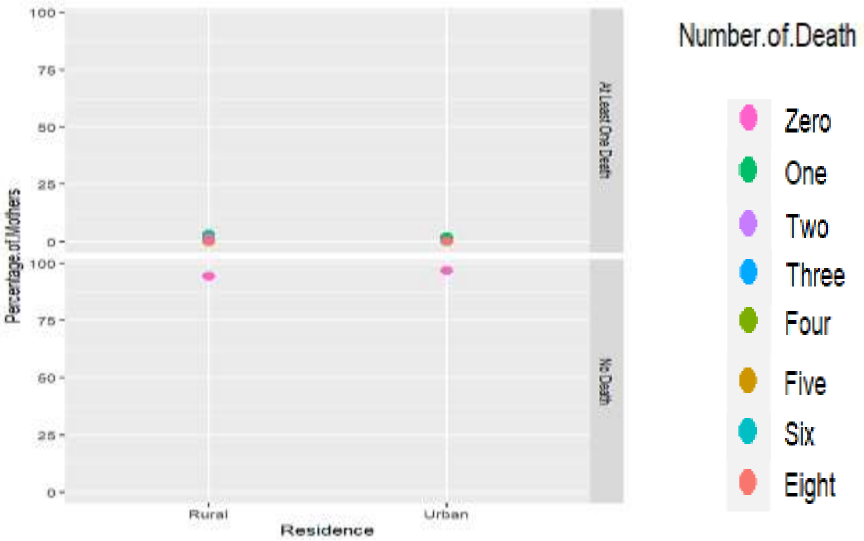

Figure (4.5) Percentage of Mothers Experiencing Under-five Mortality by Residence of Mothers

Source: Calculated from Appendix Table (A- 1)

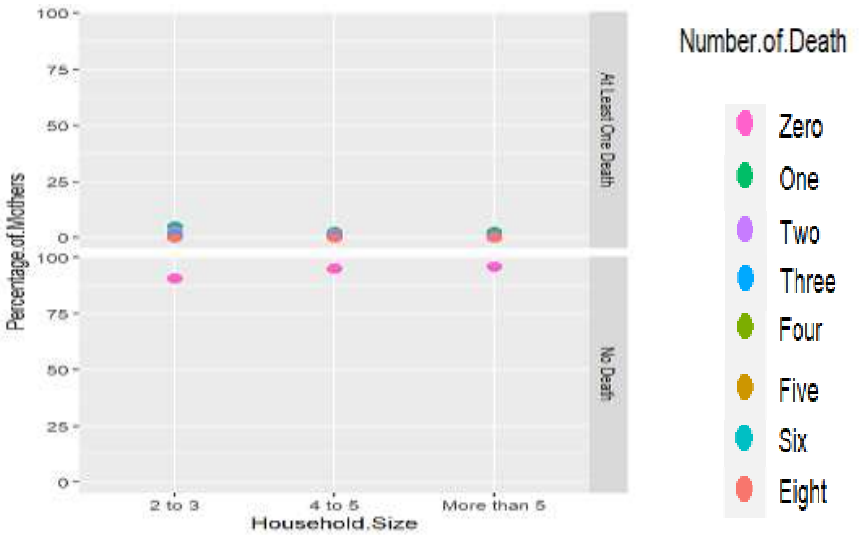

Figure (4.6) Percentage of Mothers Experiencing Under-five Mortality by Household Size

Source: Calculated from Appendix Table (A-1)

The results in Figure (4.6) show that mothers' household size may have effects on the degree of experiencing under-five mortality. It is found that (9.19%) of mothers who had 2 to 3 children experienced under-five mortality whereas (4.84%) of mothers with 4 to 5 children and mothers with more than five children experienced under-five mortality.

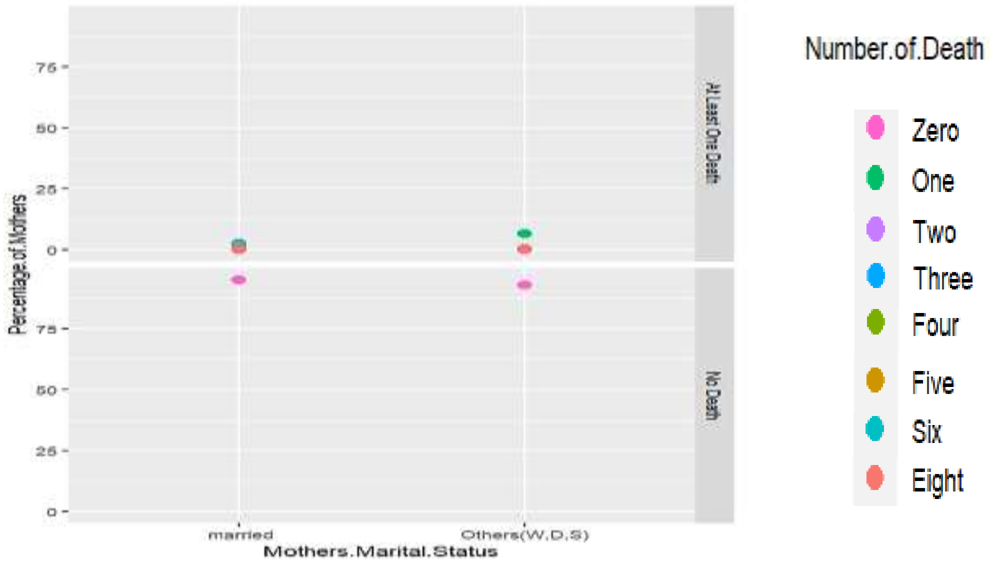

Figure (4.7) Percentage of Mothers Experiencing Under-five Mortality Mother's Marital Status

Source: Calculated from Appendix Table (A-1)

It is also found that, mother's marital status may have effects on the degree of experiencing under-five mortality. Other mothers who were widowed, divorced and separated had a higher proportion (7.06%) of experiencing under-five mortality compared to married mothers (5%).

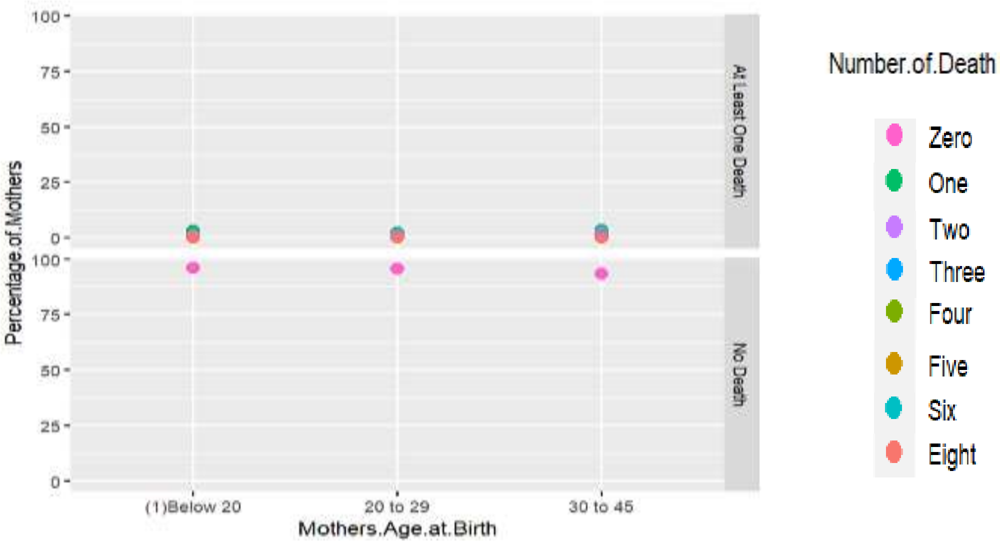

Figure (4.8) Percentage of Mothers Experiencing Under-five Mortality by Mothers Age at Birth

Source: Calculated from Appendix Table (A-1)

As seen in Figure (4.8), mother's age at birth may have effects on the degree of experiencing under-five mortality. It was found that women with higher age were likely to give more birth and giving more births raised the risk of experiencing under-five mortality. Also experiencing under-five mortality may influence parents to give more births. Accordingly, mother's age at birth may have influence on no experiencing under-five mortality with opposite slope.

As shown in Figure (4.9), childbirth order may have effects on the degree of experiencing under-five mortality. Regarding birth order, it was the highest percentage of women (12.29%) with children whose birth order was fourth or above have experienced under-five mortality whereas it was the lowest percentage of women (3.1%) with children whose birth order was first have experienced under-five mortality. Also, the slope for the percentage of women who had no experience with under-five mortality shows a trend with opposite slope.

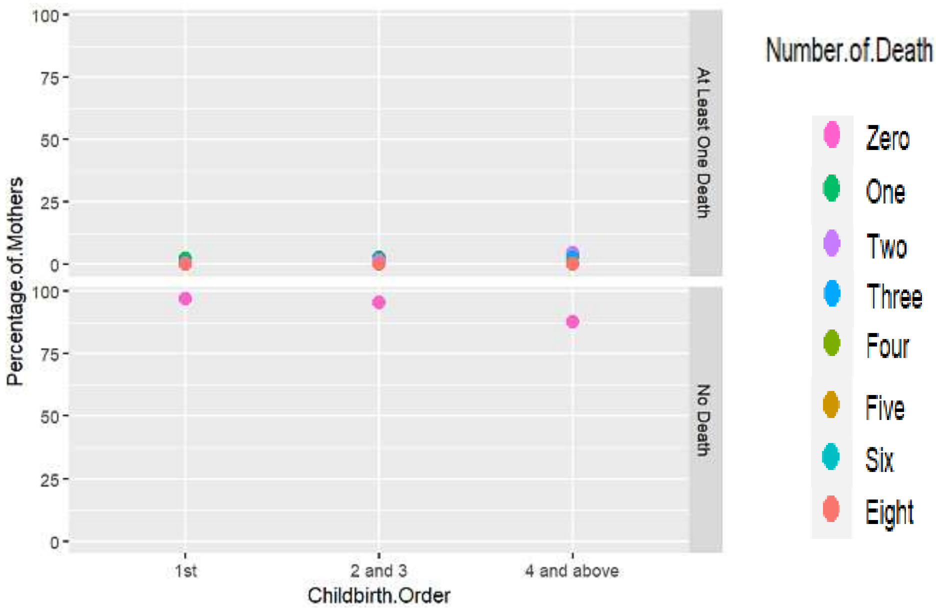

Figure (4.9) Percentage of Mothers Experiencing Under-five Mortality by Childbirth Order

Source: Calculated from Appendix Table (A-1)

As described in Figure (4.10), place of delivery may have effects on the degree of experiencing under-five mortality. It indicates that (3.24%) of mothers with delivery in a public place have experienced under-five mortality while (6.25%) of mothers with delivery in a private place have experienced under-five mortality.

