THE BMI: MEASUREMENT, PHYSICIAN COSTS AND DISTRIBUTIONAL DECOMPOSITION

THE BODY MASS INDEX (BMI): MEASUREMENT, PHYSICIAN COSTS AND DISTRIBUTIONAL DECOMPOSITION

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A Thesis Submitted to the School of Graduate Studies in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy

McMaster University

DOCTOR OF PHILOSOPHY (2016) McMaster University
(Health Policy Ph.D. Program) Hamilton, Ontario

Title:	The Body Mass Index (BMI): Measurement, Physician Costs and Distributional Decomposition
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Number of Pages:	xi, 155

Abstract

This thesis comprises three chapters involving the analysis of the body mass index (BMI) in health economics. The first chapter evaluates two correction models that aim to address measurement error in self-reported (SR) BMI in survey data. This chapter is an addition to the literature as it utilizes two separate Canadian datasets to evaluate the transportability of these correction equations both over time and across different datasets. Our results indicate that the older method remains competitive and that when BMI is used as an independent variable, correction may even be unnecessary. The second chapter measures the relationship between long-term physician costs and BMI. The results show that obesity is associated with higher long-term physician costs only at older ages for males, but at all ages for females. We find that accounting for existing health conditions that are often associated with obesity does not explain the increase in long-term physician costs as BMI increases. This indicates that there is an underlying relationship between the two that we could not account for in our econometric models. Finally, the third chapter decomposes the differences in BMI distributions of Canada and the US. The results show that the differences between BMI levels, both over time and across countries, are increasing with BMI; meaning the highest difference is observed at the right tail of the two distributions. In analysis comparing two points in time, these differences are solely due to differences in the returns from attributes and the omitted variables that we cannot account for in our models. In cross-country analysis, there is evidence that the differences observed below the mean can be explained by the differences in characteristics of the two populations. The differences observed above the mean are again due to those in returns and the omitted variables.

Acknowledgements

I would like to thank professors Paul Contoyannis and Arthur Sweetman for accepting to supervise my Ph.D. studies. I took my first course in health economics from Dr. Contoyannis, and it was during this very early stage that we both realized the parallels in our perspectives. Unlike most of my peers, I knew whom I wanted to be my supervisor at the end of my very first semester at McMaster University. My interactions with him led me to develop my research questions for this dissertation early on my studies. The end of my first academic year corresponds with the time Dr. Sweetman joined Department of Economics as a professor in Economics and Ontario Research Chair in Health Human Resources. I know I am extremely fortunate that he found my ideas for this dissertation interesting and accepted to co-supervise me. I will be forever indebted to both of them for their guidance and great support in not only the dissertation phase but in every aspect of this challenging journey.

I met Professor Jim Dunn at one of the first courses that I took on Health Policy; Systems, Services and Policy. I remember the time when he taught us the determinants of population incidence rates while drawing our attention to the differences in the distribution of systolic blood pressure in two separate populations. His insight on what this graph means for us in health policy really opened my mind to see the bigger picture beyond all the graphs and numbers. I am truly thankful that he accepted to be in my supervisory committee and spared his precious time to support my progress in the program.

My learning advancement in McMaster has never been limited to courses that I had taken. I learned many things in the Polinomics sessions and the monthly HEAM meetings with fellow health economics researchers. Throughout the years, my interactions with professors Jerry Hurley, Michel Grignon, Jean-Eric Tarride, Emmanuel Guindon, Phil DeCicca and David Feeny taught me many great things. I know every little thing that I learned from them is a crucial building block of my career. My appreciation to them for sparing their time to share their wisdom with us will never be enough.

Without a doubt, one of the most important persons during my PhD studies has been Lydia Garland. Her title might be the program administrator for Health Policy program, but she has always been there to the rescue like a hero and made miracles a reality. For everything she has done for me, I know it was not her call of duty that has driven her but the kindness of her heart. Surely, the friendly atmosphere in the department was not limited to Lydia. I really appreciate everything that Gioia Buckley and Lyn Sauberli have done at the Centre for Health Economics and Policy Analysis (CHEPA) to help and support me in all these years.

I am sure I cannot finish thanking all the people who have helped me on this long journey, so I kindly ask them to excuse me from now. Before I end by thanking my family, there is one more important person I would like to acknowledge. Professor Umberto Eco demanded his readers to "[…] think hard, for neither the mystery itself nor the evidence is easy."[1] It is only the fate's unfortunate coincidence that we lost him in the same year that I am getting my PhD. I still remember seeing his lengthy curriculum vitae in my late teens and being impressed by all his academic achievements. I am sure this had an impact on helping me find my own direction in life.

Finally, I would like to express my deepest gratitude to my family, especially my mother, Nadire Ornek. After my father's death, what she did alone to bring my brother and me up required being a superhuman. She is the strongest women that I have ever met and even though she is tens of thousands of kilometers away, her existence has always given me the power to carry on. I dedicate this thesis first to her and then to my brother Hakan Ornek.

[1] Eco, Umberto., & Martini, Cardinal Maria (2000). *Belief or nonbelief?: a confrontation*. Arcade Publishing, New York

Disclaimer

The analyses of all three chapters were conducted at Statistics Canada's Research Data Centre (RDC) at McMaster University and I would like thank the staff for their generous assistance. The RDC is supported by funds to the Canadian Research Data Centre Network (CRDCN) from the Social Sciences and Humanities Research Council (SSHRC), the Canadian Institute for Health Research (CIHR), the Canadian Foundation for Innovation (CFI), and Statistics Canada. Although the research and analysis are based on data from Statistics Canada, the opinions expressed do not represent the views of Statistics Canada.

The access to National Health and Nutrition Examination Survey Data (the US data) was publicly available through Centers for Disease Control and Prevention (CDC)'s website.

> "Centers for Disease Control and Prevention (CDC). National Center for Health Statistics (NCHS). National Health and Nutrition Examination Survey Data. Hyattsville, MD: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, 2016, http://www.cdc.gov/nchs/nhanes/nhanes_questionnaires.htm"

Preface

Chapter 1 is co-authored with professors Arthur Sweetman and Paul Contoyannis. It is in preparation to be submitted to a journal. Chapter 2 is co-authored with Professor Arthur Sweetman and Chapter 3 is co-authored with professors Arthur Sweetman and Paul Contoyannis. I was responsible for the empirical analysis, participated in all stages of the research, and wrote the manuscripts.

Table of Contents

List of Tables

List of Figures

Introduction

This thesis focuses on the use of the body mass index (BMI), and applies it in quantitative research to addresses policy-relevant questions through the application of various microeconometric techniques. It consists of three chapters on BMI addressing: its measurement in survey data, its association with long-term physician costs and the distributional decomposition of BMI between two populations. These chapters help improve the quality of quantitative analysis using BMI data, demonstrate the relationship between long-term physician costs and BMI and explain the differences in BMI distributions of Canada and the US that we observe over time and between the two countries through a set of sociodemographic and socioeconomic variables.

Measurement error in self-reported (SR) height and weight information in survey datasets is a widely known issue. Individuals tend to over-report their height or under-report their weight, and this tendency varies with the design of the survey and the mode of the interview. The traditional way of correcting for this measurement error is to use an Ordinary Least Squares (OLS) based adjustment method. Various studies use this method (Cawley and Burkhauser, 2008; Cawley and Meyerhoefer, 2012; Cawley, 2004, 2000a; Gil and Mora, 2011; Rowland, 1990), in which directly measured (DM) body measurement is regressed on its SR counterpart in a dataset which has both types of data and predictions from this are used to correct SR BMI in the dataset of interest. As an alternative, recently Courtemanche et al. (2014, 2015) put forward another correction method as an improvement over the OLS one. Instead of basing corrections on the actual values of SR measurements, this method uses percentile ranking (PR) of the SRs and DMs. In their method, they first generate PRs using one dataset with both types of measurements and then apply these, instead of SR measurements, as the explanatory variable to predict corrected measurements using OLS regression. They claim that this method is better suited to cope with differences in survey designs as long as these rankings are the same across datasets. They argue that this should be the case if the datasets are representative of the same population.

Chapter 1 exploits the opportunities provided by rich Canadian datasets, where DM and SR data are available for a nationally representative sample in different survey cycles and different datasets. In contrast, in the US, where most of the literature has focused, there is only one nationally representative dataset, the National Health and Nutrition Examination Survey, that houses both DM and SR BMI to generate correction equations to be applied to other surveys which collect only SR BMI. Given the improvement claims of the PR method, Courtemanche et al. (2014, 2015) were not able to test the applicability of its correction equations over time and across different datasets. In this chapter we evaluate the PR's promise as an improvement over the SC in each of the three distinct scenarios (same dataset & same cycle, same dataset & different cycles and different datasets) by contrasting their mean squared prediction error,[2] and their performance in correctly classifying individuals into corresponding BMI categories. We also compare both the SR and corrected BMI values against the DMs when BMI is used as an independent variable in a regression predicting a set of health conditions using the CCHS 2008. Our results show that when BMI is used as a dependent variable, where minimizing measurement error and correctly classifying individuals into BMI categories are important, the SC performs better than the PR under almost all scenarios. If, however, BMI is used as an independent variable to predict a health condition, then it is debatable whether correcting for measurement error is necessary since the estimates obtained by either correction model do not outperform those made using SR BMI.

[2] Where the prediction error is calculated as DM minus (SC or PR).

Chapter 2 is a detailed investigation of the association between BMI and long-term physician costs. To our knowledge, neither the long-run relationship between BMI and health care costs for the population, nor a detailed look at the shape of the relationship, has been addressed previously. The research largely benefitted from the availability of linked administrative datasets under a McMaster Pilot Project which provided the opportunity to link longitudinal administrative datasets from Ministry of Health and Long-Term Care with the first cycle of the Canadian Community Health Survey (CCHS). We estimate long-term physician costs of obesity to the health care system in Ontario using the CCHS 1.1 (2000/01) linked with Ontario Health Insurance Plan (OHIP) data. The CCHS allows us to observe the individuals' body mass index (BMI) in addition to other personal characteristics, their self-reported health status, sociodemographic and socioeconomic attributes. The OHIP data cover the years 1999/00 to 2009/10 and includes information on physician demographics, services provided and the amounts billed. We observe the individuals' BMI in 2000/01 and apply nonparametric and semiparametric models, as well as repeated annual regression analysis. We use two-part models to investigate the association between point-in-time BMI and long-term physician costs across different age groups for males and females. We find the difference between the average net present value of physician costs between normal weight and obese individuals to be higher only in later ages in males, about 23%, but in all ages for females; ranging from 19% to 33% across age groups. For both sexes, this relationship is relatively linear until BMI reaches what is considered to be morbidly obese. We only observe obesity to be associated with higher long-term physician costs for males aged between 46 and 65. Even so, the cost difference between class I obese and normal weight males seems to be around $100 on average over eleven year period. Controlling for existing health conditions reduces the magnitude of this relationship, but does not alter its overall shape. Annual regression analysis shows that physician cost differences between obese and overweight individuals range between $40 and $200 in males but generally not statistically significantly different, except in the long-term. For females, the same difference range between $80 and $280 and it is generally statistically significant.

Chapter 3 analyzes both over time and cross-country differences in BMI distributions of Canada and the US. It employs two novel methods for distributional decomposition to account for the differences in BMI distributions and undertakes a sophisticated approach to the calculation of statistical inference.

Using the 1999/2000 and the 2013 cycles of the Canadian Community Health Survey, and data from 1999/00, 2001/02, 2009/10 and 2011/12 for the US National Health and Nutrition Examination Survey, we examine the relationship between sociodemographic variables and the distribution of BMI. We do this by comparing distributions across time within each country and by comparing the US and Canadian BMI distributions cross-sectionally for men and women separately. In order to decompose differences in distributions into components attributable to differences in covariates such as income and education, and differences in conditional distributions given covariates, we apply the methods proposed by Chernozhukov et al. (2013), and Firpo, Fortin and Lemieux (2009). Both methods allow decomposing quantiles of the distribution of BMI, but the former performs better at the tails of the distribution, whereas the latter produces results that are independent of the order in which explanatory variables are analyzed. We observe an increase in BMI levels along BMI distributions over time in each country. Our results indicate that changes in the BMI distributions in each country are mostly related to differences in conditional distributions given covariates for both men and women. In cross-country decompositions, differences in conditional distributions given covariates are the main reason for the discrepancy of BMI distributions of males. However, in females, there is statistically significant evidence that differences in distribution in some covariates, including age, immigration status, post-secondary education, equivalent household income and an indicator for living below the poverty line or experiencing food-insecurity explain at least some part of the difference we observe between the two countries.

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Chapter 1
An Evaluation of Models to Correct Errors in Self-Reported Measurements of the Body Mass Index

1.1 Introduction

Systematic measurement error in self-reported (SR) measures of height and weight in survey data is well documented.[3] Cawley et al. (2015) identify the measurement error in weight to be a non-classical error, where underweight individuals overreport their weight and the overweight and obese underreport. Both the underreporting of weight and the overreporting of height lead to underestimates of body mass indices (BMIs) and the prevalence of obesity in the population. Relying on SR BMI in obesity research not only leads to underestimates of prevalence rates, but is also argued to lead to biased estimation of any association between obesity and health conditions (e.g. Cawley et al., 2015; Chiolero et al., 2007; Dutton and McLaren, 2014; Santillan and Camargo, 2003).

[3] Plankey et al. (1997); (Cawley et al., 2015);Bes-Rastrollo et al. (2011); Flood et al. (2000); Hill & Roberts (1998); Kovalchik (2009); McAdams et al. (2007); Nawaz et al. (2001); Niedhammer et al. (2000); Santillan & Camargo (2003); Stewart (1982); Villanueva (2001); Shields et al. (2008); O'Neill & Sweetman (2012); Hayes et al. (2011); Spencer et al. (2002);Connor Gorber et al. (2007); Connor Gorber & Tremblay (2010).

Although measurement error in SR responses is problematic, they are less costly to collect than direct measurements (DMs) taken by trained professionals. Collecting only SRs responses allows survey sample sizes to be considerably larger than otherwise feasible for a given budget. Consequently, surveys commonly obtain SR body measurements. Surveys that collect DM height and weight information are typically conducted on a smaller scale due to both the expense to researchers and the response burden for participants. Also, surveys with DM may not be viable substitutes for large scale/scope surveys with SRs as since surveys with DMs usually contain fewer sociodemographic and socioeconomic attributes. A few surveys collect both, at least for a subset of respondents, and these are crucial for understanding the relevant measurement error, the difference between DM and SR, and provide a basis for its analysis and correction.

Various studies address this measurement error in SR body measurements by applying an Ordinary Least Squares (OLS) based adjustment method (Cawley and Burkhauser, 2008; Cawley and Meyerhoefer, 2012; Cawley, 2004, 2000a; Gil and Mora, 2011; Rowland, 1990). In this method, DM body measurement is regressed on its SR counterpart in a dataset which has both types of data and predictions from this are used to correct SR BMI in the dataset of interest. Recently, Courtemanche et al. (2014, 2015) put forward an alternative correction method as an improvement over the OLS one. Instead of basing corrections on the actual values of SR measurements, this method uses percentile ranking (PR) of the SRs and DMs. In their method, they first generate PRs using one dataset with both types of measurements and then apply these, instead of SR measurements, as the explanatory variable to predict corrected measurements using OLS regression in the same fashion as the OLS adjustment method. They claim that this method is better suited to cope with differences in survey designs as long as these rankings are the same across datasets. They argue that this should be the case if the datasets are representative of the same population.

We evaluate the PR's promise as an improvement over the SC in each of the three aforementioned scenarios by contrasting their mean squared prediction error,[4] and their performance in correctly classifying individuals into corresponding BMI categories. We also compare both the SR and corrected BMI values against the DMs when BMI is used as an independent variable in a regression predicting a set of health conditions using the CCHS 2008. To our knowledge, this is the first study that uses this cycle of the CCHS to look at this association - some of our results differ from those obtained with the CCHS 2005.

In summary, our findings indicate that when BMI is used as a dependent variable, where minimizing measurement error and correctly classifying individuals into BMI categories are important, the SC performs better than the PR under almost all scenarios. If, however, BMI is used as an independent variable to predict a health condition, then it is debatable whether correcting for measurement error is necessary since the estimates obtained by either correction model do not outperform those made using SR BMI. For males, the number of estimates closest to the DM results is the same for the PR and SR, and for females more estimates using SR are closest to the DM ones.

The next section provides a detailed literature review, following descriptions of the datasets we use. After that, we explain the methodologies used in this analysis. This is followed by the results and discussion sections, in which we present our findings, discuss our interpretations and disclose the limitations of the study.

[4] Where the prediction error is calculated as DM minus (SC or PR).

1.2 Literature Review

Using Canadian datasets, Connor Gorber et al. (2008) apply OLS regression based adjustment to correct measurement error in SR height, weight, and BMI using the 2005 Canadian Community Health Survey (CCHS). This is one of the two cycles of the CCHS that has both DM and SR measurements for a representative sub-sample. After randomly splitting this sub-sample in half they use one part to generate correction equations for SR height, weight, and BMI; they then test the model on the other half. They contrast simple model controlling only for SR measurements with an alternative including an extensive set of relevant variables, and find that the goodness of fit is improved very little with the additional variables.[5] They conclude that using the SR measurement as the only explanatory variable is sufficient. We call this the simple correction (SC) model. In a follow-up study, Shields et al. (2011) employ the SC to check the robustness of correction equations across different cycles of the same dataset, and across different datasets, using the CCHS 2005 and 2008, and the Canadian Health Measures Survey (CHMS) Cycle 1. The CHMS's survey design is quite different from that of the CCHS as explained in our data section. The authors find the correction equations work reasonably well across different cycles of the same dataset, but to be less effective across different datasets. This is due to differences in the survey designs, which alter the magnitude of the measurement error.

Courtemanche et al. (2014, 2015) test their method against an expanded version of the SC with multiple explanatory variables using three different datasets that have samples representative of the US population. The National Health and Nutrition Examination Survey (NHANES) is the

[5] Plankey et al. (1997) also look into additional explanatory variables and different specifications in SC, and find only minimal improvements. Ljungvall et al. (2015), using a regional sample of the Swedish population, argue that education level in females is a statistically significant determinant of this measurement error in self-reported responses.

dataset with both types of body measurements used to generate correction equations. They apply these equations to the Behavioral Risk Factor Surveillance System (BRFSS) and the American Time Use Survey (ATUS), which have only SR measures. They all cover the period between 2007 and 2008. By race and sex, the authors first compare the DM BMI distributions from the NHANES with the post-correction distributions from the BRFSS and the ATUS. They find the PR corrected distributions to be statistically indistinguishable from the distribution of DM BMI of the same population in the NHANES, but they find statistically significant differences using the OLS adjustment method. Next, they compare the results when SR and corrected BMIs are employed as dependent and independent variables in regression analyses. For the case with BMI as a dependent variable, they use both the BRFSS and, in the 2014 paper only, the ATUS to look at the relationship between BMI and food prices. For the case with BMI as an independent variable, they use the BRFSS to look at the relationship between BMI and diabetes, and the ATUS to look at the relationship between BMI and disability. They find that when BMI is used as a dependent or an independent variable, correction changes the magnitude of the coefficients but not the conclusions drawn using SR BMI.

Unfortunately, given their data, Courtemanche et al. (2015, 2014) cannot look at the applicability of correction equations over time and nor can they study the suitability of correction equations across different surveys. We are able to test both these issues. Two cycles of each of the CCHS and the CHMS have both SRs and DMs and are representative of the Canadian population. They allow us to compare the PR with the SC under three distinct scenarios that demonstrate their suitability to be used over time and across different datasets. First, we compare them within the same cycle of the same survey. Second, we look at the appropriateness of the correction equations obtained in one cycle (year) of a survey on another cycle, testing their suitability over time. Finally, we examine the applicability of correction equations obtained in one survey for a different survey that is contemporaneous.

1.3 Data

This study uses the master files of Statistics Canada's CCHS, cycles 2005 and 2008, and the first two cycles of the CHMS that cover the period 2007 to 2009, and 2009 to 2010. These cycles of the CCHS collected both SR and DM body measurements for a random sub-sample, whereas the CHMS did so for the full sample. These two surveys are repeated cross-sections that are representative of 98% and 96.3% of the selected age groups of the Canadian population, respectively. Excluded from their coverage are individuals living on Indian Reserves and Crown Lands, institutional residents, full-time members of the Canadian Forces, and residents of certain remote regions. The age groups that they focus on are; 12 and over in the CCHS, 6 to 79 in the CHMS cycle 1 and 3-79 in the CHMS cycle 2.[6]

For our purposes, the most important difference between the two survey designs is how body measurements were collected. Respondents to the CCHS were not told that the interviewer would measure them at the end of the interview, on the other hand those in the CHMS were informed that the survey has two parts and that the household interview would be followed by a physical examination that includes measurement of their height and weight. One might, therefore, expect less measurement error in the CHMS. Lastly, in the CCHS the measurements were taken by trained interviewers, but in the CHMS health measurement specialists were used. Overall response

[6] This information is found in Statistics Canada user guides, which are not publicly available.

rates to the DM components of the surveys are comparable.[7] In the DM subsamples of the CCHS the response rate was 55.9% in 2005 and 50.7% in 2008, and in the CHMS it was 51.7% in cycle 1 and 55.5% in cycle 2 (Shields et al., 2011).

Our sample for analysis consists of the adult population, ages 18 and over for whom both SR and DM height and weight measures exist. We also drop those with missing values for any variable used in the analysis and eliminate the outliers in body measurements.[8] We exclude pregnant and breastfeeding females, as the calculation of BMI is not recommended for them. Finally, we ignore underweight individuals (according to DM BMI) due to their small sample sizes. Instead of using the derived SR and DM BMI variables provided in the datasets, we calculate them manually using the BMI formula in order to eliminate rounding.

Like Connor Gorber et al. (2008), in our preliminary analysis we did not find a considerable improvement when the OLS adjustment method is specified with other relevant explanatory variables in addition to SR. Following Shields et al. (2011), we specify the OLS adjustment method using the SR measurement as the only explanatory variable, which we call the SC. In the PR, following Courtemanche et al. (2015, 2014), we use a list of sociodemographic variables when estimating correction equations. In addition to the predicted percentile ranked BMIs of the observations, they use age (second order polynomial), sex, their interaction, race in their

[7] In the CCHS, 'overall' is the combination of the household response rate to both the subsample and the direct measurement component. In the CHMS, it is the combination of the response rates of households that complete the questionnaire and participated in the subsequent physical examination.

[8] Even after eliminating missing values of height and weight, we observe unexpectedly large differences between SR and DM BMI in the CCHS for a number of observations at both ends of the scale. We suspect these were due to either the confusion of the respondents in disclosing the unit in which they reported their weight (i.e., pounds or kg), or recording mistakes on the part of the interviewer when entering the values into the system. We identify 5 standard deviations away from mean measurement error (DM-SR) of height, weight or BMI as the threshold point to define outliers. Based on this definition, after dropping the missing values we do not drop further observations in the CHMS.

specifications. We also added the province of the respondent in the list of explanatory variables that we use in the PR method.

Dummy variables for race are white (reference), Aboriginal, African and Caribbean, Asian (Korean, Japanese, Chinese), South Asian, Southeast Asian (including Filipino), Middle Eastern (West Asian & Arab), Latin American and Other (including mixed race). Dummy variables for province of residence include different sets of provinces in the CCHS and the CHMS. The former include all ten provinces (sub-sample involving DM was not undertaken in the territories), but the latter was conducted only in 7 provinces (excluding Prince Edward Island, New Brunswick, and Saskatchewan). In both surveys, Newfoundland and Labrador is used as the reference category.

Predicting obesity-related health conditions is done using the CCHS 2008 only, as comparisons under different scenarios were not of interest. There are a number of studies that look at the associations between obesity and the same set of health conditions using the CCHS 2005 (e.g., Shields, Gorber, and Tremblay (2008); Connor Gorber et al. (2008); Dutton and McLaren (2014)), but to our knowledge this is the first to undertake the analysis using the CCHS 2008. The six health conditions studied are: diabetes, heart disease, high blood pressure, arthritis, activity limitation (often or sometimes) and self-perceived health (fair or poor). Individuals are classified as normal weight if their BMI is 18.5 to 25, overweight if it is 25 to 30, and obese if it is 30 or over. Obesity is further divided into classes that signify the severity of the condition. A BMI from 30 to 35 is categorized as class I, 35 to 40 is class II, and BMI over 40 is class III (Health Canada, 2012). Analyses of predicted obesity-related health conditions are restricted to those 40 years old or older in order to be comparable to the previous literature. It is presumed that the interaction between obesity and aging is related to these health conditions, rather than the immediate link between body fat and adverse health. Therefore, previous studies argue that these health conditions are more often a concern among middle-aged or older individuals than younger adults.

1.4 Methodology

The first scenario we examine -- same survey and same year -- is the most straight-forward, but of limited use in practice. The second scenario -- same survey but different years -- is relevant in situations where DM is not collected in every cycle of a survey. For instance, though the CCHS begins with 2000/01 and is ongoing, only the 2005 and 2008 cycles collect both DM and SR body measurements for a randomly selected sub-sample of respondents.[9] All other cycles of the CCHS collect only the SR measurements, leaving only those two cycles to be relied upon in generating correction equations. The third scenario -- using a correction equation based on one survey to correct SR BMI in another survey -- is probably the most useful for researchers. For example, in the US context, where the NHANES is the only dataset that collects both DM and SR measures for a nationally representative sample, researchers (e.g., Cawley and Burkhauser, 2006; Cawley, 2004, 2000; Chou et al., 2004; Rowland, 1990)[10] use the NHANES to generate correction equations to correct measurement error in SR measures in other datasets. Courtemanche et al. (2015, 2014) also use the NHANES to demonstrate their method and provide evidence to argue for its use over the SC in the US context. In this paper, we are able to evaluate their method more rigorously using Canadian datasets. Especially, measurement error is likely to be different if respondents did not know that their body measurements would be taken after the interview. Like the CHMS,

[9] Although DM is also collected in the CCHS 2.2, there are few observations with both SR and DM measures due to different objectives of this cycle of the survey.

[10] Lindeboom, Lundborg, and van der Klaauw (2010) use data from the British National Child Development Study and borrowed the prediction equations used by Cawley and Burkhauser (2006) [cited in the authors' manuscript as Burkhauser and Cawley (2008).The equations only appear in the working paper version (2006) of that paper]

respondents of the NHANES are informed that the survey has two components, home interview and health examination, and that the health examination includes body measurements (Centers for Disease Control and Prevention, 2013). Therefore, using the CCHS and the CHMS, we can explore the appropriateness of applying correction equations across different surveys that differ in this aspect of their design and inform those who use the NHANES.

Like Connor Gorber et al. (2008) and Shields et al. (2011), we randomly split each cycle of the CCHS in the first and second scenarios.[11] In the latter scenario, both the CCHS 2005 and 2008 are used to generate correction equations. This allows us to demonstrate the appropriateness of using correction equations from an older cycle on a more recent one and vice versa. In the third scenario, we pool the first two cycles of the CHMS to increase the sample size and pair it with the CCHS 2008, then generate correction equations in one to be applied on the other. At all steps of the analysis, we use the sample weights provided by Statistics Canada.

1.4.1 Simple Correction Method

Lee and Sepanski (1995) provide the theoretical background and assumptions of the model. It involves OLS regression of DM measurements on the SR measurements. The SC used in our analysis is:

$$DM_i = \beta_0 + \beta_{SR} SR_i + \varepsilon_i \tag{1}$$

[11] We use cross-validation where the correction equations generated in one half of the sample (training sample) are applied to the other (validation sample) and compared against the DM values.

We first estimate equation 1 by using the dataset in which both DM and SR exist, and then we use these results in the prediction of the DM values for the target dataset. The analysis is done separately for each sex.

It is crucial to note the contrast between this specification of the OLS adjustment method and the way Courtemanche et al. (2015, 2014) specify it when comparing the two methods in their paper. They generate sex and race specific correction equations using both methods. In our comparison, we generate only sex-specific SC to compare against age, sex, race and geography specified PR equation method. Although this specification may put the SC in an unfair comparison, we choose to follow the specification adopted by Connor Gorber et al. (2008) and Shields et al. (2011).

1.4.2 Percentile Ranking

Courtemanche, Pinkston, and Stewart (2014) argue that the SC is sensitive to differences in survey design and inappropriate when correction equations generated in one dataset need to be applied to correcting SR measurements in another. Their method relies on different assumptions about the relationship between SR and DM data. Instead of using the actual SR values directly in the regression to obtain predictions for correction equations, it uses the information obtained from those values; PRs of the observations in the distribution of SR variable. By doing this, a restriction is placed on the PR of each observation, conditional on other characteristics, in the distribution of the corrected measurement.

In the first step, cumulative distributions of the SR observations in two datasets, one needing correction and the other with both types of measurements, are generated by sex and race groups to obtain a PR of the observations in each dataset. The second step involves generating cubic splines ($SRsplines_i$) to obtain flexible functions of these PRs and using them as explanatory variables in a linear regression, along with age, sex, race and province of the respondent as in equation 2.[12]

$$DM_i = \beta_1 Age_i + \beta_2 Age_i^{\,2} + \beta_3 Female_i + \beta_4 Female\ _i x\ Age_i + \beta_5 Female\ _i x\ Age_i^{\,2} + \beta_{Fsp} Female\ _i x\ SRsplines_i + \beta_R race_i + \beta_p province_i + \varepsilon_i \qquad (2)$$

As in the SC, the final step involves the estimates of equation 2, but without a constant, to be used in prediction of the DM values in the target dataset. Courtemanche, Pinkston, and Stewart (2014) do not generate separate correction equations by sex, but use interactions instead.[13] Once the predictions are obtained for the target sample, we perform further analyses for males and females separately.

Courtemanche, Pinkston, and Stewart (2014) suggest that calculating corrected BMI values in two steps, correcting weight and height first and then calculate BMI, instead of correcting BMI directly in one step would increase the precision of corrected BMIs and reduce the mean squared prediction error (MSE). We use both 1-step and 2-step (2S) approaches in generating corrected BMI for each method.

[12] Courtemanche, Pinkston, and Stewart (2014) interacted race with sex, a third order age polynomial and splines. In our case, doing so resulted in multiple omitted variables due to collinearity, because our race variable has more categories than the one used by them. Also, we use a second degree polynomial of age, as cubed age was not statistically significant in the preliminary analysis. Furthermore, we control for the province that the individual lives in as an additional explanatory variable as noted earlier. Thus, we adopted the alteration to their specification of their final step as shown in equation 2.

[13] The results were not substantively different when we used separate male/female correction equations with PR.

1.4.3 Prediction of Health Conditions

We use logistic regression to predict the odds of having each of the six health conditions listed earlier for overweight, obese class I and obese class II & III BMI categories (normal weight is the reference group).We control for age in the regressions and the analysis is done for males and females separately. The estimates are presented as adjusted odds ratios and the aim is to compare the estimates produced by SR, SC or PR with the results of DM in terms of their magnitude and statistical significance. The model can be shown as:

$$Logit(HC)_i = \alpha_0 + \phi_A Age_i + \phi_{bc,m} BC_i + \varepsilon_i \qquad (3)$$

where dependent variable is a dummy variable for one of health conditions, and $\phi_{bc,m}$ symbolizes the log odds ratios for overweight, obese class I and obese class II & III BMI categories according to *m*, where *m*={DM, SR, SC, PR}.

