

**Spatial Analysis of Child Mortality in South Africa in
Relation to Poverty and Inequality: Evidences from the
2011 census**

by

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PLAGIARISM DECLARATION

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ABSTRACT

Subnational estimates of child mortality are difficult to produce and are rare in Sub-Saharan Africa. It is the overall aim of this research to derive estimates of child mortality rates for the municipalities and provinces of South Africa using the 2011 census data, and to assess the results in relation to the level of poverty and inequality. The estimation of child mortality rates is achieved through the use of direct synthetic cohort methods with Bayesian spatial smoothing. The Bayesian spatial smoothing process is used to generate municipal level estimates of child mortality rates. The model utilises information from neighbouring municipalities by controlling the effects of women's education and HIV/AIDS. It is found that there are clear and significant spatial differentials in child mortality in the country, where at province level the under-five mortality rate ranges from 26 deaths per 1000 live births in the Western Cape (WC) to 71 deaths per 1000 live births in KwaZulu-Natal (KZN). At municipal level, it ranges from as low as 24 deaths per 1000 live births in the City of Cape Town (in WC) to as high as 109 deaths per 1000 live births in uPhongolo (in KZN)). Furthermore, the estimates obtained are reasonable, and those at national and province level are in agreement with results from many other researches. In evaluating the spatial differentials in child mortality with the levels of poverty and inequality, it is shown that child mortality is higher in poorer areas and vice-versa, although there are some cases where an inverse relationship is observed. For instance, several municipalities in Limpopo province scored relatively lower child mortality rates though the level of poverty is very high. It is also shown that the distribution of income similarly matters to some extent as greater child mortality is observed in more unequal areas – although the degree of association is not as strong as that of poverty. These results are confirmed by multilevel logistic regression model of child mortality. The findings of this study may help the government to implement policies more effectively and make more focused decisions in the fight for the reduction of child mortality in the country.

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1. INTRODUCTION

1.1 Background

Disparities in health and mortality have been the concern of development agencies, governments and the international public health community for many years. Various declarations were signed by leaders of nations and representatives of key international organisations so that the gap would be reduced to a noteworthy level (WHO 1978). Especially reducing child mortality to improve the health of children is one of the eight Millennium Development Goals (MDGs) and the topic of many researches. Child mortality is considered to be one of the key measures of a country's health system, and rates of child mortality of an area have long been believed to be important indicators of health status and socioeconomic development (Kabir, Islam, Ahmed *et al.* 2001; IGME 2013a). This is due to its sensitivity to various changes that affect the health of the entire population, such as disease epidemics and economic development, and to other changes that affect general living conditions, such as social well-being and the quality of the environment (Reidpath and Allotey 2003).

According to a UN report on child mortality, child mortality in South Africa has declined from 61 deaths per 1000 live births in 1990 to 45 deaths per 1000 live births in 2012 (IGME 2013a). The performance of the country in this regard is, however, found to be low compared to many other countries' performance. For instance, the world has made substantial progress in reducing the under-five mortality rate by 47 per cent in the period 1990-2012 while South Africa has attained a reduction of only about 26 per cent, which makes the country very unlikely to achieve the MDG goal number four – targets to have an infant and under-five mortality rates of 18 and 20 per 1000 births respectively by 2015 (StatsSA 2013). Although HIV/AIDS is usually quoted as the main reason for this low performance, the role of poverty and inequality should not be ignored. It has been reported that the health of infants and children in South Africa is largely influenced by social and economic conditions under which they live and approximately 66 per cent of children in the country live in poverty, with a monthly household income of less than R1200 per month (Whiting 2013).

Furthermore, child mortality rates in the country have been found to be much higher in certain geographical areas and disadvantaged social groups. Many studies in

different countries show that the geographic distribution of health problems and their relationship to potential risk factors can be invaluable for cost effective intervention planning. Addressing inequalities in health status and access to health care services within countries is as important as addressing these issues among countries, and hence, in order to effectively address the problem and work towards further reductions of child mortality in the country it is essential that the efforts be focused more on lower administrative levels as, at municipality level for example, opposed to concentrating only on the level of mortality at national level (Freedman, Waldman, Pinho *et al.* 2005).

1.2 Importance of the study

Accurate and timely estimates of child mortality at lower geographical units are very important for a country in order to evaluate the effectiveness of intervention programmes as well as for policy planning. In addition, studying this in relation to poverty and inequality will help to make more focused and potentially effective decisions. Many of the researches conducted so far on child mortality in South Africa lack comprehensiveness in that either they focus only on country or province level, or certain specific geographical areas. To the best of our knowledge, there is not any research which attempts to estimate child mortality of the country at municipal level. Besides, very few of these researches tried to analyse the relationship of child survival with poverty and inequality. Thus the research is unique because it will provide new and comprehensive estimates of child mortality for the country at lower administrative units, specifically for the municipalities of South Africa, and it helps to see how these estimates are related with poverty and inequality.

1.3 Objectives of the research

The primary objective of this research is to estimate infant and child mortality rates for the municipalities and provinces of South Africa using the 2011 South African census and to study the spatial differentials in relation to poverty and inequality. The hypothesis is that there are significant spatial variations of child mortality associated with socioeconomic differentials in the country, hence deriving estimates at lower administrative levels helps to achieve faster and greater reduction of child mortality in the country.

The study aims to achieve three specific objectives. First, it attempts to estimate child mortality rates at municipal, provincial and national levels using the 2011 census data. The direct synthetic cohort method is employed to estimate the rates at national and province level while Bayesian spatial smoothing techniques are used to derive the estimates at municipal level. Second, it assesses the estimates of child mortalities in relation to poverty and inequality at different levels after computing measures of poverty and inequality from the census data. Third, it aims to identify important risk factors for child mortality in South Africa and study their impact on child survival using data on children born twelve months before the census date. A three-level logistic regression model is used where child, municipality and province are the first, second, and third levels.

1.4 Dissertation organisation

This thesis is divided into five chapters. Chapter 1 gives the background of the study, the importance of the study, and the main objectives of the research. The literature on child mortality in South Africa, methods of estimating child mortality and its correlates are presented in Chapter 2. This is where the findings of other studies which are relevant for the research are presented and childhood mortality and its correlates in South Africa are also discussed. Chapter 3 discusses the quality of the 2011 South African census, the methods of child mortality estimations and smoothing used in the research as well as basic techniques of measuring poverty, living standard and inequality. It also discusses the multilevel logistic regression model including the identification of the dependent and independent variables, the methods of estimating the parameters of the model and model adequacy checking. The results of all the analysis with some descriptions are presented in Chapter 4. Finally, Chapter 5 gives a discussion of the results and major conclusions which can be inferred from the results, limitations of the research and scope for future researches.

2. LITERATURE REVIEW

This chapter reviews the literature on child mortality. It comprises 5 sections. The first section looks at the general overview of child mortality while the second one concentrates on its trends and spatial differentials in South Africa. Sources and methods of estimating child mortality as well as smoothing techniques are discussed in the third section. In the fourth section, the association between child mortality and poverty and inequality is reviewed together with the definitions and measurements of poverty and inequality. Finally, the Mosley and Chen analytical framework and demographic, socioeconomic and environmental factors affecting child mortality are revised.

2.1 Overview of child mortality

Disparities in health and mortality have been the concern of government and non-government organisations for many years. Various declarations were signed by leaders of nations and representatives of key international organisations to address the issue at different times so that the gap could be reduced at a noteworthy level. The famous declaration in Alma-Ata in 1978 with the goal of “health for all by 2000” (WHO 1978) followed by the Millennium Development Goals (MDGs) in 2000 are the two declarations quoted most frequently in the past three and half decades. Both of these declarations state that health and mortality disparities are politically, socially and economically unacceptable. The MDGs are the current priorities of the United Nations (UN) and require the commitment of member countries to the realisation of eight major goals and eighteen targets by the year 2015. Of particular interest to this study is goal number four that focuses on reducing child mortality by two-thirds between 1990 and 2015. Child mortality is usually monitored using two indicators: Infant mortality – death between birth and first year of life – and Under-five mortality (U5M) – death between birth and the fifth year of life. Child mortality in this research may refer to deaths of infants and under-five children interchangeably though efforts are made to state them explicitly.

The main reason for the greater attention given to infant and child mortality by governments and various organisations is that they are considered to be key measures of a country’s health that are crucial to monitor. The rates of infant and child mortality of an area have long believed to be important indicators of health and development.

Biologically, children have much weaker immune systems than adults and are therefore far more vulnerable to environmental or social complications (Caldwell 1996). In addition, they are unable to care for themselves and are hence completely dependent on others. As a result, children are generally the group first and most strongly affected by standards of living. Likewise, advances in health or social conditions are often first observed in improvements in child mortality (Omran 1971).

Studies on child mortality have accumulated a huge list of possible determinants, including individual- and community-level factors such as maternal age, race, income, sanitation, water source, electricity, urban/rural residence, region of residence, household composition, occupation, female education, and access to health care (Caldwell 1979; Hobcraft, McDonald and Rutstein 1985; Victora, Wagstaff, Schellenberg *et al.* 2003; Wang 2003; Omariba, Beaujot and Rajulton 2007; Kembo and Ginneken 2009). Some of these factors are also studied in this research and hence, they will be discussed in detail in section 2.5.

Child mortality rates vary considerably among different countries and regions of the world. According to estimates developed by UN Inter-agency Group for Child Mortality Estimation (IGCME), under-five mortality rates (U5MR) in 2012 were highest in Sierra Leone, with an estimated 182 deaths per 1000 live births and lowest in Iceland and Luxembourg, where there are fewer than 2.5 deaths per 1000 live births (IGME 2013a). The level of mortality has been found to be highly correlated with the relative development status of a country, with 25 times higher rates in the least developed countries compared to the most developed countries (153 deaths per 1000 children vs. 6 deaths per 1000 children) (WB 2013). This has to do with many other factors, but the role of poverty in provoking mortality is undeniable. For instance, if we consider availability of skill attendant at birth as one factor, UNICEF has reported that the world's poorest children are 2.7 times less likely than the richest ones to have skill attendant at birth (UNICEF 2014). Despite differentials, child mortality rates in the last several decades have declined substantially worldwide with estimates falling globally from 191 deaths per 1000 live births in 1960 to 76 deaths per 1000 live births in 2005 and 48 deaths per 1000 live births in 2012 (IGME 2013a). While every nation has experienced some level of decline, there is a great amount of disparity in the overall amount of decline. For instance, countries such as Turkey, Estonia, and Saudi Arabia have had a greater than 80 per cent decline in rates of child mortality while in countries

like Botswana, Zimbabwe, Lesotho and Swaziland where child mortality had been reversed that they have yet to achieve a decline of 10-20 per cent in order to reach the rates evident in 1990. On the other hand, the decline in child mortality has increased since 2005 compared to the decline before 2005. For instance, between 2005 and 2012, there were only six countries with a decline of less than 5% (UNICEF, 2013).

The MDGs have mainly emphasised global level results for monitoring progress rather than the reduction in disparities. However, within-country variation in child mortality has also been well documented, with rates often varying substantially across different regions and social groups (Mosley and Chen 1984; Moser, Leon and Gwatkin 2005). It is said that although global results are vital for assisting policy makers to better prepare for the emerging health needs of populations, they constitute an inappropriate guide for refocusing health priorities (Heuveline, Guillot and Gwatkin 2002). This research, therefore, undertakes childhood mortality analysis in relation to poverty and inequality in South Africa at national, provincial and municipality levels to highlight concentration at lower levels of geography that in turn underscores the ineffectiveness of global indicators for monitoring progress in health achievement.

2.2 Review of trends and differentials of child mortality in South Africa

2.2.1 Trends in child mortality

Although South Africa has progressed well over the past decade, its child mortality rates are still higher than other countries with similar economic status such as Brazil, China, and Mexico as well as a number of other less developed countries including Namibia, Indonesia, Bangladesh, Philippines and many of the North African countries. South Africa's child mortality rates are, in fact, not far from the rates for Botswana, Rwanda, Tanzania and India – countries whose development indices are far below those of South Africa (WB 2013; UNICEF 2014). Based on historical estimates of child mortality developed by UN IGCM (2013a), South Africa's U5MR in the period 1990-2012 fell from 61 to 45 deaths per 1000 live births. However, the decline has not been consistent as in many other countries or the worldwide pattern. A number of researches have documented that because of the HIV endemic there had been a reversal of child mortality beginning from mid-1990 and lasting to 2005, after which it has started to decline at a higher rate due to the introduction of PMTCT (prevention of mother-to-child transmission) programme (Dorrington, Johnson, Bradshaw *et al.* 2006; Nannan,

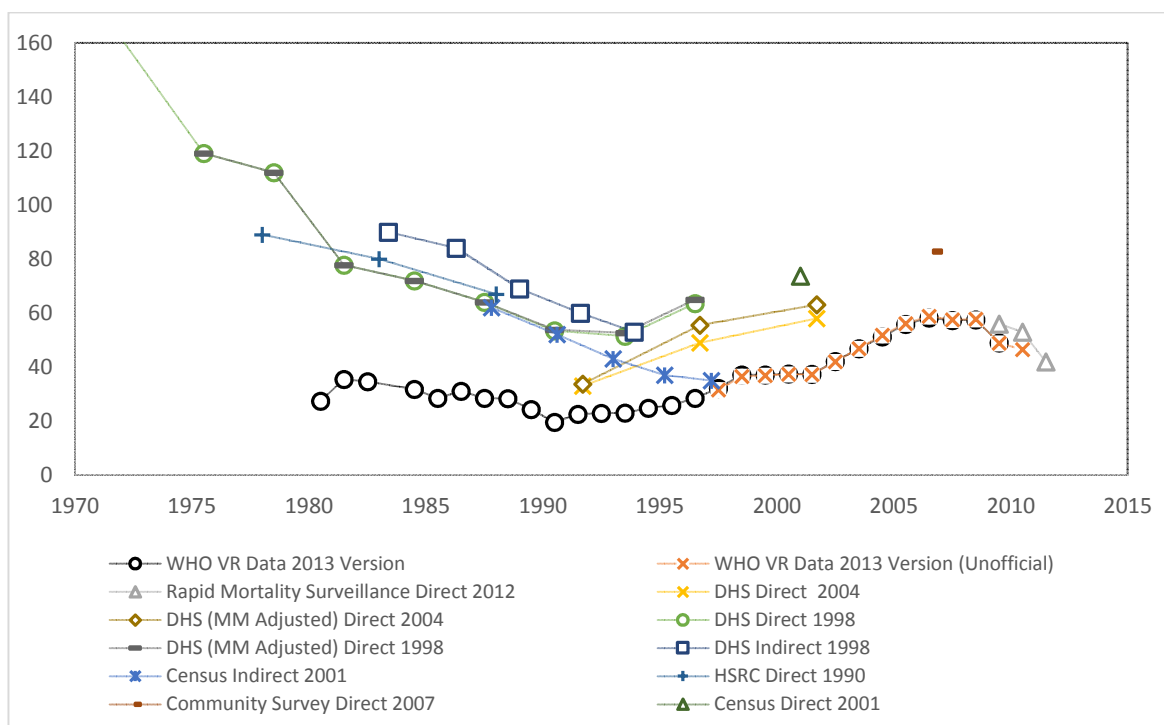
Dorrington, Laubscher *et al.* 2012; Kerbera, Lawnb, Johnson *et al.* 2013). For instance, based on Stats SA estimates, under-five mortality between 1998 and 2007 had increased from 59 to 67 deaths per 1000 births before it declined to reach a level of 53 deaths per 1000 births in 2010 (StatsSA 2013).

The major problem one might come across in reviewing South Africa's estimates of child mortality as computed by different researchers over time is the diverseness of the estimates. Different researchers have come up with different estimates, even using the same data and similar methods of estimation. Researches, which have attempted to review different studies on child mortality estimation in South Africa (Darikwa 2009; Nannan, Dorrington, Laubscher *et al.* 2012) indicate that the main reason for this problem, is the inadequate and poor quality of data available, especially for the estimates of child mortality before 1996 when there were less nationally representative data. Nevertheless, the problem of data quality still persists, though there are considerable improvements. For example, the total number of children surviving, which is a very important variable for indirect estimation of child mortality, was discarded from the 2011 census data release because of its poor quality (StatsSA 2014a). In addition, it has been reported that in the 2001 census the total number of children born to a woman is under-reported, giving implausible indirect estimates of under-five mortality rates (Dorrington, Moultrie and Timaeus 2004). These two cases from the two most recent censuses suffice to show that data quality is still a major problem in estimating child mortality in the country.

One appreciable source of estimates of child mortality for a country is the database compiled by the Inter-agency Group for Child Mortality Estimation (IGME) which was formed at the initiation of UNICEF, The World Health Organization (WHO), The World Bank and The United Nations Population Division to harmonise the works by the respective organisations in formulating child mortality indicators. They compile countries' data which they deem to be as representative as possible of the prevailing child mortality levels at a given time and use these to derive mortality trends. They use data from different sources including vital registrations, demographic and health surveys, censuses and other surveys. These estimates for South Africa from this database are shown below on Figure 2.1 (IGME 2013b). As noted above, there are significant variations on the estimates, almost every source and method producing different results, which partly depicts the unreliability and poor quality of the data in the

country. However, despite the variation, they help to understand the general trend of under-five mortality in the country that the mortality decline had been reversed around 1995 and started declining again from 2005.

Figure 2.1 Estimates of trends of under-five mortality in South Africa



Source: UN IGCME, 2013

2.2.2 Spatial differentials in child mortality

Child mortality in South Africa is characterised by large spatial differentials which are strongly associated with the level of socio-economic disparities. Geographically, the country is divided into nine different provinces: Western Cape (WC), Eastern Cape (EC), Northern Cape (NC), Free State (FS), Gauteng (GT), North-West (NW), KwaZulu-Natal (KZN), Mpumalanga (MP) and Limpopo (LP); and 234 municipalities, each reflecting broad differences in geography, environment, population, and development. In the poorer provinces like LP and MP, there are relatively low levels of infrastructure development (housing, water, sanitation, electricity, etc.), education and income, higher unemployment rates, and poor health care services (UNICEF 2013; HSRC 2014b). In contrast, in richer provinces like WC and GT there are better infrastructure development, higher income and education levels. Child mortality rates in the poorer provinces are usually estimated to be very high compared to the richer provinces.

In reviewing the studies on spatial differential of child mortality in the country, differentials at province level are better studied by several researchers than differentials at municipal level or other lower geographical units. The work by Dorrington, Timaeus, Moultrie *et al.* (2004) reports provincial estimated trends of U5M rates from 1986 to 1996 using the 1996 census. Over the period considered, the lowest and highest mortalities were recorded in WC and EC respectively. The estimate for boys per 100 live births varied from 44 in WC to 114 in EC in 1986, while in 1996 it varied from 47 in WC to 102 in EC. Similarly, the estimates for girls, respectively for WC and EC, were 30 and 107 in 1986 and 32 and 87 in 1996. In their review of available empirical data on levels and causes of child mortality in South Africa in the period 1997-2007 Nannan, Dorrington, Laubscher *et al.* (2012) also show the trends of provincial estimates of infant mortality rates over the time period. It is indicated that in each of the provinces infant mortality was mostly increasing and in some provinces, such as FS, NW, MP and GT, the rate was much higher (above 50 deaths per 1000 live births).

One comprehensive source of national and provincial estimates of child mortality is the HIV and demographic model developed by the Actuarial Society of South Africa (ASSA). The table below (Table 2.1) presents the trends in U5M rates for the country and each province based on the 2008 version of the model (ASSA 2010). It can be observed that under-five mortality rate in EC, FS, KZN and MP had been consistently higher as compared to the rates in the other provinces. One can also note from the table that child mortality was increasing in 2000 before it has started to decline in 2005 in all the provinces due to the HIV endemic as indicated previously for the national estimates.

Table 2.1 Trends of provincial estimates of U5MR (per 1000 births)

	1990	1995	2000	2005	2010	2015
EC	95.9	84.7	92.2	89.7	67.7	59.6
FS	76.1	74.0	86.1	83.9	60.2	53.5
GT	33.7	41.3	54.4	51.6	38.0	33.7
KZN	79.6	78.4	95.6	91.9	64.5	57.8
LP	51.2	50.0	55.5	56.7	40.6	36.6
MP	73.2	68.3	81.9	83.5	57.7	49.6
NC	49.9	45.1	51.2	44.2	38.2	32.2
NW	53.9	55.5	68.9	67.8	45.9	40.9
WC	42.7	36.2	41.1	34.1	27.4	23.1
SA	66.3	62.5	72.0	69.5	49.9	44.8

Source: ASSA model 2008

Unlike the number of studies at national and provincial levels, the researches on measuring child mortality at lower geographical levels are very limited. One comparable attempt with this research is by Bangha and Simelane (2008), who have used the 2001 census data to map the spatial distribution of under-five mortality at magisterial district (MD) level. They have found a significant extent of differentials in CM among MDs. For instance, based on their computation, U5M rate per 1000 births among MDs ranges from 5.6 to as high as 108.5. However, it seems that they have somehow underestimated the CM level in general. For example, it is very unlikely that provincial U5M rate in 2001 ranges from as small as 19 deaths per 1000 births in WC to only 66 deaths per 1000 births in EC as they have reported. In another study, marked geographical differentials of infant mortality is observed among provinces, districts and sub-districts (Sartorius, Sartorius, Chirwa *et al.* 2011). Especially, the Bayesian Poisson model containing only a constant and the conditional autoregressive parameters is fitted to estimate standardised mortality ratio (SMR) of infant deaths in the sub-districts of South Africa using the 2007 community survey data.

2.3 Child mortality, poverty and inequality

Poverty and social inequality are believed to have profound impact on the health of children. In this section, some literature reviews will be made concerning these two measures of social welfare in association with child mortality. Note that detailed investigation of poverty and inequality is not the focus of this research.

2.3.1 Definition and measurement of poverty

The definition of poverty may be expressed in terms of a 'poverty line' by reference to the amount of money (income) required to circumvent poverty or using a set of poverty indicators (in terms of consumption). These are respectively sometimes referred to as indirect and direct definitions of poverty (Ringen 1988). In the direct case, the set of poverty indicators identified are usually combined to create an index, called wealth or living standard index (Deaton 1997). There are, however, strengths and weaknesses with both approaches to defining poverty.

Despite the controversies on the definition, absolute and relative poverty lines are two typical poverty thresholds in measuring poverty (Ravallion 1998). Absolute poverty lines define income thresholds below which people are unable to purchase a bundle of goods and services thought to be an essential part of the basic necessities of

life in the society in which they live (Deaton 1997). Relative poverty lines, on the other hand, are ideally defined with reference to a measure of typical consumption levels or against household income. For example, in South Africa a per capita monthly income of R515 is usually used as absolute poverty line (Leibbrandt, Woolard, Finn *et al.* 2010; Finn, Leibbrandt and Levinsohn 2012) while the relative poverty line is often set at the level that includes people living below 40% of national income, with those living below 20% as being very poor (SPII 2007). The final Copenhagen Declaration of the World Summit for Social Development in 1995 banned the concept of relative poverty and suggested a new and comprehensive definition of absolute poverty (UN 1995:41) as

“----- a condition characterized by severe deprivation of basic human needs, including food, safe drinking water, sanitation facilities, health, shelter, education and information. It depends not only on income but also on access to social services.”

Once the poverty line is set, it is possible to work out different measures of poverty of a country or a region including poverty headcount ratio and poverty gap. ‘Poverty headcount ratio’ (PHCR) is the proportion of population that lives below the poverty line, while ‘poverty gap’ is the average shortfall from the poverty line expressed as a proportion of the poverty line; that is the average amount of money required by the population to be non-poor.

2.3.2 Health consequences of poverty

The health of children is largely influenced by social and economic conditions under which they live. Many studies have documented that poverty affects infant and child health and mortality in developed and developing countries (Barker 1992; Aber, Bennett, Conley *et al.* 1997; Spencer 2004; 2008; Olson, Diekema, Elliott *et al.* 2010). The rapidly growing children seem to be particularly more vulnerable to the adverse effects of poverty than adults (Penn 2005). The researches show that children from poor families are more likely to be exposed to the risks of health problems and mortality. Malnutrition, inadequate water and sanitation, environmental pollution, poor housing and insufficient health care are most of the problems which increase the likelihood of death of children in poor families. Poverty also plays a major role in pregnancy outcomes, such as preterm birth and low birth weight, stunting and underweight in early

childhood – all of which greatly affect the survival status of the children (Spencer 2008; Santos, Matijasevich, Domingues *et al.* 2009).