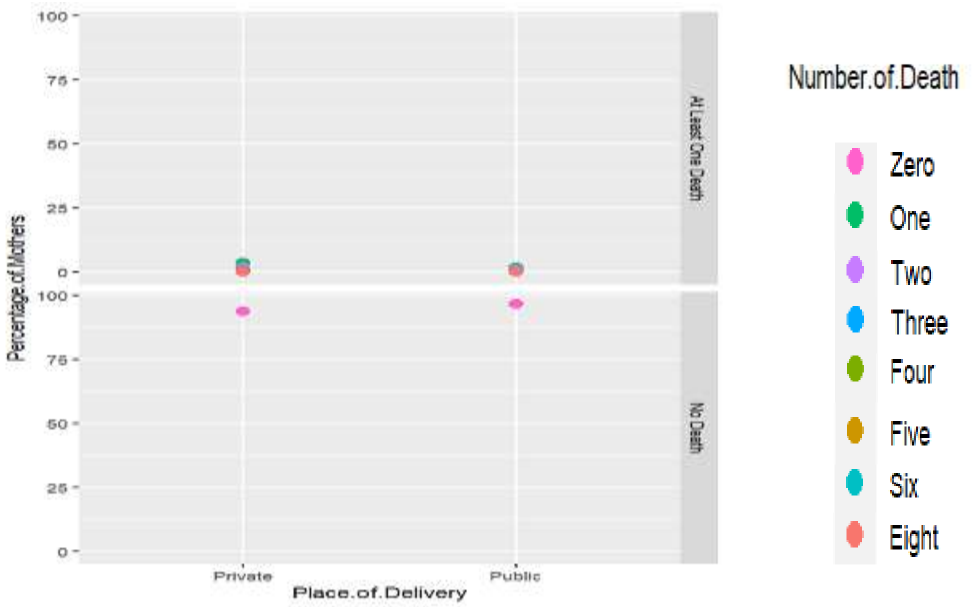

Figure (4.10) Percentage of Mothers Experiencing Under-five Mortality by Place of Delivery

Source: Calculated from Appendix Table (A-1)

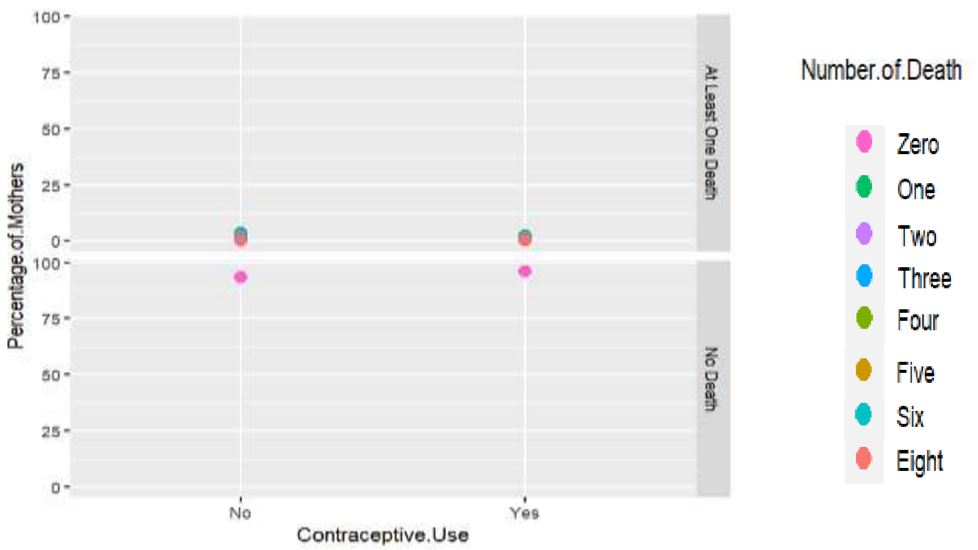

Figure (4.11) Percentage of Mothers Experiencing Under-five Mortality by Contraceptive Use

Source: Calculated from Appendix Table (A-1)

In accordance with Figure (4.11), contraceptive use may have effects on the degree of experiencing under-five mortality. There is slight proportional difference of under-five mortality between contraceptive use of mothers and no use of mothers.

Access to unimproved water and toilet among children aged under-five is a serious public health problem in many developing countries including Myanmar. As shown in Figures (4.12) and (4.13), children who were under-five years old living in households with access to both an unimproved source of water and toilet facilities had a greater risk of under-five mortality compared with living in households with improved water and toilet.

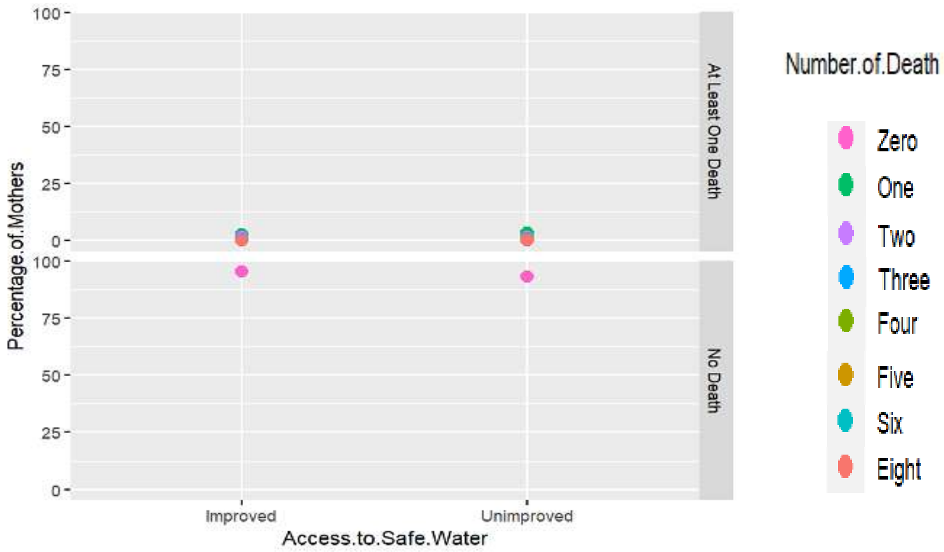

Figure (4.12) Percentage of Mothers Experiencing Under-five Mortality by Access to Safe Water

Source: Calculated from Appendix Table (A-1)

According to Figure (4.12), (6.75%) of mothers have access to unimproved water experienced under-five mortality, but (4.64%) of mothers with improved water experienced under-five mortality. Similar pattern is found for access to safe toilet. Also, the percentage of woman access to safe water and toilet who never experienced under-five mortality showed similar trend with opposite slope (Figure 4.12).

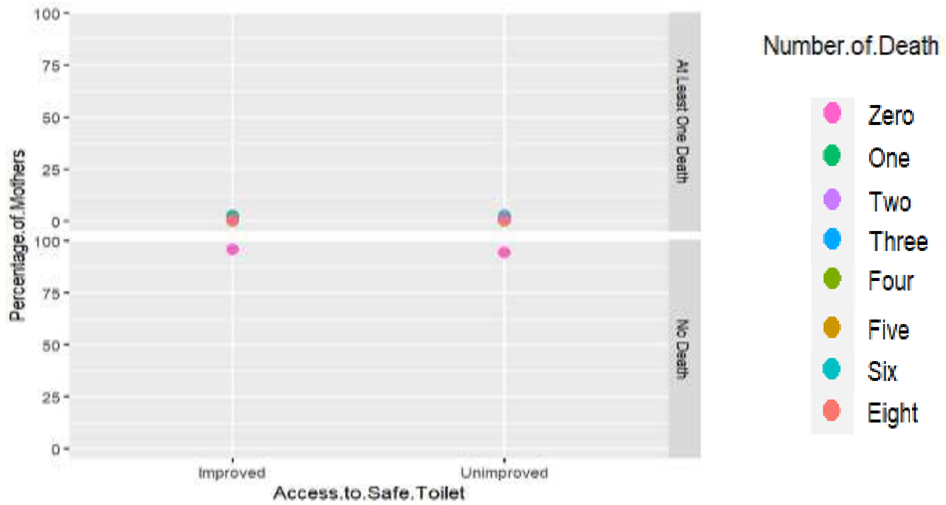

Figure (4.13) Percentage of Mothers Experiencing Under-five Mortality by Access to Safe Toilet

Source: Calculated from Appendix Table (A-1)

According to Figure (4.14), it can be seen that types of fuels for cooking may have effects on the degree of experiencing of under-five mortality. The percentage of mothers who usually used clean fuels and experienced under-five mortality was (3.80%) while the percentage of mothers who usually used wood and coal and others had experience under-five mortality were (5.4%) and (5.26%) respectively.

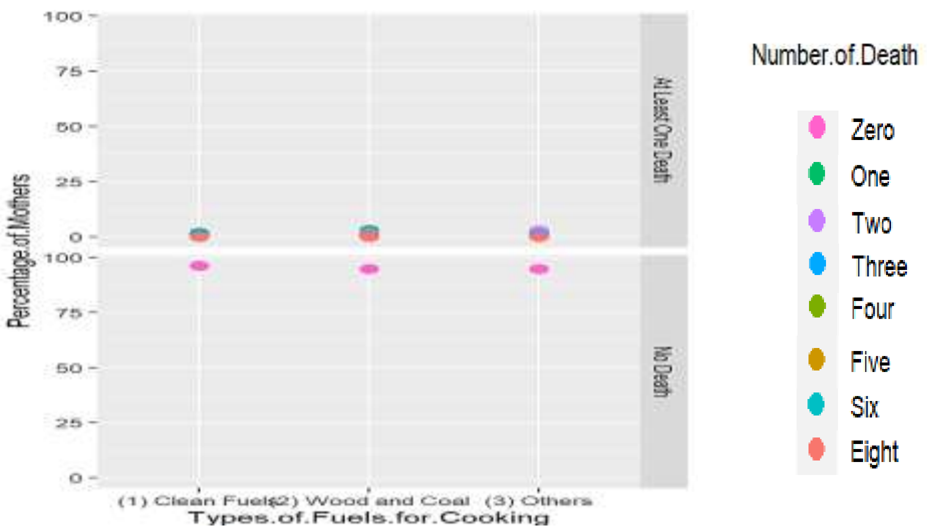

Figure (4.14) Percentage of Mothers Experiencing Under-five Mortality by Types of Fuels for Cooking

Source: Calculated from Appendix Table (A-1)

4.3 Association between Under-Five Mortality and Related Factors

Table (4.6) shows the association of selected variables with under-five mortality using Chi-square test.

Table (4.6) Association between Under-Five Mortality and Related Factors

Variables	Chi-square	P- value
Socioeconomic Factors		
Mother's Education Level	56.262***	0.000
Wealth Index	25.176***	0.000
Demographic Factors		
Place of Residence	11.678***	0.009
Household Size	8.277**	0.041
Mother's Age at Birth	18.467***	0.000
Childbirth Order	135.76***	0.000
Health Care Factors		
Place of Delivery	13.083***	0.004
Contraceptive Use	23.572***	0.000
Environmental Factors		
Access to Safe Water	15.077***	0.002
Access to Safe Toilet	15.173***	0.002
Type of Fuel for Cooking	10.022**	0.018

Source: Myanmar Demographic and Health Survey (2015-2016)

Note: ***, **, * Significant at 1 %, 5% and 10% level respectively

According to Table (4.6), it is found that association between under-five mortality and all socioeconomic factors are significant at 1% level. Likewise, the association between under-five mortality and all demographic factors are significant at 1% level. However, household size is significant at 5% level. Moreover, the association between under-five mortality and all health care factors are significant at 1% level. Furthermore, the association between under-five mortality and all environmental factors are significant at 1% level. However, association between under-five mortality and the type of fuel for cooking is significant at 5% level.

The results of the Chi-square test show that the association between under-five mortality and State and Region and the association between under-five mortality and marital status are not significant. Therefore, the these two variables are not considered in modelling the count regression models in this study.

