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Some Health Related Issues in Australia and Methodologies for Estimating Small Area Health Related Characteristics

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PREPARED BY
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ABOUT NATSEM

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GENERAL CAVEAT

NATSEM research findings are generally based on estimated characteristics of the population. Such estimates are usually derived from the application of microsimulation modelling techniques to microdata based on sample surveys.

These estimates may be different from the actual characteristics of the population because of sampling and nonsampling errors in the microdata and because of the assumptions underlying the modelling techniques.

The microdata do not contain any information that enables identification of the individuals or families to which they refer.

SUMMARY

This working paper addresses two major health related issues in Australia and provides an account of the methodologies that have been used by researchers for estimating small area health related characteristics. Findings reveal that tobacco smoking as well as overweight and obesity are two leading causes of burden of many deadly diseases and mortality in Australia. In addition, the overall social and economic costs of tobacco smoking as well as for overweight and obesity are huge, and rapidly increasing over time. A review on small area health related characteristics estimation demonstrates that a range of factors such as – social capital, socioeconomic disadvantages, geographical location and environmental factors, ethnic minority or immigrant status, social and economic class, demographic factors and lifestyle behaviours have significant effects on the variation of health related characteristics at small area levels. It is observed that there are three different sets of methodologies have been used by researchers in small area health related characteristics estimation which are 1) indirect standardisation and individual level modelling; 2) multilevel statistical modelling; and 3) spatial microsimulation modelling. Although each of these modelling approaches has its own strengths and weakness in relation to produce small area health related characteristics estimates, it seems that spatial microsimulation modelling shows significant robustness over the other methods, and may be the more precise means of estimating small area health related characteristics.

Key words

Australia, health related characteristics, methodologies, multilevel modelling, overweight and obesity, small area estimation, smoking, spatial microsimulation

1 INTRODUCTION

1.1 BACKGROUND

Health related characteristics of population in a society are significant to health promotion programs and to the provision of better health services. The efforts of feasible health planning generally target local areas, such as local health regions or small area health units. As well population specific health program planning often requires precise estimates of health behaviours of the population at small area levels. But health related data are not always available at such levels. Even if regional level knowledge of the quantitative dimensions of health related behaviours can be attained by conducting a costly sample survey, such surveys seldom generate reliable data at small geographic area such as Statistical Local Area (SLA) levels in Australia. Therefore alternative techniques are necessary to get small area estimates of health indicators.

Researchers or policymakers sometimes rely on national level or state level datasets to understand the health needs of their communities. This can be achieved by using the Small Area Estimation (SAE) techniques – commonly known as statistical models approach and geographical or spatial microsimulation modelling (Rahman 2008a). The SAE procedures can provide robust estimates of health behaviours of populations for small geographic areas to support comparisons within and between local areas such as SLA levels and state or national levels estimates. However it is unknown which small area technique produces the most valid, statistically reliable and precise estimates.

The basic problem with national or state level surveys is that they are not designed for efficient estimation at small areas (Heady et al. 2003). For any small area containing respondents to a survey, a conventional estimator of the prevalence of health related characteristics would be constructed from the survey data. Such conventional estimators mainly have the following limitations:

- prevalence estimates can only be computed for a subset of all areas which containing respondents to the survey; and

- for those small sampled areas the achieved sample size will usually be very small and the estimator will thus have low precision.

This low precision will be reflected in rather wide confidence intervals for the survey estimates that are statistically unreliable. Small area estimation using statistical models or spatial microsimulation techniques are therefore required to generate reliable small area level estimates. According to Harding et al. (2003) and Chin and Harding (2006), the national or state levels survey data or Confidentialised Unit Record Files (CURFs) data of the Australian Bureau of Statistics normally have, at best, only a broad geographical indicator of the state or territory levels in Australia, small area data are usually unavailable and they thus have to be synthesized/simulated. Due to the lack of enough sample information in small geographic areas, there is a lot of interest in creating simulated or synthetic estimators for small areas in Australia (Tanton 2007). However the estimates of small area health related characteristics such as - youth and adults smoking behaviours, characteristics of overweight and obesity etc at small area levels are not very common in Australia.

This paper addresses some important health related issues in Australia and discusses about the methodologies for estimating health related characteristics at small area levels.

The structure of this research is as follows. In rest of this introduction Section, major health related issues in developed countries, as well as in Australia are summarised. In Section 2, an overview of smoking in Australia is provided – that mostly includes smoking characteristics of adults, levels and trends of smoking, and characteristics of households smoking expenditure. In Section 3, overweight and obesity epidemic is addressed – which mainly focuses on method for measuring overweight and obesity, prevalence of overweight and obesity by some important socio-demographic and household factors, trends in overweights and obesity in Australia, and causes as well as consequences of overweight and obesity. In Section 4, a review of literature on small area health related behaviours estimation is provided. A range of methodologies such as multilevel and other statistical modelling and spatial microsimulation modelling for estimating small area health related characteristics are also discussed in this section. An overall discussion and final conclusions are precented in the last Section 5.

1.2 MAJOR HEALTH RELATED ISSUES IN DEVELOPED COUNTRIES

Health related characteristics may be conceptualized as person's intentions to achieve a certain level of health. According to Lindstrom et al. (2003), the intended level of health is determined by personal preferences for health per se, by individual preferences for the services provided by social organizations, and by constraints on time, money, psychosocial resources etc which face the individual. For example, tobacco smoking, drinking alcohol or foods habit and lifestyle characteristics associated with obesity are an individual behaviours that affects people's health.

There are lot of concern about different health related issues and its small area estimation in some developed countries. In UK, the National Centre for Social Research (NatCen) has been working on the issue of healthy lifestyle behaviours (Scholes et al. 2005). The NatCen research includes the issue of how the small area - synthetic estimation of healthy lifestyle behaviours should be used and the way in which the estimators have been developed. They used a statistical model based approach to estimate small area healthy lifestyle indicators which includes current smoking, obesity, fruit and vegetable consumption of children, fruit and vegetable consumption of adults and binge drinking. Besides Lindstrom et al. (2003) utilize a multilevel logistic regression model to investigate the influence of contextual and individual levels factors on daily smoking behaviour in Sweden. The study points out that area level social and economic disadvantage such as socioeconomic disadvantage, overcrowding and high crime rates influence individual smoking behaviour.

Moreover in the United States, health related characteristics such as smoking and obesity with physical activity are studied by several researchers. It has been observed that population level socioeconomic and health resource characteristics are important determinants of variation in hospitalization rates (Joines et al. 2003); small area level social and economic disadvantage influences individual smoking behaviour (Tseng et al. 2001). A study reveals that the state and county levels social capital in the US is associated with obesity and leisure-time physical inactivity (Kim et al. 2006). The analyses use a multilevel statistical models approach for multivariate analysis and provide some evidence for the promotion of social capital as a potential strategy for addressing the burgeoning obesity epidemic. In addition estimation of youth smoking behaviours in Canada is studied by Pickett et al. (2000). This study observed the small area prevalence of current smoking as well as smoking initiation among youth of aged 15-24 years. The authors identify the significant socio-demographic predictors for smoking behaviours in Canada. It is noteworthy to mention that to design effective tobacco control programs; recent estimates on the incidence and prevalence of smoking are useful.

1.3 HEALTH RELATED ISSUES IN AUSTRALIA

The 2003 Australian Burden of Disease Study indicates that tobacco smoking and obesity are the two leading causes of burden of disease in Australia. Tobacco smoking is the largest single preventable cause of death and disease in Australian society (Ministerial Council on Drug Strategy 1999; Cancer Council Australia 2006) and it was estimated that tobacco smoking was responsible for about 8 percent of the total burden of disease and injury for all Australians (AIHW 2006; Begg et al. 2007). However estimating the number of deaths due to tobacco smoking is difficult due to the fact that smoking is one of the prominent risk behaviour for a wide range of diseases.

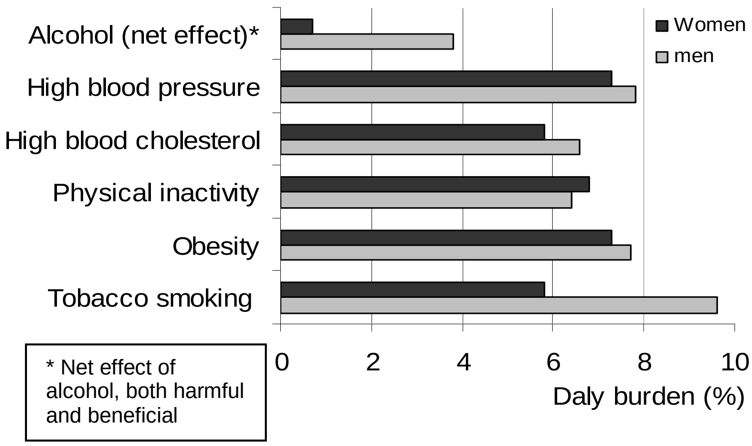

Figure 1-1: Ill-health burden attributable to selected risk factors in Australia, 2003
(Source:Begg et al. 2007; Australia 2020 Summit 2008)

Recently it has been reported that more than three-quarters (80 percent) of all deaths in Australia are attributable to six groups of diseases – which are cancers, cardiovascular problems, injuries, mental illness, diabetes and chronic respiratory disease (Australia 2020 Summit 2008). Cancers as well as cardiovascular diseases are remarked as the main annual national burden of diseases. Tobacco smoking, obesity, physical inactivity, high blood cholesterol level, high blood pressure, and alcohol are considered as the selected risk factors for those six groups of illness and then mortality (see, Fig. 1-1). Almost one in four adults (that is 23 percent) currently smoked; 21 percent are regular daily smokers and 2 percent smoked less often than once a day, while 47 percent reported that they had smoked occasionally (ABS 2006b). The daly burden of illness attributed to the risk factor smoking is 10 percent for men and 6 percent for women, and about 18 percent of Australians is daily smokers (Australia 2020 Summit 2008). In addition the report also indicates three groups of risk factors to health in Australia – which are lifestyle behaviours (such as tobacco smoking, alcohol, physical inactivity, illicit drugs, low fruit and vegetable consumption, unsafe sex etc) physiological states (obesity, high blood pressure, high blood cholesterol, osteoporosis etc) and social and environmental factors (urban air pollution, intimate partner violence, child sexual abuse, occupational exposures and hazards etc). Therefore the small area estimates of health related characteristics should be very informative for federal, states, and local levels policy makers to address the health challenges in Australia and to plan for advance health promotion programs integrated with healthy lifestyle behaviours.

2 SMOKING IN AUSTRALIA: AN OVERVIEW

The health related characteristic tobacco smoking is an important and preventable cause of death and many illnesses (Hill et al. 1998; Stephens and Siroonian 1998). It has been reported that a large number of deaths are attributable to smoking, and tobacco smoking is not only a major cause of respiratory sickness, cancer and circulatory disease, it also contributes huge burdens to the society in terms of lost economic productivity and health care expenditure (see Pickett et al. 2000 and references therein). Each year there are an estimated 1.2 million new cases of lung cancer around the world and among them almost 90 percent cases are attributable to smoking (Stewart and Kleihues 2003).

Smoking is the largest single cause of death in Australia. Some diseases – in particular cancer that mainly attributed from smoking causes a large number of deaths. A study reveals that about eight thousands Australians have been died in 2003 from smoking-related cancer (Begg et al. 2007). Besides smokers have a higher risk of contracting some common illnesses which are - cardiovascular diseases, respiratory diseases, and bowel, eye, mouth, dental muscular diseases as well as reproductive diseases.