Substantial socio-economic disparities lie behind the challenges faced by children in South Africa where there is huge gap between rich and poor and child poverty is far higher than that of the general population (UNICEF 2013). The National Planning Commission estimated that 39% of people in South Africa live below the R432 per person per month poverty line (National Planning Commission 2011) while approximately 66% of children in the country live in poverty, with a monthly household income of less than R1200 per month (Whiting 2013). Moreover, according to the report by UNICEF, the percentages of children living in poverty using R575 per month as poverty line were 73, 64 and 60 respectively in 2003, 2008 and 2010 (UNICEF 2013). This report also revealed provincial poverty levels as: LP (80.1%), EC (77.5%), KZN (73.1%), MP (71.5%), FS (69.4%), NW (68%), NC (67.3%), WC (38.7%), and GT (38%), showing how big is the poverty differentials among provinces. In a recent report by Human Science Research Council (HSRC 2014b), it is also indicated that currently the poorest provinces are LP, EC and KZN, and hence they attract particular emphasis.

The overall trend of income distribution and poverty for the period 1993-2004, as studied by Leibbrandt, Woolard, Finn *et al.* (2010), indicates that using R3000 per capita income per year as poverty line, the proportion of poor people in the country had decreased from 40.6 per cent in 1993 to 33.2 per cent in 2004. In a latest report released by Statistics South Africa (StatsSA 2014b) the percentage of the population that is poor has decreased from 57.2 per cent in 2006 to first 56.8 per cent in 2009, and then to 45.5 per cent in 2011, using inflation-adjusted poverty lines of R431, R577 and R620 (monthly per capita income) respectively for 2006, 2009 and 2011. This report shows that the level of poverty in the country is still very high, although it is declining to some extent. Even though South Africa has the largest economy on the continent, 45.5 per cent of its people live on less than 2 dollars each day. The impact of this on children's health is undeniable, based on the evidences discussed in the first paragraph of this section.

Poverty may also impact child mortality through HIV/AIDS which is the most frequently quoted reason for the death of children in the country. This is because an increase in poverty exacerbates the spread of HIV, hence triggering more deaths of

children. On the other hand, besides its being the primary cause of death, an increase in HIV/AIDS also causes the deaths of more children by aggravates poverty. One may see Ganyaza-Twalo and Seager (2005) for a detailed literature review of the two-way link between poverty and HIV/AIDS.

2.3.3 Income inequality and child mortality

In addition to the level of poverty, mortality is also associated with the distribution of income in both developed and developing countries (Flegg 1982; Waldmann 1992; Judge 1995; Wilkinson 1995; Wagstaff 2000; Rodgers 2002; Olson, Diekema, Elliott *et al.* 2010). A significant association of infant mortality and income distribution in 59 developing countries is found in the study by Flegg (1982). Similarly, based on the analysis of data from 70 countries Waldmann (1992) found that, the rise of infant mortality is associated with 5 per cent increase of income of the richest 5 per cent of the population, keeping the incomes of the poorest 20% constant.

South Africa is known to have a very high level of income inequality characterised by huge racial differentials and evidences show that inequality is still on increasing trend even in the post-apartheid period (Van der Berg and Louw 2004; Leibbrandt, Woolard, Finn *et al.* 2010; StatsSA 2014b). Based on the computation by Leibbrandt, Woolard, Finn *et al.* (2010) the Gini index¹ for the country has increased consistently from 0.66 in 1993, to 0.68 in 2000 and 0.70 in 2008. On the other hand, Statistics South Africa has estimated the Gini index for 2006, 2009 and 2011 to be 0.72, 0.70 and 0.69 respectively – indicating a small decline but still showing a very high degree of inequality. This persistent increase is also for all population groups. The impact of this rising inequality in mortality in general, however, has not been studied so far. As part of this study, an attempt will be made to assess the relationship between child mortality and income inequality as measured by Gini index at national, provincial and municipal levels.

¹ Gini index/coefficient is a widely used measure of income inequality that condenses the entire income distribution into a single number between 0 to 1; the higher the number the greater the inequality. See Section 3.6.3 for more description.

2.4 The Mosley and Chen analytical framework and factors associated with infant and child mortality

Mortality of children has been explained by different theories such as the social and economic explanation, the public health explanation, and the Mosley and Chen analytical framework (Mosley and Chen 1984). The Mosley and Chen framework is the most accepted framework for the study of child morbidity and mortality in the developing world, where the levels of infant and under-five mortality are high. The basis for this framework is that social and economic factors have to operate through the set of proximate determinants in order for them to have an impact on child mortality (Mosley and Chen 1984). The framework combines the methodologies of social and medical science and provides a better understanding and a clearer distinction between the causes of diseases and the causes of deaths.

The approach to the study of child survival is based on the following 5 premises by Mosley and Chen (1984). First, in order for a society to progress, over 97 per cent of children born in the country or society must survive the first 5 years of life. This is most unlikely, particularly in the developing world, where health hazards and infectious diseases are still prevalent. The second premise is that improvement in child survival probabilities in any society is due to the operation of social, economic, biological, and environmental factors. In the third premise, Mosley and Chen (1984) further emphasise that the socioeconomic factors must operate through the set of proximate determinants to directly influence the risk of diseases and the outcome of diseases. The fourth premise is that the specific diseases and nutrient deficiencies observed in the surviving population should be regarded as indicators of the operations of the proximate determinants. The fifth and final premise is that several disease processes may eventually lead to child mortality.

Mosley and Chen then identified a set of proximate determinants that directly have an impact on the morbidity and mortality of children. The factors are then grouped into 5 categories: Maternal factors (age, parity and birth interval), environmental contamination (air, food/water/fingers, skin/soil/inanimate objects, insect vectors), nutrient deficiency (calories, protein, micronutrient, vitamins and minerals), injury (accidental, intentional); the last category is personal illness control (personal preventive measures, medical treatment). It is within this framework that many studies on child mortality and its correlates have been carried out. This study also follows this

framework but based on the following classifications. Note that in the specific case of South Africa, one need to consider also the impact of HIV.

2.4.1 New-born demographic factors

Infant and child mortality differential by sex of the child is a well-recognised fact (Hill and Upchurch 1995; Mustafa and Odimegwu 2008; Kembo and Ginneken 2009; Boco 2010). The probability of male children dying is higher than that of female children. This is particularly common in societies in which there is less gender discrimination, like South Africa (Kaufman 1997), unlike the situation in India and some other Asian countries where females are disadvantaged (Singh, Hazra and Ram 2007). Using 35 countries' DHS data, Hill and Upchurch (1995) indicated that higher mortality rates for male children as compared to their female counterparts is a common phenomenon in most populations. Their results show that in most of the countries studied, girls have a significant survival advantage over boys for both infants and under-five children. However, the differential in mortality between boys and girls is more apparent during the first month of life than afterwards (Hobcraft, McDonald and Rutstein 1985). A small difference of infant and child mortality between boys and girls is observed in South Africa and Zimbabwe from studies by Kaufman (1997) and Kembo and Ginneken (2009) respectively. After controlling various maternal, socioeconomic and environmental determinants, the risk of infant and mortality of boys is slightly higher than that of girls.

The age of the child is also another factor associated with the mortality of children. It has been studied by many scholars on the subject. The obvious direction of the relationship is negative in that the longer the child survives, the less his/her risk of dying.

2.4.2 Maternal factors

Among the proximate determinants of child mortality related to the characteristics of the mother, researchers have focused on demographic factors such as age of mother at child's birth, parity, and preceding birth interval, and socio-economic factors including level of education, and employment status (Hobcraft, McDonald and Rutstein 1985; Kabir, Islam, Ahmed *et al.* 2001; Omariba, Beaujot and Rajulton 2007; Kembo and Ginneken 2009; Boco 2010).

For instance, the study by Kabir, Islam, Ahmed *et al.* (2001), using the 1993/4 Bangladesh DHS data, with a primary objective of determining important factors affecting infant and child mortality discovered that the risk of child survival at infancy and post infancy is much higher among women who are older than 16 years relative to younger women, and that the effect is more pronounced on infant mortality than child mortality. Similar results are found by Kembo and Ginneken (2009) in Zimbabwe in their study of factors associated with infants and child mortality in the country. After controlling for some socioeconomic, environmental and maternal determinants, a 13.2 and 41.6 per cent higher child and infant mortality risks are found for children born from women aged 30-39 years in comparison with children of women aged less than 20 years. The risk of infant mortality, however, is 8.1 per cent lower for children of women aged 30-39 years relative to children of women aged 40-49 years while the risk of child mortality is higher by 73.8 per cent. Another study by Hobcraft, McDonald and Rutstein (1985), where 39 world fertility surveys were used found that mortality is higher among children of younger women (teenage mothers), particularly mortality before age two. The study found no evidence of higher risk of mortality among children of older women as has been found in other studies. In contrast, in a study on the determinants of infant and child mortality in Kenya, using the 1998 DHS, Omariba, Beaujot and Rajulton (2007) indicate that the risk of dying at infancy is higher for children born to older women (35+ years). These children have an about 33 per cent higher risk of dying relative to infants born to women aged 20-24 years. The relative risk of child mortality is 35 per cent higher among children born to teenage mothers compared with children of mothers aged 20-24 years. All findings point to a higher risk of dying for infants and older children of teenage mothers when compared with children born to older mothers. According to Kabir, Islam, Ahmed *et al.* (2001), teenage mothers are faced with high risk of their children dying probably due to biological complications as they are more likely to give birth to underweight children. As Mosley and Chen (1984) have indicated, mothers have to have proper skills, and be able to take proper care of themselves and their children, which is not likely to be the case with younger women.

Short birth interval is also considered as a determinant of child mortality because it obviously makes mothers stop breastfeeding at earlier time which has a significant contribution to a higher risk of mortality (Hobcraft, McDonald and Rutstein 1985). In addition, the short interval may have an effect on the next child since women who give birth within short preceding birth intervals may not have sufficient time to

restore their nutritional reserves (Mondal, Hossain and Ali 2009). This implies that when there is maternal depletion caused by pregnancies and lactation, the survival chances of children are reduced and that a child born after a short interval is likely to be born with low birth weight, which is one of the factors associated with poor survival of a child, especially at early ages. According to Hobcraft, McDonald and Rutstein (1985), births that occur within 24 months of the index births are associated with higher risk of dying than births that happen beyond two years

Rustein (2005, 2008) has studied the impact of preceding birth interval on neonatal, infant and under-five mortality using 17 developing countries' DHS data and found a negative relationship between the risk of dying at neonatal, infant and child ages and the length of the preceding birth interval. In the countries studied neonatal and infant mortality respectively are about 55 and 58 per cent higher when the birth interval is between 18 and 23 months relative to when the interval is 36-47 months.

The combined effect of birth order and birth interval was also studied by some researchers including Mustafa and Odimegwu (2008) and Kembo and Ginneken (2009). The identified correlation is that higher birth order children with short preceding birth intervals tend to have a lower chance of survival than children of lower birth order. However, infants are more affected by higher birth order with short preceding birth interval than children older than one year.

2.4.3 Socioeconomic factors

The relationship between child mortality and socioeconomic factors has been studied by many researchers (Cleland 1990; Hobcraft 1993; Sastry 1996; Wagstaff 2000; Bawah and Zuberi 2005; Mustafa and Odimegwu 2008). The socioeconomic factors considered in this research as adopted from the Mosley and Chen (1984) framework are mother's level of education, place of residence, employment status of the mother, income poverty of the mother.

Mother's education is considered to be the most socioeconomic variable affecting child survival. It may affect child survival by influencing her choices and improving her skill on contraception and other health care practices. The relationship has gained the attention of many researchers. An increased chance of survival can even be associated with a small increase on amount of education of mothers ((Hobcraft 1993). Cleland (1990) indicates that the improvement of child survival due to mother's

education is because of the modest effect of education on health knowledge and beliefs. As births to teenage mothers are associated with a high risk of mortality at the early ages of the child, mother's education has an advantage by delaying the age at first birth. It may also be related to factors that form and change the economic choices and health-related practices of individuals. Some studies, however, have shown that the degree of association in Sub-Saharan Africa is weaker than in other regions. Hobcraft (1993) suggests that the reason for this is the weak health infrastructure in the sub-continent.

Studies have found that the risk of death of children is lower in the urban areas compared with the rural areas (Kabir, Islam, Ahmed *et al.* 2001; Kembo and Ginneken 2009). This is the general expectation considering that the level of development is more advanced for urban than for rural areas. However, there are some studies that have found contradictory results, where children in rural areas have the lower risk of dying than their urban counterparts (Manda 1998). However, such findings are quite unusual considering that urban areas are associated with better socioeconomic and environmental factors that contribute to the reduction of child mortality.

The employment status of the mother can affect child survival in both directions. It may prevent her from giving care for the child including breastfeeding and hence, the child's survival be negatively affected (Hobcraft, McDonald and Rutstein 1985). For instance, in India greater child loss is experienced among working mothers than non-working mothers (Kishor and Parasuraman 1998). On the other hand, a working mother helps her family by increasing the household income, which may increase the likelihood of survival of the child.

As discussed above poverty has a detrimental impact the survival of children. It plays a major role starting from pregnancy-related complications to later childhood health problems. The greater risk among poor children relates to their greater exposure to the multiple risk factors. In this research, the income poverty indicator variable based on the average per capita income of the mother is considered as one factor of child survival.

2.4.4 Environmental factors

The environment in which the child lives has long been considered to have an impact on its survival status. Commonly, factors related to the environment are: dwelling type, source of drinking water, type of toilet facilities, access to electricity, material floor made

of, etc. Environmental contamination is one of the proximate determinants of child mortality outlined by Mosley and Chen (1984). Various studies have included household environmental variables as determinants of infant and child mortality, and have found strong association (Kabir, Islam, Ahmed *et al.* 2001; Bartlett 2005; Kembo and Ginneken 2009; Kazembe, Clarke and Kandala 2012). However, such researches found out that environmental factors may not have an independent effect on childhood mortality but are influenced by some socioeconomic factors. Environmental factors in this research are not studied individually. Rather, an index containing the combined information is constructed using the multivariate statistical technique. This latent variable is supposed to capture the most relevant information concerning the environment within which the child lives, and hence it is named as living standard (LS) index. It is further categorised into 5 quintiles for ease of assessing child mortality differentials among the quintiles comparing different areas like provinces and municipalities.

2.4.5 Other factors

HIV is one of the major factors for the reversal of child mortality decline in Sub-Saharan Africa and its impact has been studied by various researchers (Ng'weshemi, Urassa, Usingo *et al.* 2003; Zaba, Marston and Floyd 2003; Dorrington, Johnson, Bradshaw *et al.* 2006). In addition to the direct effect, HIV can also affect child mortality indirectly through maternal HIV infection. If the mother dies of HIV, even if the child is not infected, the fact that the child will be an orphan increases the risk of dying by severely affecting child's health (Ng'weshemi, Urassa, Usingo *et al.* 2003). However, as indicated by Zaba, Marston and Floyd (2003), there is a lack of evidences on by how much it is affecting mortality of children, i.e. disentangling the share of HIV from other background causes of death.

Another two important factors which might have a significant effect of the survival of children, as we discussed in section (2.3), are income poverty and inequality. The impact of these factors will also be investigated in this research.

2.5 Methods of estimating child mortality

2.5.1 Data sources for estimating child mortality

The three common sources of data for child mortality estimation are vital statistics, sample surveys and censuses. Among these, the incompleteness of a vital registration

system in developing countries makes such sources of data unsuitable. In most cases, large-scale nationally representative surveys like the Demographic and Health Surveys (DHSs), which include detailed birth histories of women, are the main options in countries where the vital registration system is very weak. For instance, a number of studies have used the 1998 and 2003 South African DHSs in order to estimate child mortality in the country. The main limitation of such surveys, however, is that they are not representative at lower geographical areas such as districts and municipalities. Therefore, census is the preeminent alternative to compute mortality rates at lower geographical areas in the absence of complete vital registration system. There are two reasons for this: first census covers every administrative area (it includes all municipalities at least) and second, it has a far greater sample size than sample surveys for better statistical analysis (the 10 per cent census data has much more observations than the whole data from DHS or any other big survey).

2.5.2 Direct and indirect methods of estimating child mortality

By using census data, child mortality can be estimated following different approaches depending on the type of questions asked in the census. The most commonly used method in developing countries is the Brass ‘children ever born/children surviving’ technique which requires information on total number of children born and total number of surviving children by age of mothers in a 5-year age group (Moultrie, Dorrington, Hill *et al.* 2013). The procedure of determining the mortality rates in this approach involves determining the proportion of children who have died in each age group and multiplying the proportion by appropriate correction factors derived, based on the fertility patterns of the population.

The other approach is direct computation of mortality rates from household deaths occurred some period of time, usually 12 months, before the census night as reported by households. This method of estimating child mortality rates requires data on the date of birth of every child, their survival status and the date of death or age at death for those children who have died (Moultrie, Dorrington, Hill *et al.* 2013). The synthetic cohort life table approach, which is used in this research, determines the probability of dying between birth and certain age from the mortality experiences of a real cohort. The infant and under-five mortality rates are estimated by generating a complete life table up to age 5.

Given the number of deaths of children aged x in that year, D_x , and the corresponding mid-year population, P_x , it is possible to compute the central death rate ${}_1M_x = D_x/P_x$ and convert these rates to probability of dying between ages x and $x+1$ denoted by ${}_1q_x$ for $x = 0, 1, 2, 3, 4$ using different approaches. Infant and under-five mortality rates can then be computed easily from the life table constructed. However, the infant mortality rate or the probability of dying between birth and age one (${}_1q_0$) is commonly approximated by the ratio of total number of deaths under age one to the total number of births occurred in the same periods. This is because census counts are particularly inaccurate at the younger ages (Siegel and Swanson 2004).

In the case of South Africa, all the three most recent censuses conducted in 1996, 2001 and 2011 have incorporated summary birth history questions from which child mortality rates would be estimated indirectly using the Brass method. In addition, the 2001 and 2011 censuses have included questions about deaths happened in households 12 months prior to respective census dates for direct estimation of child mortality. However, the number of children born to women of reproductive age in the 2001 census is found to be under-reported significantly resulted in inflated estimates of under-five mortality rates (Dorrington, Molutrie, Timues, 2004). Furthermore, the number of surviving children to a woman reported in the 2011 census was not released with the 10 per cent unit level record as it was deemed to be problematic (StatsSA 2014a). Therefore, this study uses the household death data of the 2011 census for direct estimation of child mortality rates at different geographical levels. This has the added advantage of obtaining more recent estimates of child mortality than estimates we would have obtained from Brass indirect estimation method using summary of birth histories data.

2.5.3 Spatial smoothing techniques

One of the main concerns in estimating mortality at smaller geographical areas is that the number of events/deaths would be too small so that the estimates might be unstable or unreliable (Waller and Gotway 2004; Lunn, Jackson, Best *et al.* 2013). Especially in less populated areas a few child deaths can result in a big change on the mortality estimates as these rates have higher variances. One way of improving the quality of estimates in such cases is employing spatial smoothing techniques. In this regard, a variety of spatial smoothing methods have been suggested which make use of data

values of neighbouring areas. A simple approach of smoothing a given rate in an area is to determine a local mean or median from each observation in that area and its neighbours (Waller and Gotway 2004). The method of adopting this approach is called locally weighted averages spatial smoothing (LWASS). A spatial weights object is used to specify the neighbourhood relationships among observations. Neighbourhood relationships may be defined based on distance, areas that fall within a certain distance from the centre of the area; or adjacency, areas which are physically connected with the area of interest. Another method of spatial smoothing is through nonparametric regression (NPR). It helps to estimate rates by fitting a nonparametric regression model instead of simply computing an average. The most commonly used method of such type is called locally weighted polynomial regression (LWPR), which uses the values of the independent variables from neighbourhood areas (Cleveland and Devlin 1988).

The last method of spatial smoothing is Bayesian spatial smoothing (BSS), which relies on the concept of Bayesian statistics, an emerging discipline in modern statistics. The basic principle of Bayesian statistics is that rather than relying entirely on the observed data, stronger and more stable measures can be obtained by combining the data with some additional information known in advance, called priori information. In other words, given both the data (expressed as likelihood function) and some prior information for the parameters of interest, the method attempts to generate a conditional distribution, known as posterior distribution, which can be used to make the inferences.

To specifically illustrate the link among the concepts of prior, likelihood and posterior functions as described by Waller and Gotway (2004), let the vector of data be $Y = (y_1, y_2, \dots, y_n)$ and a corresponding model parameters $\pi = (\pi_1, \pi_2, \dots, \pi_k)$. If we allow $f(\cdot)$ to denote a general probability density function, we have

$$\begin{aligned}
 \text{prior} &= f(\pi) \\
 \text{likelihood} &= f(Y | \pi) \\
 \text{posterior} &= f(\pi | Y) = \frac{f(Y | \pi)f(\pi)}{C}
 \end{aligned} \tag{2.1}$$

where

$C = \int f(\mathbf{Y} | \boldsymbol{\pi}) f(\boldsymbol{\pi}) d_{\boldsymbol{\pi}}$ denotes a normalising constant to ensure that the posterior density integrates to 1. One may refer to the texts by Carlin and Louis (2000), Gelman, Carlin, Stern *et al.* (2004) or Gill (2002) to have a thorough understanding of Bayesian inference and its applications. The theoretical detail of Bayesian statistics is beyond the scope of this research and it suffices to note that incorporating the prior information provides a much more complete picture of uncertainty in the estimation of unknown parameters than relying only on the likelihood function.

In applying Bayesian techniques to spatial smoothing, priors are derived from data in other areas based on the assumption of spatial autocorrelations. The resulting posterior distribution obtained is characterised by a compromise between the estimates in each area and the estimates in neighbouring areas.

Assume that the number of children died y_i represent a random variable, each following a binomial distribution with parameters $\boldsymbol{\pi}_i$, risk of dying (probability) and n_i , total number of children in the area. Given this, we have

$$y_i | \boldsymbol{\pi}_i \stackrel{ind}{\sim} \text{Binomial}(n_i, \boldsymbol{\pi}_i) \quad (2.2)$$

Under this model, we are assuming that y_i are conditionally independent given $\boldsymbol{\pi}_i$. This does not mean that the Y_i are mutually independent; rather, it implies that any spatial correlation observed in the Y_i is a function of a spatial trend in either the population sizes n_i or the risks, $\boldsymbol{\pi}_i$. Since the Y_i are conditionally independent given the $\boldsymbol{\pi}_i$ parameters, the likelihood takes a particularly simple form as the product of the conditional distribution given in equation (2.4) across all areas $i = 1, 2, \dots, k$

A Bayesian analysis treats the $\boldsymbol{\pi}_i$ as random variables and a prior distribution must be defined for each $\boldsymbol{\pi}_i$. The prior mean and variance of $\boldsymbol{\pi}_i$ respectively can be denoted by $E_{\boldsymbol{\pi}}(\boldsymbol{\pi}_i) = m_{\boldsymbol{\pi}_i}$ and $\text{Var}_{\boldsymbol{\pi}}(\boldsymbol{\pi}_i) = \boldsymbol{\nu}_{\boldsymbol{\pi}_i}$ (Marshall 1991), while from equation (2.2) the conditional mean and variance of each observed rate of mortality of each area, r_i are

$$\begin{aligned}
E(r_i | \pi_i) &= E[(y_i / n_i) | \pi_i] = \pi_i \\
\text{Var}(r_i | \pi_i) &= \text{Var}[(y_i / n_i) | \pi_i] = \pi_i / n_i
\end{aligned}
\tag{2.3}$$

The unconditional mean and variance of the rate observed in area i , r_i can be determined as follows where E_r and E_π / Var_r and $\text{Var}_\pi /$ denote expectation /variance/ with respect to the marginal distribution of r and π respectively.

$$\begin{aligned}
E_r(r_i) &= E_\pi E(r_i | \pi_i) = E_\pi(\pi_i) = m_{\pi_i} \\
\text{Var}_r(r_i) &= \text{Var}_\pi(\pi_i) + E_\pi(\pi_i / n_i) = v_{\pi_i} + m_{\pi_i} / n_i
\end{aligned}
\tag{2.4}$$

The best linear Bayes estimator of π_i can then be derived by minimising the expected total squared-error loss (see Marshal 1991)

$$\hat{\pi}_i = m_{\pi_i} + C_i(r_i - m_{\pi_i}) = C_i r_i + (1 - C_i)m_{\pi_i}
\tag{2.5}$$

where

$C_i = v_{\pi_i} / (v_{\pi_i} + m_{\pi_i} / n_i)$, called the shrinkage factor, is the ratio of the prior variance to the data variance. It measures by how much the crude rate $r_i = y_i / n_i$ “shrinks” towards the prior mean. One can easily note that the estimator given above is a weighted average of the crude estimate and the prior mean. However, in order to compute the estimates, the values of m_{π_i} and v_{π_i} must be determined. In this regard, there are two approaches: empirical and full Bayesian spatial smoothing approaches (EBSS and FBSS). In EBSS these unknown parameters are estimated from the data itself; for example, by assigning the same prior mean and variance for all areas (Marshall 1991). In FBSS, however, the parameters of the prior distribution are considered to be random variables by themselves with their own distributions, resulting in a hierarchical model where the first level of the model is defined by the observed data itself and the second level of the model, the prior distribution, defines spatial dependency between nearby areas through its hyper-parameters (Bernardinelli and Montomoli 1992). In the third level of the model, hyper-prior distributions for the hyper-parameters are defined. The hyper-prior distributions provide information on prior belief about how similar neighbouring areas should be. As Bernardinelli and Montomoli (1992) indicated, the

inclusion of this additional uncertainty about the prior distribution allows for the calculation of credibility intervals which can be used to assess confidence in the estimates.