4.4 Statistical Models for Under-Five Mortality

This study used variable selection to identify the predictors in the model. This was done on Poisson regression model as it is the benchmark for other count regression models. This selection method addresses where variables were removed with respect to the p-value in the process. The result recognized that independent variables like mother's education level, wealth index, household size, childbirth order, access to safe water and type of fuels for cooking are statistically significance and the other variables are found to be non-significance and thus are excluded from analysis. This study applies six count regression approaches to model the number of under-five mortality. Those models are Poisson, negative binomial, the zero-inflated Poisson, zero-inflated negative binomial, hurdle Poisson and hurdle negative binomial regression models. The zero-inflated regression model assumes that the outcome variable is generated by two processes: a Poisson or negative binomial that generates the count of deaths, and a binary process that generates the excess zeros. To select the most appropriate count model, the dependent variable in this study is under-five mortality, and the independent variables include socioeconomic, demographic, health care, and environmental factors.

4.4.1 Goodness of Fit and Test of Over Dispersion

The assumption of Poisson distribution is violated. The results of goodness of fit for negative binomial and dispersion test were shown in Appendix Figure (A-1). It can be seen that the residual ones spread out more for the Poisson regression models compare to the negative binomial regression model. This is a sign that a negative binomial regression model is more likely to appropriate since the residuals of that model are smaller. And then, it is also performing a likelihood ratio test to determine if there is a statistically significant difference in the fit of the two regression models.

Table (4.7) Test for Over Dispersion

Criterion	Model	Value	P-value
LRT	P	-1153.11	0.0000
LRT	NB	-884.64	0.0000

As shown in Table (4.7), the formal test of over dispersion in Poisson versus negative binomial regressions $H_0: \alpha = 0$ (no over dispersion in the dataset) vs $H_1: \alpha > 0$ (there is an over-dispersion in the data set). Since the likelihood ratio statistic (-2 [-1153.11 – (-884.64)] =536.94 with p-value = 0.0000 is found to be statistically significant and it indicates that there is an over-dispersion. As a result, the negative binomial regression model was appropriate for the analysis of under-five mortality data as compared to the Poisson model.

4.4.2 Parameter Estimate of Poisson Regression Model

One statistical model that has been used in the analysis of under-five mortality is the Poisson regression model. The significance of the parameter estimates, along with their corresponding standard errors, is presented in the Table (4.8).

Table (4.8) Estimated Coefficient Poisson Regression Model

	Estimate	Exp(b)	S. E.	Z value	Pr (> |z|)
Intercept	-1.3344***	0.2633	0.2640	-5.0550	0.0000
Mother's Education Level (No Education, Ref:)					
Primary	-0.7152***	0.4891	0.1369	-5.2240	0.0000
Secondary and above	-0.8142***	0.4430	0.1896	-4.2950	0.0000
Wealth Index (Poor, Ref:)					
Non-poor	-0.5650***	0.5683	0.1570	-3.5990	0.0000
Household Size (2-5, Ref:)					
More than 5	-1.0145***	0.3626	0.1309	-7.7480	0.0000
Childbirth Order (1st Birt Ref:)					
Second and Third	0.5089***	1.6634	0.1701	2.9920	0.0028
Fourth and above	2.0810***	8.0129	0.1785	11.6580	0.0000
Contraceptive Use (No, Ref:)					
Yes	-0.2316*	0.7933	0.1199	-1.9310	0.0535
Access to Safe Water (Improved, Ref:)					
Unimproved	0.2887**	1.3346	0.1291	2.2350	0.0254
Types of Fuel for Cooking (Clean Fuels, Ref:)					
Solid Fuels	-0.9493***	0.3870	0.1818	-5.2230	0.0000

Source: Myanmar Demographic and Health Survey (2015-2016)

Note: ***, **, * Significant at 1 %, 5% and 10% level respectively. Ref: Reference category of the variables

The fitted Poisson regression model as follows

$\ln(\lambda)$ = -0.2633 -0.4891 (mother's education level = primary) -0.4430 (mother's education level = secondary and above) -0.5683 (wealth index = non-poor) -0.3626 (household size = more than 5) +1.6634 (child birth order = second and third) +8.0129 (child birth order = fourth and above) -0.7933 (contraceptive use) +1.3346 (access to safe water) -0.3870 (types of fuel for cooking = solid fuels) (4.1)

The coefficients associated with each predictor variable in the Poisson regression model represent the estimated change in the log-count of deaths for a one-unit change in that predictor, holding all other variables constant. Being mother's education level with primary level decreases the expected number of under-five mortality by 51 percent, holding all other variables constant. Similarly, mother's education level with secondary and above decrease the expected number of under-five mortality by 56 percent holding all other variables constant.

Holding all other variables constant, the expected log count of under-five mortality is 0.57 units lower for children in non-poor households compared to children in poor households. The expected log count of under-five mortality is 0.36 units lower for children in households with more than five members compared to children in households with five or fewer members while holding all other variables constant.

The expected log count of under-five mortality is 1.7 units higher for children with a birth order of second or third compared to first-born children while holding all other variables constant. The expected log count of under-five mortality is 8.0 units higher for children with a birth order of fourth or above compared to first-born children while holding all other variables constant. Holding all other variables constant, the expected log count of under-five mortality is 0.79 units lower for children in households where contraceptives are used compared to households where contraceptives are not used.

Holding all other variables constant, the expected log count of under-five mortality is 1.33 units higher for children in households without access to safe water compared to households with access to safe water. the expected log count of under-five mortality is 0.39 units lower for children in households using non-solid fuels for cooking compared to households using solid fuels for cooking while holding all other variables constant,

4.4.3 Parameter Estimation of Negative Binomial Regression Model

Another statistical model that has been used in the analysis of under-five mortality is the negative binomial regression model. Table (4.9) presents parameter estimates with their corresponding standard error.

Table (4.9) Estimated Coefficient of Negative Binomial Regression Model

	Estimate	Exp(b)	S. E	Z value	Pr (> |z|)
Intercept	-1.3515***	0.2588	0.3484	-3.8790	0.0001
Mother's Education Level (No Education, Ref:)					
Primary	-0.5630***	0.5695	0.2127	-2.6460	0.0081
Secondary and above	-0.7564***	0.4694	0.2643	-2.8620	0.0042
Wealth Index (Poor, Ref:)					
Non-poor	-0.5366***	0.5848	0.2052	-2.6140	0.0089
Household Size (2-5, Ref:)					
More than 5	-0.8327***	0.4349	0.1906	-4.3690	0.0000
Childbirth Order (1st Birt Ref:)					
Second and Third	0.4400**	1.5527	0.2041	2.1560	0.0311
Fourth and above	1.9054***	6.7222	0.2472	7.7080	0.0000
Contraceptive Use (No, Ref:)					
Yes	-0.3272*	0.7210	0.1691	-1.9350	0.05295
Types of Fuel for Cooking (Clean Fuels, Ref:)					
Solid Fuels	-0.8773***	0.4159	0.2439	-3.5970	0.0003

Source: Myanmar Demographic and Health Survey (2015-2016)

Note: ***, **, * Significant at 1 %, 5% and 10% level respectively. Ref: Reference category of the variables

The fitted negative binomial regression model as follows

ln(λ) = -0.2588 -0.5695 (mother's education level = primary) -0.4694 (mother's education level = secondary and above) -0.5848 (wealth index = non-poor) -0.4349 (household size = more than 5) +1.5527 (childbirth order = second and third) +6.7222 (child birth order = fourth and above) -0.7210 (contraceptive use = yes) -0.4159 (types of fuel for cooking = solid fuels) (4.2)

The results in Table (4.9) shows that the expected log count of the under-five mortality 0.60 units lower for individuals with primary education compared to those with no education while holding all other variables constant. Additionally, the expected log count of the response variable is 0.47 units higher for individuals with secondary or higher education compared to those with no education while holding all other variables constant. The expected log count of under-five mortality is 0.58 units lower for individuals in non-poor households compared to those in poor households, assuming all other variables are held constant

Moreover, the expected log count of the under-five mortality is 0.4349 units lower for individuals in households with more than five members compared to those in households with five or fewer members while holding all other variables constant.
Furthermore, the expected log count of the response variable is 1.55 units higher for individuals with a birth order of second or third compared to those with a first-born birth order while holding all other variables constant. The expected log count of the under-five mortality is 6.72 units higher for individuals with a birth order of fourth or above compared to those with a first-born birth order.

In this study, contraceptive use has been found to have a significant effect on under-five mortality. Specifically, the expected log count of the response variable is 0.72 units lower for individuals who use contraceptives compared to those who do not. Additionally, the type of fuel used for cooking has also been found to have a significant effect on under-five mortality. When holding all other variables constant, the expected log count of under-five mortality is 0.42 units lower for individuals in households using non-solid fuels for cooking, in comparison to those in households using solid fuels for cooking.

4.4.4 Parameter Estimation of Zero-Inflated Poisson Regression Model

Another statistical approach employed in the examination of under-five mortality is the zero-inflated Poisson regression model. The parameter estimates, along with their corresponding standard errors, are displayed in Table (4.10).

Table (4.10) Estimated Coefficient of Zero-Inflated Poisson Regression Model

Positive count	Estimate	Exp(b)	S. E	Z value	Pr (> |z|)
Intercept	-0.2484	0.7801	0.3840	-0.6470	0.5178
Household Size (2-5, Ref:)					
More than 5	-0.4169**	0.6591	0.1956	-2.1320	0.0330
Childbirth Order (1st Birth Ref:)					
Second and Third	0.5985*	1.8193	0.3616	1.6550	0.0979
Fourth and above	1.5037***	4.4983	0.3325	1.5220	0.0000
Types of Fuel for Cooking (Clean Fuels, Ref:)					
Solid Fuels	-0.6494***	0.5224	0.1975	-3.2890	0.0010
Zero count	**Estimate**	**Exp (b)**	**S. E**	**Z value**	**Pr (> |z|)**
Intercept	1.3393***	3.8163	0.3802	3.5220	0.0000
Mother's Education Level (No Education, Ref:)					
Primary	0.7162***	2.0466	0.2005	3.5720	0.0004
Secondary and above	1.0500***	2.8577	0.2446	4.2930	0.0000
Household Size (2-5, Ref:)					
More than 5	0.6400***	1.8966	0.2279	2.8090	0.0050
Childbirth Order(1st Birth Ref:					
Second and Third	0.1843	1.2024	0.3746	0.4920	0.6227
Fourth and above	-0.6393*	0.5277	0.3756	-1.7020	0.0887

Source: Myanmar Demographic and Health Survey (2015-2016)

Note: ***, **, * Significant at 1 %, 5% and 10% level respectively. Ref: Reference category of the variables

The fitted zero-inflated Poisson regression model as follows

$\ln(\lambda)$ = -0.7801 -0.6591 (household size = more than 5) +1.8193 (childbirth order = second and third) +4.4983 (child birth order = fourth and above) -0.5224 (types of fuel for cooking = solid fuels) (4.3)

$\text{logit}(\text{w})$ = 3.8163 +2.0466 (mother's education level = primary) +2.8577 (mother's education level = secondary and above) +1.8966 (household size = more than 5) +1.2024 (child birth order = second and third) -0.5277 (child birth order = fourth and above) (4.4)

The results in Table (4.10) shows that estimated zero-inflated Poisson regression model fits the results of incidence counts, and the coefficients can be interpreted as follow: for a one-unit change in the predictor variable, the log of the response variable is expected to change by the value of the regression. In zero-inflated Poisson regression model, for every one unit increase in a unit of the significant predictors, the log number of under-five mortality is expected to increase or decrease by approximately the corresponding coefficient in the column of coefficient.