This section provides an overview of smoking in Australia – that effectively focus on the level and trends of smoking, smoking characteristics of adults, and smoking expenditure of Australians by various socioeconomic and households attributes. Some of the consequences of tobacco smoking in Australian society are also reported here.

2.1 LEVEL AND TRENDS OF SMOKING

The levels of smoking for males are higher than the levels of smoking for females in Australia. The estimated prevalence of tobacco smoking among Australian males aged 18 years and over was 26 percent in 2004-05, while among females the prevalence rate was estimated to be 20 percent; this average the prevalence rates of tobacco smoking to 23 percent for Australian adults (see Fig.2-1).

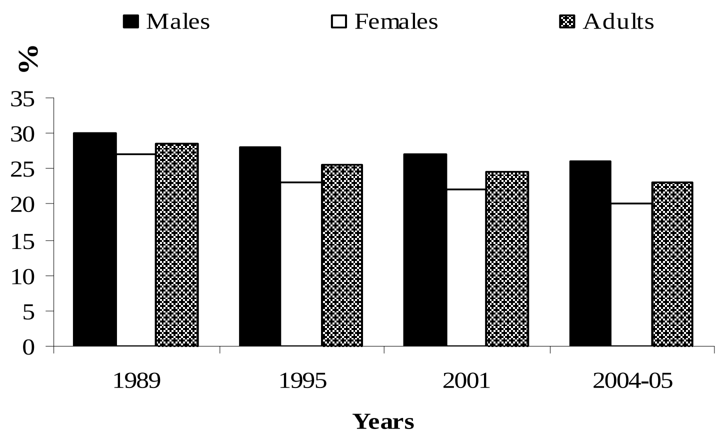

Figure 2-1: Level and trend of smoking prevalence in Australia's adults
(Source: Hill et al. 1998; National Health Surveys 1995, 2001 and 2004-05 (ABS 1995, 1996, 2002, 2006c))

In addition the trends in tobacco smoking for both males and females have steadily decreased during recent decades. Figure 2-1 demonstrates that over the period 1989 to 2005, the average prevalence of tobacco smoking among Australian adults decreased by nearly 6 percent – from about 29 percent to 23 percent. Note that although the female smokers rate within this time period decreased rationally by about 7 percent, the male smokers' rate declined by only 4 percent.

2.2 AGE AND SEX SPECIFIC SMOKING RATE IN 2004-05

Table 2.1 shows the age and sex specific tobacco smoking rates among Australian adults. Smoking rates are highest in younger age groups for both of males and females. In particular, the highest rates of smoking for males were reported in the 18-24 years age group (34 percent) and for women in the 25-34 years age group (26 percent). The smoking rates among Australian adults decreased with their increasing age.

Table 2-1: Age and sex specific smoking rate among adults in Australia

	Percentage of population		
Age group	Males	Females	Adults
18-24	34	25	29.5
25-34	33	26	29.5
35-44	32	25	28.5
45-54	26	22	24.0
55-64	21	14	17.5
65-74	13	9	11.0
75+	5	4	4.5

(Source: National Health Survey 2004-05 (ABS 2006c)

2.3 HOUSEHOLDS EXPENDITURE ON TOBACCO SMOKING

The 2003-04 household expenditure survey reveals that about 26.3 percent households in Australia have weekly expenditure on smoking products. From weekly income, 8.3 percent of Australian households spent more than 50 dollars for smoking; among them 3.9 percent spent more than 75 dollars (see fig. 2-2). Additionally one in each ten households has up to 25 dollars weekly expenditure on tobacco products and 8.4 percent households spent more than 25 dollars to 50 dollars.

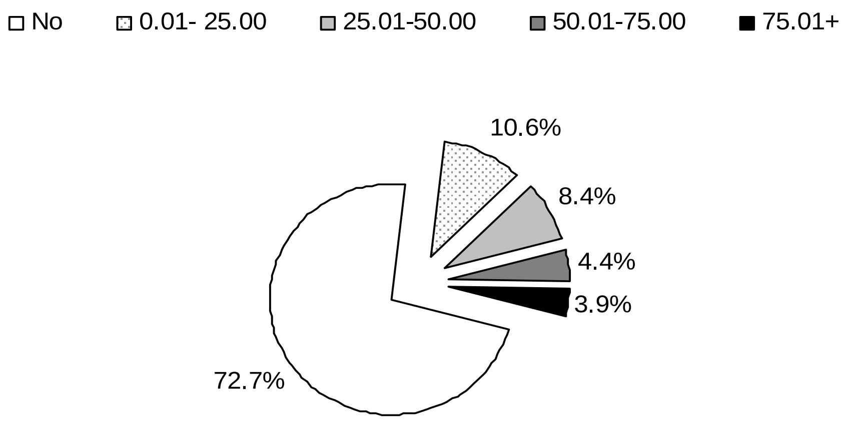

Figure 2-2: Households weekly expenditure for smoking in Australia, 2003-04
(Source: The 2003-04 Household Expenditure Survey, Australia (ABS 2006a))

2.4 HOUSEHOLDS INCOME AND SMOKING EXPENDITURE

Figure 2-3 shows the weekly income distribution for Australian households. Households have negative, zero and a weekly income more than 5751 dollars are excluded from this distribution. Result reveals that more than half (53.4 percent) of the Australian households have weekly total income of 1 to 1000 dollars among them 17.7 percent households have weekly income between 251 and 500 dollars. About 8 percent of households have weekly income less than or equal to 250 dollars. Besides, nearly 12.8 percent of households in Australia have weekly total income more than 2000 dollars. The average weekly total income of a household in Australia was approximately 1110 dollars in 2003-04 which indicates that three-fifths (59.0 percent) of Australian households have weekly total income below the average value. Moreover, the median weekly income of Australian household was about 933 dollars.

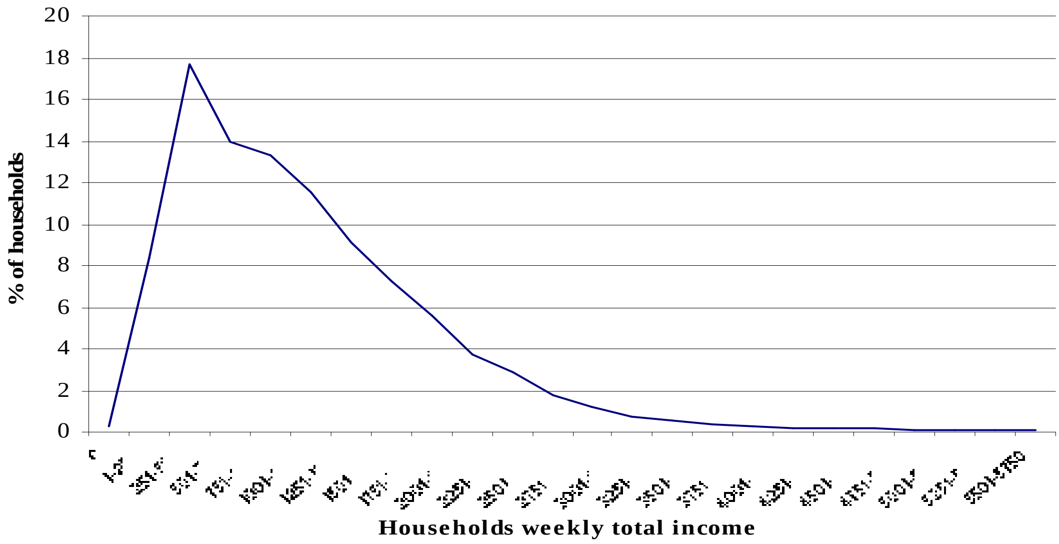

Figure 2-3: Distribution of weekly total income for the Australian households
(Source: The 2003-04 Household Expenditure Survey, Australia (ABS 2006a))

The percentage distribution of households having smoking expenditure by their weekly income is provided in table 2-2. For household within weekly total income 251-500 and 751-1000 dollars the differentials of smoking expenditures are the highest and the lowest respectively. In fact, households in the weekly income levels between 1001 and 1750 dollars have higher expenditures (more than 75 dollars per week) on tobacco products compared with households of other income levels. The proportions of households having more than 75 dollars smoking expenditure are lowest in the income group less than 250 dollars, but for the lower smoking expenditure class (up to 25 dollars per week) the proportions of households are higher within this less earner group and the highest in the income level 251-500 dollars. In different weekly income levels, however, the differentials of smoking expenditures fluctuate and a pattern of smoking behaviours in accordance with various range of household smoking expenditure comes into view (see fig. 2-4). In general, the analyses demonstrate that smoking expenditures of Australian households increase with weekly income levels up to 1000 dollars and then decrease with increasing income.

Table 2-2: Distribution of households having smoking expenditure by weekly income, 2003-04

HH weekly income	% of households within different levels of smoking expenditure			
	0.01-25.00	25.01-50.00	50.01-75.00	75.01+
1-250	9.9	6.7	4.6	3.4
251-500	18.5	14.1	9.5	11.6
501-750	13.5	16.4	17.1	13.1
751-1000	15.2	16.0	15.5	14.6
1001-1250	11.7	13.1	12.8	14.2
1251-1500	9.4	9.8	8.9	14.2
1501-1750	5.8	7.2	10.2	11.2
1751-2000	5.0	4.8	7.9	5.6
2001-2500	6.3	6.2	5.3	7.5
2501+	4.8	5.5	8.2	4.9

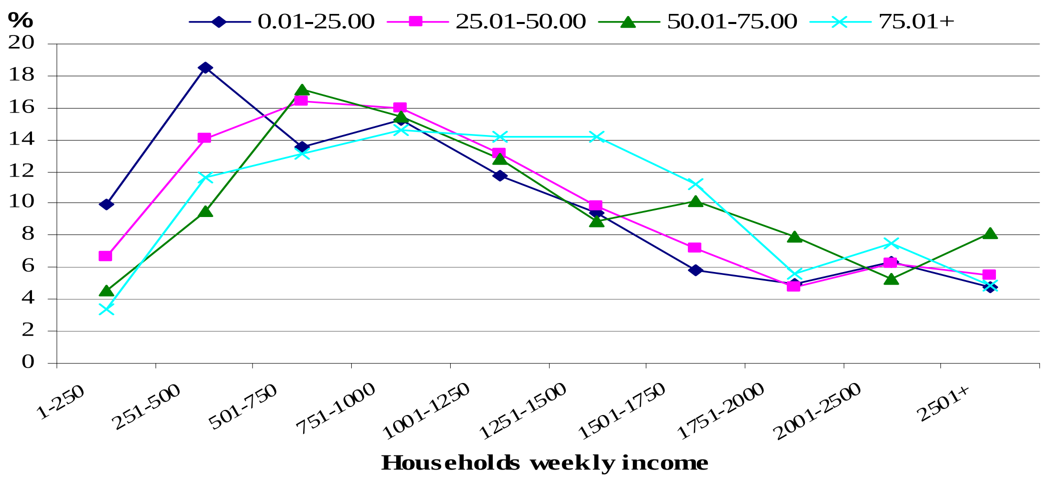

Figure 2-4: Distribution of households by their weekly income and smoking expenditure

2.5 TENURE TYPE AND SMOKING EXPENDITURE

Percentage of households having different levels of smoking expenditures is given in figure 2-5 according to tenure type. Renter households have higher smoking expenditure than households owning house without or with a mortgage as well as other tenure type. Nearly 40 percent of renting households have some smoking expenditure, in which 16.7 percent households have weekly tobacco expenditure up to 25 dollars.