Despite the advantages of using Bayesian inference, the process of constructing posterior distribution has been a big challenge due to the complex nature of the function to integrate. However, with the advent of a sampling method known as the Markov Chain Monte Carlo (MCMC) which was developed in 1990s together with the great development of computing technology, it is possible to simulate a posterior distribution (Gill 2002; Ntzoufras 2009). The Markov chain is a series of random states wherein each future state is only dependent on the current state and is independent of any past states, known as the Markov property. The Monte Carlo specification, on the other hand, helps to create a set of simulated values that share the same distributional property as the posterior distribution and describe it by using empirical summaries of these simulated values.

In using MCMC to simulate a posterior distribution, a Markov chain consists of a set of states in which each state contains a value for the parameter of interest. The chain begins in a starting state (defined by an initial probability distribution) and then moves successively to additional states. After a number of steps, the Markov chain should eventually stabilise so that the value of the parameter in each successive state is determined only by the current state and a probability distribution defined by the combined effect of the data and prior distribution. Once the posterior distribution has been effectively simulated, it is then possible to sample values from the Markov chain which accurately represent the values from the posterior distribution (Besag, York and Mollie 1991).

There are several MCMC methods that can be used to simulate samples of the posterior distribution of which, Gibbs sampling is the most common that has been used for over two decades. Gibbs sampling consists of assigning starting values for all parameters. In the first iteration, the first parameter is assigned an “updated” value obtained by randomly sampling the conditional probability distribution given the values of all other parameters and the observed data/prior distribution (Besag, York and Mollie 1991; Gill 2002; Ntzoufras 2009). Next, the second parameter is also assigned a new value sampled from the probability distribution given the new value of the first

parameter, the starting values of the other parameters, and the data. This process continues until all parameters have been assigned new values resulting in the completion of one Markov chain. Then, in the next iteration, the first parameter is given a new value dependent, again, on the probability distribution, the data, and the new values assigned to all the other parameters in the first iteration. This process continues until eventually the chain converges so that the values of all parameters are determined by the combined effect of the observed data and the probability distribution, the prior distribution.

The use of EBSS or FBSS is very common, especially among public health researchers usually to smooth disease or mortality rates. There are, however, relatively fewer works by demographers partly because demographers are generally more interested on national level estimates of demographic rates than at lower geographic areas. To name some of the works, Potter, Schmertmann, Assunção *et al.* (2010) have successfully mapped fertility rates in Brazil at municipal level using the Bayesian approach. In the same country, McKinnon (2010) in her study of child mortality, has applied FBSS technique to smooth municipal level estimates of under-five mortality originally computed by applying Brass's 'children ever born/children surviving' method. She has also attempted to improve the estimates by incorporating the average years of education of women living in the municipalities as a predictor of child mortality in addition to the estimates generated by considering only spatial autocorrelation.

3. DATA AND METHODS

3.1 Data source and data quality assessment

The study uses data from the 10 per cent unit record of the 2011 *de facto* population and housing census of South Africa which was the third census to be conducted in the country after the instauration of democracy. The main objective of the census was to provide statistics on population, demographic, social, economic and housing characteristics (StatsSA 2014a). Based on the location of persons on the census night (9/10 October 2011), three types of questionnaires were used for three specific target groups: the population in a household set-up, the population in collective living quarters such as old age homes, prisons, hospitals, and the population in transit (departing/leaving the country). The population in a household set-up forms the basis for planning and service delivery. The household questionnaire was therefore designed to collect comprehensive information from this group. The 10 per cent sample data consists of data on Demographics, Migration, General health functioning, Parental survival and income, Education, Employment, Fertility, Household characteristics and Mortality variables.

3.1.1 Reported household death data

The mortality data at household level is obtained using responses to section *I* of the household questionnaire of the census. Respondents were asked if there had been a death(s) in the household in the past 12 months between 10 October 2010 and 9 October 2011. If they respond ‘yes’ then they were to provide information on the month and year of death, the sex and age of the deceased at the time of death and the cause of death. Based on an assessment report on household deaths released by Stats SA together with the 10 per cent sample data, there were a significant under-reporting of deaths due to one or more of the following reasons: respondent fatigue, sensitivity of the mortality questions, poor training strategy and lack of supervision during data collection (StatsSA 2014a). Hence, the variables of interest: age at death, month of death, year of death and the sex of the dead child, had in some instances missing and implausible non-missing responses. These were edited by Statistics South Africa and it is not possible to look at the significance of the impact of the editing procedures on the quality of the data as the final data released do not show the records which were imputed or deleted.

Considering the 10 per cent sample census data released by Stats SA, there are 5 119 (un-weighted) reported deaths of children under the age of 5 years, which represent 58 208 household deaths in the South African population after applying the given household weights to scale up the sample to the population as a whole. It is reported that 2.6 per cent of the deaths have ages labelled as inconsistent and hence they are imputed for the purpose of this research. The procedure followed for imputation is to apportion the total inconsistent ages according to the age distribution and randomly assigning over the death records within each age. The overall distribution of the deaths by age at death (grouped as 0, 1-4, 5-9 95+) and sex is shown below on Figure 3.1. It seems that the data is of good quality with regard to reflecting the general pattern of mortality in South African population. The shares of the deaths of children under age 1 and age 5 are found to be 8.8 % and 11.9% respectively.

Figure 3.1 Age distribution of the number of household deaths



Source: Stats SA census 2011

3.1.2 Data on survival of last child born

Women aged 12 to 50 years who had at least one live birth, excluding stillbirths, were asked about the survival of their previous birth. If there were multiple births, only the information on the last birth was recorded. They gave responses to the following:

- i. the date of birth of the last child born by day, month and year of birth;
- ii. the sex of the last child born; and

- iii. the survival status of the last child born, whether child is still alive or dead. If the survival status is death, then the day, month and year of death are reported

If the woman failed to remember the day and the month, she was encouraged to specify the year in which the last child was born or the year of death.

It is common in surveys or censuses of this nature to have unreported birth dates, survival status and gender for last live birth. The overall quality of the reported data can be assessed based on the information provided in Table 3.1 which shows the summary of proportion of unreported, reported as ‘unknown’ or implausible values. The wrongly reported cases, such as women who have stated an implausible year in which the last child was born with the current age of the mother are labelled as ‘inconsistent’ values by Statistics South Africa. It can be seen from the table that the day, month and year of death variables are badly reported and hence will not be used for our analysis. On the other hand, the missing, unknown or inconsistent year, month and day of birth variables are imputed for the purpose of this research. The year of birth is imputed by first apportioning the number of invalid cases into valid years based on the respective proportions from the valid years reported, and randomly distributing over each of the cases using pseudo-random numbers. The imputations of month and day variables, however, are done by assigning valid months and days uniformly. Improper values for sex and child’s survival status are totally deleted from the analysis.

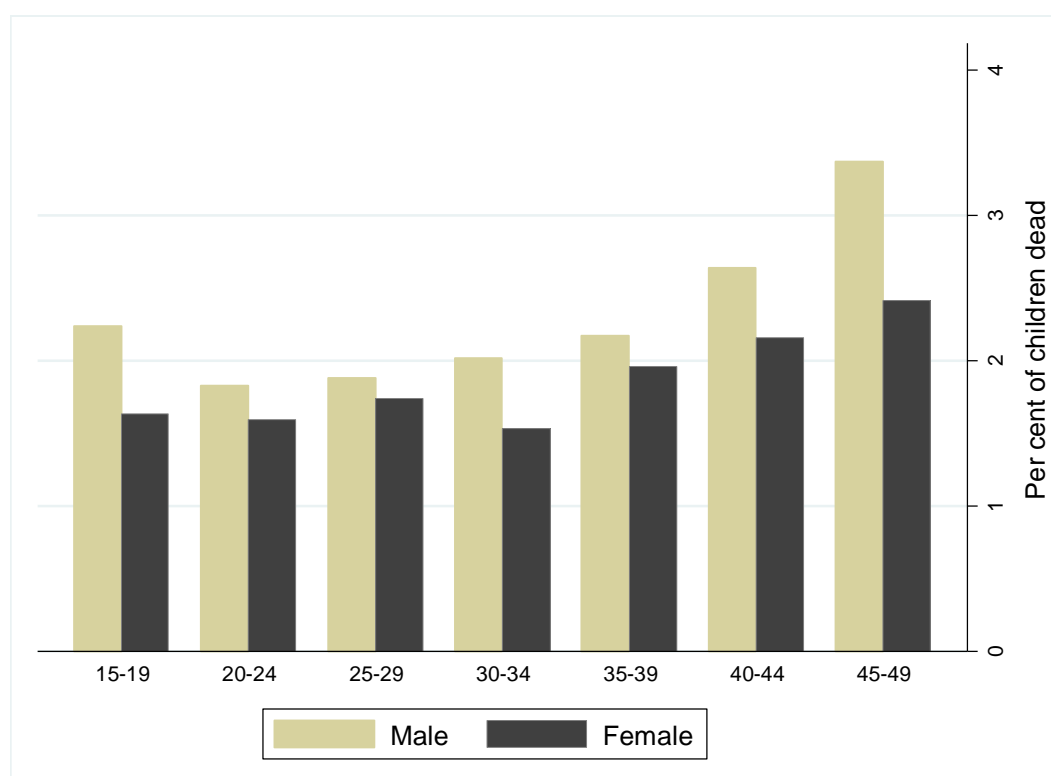
Table 3.1 Percentages of missing, unknown and inconsistent values of data on last birth of women

Variable	Missing	Unknown	Inconsistent	Total invalid
Day of Birth	3.4%	0.6%	0.2%	4.2%
Month of Birth	0.7%	0.2%	3.1%	4.0%
Year of Birth	0.0%	0.2%	3.4%	3.6%
Sex of Child	0.0%	0.1%	1.3%	1.4%
Survival Status	0.0%	0.9%	0.1%	1.0%
Day of Death	18.8%	1.7%	0.4%	20.9%
Month of Death	19.4%	0.7%	0.4%	20.5%
Year of Death	16.7%	1.0%	0.4%	18.1%

Source: Stats SA census 2011

The sex-ratio at birth is found to be 102.5 male births to 100 female births, which is a reasonable estimate for South Africa. Figure 3.2 shows the proportion ‘dead by age of mother’ and ‘sex of the children born 12 months before the census’. It can be seen that the proportion of dead for male births is always higher than that of female births for all the age groups of mothers. Nationally, the percentages of children died for male and female children born 12 months before the census are computed to be 2.6% and 1.8% respectively. While the higher male death figure is as expected as in many literatures, the magnitude of the difference for the last age group of mothers seems to be exaggerated to some extent.

Figure 3.2 Proportion of children dead by age of mothers and sex of the child

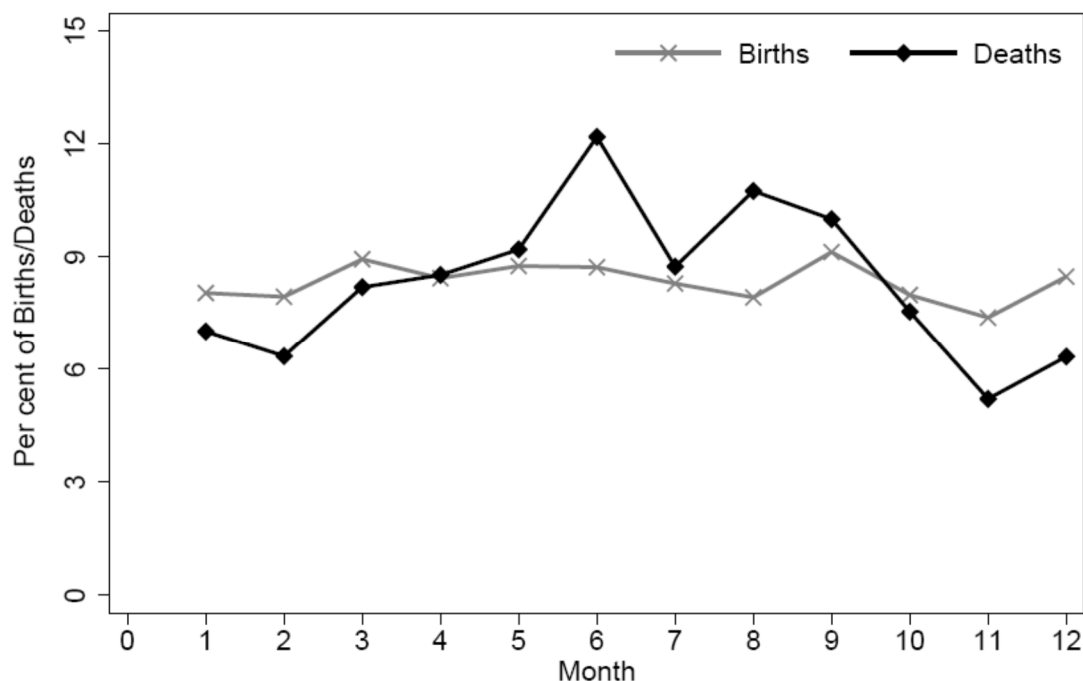


Source: Stats SA Census 2011

Births and deaths that occurred 12 months before the census date serve as the most important input data used in this research. Hence, as a way of assessing the quality of these data Figure 3.3 displays the distribution of births and deaths that occurred 12 months before the census date over the months of the year. It can easily be seen that the birth’s data are more or less uniformly distributed over the months while the death data are significantly far from uniformity –higher and lowest number of deaths are reported

in 6 and 11 months before the census respectively. This might be due to the problem of age heaping in reporting date of deaths or a census data editing problem by Stats SA.

Figure 3.3 Monthly percentage distribution of births and deaths that occurred 12 months before census



Source: Stats SA Census 2011

3.2 Methods of estimating child mortality

The two main demographic approaches of estimating child mortality (direct and indirect) could be applied to the 2011 South African census data. However, as the number of children surviving to mothers of reproductive age was not released with the 10 per cent sample data the Brass ‘children ever born/children surviving method’ of estimating child mortality will not be used in this research. Hence, direct synthetic cohort method is the only feasible approach from the given data. Reported deaths by households are used to compute infant and under-five mortality rates. This is achieved by calculating a complete life table for children aged 0 to 4. First, infant mortality rate, denoted by ${}_1q_0$, is approximated by the ratio of the number of deaths of children under age 1 and the number of births occurred 1 year before the census date. The number of births occurred 12 months before the census can easily be computed from the census question on day, month and year of the last birth administered to women of age 12-50 years at the census date. Then, the central mortality rate, ${}_1M_x$ for children between ages

x and $x+1$ for $x=1,2,3,4$ are determined by dividing the number of deaths of children aged x by their expected number of children or mid-year population². The mid-year population at age x are computed by first projecting back the number of survivors at the census date by exactly one year before the census using survival factors from ASSA 2008 demographic and AIDS model (ASSA 2010) to get the population size one year before the census date and then taking the average (geometric mean) of these projected numbers and the actual census counts. This implies that the number of children between age x and $x+1$ about six months before the census, ${}_1N_x$ is given by

$${}_1N_x = \left(P_x^t \times P_x^{t-1} \right)^{\frac{1}{2}} = \left(P_x^t \times \frac{P_{x+1}^t}{{}_1S_x} \right)^{1/2} \quad (3.1)$$

where

P and S respectively denote the census population counts and the ASSA model survival factors. The probability of dying between birth and before reaching their fifth birthdays, ${}_5q_0$ is then calculated as ${}_5q_0 = {}_1q_0 + (1-{}_1q_0) {}_4q_1$ where ${}_4q_1$, the probability of dying between age 1 but before reaching the fifth birthday is calculated from the central mortality rates using

$${}_4q_1 = 1 - \exp\left(-\int_1^4 \mu(x) d_x\right) \approx 1 - \exp\left(-\sum_{x=1}^4 {}_1M_x\right) \quad (3.2)$$

where

$\mu(x)$ is the actual force of mortality approximated by the central mortality rate, ${}_1M_x$. Note that in the calculation of ${}_1M_x$, it is assumed that those who die between ages x and $x+1$ do so halfway between the census date and one year before the census date.

In addition to the national estimate, infant and under-five mortality rates for each of the nine provinces of South Africa are computed following the same procedure except that instead of the national level survival factors, provincial survival factors are used from the ASSA model in order to get the respective estimates of the number of

² Mid-year refers to half-way between the census date and 12 months before the census.

children exposed to the risk of death between age x and $x+1$ for $x=1,2,3,4$ and in each province.

However, for municipal-level estimates a different approach is implemented as it is not feasible to follow the same procedure as the national or provincial level estimates. First, it is assumed that the ratio of under-five to infant mortality rate in each municipality is the same as the ratio at the respective province and hence the under-five mortality rates are computed by multiplying the infant-mortality rates by these factors (ratios). Second, the infant mortality rates are estimated by fitting a spatial Bayesian smoothing model using the number of infant deaths and births that occurred 12 months before the census in each municipality as inputs (as discussed in the next section). The original or crude mortality rates are used as initial values for the parameter of interest in the smoothing model during MCMC simulation. The smoothing is important because otherwise the estimates become unstable as there are fewer deaths in many municipalities and hence, a few more or less child deaths can greatly impact the estimates especially in less-populated municipalities. The method also helps to obtain mortality rates estimates for those municipalities which have zero observed deaths in the data.

The smoothed municipal-level infant and under-five mortality estimates are aggregated up to give a smoothed estimates of the respective rates at national and province levels. It is expected that the difference between the smoothed and unsmoothed estimates at national and province levels is very small. The real advantage of the smoothing is for the municipal-level estimates.

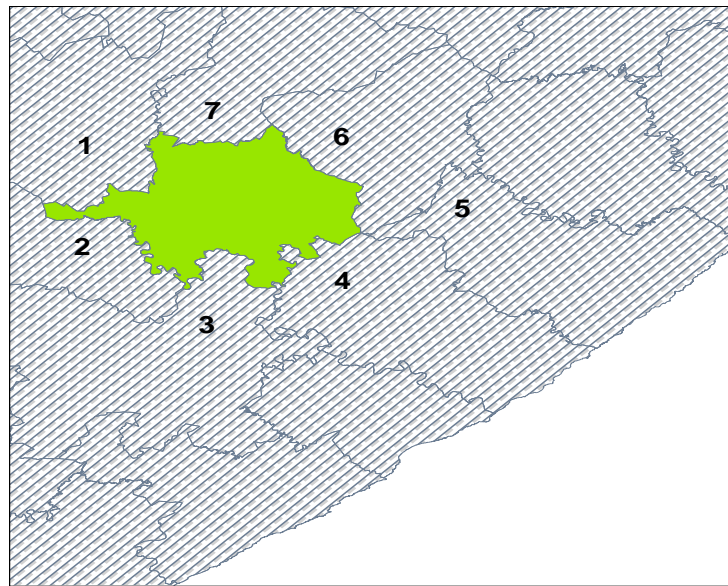
3.3 Bayesian Spatial Smoothing

3.3.1 Model specification

A full Bayesian spatial smoothing method is applied to the municipal-level infant mortality rates to improve the quality of the estimates. As discussed in Chapter 2, the parameters of the prior distribution in full Bayesian smoothing are considered to be random variables with their own distributions, resulting in a hierarchical model. The first level of the model is defined by the observed data itself while in the second level the prior distribution defines spatial dependence between nearby areas through its hyper-parameters.

In this study an adjacency matrix is used to identify neighbouring areas. Neighbours are defined as municipalities that are physically connected to one another. For example, the selected municipality shown on Figure 3.4 has seven neighbouring municipalities contributing information for its estimate of child mortality. There are a total of 234 municipalities and 1244 distinct adjacent pairs of municipalities (neighbours) in South Africa which give an average of 5.3 neighbours per municipality with the smallest number of neighbours being 1 and the largest number of neighbours being 11.

Figure 3.4 An example showing the neighbours for a municipality



To use prior distributions obtained from neighbouring areas, a hierarchical Bayesian model is employed in which the first level of the model consists of the level of child mortality in an area in which the number of child deaths reported in each municipality, Y_i , is modelled using a binomial distribution as given below.

$$Y_i \sim \text{Binomial}(p_i, n_i) \quad (3.3)$$

where

p_i is the probability that a child is dying before reaching the first birthday in municipality i and n_i is the total number of children in the municipality. The resulting fitted values of p_i will be used as a smoothed estimate of infant mortality in municipality i . This parameter of interest is modelled using a generalised linear model:

$$\log it(p_i) = \alpha + S_i \quad (3.4)$$

where α is an unstructured random effect representing the global mean of the log-relative risks for all areas and S_i is a spatially structured random effect representing the municipal-specific effects or the deviation from the global mean (Lunn, Jackson, Best *et al.* 2013).

In order to further improve the estimates; it is a good practice to include some important determinants of child mortality in the model specified above. In this regard, two variables are included: level of females' education and the level of HIV in the municipalities. Females' education is known to be a strong predictor of child mortality in many researches. On the other hand, HIV has significantly affected the mortality of children in South Africa. Therefore, the average years of schooling of women aged 15-49 in each municipality and the provincial HIV prevalence rate among adults in the 15-49 age group are included in the model specified above. HIV prevalence rates are taken from the 2012 South African national HIV prevalence, incidence and behaviour survey conducted by the Human Science Research Council (HSRC 2014a). The revised generalised linear model for the probability of death controlling for these variables becomes:

$$\log it(p_i) = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + S_i \quad (3.6)$$

where

X_{1i} and X_{2i} are respectively the education and HIV variables as defined above. The inclusion of these two variables in the model helps to effectively use the spatial neighbourhood, females' education and HIV prevalence rate to predict the probability of death for each municipality.

The second level of the hierarchical Bayesian model is the prior distributions for the random effects. An improper uniform prior distribution is assigned for the unstructured random effect, α (Lunn, Jackson, Best *et al.* 2013).

$$\alpha \sim dflat() \quad (3.7)$$

Since there is very little information available on how much education or HIV impact child mortality occurs in each municipality, very weak prior distributions for β_1 and β_2

are given by assigning a small value for the precision. In doing so, the data will be guaranteed to be the main determinant of the estimates.

$$\beta_{1i}, \beta_{2i} \sim N(0, 0.001) \quad (3.8)$$

The spatially structured random effect is assigned a conditional autoregressive (CAR) distribution with parameter τ

$$S_i \sim CAR(\tau) \quad (3.9)$$

The CAR model specifies how each S_i is related to the S_j at all other locations via a set of univariate conditional distributions. One of the most commonly used formulations (see Lunn, Jackson, Best *et al.*) which is applied in this research is

$$S_i | S_{\setminus i} \sim Normal\left(\sum_{j \neq i} \frac{w_{ij} S_j}{w_{i+}}, \frac{\tau^2}{w_{i+}}\right) \quad (3.10)$$

where

w_{ij} are weights used to express spatial dependence between municipality i and municipality j , with $w_{ij} = w_{ji}$, $w_{ii} = 0$ and $w_{i+} = \sum_j w_{ij}$. Usually w_{ij} is defined as $w_{ij} = 1$ if municipality i and j are neighbours and $w_{ij} = 0$ otherwise. Thus, the conditional mean of S_i is a weighted average of the other S_i 's. This model is available in WinBUGS (Bayesian Inference Using Gibbs Sampling), a software dedicated for Bayesian modelling, as

$$S[1:n] \sim car.normal(adj[,], weights[,], num[,], inv.tau.squared) \quad (3.11)$$

The CAR model also includes the hyper-parameter τ , the precision of the variance, which denotes how similar or variable neighbouring areas should be. Due to uncertainty in the degree of similarity in neighbouring areas, in the third level of the hierarchical model, τ is assigned its own distribution, a hyper-prior distribution, with a very weak gamma distribution.

$$\tau \sim \gamma(0.5, 0.0005) \quad (3.12)$$

To determine the standard deviation of S , τ is normally converted into the form $\zeta.S = \sqrt{1/\tau}$ where ζ is scalar.