In this study, household size and type of fuels for cooking are found to be negatively associated with under-five mortality in the positive counts. However, childbirth order is positively associated with under-five mortality. It is observed that household size is a significant influence on the number of under-five mortality. The expected under-five mortality for mothers with more than five people in the household is 0.66 times lower compared to those with a household size of two to five people. It is found that childbirth order is a significant variable on the number of under-five mortality. As birth order rises, the number of under-five deaths also increases. The expected number of under-five mortality in second and third childbirth order is 1.82 times greater as compared to that for first birth childbirth order while holding all other variables in the model constant. Moreover, the expected number of under-five mortality in fourth and above childbirth order is 4.50 times greater as compared to that for first birth childbirth order.

The finding shows that the estimated coefficient of type of fuels for cooking is statistically significant for the number of under-five mortality. The expected number of under-five mortality for mothers who used type of fuels for cooking with solid fuels is 0.52 time less than mothers who were used clean fuels controlling for other variables in the model.

The second part of Table (4.10) provides estimated odd ratio for the factor change in the odds of being in zero count group (binomial with logit link) model (no under-five death). Mother's education level and household size are significantly associated with the probability of being in zero count group.

It can be seen that mother's education level has a significant impact on the probability of being in the zero count groups. The odds of no occurrence of under-five mortality for mothers with primary education is 2.05 times greater as compared to no education level controlling other variables. In addition, the odds of no occurrence of under-five mortality for mothers with secondary and above is 2.86 times greater than as compared to no education level.

It is also observed that household size has a significant effect on the probability of being an excess zero. In addition, the odds of no occurrence of under-five mortality are 1.90 times lower for more than five household members as compared to two to five household members. It can be seen that childbirth order has a significant impact on the probability of being in the zero count. The odds of no occurrence of under-five mortality are 1.20 times greater for mothers with two to three birth orders compared to the first child. Likewise, the odds of no occurrence of under-five mortality are 0.53 times greater for mothers with two to three birth orders compared to the first child.

4.4.5 Parameter Estimation of Zero-Inflated Negative Binomial Regression Model

Another statistical model that has been used in the analysis of under-five mortality is the zero-inflated negative binomial regression model. Table (4.11) presents parameter estimates with their corresponding standard error of the excess number of zero model.

Table (4.11) Estimated Coefficient of Zero-inflated Negative Binomial Regression Model

Positive count	Estimate	Exp(b)	S. E.	Z value	Pr (> |z|)
Intercept	-0.4890**	0.6133	0.2171	-2.2520	0.0243
Childbirth Order (1^{st} Birt Ref:)					
Second and Third	0.5553***	1.7425	0.1982	2.8020	0.0051
Fourth and above	1.8566***	6.4022	0.1905	9.7470	0.0000
Contraceptive Use (No, Ref:)					
Yes	-0.4051***	0.6670	0.1399	-2.8960	0.0038
Types of Fuel for Cooking (Clean Fuels, Ref:)					
Solid Fuels	-0.5953***	0.5514	0.1730	-3.4400	0.0006
Zero count	**Estimate**	**Exp (b)**	**S. E.**	**Z value**	**Pr (> |z|)**
Intercept	0.9119***	2.4893	0.0721	12.6550	0.0000
Mother's Education Level (No Education, Ref:)					
Primary	0.7685***	2.1566	0.2024	3.7970	0.0001
Secondary and above	1.1692***	3.2194	0.2378	4.9170	0.0000
Household Size (2-5, Ref:)					
More than 5	0.7638***	2.1464	0.1750	4.3650	0.0000

Source: Myanmar Demographic and Health Survey (2015-2016)

Note: ***, **, * Significant at 1 %, 5% and 10% level respectively. Ref: Reference category of the variables

The fitted zero-inflated negative binomial regression model as follows

$$\ln(\lambda) = -0.6133 + 1.7425 \text{ (child birth order = second and third)} + 6.4022 \text{ (child birth order = fourth and above)} - 0.6670 \text{ (contraceptive use)} - 0.5514 \text{ (types of fuel for cooking = solid fuels)} \quad (4.5)$$

$$\text{logit}(w) = 2.4893 + 2.1566 \text{ (mother's education level = primary)} + 3.2194 \text{ (mother's education level = secondary and above)} + 2.1464 \text{ (household size = more than 5)} \quad (4.6)$$

According to Table (4.11), the results of positive count zero-inflated negative binomial model can be seen that contraceptive usen and types of fuel for cooking are negatively associated with the number of under-five mortality. However, childbirth order is positively associated with the number of under-five mortality.

It is indicated that the contraceptive use is a significant variable in reducing under-five mortality. The expected number of under-five mortality for mothers who used contraceptive decreased by 33% as compared to those mothers who did not use contraceptive. Moreover, type of fuels for cooking is found to be one of the important significant predictors of under-five mortality. The expected number of under-five mortality for mothers who used type of fuels for cooking with solid fuels is 0.55 times less than mothers who were used clean fuels.

The result also shows the expected number of positive counts under-five mortality in second and third childbirth order is 1.74 times greater as compared to the first birth. Moreover, the expected number of under-five mortality in fourth and above childbirth order is 6.40 times greater as compared to the first birth.

As shown in Table (4.11), mother's education level has a significant impact on the probability of being in the zero count groups. The odds of no occurrence of under-five mortality for mothers with primary education is 2.16 times greater as compared to no education level controlling other variables. In addition, the odds of no occurrence of under-five mortality for mothers with secondary and above is 3.22 times greater than as compared to no education level.

Similarly, household size has a significant impact on the probability of being in the zero counts group. The odds of no occurrence of under-five mortality with the household size of more than five is 2.15 times greater as compared to a household size of two to five while holding all other variables in the model constant.

4.4.6 Parameter Estimation of Hurdle Poisson Regression Model

The statistical model that has been used in the analysis of under-five mortality is the hurdle Poisson regression model and the results are described in Table (4.12).

Table (4.12) Estimated Coefficient of Hurdle Poisson Regression Model

Positive count	Estimate	Exp(b)	S. E	Z value	Pr (> |z|)
Intercept	-0.5438	0.5806	0.3405	-1.5970	0.1103
Childbirth Order (1st Birt Ref:)					
Second and Third	0.7184**	2.0512	0.3549	2.0240	0.0430
Fourth and above	1.6618***	5.2688	0.3286	5.0570	0.0000
Types of Fuel for Cooking (Clean Fuels, Ref:)					
Solid Fuels	-0.5209***	0.5940	0.1944	-2.6790	0.0074
Zero count	**Estimate**	**Exp (b)**	**S. E.**	**Z value**	**Pr (> |z|)**
Intercept	-1.8524 ***	0.1569	0.3313	-5.5910	0.0000
Mother's Education Level (No Education, Ref:)					
Primary	-0.5630***	0.5695	0.1888	-2.9820	0.0029
Secondary and above	-0.7154***	0.4890	0.2449	-2.9210	0.0035
Wealth Index (Poor, Ref:)					
Non-poor	-0.4581**	0.6325	0.1938	-2.3640	0.0181
Household Size (2-5, Ref:)					
More than 5	-0.8483***	0.4282	0.1788	-4.7450	0.0000
Childbirth Order (1st Birt Ref:)					
Second and Third	0.2889	1.3350	0.1983	1.4570	0.1452
Fourth and above	1.5760***	4.8358	0.2261	6.9710	0.0000
Contraceptive Use (No, Ref:)					
Yes	-0.3059*	0.7364	0.1579	-1.9370	0.0527
Types of Fuel for Cooking (Clean Fuels, Ref:)					
Solid Fuels	-0.4966**	0.6086	0.2420	-2.0520	0.0402

Source: Myanmar Demographic and Health Survey (2015-2016)

Note: ***, **, * Significant at 1 %, 5% and 10% level respectively. Ref: Reference category of the variables

The fitted hurdle Poisson regression model as follows

$\ln(\lambda)$ = -0.5806 +2.0512 (child birth order = second and third) +5.2688 (child birth order = fourth and above) -0.5940 (types of fuel for cooking = solid fuels) (4.7)

$$\text{logit}(w) = -0.1569\ -0.5695\ (\text{mother's education level = primary})\ -0.4890\ (\text{mother's education level = secondary and above})\ -0.6325\ (\text{wealth index = non-poor})\ -0.4282\ (\text{household size = more than 5})\ +1.3350\ (\text{child birth order = second and third})\ +4.8358\ (\text{child birth order = fourth and above})\ -0.7364\ (\text{contraceptive use = yes})\ -0.6086\ (\text{types of fuel for cooking = solid fuels}) \quad (4.8)$$

The results in Table (4.12) show that type of fuels for cooking is found to be one of the important significant predictors of under-five mortality. The expected number of under-five mortality for mothers who used type of fuels for cooking with solid fuels is 0.59 times less than mothers who were used clean fuels.

It is indicated that childbirth order has a significant effect on the number of under-five mortality. The estimated number of under-five mortality for mothers who had second and third childbirth order is 2.05 times greater than mothers who were first childbirth order. In addition, the estimated number of under-five mortality for mothers who were fourth and above childbirth order is 5.27 times greater than mothers who were in the first childbirth order.

The bottom half of Table (4.12), labeled "Zero Count", contains coefficients for the factor change in the odds of being in the zero counts group. Hurdle Poisson model has different sign for the estimate parameters for zero counts than the ZIP and ZINB. This is because of the way the models are defined. For the hurdle Poisson model, the zero-hurdle component describes the probability of observing a positive count whereas, for the ZIP and ZINB models, the zero-inflation component predicts the probability of observing a zero count from the point mass component.

This study found that mother's education level, wealth index, household size, contraceptive use, types of fuels for cooking are significantly negatively associated with the probability of being in zero count group. But childbirth order is positively associated with the probability of being in zero count group. Mother's education level has a significant impact on the probability of being in the zero count groups. The odds of no occurrence of under-five mortality for mothers with primary education is 0.57 times less than as compared to no education level controlling other variables. In addition, the odds of no occurrence of under-five mortality for mothers with secondary and above is 0.49 times less than as compared to no education level.

It is also observed that the wealth index significantly influences the likelihood of belonging to the zero counts group. The odds of experiencing no under-five mortality with a non-poor wealth index are 0.63 times less than as compared to a poor wealth index, while keeping all other variables in the model constant. Similarly, household size has a significant effect on the probability of being an excess zero. In addition, the odds of no occurrence of under-five mortality are 0.43 times lower for more than five household members as compared to two to five household members.

It can be seen that childbirth order has a significant impact on the probability of being in the zero count. The odds of no occurrence of under-five mortality are 1.33 times greater for mothers with two to three birth orders compared to the first child. Likewise, the odds of no occurrence of under-five mortality are 4.84 times greater for mothers with two to three birth orders compared to the first child. Moreover, contraceptive use has a significant effect on the probability of being and excess zero. The odds of no occurrence of under-five mortality for mothers who were used contraceptive is 0.74 times less than mothers who were not used a contraceptive. The odds of no occurrence of under-five mortality for mothers using solid fuels for cooking are 0.61 times lower than when compared to mothers using clean fuels, while controlling for other variables.