1.5 Results

Basic descriptive statistics for each unadjusted dataset, and corrected versions of relevant datasets, are presented in Tables 1.1A and 1.1B for males and females respectively. For all samples, on average females are shorter and lighter than males and their BMIs are lower. The magnitude of the measurement error in SR height is relatively small at the mean,[14] and the average corrected height values using the SC are almost always closer to DM values than the PR ones, except males in the

[14] Dutton and McLaren (2014) show that measurement error in height not to be an issue for adults younger than 65 years of age. These authors propose two methods for correcting measurement error in weight alone for adjusting SR BMI.

CCHS 2008 sample.[15] Measurement error for mean weight is more pronounced than for mean height, and again we find that the SC produces closer results to DM values apart from two exceptions: females in the CCHS 2005, and males in the CHMS sample whose SR responses are corrected using the CCHS 2008. For BMI outcomes, we see that the Canadian population is considered to be overweight on average. Underreporting in SR BMI is evident, and it is around 1 BMI unit on average in each sample. Further, the results show that the SC BMI is closer to DM BMI than either the PR or SR BMI with the exception of the CHMS females where the PR is closest to DM. Finally, Tables 1A and 1B show that when correcting BMI the two-step approach is preferred for the PR. Out of 14 cases, 11 of the two-step PR results are closer to the DM values as are 8 of the two-step SC results.

In addition to reducing mean prediction error, we also need to consider the variance of the prediction error when evaluating these correction methods. Tables 1.2A and 1.2B present MSEs for each approach, including unadjusted SRs for males and females respectively.[16] Interestingly, the SC produces lower MSEs than the PR in every scenario for both sexes. Moreover, the MSEs using the PR are actually higher than the MSEs from using the SR BMI in every instance. Due to the difference in its design, with respondents knowing that they will be measured in a second step, we expect to find lower MSEs in the CHMS than the CCHS. This is true for SR and SC, but not PR. In fact, the highest MSEs calculated for the PR are for the CHMS. MSEs of the SC are relatively stable; around 4.3 and 6.5 across all cases, but those of the PR fluctuate between 6.7 and 15.7. For

[15] Both methods yield the same difference in females in across different datasets scenario.

[16] $E.g\ for\ SR, MSE = E[(DM - SR)]^2 + Var(DM - SR) = [1/N \sum_{i=1}^{n}(DM - SR)]^2 + Var(DM - SR)$. We calculated this for each sex separately under each scenario. We can obtain analogous measures for SC and PR by substituting for SR.

both correction methods, MSEs are higher in females than males. Out of 14 cases, the two-step approach results in lower MSEs 9 times for the SC method, but only 6 times for the PR.

Next, in Figures 1.1A-C we visualize the distribution of measurement and prediction errors for each scenario for males and females. We clearly see under-reporting in SR BMI responses as the mean measurement errors in these graphs are all negative. This is smaller in the CHMS than the CCHS, as expected, given the anticipated effect of respondents knowing that they would be measured. Figure 1.1A has three pairs of graphs for Scenario 1 (the same survey and same cycle). In the CCHS graphs, the only noticeable difference between the two methods is for females in 2008 cycle, for whom the mean prediction error of the PR is positive (over-correction) but the mean prediction error of the SC is around zero. This was also apparent in the overall results in Tables 1.1A and 1.1B. Looking at Scenario 2, we see that the results of the CCHS 2005 corrected by the CCHS 2008 are not too different between the two methods in Figure 1.1B. The results of the CCHS 2008 corrected by the CCHS 2005, on the other hand, are better with the SC, as the PR seems to be under-correcting. Figure 1.1C shows the results for Scenario 3. In the case of the target dataset with a lower error variance and higher sample size, the CHMS corrected by the CCHS 2008, the PR results in lower prediction error than the SC, as the latter is clearly over-correcting it. When the sample size is smaller and the target error variance is higher as for the CCHS 2008 corrected by the CHMS, correction equations based on the SC are again preferable.

Most of the literature on body weight is more interested in classifying individuals into BMI categories than using BMI as a continuous variable in their analysis. Therefore, one of the main reasons for correcting BMI is to correctly classify individuals according to their body types. A common way of testing this is to look at sensitivity (proportion of those identified as normal weight, overweight or obese using SR, SC or PR to those who are identified as such using DM) and specificity (proportion of non-normal weight, non-overweight and non-obese according to SR, SC or PR to those who are identified as such using DM). These measures can, respectively, be thought of as reciprocals of false positive (type I), and false negative (type II) errors. For the three scenarios that we evaluate using these correction methods, the results are shown in Tables 1.3A-1.5B In Tables 1.3A and 1.3B, which compares results from the same survey and the same cycle for males and females respectively, we see that correction equations generally improve sensitivity for overweight and obese categories compared to SR values. For males, it is evident that the SC is better at categorizing more of these individuals than the PR in all three datasets, but for females the PR is better at classifying obese individuals in the CCHS and overweight individuals in the CHMS. As discussed in Connor Gorber et al. (2008) and Shields et al. (2011), the decrease in the sensitivity of the normal weight category is an undesirable consequence of using a correction method. Since these correction methods are shifting the SR BMI distribution to the right (see Figures 1A-C), some of those who are correctly identified as normal weight using SR BMI end up being counted as overweight after the correction. In our results, with the exception of the CCHS 2005, for both sexes this trade-off is lower in the SC than the PR. There is an inverse relationship between sensitivity and specificity. As more overweight and obese individuals are correctly classified after error correction, those who are really not normal weight are more successfully classified once the error is corrected. For instance, when we look at specificity in males, we see an overall improvement in normal weight category relative to SR. Again, the improvement achieved by the SC surpasses that by the PR in each instance. With the exception of overweight in the CHMS, specificities among overweight and obese males are reduced as a result of the SC and the PR, the latter performing worse. For females, the evidence is a little mixed, but the overall picture is very similar to that of males.

In Tables 1.4A and 1.4B, we check the adaptability of correction equations across time within the same survey for males and females respectively. The sensitivity results are almost the same for males as in those in Table 1.3A, except that the PR shows an improvement over the SC in terms of identifying more normal weight individuals correctly. The results for females are similar to those of males; the SC is classifying more individuals to overweight and obese categories than the PR. However, the PR shows improvement in classifying normal weight females relative to SR. The specificity results are more mixed than those of sensitivity. A higher proportion of non-normal weight males and females are correctly classified by the SC than the PR or SR. In both across time cases we examine here, the two correction equations identify fewer non-overweight and non-obese male and females than SR (with the exception of the overweight category for the CCHS 2005 corrected by the CCHS 2008 for females).

Tables 1.5A and 1.5B show the sensitivity and specificity outcomes for Scenario 3 for males and females respectively. When the CCHS 2008 is used to generate correction equations to be used in predicting DM BMI in the CHMS (first 3 columns), we see less reduction in the sensitivity of normal weight category in using the PR (in both males and females). We also see the PR performing worse than SR in correctly assigning overweight males and obese males and females. The SC, on the other hand, consistently assigns more of both males and females to overweight and obese categories than SR. Except for the normal weight category; both the SC and the PR perform worse than SR for specificity. When the CHMS is used to generate correction equations to be used in the CCHS 2008, we see a smaller reduction in sensitivity of normal weight and better performance in overweight males and females by the SC. The PR only does better than the SC in correctly assigning obese males and females. Specificity is again similar to the earlier findings-improvement is only for the normal weight category, and generally the PR performs worse than the SC.

Tables 1.6A and 1.6B present the predictions for obesity-related health conditions by BMI categories for males and females who are 40 years old or older respectively. Models control for age and BMI categories according to each measure. Normal weight category is used as the reference group and statistically significant differences of the point estimates for other BMI categories are noted on the results. In Table 1.6A, we see that the point estimates of the prediction of diabetes for overweight males by the PR is closer to DM results than are the SC or SR ones. In turn, those for obese class I males, predictions by SR BMI and for obese class II the ones by the SC are the closest to the DM predictions. For heart disease, overweight and obese class I categories predictions by the PR, and for obese class II & III the ones obtained by SR are the closest to the DM results. Generally, of the two correction methods, the PR produces odds ratios for obese and the SC produces odds ratios for overweight that are closer to the DM results. However, this is not to say that SR is any worse, as most point estimates are not statistically significantly different from the reference group. The similarity of the three approaches can be seen if we were to focus on the (statistically insignificantly different) magnitudes; for all 18 health conditions 7 of the SR, 4 of the SC and 7 of the PR that are closest to the DM point estimates.

In Table 1.6B, we see that for females the SC produces odds ratios for overweight that are closer to the DM results for diabetes, and both for overweight and obese class II & III for heart disease. The PR, on the other hand, produces estimates closer to the DM results in high blood pressure for obese and in arthritis for obese class I only. Overall, though, by using SR, 12 out of 18 predictions are closer to the DM results than either of the correction methods.

1.6 Discussion

BMI is known to be an imprecise measure of body fat (Cawley and Burkhauser, 2008; Gómez-Ambrosi et al., 2012; Lee, 2014; Michels et al., 1998; Wada and Tekin, 2010), but it is the most widely available form of body measurement data in surveys because of its low cost. Moreover, for cost reasons only self-reported measures are usually gathered. Because of this, most obesity studies using large samples are based on this measure. Although it may be an imprecise measure of obesity, the aim should be to use this information appropriately, until it becomes feasible to collect more precise data on individuals' body fat in these population-wide surveys.[17] There is often systematic measurement error[18] associated with this type of data, particularly among those with higher BMI. Not only does this measurement error depend on social desirability (Connor Gorber et al., 2007), it also varies by the mode of the interview (St-Pierre and Béland, 2004) or the survey design (Shields et al., 2011). Due to this shortcoming of SR BMI data, an obvious objective of any researcher on the topic is to identify and apply an appropriate correction method. The expectation is not to completely eliminate the measurement error (Plankey et al., 1997), but to reduce its magnitude to improve analysis using SR data.

This paper evaluates two such methods; one has been in use for a while (SC), and the other has been recently proposed as an improvement over the former (PR). This improvement comes in the form of offering flexibility in generating correction equations that are adaptable across different surveys, at least in theory. We tested these claims by setting up three scenarios to test the

[17] Lee (2014) proposes a new method where waist circumference is used as well as BMI to better predict percentage body fat in an individual's body. The usability of this method depends on the availability of waist circumference data, which is less likely to be SR.

[18] Using National Health and Nutrition Examination Survey (NHANES), Cawley et al. (2015) find this error to be non-classical and correlated with the measured weight.

performance of the two correction models. Our results do not convince us that the PR is able to adjust for measurement error any better than the SC, and it may be worse in many cases. When the aim is to reduce measurement error in SR BMI, which is to be used as a continuous dependent variable, the SC is always preferable over the PR in all scenarios that we analyze in this paper. In the discrete case, when correctly classifying individuals is of interest, the SC is still preferable but in certain cases the PR results in higher sensitivity for the obese category. This indicates an ability of the PR in dealing with the tails of the BMI distribution better than the SC. However, in general the PR is not consistently better in relation to specificity or sensitivity. We also show that when BMI enters as an independent variable in a regression, SR BMI performs no worse than using DM. Therefore, in such cases the correction is not recommended.

Unlike previous studies that use the CCHS 2005 in their prediction analysis (Shields, Gorber, and Tremblay (2008); Connor Gorber et al. (2008); Dutton and McLaren (2014) [19]), we do not find SR BMI categories to consistently overestimate effects using the CCHS 2008. In males, only 4 out of 18 times the magnitude of the odds ratios (regardless of their significance) for the SR is higher than that of DM. In females, odds ratios of SR are higher than DM 10 out of 18 times. When we replicate our analysis using the CCHS 2005,[20] we find the same consistent overestimation as found by previous studies. Using the NHANES 2003-2010, Cawley et al. (2015) also document that SR overestimate the relationship between BMI and health care utilization and prescription drug use. We think that it is worthwhile to note this difference in our results as the arguments made by Chiolero et al. (2007) are not supported by our findings, at least not for males, and that the conclusions reached by previous studies may not extend over time.

[19] Dutton and McLaren (2014) pool both the CCHS 2005 and 2008 into a single dataset and only include those 40 to 65 years old in their analysis.
[20] Results not shown, but they are available upon request.

Although in theory the PR method is proposed as an improvement for adaptability of correction equations across time and different datasets, Courtemanche et al. (2014) disclose that it is ideal to predict actual values on the same dataset that the correction equations are derived from and that the differences in the designs between datasets may still be a significant issue. The study that first applied the SC in the Canadian context, Connor Gorber et al.(2008), also tried alternatives such as polynomial regressions and spline regression for different weight ranges, but found no improvement over the SC. Overall, our results should be viewed as further evidence in the Canadian context that the SC is generally adequate for correcting systematic measurement error in BMI, at least in Canada.

Similar to previous findings, our results show that the main drawback of applying correction equations to SR BMI data is the reduction in sensitivity for the normal weight category. The reason behind this is the fact that measurement error is minimal among normal weight individuals and the application of correction methods over-correct their BMI leading to misclassifications (Connor Gorber et al., 2008). One study tried to improve on this by generating different correction equations for different weight quantiles, but their results show that the improvements are made for overweight and obese categories but not for normal weight (Mozumdar and Liguori, 2011). A recent study by Dutton and McLaren (2014) correct measurement error in SR weight (but not height) - their results show that cost of misclassifying normal BMI individuals is less than the results of the SC method. However, there is a trade-off between the SC and Dutton and McLaren (2014) in correctly classifying overweight and obese individuals. It is therefore recommended that researchers identify the BMI category of focus in their study before deciding on a correction method.

Table 5.1A Basic Descriptive Statistics and Mean Values (Males)

MALES	*CCHS 2005*	*CCHS 2008*	*CHMS Cycles 1&2 combined*	*CCHS 2005 corrected by CCHS 2008*	*CCHS 2008 corrected by CCHS 2005*	*CHMS cycles 1&2 corrected by CCHS 2008*	*CCHS 2008 corrected by CHMS cycles 1&2*
N	944	970	1768	944	970	3498	1894
Mean Age	44.6	43.6	44.3	44.6	43.6	44.5	42.9
Mean Height (m)							
DM	1.748	1.747	1.751	1.748	1.747	1.753	1.747
SR	-0.009	-0.011	-0.014	-0.009	-0.011	-0.013	-0.011
SC	0.002	0.003	-0.001	0.004	0.001	-0.001	0.001
PR	-0.012	-0.001	-0.002	0.014	0.015	0.005	-0.006
Mean Weight (kg)							
DM	82.054	81.88	85.203	82.054	81.88	84.561	81.752
SR	1.829	2.076	0.825	1.829	2.076	0.591	1.802
SC	-0.406	-0.11	0.434	-0.366	-0.144	-1.415	1.342
PR	-2.228	0.172	1.224	4.074	2.591	2.186	-2.577
Mean BMI							
DM	26.826	26.812	27.729	26.826	26.812	27.478	26.758
SR	0.894	1.027	0.670	0.894	1.027	0.586	0.927
SC	-0.139	-0.020	0.152	-0.161	0.005	-0.4	0.376
2S-SC	-0.025	-0.021	-0.163	0.308	0.227	0.352	0.176
PR	-0.417	0.062	0.479	0.829	0.723	0.628	-0.709
2S-PR	-0.019	-0.009	-0.459	-0.270	-0.016	-0.517	-0.845

Note: *Mean height, weight and BMI are shown for the male sample in respective datasets. 2S-SC and 2S-PR indicate that BMI values are calculated using corrected height and weight, instead of correcting BMI directly using these methods as in SC and PR.*

Table 1.1B Basic Descriptive Statistics and Mean Values (Females)

FEMALES	*CCHS 2005*	*CCHS 2008*	*CHMS Cycles 1&2 combined*	*CCHS 2005 corrected by CCHS 2008*	*CCHS 2008 corrected by CCHS 2005*	*CHMS cycles 1&2 corrected by CCHS 2008*	*CCHS 2008 corrected by CHMS cycles 1&2*
N	1093	1050	1957	1093	1050	3895	2102
Mean Age	47.8	45.9	44.9	47.8	45.9	45.4	45.6
Mean DM Height (m) and differences with SR, SC & PR							
DM	1.618	1.615	1.621	1.618	1.615	1.619	1.615
SR	-0.006	-0.006	-0.008	-0.006	-0.006	-0.009	-0.007
SC	0	-0.001	0.002	-0.001	0	-0.002	0.001
PR	0.005	-0.002	0.004	0.017	0.017	0.002	-0.001
Mean Weight (kg)							
DM	67.618	67.304	70.223	67.618	67.304	70.339	68.316
SR	2.504	2.378	1.516	2.504	2.378	1.539	2.49
SC	0.816	0.531	-0.038	0.653	0.697	-1.063	1.104
PR	-0.542	-2.743	0.166	2.235	3.460	1.288	-1.411
Mean BMI							
DM	25.869	25.837	26.732	25.869	25.837	26.813	26.218
SR	1.160	1.114	0.837	1.160	1.114	0.872	1.190
SC	0.212	0.122	-0.064	0.168	0.165	-0.358	0.357
2S-SC	-0.025	-0.024	0.050	-0.221	-0.206	-0.232	-0.205
PR	-0.339	-0.887	-0.084	0.525	0.847	0.521	-0.572
2S-PR	-0.026	-0.020	0.042	-0.300	0.894	-0.350	-0.656

Note: *Mean height, weight and BMI are shown for the female sample in respective datasets. 2S-SC and 2S-PR indicate that BMI values are calculated using corrected height and weight, instead of correcting BMI directly using these methods as in SC and PR.*

Table 1.6A Mean Squared Errors of Self-Reported and Corrected Values for BMI (Males)

MALES	*CCHS 2005*	*CCHS 2008*	*CHMS Cycles 1&2 combined*	*CCHS 2005 corrected by CCHS 2008*	*CCHS 2008 corrected by CCHS 2005*	*CHMS cycles 1&2 corrected by CCHS 2008*	*CCHS 2008 corrected by CHMS (1&2)*
SR	6.253	6.951	4.842	6.253	6.951	4.635	6.841
SC	5.377	5.616	4.391	5.380	5.617	4.395	5.769
2S-SC	5.399	5.594	4.300	5.393	5.571	4.340	5.773
PR	6.653	9.785	10.041	9.151	9.388	9.467	9.151
2S-PR	6.331	10.303	9.081	7.887	9.014	8.872	8.422

Note: Mean Squared Error for SR: $MSE = E[(DM - SR)]^2 + Var(DM - SR) = [1/N \sum_{i=1}^{n}(DM - SR)]^2 + Var(DM - SR)$. The calculations are repeated in the same fashion by replacing SC, 2S-SC, PR and 2S-PR values in the formula for respective measures. *2S-SC and 2S-PR indicate that BMI values are calculated using corrected height and weight, instead of correcting BMI directly using these methods as in SC and PR.*

Table 1.2B Mean Squared Errors of Self-Reported and Corrected Values for BMI (Females)

FEMALES	*CCHS 2005*	*CCHS 2008*	*CHMS Cycles 1&2 combined*	*CCHS 2005 corrected by CCHS 2008*	*CCHS 2008 corrected by CCHS 2005*	*CHMS cycles 1&2 corrected by CCHS 2008*	*CCHS 2008 corrected by CHMS (1&2)*
SR	8.166	7.797	6.236	8.166	7.797	6.236	7.640
SC	6.435	6.078	5.240	6.431	5.617	5.366	6.128
2S-SC	6.438	6.077	4.975	6.461	5.571	5.148	6.010
PR	9.228	10.545	14.992	10.736	11.605	12.649	9.954
2S-PR	9.639	11.896	15.701	10.627	11.128	12.716	10.168

Note: Mean Squared Error for SR: $MSE = E[(DM - SR)]^2 + Var(DM - SR) = [1/N \sum_{i=1}^{n}(DM - SR)]^2 + Var(DM - SR)$. The calculations are repeated in the same fashion by replacing SC, 2S-SC, PR and 2S-PR values in the formula for respective measures. *2S-SC and 2S-PR indicate that BMI values are calculated using corrected height and weight, instead of correcting BMI directly using these methods as in SC and PR.*

Table 1. 7A Sensitivity and Specificity: Same Dataset and Cycle (Males)

	SENSITIVITY			SPECIFICITY		
	Normal Weight	**Overweight**	**Obese**	**Normal Weight**	**Overweight**	**Obese**
CCHS 2005						
SR	95.18	73.53	62.2	83.54	83.87	98.81
	[92.19,97.07]	[66.89,79.25]	[52.49,71.02]	[79.06,87.22]	[79.07,87.74]	[96.24,99.63]
SC	78.84	88.94	78.18	95.22	79.42	97.01
	[69.06,86.15]	[83.89,92.54]	[69.02,85.21]	[92.61,96.94]	[72.79,84.77]	[94.47,98.41]
PR	73.10	83.98	72.19	94.64	73.01	94.63
	[63.52,80.93]	[77.2,89.03]	[62.44,80.21]	[91.88,96.50]	[66.28,78.83]	[90.6,96.99]
CCHS 2008						
SR	93.53	62.56	66.40	74.56	84.59	98.62
	[86.54,97.01]	[54.33,70.13]	[57.27,74.45]	[67.91,80.24]	[79.51,88.59]	[96.74,99.43]
SC	77.92	84.02	88.67	91.11	82.54	96.44
	[67.93,85.46]	[77.92,88.68]	[81.38,93.34]	[85.61,94.64]	[75.86,87.67]	[94.28,97.80]
PR	67.90	73.12	85.18	87.78	78.51	90.83
	[56.77,77.32]	[64.62,80.20]	[77.32,90.65]	[82.17,91.80]	[71.53,84.15]	[84.41,94.77]
CHMS cycles 1&2						
SR	91.35	77.40	74.32	87.65	84.43	98.07
	[86.64,94.50]	[71.80,82.16]	[67.24,80.31]	[83.89,90.63]	[80.48,87.71]	[96.88,98.82]
SC	86.84	81.04	82.45	91.65	85.81	96.38
	[81.46,90.84]	[75.58,85.51]	[75.70,87.63]	[88.02,94.25]	[81.94,88.96]	[94.87,97.45]
PR	81.24	77.97	72.98	90.66	79.44	95.23
	[75.15,86.11]	[72.52,82.61]	[65.99,78.99]	[87.17,93.27]	[75.12,83.18]	[93.26,96.64]

*95% confidence intervals are in parentheses

Note: Sensitivity shows the percentage of true positive BMI categorizations based on respective measures compared to categorizations using direct measurements. Specificity shows the percentage of true negative BMI categorization, non-normal weight, non-overweight, non-obese, based on respective measures compared to the same categorizations using direct measurements.

Table 1. 3B Sensitivity and Specificity: Same Dataset and Cycle (Females)

	SENSITIVITY			SPECIFICITY		
	Normal Weight	**Overweight**	**Obese**	**Normal Weight**	**Overweight**	**Obese**
CCHS 2005						
SR	92.86	67.93	63.95	80.05	87.89	99.62
	[89.26,95.32]	[59.91,75.01]	[54.28,72.61]	[74.72,84.48]	[84.45,90.66]	[99.15,99.84]
SC	90.83	76.95	79.46	86.88	88.27	98.17
	[85.89,94.16]	[69.55,83.00]	[70.03,86.49]	[82.31,90.41]	[84.08,91.47]	[97.09,98.85]
PR	91.44	62.37	85.01	79.61	91.00	96.22
	[85.95,94.91]	[54.12,69.97]	[75.55,91.23]	[74.48,83.92]	[86.65,94.03]	[94.20,97.56]
CCHS 2008						
SR	93.65	65.85	63.32	78.86	88.70	99.19
	[87.89,96.77]	[56.6,74.03]	[52.65,72.83]	[72.74,83.91]	[84.19,92.05]	[97.65,99.73]
SC	87.49	76.79	78.07	89.33	87.67	95.28
	[80.23,92.34]	[68.98,83.11]	[67.32,86.02]	[84.95,92.55]	[82.5,91.46]	[92.63,97.01]
PR	83.57	73.40	83.23	86.82	86.24	95.04
	[75.35,89.43]	[64.44,80.77]	[76.00,88.61]	[81.92,90.55]	[80.95,90.23]	[91.60,97.12]
CHMS cycles 1&2						
SR	95.32	74.31	80.39	87.09	91.64	99.07
	[92.80,96.99]	[68.36,79.47]	[74.40,85.26]	[83.81,89.79]	[89.15,93.60]	[97.67,99.63]
SC	89.08	79.55	90.71	91.59	90.56	97.35
	[85.05,92.12]	[73.57,84.47]	[85.91,94.00]	[88.58,93.87]	[87.69,92.81]	[95.68,98.39]
PR	79.69	80.76	86.12	91.64	84.92	95.74
	[74.34,84.16]	[75.41,85.17]	[81.18,89.92]	[88.82,93.81]	[81.49,87.81]	[93.23,97.35]

*95% confidence intervals are in parentheses

Note: Sensitivity shows the percentage of true positive BMI categorizations based on respective measures compared to categorizations using direct measurements. Specificity shows the percentage of true negative BMI categorization, non-normal weight, non-overweight, non-obese, based on respective measures compared to the same categorizations using direct measurements.

Table 1.4A Sensitivity and Specificity: Same Dataset, Different Cycles (Males)

	SENSITIVITY			SPECIFICITY		
	Normal Weight	Overweight	Obese	Normal Weight	Overweight	Obese
CCHS 2005 corrected by CCHS 2008						
SR	95.18	73.53	62.20	83.54	83.87	98.81
	[92.19,97.07]	[66.89,79.25]	[52.49,71.02]	[79.06,87.22]	[79.07,87.74]	[96.24,99.63]
SC	77.40	88.67	79.43	95.43	79.03	96.70
	[67.69,84.84]	[83.62,92.30]	[70.24,86.33]	[92.81,97.12]	[72.38,84.43]	[94.19,98.14]
PR	90.92	71.22	62.76	85.42	81.25	96.02
	[85.21,94.57]	[63.93,77.55]	[53.12,71.48]	[81.01,88.94]	[76.06,85.53]	[92.07,98.04]
CCHS 2008 corrected by CCHS 2005						
SR	93.53	62.56	66.40	74.56	84.59	98.62
	[86.54,97.01]	[54.33,70.13]	[57.27,74.45]	[67.91,80.24]	[79.51,88.59]	[96.74,99.43]
SC	78.13	81.30	84.76	87.77	81.30	97.48
	[68.13,85.65]	[73.94,86.94]	[76.95,90.26]	[81.58,92.08]	[74.62,86.54]	[95.58,98.57]
PR	84.89	78.98	67.25	84.78	79.31	98.35
	[77.24,90.30]	[72.06,84.56]	[58.32,75.09]	[79.03,89.17]	[73.74,83.96]	[96.51,99.22]

*95% confidence intervals are in parentheses
Note: Sensitivity shows the percentage of true positive BMI categorizations based on respective measures compared to categorizations using direct measurements. Specificity shows the percentage of true negative BMI categorization, non-normal weight, non-overweight, non-obese, based on respective measures compared to the same categorizations using direct measurements.

Table 1.4B Sensitivity and Specificity: Same Dataset, Different Cycles (Females)

	SENSITIVITY			SPECIFICITY		
	Normal Weight	Overweight	Obese	Normal Weight	Overweight	Obese
CCHS 2005 corrected by CCHS 2008						
SR	92.86	67.93	63.95	80.05	87.89	99.62
	[89.26,95.32]	[59.91,75.01]	[54.28,72.61]	[74.72,84.48]	[84.45,90.66]	[99.15,99.84]
SC	90.19	79.71	83.90	88.55	89.21	98.15
	[85.11,93.67]	[72.76,85.25]	[74.51,90.28]	[84.29,91.77]	[85.02,92.34]	[97.08,98.84]
PR	93.93	70.99	64.41	79.74	87.18	99.54
	[90.57,96.14]	[63.00,77.85]	[54.59,73.15]	[74.28,84.28]	[83.56,90.09]	[98.99,99.79]
CCHS 2008 corrected by CCHS 2005						
SR	93.65	65.85	63.32	78.86	88.70	99.19
	[87.89,96.77]	[56.60,74.03]	[52.65,72.83]	[72.74,83.91]	[84.19,92.05]	[97.65,99.73]
SC	87.86	76.18	77.26	88.00	87.46	95.90
	[80.55,92.67]	[68.30,82.60]	[66.59,85.27]	[83.52,91.39]	[82.29,91.27]	[93.25,97.54]
PR	94.02	51.38	63.80	73.08	87.85	97.53
	[89.94,96.51]	[42.21,60.46]	[53.57,72.92]	[66.67,78.66]	[83.62,91.10]	[93.93,99.02]

*95% confidence intervals are in parentheses
Note: Sensitivity shows the percentage of true positive BMI categorizations based on respective measures compared to categorizations using direct measurements. Specificity shows the percentage of true negative BMI categorization, non-normal weight, non-overweight, non-obese, based on respective measures compared to the same categorizations using direct measurements.

Table 1.5A Sensitivity and Specificity: Different Datasets (Males)

	SENSITIVITY			SPECIFICITY		
	Normal Weight	**Overweight**	**Obese**	**Normal Weight**	**Overweight**	**Obese**
CHMS cycles 1&2 corrected by CCHS 2008						
SR	90.07	79.91	74.20	88.95	84.46	98.03
	[86.59,92.73]	[76.36,83.05]	[69.28,78.58]	[86.66,90.89]	[81.80,86.80]	[97.03,98.70]
SC	77.06	84.69	89.76	96.19	83.70	93.94
	[72.84,80.80]	[81.51,87.41]	[86.49,92.3]	[94.54,97.36]	[81.11,86]	[92.38,95.19]
PR	87.14	77.72	71.36	88.45	81.04	96.88
	[83.39,90.14]	[74.14,80.93]	[66.46,75.80]	[86.24,90.35]	[78.14,83.64]	[95.60,97.80]
CCHS 2008 corrected by CHMS (1&2)						
SR	92.43	67.01	69.04	78.34	85.67	98.59
	[87.75,95.42]	[61.39,72.17]	[62.66,74.77]	[74.1,82.06]	[82.45,88.38]	[96.81,99.38]
SC	85.95	77.17	78.33	86.39	84.84	97.62
	[80.79,89.90]	[72.01,81.63]	[72.85,82.97]	[82.58,89.47]	[81.51,87.66]	[95.91,98.62]
PR	70.10	74.27	88.75	90.73	79.94	90.62
	[62.95,76.38]	[68.72,79.13]	[84.18,92.13]	[87.24,93.34]	[75.49,83.76]	[87.09,93.25]

*95% confidence intervals are in parentheses

Note: Sensitivity shows the percentage of true positive BMI categorizations based on respective measures compared to categorizations using direct measurements. Specificity shows the percentage of true negative BMI categorization, non-normal weight, non-overweight, non-obese, based on respective measures compared to the same categorizations using direct measurements.

Table 1.5B Sensitivity and Specificity: Different Datasets (Females)

	SENSITIVITY			SPECIFICITY		
	Normal Weight	**Overweight**	**Obese**	**Normal Weight**	**Overweight**	**Obese**
CHMS cycles 1&2 corrected by CCHS 2008						
SR	95.50	75.64	79.34	87.46	91.35	98.94
	[93.86,96.72]	[71.36,79.46]	[75.15,82.98]	[85.04,89.53]	[89.61,92.82]	[98.23,99.36]
SC	83.43	84.26	90.61	93.63	86.70	96.53
	[79.94,86.41]	[80.85,87.16]	[87.47,93.03]	[91.89,95.01]	[84.29,88.79]	[95.49,97.33]
PR	89.90	78.44	75.56	89.72	86.80	96.80
	[87.14,92.12]	[74.31,82.07]	[71.19,79.45]	[87.43,91.63]	[84.69,88.65]	[95.44,97.76]
CCHS 2008 corrected by CHMS cycles 1&2						
SR	92.67	66.97	67.93	80.19	89.95	99.34
	[89.21,95.08]	[60.83,72.58]	[60.51,74.54]	[76.31,83.58]	[87.12,92.21]	[98.65,99.68]
SC	87.83	79.29	79.44	89.12	88.74	97.85
	[83.46,91.16]	[74.37,83.47]	[72.20,85.18]	[86.25,91.45]	[85.53,91.32]	[96.79,98.56]
PR	82.06	68.90	85.92	90.55	85.68	91.51
	[77.11,86.13]	[61.94,75.11]	[79.85,90.39]	[87.69,92.80]	[82.17,88.60]	[88.26,93.93]

*95% confidence intervals are in parentheses

Note: Sensitivity shows the percentage of true positive BMI categorizations based on respective measures compared to categorizations using direct measurements. Specificity shows the percentage of true negative BMI categorization, non-normal weight, non-overweight, non-obese, based on respective measures compared to the same categorizations using direct measurements.