3.3.2 Model fitting

The parameters of the specified Bayesian models are estimated by the use of WinBUGS software which performs Bayesian inference based on the MCMC sampling scheme. The two models are fitted and compared with DIC (deviance information criterion). The first one is with only spatial structure, and the second model incorporating females' education and HIV prevalence rates. For each model 100 000 iterations are run with the initial 10 000 discarded from the use for parameter estimation. After convergence, the model with the lowest DIC is selected. Convergence is evaluated by inspecting trace and autocorrelation plots of samples for each chain, as well as other numerical summaries as shown below.

3.3.3 Model diagnostics in Bayesian modelling

To ensure that the simulated posterior distribution is an accurate representation of the true posterior distribution, some diagnostic tests are necessary. Among these, the diagnostics performed here are: Gelman-Rubin statistic and examinations of autocorrelations and Monte Carlo errors. The Gelman-Rubin statistic is used for assessing convergence of MCMC simulation. For a given parameter, this statistic assesses the variability within parallel chains as compared to variability between parallel chains. The model is judged to have converged if the ratio of between variability to within variability is close to 1.

Examination of the autocorrelation function between successive iterations of chains for the parameters is the other important tool used in Bayesian model diagnostics. This is done for each of the parameters: the proportion of children who have died (π), the spatially structured random effects (S_i), the education effect (β_1), the HIV effect (β_2) and the standard deviation of S_i . The autocorrelation values for all these parameters should be close to 0 for the model to be good.

As assessment of model accuracy, the Monte Carlo error for each parameter of interest is investigated. As a rule of thumb, to have accurate posterior estimates the simulation should run until the MC error for each parameter of interest is less than about 5% of the sample standard deviation. This ensures whether convergence and

accuracy of posterior estimates are attained and the model is appropriate to estimate posterior statistics.

3.4 Comparison of Mortality Estimates

For ease of comparison, the smoothed under-five mortality estimates for the municipalities of South Africa are compared with the estimate of the municipality which has got the smallest estimate. This helps to assess the level of disparity among the municipalities in terms of child mortality – by how much the risk of death among children differ between the best and the worst municipalities, for example. Let M_i be the final estimates of under-five mortality in municipality i and let M^s be the same estimate for standard municipality (municipality with the smallest estimate), then the index for comparing the rates can be computed as

$$SM_i = \frac{M_i}{M^s} \quad (3.13)$$

3.5 Mapping mortality estimates

Again for visualisation and further ease of comparison, the estimated under-five mortality rates of the municipalities and provinces are mapped with a GIS software. The shape files corresponding to the 2011 census which are used for creating the maps were obtained from Municipal Demarcation Board of South Africa (MDBSA 2014). They are defined as the GCS WGS 1984 geographic coordinate system and adopted the Africa Albers Equal Conic Area System for projecting the final maps. These options are available in the ArcGIS software.

3.6 Methods for measuring poverty and inequality

As examination of the relationship between child mortality and socioeconomic differentials is one of the objectives in this research, two methods of measuring poverty: based on income and living standard and one measure of inequality are considered. The measures are determined at national, provincial and municipality levels. The first approach of measuring poverty is based on monthly per capita income and comparing it with the national poverty line of the country. As the measure based on this approach is not the best method to reflect the actual living standard of the population, another measure of poverty is computed by constructing an index from different variables which

are supposed to be related with the living standard of people in a better way. The data used for the computation of poverty and inequality are exclusive from the 10 per cent household data of the 2011 census.

3.6.1 Head count poverty index – Income poverty

The poverty headcount ratio (PHCR) or index is defined as the percentage of the population whose living standards, typically measured by income/consumption, lie below a given threshold referred to as ‘poverty line’ (Deaton 1997). In this research, the absolute monthly per capita income is computed by dividing the total monthly household income by the household size while the poverty line of R515 is considered as the threshold. The PHCR can then be calculated as

$$PHCR = \frac{N_z}{N} * 100 = \frac{100}{N} \sum_{i=1}^N I(X_i \leq Z) \quad (3.14)$$

where

$I(.)$ is an indicator function that is 1 if its argument is true and 0 otherwise, X is the per capita income of people living in the area (country, province or municipality), Z is the poverty line considered, and N is the total population in the area under consideration. The sum of the indicators gives the number of people in poverty (N_z).

3.6.2 Living Standard Index (LSI)

This is an alternative measure of wellbeing of people in a society that takes into account different factors instead of only looking at income. A living standard index (LSI) is constructed based on different indicators of wellbeing from the 2011 census household data, specifically on those variables which measure how good the environment is for the child to live in. Factor analysis (FA) is chosen to be the best statistical method for constructing the index as its purpose is to group set of variables based on their correlations and condense the information into fewer factor variables called latent variables (Hair, Black, Babin *et al.* 2010). It mainly involves extracting the factor(s) by partitioning the total variance in each of the variables into variances which are shared and unique variance. The detail theory and application of FA can be found in any standard multivariate text like Hair, Black, Babin *et al.* (2010).

Sixteen variables were identified for the purpose of constructing the index from the census data. The variables are selected in such a way that each of them somehow has some contribution to the wellbeing of the household. Instead of using the variables as they are collected from the census, attempts are made to dichotomise most of them as ‘worse off’ and ‘better off’ or ‘poor’ and ‘not poor’ (0 and 1) for ease of understanding and interpretation as well as to make the units consistent across all the variables so that FA can be done without any problem. However, type of construction material for the roof and the wall are categorised into three levels. As a measure of internal consistency of the scales, *Cronbach Alpha* – a known measure of reliability – is computed giving a scale reliability coefficient of 0.8597, which is good. The descriptions of the variables used for constructing the index including some summary statistics of the variables are shown in Table 3.2.

Table 3.2 Summary of variables used for LSI construction

Variable	Category (code)	Mean	SD	Factor loading	Coefficient
Dwelling Type	House (1), Other (0)	0.66	0.48	0.384	0.066
Room per person	Greater or equal to 1 (1), less than 1 (0)	0.69	0.46	0.257	0.030
Roof made of	Tiles(3), Concrete/Block(2) Other(1)	1.98	0.66	0.431	0.058
Wall made of	Brick(3), Concrete/Block(2) Other(1)	1.93	0.60	0.388	0.067
Energy used for lighting	Electricity (1), Other(0)	0.85	0.36	0.631	0.128
Energy used for cooking	Electricity/Gas(1), Other(0)	0.77	0.42	0.674	0.123
Piped water on premises	Available (1), Not available(0)	0.73	0.44	0.667	0.106
Flush Toilet	Available (1), Not available(0)	0.60	0.49	0.717	0.179
Television	Available (1), Not available(0)	0.76	0.43	0.595	0.096
Satellite Dish	Available (1), Not available(0)	0.26	0.44	0.554	0.092
Refrigerator	Available (1), Not available(0)	0.70	0.46	0.641	0.118
Washing Machine	Available (1), Not available(0)	0.32	0.47	0.645	0.120
Vacuum Cleaner	Available (1), Not available(0)	0.17	0.38	0.536	0.097
Computer	Available (1), Not available(0)	0.22	0.41	0.555	0.105
Internet access	Available (1), Not available(0)	0.36	0.48	0.436	0.057
Rubbish collected by local authority	Yes (1), No(0)	0.62	0.49	0.625	0.104

Source: Stats SA census 2011

The first factor is found to be enough to explain about 80% of the variance in the dataset and hence it's used to construct the index. The factor loadings and the coefficients of each variable used to generate the index are also given on Table 3.2. The factor loadings are the correlations between each of the original variables and the latent variable generated (factor). The square of the factor loadings indicates the percentage of the total variance in the original variables explained by the factor. The coefficients, on the other hand, are the factor weights used in conjunction with the original values to calculate each observation's score. In other words, the index is simply a linear combination of the coefficients given and the values of the variables for each household. For ease of understanding, the constructed index is categorised into 5 quintiles which can be used as ranking the level of living standard to households. A household lying in the first quintile is categorised as to have the poorest living standard while a household lying in the fifth quintile is categorised to have the best living standard. Furthermore, households in the first two quintiles are categorised as poor and living standard poverty headcount ratio (LS PHCR) is computed for each area.

3.6.3 Gini Index – Income Inequality

The Gini coefficient or index (GI) is the most widely used index to measure the level of income inequality in a society. It is expected to be positively correlated with child mortality as greater inequality in income within communities reflects unequal access to healthcare, nutrition and other services which is likely to reduce the health of the poor (Waldmann 1992; Rodgers 2002). The GI is a number between 0 and 1, where 0 corresponds with perfect equality and 1 corresponds with perfect inequality (where one person has all the income and everyone else has zero income). It is computed from a Lorenz curve (LC) which is literally a plot of the cumulative percentage of population versus the cumulative percentage of wealth/income. From the LC, GI is then calculated as the area between the line of perfect equality and the observed LC, as a percentage of the area between the line of perfect equality and the line of perfect inequality.

In this research, GI is computed for each province and municipality of the country from the distribution of their population and income class as reported in the 2011 census. This helps us to compare provinces and municipalities according the level of income inequality in relation to the level of child mortality.

3.7 Multilevel modelling of child mortality

As the last part of the research, besides examining child mortality in relation to poverty and inequality at different geographical levels through various descriptive statistics, factors affecting child mortality are investigated by fitting multilevel logistic regression model. This is important especially to quantify the impact of socioeconomic factors including poverty and inequality on mortality of children. The investigation goes beyond simple correlation analysis between child mortality, and poverty and inequality. It also helps to address the issue of ecological fallacy where conclusion reached at aggregate level is inadequate to hold at individual level. Unfortunately, since the quality of the data on date of death of the deceased children is very poor, survival analysis is not attempted. Multilevel analysis is a suitable approach to take into account community level contexts at different levels, like at municipal and province levels, as well as individual subjects.

3.7.1 Data and variables

Using the 2011 census data, children born within 12 months before the census date are considered for this part of the research. After removing missing, unknown and inconsistent cases, there are 86 877 (un-weighted) children with valid survival status and ready for analysis. These children can be viewed as they are nested in a structure under 234 municipalities and 9 provinces as shown on Figure 3.5.

Figure 3.5 Structure of number of children in the data used for regression

	Level 3 [Provinces]	Level 2 [Municipalities]	Level 1 [Children]
South Africa	WC	25 units	8 513 units
	EC	39 units	10 455 units
	NC	27 units	1 975 units
	FS	20 units	4 958 units
	KZN	51 units	16 228 units
	NW	19 units	6 359 units
	GT	10 units	19 731 units
	MP	18 units	7 244 units
	LM	25 units	11 414 units
Total:	9 units	234 units	86 877 units

The dependent variable considered has a binary outcome indicating the survival status of the child with value 0 if the child is still alive at the census date and 1 if the child has died. Based on the literature review we had in the previous chapter, various independent variables which might affect child mortality at individual, municipal and province level are identified. The list of the variables used in the regression together with some descriptive statistics is given on Table 3.3. Missing values in the independent variables are also discarded from the analysis as they constitute only less than 1.3 per cent of the total observations.

Table 3.3 Summary statistics of the variables in the regression model

	Label	Variable	Mean	Std. Dev.	Odds of death
	Y	Child died	0.0187	0.1353	0.0190
	Child level				
	X1	Female child	0.5066	0.5000	1.2065
	X2	Age < 1 month (Neonatal)	0.1142	0.3181	0.8180
		Mother's age at birth, 20-34 (Ref)			
	X3	<20 years	0.1947	0.3960	1.0488
	X4	>34 years	0.1514	0.3584	1.1127
		Birth order, First birth (Ref)			
	X5	2	0.2955	0.4562	0.9615
	X6	3	0.1604	0.3670	1.1718
	X7	4+	0.1381	0.3450	1.5490
		Mother's education, No/primary education (Ref)			
	X8	Secondary education	0.7693	0.4213	0.7037
	X9	Higher education	0.0954	0.2937	0.3775
	X10	Mother never married	0.5288	0.4992	1.1767
	X11	Mother works	0.2005	0.4004	0.9166
	X12	Mother is Black African	0.8596	0.3474	2.0488
		Living Standard Quintiles, Q1 (Ref)			
	X13	Q2	0.2319	0.4221	0.8294
	X14	Q3	0.2036	0.4027	0.7888
	X15	Q4	0.1898	0.3922	0.6052
	X16	Q5	0.1311	0.3375	0.3585
	Municipal level				
	X17	Higher proportion of poor	0.4889	0.4998	1.3627
	X18	More educated mothers	0.7873	0.4092	0.6787
	X19	Greater income inequality	0.1497	0.3567	1.2473
	Province level				
	X20	Heavier HIV prevalence	0.6290	0.4831	1.3275

All the independent variables are defined as categorical and hence, the odds of death given in the last column of the tables measures the odds of the category compared to the reference group. Note that the independent variables are listed according to their level such that the variables on proportion of poor, mean mothers' years of education and income inequality as measured by Gini index, are identified at municipal level while HIV prevalence rate is at province level. All these four variables are defined with two categories: lower and higher magnitude of the respective measures. The lower and higher values dictate that the respective quantity in the area is less than and greater than the national estimate. For instance, about 49 per cent of the children live in municipalities where the level of income poverty is higher than the national poverty head count ratio of 41 per cent. Note also that among the child level variables, age of the child is an indicator variable showing whether the child has age of less than one month (neonatal) or not.

3.7.2 The model

As noted above, a three-level random intercept logistic regression model is considered where the first level is children born 12 months before the census while the municipalities and provinces in which the children live are the second and third levels respectively. Let π_{ijk} be the probability that child i living in municipality j and province k dies before reaching age one. Then, the three-level random intercept logistic regression model in question with the predictor variables described above can, therefore, be expressed as

$$\begin{aligned} \ln[\pi_{ijk} / (1 - \pi_{ijk})] = & \beta_{0,jk} + \beta_1 X_{1ijk} + \beta_2 X_{2ijk} + \beta_3 X_{3ijk} + \beta_4 X_{4ijk} + \beta_5 X_{5ijk} + \\ & \beta_6 X_{6ijk} + \beta_7 X_{7ijk} + \beta_8 X_{8ijk} + \beta_9 X_{9ijk} + \beta_{10} X_{10ijk} + \beta_{11} X_{11ijk} + \\ & \beta_{12} X_{12ijk} + \beta_{13} X_{13ijk} + \beta_{14} X_{14ijk} + \beta_{15} X_{15ijk} + \beta_{16} X_{16ijk}, \end{aligned} \quad (\text{level 1 model})$$

$$\beta_{0,jk} = \beta_{00k} + \beta_{17} X_{17jk} + \beta_{18} X_{18jk} + \beta_{19} X_{19jk} + u_{0,jk}, \quad (\text{level 2 model})$$

$$\beta_{00k} = \beta_{000} + \beta_{20} X_{20k} + v_{00k}, \quad (\text{level 3 model})$$

where

$v_{00k} \sim N(0, \sigma_{v_0}^2)$, $u_{0jk} \sim N(0, \sigma_{u_0}^2)$, and the notations of the independent variables are as given on the ‘Notation’ column in Table 3.4 above. The coefficients $\beta_1, \beta_2, \dots, \beta_{20}$, called fixed effects, measure the impact of the corresponding predictor variable on the log of odds of death while β_{0jk} , the random effect, measures the combination of municipal and provincial level effects as defined in the second and third level of the model. Unlike ordinary logistic regression, there are two types of residual terms, u_{0jk} and v_{00k} , defined at level 2 and level 3 respectively and assumed to be normally distributed with mean zero and constant variance.

3.7.3 Parameters estimation and model diagnostics

There are two commonly used estimation methods for multilevel logistic regression models: quasi-likelihood (QL) approach and Bayesian approach with Markov Chain Monte Carlo (MCMC) methods (Goldstein 2011). In QL approach, the non-linear logistic regression equation is estimated first using a Taylor series expansion which approximates a nonlinear function by an infinite series of terms (Breslow and Clayton 1993). If the Taylor series is expanded about the fixed and the random parameters, then the estimation is known as penalised quasi-likelihood (PQL) (Breslow and Clayton). Once the quasi-likelihood has been formed, unbiased estimates of the random parameters can be found by applying either iterative generalised least squares (IGLS) or restricted generalised least square (RGLS) which are estimation procedures in the case of continuous response variables (Goldstein 2011). On the other hand, the Bayesian approach using MCMC estimation methods can be used by first specifying starting values prior distributions for each of the model parameters and then sequentially sampling subsets of parameters from their conditional posterior distributions using Markov chain. A discussion and technical details of MCMC estimation methods for multilevel models can be found from in Browne (2003) and Goldstein (2011)

The MCMC procedure followed by MLwiN – software dedicated for multilevel modelling and used by this research – by default assigns flat prior distributions to the parameters of the model. That is, for fixed terms $p(\beta) \propto 1$ and for random terms, $p(1/\sigma^2) \sim \text{Gamma}(\epsilon\epsilon, \epsilon\epsilon)$ where $\epsilon\epsilon$ is a very small number. After assigning initial values, usually estimates from QL methods are used as initial values, the MCMC procedure in MLwiN then performs the simulations in two phases. In the initial burn-in

period it runs until the chain converges to its stationary distribution; and in the next stage (monitoring period) it runs so that the means and standard errors of the parameters are estimated. The 2.5th and 97.5th quantiles of the chains provide Bayesian 95% credible intervals in order to make inferences concerning the estimated parameters, serving the same purpose as 95 per cent confidence intervals. For fitting the aforementioned mode, the number of iterations run are 1000 in the burn-in period and 10 000 for the monitoring period.

After running the model, residuals at municipal and province level (estimates of u_{0jk} and v_{00k}) are calculated so that the underlying assumptions, such as normality and constant variance of residuals, be investigated with the help diagnostic plots. Furthermore, as part of model diagnostics, the trace of the chains, autocorrelations (AC) and partial autocorrelations (PAC) functions at iteration t and $t-k$ having accounted for iterations $t-1, \dots, t-(k-1)$, and Monte Carlo standard errors (MCSE) are investigated for each of the posterior distributions of the parameter in the model. For the model to be good it is expected that the traces be not skewed, the AC and PAC functions be less correlated and the MCSE be close to zero. Increasing the number of iterations produces better results in all these dimensions. A comprehensive detail of parameter estimation and model diagnostics using MCMC simulations methods can be found from MLwiN manual (Rasbash, Charlton, Browne *et al.* 2012).

3.8 Software

The majority of data management and analyses are carried out with Stata 13 (StataCorp 2013) and the spatial Bayesian smoothing part is done with WinBUGS (Bayesian Inference Using Gibbs Sampling) version 14.4.3 after generating the adjacency matrix with GeoDa (Anselin 2013) from the shape files obtained from Municipalities Demarcation Board of South Africa (MDBSA 2014). In addition, the provincial and municipal-level estimates of under-five mortality rates are mapped with the help of ArcGIS/ArcMap (Esri 2012). For the multilevel modelling part, the use of MLwiN (Rasbash, Charlton, Browne *et al.* 2012) is a better choice because of its computing efficiency for large datasets and better estimation methods than the multilevel modules of Stata. It is used in conjunction with *runmulwin* – a Stata module designed to run MLwiN multilevel modelling software from within Stata (Leckie and Charlton 2013).

4. RESULTS OF ANALYSIS

This chapter summarises the main results of the analysis in this research. Estimates of child mortality from the 2011 household death data at national, provincial and municipal level will be first presented together with the Bayesian spatial smoothed estimates. The later estimates will then be assessed in relation to poverty and inequality at the respective geographical levels. Finally, the results of the multilevel logistic regression model which investigates the relationship between child mortality and its determinants will be presented.

4.1 Estimates of child mortality from household deaths data

The 2011 South African census asked questions on deaths occurred in households twelve months before the census. These data are used to determine estimates of child mortality at national, provincial and municipality levels. There are a total of un-weighted 5 119 under-five deaths enumerated by the census of which 3 710 were infant deaths. The corresponding weighted numbers are 58 208 and 42 186 respectively. Using the weighted total infant deaths and the number of births that occurred in the country one year before the census, which is calculated as 1 136 387, infant mortality rate or probability of dying before age one (${}_1q_0$) is estimated to be 37 per 1000 live births. On the other hand, the probability of dying between age one and 5 (${}_4q_1$) is computed based on the method discussed in Section 3.3 and as shown in Table 4.1 as 13 deaths per 1000 live births. Combining the estimates of ${}_1q_0$ and ${}_4q_1$, the national estimate of under-five mortality rate or the probability of dying before reaching age 5 is 49 deaths per 1000 births. Note that all these estimates of mortality are applicable to about six months before the census, i.e. April 2011. It can be easily observed that the majority of the under-five deaths, about 75 per cent, are accounted by deaths under age one. Only 25 per cent of the deaths occur between age one and 5.

Table 4.1 National level child mortality estimates

Age	No of Deaths	Average Population/Births	Central Death Rate	Mortality Rates
0	42 186	1 136 387	NA	
1	7 169	1 147 273	0.0062	${}_1q_0 = 37.12$
2	3 329	1 147 342	0.0029	${}_4q_1 = 12.76$
3	2 228	1 121 930	0.0020	${}_5q_0 = 49.41$
4	1 851	1 082 251	0.0017	

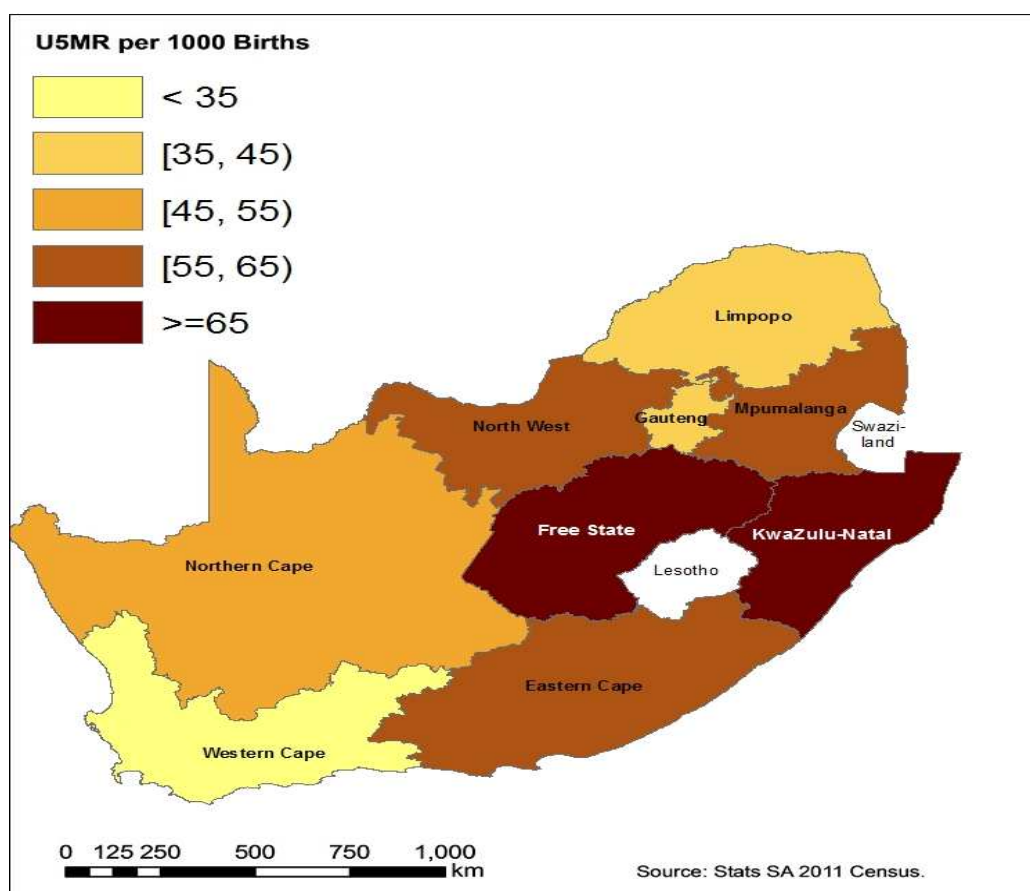
Applying the same procedure but by disaggregating the census data by province and taking provincial survival factors from ASSA model, infant and under-five mortality rates are estimated. These estimates are provided in Table 4.2 together with the smoothed estimates computed by aggregating the municipal level Bayesian smoothed estimates, which is the topic of the next section. Although there are small differences between the direct and smoothed estimates of infant and under-five mortality rates at province level, the smoothed estimates are taken to be the final estimates of child mortality in this research. As it can be seen from the table, Western Cape (WC) is the province with the lowest level of infant and under-five mortality rates, values close to 20, and 26 deaths per 1000 births respectively. It is followed by Gauteng (GT) with infant and under-five mortality rates close to 27, and 37 respectively. On the contrary, KwaZulu-Natal (KZN) and Free State (FS) have registered the highest mortality rates – about 2.7 times heavier than that of WC. They have attained an infant mortality rates of 51, and 48 deaths per 1000 births respectively while their under-five mortality rate are correspondingly 71, and 68. The mortality rates of all the remaining provinces except Limpopo (LP) are at least twice as the mortality rate of the WC. This somehow illustrates the significance of child mortality inequality among the provinces.