4.4.5 Parameter Estimation of Hurdle Negative Binomial Regression Model

A final statistical model that has been used in the analysis of under-five mortality is hurdle negative binomial model. Table (4.13) depicts the results of a hurdle negative binomial model of parameter estimates, standard error of estimates.

Table (4.13) Estimated Coefficient of Hurdle Negative Binomial Regression Model

Positive count	Estimate	Exp(b)	S. E	Z value	Pr (> |z|)
Intercept	-0.5641	0.5689	0.3497	-1.6130	0.1067
Childbirth Order (1st Birth Ref:)					
Second and Third	0.7223**	2.0293	0.3591	2.0110	0.0443
Fourth and above	1.6801***	5.3661	0.3364	4.9940	0.0000
Types of Fuel for Cooking (Clean Fuels, Ref:)					
Solid Fuels	-0.5362***	0.5850	0.2066	-2.5950	0.0095
Zero count	**Estimate**	**Exp (b)**	**S. E**	**Z value**	**Pr (> |z|)**
Intercept	-1.8524***	0.1569	0.3313	-5.5910	0.0000
Mother's Education Level (No Education, Ref:)					
Primary	-0.5630***	0.5695	0.1888	-2.9820	0.0029
Secondary and above	-0.7154***	0.4890	0.2449	-2.9210	0.0035
Wealth Index (Poor, Ref:)					
Non-poor	-0.4581**	0.6325	0.1938	-2.3640	0.0181
Household Size (2-5, Ref:)					
More than 5	-0.8483***	0.4282	0.1788	-4.7450	0.0000
Childbirth Order (1st Birth Ref:)					
Second and Third	0.2889	1.3350	0.1983	1.4570	0.1452
Fourth and above	1.5760***	4.8359	0.2261	6.9710	0.0000
Contraceptive Use (No, Ref:)					
Yes	-0.3059*	0.7364	0.1579	-1.9370	0.0527
Types of Fuel for Cooking (Clean Fuels, Ref:)					
Solid Fuels	-0.4966**	0.6086	0.2420	-2.0520	0.0402

Source: Myanmar Demographic and Health Survey (2015-2016)

Note: ***, **, * Significant at 1 %, 5% and 10% level respectively. Ref: Reference category of the variables

The fitted hurdle negative binomial regression model as follows

$$\ln(\lambda) = -0.5689 + 2.0593 \text{ (child birth order = second and third) } + 5.3661 \text{ (child birth order = fourth and above) } - 0.5850 \text{ (types of fuel for cooking = solid fuels)} \quad (4.9)$$

$$\text{logit}(w) = -0.1569 - 0.5695 \text{ (mother's education level = primary) } - 0.4890 \text{ (mother's education level = secondary and above) } - 0.6325 \text{ (wealth index = non-poor) } - 0.4282 \text{ (household size = more than 5) } + 1.3350 \text{ (child birth order = second and third) } + 4.8359 \text{ (child birth order = fourth and above) } - 0.7364 \text{ (contraceptive use = yes) } - 0.6086 \text{ (access to safe water = unimproved)} \quad (4.10)$$

According to Table (4.13), the results of positive count hurdle negative binomial model can be seen that types of fuels for cooking is negatively associated with the number of under-five mortality. However, childbirth order is positively associated with the number of under-five mortality. Moreover, type of fuels for cooking is found to be one of the important significant predictors of under-five mortality. The expected number of under-five mortality for mothers who used type of fuels for cooking with solid fuels is 0.59 times less than mothers who were used clean fuels.

Further, childbirth order has a significant effect on the number of under-five mortality. The estimated number of under-five mortality for mothers increased by a factor of 2.06 in the second and third childbirth order as compared to first childbirth order. Additionally, the estimated number of under-five mortality for mothers increased by a factor of 5.37 in the fourth and above childbirth order as compared to first childbirth order.

The zero-inflation part analysis shows that variables such as education level, wealth index, household size, childbirth order, contraceptive use and access to safe water as shown in Table (4.13). Hurdle negative binomial model has different sign for the estimate parameters for zero counts than the ZIP and ZINB. This is because of the way the models are defined. For the hurdle negative binomial model, the zero-hurdle component describes the probability of observing a positive count whereas, for the ZIP and ZINB models, the zero-inflation component predicts the probability of observing a zero count from the point mass component.

Mother's education level has a significant impact on the probability of being in the zero count groups. The odds of no occurrence of under-five mortality for mothers with primary education is 0.57 times less than as compared to no education level controlling other variables. In addition, the odds of no occurrence of under-five mortality for mothers with secondary and above is 0.49 times less than as compared to no education level.

It is also observed that the wealth index significantly influences the likelihood of belonging to the zero counts group. The odds of experiencing no under-five mortality with a non-poor wealth index are 0.63 times less than as compared to a poor wealth index, while keeping all other variables in the model constant. Furthermore, household size has a significant effect on the probability of being an excess zero. The estimated odds of having zero under-five mortalities are 0.43 times lower for households with more than five members compared to households with two to five members, while controlling for other variables in the model.

The result also shows that childbirth order has a significant effect on the probability of being an excess zero. The odds of being in the zero count with second and third childbirth orders are 1.33 times greater as compared to first birth order. In addition, the estimated odds that the number of under-five mortality becomes zero with four and above childbirth orders is 4.84 times as compared to first order childbirth order. Moreover, contraceptive use has a significant effect on the probability of being and excess zero. The odds of no occurrence of under-five mortality for mothers who were used contraceptive is 0.74 times less than mothers who were not used a contraceptive. The odds of no occurrence of under-five mortality for mothers using solid fuels for cooking are 0.61 times lower than when compared to mothers using clean fuels, while controlling for other variables.

In conclusion, under-five mortality is a critical health indicator, and statistical models can be used to analyze the factors of under-five mortality and predict the impact of interventions. The Poisson, negative binomial, zero-inflated Poisson, zero-inflated negative binomial, hurdle Poisson and hurdle negative binomial models are six statistical models that have been used in the analysis of under-five mortality. These models are useful when there is a large number of zero counts as in the case with under-five mortality data.

4.4.6 Model Selection

In this study, six different count regression models (PR, NB, ZIP, ZINB, HP, HNB) were considered. Different model selection criteria like Akaike information criterion (AIC) and Bayesian information criterion (BIC) were used to compare and identify the most appropriate count regression model that can provide better fit to the data set.

Table (4.14) Model Selection Criteria for the Count Regression Models

Model	Selection Criteria	
	AIC	BIC
PR	2006.536	2069.554
NB	1789.273	1852.291
ZIP	**1743.399**	**1812.719**
ZINB	1785.140	1848.158
HP	1778.450	1860.373
HNB	1780.297	1868.522

As shown in Table (4.14), the likelihood ratio values for all models are found to be significant. Thus, all regression models are significant. Next, this study identifies the most appropriate model by using the goodness of fit test. The model with smallest AIC and BIC was ZIP. Therefore, zero-inflated Poisson model was considered as the most appropriate model to predict under-five mortality in Myanmar. In addition, the simulation was carried out to investigate the parameters by using the zero-inflated Poisson model.

4.5 Evaluation of the Estimates of Zero-Inflated Poisson Model under Excess Zero Data Set Through Simulation

The under-five mortality data has two significant features: over-dispersion where mean is greater than variance with overdispersion test and excess-zero, which is more than 90% of observations. To take account of these two features, the previous sections used six competing models: Poisson, negative binomial, zero-inflated Poisson, zero-inflated negative binomial, hurdle Poisson and hurdle negative binomial models.

For count data, Poisson model is the first to be considered. Equal dispersion, where mean equals variance, is the significant feature of this model. To take account of over-dispersion, the negative binomial model which has been derived from the mixture of Gamma and Poisson distributions is used. Furthermore, to take account of excess-zero, zero-inflated Poisson regression is used. This zero-inflated Poisson regression model assumes that the data comes from two different generation processes and thus consists of two parts. The first part distinguishes between zero and non-zero observations, using either probit or logit model while the second part builds a Poisson regression models for non-negative observations.

To prove this fact, a simulation was conducted. Simulation is a numerical process, where data are generated from the known process and evaluation is made for the performance of model. In this section, a simulation was performed to show the performance of zero-inflated Poisson model. For simplicity, models with three independent variables including mother education, childbirth order of second and third and fourth and above, types of fuels for cooking which have significant effects on under-five mortality were used for simulation. The simulation process includes four steps.

The first step generates 4000 observations for the dependent and significance of three independent variables from the known process. The values of independent variables are generated from uniform distribution. For the logit part, the values of dependent variable are generated from Bernoulli process with regression coefficients [0.2, 0.9, 0.1]. For the Poisson part, the values of dependent variable are generated from Poisson process with regression coefficients of four significant independent variables [-0.2484, -0.4169, 0.5985, 1.5037, -0.6494].

The second step generates estimation results, regression coefficients and their standard errors, from zero-inflated Poisson model using the simulated data from the first part. The third step repeats steps 1 and 3 for 500 times and generates 500 estimates of coefficients and standard errors. The last step averages 500 observations from the previous step.

If a model performs well under excess-situation, its estimates, on average, must be the same as the coefficients from the data generation process. The results of simulation are shown in Table (4.15).

Table (4.15) Average Values of Regression Coefficients and Standard Errors of Zero-Inflated Poisson Model from Simulation

Parameters	Fitted ZIP Model	Simulated ZIP Model	
	Estimated Coefficients	Average Values of Coefficients	Average Values of Standard Errors
Intercept	-0.2484	-0.2486	0.0042
Household Size			
More than 5	-0.4169	-0.4164	0.0002
Childbirth Order			
Second and third	0.5985	0.5989	0.0001
fourth and above	1.5037	1.5037	0.0001
Type of fuels for cooking			
Solid Fuels	-0.6494	-0.6494	0.0000

Source: Own Calculation

As shown in Table (4.15), the average values of coefficients from simulated zero-inflated Poisson model are almost the same as the estimated coefficients from fitted zero-inflated Poisson model. Therefore, the results of simulated zero-inflated Poisson model is suitable for predicting Myanmar's under-five mortality. Additionally, modifying parameters are made to compare simulation results with real-world data. If the simulation closely matches the observed data, it enhances confidence in the validity and accuracy of the model.

CHAPTER V
CONCLUSION

This study intended to examine the socio-economic, demographic, health care, and environmental factors which have an influence on the under-five mortality in Myanmar based on the 2015-2016 MDHS data by applying the most appropriate zero-inflated regression model. This chapter presented the findings of the significance of each of the influencing factors of the under-five mortality as well as discussion on the most appropriate count regression model being to be used in the estimation of under-five mortality. Moreover, some recommendations were made and needs for further research was suggested based on such findings and discussions.

5.1 Findings and Discussions

This study identified the influencing factors of under-five mortality in Myanmar by using count regression models. Data of the 2015-2016 MDHS were used for the analysis. However, this study only focused on the 3670 ever-married women aged 15-49 years. Among them, 3483 women (94.90%) had never experienced under-five mortality and about 187 women (5.10%) had experienced under-five mortality due to different factors. The dependent variable in this study was the number of under-five mortality. Independent variables considered in this study are socio-economic, demographic, health care, and environmental factors such as mother's education, wealth index, place of residence, household size, mother's age at birth, birth order, place of delivery, contraceptive use, access to safe water, access to proper sanitation facilities, and types of cooking fuel. In addition, the descriptive analysis was carried out fitting count regression models such as Poisson, negative binomial, zero-inflated Poisson, zero-inflated negative binomial, hurdle Poisson and hurdle negative binomial and simulation studies to examine significant effects of independent variables on the dependent variable.