Moreover house owner with a mortgage have relatively higher expenditure on tobacco products compared to house owner without a mortgage.

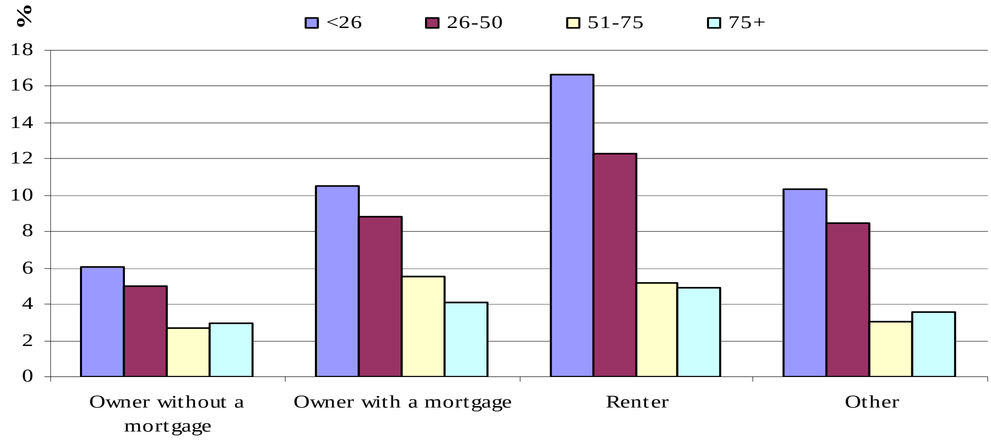

Figure 2-5: Distribution of households by tenure type and smoking expenditure

2.6 EMPLOYMENT STATUS AND SMOKING EXPENDITURE

Distribution of households by their employment status and smoking expenditure is given in figure 2-6. Households with unemployed reference person have more smoking expenditure than households with employed reference person or reference person not in labour force. It is remarkable that a half of the households with

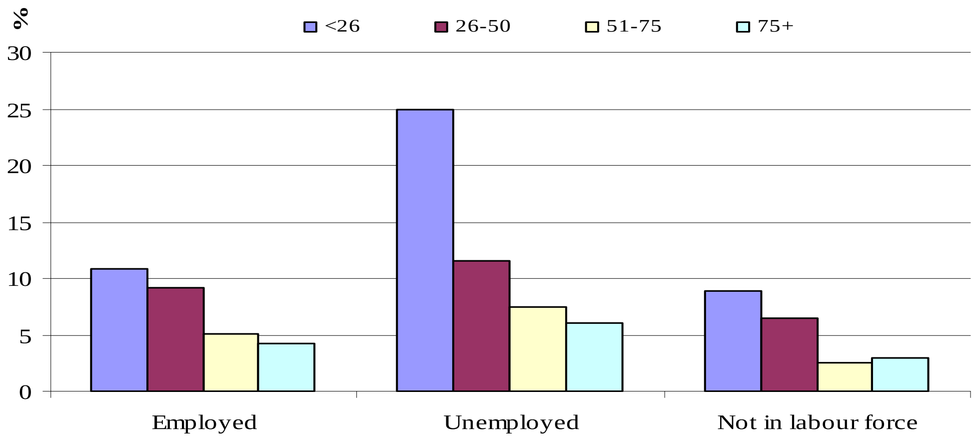

Figure 2-6: Distribution of households by employment status and smoking expenditure

unemployed reference person have relatively higher expenditure on tobacco products and about 14 percent of these households have smoking expenditure more than 50 dollars.

2.7 UNEMPLOYED PERSONS IN HOUSEHOLD AND SMOKING EXPENDITURE

Table 2-3 presents the distribution of Australian households by the levels of smoking expenditure and number of unemployed persons in the household. In Australia, all levels of smoking expenditure are more common in households with two or more unemployed persons than households with no or one unemployed persons. For instance a quarter of households (25 percent) with unemployed persons have weekly smoking expenditure up to 25 dollars which is nearly 12 percent and 17 percent more than households having one unemployed person and no unemployed persons respectively. Besides only 4 percent households with no unemployed persons have the highest level (more than 75 dollars per week) of expenditure on tobacco products. Whereas, roughly 9 percent households having unemployed persons spent more than 75 dollars per week for smoking expenditures.

Table 2-3: Distribution of households having smoking expenditure by no. of unemployed persons in the household, 2003-04

Smoking expenditure	No. of unemployed persons in the HH		
	0	1	2+
<26	8.3	13.4	25.0
26-50	7.1	10.7	12.5
51-75	6.5	12.7	15.6
75+	4.1	8.8	9.4

(Note: figures are in percentages)

2.8 SOME CONSEQUENCES OF TOBACCO SMOKING IN AUSTRALIA

In Australia, smoking is the largest single cause of death and a key risk factor for the three diseases – lung cancer, heart disease and cerebrovascular disease that cause most deaths (ABS Report 2006). For instance, smoking cause an estimated 10,378 new cases of cancer and there were 7,727 deaths from smoking-related cancer in 2003, of those deaths more than 80 percent was for lung cancer (for example, see Begg et al. 2007 and the Cancer Council website: http://www.cancercouncil.com.au/default.asp for more details) . In addition to an increased risk of cancer, smokers have an increased risk of contracting a large range of illnesses including cardiovascular diseases, respiratory diseases, bowel, eye, mouth, dental muscular, reproductive diseases etc. Moreover in 1998 – 99, the social costs of tobacco smoking in Australia were an estimated to be 21.1 billion AUD, about 2.3 percent of the gross domestic product (Cancer Council NSW 2007). The overall social costs of tobacco smoking continue to increase to 31.5 billion dollars by 2004-05 (Collins and Lapsley 2008).

2.9 CONCLUDING REMARKS

An overview of tobacco smoking for Australian adults aged 18 years and over has given in this section. Findings reveal that smoking rate is higher among younger aged adults for both sexes and it decreases with increasing age. The men smoking rate is higher than the women smoking rate among all age groups. Besides the trend of adult smoking is slowly decreasing during recent decades, and the current prevalence rate of tobacco smoking is about 23 percent. In addition more than a quarter of households in Australia have weekly expenditure on tobacco products, and nearly one in each ten households spent more than 50 dollars per week for smoking. The smoking expenditure of Australian households increases with increasing levels of weekly income up to 1000 dollars and then decreases with increasing income. Note that more than a half of the Australian households have total income between one and a thousand dollars per week. Moreover renter households have higher smoking expenditure than households owning dwelling without or with mortgage as well as other tenure type, and households with unemployed reference person have relatively more smoking expenditure than households with employed reference person or the reference person not in labour force. All levels of smoking expenditure are more common within households having two or more unemployed persons. Furthermore smoking is the largest single cause of death and a key risk factor for some deadly diseases in Australia and the overall social costs of tobacco smoking are increasing over time.

3 OVERWEIGHT AND OBESITY IN AUSTRALIA

The growth in overweight and obesity rates is becoming a major public health concern in many developed countries. Obesity as well as overweight is acknowledged to be at epidemic levels worldwide, with Australia being one of the worst affected nations. In addition the rapidly rising prevalence of obesity is taking a huge toll on global health (Wickelgren 1998; White 2003). It is well recognized that excess weight increases the risk of developing diabetes, cardiovascular disease, high blood pressure, and many others including cancer of the breast and bowel (World Health Organization 2000).

Overweight and obesity is one of the leading causes of burden of disease and mortality in Australia (Begg et al. 2007). Figure 1-1 show that obesity was responsible for about 7.5 percent of the total burden of disease and injury for Australian population in 2003; among them 7.7 percent of total for males and 7.3 percent of total for females. It has also been estimated that overweight and obesity and their associated illnesses cost Australian society and the governments a total of 21 billion dollars in 2005 (Access Economics 2006). Besides a study based on data from the United States suggests that a severe level of obesity (BMI$\geq$ 35) during early adulthood (aged 20–30 years) may reduce a life expectancy by 3 years or more (Fontaine et al. 2003). As well, as impacting on different illness and mortality, overweight and obesity has been shown to be associated with psychological and social problems (World Health Organization 2000). Overweight and obese people may be subject to discrimination and negative attitudes surrounding body weight.

This section addresses the overweight and obesity epidemic in Australia. It mainly focuses on the method for measuring overweight and obesity, prevalence of overweight and obesity by some important socio-demographic and household factors, trends in the prevalence of overweights and obesity, and causes as well as consequences of overweight and obesity in Australia.

3.1 METHOD FOR MEASURING OVERWEIGHT AND OBESITY

Although body mass index (BMI) and waist circumference are two methods for measuring overweight and obesity in the population, BMI is more commonly used than waist circumference and it is an internationally recognized standard index for grading overweight and obesity in adults. The body mass index is based on height and weight measurements of an individual. It is a weight-for-height ratio calculated by dividing individual weight in kilograms by the square of height in metres (kg/m^2). As people are more likely to know their height and weight than their waist circumference, BMI is a popular measure of overweight and obesity in the settings of population surveys, particularly in self-report surveys. Following table (3-1) shows the standard cut-off points of BMI for Australian adults recommended by the World Health Organization (2000).

Table 3-1: Cut-off points of BMI for Australian adults aged 18 years or over

BMI ((kg/m^2)	Classification of health status
BMI < 18.5	Underweight
18.5 – 24.9	Normal/good health
25.0 – 29.9	Overweight
BMI ≥ 30	Obese

(Source: World Health Organization 2000)

Among people in adult age, a person with a BMI greater than $25kg/m^2$ is considered overweight, while a BMI greater than $30kg/m^2$ is considered obese. At the other end of the BMI spectrum, a person with BMI less than 18.5 kg/m^2 is considered underweight and this health status is associated with malnutrition and poor health. However underweight is mainly a critical health problem in developing countries. Note that the above cut-off points may not be suitable for all ethnic groups as Australia is a multicultural society. For instance, people from the Asians ethnicity may have equivalent levels of risk at lower BMI or people from the Polynesians ethnicity may have equivalent levels of risk at higher BMI compared with the standard population.

3.2 PREVALENCE AND TRENDS OF OVERWEIGHT AND OBESITY

The National Health Survey 2004-05 of Australia shows that about 62 percent of males and 45 percent of females aged 18 years and over are overweight or obese and they average more than half of the Australian adults are overweight or obese (ABS 2006b). The data showed a similar prevalence of overweight and obesity for each state and territory (see fig. 3-1). Obesity rates ranged from about 17 percent in Victoria to 20 percent in South Australia, and overweight rates from 34 percent in Queensland to 36 percent in Victoria. In addition the total (overweight + obese) prevalence rate was the highest in Tasmania (about 56 percent) and the lowest in both Western Australia and the Australian Capital Territory (about 53 percent). Note that figures for Northern Territory were not available for state level comparison.