The spatial distribution of under-five mortality among the nine provinces is shown on the map in Figure 4.1. The map is created by categorising the provinces into 5 classes based on the severity of their under-five mortality rates. WC lies in the first quintile followed by GT and LP while Northern Cape (NC) seized the third quintile. KZN and FS are in the last class preceded by North West (NW), EC and MP.

Table 4.2 Provincial level direct and smoothed estimates of child mortality

Province	Direct Estimates				Smoothed Estimates		
	1q0	5q0	1q4	5q0/1q0	1q0	5q0	1q4
Western Cape	18.86	24.75	6.00	1.31	19.86	26.06	6.33
Eastern Cape	41.69	55.96	14.89	1.34	42.49	57.04	15.19
Northern Cape	40.27	52.55	12.79	1.30	38.50	50.24	12.20
Free State	47.82	68.47	21.69	1.43	47.61	68.17	21.59
KwaZulu-Natal	49.81	68.78	19.96	1.38	51.14	70.61	20.52
North West	44.98	61.79	17.60	1.37	45.15	62.03	17.67
Gauteng	25.95	36.07	10.40	1.39	26.75	37.19	10.73
Mpumalanga	41.29	58.13	17.57	1.41	42.51	59.85	18.11
Limpopo	28.37	39.27	11.22	1.38	28.87	39.98	11.43
ZA	37.12	49.41	14.09	1.34	36.03	49.95	14.45

Figure 4.1 Provincial smoothed estimates of under-five Mortality rate



Computing direct estimates of under-five mortality at municipal levels using the same procedure as applied for the national or provincial level estimates, however, is

found to be problematic as the number of deaths at municipal-level are very rare in many municipalities to generate stable estimates. Therefore, two additional tasks were necessary. First, stable estimates of infant mortality rate for each municipality are computed using Bayesian spatial smoothing technique. Second, it is assumed that the ratio of under-five mortality rate to infant mortality rate in each municipality within a province is the same as the ratio of the two quantities at the respective province. These ratios for each province are as shown in Table 4.2, which ranges from 1.3 in NC to 1.43 in FS. Therefore, the municipal-level smoothed infant mortality rates are multiplied by their corresponding factors in order to get the respective estimates of under-five mortality rates.

4.2 Spatially smoothed municipal-level Bayesian estimates of child mortality

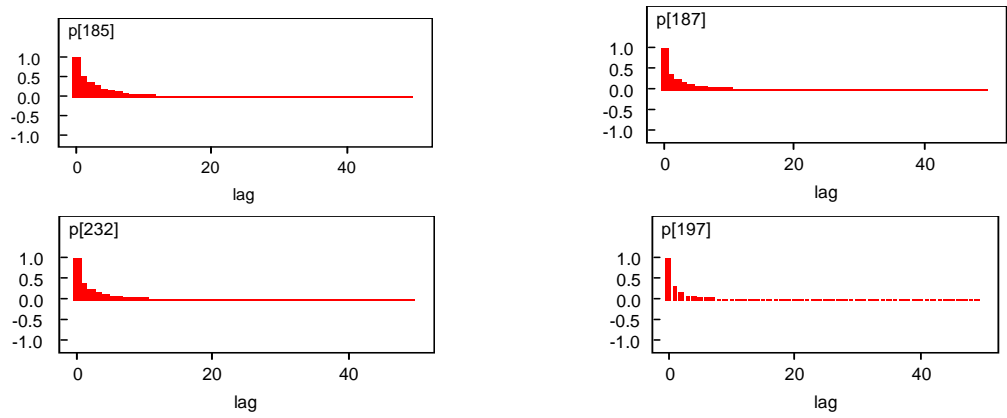
4.2.1 Results of model diagnostics

In order to address issues related to sample size and unstable (or missing) estimates of child mortality, Bayesian estimates are constructed smoothing on data in neighbouring areas. As it is discussed in Chapter Three, the main inputs for the smoothing model are the number of infant deaths and births occurred 12 months before the census. For this purpose, two different Bayesian models are compared. The first model (Model-1) is only with spatial smoothing (Model-1) – pure conditional autoregressive (CAR) model while the second one (Model-2) incorporates municipal level mean years of women education and provincial HIV prevalence rate for adults aged 15-49. After running each of the models initially for 10 000 iterations and another 100 000 iterations for monitoring stage, the respective models has returned DIC values of 1187.1, and 1164.7 respectively. Hence, the improved model by the inclusion of women education and HIV prevalence rate is the best model to estimate municipal-level child mortality rates.

Basic model diagnostics using Model-2 are also done on two of the most important parameters; namely, the proportion of children who have died (p_i) and the spatially structured random effect (S_i). The autocorrelation functions and the Brooks-Gelman-Robins (BGR) statistic plots presented on from Figure 4.2 to Figure 4.5 for four municipalities with smaller number of children and another four municipalities with larger number of children helps to show the very weak nature of autocorrelations of successive iterations of the chains and convergences of the posterior distributions of the parameters of interest.

Figure 4.2 Autocorrelation values for the proportions of children who have died (p_i) for selected municipalities

a) For municipalities with smaller number of children



b) For municipalities with higher number of children

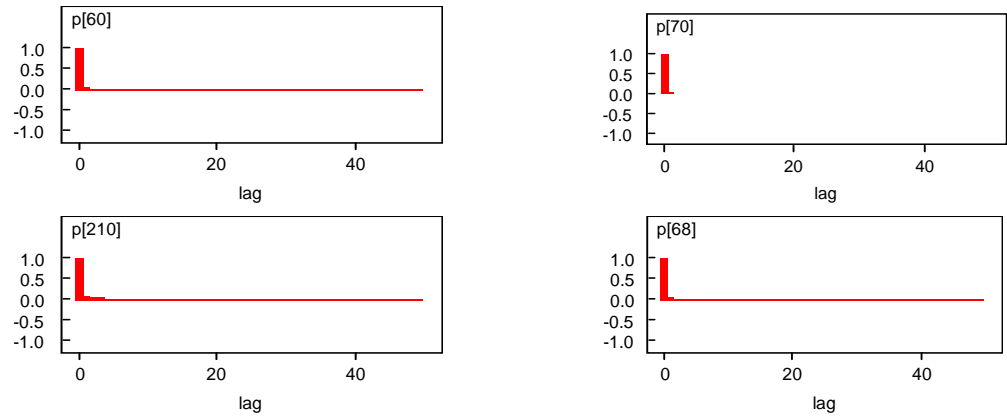
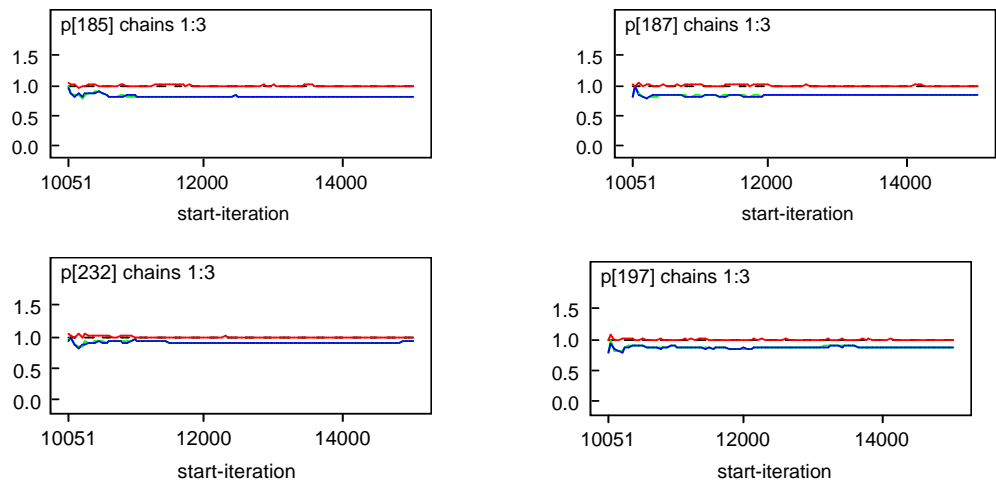


Figure 4.3 BGR statistics for the proportions of children who have died (p_i) and spatially structured random effect (S_i)

a) For municipalities with smaller number of children



b) For municipalities with larger number of children

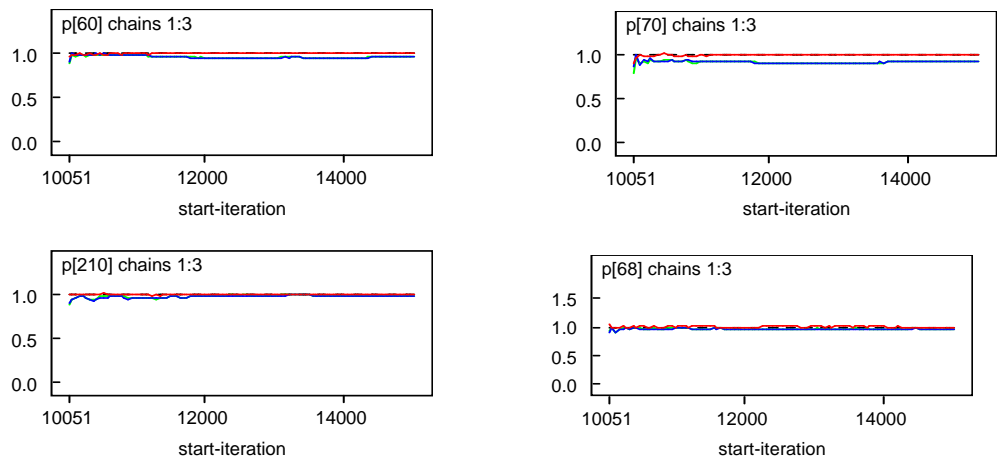
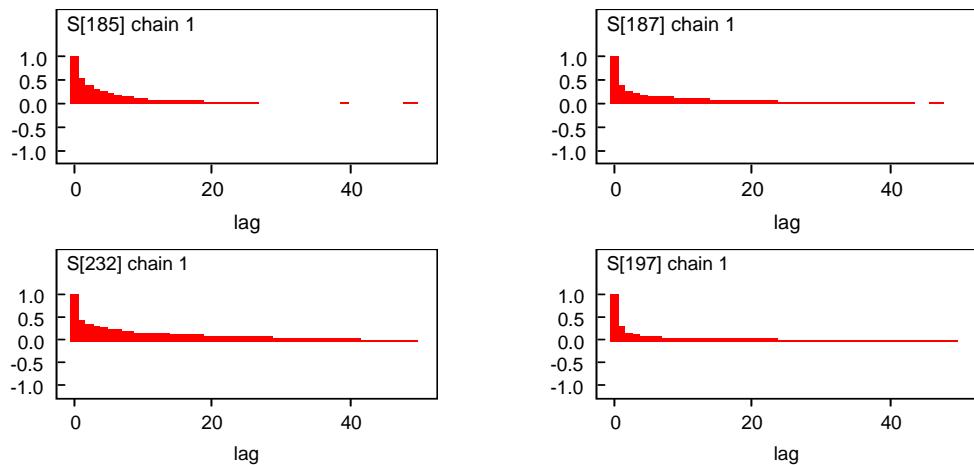


Figure 4.4 Autocorrelation values for the spatially structured random effect (S_i) for selected municipalities

a) For municipalities with smaller number of children



b) For municipalities with larger number of children

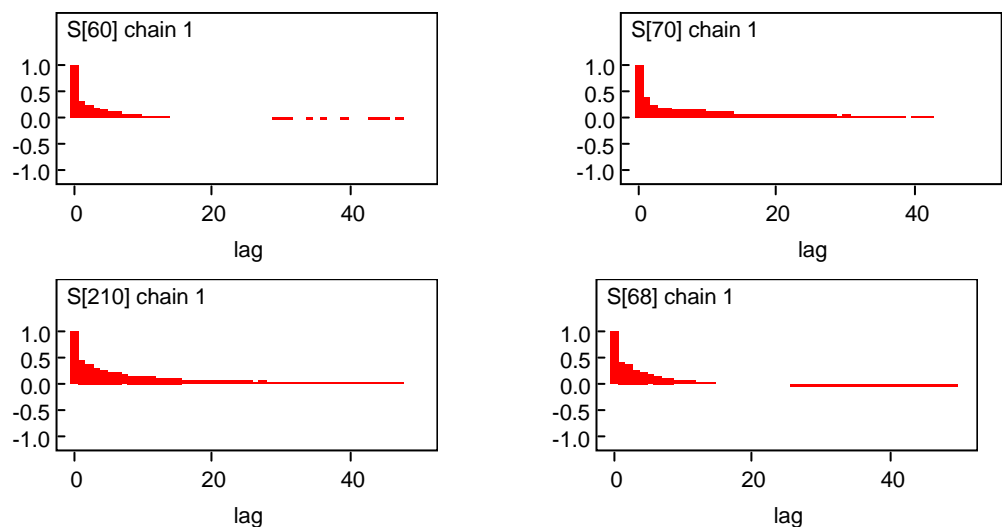
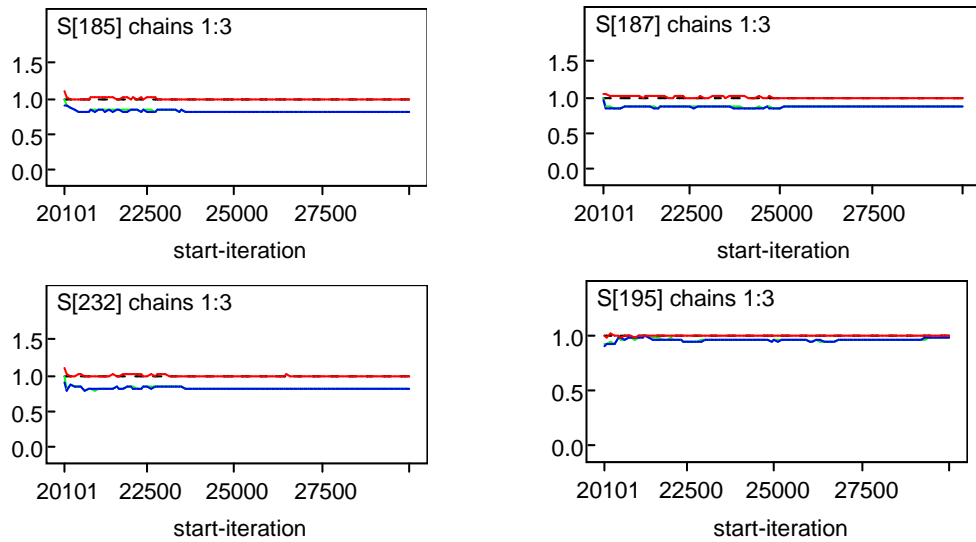
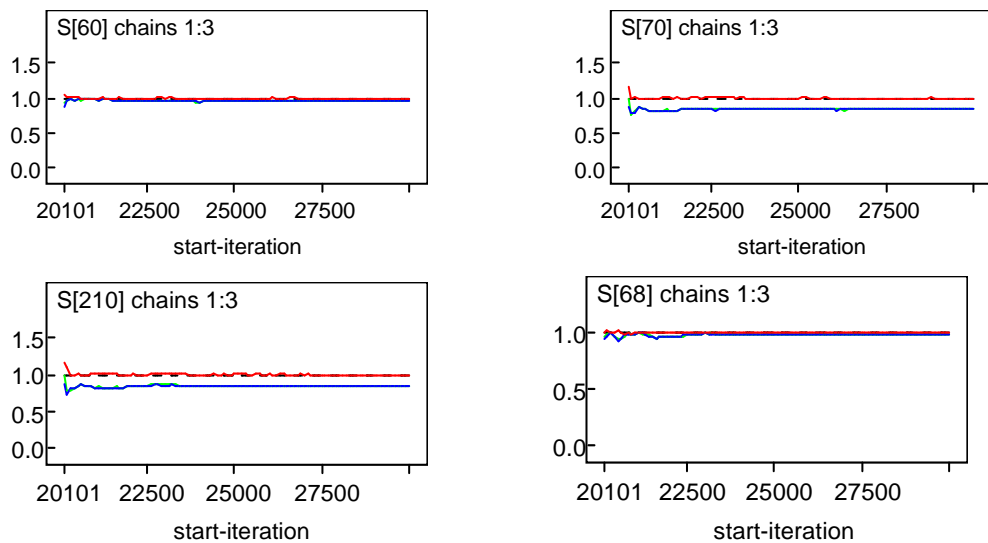


Figure 4.5 BGR statistics for the spatially structured random effect (S_i) for selected municipalities

a) For municipalities with smaller number of children



b) For municipalities with larger number of children



The model is then used to generate estimates of infant and under-five mortality rates to each municipality. The inclusion of the two variables in the CAR model has improved the estimates to some extent. This can, to some extent, be demonstrated by looking at the relationship between the under-five mortality estimates and the two included variables as indicated in the two scatter plots shown in Figure 4.6 and 4.7 below. A decrease in child mortality is associated with an increase in women's mean years of education and a decrease in adult HIV prevalence rate. Specifically, there are

significant correlations between U5MR and women's education and HIV prevalence resulting in a correlation coefficients of -0.50 and 0.76 respectively. However, it is important to note that there is a high level of variability in estimates of child mortality at all levels of education and at areas where the HIV prevalence is higher.

Figure 4.6 Under-five mortality rate and mean years of mothers' education

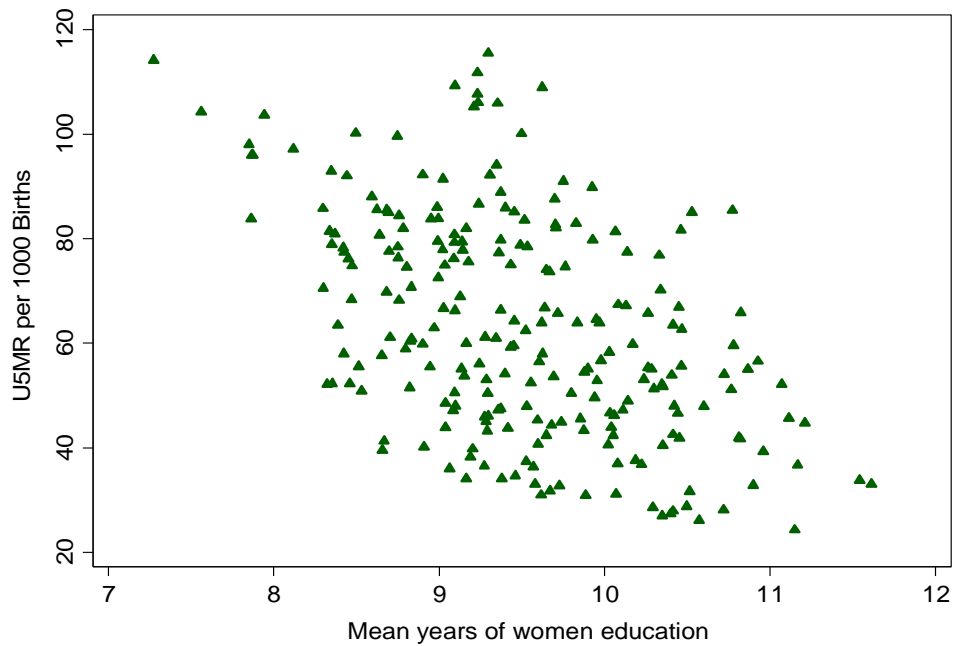
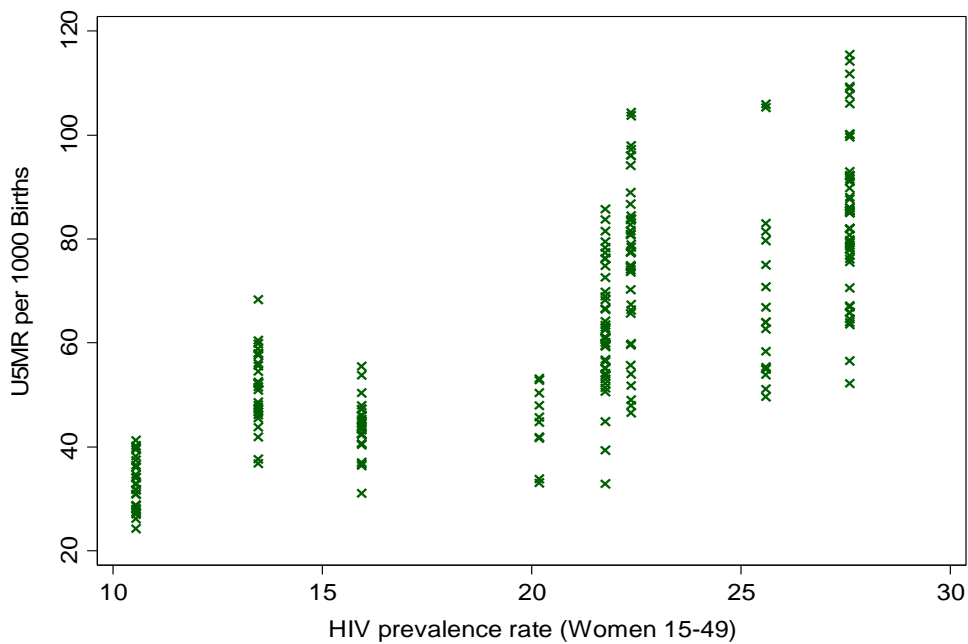


Figure 4.7 Under-five mortality rate vs HIV prevalence rate

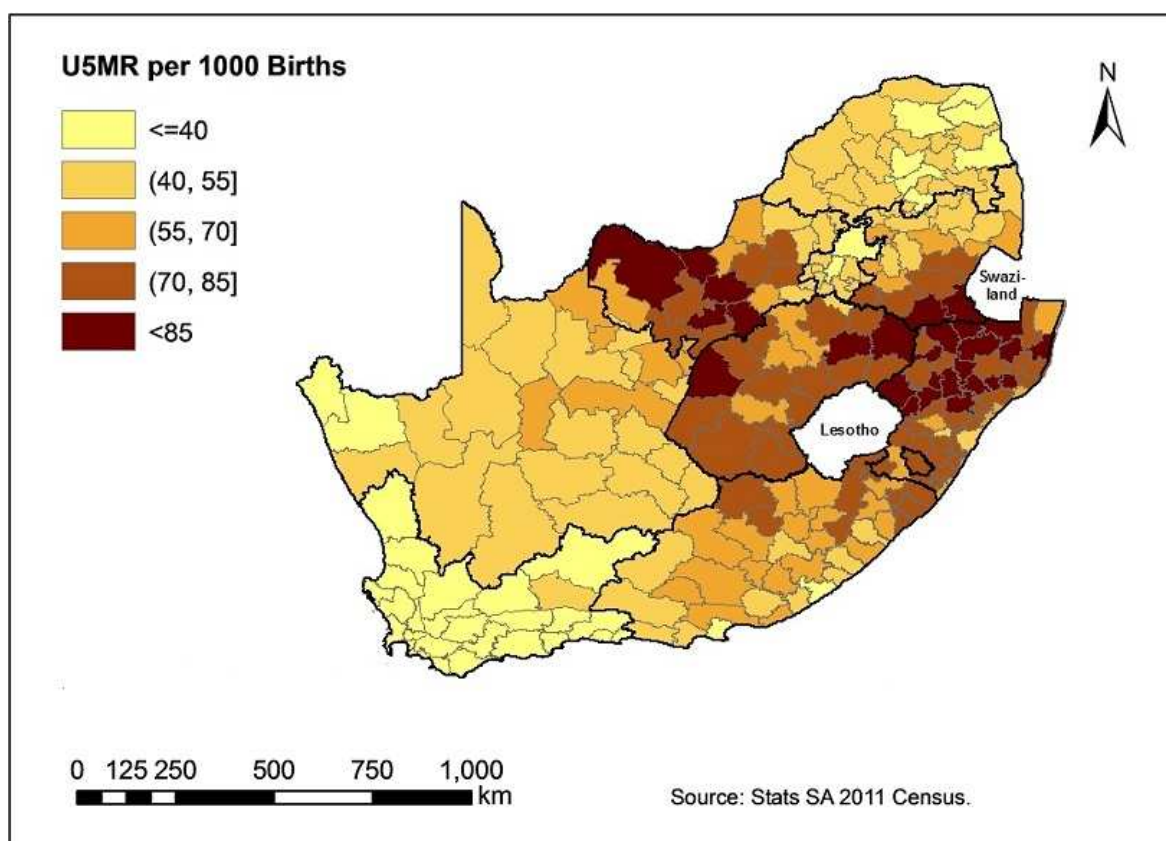


4.2.2 Estimates of municipal level infant and child mortality rates

The final municipal level estimates of infant and under-five mortality rates are provided together with other relevant statistics in Table 4.4. The municipalities in the table are ranked based on their level of U5MR. In addition, the estimates of child mortalities are associated with geo-referenced data of the municipalities and mapped as shown on Figure 4.8. The map presents the estimates of U5MRs per 1000 live births with the following breakdown: 16 per cent of municipalities have under-five mortality rates of less than 40, 29 per cent have values between 40 and 54, 19 per cent have values between 55 and 69, 24 per cent have values between 65 and 84, and 12 per cent have values of 85 and above. The map helps one to see the spatial patterns of child mortality in the country in that mortality is heavier in north-east, central and north-west part and lighter in south-east and northern parts of the country. Among all the municipalities, City of Cape Town (CCPT) has got the minimum under-five mortality of 24.0 deaths per 1000 live births while uPhongolo of the KwaZulu-Natal province has recorded the maximum rate of 109.1 which is about 4.6 times higher than the mortality rate of CCPT. This implies that the probability that a child who is born in uPhongolo is 4.6 times more likely to die before reaching its fifth birthday than a child who is born in CCPT.