In this study, it can be seen that approximately 94.9% of the mothers had never experienced under-five mortality in their lifetime whereas 5.1% of the mothers had experienced under-five mortality. Hence, it was obvious that there was an excess zero and high variability in the non-zero values in this study. And then, there was possibility of over dispersion because the variance of under-five mortality was larger than the mean. To predict the number of under-five mortality in Myanmar, negative binomial model would be better than the Poisson model to use. However, the zero-inflated models could be fitted better with the under-five mortality under consideration of excess zeros.

From the perspective of developing policies, it's critical to investigate why some mothers' children died before age five while other mothers never experienced such a thing. Socioeconomic, demographic, healthcare, and environmental factors may also have an impact on the causes of mortality in children under the age of five.
The findings showed that under-five mortality was experienced by mothers with no education but not by mothers with higher education. This result served as further justification for the use of zero-inflated count data models, in which variables affecting zero counts can be separately modelled.

Another significant influence on under-five mortality is the wealth index. women from wealthy households experienced under-five mortality at a lower rate than women from poorer households. The potential effects of a mother's place of residence on the likelihood of experiencing under-five mortality. The results indicate that under-five mortality was experienced by mothers residing in rural areas, while mothers from urban areas did not experience such events. The place of residence appears to play a significant role in the prevalence of under-five mortality.

The findings indicate that mothers' household size may have an impact on how frequently children under the age of five die. It has been discovered that under-five mortality was more common among mothers with two to three children than it was among women with four to five children or more. The order of birth may indeed influence the under-five mortality rate. When considering birth order, it becomes evident that the percentage of women with children whose birth order was fourth or higher experienced a higher under-five mortality rate compared to women whose children were firstborn. Furthermore, an inverse trend is observable in the percentage of mothers who had no prior experience with under-five mortality.

Using contraceptives may have a minor impact on the under-five mortality rate. There is only a slight proportional difference in under-five mortality between mothers who use contraceptives and those who do not. It appears that the choice of cooking fuel can indeed influence under-five mortality. Mothers who regularly use clean fuels experience fewer under-five deaths than those using wood, coal, and other sources. The association between under-five mortality and all socioeconomic, demographic, health care, and environmental factors is significant at the 1% level. Notably, household size is significant at the 5% level, and the type of fuel used for cooking shows a significant association with under-five mortality at the 5% level.

By comparing of parameter estimations in each zero-inflated regression model, zero-inflated Poisson model was the most appropriate model with smallest AIC and BIC. Argawu and Mekebo (2022) showed that zero-inflated Poisson model was found to be the best model which revealed that mother's age, marital status, mother's age at first birth, place of delivery, current contraceptive type used, type of cooking fuel, residence, region, religion, time to get drinking water, number of children at home, birth order, and birth type were significant factors to determine under-five mortality in Ethiopia. Furthermore, Abera and Yohannis (2022) claimed that zero-inflated Poisson regression model was found to be the best fit for the collected data in which education of husband, source of water, mother occupation, kebele of mother, prenatal care, place of delivery, place of residence, wealth of household, average birth interval and average breast feeding were found to be statistically significant determinants of under-five mortality. Hence, the results of those studies are similar to the results of this study.

The findings of this study indicated that most of the socioeconomic, demographic and health care variables influenced on the under-five mortality. There were some significant findings from zero-inflated regression models. According to the results, mother's education level, household size, childbirth order and type of fuels for cooking had statistically significant effects on under-five mortality at 5% level of significance. Another similar finding was also found in the study of Zinabu et al. (2012) also claimed that mother's education status, birth order, number of children and household size had statistically significant impacts to determine the infant and child mortality in Ethiopia. Moreover, Yenew (2015) in which state and region and mother's level of education in Ethiopia was significant. Hence, the general results of those study are similar with the results of the current study.

It was also observed that there was a negative relationship between under-five mortality and size of household. It means that households with a large family member can reduce the number of deaths for under-five children compared with those with a small family member. The similar findings were evidenced in a study from Ethiopia (Alito and Girmma, 2021) in which the presence of more household members in the family had a negative effect on under-five mortality. In that, households with six up to nine members and ten and more members have lower under-five mortality rate as compared to households with less than five members. This could be because a family with more members are able to look after and take care of their child. Perhaps mothers with more children are better experienced in childbearing and possess more knowledge of childbearing practices. Hence, the results of that study are in keeping with some results of Myanmar as in this study.

In addition, it was found that the childbirth order was one of another important determinant factors of under-five mortality in this study. The children with later birth order have more chance to die compared to those with earlier birth order. The similar findings were found in some previous studies: Tai et al. (2019) studied the risk of child mortality that was significantly higher for children with the fourth and fifth birth orders and sixth or more birth orders respectively; Fenta et al. (2020) also showed that the death rate of non-zero under-five whose order of birth is four and above increased by 47.9% as compared to children of a first order of birth; Gobebo (2021) claimed that children of later birth order had higher risk of under-five mortality compared to those children of earlier birth order. A possible reason might be that the later birth orders decrease the care given to the child by mother, that is, the reason of having more children. Furthermore, the intra-familiar competition for foods and other limited resources essential for child's needs will increase. Hence, the results of those studies are also similar to the results of this study conducted in Myanmar.

Furthermore, it was found that type of fuels for cooking was one of the important factors of under-five mortality in this study. Specifically, mothers who used solid fuels for cooking were associated with an expected under-five mortality rate that is lower than that of mothers who used clean fuels, even when accounting for other variables in the model. The difference finding was found in some previous studies: Suliman et al. (2017) studied a significant and positive impact of wood fuel consumption on both under-five and adult mortality; Imo and Wet-Billings (2021) explored that a significant association between under-five mortality risk and both high neighborhood poverty and the use of solid cooking fuels indoors; Rana et al. (2021) examined that the risk of under-five mortality was higher among children from households with solid fuel compared to children from households using clean fuel. A possible reason might be that cooking place along with solid fuel effect on under-five mortality because cooking inside the house with solid fuels maximizes the concentration of airborne taxic pollutants in the household.

Additionally, simulation was employed in this study to evaluate the accuracy of the zero-inflated Poisson model estimations, primarily because the average estimates derived from the ZIP model did not closely align with the fitted values.

5.2 Recommendations

Based on the findings of this study, some recommendations were made. This study mainly focused on the under-five mortality in Myanmar. As mentioned by the results, it was observed that among the socioeconomic, demographic and health care factors such as household size, childbirth order and type of fuels for cooking were the main determinants of under-five mortality in Myanmar.

According to the findings concerning with household size, the family with more members were able to take care of their children. Therefore, the government should provide the household members with some kind of knowledge sharing and education programs. Moreover, it was also observed that children with birth orders of second, third, fourth, and higher typically received less care from their mothers. Contraceptive use is crucial for reducing under-five mortality rates and for supporting evidence-based advocacy to expand the utilization of family planning services. Contraceptive use, or family planning, enables women to space and limit their childbearing during high-risk maternal ages, thus helping to avoid pregnancies that are too closely spaced or unwanted. This also contributes to a reduction in under-five mortality rates by lowering birth order through the use of contraceptives. Another possible reason is that low total fertility can be associated with lower death rate of children due to the use of high contraceptive prevalence rate. Hence, both public and private organizations should evenly distribute the knowledge of contraceptive use to all people in Myanmar

Based on the findings, most of the educated women had the awareness of how to care her children before and after births and enable her to change feeding and childcare practices by shaping and modifying the traditional familial relationships. It was obvious that the education level of mothers plays an important role in child survival. Hence, the government should improve mother's educational status to enhance more effective and preventative health care practices and efforts. It also needs to extend education programs aimed at educating mothers. If it would be implemented in a good performance, it affected on the mother's productivity in regard with the reduction of under-five mortality.

In addition, both public and private hospitals in Myanmar were understaffed due to a national shortage of doctors and nurses. Public hospitals lacked many basic facilities and equipments. Thus, the challenges for people of Myanmar in progressing towards universal health coverage are the township health plans that must include all providers of health care: public, private and NGOs. Many station hospitals did not perform well and provide poor-quality services. Inadequate staffing, insufficient supplies and outdated equipment exacerbate this situation. Finally, the institutions concerned with government and other involved stakeholders should make comprehensive prevention strategies; commitment and leadership are needed to ensure child health services and resources are needed to accelerate progress to achieve Sustainable Development Goals 3 in 2030, to reduce under-five mortality in Myanmar.

5.3 Needs for Further Research

The under-five mortality is a common indicator of mortality level which has a significant impact on the health care status especially in developing countries. As a developing country, Myanmar still needs to improve health care services including health care services for children. Hence, the major factors influencing the under-five mortality are needed to explore in order to provide polices and plannings to improve child health. These are the reasons why this study investigates the under-five mortality of Myanmar using the data from 2015-2016 MDHS. However, the 2015-2016 MDHS data has some limitations. So, some variables related to under-five mortality such as underweight births, complications during birth, and diseases including pneumonia, diarrhea, malaria, sepsis, and birth asphyxia, non-disease causes of death, drowning were not included in this study.

In addition to considering the types of cooking fuel, it is essential to take into account the specific cooking location or setting, whether it is done outdoors or indoors. This distinction is crucial for developing comprehensive policies and recommendations related to clean cooking and indoor air quality. To study the specific impact of solid fuels and clean fuels on under-five mortality in Myanmar, researchers would need to gather data on household energy use, health outcomes, and relevant socio-demographic factors from a representative sample of households. Therefore, it is suggested to add those variables in further studies. Only then, it enables a more in-depth analysis on the under-five mortality.

In addition, it is recommended to consider the number of child deaths that occurred by some mother-related factor or health variables such as smoking status, diabetes, hypertension and heart disease. Future researchers should not ignore one important aspect on under-five mortality after COVID-19 pandemic as the number of births has decreased due to the post-COVID effects on the affected mothers.

In the future, the Bayesian analysis method can be used as an alternative approach to get the different results in conducting research on the under-five mortality in Myanmar. Further studies can also investigate how each zero-inflated models fit with the different proportion of zeros through simulation experiments.

The results of all these further studies will surely reinforce the reduction of mortality for children under-five as one of the main targets of better public health policies in Myanmar in the future.