Table 1.6A Odds Ratios of Health Conditions (Males)

(N=1179)	DM	SR	SC	PR
Health Condition				
Diabetes				
Overweight	1.54	0.70	1.17	1.24
	[0.70,3.40]	[0.35,1.39]	[0.53,2.58]	[0.57,2.70]
Obese Class I	2.18*	1.84	1.64	1.72
	[0.99,4.82]	[0.83,4.08]	[0.74,3.63]	[0.81,3.67]
Obese Class II & III	3.85***	2.88*	4.24***	2.92*
	[1.40,10.64]	[0.85,9.76]	[1.54,11.66]	[1.00,8.55]
Heart Disease				
Overweight	1.42	0.81	2.38*	2.00*
	[0.63,3.20]	[0.39,1.65]	[0.89,6.31]	[0.82,4.86]
Obese Class I	2.21*	1.63	3.43**	2.63*
	[0.89,5.53]	[0.65,4.08]	[1.19,9.88]	[0.99,7.04]
Obese Class II & III	1.35	1.23	2.87	1.66
	[0.49,3.70]	[0.38,3.93]	[0.88,9.38]	[0.54,5.10]
High Blood Pressure				
Overweight	1.74**	1.77**	1.86**	1.96**
	[1.04,2.91]	[1.13,2.79]	[1.11,3.40]	[1.17,3.28]
Obese Class I	3.70***	3.60***	3.75***	3.26***
	[2.07,6.63]	[1.97,6.57]	[2.07,6.79]	[1.82,5.85]
Obese Class II & III	4.18***	4.11***	5.59***	5.76
	[1.88,9.30]	[1.59,10.61]	[2.41,12.95]	[2.44,13.63]
Arthritis				
Overweight	1.66	1.32	1.54	1.25
	[0.82,3.36]	[0.72,2.43]	[0.76,3.14]	[0.62,2.54]
Obese Class I	1.54	1.33	1.44	1.49
	[0.74,3.22]	[0.62,2.81]	[0.67,3.09]	[0.67,3.31]
Obese Class II & III	2.30*	2.95**	3.66**	2.50*
	[0.87,6.13]	[1.03,8.50]	[1.35,9.96]	[0.90,6.91]
Activity Limitation (often or sometimes)				
Overweight	1.04	1.33	0.87	0.68
	[0.62,1.76]	[0.85,2.09]	[0.52,1.46]	[0.41,1.14]
Obese Class I	1.77*	1.69*	1.24	1.46
	[0.99,3.16]	[0.92,3.08]	[0.69,2.22]	[0.81,2.61]
Obese Class II & III	1.30	1.80	1.76	1.08
	[0.57,2.96]	[0.70,4.63]	[0.75,4.11]	[0.46,2.53]
Self-perceived health (fair or poor)				
Overweight	0.95	1.02	0.69	0.85
	[0.54,1.68]	[0.60,1.73]	[0.39,1.23]	[0.48,1.51]
Obese Class I	2.41***	2.69***	1.84*	2.06**
	[1.31,4.41]	[1.43,5.07]	[0.98,3.46]	[1.11,3.79]
Obese Class II & III	2.92*	5.20**	3.86**	2.64
	[0.95,8.94]	[1.31,20.65]	[1.29,11.57]	[0.83,8.40]

** 10 %, ** 5%, *** 1% significance levels. 95% confidence intervals are in parentheses.*

Note: Dataset used is CCHS 2008. Sample consists of males ages 40 and over. Models control for age. Normal Weight is the reference group. Underweight group is excluded from analysis due to small sample sizes.

Table 1.6B Odds Ratios of Health Conditions (Females)

(N=1432)	DM	SR	SC	PR
Health Condition				
Diabetes				
Overweight	2.59*	1.94*	2.61**	2.74***
	[0.99,6.75]	[0.93,4.07]	[1.16,5.88]	[1.16,6.50]
Obese Class I	3.81**	4.12***	4.66***	4.95***
	[1.26,11.54]	[1.59,10.72]	[1.83,11.86]	[1.95,12.58]
Obese Class II & III	6.79***	7.02***	10.68***	9.74***
	[2.11,21.83]	[2.10,23.39]	[3.73,30.62]	[2.78,34.21]
Heart Disease				
Overweight	0.85	1.09	0.85	0.93
	[0.41,1.78]	[0.55,2.14]	[0.41,1.79]	[0.43,2.03]
Obese Class I	0.77	0.80	0.65	0.65
	[0.34,1.74]	[0.34,1.86]	[0.28,1.51]	[0.28,1.52]
Obese Class II & III	0.50	0.61	0.56	0.57
	[0.15,1.71]	[0.13,2.81]	[0.16,1.96]	[0.12,2.76]
High Blood Pressure				
Overweight	1.81**	1.74**	1.21	1.30
	[1.04,3.15]	[1.06,2.86]	[0.69,2.11]	[0.73,2.31]
Obese Class I	2.17**	3.17***	2.57***	2.49***
	[1.14,4.11]	[1.62,6.22]	[1.36,4.87]	[1.32,4.69]
Obese Class II & III	2.29*	2.41	2.11	2.19
	[0.92,5.72]	[0.69,8.38]	[0.77,5.79]	[0.63,7.62]
Arthritis				
Overweight	1.00	0.97	0.81	0.87
	[0.63,1.61]	[0.63,1.49]	[0.51,1.29]	[0.54,1.40]
Obese Class I	1.62	2.47***	1.50	1.62
	[0.91,2.87]	[1.35,4.51]	[0.85,2.65]	[0.94,2.70]
Obese Class II & III	2.92***	2.88**	3.19***	2.53***
	[1.51,5.63]	[1.24,6.68]	[1.59,6.41]	[1.08,5.92]
Activity Limitation (often or sometimes)				
Overweight	0.88	0.87	0.84	0.81
	[0.56,1.39]	[0.56,1.36]	[0.53,1.33]	[0.51,1.29]
Obese Class I	1.64*	1.84**	1.20	1.00
	[0.95,2.82]	[1.05,3.22]	[0.72,2.02]	[0.60,1.67]
Obese Class II & III	1.59	1.55	1.53	1.91
	[0.83,3.03]	[0.74,3.26]	[0.76,3.08]	[0.84,4.36]
Self-perceived health (fair or poor)				
Overweight	0.92	0.82	0.68	0.78
	[0.51,1.67]	[0.48,1.38]	[0.38,1.22]	[0.42,1.42]
Obese Class I	1.19	1.55	1.03	1.07
	[0.57,2.49]	[0.73,3.28]	[0.49,2.16]	[0.52,2.19]
Obese Class II & III	1.33	1.40	1.20	1.20
	[0.57,3.07]	[0.48,4.04]	[0.49,2.98]	[0.40,3.63]

** 10 %, ** 5%, *** 1% significance levels. 95% confidence intervals are in parentheses.*

Note: Dataset used is CCHS 2008. Sample consists of females ages 40 and over. Models control for age. Normal Weight is the reference group. Underweight group is excluded from analysis due to small sample sizes.

Figure 1.2A Distribution of Raw and Corrected Differences: Same Dataset and Cycle

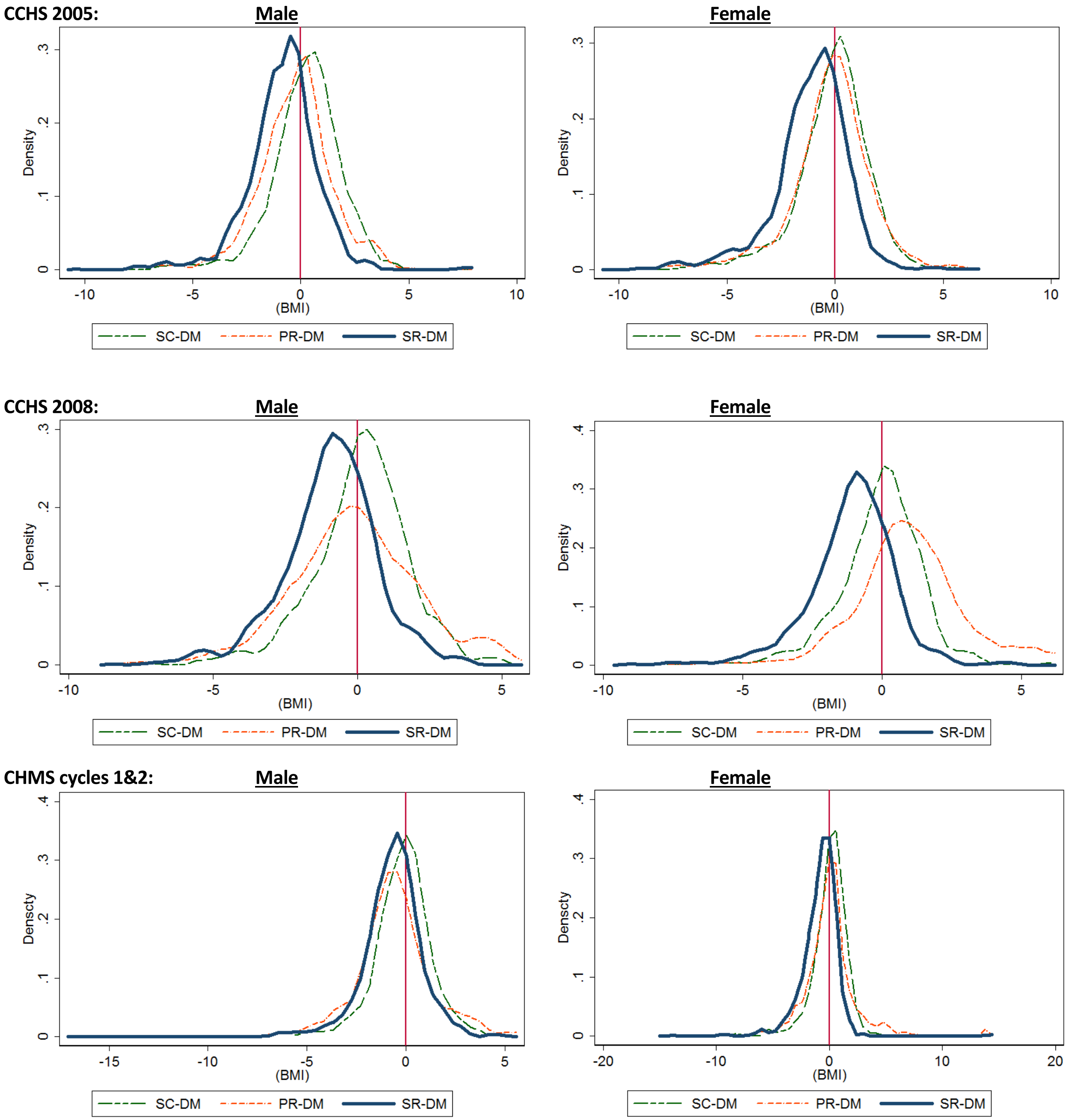
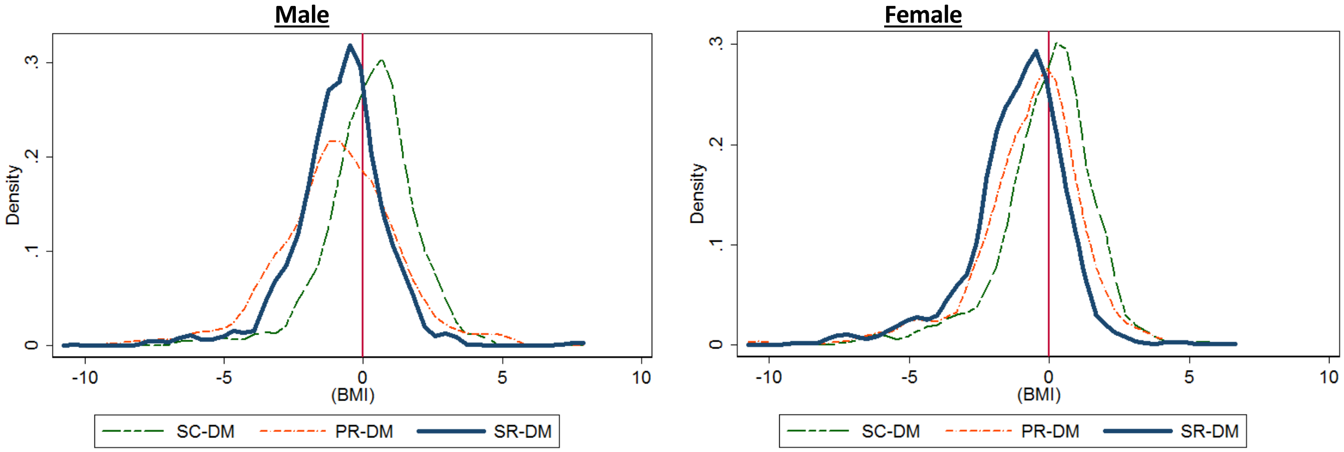


Figure 1.1B Distribution of Raw and Corrected Differences: Same Dataset, Different Cycles

CCHS 2005 corrected by CCHS 2008:



CCHS 2008 corrected by CCHS 2005:

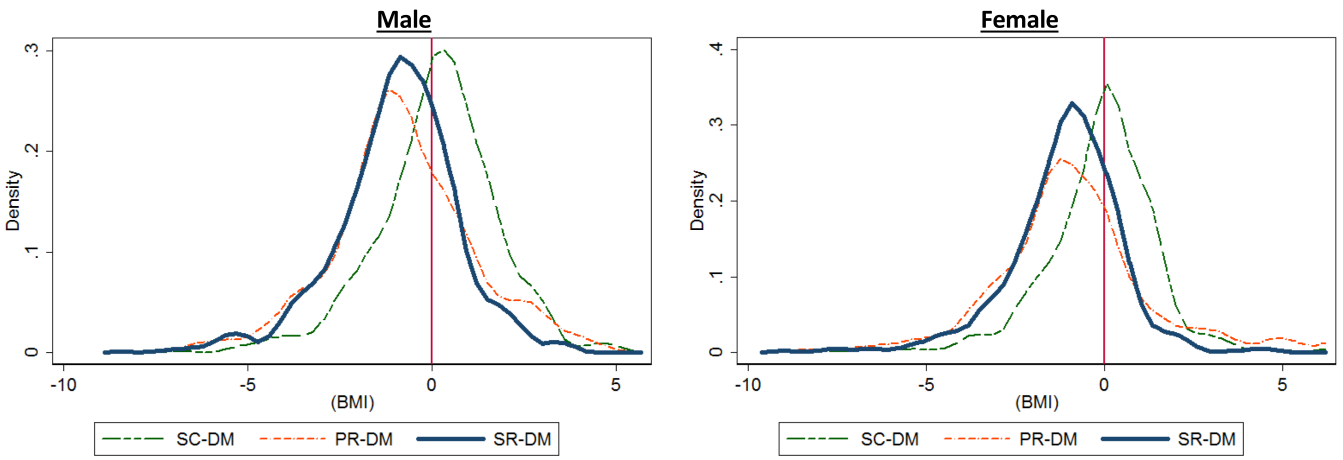
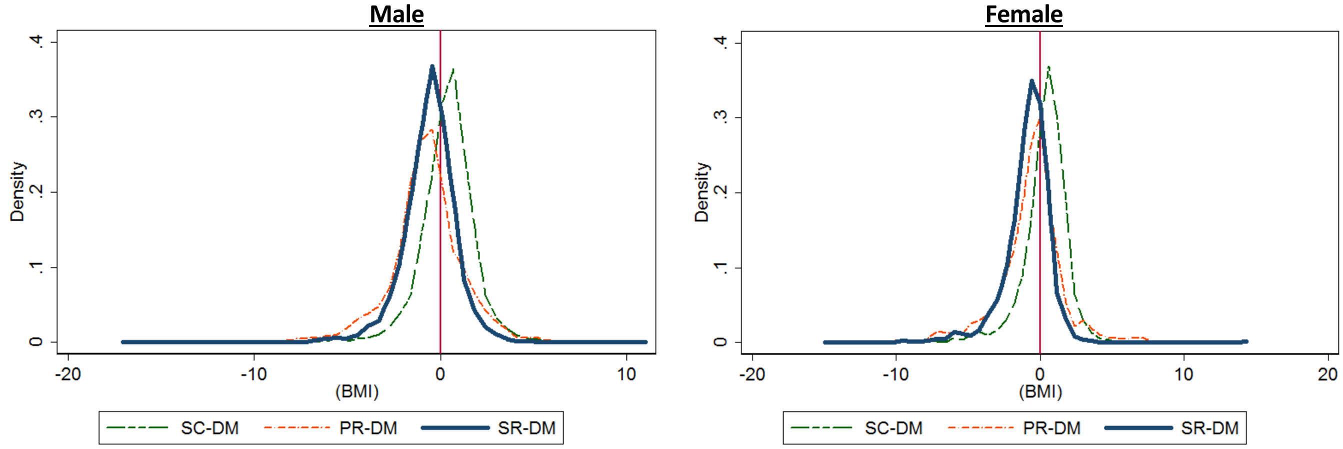
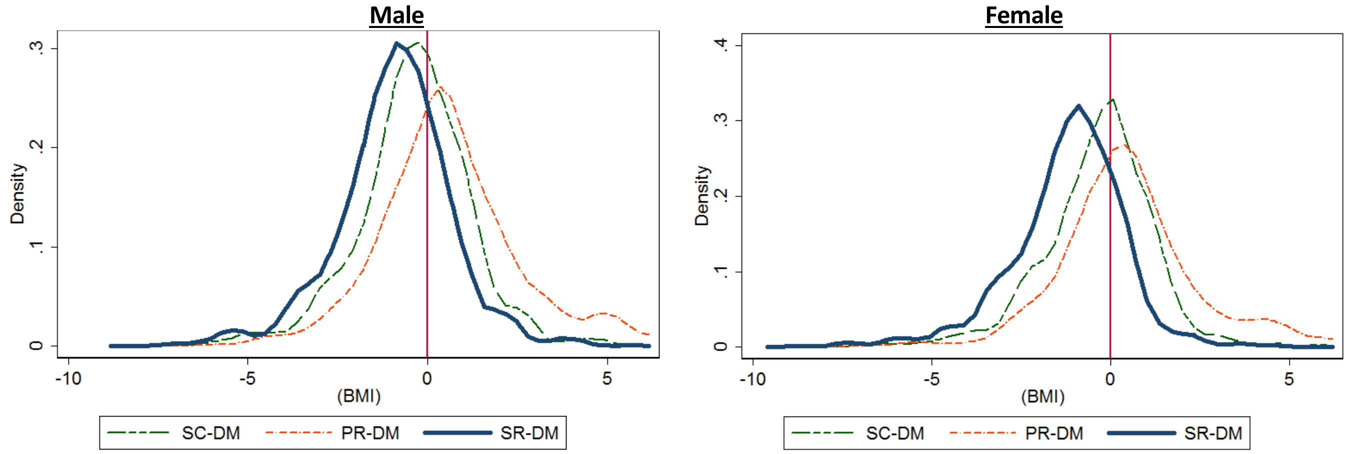


Figure 1.1C Distribution of Raw and Corrected Differences: Different Datasets

CHMS cycles 1&2 corrected by CCHS 2008:



CCHS 2008 corrected by CHMS cycles 1&2:



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Chapter 2
Long-term Physician Costs Associated with Obesity in Ontario

2.1. Introduction

The relationship between obesity and health care costs are found to be stronger than either smoking or alcohol consumption (Sturm, 2002). In order to analyze this relationship, researchers need to quantify body fat and obtain (or estimate) total health care costs for the relevant population. Although not the best way of measuring body fat (Cawley and Burkhauser, 2008; Gómez-Ambrosi et al., 2012; Michels et al., 1998; Wada and Tekin, 2010), the most widely used measure is the body mass index (BMI). BMI is calculated by dividing an individual's weight in kilograms by the square of his or her height in meters.[1] Its popularity is based on its practicality. The availability of height and weight information in almost every health survey makes measuring BMI convenient compared to other body measurements such as waist circumference, waist-to-hip ratio, bioelectrical impedance analysis or underwater weighing.

[1] According to the current convention used by the WHO (2014), an individual is considered to be normal weight if his or her BMI is 18.5 or more but less than 25, overweight if it is 25 or more but less than 30, and obese if it is 30 or more. Obesity is further divided into three classes that signify its severity. Obese class 1, BMI between 30 and 35, is considered to be moderate obesity. Morbid obesity is stratified into classes 2 and 3. Those with BMI between 35 and 40 are categorized as obese class 2 and those with 40 and more as class 3.

Studies that consider BMI categories attach much importance to the threshold points in BMI distribution. For instance, many studies in the literature adopt a prevalence-based approach (Swinburn et al., 1997; Wolf and Colditz, 1998; Birmingham et al., 1999; Katzmarzyk and Janssen, 2004; Anis et al., 2010; Konnopka et al., 2011). In this approach, researchers first make a list of comorbidities that are associated with obesity and calculate the relative risk of developing each for an obese or overweight individual versus a normal weight one. Next, they obtain estimates of the health care costs associated with each of these comorbidities. Then, the health care cost differences between normal weight and overweight or obese individuals are calculated using the relative risks associated with each BMI category. By adding these up, researchers estimate the overall difference in the total healthcare costs for an obese or overweight individual versus a normal weight. Finally, by using the prevalence rate of obesity in the target population and the population size, researchers estimate the additional health care cost burden associated with obesity in that population.

When it is not possible to observe the actual health care costs of individuals, this remains a valid approach to use at a cost of disease study. However, there are two underlying shortcomings in prevalence-based approaches. First, the list of comorbidities considered by researchers could be different among studies (Thompson and Wolf, 2001). This translates into substantial variation in estimates of the cost of obesity for the same population and incomparable estimates between studies. Second, calculating total health care costs by adding up costs associated with each comorbidity does not take into consideration the interdependencies between comorbidities. This potentially leads to overestimation of the total health care costs (Bierl et al., 2013). Alternatively, when it is possible to access administrative health care data, the differences in health care costs and utilization patterns of individuals as a function of BMI can be observed more precisely.

Using the Canadian Community Health Survey (CCHS) 2000/01 linked with longitudinal administrative records, we observe personal attributes of individuals and their costs over time on this representative sample. The question that this study answers is: *regardless of changes in BMI over time, how do physician costs differ given BMI at the time of the CCHS*? First, we look at the relationship between BMI and the average of annual physician costs over these eleven years (AAPC), with and without controlling for covariates. This allows us to observe the conditional and unconditional associations between BMI and AAPC. By controlling for a list of potentially endogenous covariates- comorbidities associated with obesity, we assess if and how the unconditional association between BMI and the AAPC changes. We also estimate the average physician cost for normal weight, overweight and obese adults over 40 years of age, by sex, for every fiscal year that we have data on.

The severity of obesity is important, but comparing health care cost differences between obese and normal weight groups does not provide information about this relationship throughout the BMI distribution. Instead, focusing on changes in health care costs throughout a BMI distribution is more informative without attaching too much emphasis on threshold points. In this study we take this alternative approach and use linked survey data which includes actual individual level observations on health care costs rather than group level estimates of them. One of our contributions is the application of nonparametric and semiparametric models, which were not used in this literature before, to show the relationship between long-term physician costs and BMI as a continuous variable. In order to make our results comparable with previous studies in the literature, we also provide annual physician cost estimates for normal weight, overweight and obese groups over 11 years of data. Our results indicate that obesity significantly increases health care costs for females at all ages, but only does for males when they are older. Annual regression analysis shows that physician costs between obese and overweight individuals are generally statistically significantly different in females but only long-term in males.

This paper is organized as the following. The next section offers a literature review. We then describe the datasets and various methodologies used in this analysis. This is followed by a presentation of the results followed by a discussion and disclosure of the limitations of the study.

2.2 Literature Review

Finkelstein, Fiebelkorn, and Wang (2003) use Medical Expenditure Panel Survey (MEPS) to obtain an estimate of total health care costs for a representative sample of the adult population of the United States (US) and merge this with the National Health Interview Survey (NHIS) which includes the BMI of respondents. They find healthcare costs attributable to obesity to be 5.3% of the overall medical spending in the US. Again using the MEPS, Finkelstein et al. (2008) calculate the lifetime health care cost of living with obesity for an extended period. According to their findings, lifetime health care costs attributable to obesity are higher for white men and women, and black women if they experience chronic obesity from at age 20 and stay that way for the rest of their lives. However, for black men only becoming obese after age 65 is more costly. Furthermore, Finkelstein, Trogdon, and Cohen (2009) compare the cost differences by payer type in the US. They find that 8.5% of Medicare spending, 11.8% of Medicaid spending, 12.9% of private payer spending and 9.1% of hospital inpatient, outpatient (emergency room, dental, vision, homecare, etc.) and pharmaceutical expenses as a whole is attributable to obesity in 2006. These differences across payers in the US health care system are related to differences in the prevalence of obesity across different sociodemographic and socioeconomic population groups, and type of services covered by each payer. Since the US has fragmented health care pricing, the cost varies across the same health care services provided under different insurance plans. Therefore the utilization patterns might be more comparable than costs both within the US and in international comparisons.

Some studies from the US use administrative data for Kaiser members in various states (Quesenberry et al., 1998; Raebel et al., 2004; Thompson et al., 2001). These studies consider the cost differences for individuals, who are assumed to have similar socioeconomic characteristics, and compare the health care cost differences related to obesity across them. In general, their findings confirm that, health care utilization and costs are higher among the obese than normal weight people and that these differences increase with the severity of obesity. Although estimates using insurance provider administrative data are likely to be accurate and comparable to other groups with similar characteristics, it is hard to generalize their results to the whole US population. Studies from a jurisdiction with universal health care coverage and based on a single-payer system would be preferable for international comparisons. Even in such contexts, the basket of services covered in each health care system may differ and needs to be considered when making comparisons across countries.

Gupta and Greve (2009, 2011) provide evidence from Denmark, which has a single-payer health care system (PNHP, 2010). They look at the variation in health care utilization for overweight and obese relative to normal weight individuals using The National Health Insurance Survey from Denmark linked with administrative records. Their administrative records allow them to observe general practitioner use and inpatient and outpatient hospital utilization. For their sample, they choose to focus on only the wage-earning adults between ages 25 and 60 to eliminate any heterogeneity with respect to demand for physician services due to work status and employment type. They dichotomize the utilization patterns into frequent and infrequent users within each BMI category finding no difference in health care utilization patterns across all three BMI categories for infrequent users. However, they find higher demand for primary care physician services among overweight and obese individuals who are frequent users. Although this may be attributable to certain underlying characteristics and not necessarily the adverse health conditions associated with obesity, they find evidence that infrequent users who are overweight and obese increase their health care utilization over time. They link this to differences in time preferences and the lack of demand for preventive care of overweight and obese individuals.[2]

In the Canadian context, which also has a single-payer health care system, Trakas, Lawrence, and Shear (1999) utilize individual level data to explore the association between obesity and health care utilization. The authors find that obese individuals are more likely to consult with physicians and be prescribed more medications. In their analysis, they rely on self-reported responses in the National Population Health Survey (NPHS). Self-reported responses may exhibit some degree of recall bias or reporting error. For instance, Baker, Stabile, and Deri (2004) find discrepancies when they compare the self-reported responses in the NPHS on having certain health conditions with the administrative records of the respondents. If this reporting error also persists in the self-reported health care utilization responses, then administrative health care records are the only way to ensure accuracy.

[2] Gupta and Greeve (2009) acknowledge that they base this link to time preference without actually having any means of actually measuring it (p. 21). Theirs is a contemplation on their results, while citing Cawley (2006) on p. 5, Borghans and Golsteyn (2005); Cutler and Glaeser (2005); Komlos et al. (2004); Smith et al. (2005) on p. 6 for their basis for making the linkage between bodyweight and time preference.

Our study makes use of administrative health care records from Ontario linked with the CCHS cycle 1.1 (2000/01). It builds on three earlier studies which used similar linked datasets to investigate the cost of obesity for Ontario's health care system.

Finkelstein (2001) uses the NPHS 1995/96 linked with the Ontario Health Insurance Plan (OHIP) administrative data for the year prior to the survey.[3] He investigates how the interaction between cigarette smoking and obesity is associated with physician costs in the population in between ages 40 and 79. He finds that even for non-smokers, the average incremental increase in annual physician costs (APC) of moderately obese individuals to be twice, and morbidly obese to be more than three times more, than overweight. The duration of smoking is proportionally related to the increase in physician costs for all BMI categories.

The second study is by Janssen, Lam, and Katzmarzyk (2009). They utilize the CCHS cycle 1.1 (2000/01) linked with OHIP 2002/03 data to look at the association between APC and obesity separately for each sex and age group. They find the APC of obese males to be 15%, and that of females to be 18%, higher than those of normal weight. They only find statistically significant higher costs for older obese adults (ages 60 and up) relative to those of normal weight. It is also worth noting that their findings show the cost difference between overweight and normal weight individuals not to be statistically significant. These two studies use BMI categories instead of using BMI as a continuous variable, and they do not correct for the measurement error in self-reported BMI data in the CCHS 1.1. Consequently, they potentially miscategorised individuals and underestimate prevalence and severity of obesity in their sample.

[3] The selection of the fiscal year of the OHIP data was not intentional. It was the only year that Finkelstein (2001) was granted access.

In the third study we build on, Tarride et al. (2012) take a comprehensive approach to estimate not only physician costs, but also hospital and day surgery costs and document utilization patterns associated with obesity. They use the CCHS 1.1 linked with OHIP data to estimate physician costs and the CCHS 1.1 linked with Discharge Abstract Database Inpatient and Day Procedures administrative datasets to account for hospitalization costs. As for the measurement errors in the self-reported BMI in the CCHS 1.1, they use correction equations suggested by (Shields et al., 2011). They look at each respondent's administrative records between 6 months before and 6 months after his or her survey interview date. According to their results, obese individuals are about twice as likely to have three or more physician-diagnosed medical conditions as normal weight individuals. Relative to those of normal weight, they estimate the annual hospital costs of obese to be 40% and their physician costs to be 23% higher. Only among females are the differences in the total health care cost between obese and normal weight statistically significant. Furthermore, females have higher physician, day procedures and hospitalization costs than males. They find no statistical difference in hospitalization and day procedures costs between overweight and normal weight individuals. Like Janssen, Lam, and Katzmarzyk (2009), they also do not interact age with sex when looking at costs associated with obesity. Across age groups, they find the cost difference between obese and normal weight to be the highest in middle-aged group (ages 40 to 59, (36%)), whereas among young adults (ages 18 to 39) and older adults (ages 60 and up) to be around 20%.

The main limitation of these earlier studies has been their short-term focus. This was partly due to data availability and partly in their assumption that body weight fluctuates over time. The dataset we use provides administrative records on physician costs for one year before and ten years after the CCHS 1.1. We suspect that, over the eleven years we observe them, if a considerable number of individuals experience changes in their BMI categories, we should get mixed results in our annual cost analysis. Should we find these trends to be consistent over time, then this can either be an indication that the trend in changes in BMI is similar for everyone (everybody accumulated more fat), or that BMI and physician costs have a lingering relationship[4] that does not change over the short-term.[5]

The next section describes the datasets we use and explains how we adapted them for our purposes.