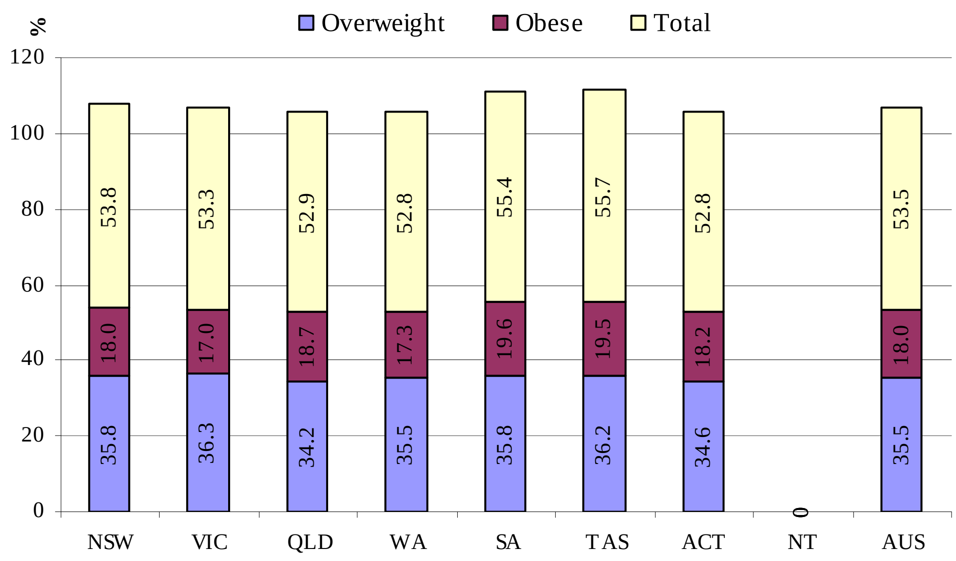

Figure 3-1: Prevalence of adults overweight and obesity in Australia, 2004-05
(Source: after http://www.aihw.gov.au/publications/aus/ah06/ah06-c07.pdf)

Moreover the prevalence of overweight and obesity increased significantly between 1995 and 2004–05 surveys (ABS 2006c). Compared to the estimates from previous survey the proportion of adults classified as overweight or obese has increased by about 10 percent for men and 8 percent for women from 52 percent and 37 percent respectively in 1995. The prevalence of obesity among Australian adults in 1995 and 2004–05 surveys was about 11 percent and 16 percent respectively, while the prevalence of overweight also increased noticeably between 1995 and 2004–05 surveys from about 30 percent to 33 percent.

3.3 AGE AND SEX SPECIFIC PREVALENCE RATES OF OVERWEIGHT AND OBESITY

Figure 3.2 reveals that the prevalence of overweight and obesity for males are higher than that for females in all age groups. In general, the prevalence rates of overweight and obesity for both men and women increased gradually up to the older age group 55-64 years, and then the prevalence rates decreased with increasing age. A sharp increasing was observed between younger age groups (18-24 and 25-34 years) compare to other age groups. However, the prevalence rate for males was more sharply increased than the prevalence rate for females. In contrast, between older age groups (65-74 and 75 years and over) the prevalence rate of overweight and obese for females decreased rapidly than the rate for males.

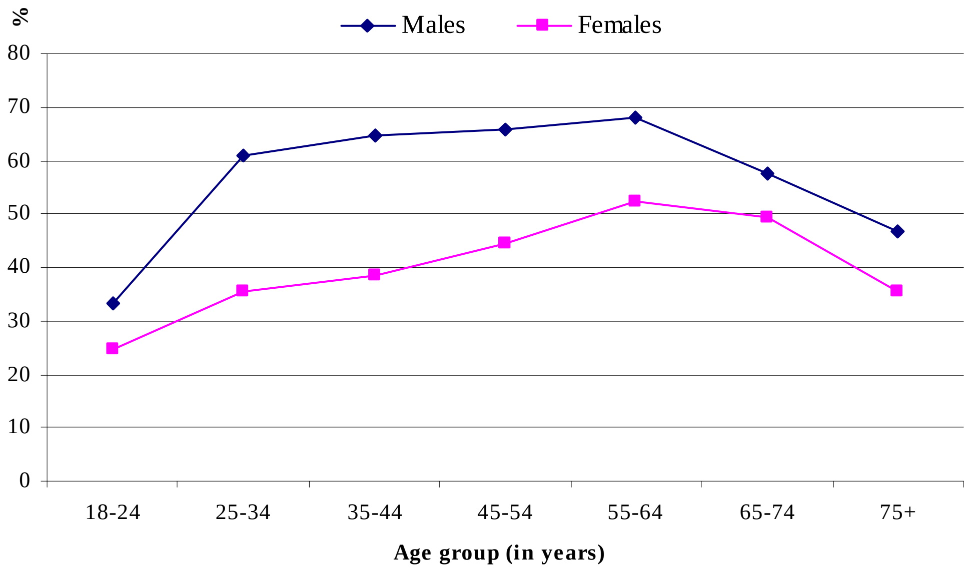

Figure 3-2: Overweight and obesity for males and females by age groups, 2004-05
(Source: National Health Survey, Australia 2004-05 (ABS 2006c))

Age and sex specific recent statistics of the prevalence of obesity are given in table 3-2. In Australia about 20 percent of males and 22 percent of females aged 18 years or more are obese. Obesity is more common in middle to older aged Australians and the prevalence rates of obesity are highest in 55-64 years age group for both sexes (25.8 percent for males and 35.6 percent for females). In addition younger aged females are less prevalently obese than males. Figures show that about 2 percent more males are in obesity condition than females within the age groups 18-19 and 20-24 years.

Table 3-2: Age and sex specific obesity rate among adults in Australia

Age group (Years)	Prevalence of obesity (%)	
	Males	Females
18-19	8.6	6.6
20-24	11.1	9.3
25-34	19.4	13.5
35-44	19.9	21.2
45-54	23.2	29.2
55-64	25.8	35.6
65-74	22.2	31.9
75+	14.2	16.9
Adults	20.3	22.4

(Source: after Access Economics 2008)

3.4 PREVALENCE OF OVERWEIGHT AND OBESITY BY NON-SCHOOL EDUCATION

Table 3-3 presents the prevalence rates of overweight and obesity for Australian adults by their highest non-school educational qualification. Adults with a diploma or higher education qualifications were less likely to be obese than those with other or no post-school qualifications. In 2004-05, approximately one adult in each fifth adults (20 percent) of those without a non-school educational qualification, and 19 percent of those with other non-school qualifications (for example, trade certificate), were classified as obese. By comparison, nearly 13 percent of those with a diploma or higher education qualification were classified as obese. Moreover about 37 percent of Australian who hold other non-school educational qualification was in an overweight condition.

Table 3-3: Non-school education of adults and overweight and obesity, 2004-05

Highest non-school educational qualification	BMI category*	
	Overweight	Obese
Other educational qualification	36.9	19.3
No non-school education	35.5	20.4
Diploma or higher education	34.8	12.9

*BMI category are based on table 3.1 and figures are in percentage

(Source: National Health Survey, Australia 2004-05 (ABS 2006c))

3.5 PREVALENCE OF OVERWEIGHT AND OBESITY BY HOUSEHOLD INCOME

The prevalence of overweight and obesity of adults by household income levels are given in table 3-4. Result shows that the prevalence of overweight increases with household income levels, where as the prevalence of obesity decreases with the increasing levels of household income. Adults in a high income level households were less likely to be obese than those within a middle or low income levels households. For instance, about 21 percent adults lived in a low income household were in obese situation - which is almost 6 percent more than of those lived in a high income household (14.9 percent). Besides about 32 percent and 36 percent of adults were classified as obese who were resided in low and middle income levels households respectively. By comparison, nearly 38 percent of high income level households' adults were classified as obese that is approximately 6 percent more than for low income group adults.

Table 3-4: Income of households and overweight and obesity among adults, 2004-05

Household income levels**	BMI category*	
	Overweight	Obese
Low income	32.3	20.6
Middle income	35.7	17.3
High income	37.6	14.9

*BMI category are based on table 3.1 and figures are in percentage
**Gross weekly equivalised household income. Low, middle and high income levels are classified by households are in the lowest, third and highest quintiles of household income distribution

(Source: National Health Survey, Australia 2004-05 (ABS 2006c))

3.6 Causes of overweight and obesity

Overweight and obesity is a health condition of excess body fat which mainly occurs when the energy intake from foods and drink is greater than the energy expended through physical activity over a period of time. A wide range of factors may be implicated in rising levels of overweight and obesity, some of the key causes are - lack of exercise, eating more calories/energy-dense foods than utilized, sedentary lifestyles, poor dietary habits, chronic stress, changes in family structures and dynamics, as well as genetic factors. Recent research reveal that increasing rates of obesity can be attributed to both a rise in energy intake and a decline in physical and incidental activity (World Health Organization 2000; Catford and Caterson 2003). For illustration, the mean energy intake increased by 15 percent among males and 12 percent among females in Australia between 1985 and 1995 (Cook et al. 2001). At the same time, physical activity levels of Australians have declined over the last few decades, as in most developed countries.

Besides overweight and obesity is not only a health but also an economic phenomenon. The economic causes of obesity is studied by Finkelstein et al. (2005). The authors claim that technological advancements is a core economic causes of obesity, and overweight and obesity may result from poor information and addictive behaviour and/or as a result of living in an increasingly obesogenic environment.

3.7 Consequences of overweight and obesity

Obesity and overweight not only burdens the health care system but also strains economic resources, and has far reaching social and emotional consequences (Wellman and Friedberg 2002; Finkelstein et al. 2005). An overall consequence of overweight and obesity are presented in figure 3-3.