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APPENDIX (A)

Table (A-1)

Summary Statistics of Some Important Variables Related to Under-five Mortality

		Number of Child Death										
Variables with Category		0	1	2	3	4	5	6	8	Total Death	Mean	Std.De
Mother's Education Level	No Education	513	19	26	10	0	3	1	0	59	0.2133	0.7224
	Primary	1560	52	23	6	1	0	0	1	83	0.0779	0.4040
	Secondary	1103	28	6	2	1	0	0	0	37	0.0439	0.2713
	Higher	307	3	1	4	0	0	0	0	8	0.0534	0.3661
Household Wealth Index	Poor	1676	62	41	15	1	3	1	1	124	0.1233	0.5400
	Middle	606	22	6	3	0	0	0	0	31	0.0675	0.3320
	Rich	1201	18	9	4	1	0	0	0	32	0.0422	0.2903
State and Region	Kayah	26	1	0	0	0	0	0	0	1	0.0370	0.1925
	Kachin	137	4	1	0	1	0	0	0	6	0.0699	0.4051
	Kayin	111	4	0	2	0	0	0	0	6	0.0855	0.4270
	Chin	41	4	2	0	0	0	0	0	6	0.1702	0.4809
	Sagaing	394	9	4	4	0	0	0	0	17	0.0706	0.3792
	Taninthayi	100	3	3	0	0	0	1	1	8	0.2129	1.0142
	Bago	307	8	6	0	0	0	0	0	14	0.0623	0.3100
	Magway	248	6	4	1	0	0	0	0	11	0.0656	0.3403
	Manda;ay	368	11	5	5	0	0	0	0	21	0.0925	0.4327
	Mon	121	3	1	0	0	0	0	0	4	0.0400	0.2342
	Rakhine	244	6	2	2	0	0	0	0	10	0.0630	0.3499
	Yangon	388	6	6	0	0	0	0	0	12	0.0450	0.2705
	Shan	477	15	18	7	0	3	0	0	43	0.1673	0.6368
	Ayeyarwaddy	445	19	4	1	1	0	0	0	25	0.0723	0.3503
	Nay Pyi Taw	76	3	0	0	0	0	0	0	3	0.0379	0.1924
Place of Residence	Rural	2616	84	51	17	1	3	1	1	158	0.0973	0.4674
	Urban	867	18	5	5	1	0	0	0	29	0.0525	0.3284
Household Size	2-3	405	22	14	5	0	0	0	0	41	0.1457	0.2374
	4-5	1459	38	27	10	1	0	0	0	76	0.0821	0.3822
	More than 5	1585	42	15	7	1	3	1	1	70	0.0761	0.4576
Marital Status	Married	3325	91	55	22	2	3	1	1	175	0.0869	0.4439
	Others (Widowed, Divorced, Separated)	158	11	1	0	0	0	0	0	12	0.0765	0.2879
Mothers' age at Birth	Below 20	370	12	4	0	0	0	0	0	16	0.0518	0.2646
	20-29	1908	47	28	9	0	0	0	0	84	0.0653	0.4409
	30-45	1205	43	24	13	2	3	1	1	87	0.1293	0.5847
Childbirth Order	First	1439	38	6	2	0	0	0	0	46	0.0377	0.2291
	2-3	1530	42	23	4	0	0	0	0	69	0.0625	0.3201
	4 and above	514	22	27	16	2	3	1	1	72	0.2747	0.8641
Place of Delivery	Home	2057	77	43	17	2	3	1	1	144	0.1140	0.5136
	Public	1165	23	12	4	0	0	0	0	39	0.0490	0.2942
	Private	261	2	1	1	0	0	0	0	4	0.0264	0.2369
Contraceptive Use	No	1358	52	28	11	1	3	1	1	97	0.1196	0.5458
	Yes	2125	50	28	11	1	0	0	0	90	0.0646	0.3478
Access to Safe Water	Improved	2751	75	43	14	1	0	0	1	134	0.0745	0.3893
	Unimproved	731	27	13	8	1	3	1	0	53	0.1299	0.5811
Access to Safe Toilet	Improved	1826	55	21	8	1	0	0	0	85	0.0654	0.3385
	Unimproved	1657	47	35	14	1	3	1	1	102	0.1092	0.5242
Types of Fuels for Cooking	Clean Fuels	658	13	3	9	1	0	0	0	26	0.0731	0.2027
	Wood and Coals	2663	86	48	12	1	3	1	1	152	0.0892	0.8389
	Others	162	3	5	1	0	0	0	0	9	0.0936	0.1967
Total		3483	102	56	22	2	3	1	1	187	3670	

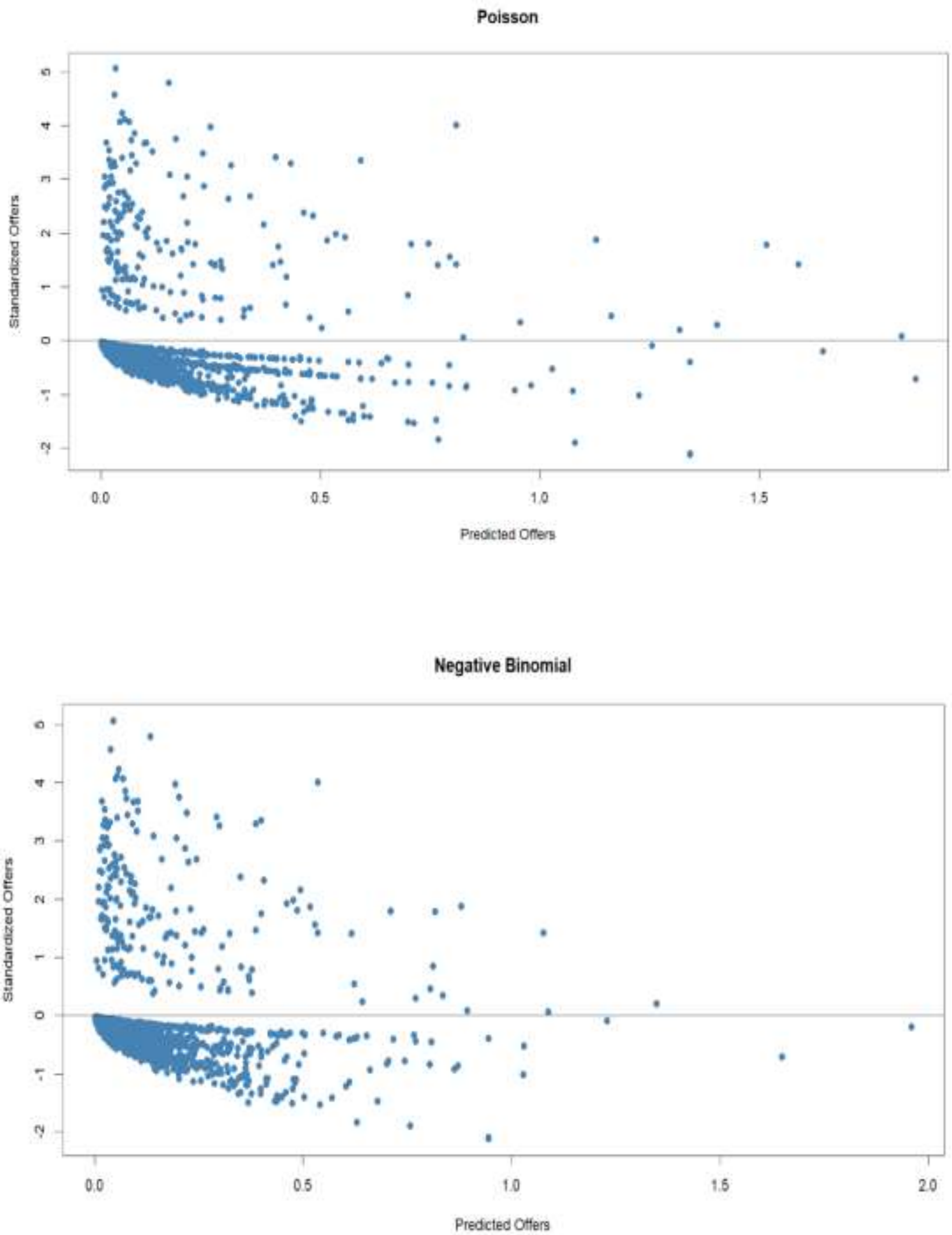

Figure (A-1) Test of Overdispersion

APPENDIX (B)

Table (B-1)

```
Call:
glm(formula = U5M2 ~ EDU1 + WI1 + HHS2 + CBO + CU + W + F1,
family = "poisson",
    data = data, weights = wt)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6720  -0.3921  -0.2494  -0.1438   5.1103

Coefficients:
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)              -1.3344     0.2640  -5.055 4.30e-07 ***
EDU1primary              -0.7152     0.1369  -5.224 1.75e-07 ***
EDU1secondary and above  -0.8142     0.1896  -4.295 1.75e-05 ***
WI1B_Non-Poor            -0.5650     0.1570  -3.599  0.00032 ***
HHS2B_more than five     -1.0145     0.1309  -7.748 9.30e-15 ***
CBO2 to 3                 0.5089     0.1701   2.992  0.00277 **
CBO4 and above            2.0810     0.1785  11.658  < 2e-16 ***
CUYes                    -0.2316     0.1199  -1.931  0.05346 .
WUnimproved               0.2887     0.1291   2.235  0.02540 *
F1Soild Fuels            -0.9493     0.1818  -5.223 1.76e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 1867.0  on 4030  degrees of freedom
Residual deviance: 1547.3  on 4021  degrees of freedom
AIC: 2006.5

Number of Fisher Scoring iterations: 6

[1] 2006.536
[1] 2069.554
Analysis of Deviance Table

Model 1: U5M2 ~ EDU1 + WI1 + RES + HHS2 + MAB2 + CBO + PD + CU +
W + T +
    F1
Model 2: U5M2 ~ 1
  Resid. Df Resid. Dev  Df Deviance  Pr(>Chi)
1      4017     1543.2
2      4030     1867.0 -13  -323.81 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
         GVIF Df GVIF^(1/(2*Df))
EDU1 1.551244  2        1.116015
WI1  1.596495  1        1.263525
HHS2 1.222706  1        1.105760
CBO  1.448464  2        1.097051
CU   1.088501  1        1.043312
W    1.060120  1        1.029621
F1   1.595109  1        1.262976
```

```
                          Estimate Exp_Estimate
(Intercept)             -1.3343817    0.2633209
EDU1primary             -0.7151875    0.4891004
EDU1secondary and above -0.8141548    0.4430136
WI1B_Non-Poor           -0.5650197    0.5683490
HHS2B_more than five    -1.0144679    0.3625953
CBO2 to 3                0.5088725    1.6634147
CBO4 and above           2.0810485    8.0128657
CUYes                   -0.2315605    0.7932947
WUnimproved              0.2886679    1.3346484
F1Soild Fuels           -0.9493012    0.3870114
# Overdispersion test

       dispersion ratio =    1.791
  Pearson's Chi-Squared = 7201.053
                p-value =  < 0.001


      Overdispersion test
data:  PR1
z = 6.0111, p-value = 9.216e-10
alternative hypothesis: true dispersion is greater than 1
sample estimates:
dispersion
  1.462754

Likelihood ratio test

Model 1: U5M2 ~ EDU1 + WI1 + HHS2 + CBO + CU + W + F1
Model 2: U5M2 ~ 1
  #Df   LogLik Df  Chisq Pr(>Chisq)
1  10  -993.27
2   1 -1153.11 -9 319.68  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Table (B-2)

```
Call:
glm.nb(formula = U5M2 ~ EDU1 + WI1 + HHS2 + CBO + CU + F1, data = 
data, 
    weights = wt, init.theta = 0.128414242, link = log)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-0.9534  -0.3521  -0.2344  -0.1405   3.1839  