For such ease of comparisons, the under-five mortality rate estimates of all municipalities are divided by the minimum under-five mortality rate (CCPT) in order to get a kind of standardised mortality index (SM). These index and the corresponding under-five mortality ranks for each of the municipalities are also given in Table 4.4. From this table one can appreciate the degree of differential of child mortality among municipalities in South Africa. In the time period where the mortality estimate applies, the under-five mortality rate of 60 per cent of the municipalities is more than twice the mortality rate of the city of Cape Town. Furthermore, in 30 per cent of the municipalities, child mortality is three times higher while in 7 per cent of the municipalities the mortality is four times higher than the mortality in CCPT. Further interpretation of child mortality estimates in relation to poverty and inequality will be given later.

Figure 4.8 Spatially smoothed municipal-level estimates of U5MRs



Generally, there are far less variation in municipalities that are geographically close, but there is clear and consistent evidence of elevated mortality levels in municipalities in provinces like KwaZulu-Natal and North West and lowest levels in municipalities of the Western Cape, Gauteng and Limpopo. Summary statistics of municipal-level under-five mortality estimates in each province are given on Table 4.3. The information in the table together with the map helps to appreciate not only the magnitude of child mortality in the municipalities within provinces but also the degree of variation in mortality in each of the provinces. One can understand from the given table that Western Cape has the lowest average child mortality rate and the fourth lowest dispersion in child mortality considering coefficient of variation (CV) as a standard measure of variation. On the other hand, while most of the municipalities in Kwazulu-Natal province have registered the highest mortality rates, the variation in mortality among them is not found to be the highest. The greatest disparity in child mortality among municipalities is observed in North-West and Mpumalanga provinces with a CV of 25 and 24 per cent respectively. The municipalities in Limpopo province, on the other hand, have the lowest variation in child mortality, scoring a CV of about 12

per cent indicating that they are the most alike relative to municipalities in other provinces. Nationwide, the 234 municipalities vary in child mortality by 33 per cent while the mean and median values are 61 and 62 respectively. The box plots shown in Figure 4.5 present the combined information of extent and disparity of the mortalities among municipalities in each province.

Table 4.3 Summary Statistics of U5MR Municipal-level estimates

Province	n	Mean	Median	Min	Max	SD	CV
Western Cape	39	32.28	32.18	23.97	40.41	4.72	14.61
Eastern Cape	20	60.99	59.31	32.28	82.18	11.26	18.46
Northern Cape	10	50.10	50.82	36.13	66.07	6.89	13.74
Free State	51	74.67	74.46	54.14	91.57	9.45	12.66
KwaZulu-Natal	25	81.09	81.54	50.80	109.08	13.60	16.77
North West	18	72.28	75.43	45.51	99.06	18.28	25.29
Gauteng	27	43.51	44.18	32.48	51.71	6.79	15.61
Mpumalanga	19	66.27	61.93	48.39	100.51	15.70	23.69
Limpopo	25	42.76	42.90	30.60	53.97	5.12	11.97
ZA	234	60.84	61.55	23.97	109.08	19.79	32.52

Figure 4.9 Distribution of municipal level estimates of U5MR among the provinces

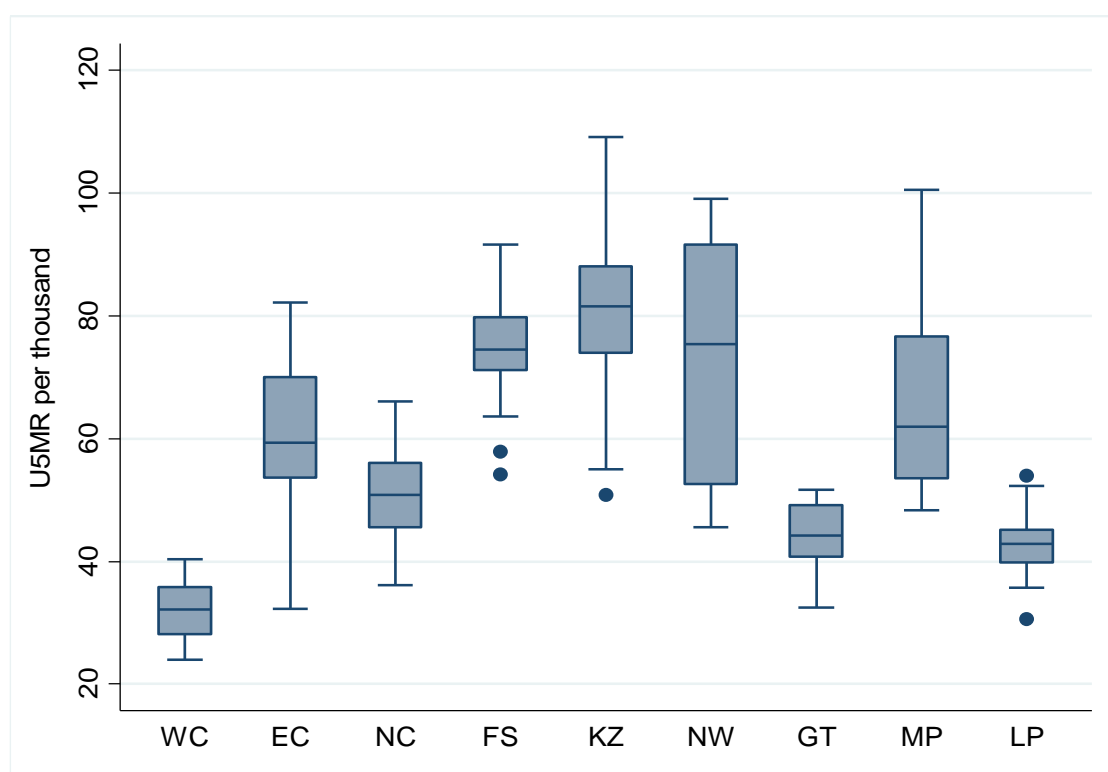


Table 4.4 Municipal level estimates of infant and under-five mortality rates with the level of poverty and inequality♣

Province	Municipality	IMR	U5MR	PHCR	GI	LS PHCR	SMR	Ranks			
								U5M	PV	II	LSP
WC	City of Cape Town	18.3	24.0	29.6	0.673	16.9	1.00	1	33	86	14
WC	Mossel Bay	19.7	25.8	34.4	0.655	14.3	1.08	2	48	55	3
WC	Knysna	20.4	26.6	34.9	0.704	27.2	1.11	3	52	170	60
WC	Overstrand	20.6	27.0	32.0	0.648	20.9	1.13	4	40	47	25
WC	Bitou	21.0	27.5	37.2	0.706	24.5	1.15	5	72	176	46
WC	Stellenbosch	21.2	27.7	33.7	0.681	20.6	1.16	6	44	104	24
WC	George	21.6	28.2	31.4	0.652	19.2	1.18	7	38	52	20
WC	Drakenstein	21.7	28.4	28.4	0.667	15.1	1.18	8	23	75	7
WC	Breede Valley	23.3	30.4	28.7	0.651	24.1	1.27	9	27	50	43
WC	Theewaterskloof	23.3	30.5	27.9	0.647	21.7	1.27	10	21	42	28
LP	Thulamela	22.2	30.6	60.1	0.688	77.3	1.28	11	195	123	184
WC	Saldanha Bay	23.9	31.2	27.8	0.636	13.3	1.30	12	19	26	1
GT	City of Tshwane	23.5	31.3	28.4	0.663	22.0	1.31	13	24	68	31
GT	City of Johannesburg	24.0	32.2	29.7	0.694	17.2	1.34	14	34	146	15
EC	Nelson Mandela Bay	24.2	32.3	40.7	0.694	15.9	1.35	15	104	144	11
WC	Cape Agulhas	24.8	32.5	21.0	0.623	14.8	1.35	16	1	13	4
WC	Oudtshoorn	23.9	32.5	36.1	0.688	23.5	1.36	17	66	122	38
WC	Swartland	24.6	33.2	25.5	0.660	16.2	1.39	18	12	63	13
WC	Langeberg	25.6	33.5	28.8	0.677	18.5	1.40	19	28	94	16
WC	Hessequa	25.7	33.6	23.0	0.613	13.5	1.40	20	5	9	2
WC	Bergrivier	26.0	34.0	21.6	0.592	19.2	1.42	21	2	4	19
WC	Swellendam	27.1	35.4	24.2	0.627	22.1	1.47	22	9	16	32
LP	Mutale	25.9	35.7	61.9	0.707	87.5	1.49	23	206	182	208
WC	Laingsburg	27.4	35.8	23.0	0.636	30.7	1.49	24	4	28	81
LP	Polokwane	26.2	36.0	40.4	0.711	49.7	1.50	25	103	191	129
NC	Richtersveld	27.8	36.1	22.9	0.614	15.5	1.51	26	3	10	8
LP	Makhado	26.3	36.3	55.3	0.697	76.2	1.51	27	173	152	178
WC	Beaufort West	28.1	36.7	37.8	0.691	15.9	1.53	28	78	131	10
NC	Nama Khoi	28.4	36.9	29.2	0.684	16.0	1.54	29	32	112	12
WC	Witzenberg	28.7	37.5	23.4	0.639	25.7	1.56	30	7	32	50
EC	Buffalo City	28.9	38.6	42.7	0.705	38.4	1.61	31	115	171	110
WC	Kannaland	29.6	38.7	36.5	0.719	27.0	1.61	32	69	203	57
WC	Matzikama	29.9	39.0	25.3	0.658	30.4	1.63	33	11	60	77
WC	Cederberg	30.1	39.4	24.7	0.636	28.5	1.64	34	10	24	68
LP	Lepele-Nkumpi	28.8	39.6	55.3	0.704	66.2	1.65	35	173	167	153
LP	Makhuduthamaga	28.9	39.7	64.7	0.718	81.0	1.66	36	218	202	189
LP	Ba-Phalaborwa	28.9	39.8	43.0	0.698	50.4	1.66	37	116	158	131
WC	Prince Albert	31.0	40.4	35.8	0.691	26.2	1.69	38	63	132	52
GT	Randfontein	29.5	40.8	28.1	0.628	22.7	1.70	39	22	17	35
NC	Sol Plaatjie	31.6	41.0	35.5	0.695	21.7	1.71	40	58	148	27
GT	Mogale City	29.7	41.1	31.1	0.667	25.3	1.71	41	36	75	48
LP	Fetakgomo	30.1	41.5	56.3	0.710	72.4	1.73	42	181	188	166
LP	Greater Tzaneen	30.2	41.5	52.2	0.719	76.9	1.73	43	152	204	182
LP	Aganang	30.3	41.6	56.2	0.639	75.1	1.74	44	180	33	172
LP	Greater Giyani	30.8	42.3	65.3	0.704	82.2	1.77	45	219	168	191
LP	Molemole	30.8	42.4	52.7	0.697	67.7	1.77	46	158	154	157
NC	Emthanjeni	33.0	42.8	35.7	0.660	21.5	1.79	47	59	64	26
LP	Musina	31.2	42.9	35.8	0.679	45.7	1.79	48	63	100	125
LP	Greater Tubatse	31.2	43.0	53.2	0.708	76.0	1.79	49	160	184	175
LP	Bela-Bela	31.5	43.4	33.7	0.666	29.5	1.81	50	45	73	71
GT	Ekurhuleni	31.6	43.7	33.6	0.664	23.5	1.82	51	43	70	40

Province	Municipality	IMR	U5MR	PHCR	GI	LS PHCR	SMR	Ranks			
								U5M	PV	II	LSP
EC	Kouga	32.9	43.9	36.8	0.697	28.0	1.83	52	70	154	65
LP	Greater Letaba	32.0	44.0	59.7	0.685	84.3	1.84	53	192	116	196
LP	Elias Motsoaledi	32.2	44.3	56.5	0.691	70.4	1.85	54	183	129	163
NC	Mier	34.3	44.5	36.8	0.693	36.0	1.86	55	71	137	97
GT	Emfuleni	32.3	44.6	40.0	0.679	15.0	1.86	56	98	102	6
LP	Maruleng	32.6	44.8	61.3	0.731	84.2	1.87	57	204	223	195
NC	Renosterberg	34.7	45.1	38.2	0.655	27.2	1.88	58	81	56	59
LP	Lephalale	32.8	45.1	35.0	0.688	52.6	1.88	59	53	120	134
NW	Rustenburg	33.3	45.5	28.9	0.597	40.1	1.90	60	31	6	114
NC	//Khara Hais	35.1	45.6	35.0	0.685	25.2	1.90	61	54	114	47
NC	Kamiesberg	35.5	46.1	39.5	0.703	30.0	1.92	62	91	165	73
LP	Mogalakwena	33.5	46.1	53.9	0.698	60.0	1.92	63	165	155	146
LP	Ephraim Mogale	33.6	46.2	55.2	0.705	78.1	1.93	64	170	173	187
NC	Khâi-Ma	35.7	46.4	26.4	0.582	36.0	1.93	65	15	2	95
GT	Midvaal	33.9	46.8	28.6	0.651	27.0	1.95	66	26	51	56
LP	Thabazimbi	34.0	46.8	25.6	0.597	39.9	1.95	67	13	5	113
NW	Moretele	34.3	46.8	51.4	0.607	66.7	1.95	68	149	8	154
NC	Umsobomvu	36.1	46.9	44.3	0.707	29.1	1.96	69	121	182	70
NC	Siyathemba	36.5	47.4	35.8	0.672	28.1	1.98	70	61	85	66
NW	Local Mun. of Madibeng	35.0	47.8	34.3	0.648	61.2	1.99	71	47	45	148
MP	Bushbuckridge	34.6	48.4	63.9	0.690	78.0	2.02	72	214	127	185
GT	Westonaria	35.6	49.2	39.8	0.601	46.2	2.05	73	95	7	126
LP	Mookgopong	35.8	49.2	32.2	0.630	35.3	2.05	74	41	19	91
EC	Kou-Kamma	37.0	49.3	31.5	0.666	27.9	2.06	75	39	71	64
NC	Hantam	38.3	49.6	28.5	0.720	26.9	2.07	76	25	206	55
MP	Emalahleni	35.7	49.8	27.8	0.638	33.6	2.08	77	20	31	89
EC	Makana	37.5	50.0	37.5	0.698	23.5	2.09	78	76	157	40
NC	Thembelihle	38.7	50.2	38.6	0.733	39.1	2.09	79	84	224	112
NW	Moses Kotane	37.0	50.4	43.9	0.632	55.5	2.10	80	118	21	142
KZ	eThekweni	37.1	50.8	37.4	0.681	30.4	2.12	81	74	105	76
NC	Karoo Hoogland	39.2	50.8	27.3	0.723	48.0	2.12	82	18	213	127
EC	Lukanji	38.1	50.8	47.2	0.696	36.0	2.12	83	129	150	94
NC	Ubuntu	39.3	50.9	38.4	0.760	35.6	2.12	84	83	232	92
NC	Kareeberg	39.3	50.9	37.2	0.678	37.3	2.13	85	73	98	103
NC	Kgatelopele	39.4	51.1	26.1	0.685	15.6	2.13	86	14	115	9
GT	Merafong City	37.3	51.5	31.3	0.583	31.8	2.15	87	37	3	85
EC	Baviaans	38.7	51.7	35.8	0.679	20.4	2.16	88	64	101	23
GT	Lesedi	37.5	51.7	34.9	0.671	20.2	2.16	89	51	81	22
EC	Mnquma	39.2	52.2	53.8	0.642	84.7	2.18	90	164	35	198
LP	Modimolle	38.1	52.3	36.2	0.661	31.5	2.18	91	67	66	84
MP	Mbombela	37.6	52.5	40.3	0.711	48.9	2.19	92	101	192	128
NW	Tlokwe City Council	38.6	52.6	35.7	0.672	22.3	2.19	93	60	83	33
EC	Camdeboo	39.5	52.7	39.4	0.699	19.5	2.20	94	90	159	21
NC	Ga-Segonyana	40.9	53.0	47.3	0.706	62.1	2.21	95	130	178	150
MP	Steve Tshwete	38.3	53.5	26.7	0.629	22.0	2.23	96	17	18	29
MP	Dr JS Moroka	38.4	53.6	54.2	0.637	61.0	2.24	97	167	29	147
EC	Great Kei	40.2	53.6	51.2	0.743	70.8	2.24	98	146	228	164
EC	Ngqushwa	40.2	53.6	53.2	0.576	86.0	2.24	99	159	1	202
MP	Thaba Chweu	38.5	53.8	28.9	0.636	43.6	2.25	100	30	26	120
LP	Blouberg	39.3	54.0	62.1	0.711	82.0	2.25	101	207	189	190
NC	Kai !Garib	41.7	54.0	26.4	0.641	43.6	2.25	102	16	34	119
FS	Metsimaholo	38.1	54.1	35.9	0.693	23.7	2.26	103	65	136	41
NC	Tsantsabane	42.1	54.6	33.3	0.717	36.0	2.28	104	42	201	96
EC	King Sabata Dalindyebo	41.2	54.9	56.1	0.729	72.0	2.29	105	179	220	165

Province	Municipality	IMR	U5MR	PHCR	GI	LS PHCR	SMR	Ranks			
								U5M	PV	II	LSP
KZ	The Msunduzi	40.1	55.0	39.7	0.702	38.1	2.29	106	94	163	109
EC	Nkonkobe	41.4	55.1	52.5	0.661	68.7	2.30	107	156	67	160
NC	Siyancuma	43.2	56.0	41.1	0.710	37.4	2.34	108	105	187	106
NC	IKheis	43.4	56.3	42.3	0.702	53.5	2.35	109	113	164	137
NC	Gamagara	43.5	56.3	23.3	0.652	26.5	2.35	110	6	53	53
MP	Thembisile	40.6	56.6	51.3	0.644	53.9	2.36	111	148	39	138
NC	Dikgatlong	44.1	57.2	49.8	0.644	37.2	2.39	112	139	38	102
EC	Amahlathi	43.2	57.5	52.5	0.675	76.3	2.40	113	155	91	180
EC	Nxuba	43.4	57.8	48.5	0.670	37.4	2.41	114	135	79	104
FS	Mangaung	40.8	57.8	34.8	0.694	26.8	2.41	115	50	143	54
NW	Mafikeng	42.6	58.1	43.6	0.712	51.2	2.42	116	117	193	132
NC	Phokwane	44.8	58.1	45.7	0.721	37.1	2.42	117	124	208	101
EC	Blue Crane Route	43.7	58.3	43.9	0.734	25.6	2.43	118	119	225	49
NC	Magareng	45.3	58.7	49.6	0.663	23.7	2.45	119	138	69	42
EC	Sundays River Valley	44.3	59.0	40.3	0.620	45.2	2.46	120	102	12	123
EC	Sakhisizwe	44.4	59.2	55.0	0.725	74.5	2.47	121	169	217	171
EC	Ikwezi	44.5	59.3	51.2	0.657	25.9	2.47	122	146	58	51
EC	Inxuba Yethemba	44.5	59.3	38.1	0.695	15.0	2.47	123	80	148	5
EC	Maletswai	45.4	60.5	39.7	0.693	29.7	2.52	124	94	140	72
MP	Govan Mbeki	43.6	60.8	35.1	0.689	23.0	2.54	125	56	125	37
EC	Intsika Yethu	45.8	61.0	57.4	0.678	93.9	2.54	126	187	97	224
EC	Mbhashe	46.2	61.5	62.5	0.683	94.9	2.57	127	208	109	230
KZ	uMngeni	45.0	61.5	28.8	0.690	28.3	2.57	128	29	127	67
MP	Umjindi	44.4	61.9	30.7	0.644	38.8	2.58	129	35	38	111
MP	Victor Khanye	44.4	61.9	39.6	0.678	30.9	2.58	130	92	95	82
KZ	Umdoni	45.3	61.9	38.7	0.693	54.3	2.58	131	85	138	139
EC	Ndlambe	46.7	62.2	41.7	0.708	33.9	2.60	132	108	183	90
KZ	Mandeni	45.7	62.5	46.1	0.643	69.8	2.61	133	125	36	161
FS	Moqhaka	44.9	63.6	37.7	0.675	18.6	2.65	134	77	90	17
KZ	KwaDukuza	46.5	63.6	33.9	0.683	54.6	2.65	135	46	109	140
KZ	uMhlathuze	46.6	63.7	37.9	0.684	36.6	2.66	136	79	112	99
NW	Ramotshere Moiloa	47.1	64.1	50.5	0.681	67.0	2.68	137	142	103	155
EC	Umzimvubu	48.3	64.2	61.1	0.703	91.6	2.68	138	200	166	217
EC	Tsolwana	48.4	64.5	51.8	0.649	68.7	2.69	139	151	48	159
MP	Emakhazeni	46.4	64.6	35.0	0.645	33.1	2.70	140	55	40	88
KZ	Greater Kokstad	47.3	64.7	38.7	0.693	37.4	2.70	141	86	135	105
KZ	Hibiscus Coast	47.5	65.0	38.2	0.693	55.7	2.71	142	82	140	143
NW	City of Matlosana	47.9	65.2	41.2	0.678	18.8	2.72	143	106	99	18
EC	Nyandeni	49.6	66.0	69.3	0.674	94.8	2.75	144	229	88	229
NC	Joe Morolong	51.0	66.1	61.6	0.748	86.8	2.76	145	205	229	204
EC	Mhlontlo	50.1	66.6	63.1	0.655	93.7	2.78	146	210	55	222
EC	Emalahleni	50.7	67.4	57.3	0.650	85.6	2.81	147	185	49	201
FS	Matjhabeng	47.9	67.8	42.0	0.667	22.0	2.83	148	109	77	30
KZ	Umhlabuyalingana	49.8	68.1	67.9	0.721	91.6	2.84	149	225	210	216
MP	Nkomazi	49.0	68.3	55.9	0.696	67.4	2.85	150	175	149	156
EC	Senqu	52.6	70.0	56.1	0.660	76.1	2.92	151	178	63	177
FS	Mafube	50.1	71.0	47.7	0.688	27.9	2.96	152	133	124	63
FS	Ngwathe	50.4	71.4	45.2	0.683	22.8	2.98	153	123	107	36
FS	Kopanong	50.8	71.9	38.9	0.716	24.4	3.00	154	88	198	45
FS	Mantsopa	50.8	72.0	42.2	0.714	32.4	3.00	155	111	197	87
EC	Gariep	54.2	72.1	38.9	0.694	30.4	3.01	156	87	142	78
FS	Naledi	51.0	72.2	48.8	0.710	30.9	3.01	157	136	185	83
MP	Dipaleseng	51.9	72.3	39.9	0.635	32.0	3.02	158	96	23	86
KZ	Ubuhlebezwe	55.1	72.8	59.7	0.684	86.7	3.04	159	193	113	203