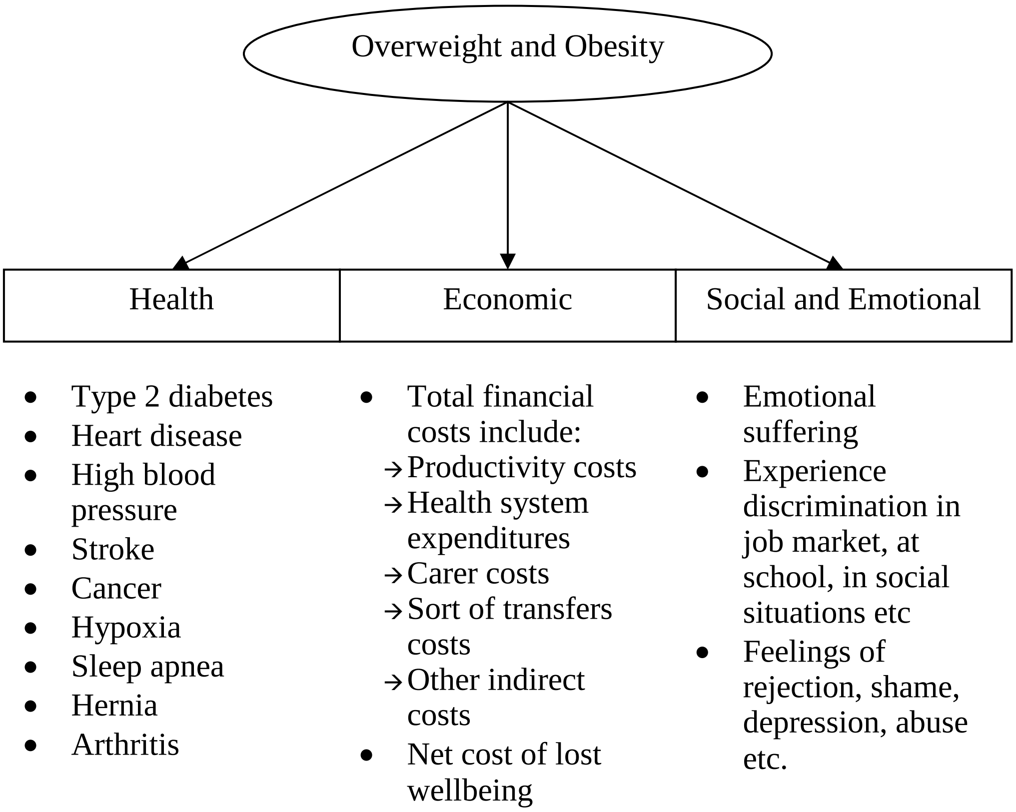

Figure 3-3: A pictograph of the consequences of overweight and obesity

Obesity and overweight epidemic is associated with several serious health conditions including: type 2 diabetes mellitus, heart disease, high blood pressure, stroke and cancers of the postmenopausal breast, colon, endometrium and kidney. In particular, obesity is strongly linked to type 2 diabetes, identified as one of the six National Health Priority Areas in Australia (Department of Health and Aging 2008). Besides obesity is an independent risk factor for heart disease, hypoxia, sleep apnea, hernia, and arthritis (Wellman and Friedberg 2002), and it is second one of the two leading causes of death in Australia (Begg et al. 2007). Globally, the proportions of the global burden of disease attributable to high BMI/overweight and obesity were 58 percent of Type 2 diabetes, 21 percent of heart disease, 39 percent for hypertensive disease, 23 percent for ischaemic stroke, 12 percent for colon cancer, 8 percent for postmenopausal breast cancer and 32 percent for endometrial cancer in women and 13 percent for osteoarthritis (James et al. 2004; Access Economics 2008).

Besides economic consequences of overweight and obesity includes increasing overweight and obesity-related medical care and welfare expenditures. An updated estimate for Australia by Access Economics (2008) reveal that the total economic costs of overweight and obesity is 58.2 billion in 2008. Prior to this however in 2005, the economic costs were significantly lower at 21.0 billion, including 3.8 billion in total financial costs and 17.2 billion in net cost of lost wellbeing. The total financial cost of overweight and obesity in 2008 was estimated as nearly 8.3 billion; of this - productivity costs were estimated as 3.6 billion (44 percent), health system costs were 2.0 billion (24 percent), carer costs were 1.9 billion (23 percent), and other transfers costs such as taxation revenue forgone, welfare and other government payments were 727 million (9 percent) and other indirect costs were 76 million. Additionally, the net cost of lost wellbeing was valued at a further 49.9 billion in 2008 estimate.

Moreover emotional suffering may be among the most painful aspects of overweight and obesity. The Western developed societies commonly emphasize physical appearance and often equate attractiveness with slimness, especially for women. Such messages may be devastating to overweight and obese people. Typically people in Western communities think that obese and overweight individuals are gluttonous, lazy, or both, even though this is not true. As a result, overweight and obese people often face prejudice or discrimination in the job market, at school, and in social situations. On top of that feelings of rejection, shame, or depression are common. Overweight and obese employees generally believe that weight-based discrimination by employers is relatively common.

Several studies have been conducted on weight-based employment discrimination issues in the United States. For instances, a study demonstrates that employers are likely to discriminate based on a person's weight in all aspects of employment, including decisions on who to hire and fire (Finkelstein and Trogdon 2008). Another recent study reveals that about 8 percent of men and 16 percent of women have experience that they had faced discrimination because of their overweight and obesity (Puhl et al. 2008). Further among those people who had faced such discrimination, 60 percent people reported that they had experienced work-related discrimination, such as not being hired, being passed over for promotion, or being wrongly fired. However younger individuals with a higher BMI had a particularly high risk of weight or height discrimination regardless of their race, education and weight status (Puhl et al. 2008), and such discrimination is more prevalent for women than for men (Carpenter 2006; Finkelstein and Trogdon 2008; Puhl et al. 2008).

3.8 Concluding remarks

The health related issue overweight and obesity epidemic in Australian adults has been addressed in this section. The body mass index method of measuring overweight and obesity shows that more than half of the Australian adults are overweight or obese and the epidemic is more common in males than females. Trends of the prevalence of overweight and obesity are increasing in Australia and during last ten years the prevalence rates have been increased dramatically. Analyses demonstrate that the rates of overweight and obesity increased with age up to 64 years and then decreased with their age for both sexes. Likewise obesity is more common in middle to older aged Australians and the prevalence rates of obesity are highest in 55-64 years age group for both males and females. However in their young age females are less prevalently obese than males. Besides a diploma or higher education qualified adults were less likely to be overweight and obese than those with other or no post-school qualifications. Findings reveal that the prevalence of overweight increases with household income levels, where as the prevalence of obesity decreases with the increasing levels of household income. Moreover the causes of overweight and obesity may include a wide range of key factors such as - lack of exercise, eating more calories/energy-dense foods than utilized, sedentary lifestyles, poor dietary habits, chronic stress, changes in family structures and dynamics, genetic factors etc, the increasing rate of obesity is attributed to both a rise in energy intake and a decline in physical and incidental activity. Overweight and obesity may also result from the economic causes such as - technological advancements, and poor information and addictive behaviour and/or as a result of living in an increasingly obesogenic environment. Furthermore an assessment of the consequences of overweight and obesity illustrates that overweight and obesity is not only burdens the health care system but also strains economic resources of the nation, and has far reaching social and emotional consequences in individuals' life.

4 METHODOLOGIES FOR ESTIMATING SMALL AREA HEALTH RELATED CHARACTERISTICS

Some studies have recently produced small area estimates of health related characteristics in the developed world – particularly in the United Kingdom, United States and Canada. A range of methods have been used in those studies to produce small area health behaviours estimates. Typically all of these methodologies can be classified as three sets of distinct approaches:

1) Indirect standardisation and individual level modelling;
2) Multilevel statistical modelling; and
3) Spatial microsimulation modelling.

At first a review of relevant literature on small area health related characteristics estimation is provided in this Section. Then each of the modelling approaches is conferred in turn, setting out its usefulness and limitations in order to infer the selection of method for using in future research.

4.1 REVIEW OF LITERATURE ON SMALL AREA HEALTH BEHAVIOURS ESTIMATION

Recently published literatures suggest that health related behaviours and health outcomes are significantly influenced by the small area variations in social capital (Lindstrom et al. 2000; Pickett and Pearl 2001; Tseng et al. 2001; Macintyre et al. 2002; Joines et al. 2003; Lindstrom et al. 2003; Mohan et al. 2005; Kim et al. 2006). Social capital is defined by many scholars as a population level attribute that measures social relations and connections among people and social organization of communities (Kawachi and Berkman 2000; Bolin et al. 2003; Kim et al. 2006) which may have variation by geographic settings. Social capital is described as the glue that holds people together and enables them to build stronger communities through multidimensional ways. This may promote favourable health related behaviours, such as stopping or reducing smoking, by promoting more rapid transmission of health information, adaptation of health behaviour norms, and social control over deviant health related characteristic (Bolin et al. 2003).

Most of the studies in this growing field have been conducted in the North America and Europe. Kim et al. (2006) reveals that the US state and county levels social capital is associated with obesity and leisure-time physical inactivity. The authors use a multilevel statistical modelling for multivariate analysis and provide some evidence for the promotion of social capital as a potential strategy for addressing the burgeoning obesity epidemic. Other studies in USA suggest that population level socioeconomic and health resource characteristics are important determinants of variation in hospitalization rates (Joines et al. 2003); small area level social and economic disadvantage influences individual smoking behaviour (Tseng et al. 2001). Besides estimation of youth smoking behaviours at provincial levels in Canada is studied by Pickett et al. (2000). This study observed the small area prevalence of current smoking as well as smoking initiation among youth of aged 15-24 years. The authors used a simple individual level modelling and logistic regression analysis to identify the significant socio-demographic predictors for smoking behaviours. Result of this research demonstrates that unemployment and lower levels of education were two significant factors for both of current smoking and the smoking initiation, and age was the most significant predictor for smoking initiation among Canadian youths. A better level of social capital may positively influence the health behaviours (such as leisure time physical activities and smoking initiation or avoid/quite smoking) of young people.

Furthermore Mohan et al. (2005) reports on various combinations of individual level and multilevel models incorporating individual attributes, health related behaviours, small area measures of deprivation, and small area measures of social capital in England and observed the evidence from their spatial scale analysis that the small area measures of social capital exert a beneficial effect on health related characteristics. In addition to investigate the influence of contextual and individual levels factors on daily smoking behaviour in Sweden - Lindstrom et al. (2003) utilize a multilevel logistic regression model and obtained that individual social capital measured by social participation marginally affected the total neighbourhood variance in daily smoking. This study also points out that area level social and economic disadvantages such as socioeconomic disadvantage, overcrowding and high crime rates influence individual smoking behaviour.

High level of social capital may associated with better health behaviours and health outcomes, through positive social norms, social networks, social support, and the availability of strong organizational processes' influencing the availability and use of health care services (Kawachi and Berkman 2000). The levels of social capital should vary from place to place by geographical settings. Thus, health related characteristics depend not only on individual factors such as age, sex, employment status, etc. but also on the geographic location or the surrounding environment in which persons live and work (Mohan et al. 2005). Controlling for regional population level variables, higher social capital may be associated positively with individual's personal health attributes and negatively with mortality, with lower levels of risky behaviours associated with binge drinking, with infectious diseases, with drug use, and with tobacco smoking.

Moreover studies in different western countries reveal that a set of demographic and socioeconomic factors such as age (Taioli and Wynder 1991; Lindstrom et al. 2000), gender (Lindstrom et al. 2000), socioeconomic status (Tillgren et al. 1996; Lindstrom et al. 2000), and ethnic minority/immigrant status (Lindstrom and Sundquist 2002) influence the decisions of individuals to smoke and to stop smoking. Characteristics of the residential area may also influence smoking behaviour: areas of higher social status may, for instance, provide social and cultural contexts that influence smoking prevalence.

Moon et al. (2007) shows age×sex×ethnicity specific disaggregated geography of obesity in England. The study used a statistical model based small area estimation technique known as multilevel small area estimation approach. The details of this statistical approach has been discussed by many researchers (for instance, see Twigg et al. 2000; Rao 2003; Saei and Chambers 2003a; Moura et al. 2005 among many others). It is considered as a highly effective approach to the generation of small area estimates in the absence of robust routine local level survey data (Bajekal et al. 2004). The approach builds on earlier non multilevel model related approaches to small area estimation (see Charlton 1998).

This statistical model based approach initially involves in developing multilevel models from national level survey data. These assess the extent to which individual and area factors predict an individual risk of being overweight or obese. The parameter estimates from these models are then used, with census and other administrative data for local areas, to estimate the prevalences of obesity. For example, the model might predict the risk of obesity if a person is male (by sex), middle aged (35-54 years by age), bachelor degree holder (by educational qualification), full-time employed (by labour force status), married (by marital status) and lives in a dwelling or an area characterized by non-private dwelling or high levels of car ownership respectively. Census data will show the numbers of such characterized men living in any geographic small area and also provide information about the non-privet dwelling type or level of car ownership in the area. The combination of survey and census data enables estimated prevalences to be generated for all target small areas in a country.