Coefficients:
                        Estimate Std. Error z value Pr(>|z|)    
(Intercept)              -1.3515     0.3484  -3.879 0.000105 ***
EDU1primary              -0.5630     0.2127  -2.646 0.008134 ** 
EDU1secondary and above  -0.7564     0.2643  -2.862 0.004215 ** 
WI1B_Non-Poor            -0.5366     0.2052  -2.614 0.008943 ** 
HHS2B_more than five     -0.8327     0.1906  -4.369 1.25e-05 ***
CBO2 to 3                 0.4400     0.2041   2.156 0.031071 *  
```

```
CBO4 and above           1.9054     0.2472   7.708 1.28e-14 ***
CUYes                   -0.3272     0.1691  -1.935 0.052953 .
F1Soild Fuels           -0.8773     0.2439  -3.597 0.000322 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for Negative Binomial(0.1284) family taken
to be 1)

    Null deviance: 870.14  on 4030  degrees of freedom
Residual deviance: 712.70  on 4022  degrees of freedom
AIC: 1789.3

Number of Fisher Scoring iterations: 1


              Theta:  0.1284
          Std. Err.:  0.0203

 2 x log-likelihood:  -1769.2730
[1] 1789.273
[1] 1852.291
                          Estimate Exp_Estimate
(Intercept)              -1.3514974    0.2588524
EDU1primary              -0.5629765    0.5695114
EDU1secondary and above -0.7563548    0.4693743
WI1B_Non-Poor            -0.5365551    0.5847592
HHS2B_more than five     -0.8327249    0.4348627
CBO2 to 3                 0.4400227    1.5527425
CBO4 and above            1.9054196    6.7222279
CUYes                    -0.3271658    0.7209642
F1Soild Fuels            -0.8773230    0.4158948
```

Table (B-3)

```
Call:
zeroinfl(formula = U5M2 ~ HHS2 + CBO + F1 | EDU1 + HHS2 + CBO,
    data = data, weights = wt, dist = "poisson")

Pearson residuals:
     Min       1Q   Median       3Q      Max
-0.78035 -0.22611 -0.14633 -0.08696 12.50621

Count model coefficients (poisson with log link):
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)           -0.2484     0.3840  -0.647  0.51775
HHS2B_more than five  -0.4169     0.1956  -2.132  0.03302 *
CBO2 to 3              0.5985     0.3616   1.655  0.09789 .
CBO4 and above         1.5037     0.3325   4.522 6.13e-06 ***
F1Soild Fuels         -0.6494     0.1975  -3.289  0.00101 **

Zero-inflation model coefficients (binomial with logit link):
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)               1.3393     0.3802   3.522 0.000428 ***
EDU1primary               0.7162     0.2005   3.572 0.000354 ***
EDU1secondary and above   1.0500     0.2446   4.293 1.76e-05 ***
HHS2B_more than five      0.6400     0.2279   2.809 0.004971 **
```

```
CBO2 to 3                0.1843     0.3746   0.492 0.622734
CBO4 and above          -0.6393     0.3756  -1.702 0.088699 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Number of iterations in BFGS optimization: 17
Log-likelihood: -860.7 on 11 Df
[1] 1743.399
[1] 1812.719
                               Estimate Exp_Estimate
count_(Intercept)            -0.2483902    0.7800555
count_HHS2B_more than five   -0.4169040    0.6590842
count_CBO2 to 3               0.5984725    1.8193376
count_CBO4 and above          1.5036952    4.4982806
count_F1Soild Fuels          -0.6493848    0.5223670
zero_(Intercept)              1.3392883    3.8163266
zero_EDU1primary              0.7162015    2.0466442
zero_EDU1secondary and above  1.0500198    2.8577078
zero_HHS2B_more than five     0.6400380    1.8965529
zero_CBO2 to 3                0.1842941    1.2023694
zero_CBO4 and above          -0.6393159    0.5276533
```

Table (B -4)

```
Call:
zeroinfl(formula = U5M ~ CBO + CU + F1 | EDU1 + HHS2, data =
data,
    weights = wt, dist = "negbin")

Pearson residuals:
     Min       1Q   Median       3Q      Max
-0.71913 -0.22707 -0.15516 -0.09198 12.85697

Count model coefficients (negbin with log link):
               Estimate Std. Error z value Pr(>|z|)
(Intercept)     -0.4890     0.2171  -2.252 0.024323 *
CBO2 to 3        0.5553     0.1982   2.802 0.005078 **
CBO4 and above   1.8566     0.1905   9.747  < 2e-16 ***
CUYes           -0.4051     0.1399  -2.896 0.003782 **
F1Soild Fuels   -0.5953     0.1730  -3.440 0.000581 ***
Log(theta)       2.8290        NaN     NaN      NaN

Zero-inflation model coefficients (binomial with logit link):
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)              0.91199    0.07206  12.655  < 2e-16 ***
EDU1primary              0.76853    0.20238   3.797 0.000146 ***
EDU1secondary and above  1.16919    0.23778   4.917 8.78e-07 ***
HHS2B_more than five     0.76378    0.17497   4.365 1.27e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Theta = 16.9291
Number of iterations in BFGS optimization: 40
Log-likelihood: -882.6 on 10 Df
[1] 1785.14
[1] 1848.158
```

```
                               Estimate Exp_Estimate
count_(Intercept)            -0.4889754    0.6132544
count_CBO2 to 3               0.5553211    1.7425005
count_CBO4 and above          1.8566485    6.4022439
count_CUYes                  -0.4050668    0.6669323
count_F1Soild Fuels          -0.5953221    0.5513850
zero_(Intercept)              0.9119900    2.4892713
zero_EDU1primary              0.7685337    2.1566017
zero_EDU1secondary and above  1.1691879    3.2193770
zero_HHS2B_more than five     0.7637776    2.1463690
```

Table (B-5)

```
Call:
hurdle(formula = U5M ~ CBO + F1 | EDU1 + WI1 + HHS2 + CBO +
    CU + F1, data = data, weights = wt, dist = "poisson")

Pearson residuals:
     Min       1Q   Median       3Q      Max
-0.73300 -0.22065 -0.14501 -0.08702 12.06832

Count model coefficients (truncated poisson with log link):
               Estimate Std. Error z value Pr(>|z|)
(Intercept)     -0.5438     0.3405  -1.597  0.11025
CBO2 to 3        0.7184     0.3549   2.024  0.04296 *
CBO4 and above   1.6618     0.3286   5.057 4.26e-07 ***
F1Soild Fuels   -0.5209     0.1944  -2.679  0.00738 **
Zero hurdle model coefficients (binomial with logit link):
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)               -1.8524     0.3313  -5.591 2.26e-08 ***
EDU1primary               -0.5630     0.1888  -2.982  0.00286 **
EDU1secondary and above   -0.7154     0.2449  -2.921  0.00349 **
WI1B_Non-Poor             -0.4581     0.1938  -2.364  0.01807 *
HHS2B_more than five      -0.8483     0.1788  -4.745 2.09e-06 ***
CBO2 to 3                  0.2889     0.1983   1.457  0.14517
CBO4 and above             1.5760     0.2261   6.971 3.14e-12 ***
CUYes                     -0.3059     0.1579  -1.937  0.05272 .
F1Soild Fuels             -0.4966     0.2420  -2.052  0.04016 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Number of iterations in BFGS optimization: 11
Log-likelihood: -876.2 on 13 Df
[1] 1778.45
[1] 1860.373
                               Estimate Exp_Estimate
count_(Intercept)            -0.5437574    0.5805627
count_CBO2 to 3               0.7184303    2.0512109
count_CBO4 and above          1.6618100    5.2688388
count_F1Soild Fuels          -0.5209485    0.5939569
zero_(Intercept)             -1.8524029    0.1568598
zero_EDU1primary             -0.5629779    0.5695106
zero_EDU1secondary and above -0.7154297    0.4889820
zero_WI1B_Non-Poor           -0.4581282    0.6324664
zero_HHS2B_more than five    -0.8482578    0.4281602
zero_CBO2 to 3                0.2889232    1.3349892
zero_CBO4 and above           1.5760426    4.8357806
zero_CUYes                   -0.3059266    0.7364406
zero_F1Soild Fuels           -0.4966472    0.6085676
```

Table (B-6)

```
Call:
hurdle(formula = U5M ~ CBO + F1 | EDU1 + WI1 + HHS2 + CBO +
    CU + F1, data = data, weights = wt, dist = "negbin")

Pearson residuals:
     Min       1Q   Median       3Q      Max
-0.72770 -0.22046 -0.14470 -0.08693 11.99160

Count model coefficients (truncated negbin with log link):
               Estimate Std. Error z value Pr(>|z|)
(Intercept)     -0.5641     0.3497  -1.613  0.10671
CBO2 to 3        0.7223     0.3591   2.011  0.04429 *
CBO4 and above   1.6801     0.3364   4.994 5.92e-07 ***
F1Soild Fuels   -0.5362     0.2066  -2.595  0.00945 **
Log(theta)       3.3561     2.7748   1.209  0.22647
Zero hurdle model coefficients (binomial with logit link):
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)              -1.8524     0.3313  -5.591 2.26e-08 ***
EDU1primary              -0.5630     0.1888  -2.982  0.00286 **
EDU1secondary and above  -0.7154     0.2449  -2.921  0.00349 **
WI1B_Non-Poor            -0.4581     0.1938  -2.364  0.01807 *
HHS2B_more than five     -0.8483     0.1788  -4.745 2.09e-06 ***
CBO2 to 3                 0.2889     0.1983   1.457  0.14517
CBO4 and above            1.5760     0.2261   6.971 3.14e-12 ***
CUYes                    -0.3059     0.1579  -1.937  0.05272 .
F1Soild Fuels            -0.4966     0.2420  -2.052  0.04016 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Theta: count = 28.6768
Number of iterations in BFGS optimization: 22
Log-likelihood: -876.1 on 14 Df
[1] 1780.297
[1] 1868.522
                               Estimate Exp_Estimate
count_(Intercept)            -0.5640685    0.5688898
count_CBO2 to 3               0.7223456    2.0592577
count_CBO4 and above          1.6801067    5.3661287
count_F1Soild Fuels          -0.5361747    0.5849817
zero_(Intercept)             -1.8524029    0.1568598
zero_EDU1primary             -0.5629779    0.5695106
zero_EDU1secondary and above -0.7154297    0.4889820
zero_WI1B_Non-Poor           -0.4581282    0.6324664
zero_HHS2B_more than five    -0.8482578    0.4281602
zero_CBO2 to 3                0.2889232    1.3349892
zero_CBO4 and above           1.5760426    4.8357806
zero_CUYes                   -0.3059266    0.7364406
zero_F1Soild Fuels           -0.4966472
```

Table (B-7)

Variable	Obs	Mean	Std. Dev.	Min	Max
p_beta0r	500	-.248625	.0295925	-.3398551	-.151111
p_beta1r	500	-.4164208	.0124858	-.4593403	-.3833106
p_beta2r	500	.5989424	.0115316	.5640072	.6346657
p_beta3r	500	1.503702	.0135072	1.463829	1.546007
p_beta4r	500	-.6494369	.0120756	-.683167	-.6098993
p_v_beta0r	500	.0041985	.0002312	.0036332	.0049769
p_v_beta1r	500	.0001657	.000027	.0000744	.0002425
p_v_beta2r	500	.0001452	.0000246	.0000475	.0002175
p_v_beta3r	500	.0001746	.0000445	.0000341	.0003058
p_v_beta4r	500	-.0000126	.0000201	-.0000906	.0000438