Province	Municipality	IMR	U5MR	PHCR	GI	LS PHCR	SMR	Ranks			
								U5M	PV	II	LSP
EC	Inkwanca	53.3	73.3	46.9	0.670	24.4	3.06	160	128	80	44
KZ	Ndwedwe	53.7	73.4	60.3	0.625	91.0	3.06	161	196	14	215
EC	Elundini	55.3	73.5	59.2	0.710	88.8	3.07	162	190	187	211
KZ	Endumeni	54.1	74.0	39.0	0.661	27.3	3.09	163	89	65	61
FS	Masilonyana	52.6	74.4	47.5	0.659	30.2	3.10	164	132	61	74
EC	Engcobo	56.0	74.5	63.4	0.713	94.2	3.11	165	211	195	227
FS	Dihlabeng	52.7	74.5	34.5	0.700	27.1	3.11	166	49	162	58
NW	Kgetlengrivier	54.9	74.7	42.2	0.705	45.6	3.11	167	112	173	124
KZ	Umzumbe	54.8	74.9	64.5	0.636	92.6	3.12	168	217	27	220
KZ	uMlalazi	54.9	74.9	54.7	0.696	79.3	3.13	169	168	151	188
EC	Ngquza Hill	56.6	75.3	69.5	0.734	94.5	3.14	170	230	226	228
NW	Ditsobotla	55.5	75.4	47.4	0.722	54.9	3.15	171	131	211	141
KZ	Mtubatuba	55.2	75.5	56.1	0.726	73.1	3.15	172	177	218	168
KZ	Impendle	55.5	75.8	59.3	0.647	87.0	3.16	173	191	41	206
NW	Ventersdorp	55.8	75.9	52.5	0.694	58.4	3.16	174	155	146	145
KZ	Richmond	55.8	76.2	46.7	0.690	78.1	3.18	175	127	128	187
EC	Matatiele	57.5	76.4	58.8	0.672	87.0	3.19	176	188	83	205
KZ	Ingwe	56.0	76.5	61.2	0.727	93.3	3.19	177	202	219	221
MP	Albert Luthuli	55.1	76.6	55.4	0.720	65.9	3.20	178	174	207	152
KZ	Umzimkhulu	56.1	76.7	64.4	0.673	91.6	3.20	179	216	87	218
FS	Mohokare	54.8	77.5	46.5	0.720	37.6	3.23	180	126	205	107
KZ	Mkhambathini	56.8	77.6	44.2	0.632	85.0	3.24	181	120	20	200
FS	Letsemeng	55.0	77.7	40.2	0.667	30.7	3.24	182	100	76	80
MP	Msukaligwa	56.1	78.1	36.3	0.686	37.7	3.26	183	68	118	108
EC	Ntabankulu	58.9	78.3	69.8	0.674	95.4	3.26	184	231	89	233
FS	Maluti a Phofung	55.4	78.4	56.1	0.683	53.5	3.27	185	177	106	137
KZ	Kwa Sani	57.6	78.7	23.5	0.657	52.0	3.28	186	8	59	133
KZ	Ezingoleni	57.6	78.7	60.0	0.648	90.8	3.28	187	194	44	214
KZ	Mfolozi	57.7	78.8	57.4	0.648	75.5	3.29	188	186	46	174
FS	Setsoto	56.1	79.4	50.2	0.704	40.5	3.31	189	140	169	115
MP	Lekwa	57.2	79.6	35.4	0.677	22.5	3.32	190	57	94	34
FS	Nala	56.7	80.2	51.3	0.684	30.2	3.35	191	147	110	75
EC	Port St Johns	60.5	80.3	72.0	0.730	96.5	3.35	192	233	222	234
NW	Naledi	59.2	80.4	39.9	0.693	37.0	3.35	193	97	140	100
NW	Greater Taung	59.2	80.4	60.9	0.687	82.5	3.36	194	199	119	192
NW	Lekwa-Teemane	59.6	81.0	40.2	0.706	28.6	3.38	195	99	180	69
KZ	Vulamehlo	59.7	81.5	63.1	0.620	94.0	3.40	196	209	11	225
KZ	Emnambithi/Ladysmith	59.7	81.5	48.4	0.700	43.8	3.40	197	134	161	121
KZ	Mpofana	59.8	81.6	37.4	0.668	45.2	3.40	198	75	78	122
KZ	Newcastle	60.0	81.9	51.7	0.724	30.5	3.42	199	150	215	79
KZ	uMuziwabantu	60.1	82.0	61.2	0.678	87.3	3.42	200	203	97	207
KZ	Maphumulo	60.1	82.0	66.2	0.688	94.2	3.42	201	221	121	226
EC	Mbizana	61.9	82.2	71.5	0.711	95.3	3.43	202	232	190	232
KZ	Hlabisa	60.3	82.3	63.8	0.724	87.9	3.43	203	213	214	210
KZ	uMshwathi	60.4	82.4	42.1	0.647	75.3	3.44	204	110	43	173
FS	Tswelopele	58.7	83.0	50.2	0.692	27.9	3.46	205	141	134	62
KZ	Ulundi	61.5	83.9	60.9	0.716	70.0	3.50	206	198	199	162
KZ	Jozini	61.8	84.3	66.5	0.784	84.0	3.52	207	222	234	194
FS	Nketoana	60.2	85.1	41.3	0.722	36.2	3.55	208	107	212	98
KZ	Dannhauser	63.0	85.9	64.2	0.625	77.0	3.58	209	215	15	183
KZ	Imbabazane	63.8	87.0	68.1	0.638	93.8	3.63	210	226	30	223
KZ	Nkandla	64.1	87.4	63.7	0.705	90.0	3.65	211	212	174	213
KZ	Umvoti	64.5	87.9	49.3	0.672	76.0	3.67	212	137	83	176
KZ	Umtshezi	64.6	88.1	52.4	0.751	49.8	3.68	213	153	230	130

Province	Municipality	IMR	U5MR	PHCR	GI	LS PHCR	SMR	Ranks			
								U5M	PV	II	LSP
KZ	Ntambanana	64.6	88.1	67.0	0.692	92.5	3.68	214	224	133	219
KZ	The Big 5 False Bay	65.1	88.7	56.5	0.775	72.5	3.70	215	184	233	167
FS	Phumelela	63.6	89.8	44.9	0.666	42.4	3.75	216	122	72	118
NW	Tswaing	67.5	91.6	56.3	0.706	65.1	3.82	217	182	178	151
NW	Kagisano/Molopo	68.8	91.6	59.2	0.739	82.9	3.82	218	189	227	193
NW	Mamusa	68.3	92.6	53.7	0.716	41.6	3.86	219	162	200	117
FS	Tokologo	64.9	93.3	42.6	0.713	56.9	3.89	220	114	196	144
KZ	Indaka	69.6	94.8	72.1	0.635	76.3	3.96	221	234	22	179
KZ	Nongoma	69.9	95.2	66.7	0.706	87.6	3.97	222	223	179	209
KZ	Mthonjaneni	70.0	95.3	51.0	0.676	76.6	3.98	223	143	92	181
NW	Maquassi Hills	72.7	98.4	53.7	0.725	35.8	4.11	224	161	216	93
NW	Ratlou	73.1	99.1	61.2	0.698	89.1	4.13	225	201	156	212
MP	Pixley Ka Seme	72.0	99.9	52.6	0.751	40.8	4.17	226	157	231	116
MP	Mkhondo	72.5	100.5	53.9	0.721	61.4	4.19	227	166	210	149
KZ	Nqutu	73.9	100.6	68.4	0.656	84.4	4.20	228	227	57	197
KZ	Okhahlamba	75.0	102.1	66.0	0.712	85.0	4.26	229	220	194	199
KZ	Abaqulusi	75.9	103.3	53.7	0.729	52.8	4.31	230	163	221	135
KZ	Emadlangeni	76.1	103.5	51.1	0.691	67.8	4.32	231	144	130	158
KZ	eDumbe	77.8	105.8	60.6	0.686	73.6	4.41	232	197	117	169
KZ	Msinga	79.4	107.9	68.7	0.699	95.1	4.50	233	228	160	231
KZ	uPhongolo	80.2	109.1	55.3	0.705	74.2	4.55	234	171	175	170

♠ Note the notations in the headings – IMR: Infant mortality rate per thousand; U5MR: under-five mortality rate per thousand; PHCR: per cent income poverty head-count ratio; GI: Gini index; LSPHCR: living standard poverty head-count ratio; SMR: standardised mortality rate; U5M: under-five mortality; IP: income poverty; II: income inequality; LSP: living standard poverty.

4.3 Estimates child mortality in relation to poverty and inequality

Having discussed the differentials in mortality among provinces and municipalities, it is quite important to address the matter in relation to poverty and inequality. It helps to appreciate how the disparities of child mortality among the geographical areas discussed above are associated with poverty and inequality. For this purposes, two measures of poverty and one measure of inequality are computed using the methods stated in the previous chapter. Poverty head count ratio (PHCR) based on per capita monthly income (poverty line of R515), and poverty based on living standard (LS) index (households in the first two LS quintiles are considered as poor), are the two measures of poverty while Gini index (GI) is computed as a measure of income inequality.

The proportion of poor people at national level is estimated to be about 40 per cent both in terms of income and LS index while income inequality as measured by Gini index is estimated to be 0.72. In order to understand the relationships at province level,

Table 4.5 explicitly presents the information for each province. There are large differences in poverty among the provinces which range from 30 to 54 per cent in terms of income and from 18 to 69 per cent in terms of LS index while the variation in inequality is very low, Gini index ranging only from 0.68 to 0.72. These economic disparities can be compared with health differentials as measured by under-five mortality rates (26-71 deaths per 1000 births). Western Cape (WC) has not only registered the lowest child mortality rate but also had the smallest measures of poverty and inequality. It is only 18 per cent of the people living in the province that are classified as poor in terms of living standard as compared to 30 per cent based on per capita monthly income. On the other hand, KwaZulu-Natal (KZN), the province with the highest child mortality rate, stands but third and second from the last in terms of poverty and inequality respectively. Limpopo and Eastern Cape (EC) are the first and second poorest provinces based on both measures of poverty while EC seemed to be relatively the most unequal province, followed by KZN. It is apparent that Limpopo is the only province which had lower mortality rate unlike its higher level of poverty in both dimensions considered in this research. Somehow on the contrary, although Free State has better poverty estimates, the third (LS) and fourth (income) lowest, child mortality is found to be much higher.

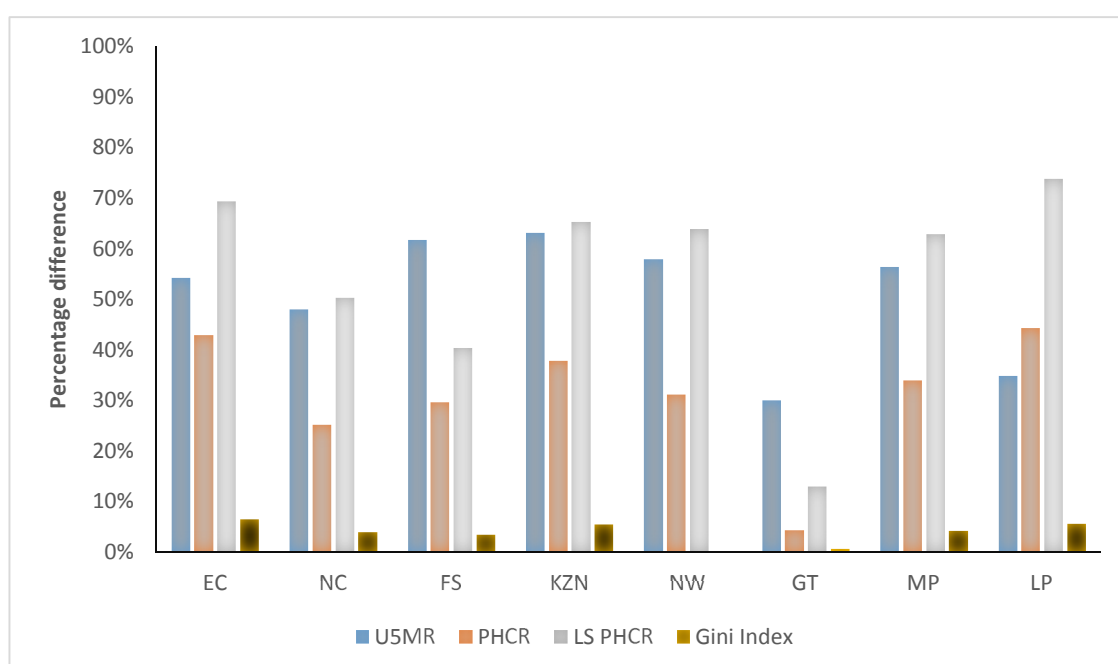
Table 4.5 Estimates of U5MR, poverty and inequality at province level

Province	U5MR	PHCR (Income)	PHCR(LS Index)	Gini Index
Western Cape	26.06	30.22	18.06	0.6771
Eastern Cape	57.04	53.06	58.83	0.7243
Northern Cape	50.24	40.38	36.39	0.7054
Free State	68.17	42.92	30.33	0.7022
KwaZulu-Natal	70.61	48.66	52.06	0.7164
North West	62.03	43.87	50.03	0.6790
Gauteng	37.19	31.59	20.77	0.6824
Mpumalanga	59.85	45.73	48.65	0.7071
Limpopo	39.98	54.34	68.79	0.7174
<i>ZA</i>	<i>49.95</i>	<i>40.73</i>	<i>40.22</i>	<i>0.7156</i>

Note: U5MR is per thousand while PHCRs are expressed as percentages

It is also attempted to make comparison of estimates from other provinces with Western Cape as it has the lowest estimates in terms of both child mortality and income poverty, living standard poverty and income inequality. Figure 4.10 displays the percentage deviations of each of the four quantities from the corresponding estimates of Western Cape Province. The prime differences are in child mortality and living standard followed by income poverty while the difference income inequality is the smallest in all the provinces.

Figure 4.10 Comparison of provincial estimates of U5MR, poverty and inequality with WC's estimates



The estimates of poverty and inequality for the 234 municipalities are also computed and are given together with the smoothed estimates of under-five mortality rates and other related statistics in Table 4.4. It is evident that in most cases both measures of poverty are positively related with child mortality in that municipalities with lighter mortality rates have lower proportion of people living under poverty and in municipalities with heavier child mortality have recorded higher proportion of poor people. In this regard, it must be noted that the poverty measure computed based on the living standard index has shown a stronger association with child mortality – correlation coefficient of 0.573, than the poverty measures computed based on per capita income alone – correlation coefficient of 0.475. In both measures, however, there are many exceptions in that lower poverty does not necessarily guarantee lighter

mortality and vice versa. For instance, although Thulamela, a municipality in Limpopo province, is ranked as the 195th and 184th poorest municipality in terms of income and living standard respectively, it has recorded the 13th lowest under-five mortality rate. Similarly, Mutale, another municipality in Limpopo, has the 23rd smallest under-five mortality while respectively scoring a rank of 206 and 208 in terms of income and living standard poverty. On the other hand, municipalities like Mpofana (in KZN province) with income poverty rank of 75th and Maquassi Hills (in NW province) with living standard poverty rank of 93 had registered among the highest mortality rates with ranks of 198th and 224th respectively.

The relationship between income inequality and child mortality, however is not as strong as the relationship between child mortality and poverty. In general, all municipalities experienced a very high level of inequality, Gini index ranging from 0.576 in Ngqushwa (in EC province) to 0.784 in Jozini (in KZN province) and 79 per cent of all the 234 municipalities scoring a Gini index greater than 0.65. Nonetheless, there is a weak positive correlation, $r = 0.271$, between income inequality and child mortality implying that on average there are more deaths in municipalities where the people are more unequal in terms of income than in municipalities with less unequal people. However, it is not surprising that there are inverse relationships between income inequality and child mortality in many municipalities including Nqutu and Dannhauser (both in KZN) with much lower inequality and higher mortality, and Knysna and Bitou (both in WC) with much higher inequality but lower mortality.

For a better understanding of the relationship among child mortality, poverty and inequality, municipalities are divided into poverty and inequality quintiles and the corresponding average under-five mortality rates are then computed in each quintile. This information is provided below in Table 4.6. In each of the three cases, an increasing trend of child mortality is observed along the quintiles, confirming that on average an increase in poverty and inequality is associated with an increase in mortality of children. However, the magnitude of the changes in mortality along the quintiles of income inequality (Gini Index) are smaller, which supports the points raised above that child mortality has stronger association with income and living condition than income inequality.

Table 4.6 Under-five mortality rates under poverty and inequality quintiles

Quintiles	Mean U5MR in Quintiles of		
	PHCR (income)	PHCR(LS index)	Gini Index
Q1	42.77	44.00	54.99
Q2	53.41	57.43	58.40
Q3	65.51	63.32	59.25
Q4	67.87	66.10	61.08
Q5	74.97	73.64	70.72
Corr coefficient	0.4749	0.5727	0.2706

Table 4.7 presents the poverty and inequality measures for the top and last 15 municipalities according to the child mortality rankings and their corresponding ranks in in poverty and inequality. All the top municipalities are in Western Cape except Thulamela (in Limpopo), City of Tshwane (in Gauteng), Nelson Mandela Bay (in Eastern Cape) and City of Johannesburg (in Gauteng) while the majority of the last municipalities are in KwaZulu-Natal followed by Mpumalanga (Mkhondo and Pixley Ka Seme), North West (Ratlou and Maquassi Hills) and Free State (Tokologo) provinces. This undoubtedly depicts the spatial accumulation of child mortality in the country. The top 15 best municipalities have recorded an average under-five mortality rate of 28.8 per thousand as opposed to 100.6 per thousand by the bottom 15 municipalities. If one is interested to compare these results with the average measures of poverty and inequality (the details are given in Table 4.4), the mean income poverty head-count ratios are 31 and 61 per cent respective for the first 15 and the last 15 municipalities while the mean living standard poverty head-count ratios are 23 and 76. The measure of income inequality (Gini index) has resulted in a mean value of 0.67 and 0.70 respectively for the top 15 and bottom 15 municipalities. All these give additional confirmation on the fact that child mortality is heavier in municipalities where poverty and inequality are worse, and that the association is weaker with inequality than poverty.

Table 4.7 15 best and worst municipalities in terms of under-five mortality and their associated rankings in poverty and inequality

Municipality	Province	U5MR	Ranks			Municipality	Province	U5MR	Ranks		
			PHCR	LS PHCR	GI				PHCR	LS PHCR	GI
City of Cape Town	WC	23.97	33	14	86	uPhongolo	KZN	109.08	171	170	214
Mossel Bay	WC	25.80	48	3	55	Msinga	KZN	107.91	228	231	76
Knysna	WC	26.62	52	60	170	eDumbe	KZN	105.77	197	169	88
Overstrand	WC	26.97	40	25	47	Emadlangeni	KZN	103.53	144	158	59
Bitou	WC	27.48	72	46	176	Abaqulusi	KZN	103.26	163	135	227
Stellenbosch	WC	27.69	44	24	104	Okhahlamba	KZN	102.08	220	199	201
George	WC	28.19	38	20	52	Nqutu	KZN	100.60	227	197	10
Drakenstein	WC	28.38	23	7	75	Mkhondo	MP	100.51	166	149	148
Breedde Valley	WC	30.40	27	43	50	Pixley Ka Seme	MP	99.89	157	116	234
Theewaterskloof	WC	30.48	21	28	42	Ratlou	NW	99.06	201	212	102
Thulamela	LP	30.60	195	184	123	Maquassi Hills	NW	98.44	161	93	230
Saldanha Bay	WC	31.18	19	1	26	Mthonjaneni	KZN	95.34	143	181	51
City of Tshwane	GT	31.29	24	31	68	Nongoma	KZN	95.24	223	209	128
City of Johannesburg	GT	32.18	34	15	146	Indaka	KZN	94.81	234	179	32
Nelson Mandela Bay	EC	32.28	104	11	144	Tokolologo	FS	93.34	189	193	205

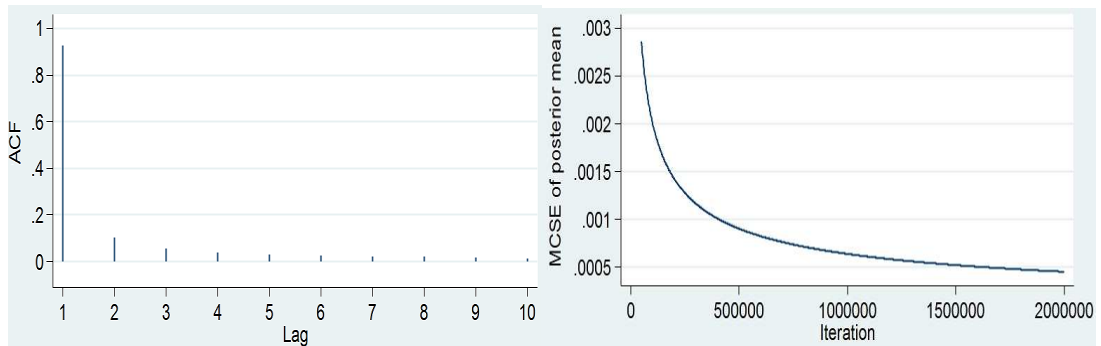
4.4 Results from multilevel logistic regression model

4.4.1 Model diagnostics

A three-level logistic regression model is fitted on the survival status of children born twelve months before the census. The parameters of the model are estimated using the Bayesian MCMC procedure by running the simulation for 1000 burn-in and 10000 monitoring period. After fitting the model, the reasonableness of the parameter estimates are assessed by looking at some diagnostics plots including the autocorrelation plots of successive iterations of the chains and Monte Carlo standard error plots for checking convergence of the posterior distributions. These is done for each of the fixed and random terms in the model and; as examples, Figure 4.11 presents the two plots for one fixed term (HIV variable) and one random term (municipal-level effect). In addition, the normal probability plots given in Figure 4.12 show that the assumptions of normality of the residual terms at municipality and province level are approximately maintained.