Multilevel statistical models allow for the estimation of contextual effects of small area level factors by accounting for the spatial clustering of individuals within regions (Subramanian et al. 2003). Multilevel logistic models with random intercepts can be estimated using MLwiN software (Rasbash et al. 2000), based upon the predictive/penalized quasi-likelihood approximation of a second-order Taylor linearization procedure (Goldstein and Rasbash 1996). Each set of 2-level and 3-level models applied the logit function, with the logarithm of the odds of obesity and logarithm of the odds of no moderate to vigorous physical activity as outcomes in separate models. Kim et al. (2006) estimates the odds ratio associations and 95 percent confidence intervals of state- and county-level social capital with obesity and with physical inactivity, each adjusted for the state-level Gini coefficient and percentage of Black residents, state-/county-level mean household income, and individual-level socio-demographic and socioeconomic characteristics. The authors have tested the interactions between the variables corresponding to the combined dichotomous state- or county-level social capital measure and the gender and race/ethnicity variables by another set of models. This study also examined the effect of including the sprawl or income inequality measure on the estimated association between state-/county level social capital and the health related outcome (see Kim et al. 2006).

Moreover, a number of lifestyle behaviours and environmental factors contributed to increase the prevalence rate of obesity, including availability of food, falling real prices of food, expenditure on food, food habits of individual, and more time spend being physically inactive. The relative importance of some of the factors driving obesity rates may vary across region to region. Recent studies on childhood obesity in UK shows that different obesogenic environmental factors such as children's food habits (fruit and vegetable consumption, school meal consumption), household food expenditure, television ownership, perceived social capital, urbanisation, socio-economic group, size and source of household income, personal computer ownership, internet access and physical activity levels are significant determinants of childhood obesity in Leeds and their relationships are not uniform across the Leeds Census lower Super Output Areas (SOAs) or the small area in Leeds (Procter 2007; Procter et al. 2008). The authors reveal the estimates of global and small area levels' relationships between the obesogenic covariates and childhood obesity utilizing the geographically weighted regression model and spatial microsimulation techniques. They also sketch the important geographical variation of these estimates across Leeds, and demonstrate that planning more appropriate interventions to focus on specific localities should be the key to health policy maker's success for reducing prevalence of childhood obesity and this may be a more informative pose for a health planner to work from.

4.2 INDIRECT STANDARDISATION AND INDIVIDUAL LEVEL MODELLING

This set of small area health related characteristics modelling approach is very easy and straightforward. It usually follows a simple indirect standardisation procedure or some models that are based on individual level covariates from the Confidentialised Unit Records Files (CURFs) or from the Census data. A brief description of each of these methods is provided here.

Simple indirect standardisation procedure involved applying national level estimates derived from survey data to small area-level population counts to generate small area estimates (Bajekal et al. 2004). This procedure can be clarified by an example. Suppose a researcher be interested on an indirect estimate of the proportion of youth (aged 18-24 years) smoking in a particular SLA in Australia. At first, the researcher can estimates the national/state level proportion of youth smoking from the National Health Survey data. Then using these national estimates to the census counts of youth within same age group for the particular SLA would give an estimate of the number of youth that smoke in that SLA, from which the proportion could be estimated simply by dividing the number of youth smoker by the total census count of youths in that particular SLA. Essentially, therefore, the national prevalence rates of smoking for youth is weighted by the proportion of youth in that prespecified age group in the small area or SLA. Gibson and Asthana (2001) used this method to calculate the prevalence of heart disease, and Pickering et al. (2004) used it to generate the estimates for smoking at small area level in England.

The main advantages of the simple indirect standardised procedure are – 1) it is easy and inexpensive to apply since the cell proportions at the local level are available from the Census, and the national estimates for demographic classes are easily obtainable from national surveys such as the National Health Survey of Australia; 2) the approach is flexible to calculate estimates at the national level and use them – for instance, a possible option is to adjust the method by calculating rates for different types of areas using some form of area classification (such as major cities and countryside or urban and rural, quintiles of deprivation or income etc), and use them to the constituent small areas in each type; and 3) the estimates produced by this method for each small area within a larger area can be ratio adjusted so that a weighted average of the adjusted small area estimates equals the direct estimate for the larger area. On the other hand the main weakness of this approach is that it considers the notion that the national level prevalence rates for each subgroup apply uniformly across all small areas. That means it assumes that the differences in health behaviour measures between areas are due solely to differences in their socio-demographic composition. However research has shown that individual health related behaviour, even within the same social group, varies by contextual factors operating at the small area level (Macintyre et al. 2002). To deal with such small area differences in health related behaviour a more complex model is needed to effectively capture the variation between small areas that exists over and above that due to differences in their demographic and social composition (see Bajekal et al. 2004).

Besides, an extension of the indirect standardisation method is known as individual level modelling approach. This type of modelling is to use the modelled relationship between individual health behaviour measures obtained from an obtainable data against a set of covariates for the same individuals recorded in the survey data. In general, the covariates chosen for the model are those that are available as counts for all small areas (for example, covariates from the Census or CURFs data). The individual level modelling estimates the probability of the health behaviour of a person (for example, smoking, overweight and/or obesity, heart disease etc), given a set of specific known characteristics of that person such as - age, sex, education, marital status and economic class. Regression models – in particular logistic regression, linear regression etc can produce such probabilities and a selection of more and functionally better covariates may greatly improve the fit of models. The model-based probabilities are then converted into estimated proportions in each subgroup individuals defined by the covariates who fall into the relevant health category. These proportions are then applied to the covariate counts available from the Census to derive an overall estimate for the small area in much the same way as for simple indirect standardisation procedure. This modelling approach has been used by (Flowers 2003). The author uses *logistic regression* model to calculate the probabilities of coronary heart disease for $age \times sex \times social\ class \times ethnicity$ groups.

In fact, logistic regression can model how the probability of an event may be affected by one or more predictor variables or covariates. That means it can detect changes in measurements that are brought about by addition of a new predictor to the regression equation. A remarkable feature of this model is that it makes no assumption about the distribution of the predictor variables. They do not have to be normally distributed, linearly related or of equal variance within each group. A mathematical expression of logistic regression equation is a follows:

$$\log it\{p(x)\} = \log\left\{\frac{p(x)}{1-p(x)}\right\} = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k$$

where, β_0 is the intercept of the logistic regression equation, β_i is the regression coefficient of the predictor variable $x_i\,(i = 1,2,\ldots k)$, and p is the logistic function.

Note that, even though the inclusion of more and better selection of survey covariates is likely to greatly improve the fit of such individual level models, researchers are restricted in the choice of covariates for synthetic estimation by the requirement to have equivalent covariate information for all areas. Hence the main drawback of the individual level modelling is the concerns of its data requirements. This form of small area health behaviours estimation requires an exact correspondence between the covariates used in the model and data available from the Census or other administrative data sources. Nonetheless the limited number of cross classifications of socio-demographic information such as age, sex, ethnicity, socioeconomic class available from the census restricts the choice of covariates in these models.

4.3 MULTILEVEL STATISTICAL MODELLING

A more complex set of models that have recently used in small area health related characteristics estimation is know as multilevel statistical modelling. The approach extends more traditional statistical techniques by explicitly modelling social context. For example, it can explain the variability in human behaviours and attitudes, as well as how their behaviours and attitudes are modified and constrained by shared membership of social contexts (such as the family composition, community, and residential location etc). In other words, multilevel statistical models can assess the contributions of individual and small area level factors to both between individual and between area variability, showing how individual level and area level factors can contribute to the variability at both levels. As well this type of analysis allowed for the possibility that different factors contribute to within small area and between small area variability, and permitted estimation of area level effects after accounting for compositional differences across small areas (Twigg and Moon 2002). Using the multilevel modelling technique statistical models can be applied to survey data that simultaneously accounts for either individual and small area level effects or small area random effects on health related behaviours such as smoking. Hence the models are also known as statistical mixed models or random effects models.

In multilevel statistical modelling a random effects specification at small area levels is necessary. This specification generally assumes that significant systematic variation between small areas remain after given an account for the effects of covariates in the model. Such unexplained variation is modelled through the addition of small area specific random parameters to the fixed effects (Saei and Chambers 2003b). Therefore multilevel models have extended ability to incorporate unexplained variability between small areas into the health related behaviours estimation procedures.

Using mathematical notations a simple two level model can be expressed as

$$SS = \alpha_j + \beta_j Income + \varepsilon_{ij}$$

where *SS* represents the smoking status of individual, ε_{ij} is the error term for individual i in the j^{th} small area, and α_j and β_j represent the intercept and slope parameters respectively which are random, that means, they varies from small area to small area such as SLA to SLA in Australia.

In general, populations of interest to economic and social researchers have a hierarchical or nested structure. This type of populations can be thought of as pyramids shape with different numbers of levels. For example, individuals live in households which, in turn, are located in geographically defined small area communities. There are three levels which are - individuals as the base level or level one, households as an intermediate level and small area communities as the highest level or level three. Further some populations have a cross-classified structure. For example, patients can be defined by their family doctor and by the hospital they attend. So far the developments in multilevel statistical modelling most of them have been concerned with analyzing data with a nested structure. Nevertheless, although in theory there is no limit to the number of levels of a hierarchy within populations, in practice researchers are rarely in the position to carry out analyses with more than four levels of nesting due to computational constraints.

According to Bajekal et al. (2004), there are two main features of multilevel statistical models that make it suitable for producing synthetic estimates for small areas. Firstly, multilevel models are suited to the clustered nature of social surveys for which individuals are clustered within households which in turn are clustered within suburbs or postcode sectors. By using the clustering information it provides more accurate standard errors, confidence intervals and significance tests, and these generally will be more ‘conservative’ than the traditional estimates obtained by ignoring the presence of clustering in the data (Goldstein 2003; Bajekal et al. 2004). Secondly, by allowing the use of covariates measured at any level of the hierarchy, multilevel model enables researchers to explore the extent to which any differences between geographical small areas such as wards (or SLAs in Australia) are associated with individual, household and small area level characteristics (Goldstein 2003).

At first Twigg et al. (2000) outlined a multilevel statistical modelling approach in small area health related behaviours estimation as an innovative way. The study used both individual and area-level covariates to obtain prevalence estimates of smoking and problem-drinking for each ward in England by combining survey data from the health survey of England with small area census data. The approach was an advance towards the methodology for capturing small area effects in the model and regarding the creation of small area data on health related behaviours over the simple standardisation procedure and individual level modelling.

In general, the approach proposed by Twigg and colleagues involves in three stages. Bajekal et al. (2004) illustrates them by discussing the estimates of smoking prevalence. At the first stage, for those small areas covered by the health survey of England, a multilevel model of individual smoking behaviour using both individual (sex, age and marital status) and area level predictors (for example, the survey estimate of the percentage of private rented households in the postcode sector) was fitted to the survey data. For the second stage, the model parameters of individual and area effects, as well as their interaction effects were combined to estimate the proportion of smokers in each combination of age, sex and marital status, resident in wards with varying proportions of private renters and car owners. At the last stage, these estimates were then applied to the corresponding census counts to provide a synthetic estimate of smoking prevalence for all wards in England.