2.3 Data

2.3.1 CCHS

The CCHS 1.1 Ontario Share File houses data for Ontario residents who had given permission to have their survey responses to be linked with administrative datasets - about 87% of Ontario respondents. Our targeted sample is the adult population of Ontario who are between ages18 and 65 at the time of the survey (2000/2001).[6] Since it is not recommended to calculate BMI for pregnant or breastfeeding women, we exclude them according to their self-reports in the survey. The CCHS provides information on personal characteristics, self-reported health status, sociodemographic and socioeconomic attributes. Personal characteristics include BMI which is derived from their self-reported height and weight data. We address suspected measurement error in self-reported height and weight by utilizing the correction equations suggested by

[4] Accumulating body fat may have long term impact on one's health, regardless of subsequent weight loss.
[5] In the former, we contemplate that if 100 obese individuals became normal weight or overweight, than there must be 100 other who became obese in that period. Therefore, the number of individuals per BMI category remained the same more or less. In the latter, we suspect that the relationship between body fat and medical needs could have long term consequences.
[6] The decision to cap age at 65 is related to attrition that we observed in OHIP data. See Appendix B.

Connor Gorber et al. (2008).[7] To deal with outliers in the BMI distribution caused by severe reporting or recording errors, we drop observations below the 1st percentile or above the 99th percentile of the BMI distribution of each sex. Other variables that we include are age, sex, race, total household income, number of people in the household, education level, marital status, being born in Canada, living in urban or rural area, location of their residence per Ontario District Health Council,[8] being a smoker, physically active, having diabetes, heart disease, cancer or chronic diseases and the their self-perceived health. Individuals who have missing or invalid responses to any of these variables are excluded from our analysis.[9]

Since we link the OHIP records with the CCHS share file, our sample includes those who have no OHIP records in some years, who constitute zero cost individuals in a given year. We observe physician claims for about 90% of the sample in the year they were surveyed. This rate gradually decreases. We suspect this is due to both emigration from Ontario and mortality. Unfortunately, we cannot observe either in these data. We developed an algorithm to adjust the sample weights (see Appendix C). Adjusted sample weights are used throughout the analysis.

2.3.2 OHIP

OHIP covers all permanent residents of Ontario except personnel of the Canadian Forces and Royal Canadian Mounted Police, inmates of federal prisons, and a very small number of others (Government of Canada, 2012). The OHIP dataset contains all claims made by physicians and some

[7] Correction equations for CCHS 2005 are used for CCHS 1.1, as it is not possible to generate them for 1.1. The study by Shields et al. (2011b) that Tarride et al. (2012) takes their correction equations from, is the extension of the study by Connor Gorber et al. (2008). Shields et al. (2011b) argue that correction equations are compatible between different cycles of the CCHS.-mention chapter 1?
[8] For the complete list of Ontario District Health Councils please refer to Statistics Canada (2013)
[9] In the cases where the group with missing values large, a new category is created for those with missing values.

diagnostic and laboratory tests conducted outside of hospitals. It includes the age and sex of patients, and the type, cost and date of these services.

As explained in Appendix D, we convert all physician services into their fee-for-service equivalent to facilitate comparisons. We calculate total APC of each individual using this new variable. We then use the inflation calculator at the Bank of Canada's (2014) website to adjust these to 2013 dollar values. We use these inflation-adjusted physician costs throughout our analysis.

2.4 Methodology

We adopt several estimation techniques in this analysis. First, we look at the overall shape of the relationship between BMI and the AAPC across three age groups (ages 18-29, 30-45, and 46-65) for both sexes using both unconditional nonparametric and conditional semiparametric methods. In the latter, we control for age, sociodemographic variables and existing health conditions that are associated with obesity. We believe these covariates, except age, to be endogenous and suspect that they may account for the underlying relationship between BMI and the physician costs. We also conduct an annual cost analysis, repeated over eleven years, using two-part models. This allows us to demonstrate differences in AAPC of normal weight, overweight and obese individuals over the eleven-year period.

We explain each of these methods more in detail in the following subsections.

2.4.1 Nonparametric and Semiparametric Models

In our nonparametric model, we use kernel-weighted local polynomial smoothing (Gutierrez et al., 2003) to estimate the following model that is not conditional on covariates:

$$AAPC_i = f(BMI_i) + \varepsilon_i \quad (1)$$

where $AAPC_i$ is the average of annual physician cost of individuals over eleven years, $f(.)$ is some unknown function, and the error term, ε_i, has $E(\varepsilon_i) = 0$ and $V(\varepsilon_i) = 1$. Estimating $f(.)$ without imposing any assumptions on the relationship between BMI and the AAPC is done by using kernel-weighted local polynomial smoothing. Each of the six age-sex groups is modeled separately.

We estimate Robinson's (1988)[10] semiparametric model separately by sex controlling initially only for age, and then adding a set other control variables:

$$Log(AAPC_i) = \gamma_0 + \beta_{Ai} Age_i + f(BMI_i) + \varepsilon_i \qquad (2)$$

$$Log(AAPC_i) = \gamma_0 + \beta_{Ai} Age_i + \delta_i S_i + \theta_i H_i + f(BMI_i) + \varepsilon_i \qquad (3)$$

wherein both models the natural log of $AAPC_i$[11] is the dependent variable and mean deviated *Age* enters the model parametrically as a fourth order polynomial..

2.4.2 Annual Regressions Using Two-Part Model

Annual regressions similar to those by Janssen, Lam, and Katzmarzyk (2009), and Tarride et al. (2012) are also estimated, but they are repeated for each fiscal year. Like them, we use a two-part

[10] We used semipar Stata package by Verardi and Debarsy (2012), slightly modified to incorporate a graphing option and suppress scatter plots.

[11] We use Log AAPC specification for semiparametric part, as convergence was not achieved using AAPC in levels as in the nonparametric part, in which results are easier to interpret. In order to test consistency, we also replicate nonparametric analysis with Log AAPC. These results are shown in Appendix, Figure 2.AP1, and are comparable to semiparametric results.

model following the recommendations of Diehr et al. (1999). The first part is a logistic regression to find the odds of having any physician cost in a given year. The second part is a generalized linear model (GLM) conditional on having positive physician costs in that year. Following Diehr et al. (1999), we specify the log link function as the gamma distribution to account for heteroscedastic variance.

Part I

$$Logit(APC_i > 0, X_i) = \ell(\beta_0 + \beta_i X_i) \qquad (4)$$

Part II

$$E(APC_i | APC_i > 0, X_i) = g^{-1}(\beta_0 + \beta_i X_i) \qquad (5)$$

Combined

$$E(APC_i | X_i) = Pr(APC_i > 0, X_i) \times E(APC_i | APC_i > 0, X_i) \qquad (6)$$

The vector of independent variables, X_i, used in both parts are the same. We use three specifications in these regressions. In Specification A we only control for mean-deviated age and its 4th degree polynomials. In Specification B we add dummy variables for smoking status (daily and occasionally; not smoking is the reference category), alcohol drinking (regular, occasional or formerly drinking; not drinking being the reference), physical activity level (either active or moderately active; not being physically active is the reference) and a variable for their household income after adjusting for the household size.[12] Finally, in Specification C we additionally control

[12] Household income divided by the square root of the number of people living in the same household.

for having diabetes, heart disease, cancer, chronic diseases, self-perceived poor health (fair and poor self-perceived health; good, very good and excellent self-perceived health being the reference), being either high-school graduate, or having some level of post-secondary education (not being high-school graduate being the reference), having been previously married (widow, separated, divorced), or currently being married or in a common law relationship (single being the reference) and living in urban area (rural being the reference). We use these same definitions for the variables in the semiparametric analysis.

Total APC is calculated by multiplying the predicted probability of having any physician costs from part I with the predicted APC for each observation from part II. We then calculate the mean of APC for normal weight, overweight and obese males and females. For statistical inference, we set up a bootstrap procedure to repeat the calculation of the mean APCs for each BMI category 1,100 times.[13] Point estimates for mean APC for each group and their corresponding 95% confidence intervals are represented in graphs.

2.4.2.1 Power GLM Extension

To test the *a priori* assumptions in parametric GLM specifications recommended by Diehr et al. (1999), the gamma variance and log link function specifications, we employ a nonparametric GLM model, the power GLM, developed by Basu and Rathouz (2005). It requires no a *priori* assumptions as nonparametric link and variance functions are estimated simultaneously.[14] We did not pursue similar bootstrap procedures to calculate confidence intervals for this verification step.

[13] 1,100 repetitions are specified to compensate for non-convergent results (target was 1,000). Seed is set to 007. After sorting the mean values in the saved bootstrap data, 25th and 975th observations are recorded as the lower and upper bound of 95% confidence intervals for the mean APC of each body type per sex.

[14] We use *pglm* Stata package developed by Basu (2005): http://faculty.washington.edu/basua/software.html. We use *vf(q)* option to specify a quadratic-variance function rather than a power-variance function.

Consequently, the corresponding graphs show only the estimated mean of APC for each BMI category in each year. We use these to compare the overall shape to a semiparametric two-part model.

2.5 Descriptive Statistics

Table 2.1 shows overall summary statistics and those for normal weight, overweight and obese BMI categories for three age groups by sex. The sample size of the underweight category is too small to include in our descriptive statistics as per Statistics Canada’s Research Data Centre data disclosure policy. The majority of younger adults (ages 18-29) are normal weight and the share of those overweight increases with age for both sexes. On average females are very slightly below the threshold for overweight, whereas males are almost 1.2 BMI points over that threshold. Furthermore, the ratio of those who are overweight and obese in each age group is higher for males. On average, physician costs over the eleven year period are around $3,000 higher for females, and increase with age.[15] For females they increase with BMI for each age group, but do so only for the oldest age group for males. We find the difference between average net present value of physician costs between normal weight and obese individuals to be higher only in later ages in males, about 23%, but in all ages for females; ranging from 19% to 33% across age groups

2.6 Regression Results

Our nonparametric analysis in Figures 2.1A (males) and 2.1B (females) shows the shape of the relationship between BMI and the AAPC for the three age groups without conditioning on other

[15] NPV is calculated using 3% discount rate, after adjusting all dollar figures for the year 2013 using Bank of Canada's (2014) inflation calculator.

variables. In these graphs BMI is on the horizontal axis while AAPC in $2013 is on the vertical , and population density is on the right, vertical axis. The smooth curve on the graphs reflects changes in the AAPC with changing BMI. The vertical lines are added to differentiate normal weight, overweight, obese and morbidly obese. Additionally, the superimposed kernel density represents the BMI distribution of the relevant population. It is worth noting that Figures 2.1A and 2.1B have the same vertical scales to facilitate comparisons.

A comparison of Figures 2.1A with 2.1B reveals that females have higher AAPC than males across all age groups. One can speculate that this is due to fertility, differences in preferences over using the health care system and health consciousness. In Figure 2.1A, we see that for young and middle-aged adult males, increase in BMI does not correspond to an increase in physician costs until BMI reaches morbidly obese levels. Even among morbidly obese middle-aged males, the evidence can be argued to be mixed due to large confidence intervals. Considering the 95% confidence intervals, it is not possible to argue that obese class I middle-aged males have higher AAPC than normal weight ones. More interestingly, we see that a local minimum of AAPC among middle-aged males is reached by those at the threshold of being obese (BMI=30). On the other hand, we see that among older males the local minimum at AAPC is observed for those at the threshold of being overweight. BMI has a positive correlation with AAPC until the threshold of being morbidly obese. Again in older adults, the evidence for those morbidly obese is mixed. Overall, we only see a consistently positive correlation between BMI and AAPC among males aged 45 to 65, whose BMIs are between overweight and obese class I. In Figure 2.1B, we see consistently positive correlations between BMI and AAPC in females at all ages. The evidence for young females is mixed, but we see this positive correlation over a large portion of their BMI distribution. This positive correlation is quite clear for middle-aged and older females.

The parametric portion of our semiparametric analysis is shown in Table 2.2. Model 2 can be viewed as a replication of our nonparametric analysis in which we separately analyzed three age groups. We see age is highly statistically significant for both sexes, but the magnitude of its coefficient is higher in males than females. This is similar to our nonparametric results, where we see a positive correlation between BMI and AAPC only among older males. In Model 3, we see that existent health conditions, self-perceived poor health, living in an urban environment and being born in Canada are all highly statistically significant variables. Only the last one has a negative sign on its coefficient, which indicates that after controlling for other covariates, non-immigrants have lower long-term physician costs given any BMI level. Controlling for these variables removes the statistical significance of age only in females.

Figure 2.2 shows graphs depicting the relationship between BMI and the logarithm of AAPC in 2013 dollars for both sexes, for models 2 and 3. Comparing graphs between Model 2 and Model 3, we see that controlling for covariates does not change the overall shape of the relationship. It only slightly reduces the magnitude as shown with a downward shift in graphs and slightly smoother curves.[16]

Figures 2.3A and 2.3B show annual regression results, for males and females respectively. These figures show connected point estimates for mean APC for normal weight, overweight and obese individuals in a given year and the corresponding confidence intervals. Firstly and similar to our semiparametric results, we see that controlling for covariates in the two-part model does not change the relationship between physician costs and BMI as we compare specifications A, B and C.

[16] In order to cross-check our interpretation of the semiparametric analysis, we performed a peripheral analysis with artificial data. The results show that controlling for a set of correlated dummy variables sometimes shifts the curve and at other times alters the shape of the relationship. The syntax is available upon request.

For all specifications, we do not observe any noticeable changes in the trend over time. Both sexes experience an increase in physician costs over time even after controlling for aging. In Figure 2.3A, even though the point estimates of mean APC of obese are higher than overweight, the lower bound of its 95% confidence interval is almost always within the confidence interval boundaries of overweight, except in 2006/07 and 2009/10 fiscal years. Due to the same reasoning, it is also apparent that the difference between overweight and normal weight males is not statistically significant. Therefore, it is hard to argue that obesity is associated with higher physician costs in males, which is similar to our nonparametric results. In Figure 2.3B, we see that the lower bound of the 95% confidence interval for obese females does not intersect with the confidence interval of overweight as much as for males. Especially in the last two fiscal years that we observe physician costs, it is clearly evident that obese females have statistically significantly higher physician costs than overweight females. Confidence intervals of overweight and normal weight females mostly intersect with each other until the last two fiscal years. However, after 2008/09 fiscal year (8 years after we observe them in the CCHS 1.1), there is an apparent statistically significant difference between the two estimates with overweight females incurring higher physician costs than normal weight females. Figure 2.4 shows the results of our power GLM extension to see if the trend would be the same without our *a priori* assumptions in the parametric specification of the GLM in the two-part model. These estimations are done only on the Specification B, since it is the midway specification, and we see no need to replicate this part of the analysis on all three specifications. When compared with their GLM counterparts, the intercept, and the overall trend are almost identical in graphs of both sexes. Therefore, we conclude that recommendations of Diehr et al. (1999) in analyzing health care cost data are reasonable.

2.7 Discussion

This study investigates how an individual's BMI is associated with physician costs in the long term. It utilizes the opportunity of linking eleven years of administrative physician cost data with a cross-sectional survey. This allows us to observe not only the physician costs incurred by individuals in a given fiscal year, but also their personal characteristics, self-reported health conditions, sociodemographic and socioeconomic status. In our analysis, we use several different estimation techniques to answer our research question and validate our results. We focus on both the eleven year average of the physician costs as well as repeated analysis of annual costs.

The results suggest that being overweight or moderately obese is not necessarily associated with higher long-term physician costs than being normal weight among younger and middle-aged males. Although our nonparametric results are not linear, when you consider the 95% confidence intervals on these graphs, it is hard to argue overweight and moderate obesity (class I) is associated with higher AAPC. Among males between ages 30 and 45, we see that BMI level 30 corresponds to the minimum long-term physician costs. Similarly for males ages 46 to 65, whose minimum long-term physician costs corresponds to a BMI level of 25 (the threshold for being overweight). We only observe obesity to be associated with higher long-term physician costs for males aged between 46 and 65. Even so, the cost difference between class I obese and normal weight males seems to be around $100 on average over eleven year period. Among females, there is a slight but steady positive relationship between increases in BMI and long-term physician costs for ages 18 to 29 and 30 to 45. While morbid obesity is associated with higher long-term physician costs for both sexes and any age group, it is very pronounced in all age groups among females.

Semiparametric analysis validates the existence of a positive relationship between long-term physician costs and BMI, even after controlling for a list of covariates that are statistically significantly related to logarithmic AAPC. Murphy et al. (2006) find obesity to be associated with cardiovascular problems in adults between ages 45 and 64. We would expect controlling for existing health conditions would change the nature of the relationship between BMI and the physician costs, but we do not see such a change in Figure 2.

If enough individuals lost weight between the time we observe their BMI and the end of eleven-year period, and if changes in BMI have an immediate impact on physician costs in short-term, then we would expect the results of our annual regressions to be mixed, in the sense that the differences we see among body types should diminish over time. On the other hand, if we believe that the relationship between body fat and physician costs takes time to develop, then our original research question can be answered with these results. Although in Figure 3A we show that obese males do not necessarily incur higher costs than overweight males, due to intersecting confidence intervals this does not mean that the changes in individuals' BMI have mixed results. Even in the year of the survey, 2000/01, we observe the same relationship in overweight and obese males. Considering that Janssen et al., (2009) and Tarride et al. (2012) also do not find physician costs to be statistically significantly different between obese and overweight males in the short-term, we would argue that our conclusion is valid and that we see a statistically significant difference only in the long-term. In Figure 3B we see the same consistent pattern of statistically significant difference between obese and overweight for females.

We check the adequacy of the priori assumptions that lead to log link and gamma distribution specification of the GLM regressions in the second part of the two-part model by replicating the two-part model using the power GLM method. This method allows for simultaneous nonparametric identification of the link function and a flexible variance structure, and therefore eliminates the need for *a priori* assumptions. Even so, the results in Figure 4 demonstrate that the conclusions we reach by parametric GLM with gamma variance distribution and log link function specifications do not change. Results for obese, overweight and normal weight are very close to each other and only seem to start to have differences in the long-term in males. In females, the relationships of all three BMI categories seem to be the same. Therefore, we can confirm that log link and gamma distribution specification in GLM regression in a two-part model is adequate for health care cost modeling.

The gender difference we observe in association between BMI and physician costs could have many reasons. Even though we drop females who are pregnant or breast feeding at the time of the survey, it is possible that a portion of this physician cost difference is due to fertility related health care needs. The higher physician costs associated with obesity (high BMI levels) in females at all ages then could either be due to their higher demand for health care to stay healthy or through increased care of physicians who may be aware of the short and long term consequences of the adverse health effects of their patients' high fat accumulation. On the other hand the age dimension of obesity's association with higher physician costs among males mostly indicate weaker physiological stance at older ages.

There is also uncertainty regarding why higher BMI at morbidly obese levels is associated with higher physician costs. This could be related to the complications associated with observed higher relative risk of mortality among morbidly obese than obese, overweight or normal weight individuals – all of whom have similar relative risk of mortality (Orpana et al., 2009). However, in our study, it is hard to distinguish if the higher costs are due to the demand or supply side of the health-care market. Since we do not see a change in the relationship after we control for the existing health conditions, we cannot conclude that the higher physician costs at high BMI levels are related to these serious health conditions that obesity is associated with. Bertakis and Azari (2005) show that on average obese patients have more physician visits and they are prescribed more diagnostic services compared to normal weight individuals. One of their explanations is that physicians are more likely to refer to specialists and prescribe more diagnostic services for those who make frequent visits and have persistent medical complaints. This supposes that physicians may be altering the way they provide care for obese patients, assuming that they might have more health concerns.

Ontario reformed its primary care model in 2006 (Kralj and Kantarevic, 2012). One of the reforms was to offer primary care physicians alternative remuneration schemes, where they receive a predetermined amount for each patient that they roster. Although these predetermined amounts are based on age and sex of each patient (Health Force Ontario, 2014), in the past the MOHLTC made adjustments on the payments received by primary care physicians who roster acute patients (Ministry of Health and Long-Term Care, 2014). Similar adjustments might be needed in future for other issues that exceed expected expenses incurred by physicians; e.g. for morbidly obese patients. This is important for two reasons: First, in order to avoid cream-skimming by physicians through not adding morbidly obese patients to their rosters. Secondly, to avoid the unfair distribution of morbidly obese patients to the primary care physicians, as obesity is linked to lower socioeconomic status and the geographical distribution of morbidly obese individuals may not be homogenous. Our results suggest that the MOHLTC may like to consider making similar adjustments for morbidly obesity patients by considering patients' BMI as one of the characteristics when determining capitation fees. It is also important to underline that this analysis remains relevant to other jurisdictions where the health care costs are funded mainly by public financing.

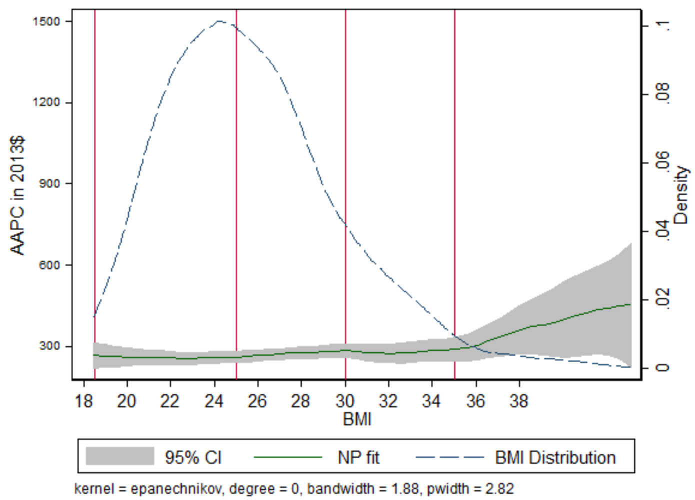
Allison, Zannolli, and Narayan (1999) argue that the lifetime cost of obesity be overestimated in most studies, because they do not take into consideration the higher mortality rates associated with being obese. Cawley and Meyerhoefer (2012) argue that in order to obtain the most accurate results a causal analysis should be undertaken.. In their study, they attempt to undertake this by using an instrumental-variable approach in which they use BMI of the individual's oldest biological child as the instrument. They claim that their results better account for the health care costs of obesity in the US, because other studies tend to underestimate the true cost by not accounting for obese individuals who are obese due to their medical conditions or due to being poor and not having adequate access to health care. Since Canada has a universal healthcare system, the problems about access to care should not be such an issue in our context. Therefore we believe our results do not underestimate the associated physician costs, even if it is a correlation study.

The potential limitations of these results are several. First of all, we have no data on the on-reserve aboriginal population in Canada. Secondly, we cannot observe pharmaceutical expenses. Comparing the literature from Canada with that from the US, Canadian results underestimate total costs associated with obesity as it is shown by Raebel et al. (2004) that the increase in the total health care costs for obesity is mainly driven by pharmaceutical expenses. Thirdly, we make certain adjustments to physician cost data and sampling weights, which is not ideal. These are made after very careful considerations, as explained in the Appendix C. We also correct for self-reported BMI using the correction models suggested by the Statistics Canada.

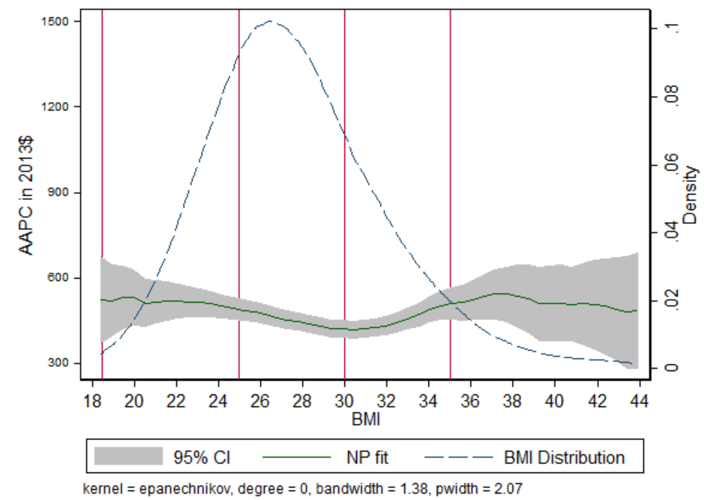
However, as Dutton and McLaren (2014) find out, corrected BMI performs worse in predicting health conditions than the self-reported ones. Therefore, the correction may not even be necessary.

Figure 2.4A Nonparametric estimates of Physician Billings and the BMI distribution (Males)

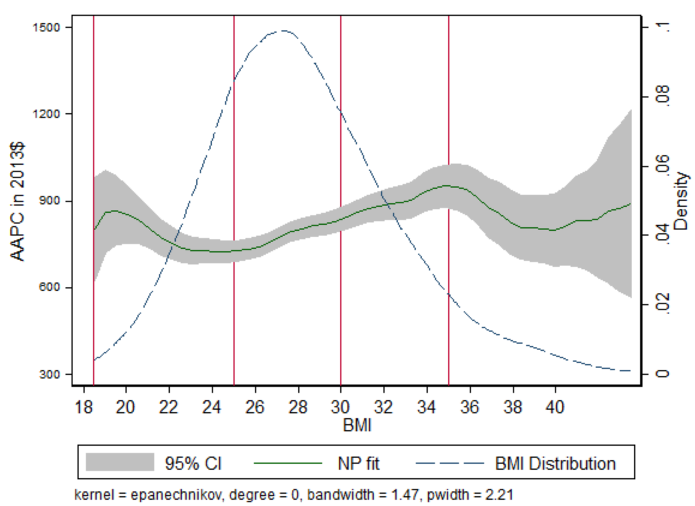
Ages 18 – 29



Ages 30 - 45



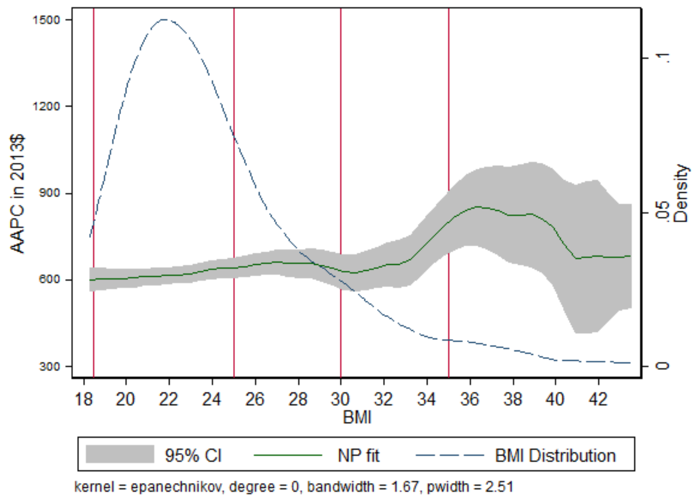
Ages 46 - 65



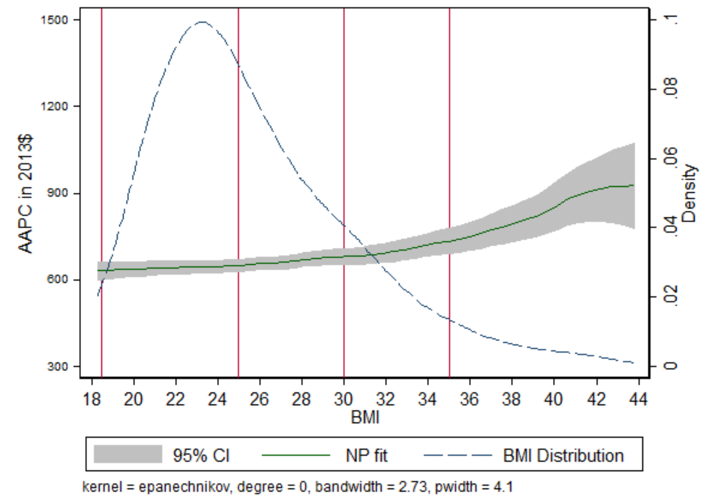
Note: The relationship between average annual physician costs over the long-term with BMI values obtained in a single year are shown for three age groups.
AAPC is average of annual physician costs over 11 years (1999/00 – 2009/10). They are adjusted for inflation and represent 2013 dollars.
BMI is obtained from a single year, 2000/01, using bias corrected self-reported responses in the CCHS 1.1

Figure 2.1B Nonparametric estimates of Physician Billings and the BMI distribution (Females)