Figure 4.11 Autocorrelations of iterations at different lags and Monte Carlo standard error of posterior mean

a) For HIV fixed effect parameter estimate



b) For municipal-level random effect parameter estimate

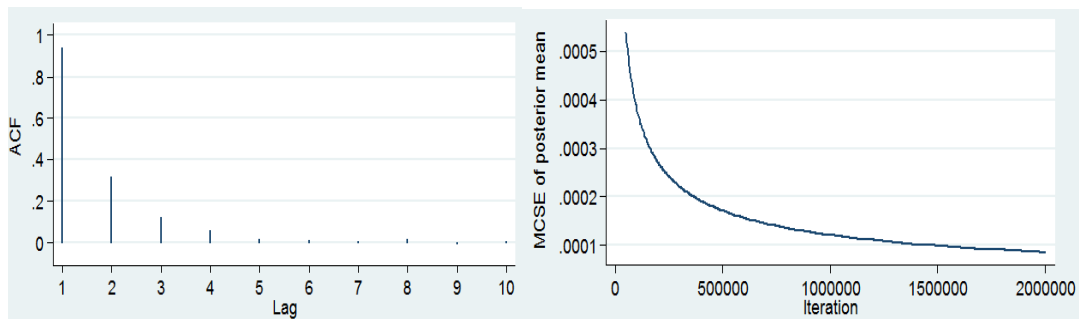
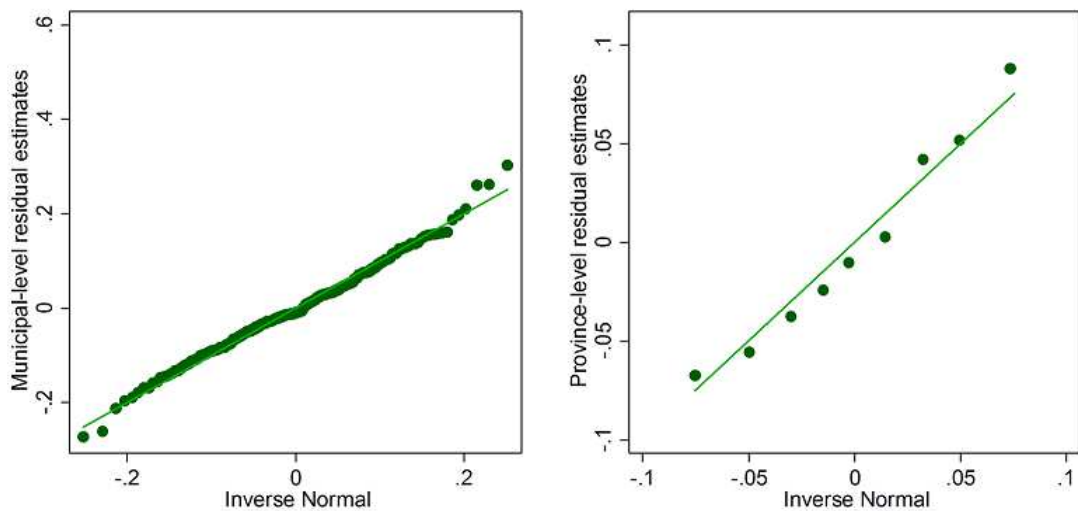


Figure 4.12 Normal probability plots for municipal-level and province-level residual estimates



4.4.2 Regression model output

The final result of the regression is as shown in Table 4.8. All parameter estimates are measured on the log-odds (logit) scale. In order to make more specific and meaningful inference about the effect of the risk factors on the mortality of children, the odds ratios (ORs) are given corresponding to each coefficient estimate in the same table. Note that

among the independent variables, proportion of poor people, income inequality and mean years of mother's education are measured at municipality level whereas HIV prevalence rate is computed at province level. All these four variables are dichotomised as higher and lower values of the respective quantities.

Table 4.8 Output from the multilevel logistic regression model

<i>Variable</i>	Mean	Std. Dev.	P-value	95% Cred. Interval	Odds
<i>Fixed effect parameters</i>					
Individual level					
<i>Cons</i>	(4.3871)	0.2111	0.000	(-4.811, -3.983)	0.0124
<i>Female child</i>	0.1937	0.0505	0.000	(0.096, 0.293)	1.2137
<i>Neonatal</i>	(0.1954)	0.0851	0.010	(-0.365, -0.033)	0.8225
<i>Mother's age at birth, 20-34 (Ref)</i>					
<20 years	0.0764	0.0752	0.155	(-0.069, 0.223)	1.0793
>34 years	0.0551	0.0750	0.230	(-0.093, 0.2)	1.0566
<i>Birth order, First birth (Ref)</i>					
2	(0.0075)	0.0697	0.458	(-0.142, 0.13)	0.9925
3	0.1812	0.0841	0.016	(0.017, 0.345)	1.1986
4+	0.3427	0.0889	0.000	(0.165, 0.514)	1.4088
<i>Mother's education, No/primary education (Ref)</i>					
<i>Secondary education</i>	(0.1743)	0.0712	0.009	(-0.314, -0.033)	0.8401
<i>Higher education</i>	(0.4929)	0.1369	0.001	(-0.759, -0.228)	0.6109
<i>Mother never married</i>	0.1234	0.0561	0.014	(0.014, 0.235)	1.1314
<i>Mother works</i>	0.2272	0.0712	0.001	(0.089, 0.366)	1.2550
<i>Mother is Black African</i>	0.3071	0.1107	0.002	(0.101, 0.526)	1.3595
<i>LS index quintiles, Q1 (Ref)</i>					
<i>Q2</i>	(0.1289)	0.0722	0.039	(-0.267, 0.014)	0.8791
<i>Q3</i>	(0.1519)	0.0801	0.026	(-0.309, 0.003)	0.8591
<i>Q4</i>	(0.3429)	0.0915	0.000	(-0.526, -0.172)	0.7097
<i>Q5</i>	(0.6988)	0.1336	0.000	(-0.961, -0.438)	0.4972
Municipal level					
<i>Higher proportion of poor</i>	0.0343	0.0843	0.216	(-0.129, 0.204)	1.0349
<i>More educated mothers</i>	(0.198)	0.0802	0.007	(-0.326, -0.003)	0.8204
<i>Greater income inequality</i>	0.1215	0.1405	0.103	(-0.141, 0.417)	1.1292
Province level					
<i>Heavier HIV prevalence</i>	0.3374	0.1095	0.004	(0.105, 0.541)	1.4012
<i>Random effect parameters</i>					
<i>Province effect (level 3)</i>	0.0154	0.0219	-	(0.001, 0.073)	1.0155
<i>Municipality effect (level 2)</i>	0.0511	0.0224	-	(0.010, 0.099)	1.0524

All coefficients of the four living standard dummy variables which are used as proxy indicator variables of poverty are negative and their 95% credible intervals excludes zero and hence relative to children who were in the first living standard quintile, those who were in the other quintiles were less likely to die. It can also be noted that, as expected, the better the living standard the less likely the child dies since the magnitude of the coefficients increases with the increase in quintiles – children from households positioned in the second, third, fourth and fifth wealth quintiles have 12, 14, 30 and 50 percent chances of survival compared to children in the first wealth quintile. Likewise, the income poverty has positive and significant coefficient entailing that children living in a household whose members earn a per capita income of less than the South African poverty line are more likely to die than children whose household whose members earn above the poverty line.

The two municipal level indicator variables: proportion of people under poverty and the level of income inequality as measured by Gini index, have positive coefficient although they are not significant at 95 per cent. It means that not only the level of poverty of the household but also the level of poverty and distribution of income of the community/municipality where the child lives affects the survival status of the child. A child is more likely to die in a highly poor and more unequal municipality compared to municipalities where there is lower poverty and inequality after having controlled for the effect of other risk factors. Considering the magnitude of the impact, it seems that the distribution matters more than the size of poverty in the area as the odds of dying of children in more unequal municipalities is 13 per cent higher than in less unequal municipalities while this likelihood difference is only 3.5 per cent between municipalities where poverty is higher and lower. Similarly, children living in municipalities where the average years of education of women is higher have better likelihood of survival irrespective of the education level of their own mother. They are about 16 per cent less likely to die than children living in areas where there is less education of mothers.

Considering the effect of HIV on mortality of children, it is apparent that its coefficient is positive and significant. Children in provinces with high HIV prevalence are 40 per cent more likely to die than children in other provinces after controlling other factors in the model. This indicates that HIV has the greatest impact on mortality as compared to the other community level variables considered.

The sex effect is positive and its 95% credible interval does not include zero, implying a significant positive effect of the sex of the child. More specifically, boys are 21 per cents more likely to die during their first year of life than girls, all else being equal. Similarly, age of the child significantly affects the mortality of the child in that children who survived the first month after birth are less likely to die than those who are less than one month old by about 18 per cent.

In terms of mother characteristics, the results in Table 4.8 show that mothers' age at the birth of the child is not statistically significant as the 95% credible interval contains zero. However, the estimated coefficients for the two dummy variables are positive confirming that children from mothers who are younger than 19 or older than 34 years at the birth of the child are more likely to die than children whose mothers are between 20 and 34 years old. The employment status of mothers is not also significant although it has positive relation with the mortality of children. It seems that the children of employed mothers have less probability of survival. All the other independent variables associated with mothers are significant which includes years of education, birth order, marital status and population group.

In accordance with the literature, the more education a mother gets, the less likely the mortality of her child is. Children whose mothers have completed secondary and higher education are 16 and 39 per cent respectively more likely to survive than those children whose mothers have no education or only have primary education. In addition, mothers having higher birth orders, mother who are never married or single mothers and mothers from African population group have a greater chance of mortality of their children relative to those mothers who have less birth orders, mothers who are not single and mothers from non-African population group. Specifically, the odds of survival of children of mothers having four or more children is 41% higher than first born children while third born children are 20% more likely to survive and second born children have less than one% chance of survival as compared to first born children. Similarly, there are 36 and 15% more survival chance by those children who are from non-Black African and non-single mothers respectively.

The random effects terms included in the model are also significant since the 95 per cent credible interval does not include zero in both cases. Hence, there is a unique effect for each province (level 3) and for each municipality (level 2) in addition to the

fixed effects discussed above. The reported mean values in Table 4.8 are the average random effect estimates of all provinces and all municipalities. The addition of the municipality specific effects as well as province specific effects makes the model more accurate than the fixed only model. Specifically, controlling the municipal and province level variations has on average increased the odds of death of children by 5 and 2 per cents respectively.

5. DISCUSSIONS AND CONCLUSIONS

This chapter first discusses the main results of the study and tries to see how they are compared with the findings in other studies so far. It then, describes the major limitations which must be noted in connection with the use of the results in the research and states some of the opportunities for future works. Finally, conclusion follows to pinpoint the key lessons one might take from the study.

5.1 Discussion of results

Although child mortality in South Africa has improved substantially in the last decade, after some period of reversal mainly due to HIV, the level is much higher than the mortality in many other countries' with similar economic development level. We believe that, in order to effectively address the problem and work towards further reductions of child mortality in the country it is essential that the efforts be focused more on lower administrative levels as opposed to concentrating only on the level of mortality at national level (Freedman, Waldman, Pinho *et al.* 2005). Hence, for these efforts to move forward, constructing reliable estimates of child mortality for small geographical areas should be considered as one of the first important steps. Consequently, the overall objective of this research was to produce estimates of child mortality rates for the provinces and municipalities of South Africa using the 2011 census data, and assess the differentials in relation to the level of poverty and inequality. In addition, studying the factors associated with child mortality in South Africa considering the hierarchical structure of the data and with special emphasis on poverty and inequality was the second main objective. In this chapter an attempt will be made to discuss the extent at which these objectives have been met. This involves discussing the reasonableness of the estimates of child mortality produced at national, provincial and municipal level and the validity of the results obtained on factors affecting child survival in comparison with other studies.

Estimates of infant and under-five mortality rates at national and province level are generated directly using household death data from the 2011 census. However, in attempting to estimate child mortality for smaller geographical areas it is often difficult to construct accurate estimates because population sizes also tend to be relatively small,

resulting in unstable estimates. One common approach that would help us to overcome this issue is to use Bayesian smoothing method. Hierarchical Bayesian model has been used to construct spatially smoothed estimates of child mortality for the municipalities of South Africa. The first level of the model uses the household mortality data from the 2011 South African census while in the next level the probability of a child dying before reaching age one is modelled using a binomial model with a spatially structured random effect. The prior distribution for this random effect is constructed using a conditional autoregressive (CAR) model which incorporates spatial dependence among neighbouring municipalities and allows for its impact to be greater for municipalities with more unstable data. The estimates are further improved by incorporating average years of women's education of each municipality and the provincial HIV prevalence rates of adults aged 15-49. It is assumed that the ratio of under-five mortality rate and infant mortality rate be the same at province level which helps us to get estimates of under-five mortality rates for the municipalities from the infant mortality rates obtained from the Bayesian spatial smoothing model.

Having derived the child mortality rates, the first important question has to be how the estimates are compared with those presented elsewhere. In this regard, the national level estimates can be compared with reports from Stats SA, Rapid Mortality Surveillance (RMS), ASSA model 2008, UN Inter-agency Group for Mortality Estimation (IGME), world population prospectus (WPP) and the Institute for Health Metrics and Evaluation (IHME). Table 4.1 presents the estimates of infant and under-five mortality rates from these institutions as well as the estimates from this research and estimates from a recently published paper by Udjo (2014). Given the degree of controversy about estimates of child mortality in South Africa and the fact that each of the institutions might have used different approaches and data sources to derive their corresponding values, it is fair to say that the estimates from this research are quite reasonable and consistent with most of these estimates. Relatively, both infant and under-five mortality rates from RMS are lower than the others, for instance they are less by 29 and 25 per cent compared to our estimates, while those from Stats SA seem to be a bit inflated. Despite these, the estimates from by Udjo (2014) are found to be highly exaggerated compared to the estimates from this research as well as the estimates from all other sources. It is very hard to have an infant and under-five mortality rates of 60 and 80 per 1000 respectively for South Africa in 2011 unless there is some problem with the data used or the method of estimation applied.

Table 5.1 Comparisons of national level infant and under-five mortality rates from various sources

Source	IMR per 1000 Births	U5MR per 1000 Births	Year estimate applies
ASSA model 2008	33.80	48.81	2011
UN IGME	35.00	47.00	2011
WPP	39.60	50.40	2011
RMS	28.00	40.00	2011
IHME	37.71	50.70	2011
Stats SA	39.10	56.60	2010
Udjo	60.00	80.00	2011
*2011 Census, Direct	37.12	49.41	2011
*2011 census, Smoothed	36.03	49.95	2011

* According to this research computation

In attempting to compare the provincial and municipal levels of estimates of child mortality rates it must be noted that there are very few sources to compare with, especially with regard to municipal level estimates. Table 5.2 helps to compare the provincial estimates in this study with estimates from ASSA 2008 model and the research paper by Udjo (2014). In comparing against the ASSA model estimates, our provincial estimates are reasonable and consistent for six of the nine provinces – with percentage differences ranging only from 0.2 to 12.6 per cent. The estimates for North-West (NW), Northern Cape (NC) and Free State (FS) from ASSA model, however, are underestimated by 38.2, 36.6 and 17.5 per cent respectively compared to our estimates. However, as in the national level the estimates by Udjo (2014) for all the provinces are much higher –percentage differences varying from about 28 to 51.

Table 5.2 Comparisons of provincial level under-five mortality rates from various sources

Province	ASSA	Direct	Smoothed	Udjo
Western Cape	26.53	24.75	26.06	36.1
Eastern Cape	65.25	55.96	57.04	75.6
Northern Cape	36.78	52.55	50.24	76.5
Free State	58.02	68.47	68.17	104.1
KwaZulu-Natal	62.74	68.78	70.61	102.9
North West	44.88	61.79	62.03	89.4
Gauteng	37.13	36.07	37.19	75.1
Mpumalanga	54.71	58.13	59.85	96.0
Limpopo	39.92	39.27	39.98	67.0
ZA	48.81	48.76	49.95	80.0

As there are no studies so far which have attempted to generate municipal-level child mortality estimates, it is not possible to compare the estimates computed for the municipalities. The magisterial district level under-five mortality rates derived by Bangha and Simelane (2008) using the 2001 census data may be compared roughly with our estimates though neither the geographical unit nor time reference points are the same. However, one can observe that the estimates for the magisterial districts are somehow underestimated to some extent as for some similar areas their estimates at that time (2001) are much lower than our estimates after ten years (2011). For instance, their provincial under-five mortality rates only ranges from 19 in Western Cape to 66 in Eastern Cape which are very unattainable estimates in 2001. This may be partly due to the fact that the 2001 census data has some problems as noted by Dorrington, Moultrie and Timaeus (2004) in their monograph.

Another way of evaluating the quality of the smoothed municipal level estimates is to compare the robustness of the estimates with the crude estimates and smoothed but not improved by women education and HIV prevalence rate. Table 5.3 describes some summary statistics concerning these estimates. It is evident from the table that the Bayesian method has produced more stable and accurate results compared to the crude estimates as they have smaller variation. On the other hand, incorporating women education and HIV prevalence rate into the hierarchical Bayesian model has very little impact on the overall estimates. However, the real benefit of this adaptation can be felt in individual municipalities whose level of education and HIV prevalence differ from those of nearby municipalities. In such cases, by incorporating these two variables into the construction of estimates of child mortality, these differences are recognised and more reliable estimates can be obtained. The correlations between the two covariates and child mortality rates are much stronger in the case of the Bayesian estimates than the crude rates. It is also very important to note that there are 11 municipalities with missing crude estimates of child mortality, but there are no municipalities with missing Bayesian estimates of child mortality. The general approach was also used by McKinnon (2010) to find under-five mortality rates for the municipalities of Brazil and it can be observed that our results are similar in that the use of Bayesian smoothing together with women education has improved the estimates reasonably.

Table 5.3 Summary statistics on crude and Bayesian estimates of U5M rates at municipal-level

Statistic	Crude estimates	Bayesian-Spatial only	Bayesian-with Education and HIV
No of municipalities	223	234	234
Mean	64.55	59.48	60.84
Median	57.41	57.44	58.18
Standard deviation	31.57	19.49	19.79
Coefficient of variation (%)	48.90	32.77	32.52
Minimum	8.72	24.64	23.97
Maximum	200.31	118.23	109.08
Correlation with Education	-0.34	-0.38	-0.51
Correlation with HIV	0.40	0.72	0.76
Missing municipalities	11	0	0

The child mortality differentials are believed to be highly associated with the level of poverty and inequality. Poverty in this research is measured both using income and living standard. Income poor people are those who earn an average monthly household per capita income of less than R515 while living standard based poverty is defined from an index constructed using factor analysis on a bunch of variables assumed to affect wealth or living standard of household members. Their living standard is considered to be poor if the index lies either on the first or second quintile while those household whose index lying in the third, fourth or fifth quintiles as considered to be non-poor. Our estimates of poverty seem reasonable. The estimates of poverty are quite reasonable compared to Stats SA estimates (StatsSA 2014b). For instance, Stats SA has estimated the percentage of people living under poverty line of R443 to be 32.3 per cent while our estimate is 41 per cent at R515 poverty line.

The proportion of poor people in provinces and municipalities are in general found to be positively correlated, as expected, with the level of child mortality in the respective areas – 95 per cent significant correlation coefficients of 0.49 and 0.58 respectively for income and living standard dimension of poverty. However, there are some exceptions in that higher poverty does not necessarily imply higher child mortality and vice-versa. Many municipalities in Limpopo province including Thulamela and Mutale, for example, have scored lower mortality rates although the levels of poverty remain very high in both dimensions of poverty. This may suggest that socioeconomic differentials are not the sole determinants of child mortality but a combination of many other factors too.

Having used the Gini coefficient as a measure of the level of income distribution with in provinces and municipalities, it is also found that income distribution is associated positively with child mortality. However, the degree of association is weak relative to that of poverty resulting in only a 0.17 significant correlation coefficient at municipal-level – significant at 95 per cent level of confidence.

In order to complement the descriptive results on the association of child mortality, and poverty and inequality, an individual level model is fitted using data on the survival status of children born twelve months before the census and its factor which include several demographic and socioeconomic variables. The hierarchical nature of the data was taken into account in the process by considering provinces, municipalities and children as third, second and first levels respectively – hence, fitting a three-level logistic regression model employing Bayesian MCMC procedure for estimating the parameters of the model. The results obtained from this regression model suggest that child mortality in South Africa is jointly determined by the observed individual demographic and socioeconomic characteristics of the child and mother, and by municipal and province level covariates, as well as unobserved municipal-level and province-level effects

Among the demographic factors incorporated in the model, only age of mother at birth is not significant and the direction of relationships, including for age of mother, are all in agreement with other studies before (Hobcraft, McDonald and Rutstein 1985; Hill and Upchurch 1995; Kembo and Ginneken 2009; Boco 2010). Higher birth order and sex of the child have greater impact on the likelihood of child survival compared to other demographic factors considered.

All the socioeconomic variables considered at level-one of the model are significant at 95 per cent confidence level and are in agreement with the results from other researches (Mosley and Chen 1984; Hobcraft 1993; Sastry 1996; Kabir, Islam, Ahmed *et al.* 2001) as well as our child mortality estimation results presented above. For instance, children of black African mothers have a higher risk of death as compared to other population groups while those who are from better educated mother have much lower risk of death. As expected, the living standard (LS) index, which is used as a measure of poverty, is highly significant too in that the higher the LS index of the household where the child lives the less likely the risk of dying. Note that because of

multicollinearity issue the household income poverty indicator variable is not included in the model – LS index and income poverty have a strong correlation coefficient of 0.85. Hence, in relation to poverty the result could be interpreted as, for example, children in the least poor and the second least poor household have more than 50 per cent and 30 per cent chance of survival respectively as compared to those living in the poorest households. Children living in municipalities where the level of income poverty and inequality is higher have greater likelihoods of death, though not statistically significant. Similarly but with greater confidence, the average years of schooling of women at municipal-level affects child survival positively while higher women HIV prevalence rate of provinces is highly related with higher risk of death of children as one expects. The results of the regression model also indicate small but statistically significant residuals which can convey province-level and municipal-level effects on the risk of dying, even after controlling for a range of child-level, municipal-level, and province-level variables.

5.2 Limitations of the study

All the analyses in this research are exclusively based on the 2011 South African census data. Therefore, the significance and reliability of the results depends on the quality of the census data which includes the quality of enumeration and data processing. It is obvious that any flaw in the census data might seriously impact the results in the research. Moreover, as the research is entirely based on cross-sectional data it is not possible to check the robustness of the methods applied with other sources of data, like previous censuses. This could not be done because the municipalities are not consistent across the censuses of South Africa conducted so far. The ideal approach would be to make use of two or more censuses which would also allow us to see the changes of the results through time in addition to helping us to judge the robustness of the methods applied in this study.

The assumptions made in converting infant mortality rates to under-five mortality rates at municipality-level that the ratios of under-five to infant mortality rates are the same for each province could also be considered as one limitation. Although it is a fair assumption to make, given the fact that the ratios have smaller variations even at province level, it is obvious that there could be some variations in the municipalities which would bring a small change to the estimated under-five mortality rates

The other main limitation is the unavailability of municipal level HIV prevalence rates, and hence the assumption that these prevalence rates are the same as the rates those at the respective provinces. Ignoring the HIV prevalence variation within provinces might especially impact the results of the regression model to some extent.

5.3 Scopes for future research

This section looks at some of interesting topics which are not addressed in this research but could be great opportunities for future research. One such case is estimating trends of child mortality rates for the municipalities of South Africa. This could be done by combining the Brass ‘children ever born/children surviving’ (CEB/CS) method of estimating child mortality together with Bayesian spatial smoothing technique. The 10 per cent sample of the 2011 census data released did not include the number of children surviving to a woman but it can be done with available data from other censuses or large surveys in future.

The other opportunity could be to reproduce the results of this research using data from two or more censuses or other sources of data so that it would be possible to see the changes in child mortality with the changes in poverty and inequality and other socioeconomic variables. In this regard, it is obvious that the use of longitudinal data would give better results.

5.4 Conclusions

The study primarily aimed to derive up-to-date estimates of child mortality for the municipalities and provinces of South Africa using the 2011 census data. This is achieved through the use of direct synthetic cohort and Bayesian spatial smoothing methods. It is revealed particularly that child mortality estimation at municipal level is possible which has never been attempted so far to the best of our knowledge. Clear and significant spatial differentials in child mortality are observed in the country – at province level, under-five mortality rate ranges from 26 deaths per 1000 births in Western Cape to 71 deaths per 1000 births in KwaZulu-Natal province, while at municipality level, it ranges from 24 deaths per 1000 births in the City of Cape Town to as high as 109 deaths per 1000 births in uPhongolo. Furthermore, the estimates obtained are reasonable and, those at national and province level are in agreement with results from many other researches.

The study also aimed to find out how the spatial differentials in child mortality in the country are associated with the level of poverty and inequality. For this purpose, poverty in income and living standard dimensions and the Gini index are computed for each municipality as well as for the provinces and the country using data from the same census. The results show that in fact child mortality is higher in municipalities which are poorer, although there are some cases where inverse relationship is observed like several municipalities in Limpopo province that though the level of poverty is very high, child mortality is much lower in comparison with many other municipalities. It is also shown that the distribution of income similarly matters to some extent as greater child mortality is observed in areas which are more unequal although the degree of association is not as strong as with that of poverty.

The last objective of the research was to investigate child mortality risk factors with special emphasis on the impact of poverty and inequality. The results from the multilevel logistic regression model of child survival suggest that most of the demographic and socioeconomic factors identified as well as the province and municipal level random effects are significant. The most determining factors are found to be HIV, living standard poverty, race, mother's education, birth order and sex of the child. These factors can bring from 50 to 21 per cent change on the odds of death of children. The municipal-level poverty and inequality variables, however, are statistically insignificant though their impacts on mortality are still positive.

Unlike its economic development status and despite policies put in place for reduction of child mortality in the country, South Africa's child mortality rate is still high and it is very unlikely that the country achieves the MDG goal number four. This research has claimed that one approach to bring better outcomes is to address the issues at lower administrative level and has tried to provide the evidences gained from the latest available census data. The results obtained may help the government to implement policies more effectively and make more focused decisions towards better reduction of child mortality in the country.

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