Moreover the Office of National Statistics in UK used a more restricted multilevel statistical model, in which the health related behaviours such as smoking status of individuals living in the survey areas were predicted using area level covariates only (see Heady et al. 2003). This approach results in a set of regression coefficient estimations that relate to between area variations. These coefficient estimates are then attached to the known area means or proportions of the covariates for all small areas, taken from the Census and other administrative data sources, to obtain synthetic estimates of health related behaviours. This restricted approach deems that controlling for differences in small area profile is all that is needed for predicting area level differences in health related behaviours. However concerns the issue of disaggregation of estimates is a potential limitation of this method.

There are some significant advantages of multilevel statistical modelling. Firstly, the approach offers a more explanatory model of health related behaviour than those methods that conduct analyses at an individual level. In particular, the multilevel statistical models take into account of both the effects of individual circumstances and the social and physical environment in which people live on their health related behaviours. Besides the inclusion of individual level covariates such as age, sex and social status in the model in combination with the corresponding census counts also permits the further generation of separate estimates for relevant demographic groups within each small area. Secondly, the multilevel statistical modelling approach can not only generate small area estimates of health related characteristics, but also it can calculate the statistical reliability measures such as confidence intervals for those estimates. Thirdly, the populations of interest to social and economic researchers have a nested structure or a cross-classified structure and multilevel statistical models analyse the levels of these structures simultaneously. As a result, questions about the appropriate level of analysis are redundant. Fourthly, this modelling technique can fruitfully be applied to repeated measures data and to multivariate data, and are especially valuable in these situations when data are missing. Finally, a range of software enables multilevel models to be fitted easily such as MLwiN, HLM, and SAS etc.

Furthermore a number of potential limitations should be beared in mind when applying the multilevel statistical modelling approach in practice. At first, in the case of inclusion of individual level covariates in the model this method imposes quite stringent data requirements as there must be an exact correspondence between those covariates used in the model and the counts available from the Census. The confines on the number of cross tabulations available for small areas such as wards/SLAs from the Census restrict the choice of covariates for the model. Therefore important individual level predictors of health related characteristics may be eliminated from the model simply because of their distribution at the small area level is unknown. Secondly, estimating the standard errors for the synthetic estimates based on a multilevel statistical model that uses both individual and area level covariates are considerably more complex than the previous approach discussed in the sub-section 4.2.

A number of published literature shows that the multilevel statistical modelling approach is becoming more popular in different fields of social and economic research. Roux (2008) study summaries past work that has used multilevel statistical models to investigate the multilevel determinants of health. A comprehensive literature review in this study demonstrates that although multilevel modelling is applicable to the study of a broad range of socio-demographic groups or socioeconomic contexts, the vast majority of applications in the health field have focused on geographically defined contexts, such as countries (Chung and Muntaner 2007), states (Kim et al. 2006; Kim and Kawachi 2007), counties (Muntaner et al. 2006), and most commonly neighborhoods defined in various ways by smaller administrative areas (Chaix et al. 2007; Rundle et al. 2007). The types of group or area level constructs have been studied in different research include - income inequality (Subramanian and Kawachi 2006), social capital (Lindstrom et al. 2003; Mohan et al. 2005; Kim et al. 2006), residential segregation, women’s status, and neighborhood characteristics such as neighborhood disadvantage or other measures of neighborhood social and physical environments (see Roux 2008). Most of the studies have used the multilevel statistical modelling to isolate associations of group or area level factors with individual level health outcomes after accounting for individual level confounders (for example, individual level variables associated with the health outcomes and with group or community membership, and, therefore, with group or community characteristics).

4.4 SPATIAL MICROSIMULATION MODELLING

In these days spatial microsimulation modelling is getting attention by the health researchers for its robustness to use geographical information at small area levels and usefulness to examine the small area impacts of policy changes. A growing number of literature supports that spatial microsimulation models are becoming increasingly popular and a powerful tool within health research to estimate current health related behaviours, future prevalence rates, cost of treatment, provision of care needs , and the potential outcomes of policy intervention at small area levels (for example see, Brown et al. 2004; Brown and Harding 2005; Procter 2007; Smith et al. 2007; Procter et al. 2008). This is a promising technique for developing detailed synthetic or simulated microdata describing household characteristics at small area level, by combining aggregate census data and more detailed individual record files or households survey datasets (Ballas et al. 2003; Chin and Harding 2006). However the creation of reliable synthetic microdata at small area levels are often very challenging in this approach for some regions. For example, spatially disaggregate reliable data are not readily available in the real world. Even if these types of data are available in some form, they typically suffer from severe limitations - in either lack of characteristics or lack of geographical detail.

Spatial microsimulation modelling can be conducted by reweighting a generally national level sample so as to estimate the detailed socioeconomic and demographic characteristics of populations and households at a small area level. An effective reweighting technique combines individual or household microdata - currently available only for large geographical areas, with spatially disaggregate data to generate synthetic micropopulation for small areas (Harding 1993). So the presence of both geographical information and detailed household characteristics which have impacts on health related behaviours in the synthetic spatial micropopulation indicates the applicability of a spatial microsimulation model to the analysis of these health behaviours. The characteristics of spatial microsimulation models and the associated theories, tools and techniques behind this approach are well documented elsewhere (for instance see, (Ballas et al. 2006; Chin and Harding 2006; Chin et al. 2006; Tanton 2007; Rahman 2008a, 2008b), and hence the details discussion of them should not be repeated.

In the literature there are broadly two methodologies for creating simulated population microdata: 1) *synthetic reconstruction* and 2) *reweighting*. The synthetic reconstruction approach includes data matching or fusion (Moriarity and Scheuren 2001; Tranmer et al. 2001) and iterative proportional fitting (Williamson 1992; Norman 1999). On the other hand the reweighting approach includes a generalised regression technique known as GREGWT (Bell 2000; Chin and Harding 2006; Rahman 2008a) and combinatorial optimisation (Huang and Williamson 2001; Ballas et al. 2003; Williamson 2007; Rahman 2008a). As reweighting techniques are currently seems to be more functional for creating spatial microdata over the synthetic reconstruction techniques (Huang and Williamson 2001), a very brief account of these techniques are provided here.

The *GREGWT* approach for creating spatial micropopulation dataset is an iterative generalised regression algorithm written in SAS macros to calibrate survey estimates to benchmarks. Calibration can be looked at either as a way of improving estimates or as a way of making the estimates add up to benchmarks (Bell 2000). That is, the grossing factors or weights on a dataset containing the survey returns are modified so that certain estimates agree with externally provided totals known as benchmarks. This use of external or auxiliary information typically improves the resulting survey estimates that are produced using the modified grossing factors.

The algorithm used in GREGWT is based on a constrained distance function known as the truncated Chi-square distance function that is minimized subject to the calibration equations for each small area (for a details about the calibration equations see Rahman 2008a). The method is also known as linear truncated or restricted modified Chi-square (see, Singh and Mohl 1996) or truncated linear regression method (see, Bell 2000)). The mathematical expression of the truncated Chi square distance function used in the GREGWT algorithm is as follows:

$$D_{\chi^2} = \sum_{k \in s} \frac{(w_k - d_k)^2}{d_k}; \text{ for } L_k \le \frac{w_k}{d_k} \le U_k$$

where d_k is the given sampling design weights, w_k is the new weights, and L_k and U_k are the pre specified lower and upper bounds respectively for each unit k in sample s.

The basic feature of this method over the linear regression is that the new weights must lie within a prespecified boundary condition for each small area unit. The upper and lower limits of boundary interval could be constant across sample units or proportional to the original sampling weights. To minimize this distance function, GREGWT algorithm used the Newton-Raphson method of iteration (Rahman 2008a). It adjusts the new weights in such a way that minimises above distance equation and produces generalised regression estimates or the simulated estimates. The simulated estimates produced by GREGWT technique have their own standard errors. GREGWT calculates these standard errors using a ‘group jackknife’ approach which is a replication based method. The group jackknife approach could use replicate weights in spatial microsimulation modelling, and the problem is basically computational, not statistical. In that method we would end up with 30 weights for each small area. For details about the group jackknife approach see for example, Bell (2000) and references therein.

Although this approach is generally robust, it suffers from the disadvantage that there has to be a fairly large number of observations in each sample selection stratum (Rahman 2008a). In practice, it is rare in a survey sample to achieve this number of observations, especially at small area levels or for micro level data. As a result, when there are too few observations in a sample stratum, the resulting standard error estimates should be statistically unreliable. Note that about 30 observations per stratum is a good minimum working number and maybe we can produce this number of observations by suitable combination of classes. However a problem for spatial microsimulation is the size of final file. For example, 1300 columns (SLA) × 30 weights = 39000 columns; then 39000 columns × 12000 households = 468 million cells in the final file.

An alternative approach to simulate spatial micropopulation dataset is the *combinatorial Optimisation (CO)* algorithm. The process involves selecting an appropriate combination of household records from available survey microdata which offers the best fit for known benchmarks constraints in the selected small areas. In the CO algorithm, an iterative process begins with an initial set of households randomly selected from the survey data, to see the fit to the known benchmark constraints for each at small domain. Then a random household from the initial set of combinations should be replaced by a randomly chosen new household from the remaining survey data to assess whether there is an improvement of fit. The iterative process continues until it is achieving an appropriate combination of households that best fits known small area benchmarks (Voas and Williamson 2000; Tanton et al. 2007; Williamson 2007). A simplified combinatorial optimisation process is given elsewhere (for instance, see Huang and Williamson 2001; Rahman 2008a). The overall CO process involves with the following five steps:

1) collect a sample survey microdata file (such as CURFs in Australia) and small area benchmark constraints (for example, from census or administrative records);
2) select a set of households randomly from the survey sample which will act as an initial combination of households from a small area;
3) tabulate selected households and calculate total absolute difference from the known small area constraints;
4) choose one of the selected households randomly and replace it with a new household drawn at random from the survey sample, and then follow step 3 for the new set of households combination; and
5) repeat step 4 until no further reduction in total absolute difference is possible.

Note that, in CO algorithm the fit of a combination of individuals to known small area benchmarks constraints is evaluated by the Total Absolute Error which is the sum of the absolute differences between estimated and observed counts. Using simple notations TAE can be defined as:

$$TAE = \sum_{ij} | O_{ij} - E_{ij} | \rightarrow 0$$

where, O_{ij} and E_{ij} are the observed and expected counts respectively for the i^{th} row in j^{th} column. Unlike distance function in GREGWT, here the TAE should be minimizing to zero. Ideally, an optimal solution (the selection of a households combination best fits the known benchmarks) would have a TAE of 0, which means there is no difference between the observed and estimated counts, in another words a ‘perfectly fit’. However the measures of standard errors are not available yet for the simulated estimates produced by CO technique.

In theory, it may be possible to obtain all possible combinations of households from a finite dataset and the set of combination that best fits the small area benchmarks. However in practice, it is almost unachievable due to computing constraints for an extremely large number of all possible solutions. To overcome this problem, the CO approach uses several ways of performing ‘intelligent searching’, effectively reducing the number of possible solutions. Williamson et al. (1998) describe this problem in more detail and explore various techniques of intelligent searching for the combinatorial optimisation process including the ‘hill climbing’ approach, the ‘generic algorithm’ approach, and the ‘simulated annealing’ approach. The authors found that modified simulated annealing stands out as the best solution. Further to improve the accuracy and consistency of outputs, Voas and Williamson (2000) developed a ‘sequential fitting procedure’, which can satisfy a level of minimum acceptable fit for every table used to constrain the selection of households from the survey sample data.