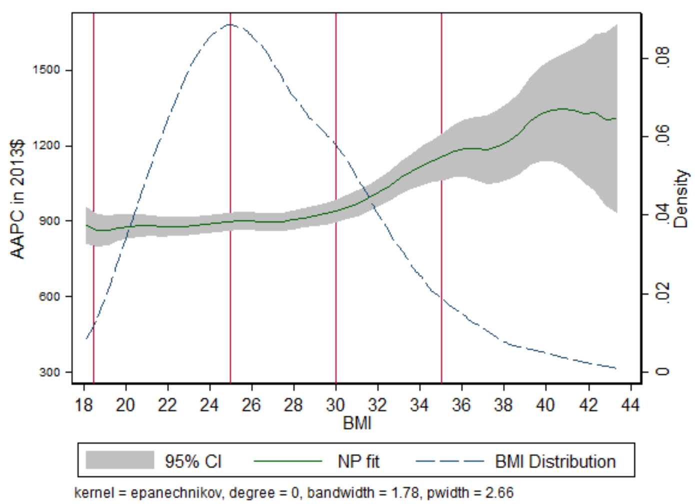
Ages 18 – 29



Ages 30 – 45

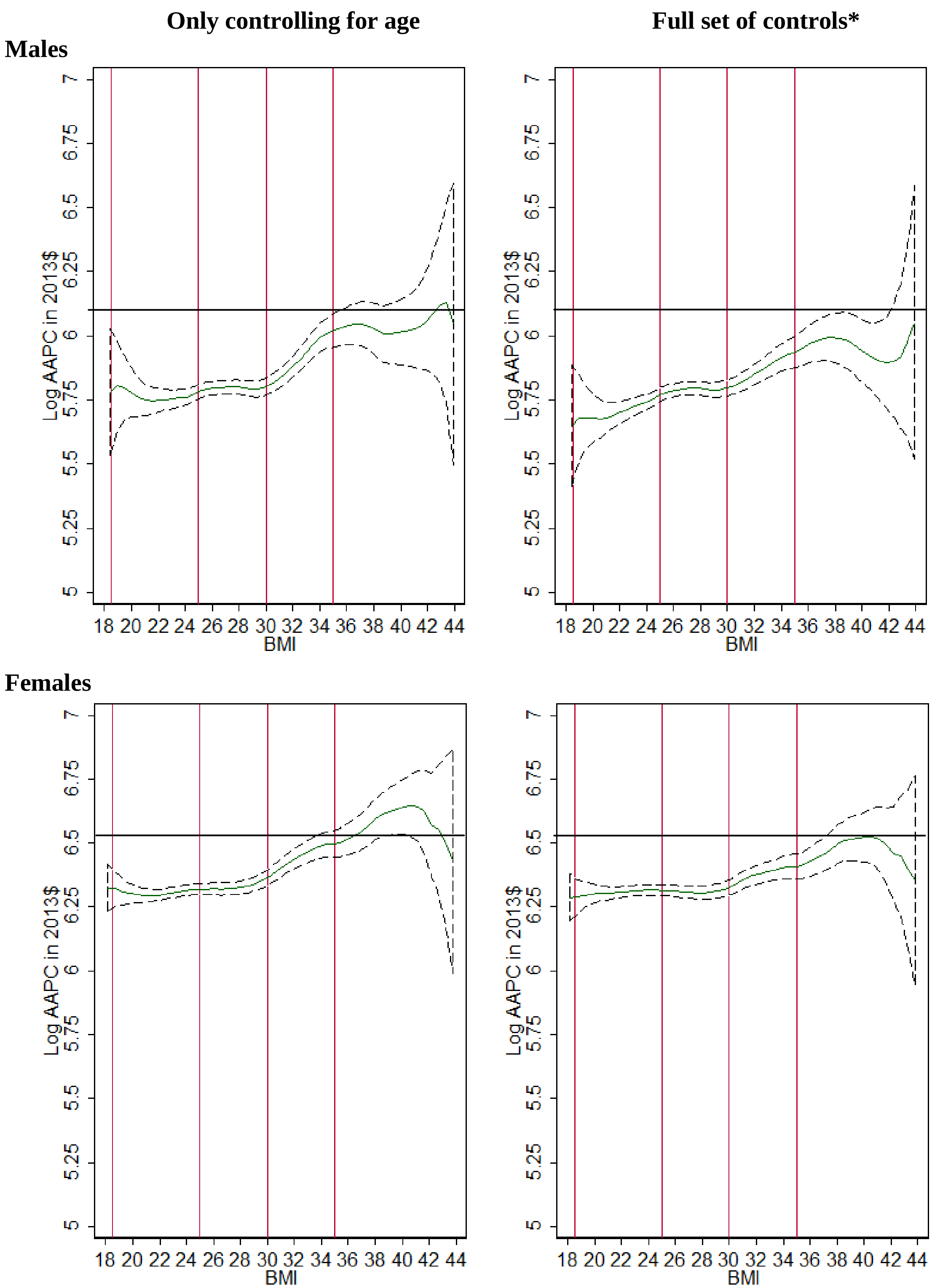


Ages 46 – 65



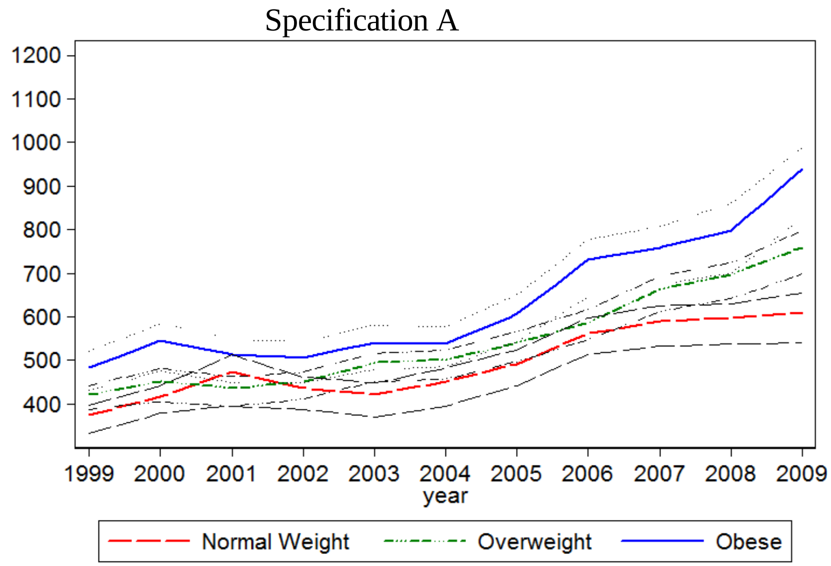
Note: The relationship between average annual physician costs over the long-term with BMI values obtained in a single year are shown for three age groups.
AAPC is average of annual physician costs over 11 years (1999/00 – 2009/10). They are adjusted for inflation and represent 2013 dollars.
BMI is obtained from a single year, 2000/01, using bias corrected self-reported responses in the CCHS 1.1

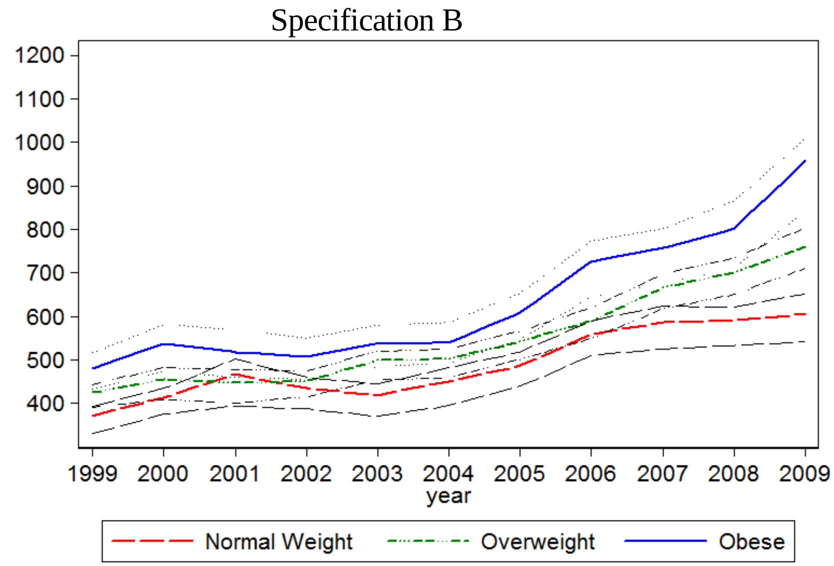
Figure 2.2 Logarithmic Average of Eleven Years of Physician Costs and BMI in 2000/01

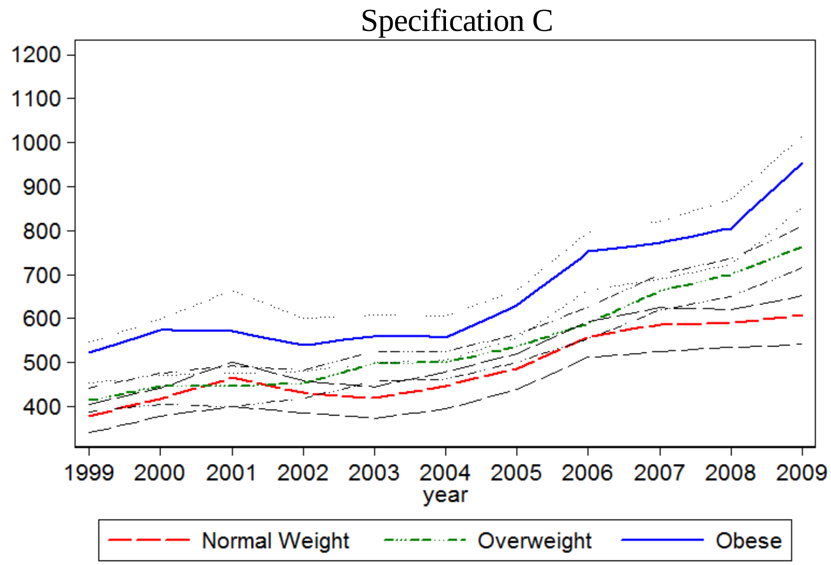


* Full set of controls include: controlling for mean-deviated age and its 4th degree polynomials, health impacting behaviours, household income level adjusted for the household size, existing obesity related health conditions, self-perceived poor health, education level, marital status, being born in Canada and living in an urban area.

Figure 2.5A Repeated Annual Two-Part Model Estimates: using GLM in part II (Males)



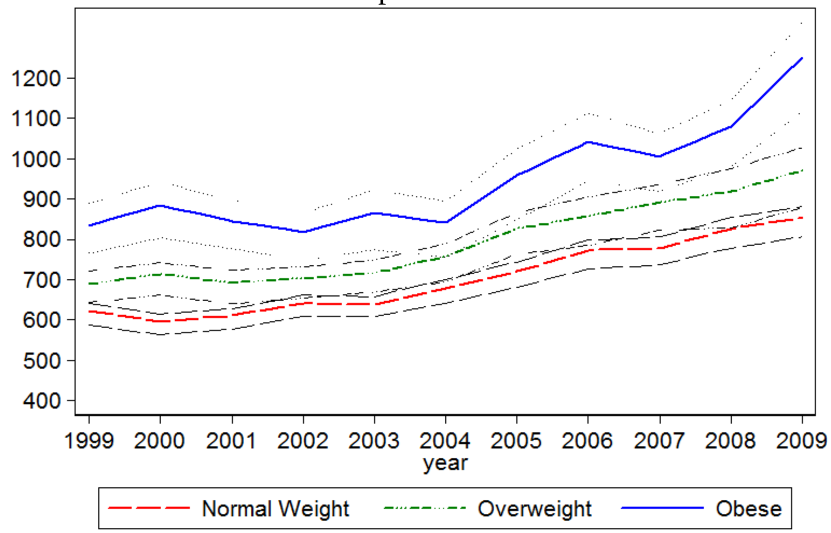




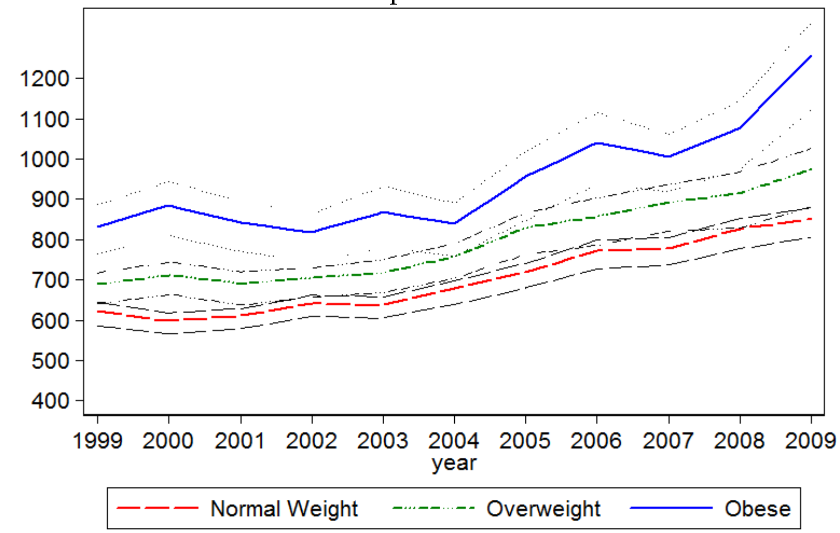
Note: Mean annual physician costs and 95% confidence intervals are shown for three body types.
y-axis shows mean annual physician costs in $2013
Specification A: controlling only mean-deviated age and its 4th degree polynomials.
Specification B: Specification A + controlling for health impacting behaviours and household income level adjusted for the household size.
Specification C: Specification B + controlling for existing obesity related health conditions, self-perceived poor health, education level, marital status, being born in Canada and living in an urban area.

Figure 2.3B Repeated Annual Two-Part Model Estimates: using GLM in part II (Females)

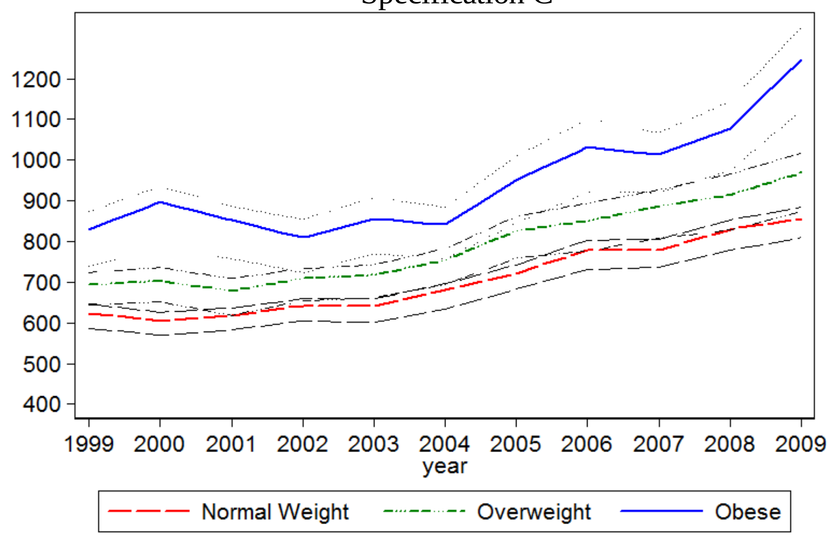
Specification A



Specification B



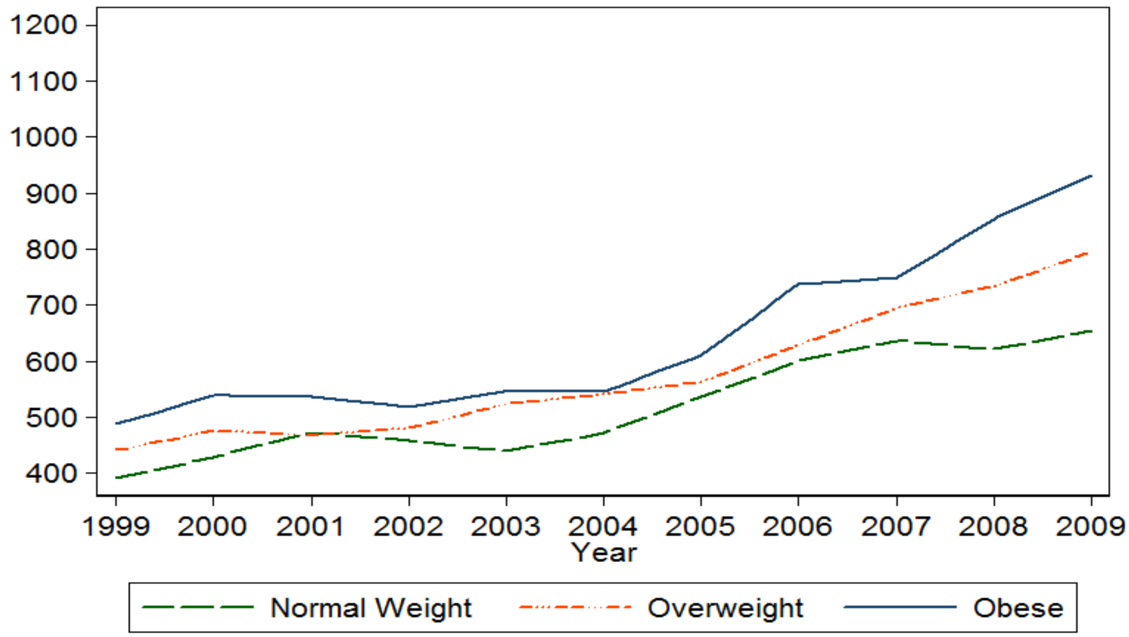
Specification C



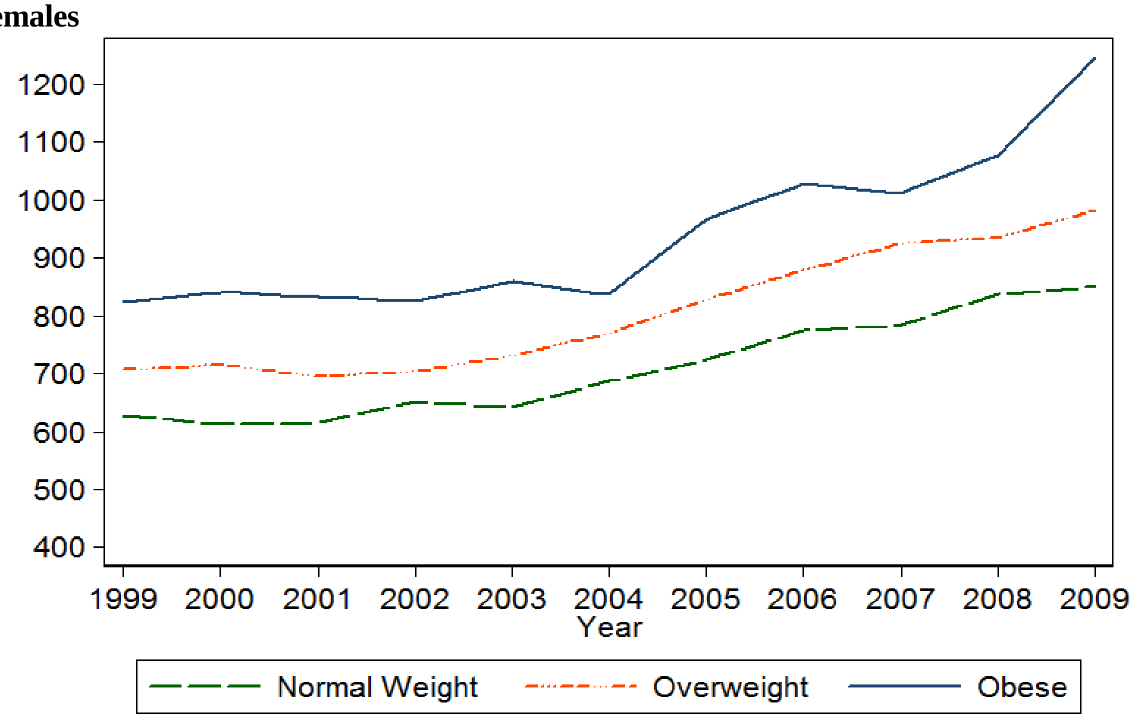
Note: Mean annual physician costs and 95% confidence intervals are shown for three body types.
y-axis shows mean annual physician costs in $2013
Specification A: controlling only mean-deviated age and its 4th degree polynomials.
Specification B: Specification A + controlling for health impacting behaviours and household income level adjusted for the household size.
Specification C: Specification B + controlling for existing obesity related health conditions, self-perceived poor health, education level, marital status, being born in Canada and living in an urban area.

Figure 2.6 Repeated Annual Two-Part Model Estimates: using Power GLM in part II (based on model Specification B)

Males



Females



Note: Mean annual physician costs and 95% confidence intervals are shown for three body types. y-axis shows mean annual physician costs in $2013

Table 2.3 Descriptive Statistics

CCHS 1.1 (Ontario)		Male	Female
All Ages			
	N	9492	10512
	Mean BMI	26.15	24.88
		(4.06)	(4.61)
	Mean NPV of 11 years of phy. costs†	$7588	$10850
		(9734)	(9998)
	Mean Age	39.65	40.49
		(12.65)	(12.68)
Age: 18-29			
	N	1841	2134
	% Normal weight (18.5≤BMI<25)	59%	66%
	Mean NPV of 11 years of phy. costs	4023	8799
		(6941)	(7553)
	% Overweight (25≤BMI<30)	30%	24%
	Mean NPV of 11 years of phy. costs	4262	9717
		(5064)	(9149)
	% Obese (BMI≥30)	11%	10%
	Mean NPV of 11 years of phy. costs	4189	10677
		(4098)	(8272)
Age: 30-45			
	N	3927	4220
	% Normal weight	37%	56%
	Mean NPV of 11 years of phy. costs	7103	9243
		(11595)	(8111)
	% Overweight	44%	26%
	Mean NPV of 11 years of phy. costs	6055	9434
		(7824)	(8825)
	% Obese	19%	18%
	Mean NPV of 11 years of phy. costs	7010	10989
		(7476)	(8802)
Age: 46-65			
	N	3724	4158
	% Normal weight	32%	43%
	Mean NPV of 11 years of phy. costs	10409	12377
		(10464)	(9931)
	% Overweight	45%	36%
	Mean NPV of 11 years of phy. costs	11337	13235
		(10657)	(11886)
	% Obese	23%	21%
	Mean NPV of 11 years of phy. costs	12842	16414
		(11544)	(15657)

Standard deviations are shown in parentheses.
†Inflation calculator at Bank of Canada's (2014) website is used to adjust to 2013 dollar values.

Table 2.4 Coefficient Results of Semiparametric Regression

	MALES		FEMALES	
	Model 2	Model 3	Model 2	Model 3
$Mean\ Deviated\ Age$	.0365***	.02968***	.00910***	.00316
	(.003)	(0.003)	(.002)	(.002)
$Mean\ Deviated\ Age^2$	.000	.000	.002***	.002***
	(.000)	(.000)	(.000)	(.000)
$Mean\ Deviated\ Age^3$	.000	.000	.000*	.000
	(.000)	(.000)	(.000)	(.000)
$Mean\ Deviated\ Age^4$	.000	.000	.000***	.000***
	(.000)	(.000)	(.000)	(.000)
Diabetes		.310***		.254***
		(.053)		(.054)
Heart Disease		.32926***		.262***
		(.060)		(.057)
Cancer		.466***		.307***
		(.117)		(.072)
Chronic Disease		.390***		.399***
		(.032)		(.028)
Smoker		-.0288		-.0617*
		(.034)		(.028)
Physically Active		.0316		-.0464*
		(.030)		(.023)
High School Grad.		.0098		.000
		(.051)		(.035)
Post Sec. Grad.		.0237		.002
		(.041)		(.031)
Married		-.0395		.0594
		(.051)		(.035)
Prev. Married		-.0272		.103*
		(.069)		(.048)
Born in Canada		-.219***		-.124***
		(.037)		(.027)
Urban		.1692***		.203***
		(.031)		(.027)
SPH (Poor) †		.475***		.427***
		(.048)		(.035)
N	9492	8928	10512	10320
$\mathbf{R^2}$	.178	.265	.0500	.1636
$\bar{\mathbf{R}}^2$	.178	.264	.0497	.1622

*95% significance level, **99% significance level, ***99.9% significance level

†Self-perceived health being poor is the reference group.

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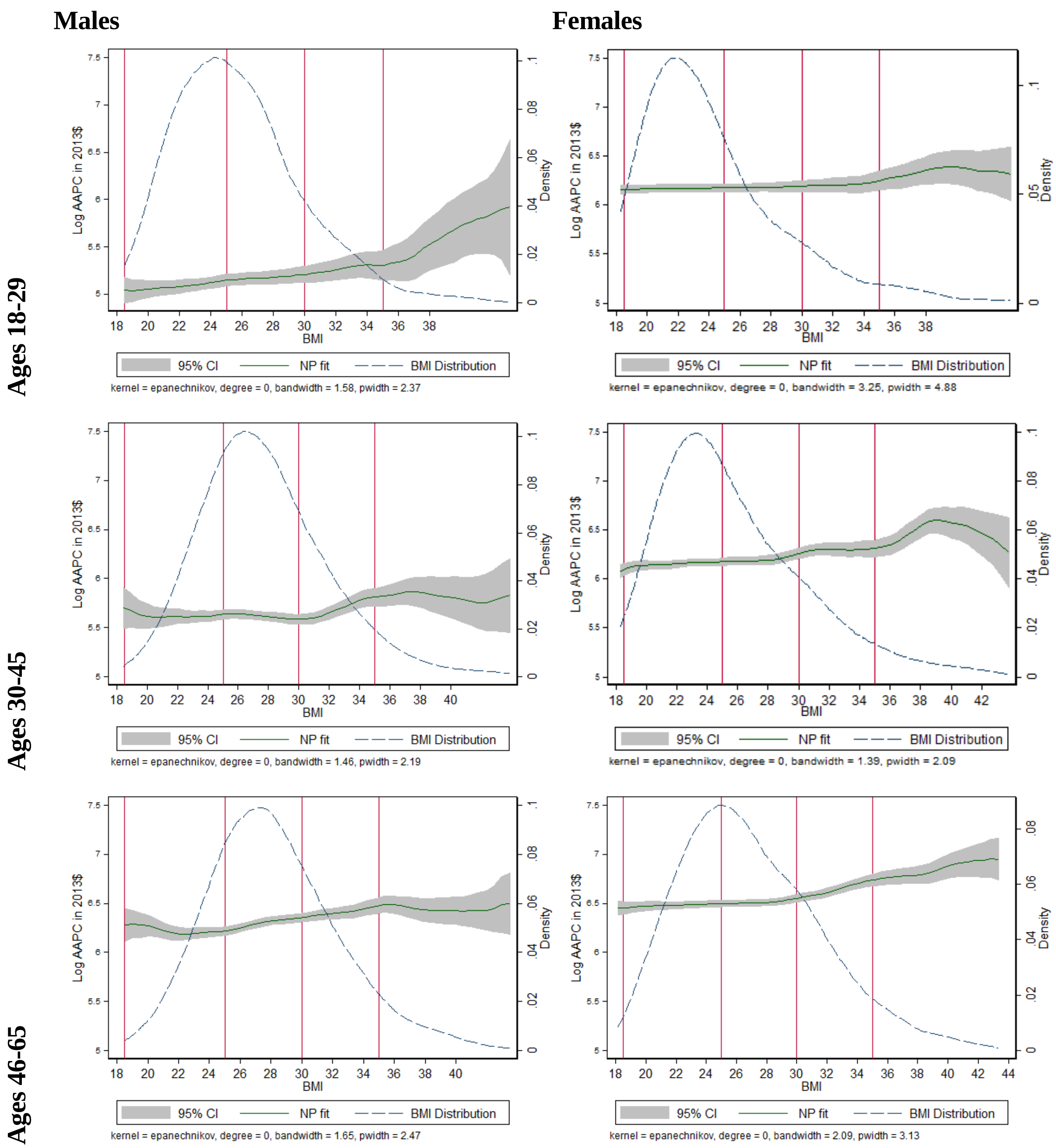
Appendix 2.A Logarithmic Specification of Nonparametric Analysis

Figure 2.AP1 Nonparametric results with logged AAPC



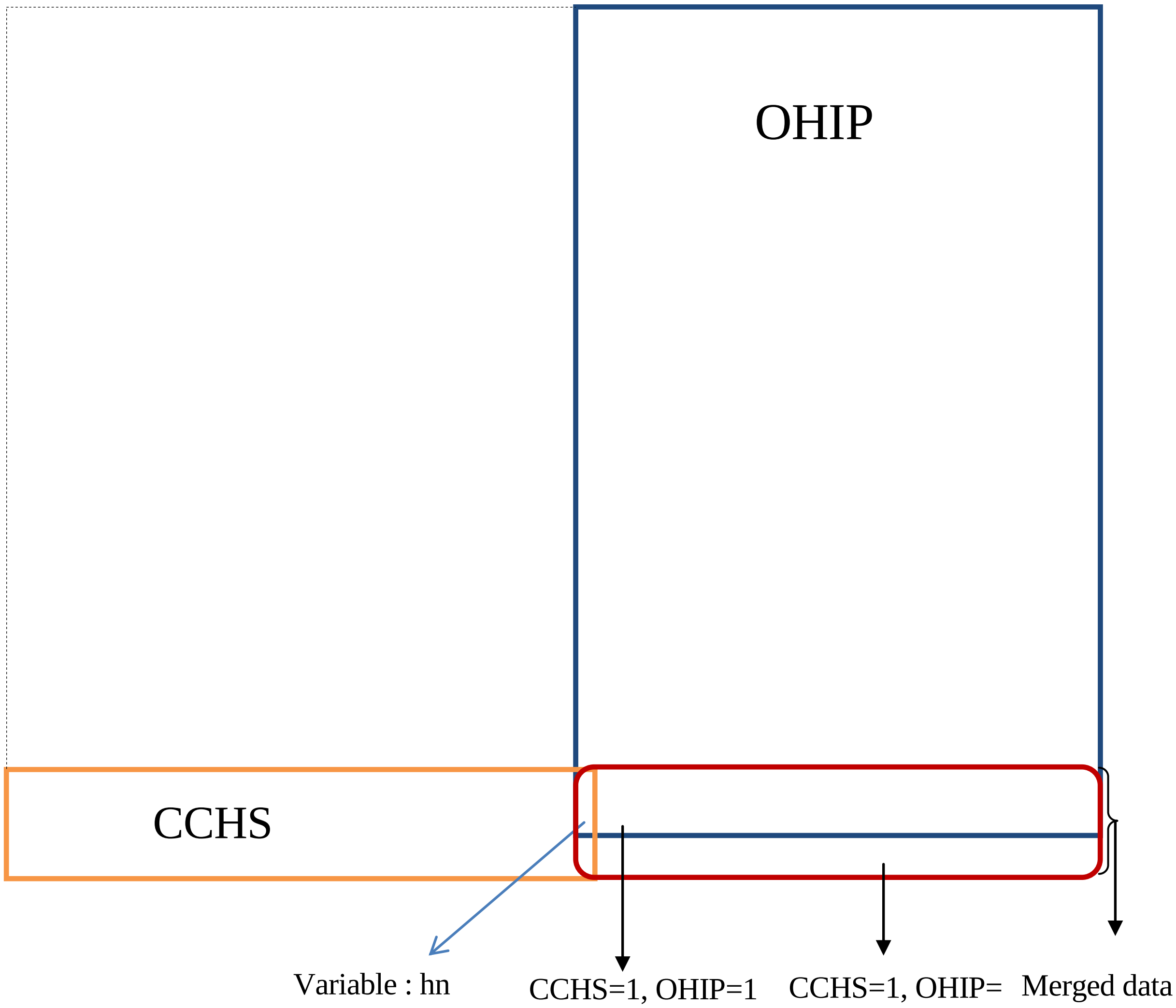
Appendix 2.B Record Linkage

The agreement between the Statistics Canada and the MOHLTC for the McMaster Pilot Project allow us to link the CCHS cycle 1.1 (2000/01) Ontario Share File with administrative records from OHIP, for the fiscal years between 1999/00 and 2009/10. The record linkage between the CCHS and OHIP datasets is done by using an identifier variable included in these datasets.

The CCHS 1.1 is a cross-sectional survey, representative of over 98% of the Canadian population. Excluded are members of the Canadian Forces, individuals living on Indian Reserves or Crown lands, full-time members of the Canadian Armed Forces, and residents of institutions and certain remote regions (Statistics Canada, 2012).

As can be seen in Figure AP2, the linking variable between the two datasets is the encrypted health number variable (hn). The CCHS Ontario Shared File only includes those from Ontario, who has agreed to have their responses linked with the administrative data in the sample. The linkage is done to create a “key” to CCHS consisting of only “hn” variable and merge OHIP with only these CCHS key file. The final linked dataset takes the form of the combination of red and orange rectangular data blocks as depicted in Figure AP2.

Figure 2.AP2 Visual representation of the data linkage



Appendix 2.C Attrition & Adjustments on the Sampling Weights

Attrition issue became apparent when we observe the ratio of individuals who did not visit a physician in a given year. It is the lowest at the year of the survey and higher for the years before and after, growing gradually with time.[37] We plot this issue with the data and show in Figure AP2. It shows the ratio of those who had no physician visits in a given year in the CCHS sample. One of the clear outcomes of our research is that the utilization of health care by females is higher than that of males in our analysis. Our further analysis also demonstrates this as we disaggregate the relationship in terms of sex. The ratio of those who did not see any physician in a given year is higher in males than females.

For the years after the survey, this issue with the apparent attrition in the data is possibly due to mortality and out of province/country mobility that we cannot account for with the variables that exist in the dataset.[38] For the discrepancy in the years before the survey, the possible explanation is the newcomers to the province. These could be accounted for, if it was possible to observe annual OHIP eligibility of the sample. Unfortunately, the Registered Persons Database (RPDB) was not included in the datasets included in the data agreement. Since our research question is the differences in the health care utilization between obese and non-obese populations of Ontario, the longitudinal investigation can only be feasible if we could convince ourselves that this attrition issue is not related to the individual's body mass index (BMI) levels. We initially investigate this in

[37] Although we had an additional OHIP dataset for the 1994/95 fiscal year in the McMaster Pilot Project, we chose not to include it in our analysis (thus not mentioned earlier) due to different reasoning that it required to compensate for the attrition issue that we observe. We called this the "new-comer effect", but did not develop an algorithm to compensate for it.

[38] There are also potentially those who become personnel of Canadian Forces or Royal Canadian Mounted Police or an inmate in federal prisons.

Figure AP3, where we observe no particular differences in the attrition trends by normal weight, overweight and obese categories. Following this, we look at BMI distributions of those who see no physician visits and those who have at least one physician visit in a fiscal year; both for the year of the survey, 2000/01, and the final year of OHIP data that we have in our dataset; 2009/10. Figure AP4 shows these two BMI distributions proportionate to the overall size of the sample to have a better understanding of the relative sizes of the two groups with each other. The first row of figures is from the 2000/01 and the second row is from the 2009/10. It is easy to see in both figures that the proportion of those who had no physician visits becomes larger with the time and that the proportion of females who visit a physician is higher than males in both years, complying with the results shown in Figures AP2 and AP3. More importantly however, the figures support the view that there are no alarming issues with the distribution of BMI of those who remain in the dataset after we first observe them in the survey, as the shapes of the BMI distributions for these groups do not change dramatically. This is an encouraging finding that we could use in our argument for moving on with our initial intention to conduct a longitudinal analysis of the data.

Since we show that the attrition does not seem to be related to BMI, a more obvious factor for mobility and mortality is age. In Figure AP5 we show that the post-survey attrition rate is relatively flat for those who are aged between 25 and 59 versus those 60 and 85.[39] We deduce that those over 60 are more likely to move out of province after their retirement or decease. Since we cannot control for either, we decided to drop those who are less than 60 years old and do not appear in the last three years of OHIP data and those over 60 years old and do not appear in the last two years of OHIP data to be out of our sample. Figure AP6 shows the differences in the follow-up

[39] These age cut-off points for the algorithm are determined using trial and error to find the best solution to the attrition problem that allows the ratio of those who had not used physician services in a given year to be kept the same or lower in subsequent years to the survey (see Figure 2.AP.6).

trends for the original sample and those who stay in the sample after we apply our decision rule. It is apparent that eliminating those who do not appear in the last three years of the OHIP from our sample greatly solved the attrition problem that we were facing. Following this finding, we created new sample weights that take into consideration this attrition issue for those who stay in the sample. We do this, similar to the method suggested by Jones, Rice, and D'Uva (2013), by estimating the probability of staying in the sample using a long list of sociodemographic and BMI variables and their interactions with female dummy variable. The inverse of the predicted probabilities of those in the sample further multiplied by the original sample weights to obtain final sampling weights that compensate for the attrition issue.

Figure 2.AP3 Attrition in CCHS 1.1 by sex (Age censored at 85)

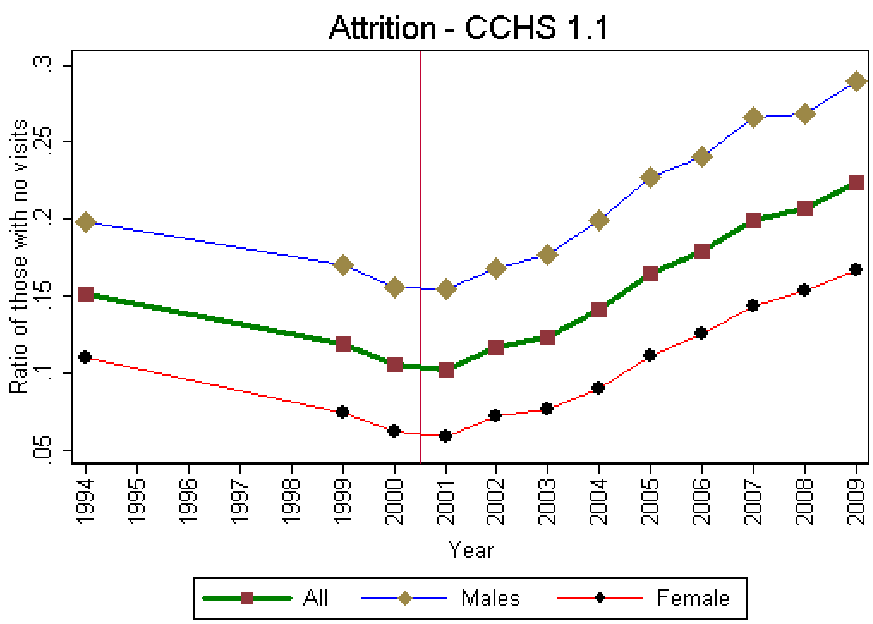


Figure 2.AP4 Attrition in CCHS 1.1 by body type (Age censored at 85)

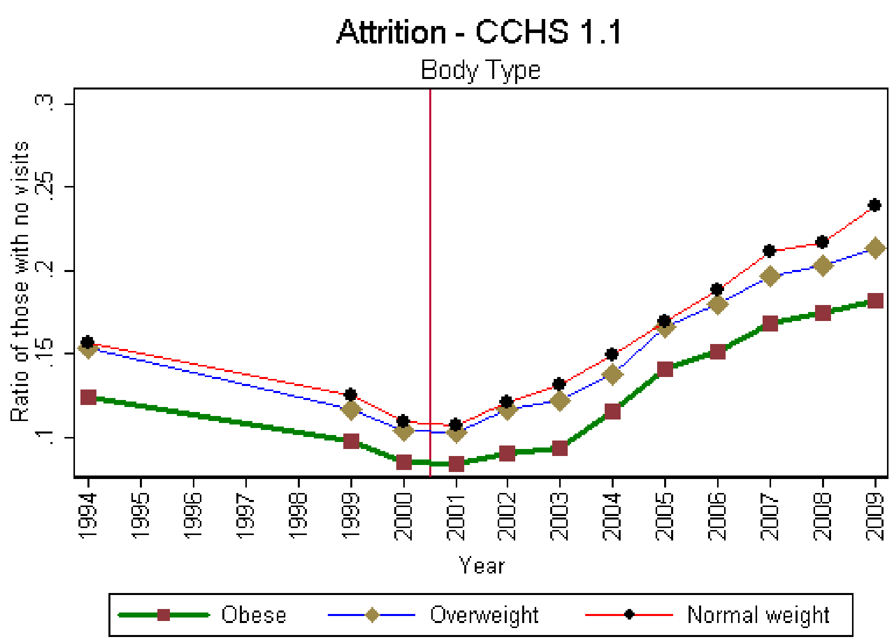


Figure 2.AP4 BMI distributions of the two groups in the attrition analysis

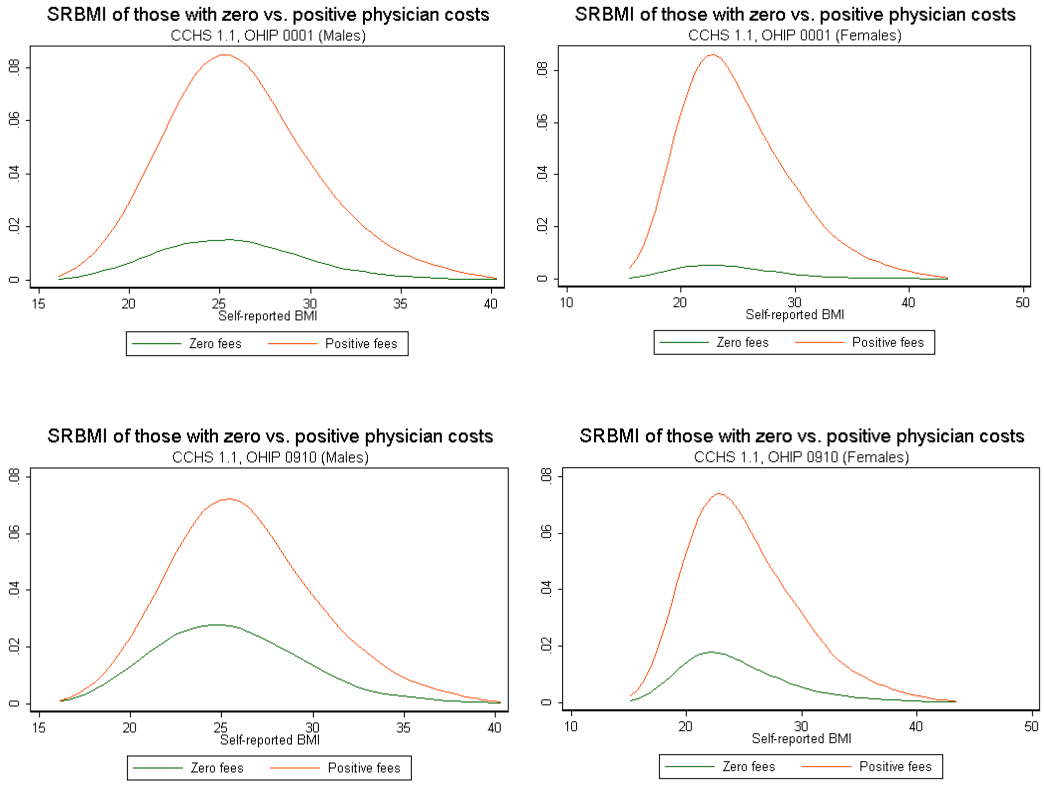


Figure 2.AP5 Attrition in CCHS 1.1 by age group (Age censored at 85)

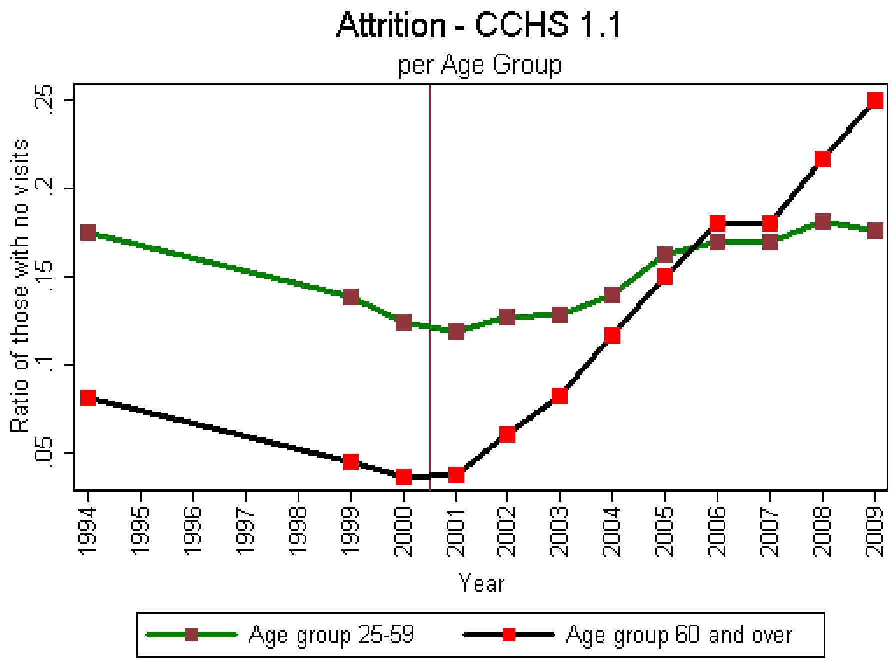
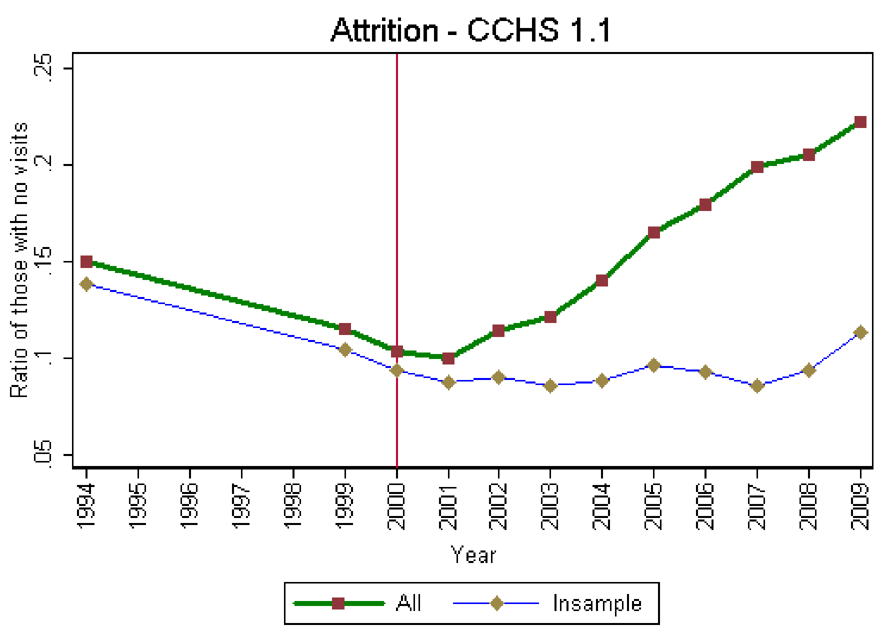


Figure 2.AP6 Solution to the attrition problem in CCHS 1.1 (Age censored at 85)



Appendix 2.D OHIP Data Clean-up and Estimation of proxy for Fee-for-service physician costs

There are two issues with OHIP data regarding the variable on the cost of physician services. First of these involves retroactive adjustments made in the system, due to which multiple entries for the same service from the same physician on the same day for the same patients appear in the data. These make sense for accounting purposes but needs to be cleaned for statistical analysis. These entries might have zero fees attached to them, or the same value twice with cancelling number of services attached to them. Our first step in tackling this issue is to drop duplicate entries in the data. Then flag the entries for the same patient, same physician, same service date and fee-schedule code that has zero fee paid values. After this, for those entries with or without zero fees, we use an algorithm that drops those entries for the same patient, physician, fee-schedule code and service date but cancel each other out as a result of retrospective adjustments.

The second issue was undeniably one of the biggest shortcomings of the dataset; the absence of "fee approved" variable. When the initial request was made for the OHIP dataset, the researchers asked for "fee paid" variable but not the "fee approved", as they were not given the complete data they had to guess the variables they needed. As a result, the dataset has the information on the final dollar value received by the physicians from the MOHLTC but not how much that physician service is worth. The difference between the two is significant when considering that the physicians under capitation or alternative/blended remuneration schemes receive lower, or no fees for the certain services they provide to the patients in their rosters but those under fee-for-service agreement get the full amount. Accounting only the fees paid to the physicians would lead us to underestimate the true cost of the services received by patients from the physicians and introduce volatile changes in their trends on the face of changing remuneration agreements. “Fee approved” variable, instead, would show the true cost of the procedure under fee-for-service agreement for all physicians. In order to compensate for this shortcoming, we have devised an algorithm to create a proxy for the approved fees. We realize that capitation/blended remuneration schemes became dominant starting from 2005/06 fiscal year (Kralj and Kantarevic, 2012). For the years before this we have simply assigned the mean “fee paid” of each procedure to all physician services. For the years 2005/06 onwards, we account for those in alternative remuneration schemes. In order to do that, we determined the 90th percentile of the fee paid of each unique fee schedule code and focus on only those higher than the 20% of the 90th percentile of these dollar values; assuming that some of those under alternative schemes receive 20% of the fee-for-service values. Then our proxy fee-for-service fee is calculated based on the mean of the fee paid of those over 20% of the 90th percentile of the fees for that particular fee schedule code or the 90th percentile for those who received lower than that. The syntax is available upon request.

Chapter 3
Decomposing Differences in the BMI Distributions of Canada and the United States

3.1 Introduction

The fundamental cause of obesity is an imbalance between an individual's energy intake and consumption (WHO, 2015), while recommendations to tackle obesity include limiting energy intake from total fats and sugars and increasing consumption of fruits and vegetables and physical activity levels. It is emphasized by the WHO (2015) that the poorest individuals may need the most support, as these changes may not be affordable for them. To a certain degree, the type of food consumed and the level of physical activity are related not only to income and education level, but also to personal attitudes towards one's own health. According to Grossman's (2000) model, these are implicit and explicit determinants of decisions which determine health stocks.

Most studies on the relationship of obesity and socioeconomic and other factors use body mass index (BMI) categories where individuals are classified under different body types according to their weight relative to their height (squared). Different BMI distributions may indicate the same obesity prevalence, but their mean, variance and other characteristics could be quite different. More generally, comparisons based on the whole distribution of BMI provide information about how populations differ throughout the distribution of BMI.

In international comparisons, the US almost always ranked as having the highest prevalence rate of obesity among its adult population (OECD, 2014). Although both are higher than the OECD average, the prevalence of adult obesity in Canada has been about 10% less than that of the US throughout the first decade of 2000s (O'Neill & O'Neill, 2007; OECD, 2014). Due to their geographical proximity and relative similarity of life-styles, a comparison between these two countries might point policy-makers to socio-demographic and socio-economic dimensions related to this difference.

This study provides evidence about how sociodemographic and socioeconomic characteristics are associated with BMI throughout its distribution. We make over time and cross-country comparisons of Canada and the United States (US), separately for males and females using nationally representative repeated cross-sectional samples over the approximate period 2000-2010. We identify how much of the differences in BMI distributions that we observe between the two groups are attributable to differences in distributions of covariates (characteristics) and how much are attributable to the differences in returns from those characteristics. We use three different decomposition methods that are complementary to each other. The well-known method by Oaxaca (1973) and Blinder (1973) provides detailed decomposition results (where the contribution of each variable is decomposed into component parts) at the mean of a distribution. The method of Firpo, Fortin, & Lemieux (2009) allows us to pursue detailed decomposition analysis at selected quantiles of the distribution. The method first estimates points on cumulative density functions (CDFs) of each group's dependent variable that correspond to the quantile of interest. The set of counterfactual proportions, which are derived from points on CDFs of each group's dependent variable, makes up the counterfactual distribution function. Under the assumption that the relationship between these counterfactual proportions and counterfactual quantiles is locally linear, the inversion is the slope of the two points on counterfactual distribution function. The method can potentially fail to produce good estimates at the two tails of the distribution, where the two points may fall on the same horizontal plane where slope is zero. To test this, we use the method put forward by Chernozhukov, Fernández-val, & Melly (2009), which should perform better in the tails of the distribution, but does not offer the calculation of detailed decomposition with the same convenience. Therefore we compare only the aggregate level decomposition results of the two quantile-based decomposition methods. After demonstrating that the results of the two methods are very similar to each other, we then move to discuss detailed decomposition results at the mean, median, 10^{th}, 25^{th}, 75^{th} and 90^{th} quantiles of the BMI distributions of the two groups investigated in each analysis.

The next section provides a review of the relevant literature. Then, we describe the two datasets we use in the analysis. After that, we explain the decomposition methodologies used and the procedures we adopt for statistical inference. This is followed by the results and discussion sections.

3.2 Literature Review

The percentages of the adult population who are obese in Canada and the United States (US) are above the OECD average (OECD, 2014). Although in many aspects similar to the US, the prevalence of obesity has recently been lower in Canada with O'Neill and O'Neill (2007) finding that the difference between the percentage of obese adults between the two countries was about 15% for both sexes in 2004. Tjepkema (2006) notes that between 1978/79 and 2004 adult obesity in Canada increased almost 10% and that the highest growth was among the severely obese population. This 10% increase in obesity prevalence corresponds to a 10% decrease in proportion of normal weight individuals as the percentage of overweight and underweight individuals in the population did not change much over that time period. Aging does not have a linear relationship with obesity as the increases in prevalence were the highest among age between 25 and 34 and ages 75 and up.

Auld and Powell (2006) investigate the difference in BMI distributions of Canada and the US through analysis of a set of sociodemographic, socioeconomic and environmental factors such as the price of fast food and fruit and vegetables and the per capita number of chain supermarkets. They use a switching regression technique to decompose the differences at the mean of the BMI distribution of each country and conclude that if the characteristics of the US population and the environmental factors in the US were to be the same as they are in Canada, this would explain one-third of the difference observed among females but make almost no difference among males. They identify the differences in the racial composition of the population to be the major factor in the inequality among female populations.

A number of studies adopt a distributional approach to investigating the differences between BMI distributions of two groups, rather than focusing on the differences in the mean. For instance, Costa-Font et al. (2008,2009,2010) provide a series of studies in which they decompose the differences in BMI distributions of Italy and Spain; two Mediterranean countries with similar diets and relatively close cultures. Costa-Font et al. (2010) decompose the differences in the prevalences of overweight, obese and morbidly obese between the two countries as they are associated with lifestyle, socioeconomic and socio-environmental variables. They find that social norms and regional BMI (as socioenvironmental variables) explain the majority of the observed difference. Costa-Font et al. (2009) adopt Machado and Mata (2005)'s decomposition method based on conditional quantile regressions. This distributional approach is able to reveal more than decomposing the means, via the Oaxaca/Blinder method, e.g., to provide information about mean-preserving changes in the dispersion which may be important in the obesity context. They find that the gap between the BMI distributions of females in both countries is due to differences in returns to covariates in each country. Especially for younger females in Spain, the authors suspect it is their behavioral differences that are associated with their higher BMI levels than their Italian counterparts.

Costa-Font & Gil (2008) use the concentration index to account for income-related inequalities in the probability of obesity in Spain and decompose it according to socioeconomic status, behavioral habits, region and interactions between age and sex. They find educational attainment and regional differences to be the most important factors in explaining the inequality.

Hajizadeh et al., (2014) also decompose the concentration index to decompose the income-related inequalities in BMI across different demographic groups and geographic regions within Canada. Their main result is that the relationship between income and BMI differs between the two sexes. While the two are positively correlated for males, they find a persistent negative correlation between the two among females in Canada. Jolliffe (2011) also demonstrate an income gradient in BMI using four decades of the US data, ranging from 1971 to 2006. He shows that positive income gradient at the left tail (underweight) and negative income gradient at the right tail (obese) of BMI distribution have been present over this period in the US. Finally, Dutton & McLaren (2016) decompose the observed regional differences in BMI distributions within Canada using a set of sociodemographic and socioeconomic variables. They pool cross-sectional data on a representative sample of Canadian adult population in years 2001, 2003 and 2007, and also adopt techniques that allow them to look not only the mean but also the centiles of the distributions. They conclude that differences in how these covariates are distributed among different regions do not explain the observed difference in their mean BMI. Instead, they argue that it is in the variation in the returns from these covariates on BMI that the regions differ from each other.

Contoyannis and Wildman (2007) use relative distributions to investigate changes in the distribution of BMI in England and Canada between 1994/95 and 2000/01. This allows them to comment on not only the differences in BMI level over time, but also to the polarization and concentration at different parts of the distribution. They document that BMI levels in both countries increased over time, but the rate of increase is higher in England than Canada and it is also more concentrated at the right tail of the BMI distribution. Houle (2010) extends this approach by comparing BMI distributions according to sex, race and education attainment in the United States. He finds race and education level to be associated with individuals being in the tails of the BMI distribution. Unfortunately, this method is quite cumbersome when a relatively large set of covariates is considered.

3.3 Data

For our analyses, we use the 2000/01 and 2013 cycles of the Canadian Community Health Survey (CCHS) for Canada and the 1999/00, 2001/02, 2009/10 and 2011/12 cycles of the National Health and Nutritional Survey (NHANES)[40] for the US.[41] Due to low sample sizes in each NHANES cycle[42], we combine the 1999/00 and 2001/02 cycles of the NHANES to establish the *Early* era sample, and 2009/10 and 2011/12 cycles as the *Recent* era sample of the US.[43] When pooling these cycles, we make the appropriate adjustments to the sample weights as suggested by the Centers for Disease Control and Prevention (CDC).[44]Since sample sizes are a lot larger in the CCHS, single cycles can be used to conduct sex-specific analyses including estimating complex models. We use cycle (1.1) 2000/01 as the *Early* era and 2013 cycle as the *Recent* era sample for Canada. Over time decompositions are done by comparing the differences in BMI between recent and early eras in each country. Cross-country decompositions are done by comparing the cross-sectional differences between the US and Canada in both eras. All analyses are conducted separately by sex.

[40] At the time of writing, the latest available fully released cycle was 2011/12. NHANES comes in separate modules and not as a single dataset. In our analysis we use the Demographics, Measurement, Weight History, Smoking, Reproductive Health (to identify those breastfeeding), Physical Activity and Alcohol consumption modules.
[41] Both datasets are repeated cross-sectional health surveys that are nationally representative of their respective populations. The CCHS only has an interview component, but the NHANES has both interview and clinical examination components. This difference between the two has an impact on the number of respondents targeted by each survey.
[42] Around 2,500 observations remain in the sample for each cycle after data modification. Whereas in the CCHS the number of observations is about 20 times the NHANES.
[43] Following the analytical guidelines for the NHANES, at least two cycles are needed to be combined to conduct age/sex/race specific analysis. The sample design of the NHANES is similar between 1999/00 and 2005/06 cycles, but it changed in terms of how racial subgroups are sampled after 2007/08 cycle. Therefore, combining these newer cycles with the older ones to create a larger pooled dataset is not feasible.
[44] Sample weights are multiplied by (1/*c*), *c* being the number of cycles pooled.

In our analysis, we focus on adult populations, aged 18 and over,[45] while excluding pregnant[46] and breastfeeding women since BMI as a body fat measurement is inappropriate for them. We control for age by centering it around the mean and allowing for a fourth-degree polynomial. The two cycles of the CCHS offer only the self-reported (SR) BMI, but the NHANES has both SR and directly measured (DM) BMI of its respondents. We use SR BMI in analysis with Canada, but use DM BMI for the US.[47]Household income in Canada is converted to its US dollar equivalent according to purchasing power parity (PPP).[48] The variables for both household income and household size are coded differently between the two datasets. We transform the relevant variables in the CCHS to follow the convention used in the NHANES in cross-country analysis, but use them as they are in over time analysis for Canada.[49] This resulted in two sets of equivalent household income variable (household income divided by square root of household size) for Canada, one for over time analysis and one for the cross-country.

We also use a set of dummy variables for respondents' sociodemographic and socioeconomic attributes. We define these dummy variables as follows. Marital status dummy

[45] In the NHANES, age is capped at 85 in early cycles and then at 80 in more recent ones, but in the CCHS the age variable is not capped. In the NHANES, age is capped at 85 in the cycles between 1999/00 and 2007/08 and then capped at 80 there onwards. We did not alter the information in the CCHS to follow NHANES in this case due to small sample size beyond those age caps.
[46] Including those who answered "don't know" or refused to answer the question of whether they were pregnant.
[47] We do not attempt to correct SR BMI for measurement error, as we show in (Ornek et al., 2016) that since we do not use BMI categories to classify individuals into different body types the correction will be trivial and would not impact the distributional analysis that we undertake. In the NHANES, we use DM BMI as the increase in sample size in using SR BMI was minimal and we choose to use the most appropriate measure that is available.
[48] The following conversion rates are used to divide CAD to convert to US dollars: 1.22747 for year 2000, 1.219598 for year 2001 and 1.215492 for 2013 (OECD.Stat, 2015).
[49] The variable in NHANES is categorical, in $5,000 incremental increases between $0 and $35,000 and in $10,000 increments until $75,000 and capped at that level in 1999/00 and 2001/02 cycles. In 2009/10 and 2011/12 cycles the cap is increased to $100,000 with an addition of a category for household incomes between $75,000 and $99,000. In order to have comparable variables in both datasets, household income in the CCHS is transformed from a continuous to a categorical variable using the same categories and assigned the mid-point income level in $1,000 in each range. Also, household size is capped at 7 in the NHANES, but at 15 in the CCHS. In cross-country analysis we use 7 as the cap for Canada, but in over-time analysis for Canada, household income is used as a continuous variable so is the cap of 15. Equivalent household income is calculated as household income divided by the square root of household size.

variables for single (reference), married and previously married (widowed, divorced or separated). Immigration status; for non-immigrants (reference), for immigrants who immigrated in the last 10 years, and for those who immigrated more than 10 years ago. For educational attainment; a set of dummy variables for not being a high-school graduate (reference), high-school graduates, having some post-secondary education, and being a post-secondary graduate or above. Alcohol consumption is measured using non-drinkers (reference), moderate drinkers (drank at most 2-3 times a month over past 12 months), and drinkers (drank at least once a week over past 12 months).[50] We also control for current smoking habit; non-smokers as the reference group and daily or occasional smokers as the control group. In the cases where the sample size of the missing values of these dummy variables was considerable (a few hundred observations or more), we add a separate dummy for them. The race variable has different categories in each country. In over time analysis for Canada we control for White (reference), aboriginal, African & Caribbean, Asian, South Asian and other races (including Latin American, Arab, West Asians and mixed-race). In the over time analysis for the US we control for White (reference), African & Caribbean, Mexican-American and other races (including other Latin American and mixed race) and in cross-country analysis we control for White (reference), African & Caribbean and other races (including all other races). Furthermore, we control for poverty in the US and Canada, which we define as living at or below the poverty line in the US, and experiencing food insecurity in Canada. The poverty line in the US is determined according to an index variable on the ratio of family income to poverty and may indicate food stamp program beneficiaries.[51] As a counterpart variable for Canada, we use a

[50] Categories are defined in the CCHS.
[51] In the NHANES, this index is calculated according to the department of Health and Human Services' guidelines. They are used in determining eligibility for a number of federal assistance programs towards poor, including Supplemental Nutrition Assistance Program (formerly Food Stamp program). These indices are year and state specific and consider

categorical variable in the CCHS that indicates if the household experienced food insecurity in the last 12 months.[52] We use poverty in the US as a proxy for controlling for experiencing food insecurity[51]as we expect to capture the income dimension of poverty through accounting for household income levels.

3.4 Descriptive Statistics

As mentioned earlier, this study involves four sets of analyses for each sex. We describe the differences in sample characteristics of the samples used in each analysis to draw attention to the differences between BMI distributions. These differences can be conceptualized as due to the differences in the distribution of characteristics or to the differences in the returns from these characteristics. The following tables show the average sample characteristics of each group.

The characteristics of the sample used in over time analysis of Canada are shown in Table 1A. When the recent sample is compared to the early sample, we see some changes over time. The average age increased by 1.7 and 2.2 years over the first decade of the 2000s for males and females respectively, while self-Reported BMI of both sexes increased by around .7 units. The proportion of single individuals increased, while the proportion married decreased over time. The recent era sample has a slightly higher proportion of immigrants. Overall, the education level is higher in the recent sample with higher proportions of high school graduates and those with post-secondary

family size of the household. For those respondents who did not provide sufficient information on family income this index was not calculated.

[52] This was a Yes/No question in the CCHS 1.1, but in the CCHS 2013 they differentiated moderate and severe food insecurity. For decomposition purposes, both moderate and severe food insecurity are combined in the analysis. Experiencing food insecurity is not exclusive to lower income households in Canada. Data shows that it is also experienced in some middle-income households.-. There is no food insecurity flag in the US data, and while personal and household incomes are present, there is no poverty flag in the CCHS. Seeing that living below poverty is linked with Food Stamp Program in the US, we decided to use these two variables interchangeably in cross-country analysis.

degrees or more. There are more drinkers and non-smokers in the recent sample than the early sample. On average, equivalent household income increased by $14,000 for males and $10,000 for females over this time period. The proportion of males experiencing food insecurity at home decreased slightly but increased by more than 50% in females. Finally, the proportion of White race members decreased while those of other races increased over time in both sexes.

Table 1B show the sample characteristics of the samples used in over time analysis in the US. The recent era sample is three years older on average than the early era sample. DM BMI is about 1 unit higher across both sexes in the recent era sample relative to the early era one. There are no considerable differences in non-immigrant and recent immigrant categories. A higher proportion of the recent era sample has some post-secondary education or higher than the early era sample, while the proportions across all other education levels decreased over time. There are slightly fewer non-drinkers and smokers in the recent era sample. As in Canada, equivalent household income increased over time by $9,000, without a change in the absolute gap between the two sexes. Like the Canadian sample, the proportion of White race decreased but those of all other races increased.

The sample characteristics of the early and recent era samples used in cross-country analysis are presented in Tables 1C and 1D respectively. In the early era, the average age of males in the US is slightly lower, but the average age of the females was almost the same. On average all groups, except Canadian females, are overweight (SR BMI ≥ 25 & <30) and there is not much difference between the two male groups. On the other hand, the average SR BMI of females in the US is more than 1 unit higher. The US sample has higher proportions of high school graduates and those with some post-secondary education. For both sexes, almost half of the Canadian sample has post-secondary education or above compared to 25% (males) and 22% (females) in the US. Lower proportions of the US sample are alcohol drinkers or smokers than the Canadian sample. Equivalent household income is slightly higher in the US, but so is the proportion that lives in poverty/food insecurity. The US sample has a lower proportion of Whites and higher proportions of African & Caribbean and other races.