Spatial microsimulation modelling may be the precise ways in which two or more sources of data can be combined. However it encounters some methodological and computational complexity. The key objective of generating simulated micropopulation dataset at small area levels is to create data that does not currently exist for small areas. Therefore validation of simulated microdata is difficult, and it may consider one of the drawbacks of the spatial microsimulation modelling. However there are some ways to deal with validation problem. For instance, one way of validating spatial microsimulation modelling outputs is to reaggregate estimated datasets to a larger levels at which observed datasets exist and compare the estimated distributions with the observed (Ballas 2001). Furthermore researchers are constantly working to improve the validation methods and/or trying to develop a new method. Within near future there should be a more reliable and effective validation approach for spatial microsimulation modelling.

In conclusion of this section, a review of literature on small area health related characteristics estimation reveals that some studies have been conducted on this issue in the developed world. Most of these studies suggest that health related behaviours and health outcomes are significantly influenced by the small area variations in social capital. Some other factors such as social and economic disadvantages, geographical location and environmental factors, ethnic minority or immigrant status, socioeconomic status, demographic factors, and lifestyle factors etc have also significant effects on the variation of health related behaviours at small area levels. Besides three different sets of modelling approaches commonly known as - indirect standardisation and individual level modelling, multilevel statistical modelling and spatial microsimulation modelling have been used by researchers to produce small area health behaviours estimates. Details account of each of these modelling approaches with its usefulness and limitations are also provided. Although each of these modelling approaches has its own strengths in relation to generate small area health related behaviours estimation, spatial microsimulation modelling approach is more robust regarding scales of small areas and also can yield the spatial microdata. Thus it seems that spatial microsimulation modelling may be the precise way to estimate small area health related characteristics.

5 DISCUSSION AND CONCLUSIONS

This working paper has addressed two major health related issues such as tobacco smoking and overweight and obesity in Australia and discussed about the methodologies for estimating health related characteristics at small area levels.

An overview of tobacco smoking for Australian adults reveals that smoking is the largest single cause of death and a key risk factor for some deadly diseases in Australia, and the overall social costs of tobacco smoking is increasing over time. Although the trend in smoking is slowly decreasing during recent decades, the current adults smoking prevalence rate is about 23 percent. Besides more than a quarter of households in Australia have weekly expenditure on tobacco products, and nearly one in each ten households spent more than 50 dollars per week for smoking. Households with unemployed reference person, having two or more unemployed persons, and in renting dwellings have significantly higher smoking expenditure. In addition more males are smoker than females and smoking rate is higher among younger aged adults for both sexes.

Overweight and obesity is another leading cause of burden of diseases and mortality in Australia. It is obvious that excess weight increases the risk of developing diabetes, cardiovascular disease, high blood pressure, and many others including cancer of the breast and bowel. Only obesity was responsible for about 7.5 percent of the total burden of diseases and injury for Australian population in 2003; among them 7.7 percent of total for males and 7.3 percent of total for females. Moreover an assessment of the consequences of overweight and obesity illustrates that overweight and obesity is not only burdens the health care system but also strains economic resources of the nation, and has far reaching social and emotional consequences in individuals' life. For instance, it has been estimated that overweight and obesity and their associated illnesses cost Australian society and the governments a total of 21.0 billion dollars in 2005, and is rising at to 58.2 billion in 2008. Also there is evidence in published literature that overweight and obese people often face discrimination in the job market, at school and in social situations, and such discrimination (for example work related discrimination - not being hired, being passed over for promotion, or being wrongly fired) is more common for females as well as younger aged individuals

The BMI measures of Australian people shows that more than half of the adults are overweight or obese and the epidemic is more common in males than females. Trends in the prevalence of overweight and obesity are dramatically increasing during last decade. Analyses demonstrate that the rates of overweight and obesity increased with age up to 64 years and then decreased with their age for both sexes. Likewise obesity is more common in middle to older aged Australians and the prevalence rates of obesity are highest in 55-64 years age group for both males and females. Prevalence of overweight and obesity increases with increasing level of household income and decreases with higher level of post school education.

Moreover the causes of overweight and obesity may include a wide range of key factors such as - lack of exercise, eating more calories/energy-dense foods than utilized, sedentary lifestyles, poor dietary habits, chronic stress, changes in family structures and dynamics, genetic factors etc, the increasing rate of obesity is attributed to both a rise in energy intake and a decline in physical and incidental activity. Overweight and obesity may also result from the economic causes such as - technological advancements, and poor information and addictive behaviour and/or as a result of living in an increasingly obesogenic environment.

It is apparent that population health and national or states economic and social wellbeing are linked to each others in a complex ways. There are a variety of research have been conducted on small area health related behaviours estimation in the USA, Canada, UK, and some other European countries, such type of research is not often in Australia. A review of literature on small area health related characteristics estimation reveals that health related behaviours and health outcomes are significantly influenced by the small area variations in social capital. Some other factors such as social and economic disadvantages, geographical location and environmental factors, ethnic minority or immigrant status, socioeconomic status, demographic factors, and lifestyle factors etc have also significant effects on the variation of health related behaviours at small area levels. Therefore the attainment of better health is not only a simple function of health policy and biomedical advance, but also it is influenced by a complex array of demographic factors, economic factors and social context into small areas that need to be identified and addressed for achieving future health goals at small area levels.

A study conducted in South Australia reveals information on an extensive range of socioeconomic and environmental conditions and risk factors that influence residents' health for both the whole of the state and for the regional levels (Government of South Australia 2005). For instance, the study provides new information on health inequalities between Indigenous and non-Indigenous South Australians as well as between different socioeconomic groups in the population at different areas. Socioeconomic inequalities in the prevalence of diseases and their associated risk factors are obvious across the Australian population (Glover et al. 2004). Therefore small area estimations of socioeconomic and health disparities may offer more informative knowledge that will help to provide direction for developing advance policies to reduce inequities across the population. It is noted that the socioeconomic environment is a powerful and potentially modifiable factor, and public policy is a key instrument to improve this environment, particularly in areas such as housing, taxation and social security, work environments, urban design, pollution control, educational achievement, and early childhood development (see Hetzel et al. 2004).

To meet the increasing demand for small area estimates in Australia, the ABS has run a project to produce a series of manuals on the theory, application and process for producing small area statistics. As a part of their project an empirical study has been conducted by ABS to obtain small area estimates of disability in Australia (Elazar and Conn 2005). This empirical study has explored three small area estimation models which are demographic synthetic, Poisson and Bernoulli models. In addition the National Centre for Social and Economic Modelling (NATSEM) is the leading research centre in this area. They develop sophisticated economic tools known as spatial microsimulation models, to produce estimates of different socioeconomic, demographic and health related characteristics of population at regional levels or small area levels in Australia (for details see at http://www.canberra.edu.au/centres/natsem/). For example, the CareMOD of NATSEM is a spatial model for examining disability, activities and of daily living status and the needs for care within small areas in New South Wales.

A conceptual framework to study on health burden is depicted in figure 5-1. According to this framework, ill-health outcomes of population are proximately determined by three groups of factors which are lifestyle behaviours, physiological states and social and environmental factors. Although lifestyle behaviour factors may have individual effect on ill-health outcomes, both the physiological states and social and environmental factors are influenced by lifestyle behaviours of the population.

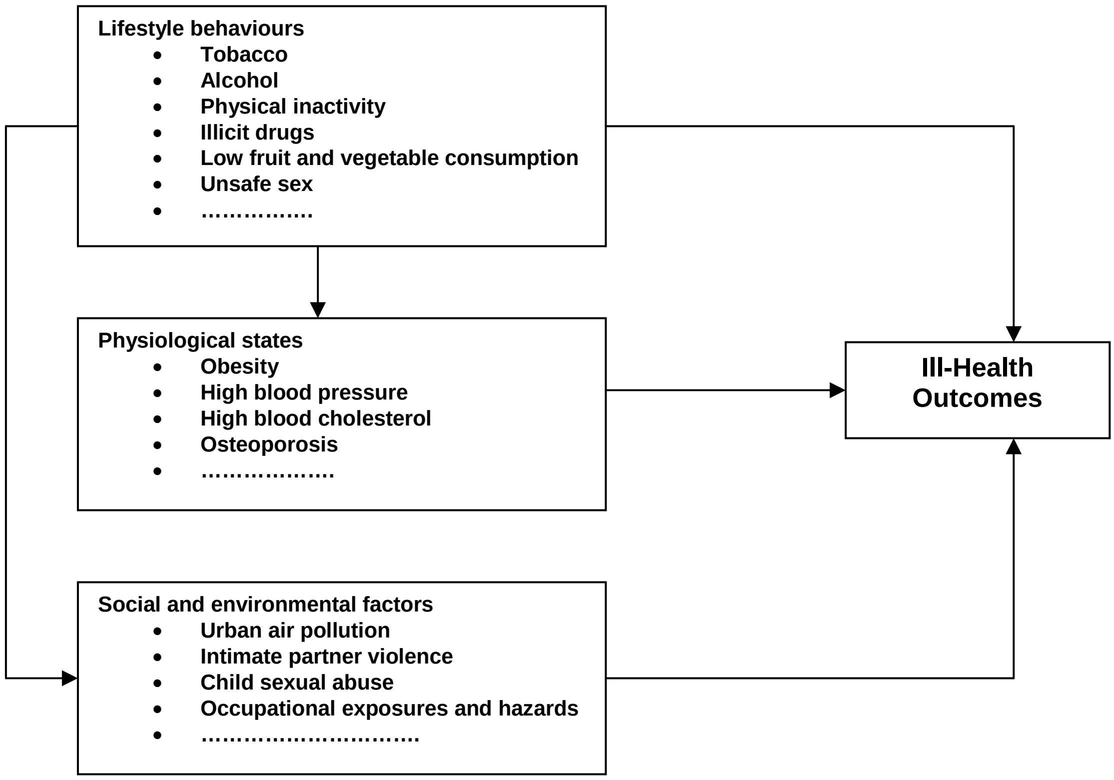

Figure 5-1: Conceptual framework to study on ill-health outcomes

In addition to providing valuable information on the selected three groups of factors for health burden of Australians (see Fig. 5-1), the small area statistics of health related issues may carry further discussions about social issues and health inequalities that extend beyond the usual health division. For example, areas like social security, taxations, local developments, housing, and environment etc can benefit from an analysis of the distribution of residents lifestyle behaviours, disease and disability, and social and environmental condition in a particular location. As well evaluation of the small area estimates of population characteristics can perhaps raise awareness of, and increase familiarization with, population health and social issues in the wider community, and can help organizations by providing reliable and more practical information at small area levels.

Furthermore, the study gives an account of the methodologies for small area health related characteristics estimation. Generally there are three diverse sets of modelling approaches – 1) indirect standardisation and individual level modelling; 2) multilevel statistical modelling; and 3) spatial microsimulation modelling, which have been used by researchers to produce small area health behaviours estimates. Each of these modelling approaches with its usefulness and limitations are also discussed herein to justify for using them in future research. It seems that, although each of these modelling approaches has its own strengths in relation to generate small area health related behaviours estimation; spatial microsimulation modelling shows significant robustness over other methods and may be the more precise way. Our future research would employ this later approach to produce the estimates of small area health related characteristics – in particular, the estimates of smoking behaviours of adults and/or estimates of the prevalence of overweight and obesity of adults at small area levels in Australia.

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