Finally, looking at Table 1D, the recent era samples do not show much difference in average age for both sexes. Compared to the early era, SR BMI increased about the same for each sex in both countries. The most notable difference is in mean equivalent household income. It is smaller between males \$600 in recent vs. \$800 in early, but higher in females; \$2,500 in recent vs. \$1,700 in early. Another noticeable difference is in the proportion those living with food-insecurity in Canada. Over time, the proportion of those decreased in males and increased in females in Canada, while poverty was at relatively similar proportions over time in the US for each sex.

3.5 Methodology

We analyze the differences in BMIs of the two groups at the mean, median, 10^{th}, 25^{th}, 75^{th} and 90^{th} quantiles, by adopting three different decomposition methods that separate the overall difference into 2 parts. The first part or covariate component shows the magnitude of the difference attributable to the differences in the distribution of characteristics in the models. The second part or the returns component, on the other hand, is due to differences in how these characteristics are related to BMI.

For the decomposition at the mean, we adopt the well-known Oaxaca-Blinder (OB) decomposition which is named after seminal papers of Oaxaca (1973) and Blinder (1973). The standard assumption of OB decomposition method is that the outcome variable Y is linearly related to the covariates X, and the error term ε is conditionally mean independent of X*:*

$$Y_{gi} = \beta_{g0} + \sum_{k=1}^{K} X_{ik}\beta_{gk} + \varepsilon_{gi} \tag{1}$$

where g=A,B (the two groups) and $E(\varepsilon_{gi}|X_i) = 0$. Then, the difference in the unconditional mean of the dependent variable of each group is separated into two parts as shown in equation 2.

$$\widehat{\Delta_O^{\mu}} = \overline{Y_A} - \overline{Y_B} = \underbrace{\hat{\beta}_{A0} - \hat{\beta}_{B0} + \textstyle\sum_{k=1}^{K} \bar{X}_{Ak}(\widehat{B_{Ak}} - \widehat{B_{Bk}})}_{\Delta_S^{\mu}} + \underbrace{\textstyle\sum_{k=1}^{K}(\widehat{X_{Ak}} - \widehat{X_{Bk}})\hat{\beta}_{Bk}}_{\Delta_X^{\mu}} \tag{2}$$

where $\hat{\beta}_{g0}$ and $\hat{\beta}_{gk}$ $(k = 1,..,K)$ are the estimated intercept and slope coefficients of K regressors, respectively, of the regression models for groups g=A,B. $\widehat{\Delta_O^{\mu}}$is the overall difference between the two means. Δ_S^{μ} shows the part contributable to the differences in return from covariates (returns) and Δ_X^{μ} shows the part attributable to the differences in the distribution of covariates between the two groups (covariates).

In order to extend decomposition techniques beyond the mean, unconditional quantiles of the dependent variable are needed so that the differences of dependent variable at different quantiles of its distribution can be calculated. Machado and Mata (2005) developed a technique that combines conditional quantile regression with simulation techniques to obtain unconditional quantiles. Their method can only provide a (path dependent) detailed decomposition (providing covariate-specific details) of the returns component, but not the covariate component and is computationally intensive. (Fortin, Lemieux, & Firpo, 2011). Firpo et al. (2009) proposed a method for the decomposition of quantiles that can provide a detailed decomposition of quantiles in the same way as Oaxaca/Blinder decomposition does for the mean.

In their method, Firpo et al. (2009) find the decomposition of proportions (which can be represented by means of binary outcomes) to be easier to tackle than the decomposition of quantiles. The method is similar to a standard regression model, except dependent variables are replaced by the recentered influence function (RIF) of the statistic of interest (quantiles in our case) as shown in equation 3. RIF's can be expressed as in equation 3.

$$RIF(y; v) = v(F_Y) + IF(y; v) \tag{3}$$

where $v(F_Y)$ is the distributional statistic of interest of the dependent variable (e.g a quantile such as the median or the mean) and $IF(y; v)$ is the influence function corresponding to an observed value of the dependent variable y for the distributional static of interest. In the case of unconditional quantiles we can represent the influence function as;

$$IF(y; v) = (\tau - \mathrm{I}\{y \leq Q_\tau\}/f_Y(Q_\tau)) \tag{4}$$

where $\mathrm{I}\{y \leq Q_\tau\}$ is an indicator function of y, y is a particular value of the dependent variable Y, $Q_\tau$is the quantile of unconditional distribution of Y and $f_Y(Q_\tau)$ is the density of marginal distribution of Y. Therefore, RIF regressions can be expressed as:

$$RIF(y; Q_\tau) = Q_\tau + \frac{\tau - \mathrm{I}\{y \leq Q_\tau\}}{f_Y(Q_\tau)} = c_{1,\tau}\mathrm{I}\{y \leq Q_\tau\} + c_{2,\tau} \tag{5}$$

where $c_{1,\tau} = \frac{1}{f_Y(Q_\tau)}$ and $c_{2,\tau} = Q_\tau - c_{1,\tau}(1-\tau)$. This leaves only the estimation of $\mathrm{I}\{y \leq Q_\tau\}$, the indicator function, to get $RIF(y; Q_\tau)$ (Fortin, Lemieux, & Firpo, 2010; Fortin et al., 2011). Simply put, $RIF(y; Q_\tau)$ can be expressed as a linear function of the explanatory variables:

$$E[RIF(y; Q_\tau)|X)] = X\beta + \varepsilon \tag{6}$$

where the parameters β can be estimated using a linear regression method and ε is an approximation error term to compensate for linearity assumption. The linearity assumption is needed to make local inversion, where the distance between the two points on counterfactual distribution function are assumed to be linear. In reality, there is still a possibility that this distance might be non-linear, so this error term in equation 6 is recognizing the existence of such an error.

The inversion from proportions based on the counterfactual distribution function is done using these recentred influence functions (RIFs) to obtain unconditional quantiles, which are used in decomposition (Fortin et al., 2011). In our case, we first regress (SR or DM) BMI on the set of covariates listed in the data section by sex for 10th, 25th, 50th, 75th and 90th quantiles, separately for each pair we would like to analyze in the decomposition. These leave us a set of recentered dependent variables in each quantile of interest for the two groups. Later, as the second step, we pool the data of these two groups and employ Oaxaca decomposition at those specific quantiles to obtain aggregate and detailed decomposition results.

In practice, there are several advantages of this method. Its computational cost is minimal and provides path independent detailed decompositions[53] of both components. Its low

[53] Another issue with estimation of detailed decompositions is the handling of reference categories of the dummy variables used in models. Results are dependent on the arbitrary choice of reference categories of the dummy variables

computational cost is due to the fact that it employs local inversion of proportions to quantiles. However, this also constitutes a potential pitfall of the method for estimates at the tails of the distribution. This is because the assumed local linearity between any two points on counterfactual distribution function, which may also lead slope to be zero on the tails of the distribution. This method first estimates proportions (points on CDFs) of each group's dependent variable that correspond to quantiles of interest and then locally invert these back to unconditional quantiles of the dependent variable. The set of counterfactual proportions along the distribution of the dependent variable makes up the counterfactual distribution function. Assuming the relationship between counterfactual proportions and counterfactual quantiles is locally linear, the method uses the slope of the distance between the two points to invert counterfactual proportions to counterfactual quantiles at the quantile of interest. Calculation of these slopes is trivial using linear probability model, probit or logit. However, since the slope of a horizontal line is zero, this local inversion may fail to estimate these slopes precisely at the tails of the distribution (areas of low density). Acknowledging this potential problem, we also use the counterfactual decomposition method (*CDECO*) proposed by Chernozhukov et al. (2013). The mechanics of their method is quite similar to that of (Firpo, Fortin, & Lemieux, 2007; Firpo et al., 2009). However it employs inversion of proportions to quantiles over the whole distribution rather than at certain quantiles. This global inversion of the counterfactual distribution function makes it possible to allow non-linearity between points. Therefore instead of assuming local linearity, the method averages over multiple

(Fortin et al., 2011). We adopt the approach suggested by Yun (2005), which expresses effects for all categories as deviations from the grand mean. In other words, it imposes a normalization on the coefficients of the categories by restricting the coefficients of the base category to be equal to the unweighted average of the coefficients of the other categories (Edoka, 2012). Also, in detailed decompositions, *Group B* coefficients are used as the reference coefficients as shown in equation 2.

points around that quantile to capture nonlinearity if it exists.[54] Although global inversion overcomes the possibility of failing at the tails, it increases the computational cost of the procedure. Moreover, obtaining detailed decomposition using CDECO is not straight forward as the results are not path independent (Fortin et al., 2011).

Our specification of CDECO is similar to that of RIFreg, except it handles both inversion and decomposition in a single step. Even though it does global inversion, it reports the results of user specified quantiles only. The counterfactual distribution is estimated using the conditional distribution of dependent variable conditional on independent variables of both groups.[55]

3.6 Statistical Inference

3.6.1 About differences in survey designs

Previous studies used Joint Canada/United States Survey of Health (JCUSH) (2002/03) for cross-country comparisons across Canada and the US (O'Neill & O'Neill, 2007; Sanmartin et al., 2002; Tjepkema, 2006). Although the use of the JCUSH eliminates the concerns about differences in survey designs, it is unfortunately not repeated after its first cycle and its response rates were lower than other national health surveys in both countries (Sanmartin et al., 2002). Statistics Canada provides 500 sets of bootstrap weights with each cycle of the CCHS to account for the complex design of the survey. However, no other information is provided as for how respondents are selected

[54] By default, it does inversion at every single percentage point (100). This can be increased or decreased by the user. We used the default setting in our analysis.
[55] These conditional distributions can be estimated by various regression methods. We used the linear quantile regression method, which is also the default model specification.

within different strata and clusters.[56] On the other hand, the CDC strongly encourages researchers to survey set the NHANES data prior to its use in the analysis.[57] After realizing that this way of survey setting the NHANES does not fit our purposes, analogously we resample the survey weights of the NHANES, with replacement, 500 times to create pseudo-bootstrap weights.

3.6.2 Asymptotic Refinement

To increase the precision of our statistical inference, we employ what Cameron and Trivedi (2005) calls "*asymptotic refinement*". In this approach, instead of estimation of standard errors directly, Cameron and Trivedi (2005) suggests estimation of pivotal statistics. A t-statistic is asymptotically pivotal since its asymptotic standard normal distribution does not depend on unknown parameters under the null hypothesis (Cameron & Trivedi, 2005). First, t-statistics for each covariate in the model are estimated using the regular sampling weights as follows:[58]

$$t_k^* = (\hat{\beta}_k^* - 0)/s_{\hat{\beta}_k}^* \tag{6}$$

where $k = (0, .., K)$ are the estimated intercept and slope coefficients. Next, using bootstrap sampling weights, 500 bootstrap t-statistics are estimated:

$$t_{b,k}^{BS} = (\hat{\beta}_{b,k}^{BS} - \hat{\beta}_k^*)/s_{\hat{\beta}_{b,k}^{BS}} \tag{7}$$

[56] Strata and clustering information for the CCHS is not released, except for one special cycle of the survey, 2.2, which is not used in this analysis.
[57] Unfortunately, due to privacy concerns they refrain from releasing the real variables on cluster on strata information in the public use files. Instead they provide masked variance pseudo-PSU (Personal Sampling Units; for setting clusters) and masked variance pseudo-stratum, however these do not have sufficient information to appropriately survey set the data.
[58] In all models, robust standard errors are used.

where $b = (1,..,500)$. The assumption here is that standard error used in both t-statistics calculations are consistent estimate of the standard deviation of the estimator (Cameron & Trivedi, 2010). Critical values for the test statistics are calculated by calculating the location of each t_k^* in the distribution of $t_{b,k}^{BS}$ for all *k*s in the model. The proportion of the area that t_k^* fall under in the $t_{b,k}^{BS}$ distribution provides us with the actual p-values for each estimator in the model.[59] Statistical inferences used in Tables 2A to 5B are these asymptotically refined p-values.

In the graphical representation of the aggregate decomposition results, we show 95% confidence intervals of the estimates in Figures 1 to 4. For Oaxaca and RIF regression methods, these confidence intervals are calculated from the distribution of $t_{b,k}^{BS}$, as shown in equation 8:

$$(\hat{\beta}_k^* - t_{.025}^C \; x \; s_{\hat{\beta}_k}^*, \hat{\beta}_k^* - t_{.975}^C \; x \; s_{\hat{\beta}_k}^*) \qquad (8)$$

, where $\hat{\beta}_k^*$ and $s_{\hat{\beta}_k}^*$ are from equation 6 and critical t-statistics are obtained from the distribution of $t_{b,k}^{BS}$, after sorting it in ascending order. The average of 12th and 13th $t_{b,k}^{BS}$ in the distribution constitute the critical value for the lower bound, $t_{.025}^C$, and the average of 487th and 488th $t_{b,k}^{BS}$ constitute the critical value for the upper bound, $t_{.975}^C$, of the 95% confidence intervals

CDECO method provides both point-wise and uniform (or functional) confidence intervals. The former is closer to the methodology we follow in the RIF approach, but the latter are presented

[59] E.g. if t_k^* is smaller than only 5 of the 500 $t_{b,k}^{BS}$ values in its distribution, then the p-value for *k* is 5/500=0.01.

by Chernozhukov et al. (2013) as having higher precision. We use these uniform confidence intervals in presenting the results of CDECO estimates in Figures 1 to 4 and Table 6.[60]

3.7 Results

3.7.1 Aggregated Decomposition Results

We first present our aggregate decomposition results, which demonstrate the overall difference between the distributions of each group, how much of this difference can be contributed to covariates and how much of it to returns . The results are presented in graphs for ease of their interpretation. These graphs show the decomposition at the mean, using OB, and at the 10^{th}, 25^{th}, 50^{th} (median), 75^{th} and 90^{th} quantiles of the BMI distributions of the two groups using both RIF regression and CDECO methods. The graphs also show 95% confidence intervals for each.

Our findings show that the overall difference between BMI distributions is increasing with BMI. This difference is mostly related to the returns part of the decomposition in over time analyses, as in most cases covariates part follows an opposite trend In many instances its estimates are statistically insignificant. In cross-country analyses, the contribution of each part of the decomposition is a little more mixed. Comparison of RIF regression results with the results of CDECO reveal that estimates of the two methods are generally very similar to each other and that the estimates of RIF regression at both tails of the distribution are almost the same as those obtained by CDECO.

[60] Due to high computation time the method takes to execute, we use 100 bootstrap replications. We advise readers not to attach too much emphasis on the statistical inference of this method's results. The method is used merely to check the results of RIF regression's point estimates.

Over time Decomposition for Canada: Recent Era (2013) minus Early Era (2001/02)

Figure 1 shows over time decomposition estimates for Canada, separately for males and females. Overall, there is a positive difference between BMI levels of recent and early era populations; meaning in roughly 10 years everyone's BMI levels are increased. The magnitude of this increase is higher as we move along the BMI distributions for each sex. Looking at Tables 2A and 2B in the Appendix, at the mean Canadian males in recent era have 0.73 units, and Canadian females have 0.66 units more BMI than the early era. The differences at the mean are higher than the differences at the median due to differences being higher in the right tail of the distribution than the left tail. The gap between the two eras at the left tail, 10^{th} quantile, is 0.15 units in females and 0.19 units in males, meaning the increase in BMI of the lowest weight group (includes underweight) was negligible over time. On the other hand, the difference in BMI between recent and early eras is the largest for those with the heaviest weight group, 90^{th} quantile, (includes morbidly obese) in both sexes. The difference in females is a little more than that in males, 1.19 units versus 1.13, meaning BMI among morbidly obese females is increasing faster than males. As mentioned, the covariates component demonstrates an opposite trend to the overall difference. Although changes would be small in magnitude, the results show that the difference between the distribution of covariates (characteristics) of recent and early eras, would reduce the mean BMI of the recent population if they had the same return from those characteristics as the population in the early era. This reduction would also be the highest among the morbidly obese 90^{th} quantile. The returns component shows how much the positive difference between BMI distributions of recent and early era populations is attributable to the differences in returns that recent population gets from their characteristics towards their BMI. Clearly, the overall difference we observe is mainly attributable to this returns part of the decomposition.

Over time Decomposition for the US: Recent Era (2009/12) minus Early Era (1999/02)

According to the results shown in Figure 2, the same conclusions drawn from over time analysis of Canada are also applicable to changes in the BMI levels of the US population over time. The main differences between the two analyses are that the difference in the US is larger along the whole BMI distribution than it is in Canada. In particular the increase at the lowest end of the BMI distribution is larger than in Canada. According the figures in Tables 3A and 3B in the appendix, at the 10th quantile, the difference in males is 0.69 units and that in females is 0.51. At the mean, these differences are 0.93 and 0.80 for males and females, respectively. At the 90th quantile, BMI of males in recent era is 1.6 units and that of females is 1.1 units higher than their counterparts in early era.

Cross-country Decomposition for Early Era: the US minus Canada

The difference between BMI distributions of the US and Canada in their respective early eras are shown in Figure 3. The most noteworthy finding is that the difference for females is six times as large as that of males at the mean and more than three times as large as males at the 90th quantile, as shown in Tables 4A and 4B in appendix. In fact, US males had lower BMI than Canadian males up to the mean of their BMI distribution. At the mean, the difference between the two becomes positive, 0.27 units, and beyond that this difference increases. US females had around 0.21 units lower BMI than Canadian females at the 10th quantile of their BMI distribution, but beyond that point their BMI is 1.23 units higher at the mean and 3.17 units higher at the 90th quantile than Canadian females. The fact that both sexes in the US had lower BMI at the 10th quantile and higher BMI at the 90th quantile than their Canadian counterparts indicate that in early 2000s both underweight and morbidly obese groups in the US were relatively worse-off than Canadians.

Another interesting difference in this cross-country analysis, when compared to over time analyses, is the contribution of covariates. For both sexes, the trend of the covariates component is parallel to the trend of the overall difference up until the median of their BMI distribution. At higher quantiles the covariates component adopts the opposite trend once again. In fact, at the 10^{th} quantile, the majority of the observed difference in BMI of females in the two countries is attributable to the covariates component. The overall results of the covariates component indicate that if the US population were to get the same return from their characteristics as Canadians, their BMI would actually be lower than Canadians. However, as the returns component demonstrates, it is the differences in the returns from these characteristics that make up for the overall difference in the BMI distributions of the two groups in the early era.

Cross-country Decomposition for Recent Era: the US minus Canada

Finally, Figure 4 shows the aggregate decomposition results for cross-country analysis in the recent era. In males, the overall difference resembles the one in early era. The discrepancy at the lower end of the distribution is still negative (the US males having lower BMI than Canadian males at 10^{th} quantile), but this difference is much less pronounced; -0.13 versus -0.41. At the other end of the distribution, the differences in 75^{th} and 90^{th} quantiles are about 0.3 units higher than they were in the early era (see Tables 4A and 5A in appendix). Females in the US, on the other hand, have higher BMI than Canadian females at all quantiles, indicating that weight gain in the US has been higher in females than it was in Canada. What is interesting to note is the decrease in the gap in female BMI levels in the recent era. The difference between BMI levels between the US and Canadian females at quantiles beyond the median of their distribution is smaller in the recent era than the early era (see Tables 4B and 5B in appendix).

In males, the differences between the BMI distributions of the two populations are not statistically significant below the mean. At the mean, 75^{th} and 90^{th} quantiles, the differences are mostly attributable to the covariates part of the decomposition. If Canadian males had the same covariate distribution as their US counterparts, their BMI would increase similar to as it did for males in the US. In contrast, the returns part of the decomposition of females explains the majority of the differences between distributions at the median and beyond given the endowment level that the females have, it is the differences in the returns from these characteristics that mostly make up for the increase in their BMI.

3.7.2 Detailed Decomposition Results

Contributions of each covariate to the covariates and returns components of the decomposition models are shown in Tables 2A to 4B in the appendix. These are the coefficients of the comparison group multiplied by the difference in the mean of the covariate between the two groups (as shown in equation 2). In over time decompositions, aggregate results show that the overall differences in distributions are mainly coming from the returns part of the decomposition. In Table 2A, we see that for Canadian males, estimates of almost all statistically significant results have negative signs, unlike the aggregate result for returns part. As a result, we see that the dominant factor in the returns part of the decomposition is coming from the differences in constants (see equation 2). This means that all other omitted variables are playing a role in constituting the difference that we observe between the BMI distributions over time. The variables we account for have opposite relationships to the conclusions we draw for returns from characteristics in the aggregate part. Interestingly, for Canadian females (Table 2B) this is not the case. Differences in constants are almost always statistically insignificant. The majority of the returns component is due to the differences in returns for being non-immigrant, equivalent household income and experiencing food insecurity along the whole distribution.

Like for males in Canada, the returns part of the decomposition of BMI of US males over time is largely due to the omitted variables (see Table 3A). However, unlike the results for Canadian males, we see some positive contribution from differences in returns to being previously married, moderate drinker, and African & Caribbean, but the main differences are again due to omitted variables. In Table 3B, the detailed decomposition results for females in over time decomposition analysis for the US also show similarities to the results of Canadian females. In almost all cases constants are statistically insignificant. Differences in return to age in its quadratic polynomial form generate the main differences in returns. Differences in returns to being a drinker and African & Caribbean are also in the same direction, but the magnitude is much smaller than that of age-squared.

In the early era cross-country analysis for males of Table 4A, the covariates part of the decomposition follows the same trend as the overall difference in 10^{th}, 25^{th} and 50^{th} quantiles. At these quantiles, differences in the characteristics for having immigrated more than 10 years ago, being a non-smoker and belonging to either African & Caribbean or other races mostly explains why BMI of males at these sections of the distribution is lower in the US than in Canada. In all other quantiles, including the 25^{th}, the difference in returns is the dominant part of the decomposition. At the 25^{th} quantile, the difference is mainly due to differences in returns to being previously married, experiencing poverty or food insecurity, being White or African & Caribbean. At the mean, 75^{th} and 90^{th} quantiles, although differences in returns to being non-immigrant, and other races make up some the returns part, it is mainly due to the omitted variables again. In Table

4B, we see that for females in the early era, cross-country differences are mostly due to differences in returns. Across all quantile levels, the only statistically significant covariate is being non-immigrant. This time in cross-country analysis, omitted variables for females constitute the main culprit in the returns part of the decomposition. In over time analysis, this is only apparent for males.

Finally, the results of cross-country analyses in the recent era are shown in Tables 5A and 5B for males and females respectively. For males, differences in post-secondary education, being a drinker and not responding to the smoking-related question are the main contributors of the covariates part of the decomposition. Below the median, the returns part is mainly due to differences in the returns to equivalent household income and being white, whereas beyond the mean of the distribution, the differences are mostly due to the omitted variables. In females, the covariates component is mainly attributable to the differences in the characteristics of non-immigrants, recent immigrants, those with post-secondary education and those experiencing poverty between the two countries. For example, the estimate for poverty in the 90th quantile means that, if Canadian females had the same difference in the proportion of those living in poverty (it is almost 17% in the US versus 6.3% in Canada – see Table 1D), their BMI would have been 0.46 units higher. The returns part is partially due to differences in returns to aging and to those with missing values for the smoking question, but is mainly due to the omitted variables once again.

3.8 Discussion

Our results show the association of the differences in body mass index distributions across two groups with a set of sociodemographic and socioeconomic variables. Unlike most studies in this literature, we tackle this while considering the whole BMI distribution rather than focusing on discrete categorizations of individuals into a few BMI categories. This enables us to comment on not only obesity, but also to the changes in other parts of the distribution both over time and across Canada and the US.

We find that in over time analysis, the differences that we observe between the groups are mainly attributable to the returns part of the decomposition. This is a particularly interesting finding with policy relevance. Unlike most policy recommendations, our results show that targeting change of characteristics of the population may not lead to changing BMI levels. Instead, our results show that both the increase in BMI in recent years and the gap in BMI levels of Canada and the US are due to the differences in the pathways between these covariates and BMI for each group. A detailed investigation of what these pathways may be is a question for future work.

In males, the differences in returns are mostly related to the omitted variables that we do (could) not control in the models. In females, age, immigration status, equivalent household income and experiencing food-insecurity or living below poverty line are the main covariates whose returns significantly contribute to the observed differences in BMI levels. In cross-country analysis, we find both the covariates and returns parts relevant in contributing to the overall difference between the US and Canadian populations at different parts of their BMI distributions. For males, cross-country differences at the median and below in early era and those of at mean and above in recent era are attributable to the differences in distributions of characteristics. For females, in the recent era, to a certain degree cross-country differences at all quantiles are due to differences in the distribution of characteristics, but in early era the differences are mainly coming from the returns part. We find evidence that differences in distributions of immigration status, race, and aging are contributing covariates among males. Among females, there is more evidence for the association of socioeconomic inequalities as education and living below poverty or experiencing food-insecurity are the significant covariates that we control for in the models.

Our results provide some important insights into understanding the structure of the differences in the prevalence of obesity between Canada and the US. The differences in BMI are primarily associated with how these attributes relate to BMI and not to the differences in the distribution of attributes. Consequently, a better understanding of how returns from these attributes relate to BMI can be made by investigating more detailed aspects of the differences in populations. Potential variables that could constitute the omitted variables that we were not able to control for include differences in food prices, the availability of nutritionally rich foods, differences in city plans, neighborhood designs, crime rates, the availability of recreational areas, and so on. An investigation of these detailed variables at national level is, however, quite difficult to achieve without having to make unhelpful generalizations. Instead, our study shows that a more detailed analysis is required but is only feasible to do across smaller geographic units; comparison of two similar regions, cities, neighborhoods, etc.

This study is not the first one to demonstrate that the relationship between socioeconomic covariates and obesity is especially important for females. Langlois et al. (2009) note that both sexes in Canada are equally likely to be obese., they find the positive association between lower household income and obesity to be significant only among women. For both sexes, higher education attainment is related to lower obesity prevalence. Che and Chen (2001) show that 35% of people in low-income households and 14% people in middle-income households in Canada experienced some form of food insecurity and that it is higher among females. Hajizadeh et al.

(2014) also document the negative correlation between income and obesity for females. However, drawing conclusions from associations between socioeconomic status and health is not straightforward. Contoyannis and Jones (2004) demonstrate that accounting for unobserved heterogeneity in the relationship between socioeconomic status and healthy lifestyles is necessary. In our context unobserved heterogeneity would be related to the differences that we mention that could be investigated at a smaller geographical scale comparison. Although we do not account for unobserved heterogeneity in this study the detailed analysis of the differences in BMI distributions provide better evidence than most of the studies in this literature.

It is evident that in order to understand sociodemographic and socioeconomic dimensions of increasing trend in BMI, it is crucial not only to identify the covariates, but also understand how these covariates are associated with BMI among different demographic groups. By establishing this, policymakers could potentially increase their reach to appropriate population groups.

This study has some limitations. Although we took utmost care in statistical inference for our estimates, the fact that we could imperfectly account for the survey design of the NHANES still exists. Other than for statistical inference purposes, the differences in the design of the CCHS and the NHANES potentially change the measurement error in the SR BMI in each survey. In the CCHS, the respondents only reported their height and weight, but in the NHANES the respondents knew at the time of the interview that they would be invited to a mobile examination clinic following the interview, and one of the procedures in the clinic would be taking the actual measurements of their body. This may naturally alter the magnitude of the measurement error that we observe across the two datasets (Ornek, Sweetman, & Contoyannis, 2016). However, we expect that someone at the 90th percentile of the SR BMI distribution to be at a similar (if not the same) quantile of the DM BMI distribution as well. When comparing the quantiles of the distributions, we choose not to correct for potential measurement error in the SR BMI as applying mean shifts at different magnitudes may be futile in this case. However, in the future we can provide this as a sensitivity analysis for this study.

Figure 3.1 Over time Decomposition for Canada: Recent (2013) minus Early (2000/01)

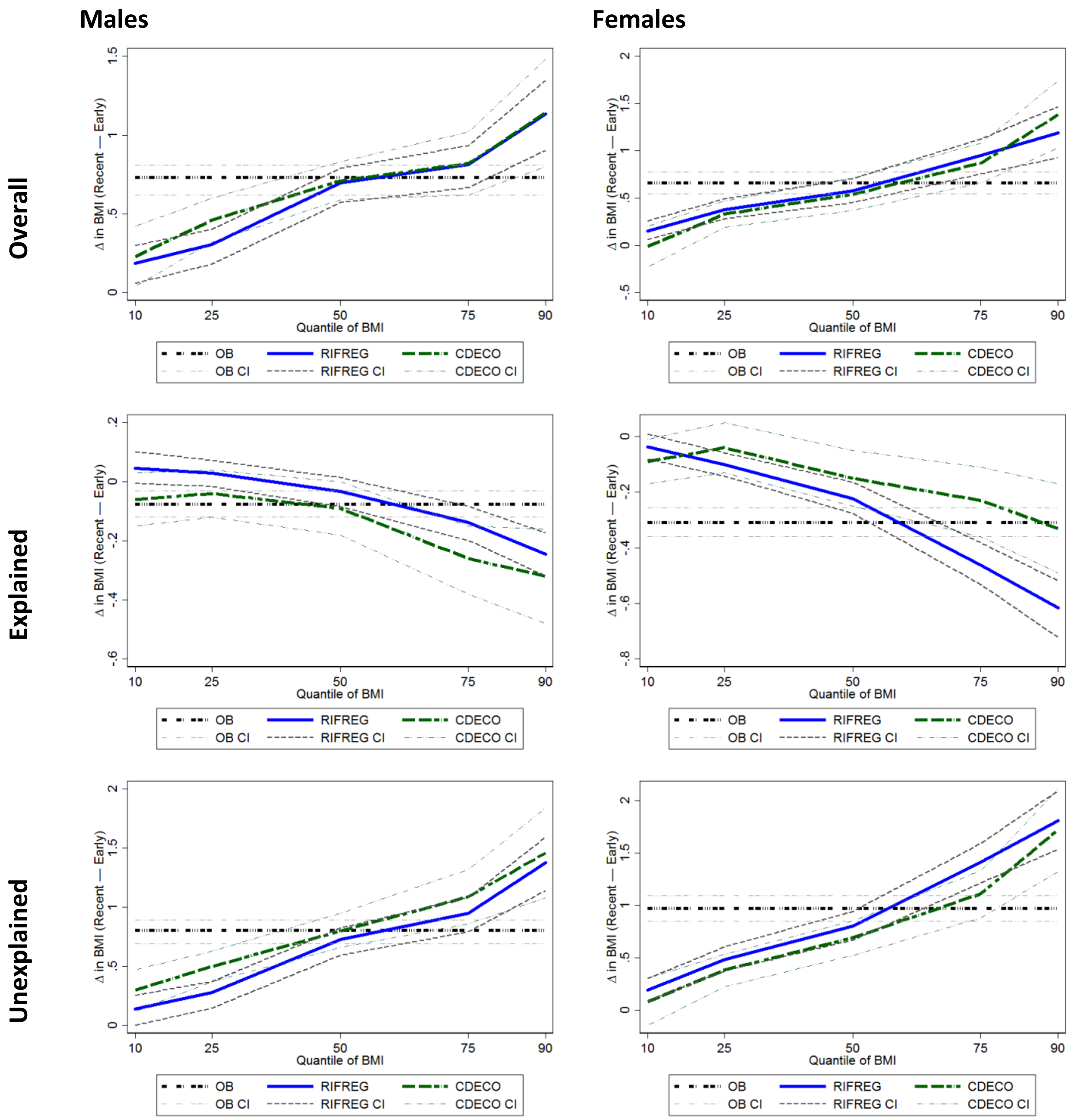


Figure 3.2 Over time Decomposition for the US: Recent (2009/12) minus Early (1999/02)

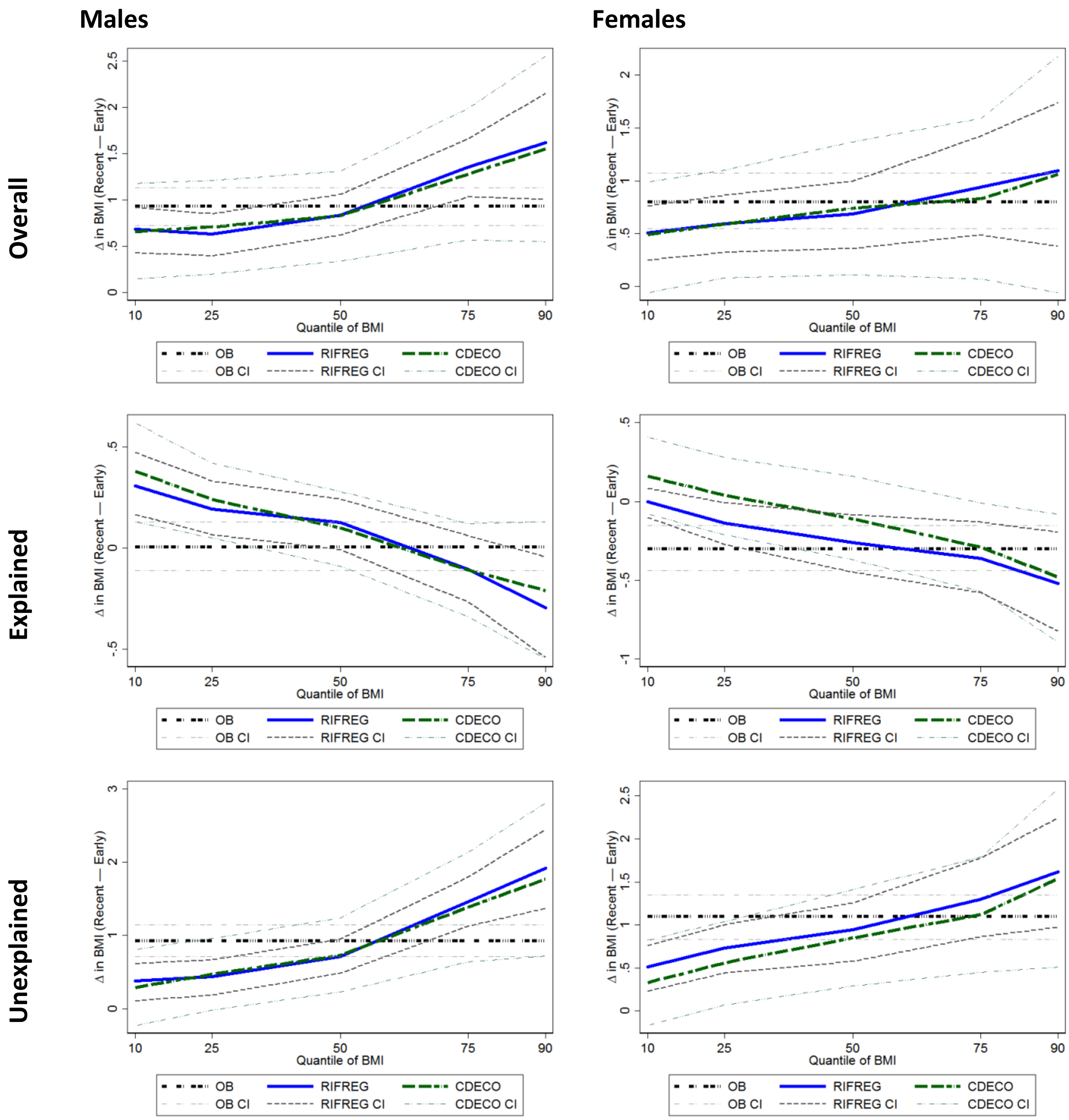


Figure 3.3 Early Era Cross-country Decomposition: the US (1999/02) minus Canada (2000/01)

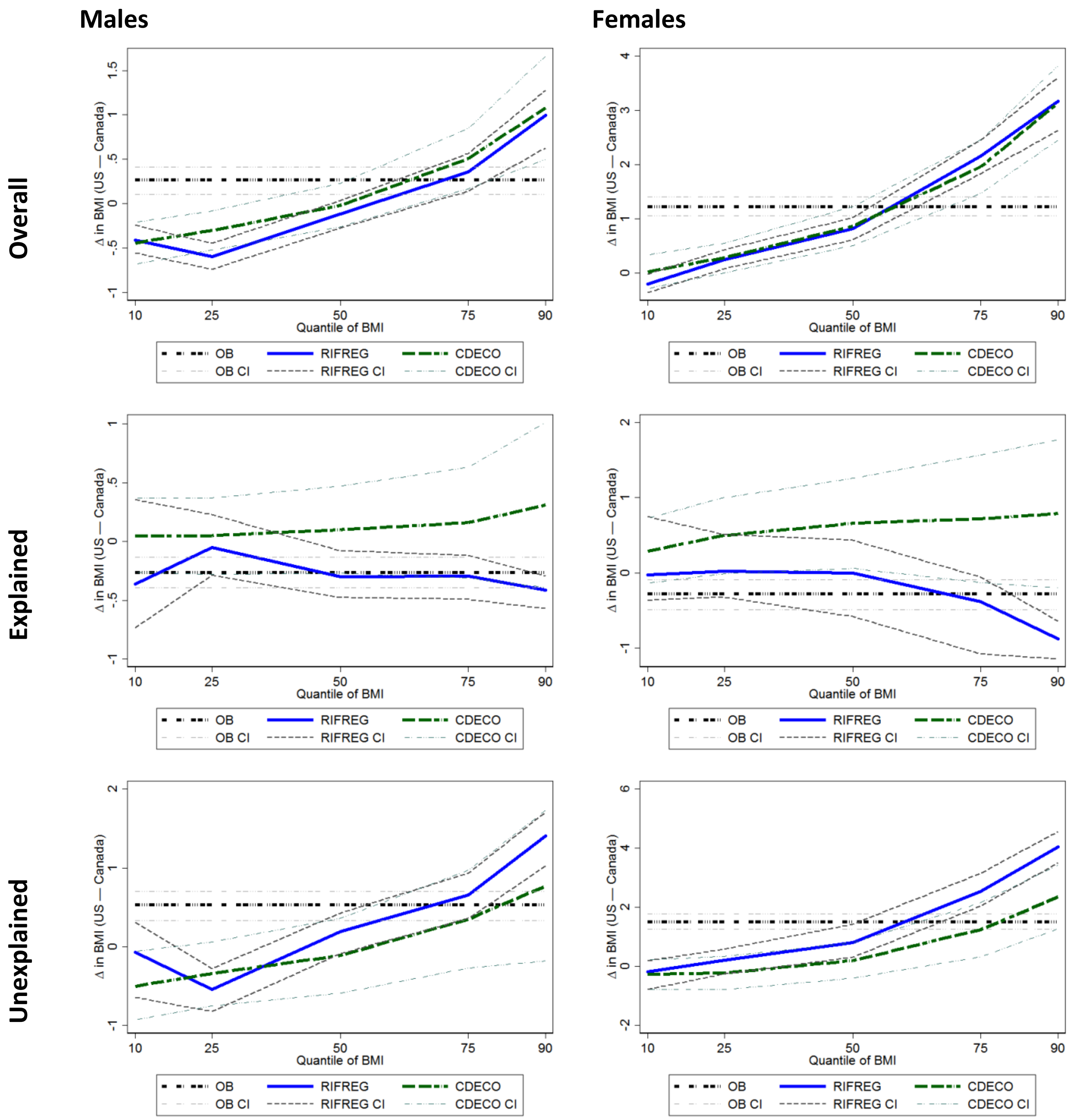


Figure 3.4 Recent Era Cross-country Decomposition: the US (2009/12) minus Canada (2013)

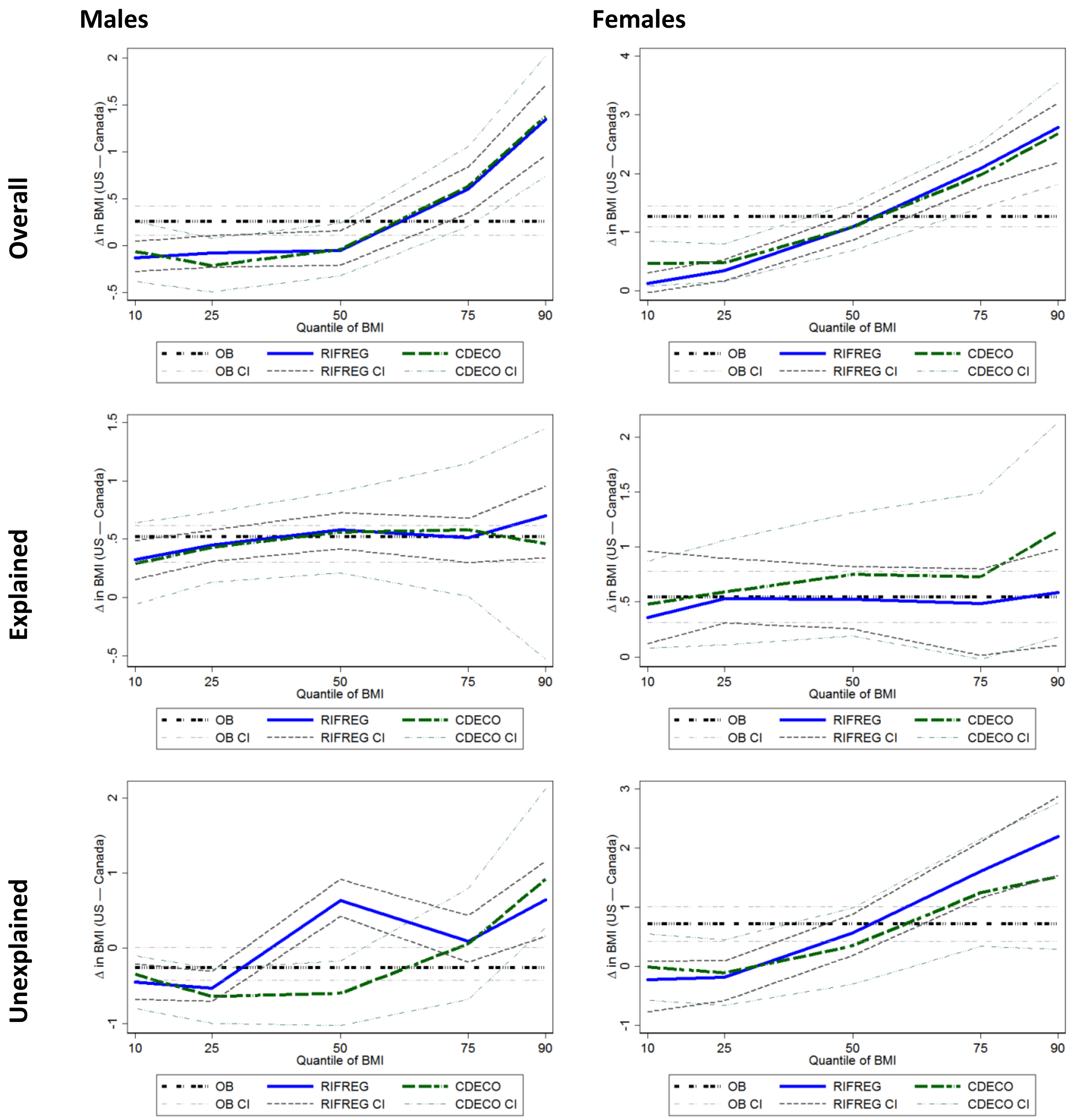

Males
Females
Overall
Explained
Unexplained
Δ in BMI (US — Canada)
Quantile of BMI
10
25
50
75
90
OB
RIFREG
CDECO
OB CI
RIFREG CI
CDECO CI

Table 3.2A CCHS Descriptive Statistics

	CCHS Early (2000/01)		CCHS Recent (2013)	
	Male	Female	Male	Female
Demographics				
Age	44.287	45.741	46.025	47.956
	(16.068)	(16.989)	(17.118)	(17.722)
Single	0.233	0.191	0.264	0.222
	(0.423)	(0.393)	(0.441)	(0.415)
Married	0.681	0.621	0.652	0.599
	(0.466)	(0.485)	(0.476)	(0.490)
Previously Married	0.086	0.188	0.085	0.180
	(0.280)	(0.391)	(0.279)	(0.384)
Non-Immigrant	0.783	0.789	0.767	0.755
	(0.412)	(0.408)	(0.423)	(0.430)
Immigrant (for 10 years or less)	0.063	0.056	0.069	0.074
	(0.243)	(0.231)	(0.254)	(0.261)
Immigrant (for more than 10 years)	0.154	0.155	0.164	0.172
	(0.361)	(0.362)	(0.370)	(0.377)
Self-reported BMI	26.133	24.980	26.863	25.640
	(4.301)	(5.139)	(4.793)	(5.670)
Education				
Not High School Graduate	0.216	0.218	0.133	0.131
	(0.411)	(0.413)	(0.339)	(0.337)
High School Graduate	0.186	0.210	0.201	0.209
	(0.389)	(0.408)	(0.401)	(0.407)
Some Post-secondary	0.083	0.087	0.058	0.050
	(0.276)	(0.283)	(0.233)	(0.219)
Post-secondary	0.509	0.479	0.592	0.598
	(0.500)	(0.500)	(0.491)	(0.490)
Education Missing Value	0.007	0.005	0.016	0.012
	(0.082)	(0.072)	(0.127)	(0.108)
Behavioural				
Non-Drinker	0.148	0.222	0.152	0.228
	(0.355)	(0.416)	(0.359)	(0.420)
Moderate Drinker	0.338	0.466	0.300	0.402
	(0.473)	(0.499)	(0.458)	(0.490)
Drinker	0.513	0.311	0.545	0.367
	(0.500)	(0.463)	(0.498)	(0.482)
Drinker Missing Value	0.001	0.001	0.003	0.003
	(0.034)	(0.029)	(0.052)	(0.053)
Non-Smoker	0.701	0.739	0.757	0.814
	(0.458)	(0.439)	(0.429)	(0.389)
Smoker	0.299	0.261	0.243	0.186
	(0.458)	(0.439)	(0.429)	(0.389)
Socioeconomic Status				
Equivalent Household Income*	31.486	27.385	45.472	37.815
	(23.612)	(19.799)	(37.375)	(29.898)
Food Insecurity**	0.070	0.049	0.062	0.079
	(0.255)	(0.217)	(0.241)	(0.269)
Race				
White	0.863	0.867	0.784	0.788
	(0.343)	(0.340)	(0.412)	(0.409)
African & Caribbean	0.015	0.018	0.027	0.031
	(0.121)	(0.133)	(0.161)	(0.174)
Asian	0.051	0.049	0.050	0.066
	(0.221)	(0.215)	(0.218)	(0.248)
South Asian	0.027	0.025	0.043	0.038
	(0.163)	(0.155)	(0.202)	(0.191)
Other Races***	0.031	0.029	0.068	0.050
	(0.174)	(0.167)	(0.252)	(0.218)
N	43317	45856	18994	22778

Note: Mean figures are presented and standard deviations of each are shown below in parenthesis
*Equivalent Household Income is a continuous variable in Canadian analysis. It is in $1000 and converted to US $ using PPP (Source OECD) and are divided by square root of household size. ** Indicates experiencing food insecurity. *** Other races include mixed race category

Table 3.2B NHANES Descriptive Statistics

	NHANES Early (1999/02)		NHANES Recent (2009/12)	
	Male	Female	Male	Female
Demographics				
Age	43.245	45.137	46.449	48.117
	(16.509)	(17.070)	(16.437)	(17.035)
Single	0.229	0.175	0.211	0.168
	(0.420)	(0.380)	(0.408)	(0.374)
Married	0.665	0.592	0.657	0.592
	(0.472)	(0.491)	(0.475)	(0.491)
Previously Married	0.106	0.232	0.132	0.239
	(0.308)	(0.422)	(0.339)	(0.427)
Non-Immigrant	0.852	0.871	0.824	0.843
	(0.355)	(0.335)	(0.381)	(0.364)
Immigrant (for 10 years or less)	0.056	0.038	0.054	0.043
	(0.231)	(0.192)	(0.227)	(0.203)
Immigrant (for more than 10 years)	0.092	0.091	0.122	0.114
	(0.289)	(0.287)	(0.327)	(0.318)
Directly Measured BMI	27.741	28.049	28.675	28.852
	(5.613)	(6.976)	(5.837)	(7.375)
Education				
Not High School Graduate	0.221	0.204	0.172	0.167
	(0.415)	(0.403)	(0.378)	(0.373)
High School Graduate	0.262	0.264	0.228	0.202
	(0.440)	(0.441)	(0.419)	(0.401)
Some Post-secondary	0.267	0.310	0.297	0.329
	(0.442)	(0.463)	(0.457)	(0.470)
Post-secondary	0.251	0.222	0.303	0.302
	(0.433)	(0.416)	(0.460)	(0.459)
Behavioural				
Non-Drinker	0.148	0.148	0.132	0.134
	(0.355)	(0.355)	(0.338)	(0.341)
Moderate Drinker	0.287	0.376	0.284	0.342
	(0.452)	(0.485)	(0.451)	(0.474)
Drinker	0.419	0.228	0.455	0.282
	(0.493)	(0.420)	(0.498)	(0.450)
Drinker Missing Value	0.147	0.248	0.129	0.241
	(0.354)	(0.432)	(0.335)	(0.428)
Non-Smoker	0.278	0.195	0.276	0.214
	(0.448)	(0.396)	(0.447)	(0.410)
Smoker	0.263	0.219	0.227	0.178
	(0.440)	(0.414)	(0.419)	(0.382)
Smoker Missing Value	0.459	0.586	0.497	0.608
	(0.498)	(0.493)	(0.500)	(0.488)
Socioeconomic Status				
Equivalent Household Income*	31.273	28.737	40.277	37.035
	(18.263)	(18.306)	(25.468)	(24.911)
Poverty**	0.122	0.169	0.146	0.173
	(0.328)	(0.375)	(0.353)	(0.378)
Race				
White	0.730	0.722	0.694	0.686
	(0.444)	(0.448)	(0.461)	(0.464)
African & Caribbean	0.094	0.108	0.099	0.119
	(0.292)	(0.311)	(0.298)	(0.323)
Mexican American	0.072	0.057	0.084	0.069
	(0.259)	(0.232)	(0.277)	(0.253)
Other Races***	0.104	0.113	0.123	0.127
	(0.306)	(0.316)	(0.329)	(0.333)
N	3996	3725	4887	4994

Note: Mean figures are presented and standard deviations of each are shown below in parenthesis.
*Equivalent Household Income is a categorical variable in the US analysis. Categories are mid-point levels, in $1000, and are divided by square root of household size. **Poverty: indicates living below poverty line and experiencing food insecurity. ***Includes non-White Hispanics and mixed races. In cross-country analysis Mexican-American group is not used, instead they are counted as Other Race

Table 3.1C Cross-country Early Era Descriptive Statistics

		CCHS Early (2000/01)		NHANES Early (1999/02)	
		Male	Female	Male	Female
Demographics					
	Age	44.274	45.710	43.550	45.515
		(16.079)	(16.973)	(16.746)	(17.301)
	Single	0.233	0.192	0.229	0.176
		(0.423)	(0.393)	(0.420)	(0.381)
	Married	0.681	0.621	0.661	0.587
		(0.466)	(0.485)	(0.473)	(0.492)
	Previously Married	0.085	0.188	0.110	0.237
		(0.279)	(0.391)	(0.313)	(0.425)
	Non-Immigrant	0.783	0.789	0.857	0.877
		(0.412)	(0.408)	(0.350)	(0.329)
	Immigrant (for 10 years or less)	0.063	0.056	0.052	0.033
		(0.243)	(0.230)	(0.222)	(0.179)
	Immigrant (for more than 10 years)	0.154	0.155	0.091	0.090
		(0.361)	(0.362)	(0.288)	(0.287)
	Self-reported BMI	26.130	24.983	26.398	26.211
		(4.296)	(5.144)	(5.204)	(6.359)
Education					
	Not High School Graduate	0.217	0.219	0.219	0.206
		(0.412)	(0.414)	(0.414)	(0.404)
	High School Graduate	0.188	0.212	0.261	0.264
		(0.390)	(0.408)	(0.439)	(0.441)
	Some Post-secondary	0.083	0.088	0.269	0.309
		(0.277)	(0.283)	(0.443)	(0.462)
	Post-secondary	0.512	0.481	0.251	0.221
		(0.500)	(0.500)	(0.434)	(0.415)
Behavioural					
	Non-Drinker	0.147	0.221	0.150	0.147
		(0.354)	(0.415)	(0.357)	(0.354)
	Moderate Drinker	0.338	0.466	0.285	0.371
		(0.473)	(0.499)	(0.451)	(0.483)
	Drinker	0.513	0.311	0.410	0.224
		(0.500)	(0.463)	(0.492)	(0.417)
	Drinker Missing Value	0.001	0.001	0.155	0.258
		(0.033)	(0.029)	(0.362)	(0.438)
	Non-Smoker	0.702	0.740	0.278	0.197
		(0.458)	(0.439)	(0.448)	(0.398)
	Smoker	0.298	0.260	0.262	0.219
		(0.458)	(0.439)	(0.440)	(0.414)
Socioeconomic Status					
	Equivalent Household Income*	30.456	26.917	31.235	28.547
		(18.423)	(17.241)	(18.245)	(18.228)
	Poverty (US) or Food Insecurity (CDN)**	0.070	0.049	0.121	0.170
		(0.255)	(0.217)	(0.326)	(0.376)
Race					
	White	0.864	0.867	0.733	0.722
		(0.343)	(0.339)	(0.443)	(0.448)
	African & Caribbean	0.015	0.018	0.095	0.110
		(0.122)	(0.133)	(0.293)	(0.313)
	Other Races***	0.121	0.115	0.173	0.168
		(0.326)	(0.319)	(0.378)	(0.374)
N		42981	45590	4091	3752

Note: Mean figures are presented and standard deviations of each are shown below in parenthesis.
* Equivalent Household Income is a categorical variable in cross-country analysis. Categories are mid-point levels, in $1000, and are divided by square root of household size. Canadian figures are converted to the US $ using PPP.
**Poverty (US): indicates living below poverty line and experiencing food insecurity, Food Insecurity (Canada) flags experiencing food insecurity
***Includes non-White Hispanics and mixed races. In cross-country analysis Mexican-American group is not used, instead they are counted as Other Race

Table 3.1D Cross-country Recent Era Descriptive Statistics

	CCHS Recent (2013)		NHANES Recent (2009/12)	
	Male	Female	Male	Female
Demographics				
Age	46.183	48.009	46.610	48.193
	(17.194)	(17.776)	(16.506)	(17.025)
Single	0.266	0.219	0.212	0.168
	(0.442)	(0.413)	(0.408)	(0.374)
Married	0.648	0.601	0.656	0.592
	(0.478)	(0.490)	(0.475)	(0.492)
Previously Married	0.086	0.180	0.133	0.241
	(0.280)	(0.385)	(0.340)	(0.428)
Non-Immigrant	0.770	0.749	0.830	0.849
	(0.421)	(0.433)	(0.376)	(0.358)
Immigrant (for 10 years or less)	0.069	0.075	0.051	0.040
	(0.253)	(0.264)	(0.221)	(0.196)
Immigrant (for more than 10 years)	0.161	0.176	0.119	0.111
	(0.367)	(0.381)	(0.323)	(0.315)
Self-reported BMI	26.824	25.526	27.087	26.800
	(4.746)	(5.618)	(5.214)	(6.516)
Education				
Not High School Graduate	0.134	0.130	0.167	0.160
	(0.341)	(0.336)	(0.373)	(0.367)
High School Graduate	0.207	0.214	0.229	0.201
	(0.405)	(0.410)	(0.420)	(0.401)
Some Post-secondary	0.063	0.052	0.299	0.332
	(0.243)	(0.222)	(0.458)	(0.471)
Post-secondary	0.595	0.604	0.305	0.306
	(0.491)	(0.489)	(0.461)	(0.461)
Behavioural				
Non-Drinker	0.149	0.231	0.132	0.135
	(0.356)	(0.422)	(0.339)	(0.341)
Moderate Drinker	0.297	0.398	0.285	0.341
	(0.457)	(0.489)	(0.451)	(0.474)
Drinker	0.541	0.359	0.455	0.284
	(0.498)	(0.480)	(0.498)	(0.451)
Drinker Missing Value	0.012	0.012	0.127	0.240
	(0.111)	(0.111)	(0.333)	(0.427)
Non-Smoker	0.762	0.820	0.279	0.216
	(0.426)	(0.384)	(0.449)	(0.411)
Smoker	0.238	0.180	0.226	0.180
	(0.426)	(0.384)	(0.418)	(0.384)
Socioeconomic Status				
Equivalent Household Income*	39.878	34.811	40.448	37.356
	(22.452)	(20.920)	(25.442)	(24.903)
Poverty (US) or Food Insecurity (CDN)**	0.049	0.063	0.143	0.168
	(0.216)	(0.242)	(0.350)	(0.374)
Race				
White	0.755	0.751	0.700	0.694
	(0.430)	(0.433)	(0.458)	(0.461)
African & Caribbean	0.021	0.027	0.099	0.119
	(0.145)	(0.161)	(0.299)	(0.323)
Other Races***	0.224	0.222	0.200	0.188
	(0.417)	(0.416)	(0.400)	(0.390)
N	24609	29557	4871	4892

Note: Mean figures are presented and standard deviations of each are shown below in parenthesis.
* Equivalent Household Income is a categorical variable in cross-country analysis. Categories are mid-point levels, in $1000, and are divided by square root of household size. Canadian figures are converted to the US $ using PPP. **Poverty (US): indicates living below poverty line and experiencing food insecurity, Food Insecurity (Canada) flags experiencing food insecurity. ***Includes non-White Hispanics and mixed races. In cross-country analysis Mexican-American group is not used, instead they are counted as Other Race

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Table 3.2A Detailed Over time Decomposition Estimates for Canada / Males: Recent (2013) - Early (2000/01)

CND (MALES)	Oaxaca/Blinder	pv	RIFreg Q10	pv	RIFreg Q25	pv	RIFreg Q50	pv	RIFreg Q75	pv	RIFreg Q90	pv
Overall												
Recent Group	26.863***	0.000	21.552***	0.000	23.716***	0.000	26.385***	0.000	29.305***	0.000	32.585***	0.000
Early Group	26.133***	0.000	21.364***	0.000	23.409***	0.000	25.690***	0.000	28.493***	0.000	31.453***	0.000
Difference	0.730***	0.000	0.188***	0.004	0.307***	0.000	0.695***	0.000	0.811***	0.000	1.132***	0.000
Explained	-0.075***	0.000	0.046	0.106	0.029	0.212	-0.033	0.160	-0.138***	0.000	-0.245***	0.000
Unexplained	0.805***	0.000	0.142**	0.034	0.278***	0.000	0.728***	0.000	0.949***	0.000	1.377***	0.000
Explained												
Age	-0.006	0.186	-0.036***	0.000	-0.020***	0.000	-0.002	0.664	0.002	0.764	-0.001	0.908
Age^2	-0.041***	0.000	-0.002	0.738	-0.017***	0.000	-0.033***	0.000	-0.064***	0.000	-0.071***	0.000
Age^3	0.013***	0.002	0.038***	0.000	0.026***	0.000	0.012***	0.004	0.001	0.724	-0.001	0.850
Age^4	-0.019***	0.000	-0.058***	0.000	-0.041***	0.000	-0.020***	0.000	0.007	0.280	0.006	0.424
Single^N	-0.008***	0.000	-0.010***	0.000	-0.012***	0.000	-0.011***	0.000	-0.008***	0.004	0.001	0.766
Married	-0.008***	0.002	-0.012***	0.000	-0.012***	0.000	-0.012***	0.000	-0.009***	0.004	0.001	0.528
Prev. Married	0.000	0.720	0.000	0.724	0.000	0.704	0.000	0.694	0.000	0.722	0.000	0.778
Non-Immig.^{N}	-0.007***	0.004	-0.008**	0.012	-0.007**	0.012	-0.007***	0.006	-0.008***	0.008	-0.008**	0.020
Immg. ≤10 yrs	-0.004*	0.086	-0.005	0.118	-0.004	0.114	-0.004	0.108	-0.004	0.100	-0.003	0.146
Immg. >10 yrs	0.002*	0.074	0.004*	0.092	0.003*	0.092	0.003*	0.072	0.002	0.136	-0.001	0.444
Not HS Grad.^{N}	-0.014**	0.042	-0.010	0.242	-0.011*	0.072	-0.015**	0.018	-0.026***	0.002	-0.024*	0.072
HS Graduate	0.000	0.704	0.004*	0.096	0.003*	0.096	0.001	0.292	0.000	0.716	-0.002	0.522
Some Postsec.	0.005**	0.046	0.001	0.686	0.001	0.706	0.003	0.114	0.009***	0.002	0.010**	0.044
Postsecondary	-0.025***	0.008	0.014*	0.088	-0.005	0.418	-0.026***	0.000	-0.042***	0.000	-0.040**	0.024
Education MV	0.003	0.324	-0.005	0.168	-0.002	0.342	0.002	0.372	0.006*	0.090	0.007	0.244
Non-drinker^N	0.001	0.346	0.000	0.726	-0.001	0.390	0.002	0.346	0.002	0.360	0.004	0.322
Mod. Drinker	-0.025***	0.000	-0.019	0.182	-0.010	0.152	-0.025***	0.004	-0.032***	0.000	-0.039***	0.000
Drinker	0.004	0.124	0.016	0.196	0.003	0.588	0.011*	0.058	0.000	0.948	-0.006	0.100
Drinker MV	-0.002***	0.008	-0.001	0.374	0.000	0.860	-0.002**	0.012	-0.002***	0.006	-0.003***	0.000
Non-smoker^N	0.028***	0.000	0.021***	0.000	0.026***	0.000	0.026***	0.000	0.029***	0.000	0.026***	0.000
Smoker	0.028***	0.000	0.021***	0.000	0.026***	0.000	0.026***	0.000	0.029***	0.000	0.026***	0.000
Eq HH Income	0.021*	0.066	0.120***	0.000	0.106***	0.000	0.046***	0.004	-0.016	0.406	-0.096***	0.000
Food Insecure	-0.001	0.356	0.000	0.880	-0.002	0.166	-0.001	0.310	0.001	0.458	-0.002	0.306
White^N	-0.052***	0.000	-0.053***	0.000	-0.049***	0.000	-0.042***	0.000	-0.048***	0.000	-0.068***	0.000
Aboriginal	0.032***	0.000	0.020***	0.000	0.023***	0.000	0.026***	0.000	0.040***	0.000	0.052***	0.000
Afr./ Caribb.	-0.002	0.330	0.004	0.318	0.004	0.132	-0.003	0.254	-0.005**	0.048	-0.015***	0.004
Asian	0.002	0.686	0.002	0.692	0.002	0.692	0.002	0.688	0.002	0.686	0.002	0.694
South Asian	-0.014***	0.000	-0.008	0.124	-0.009**	0.014	-0.010***	0.006	-0.015***	0.002	-0.022***	0.000
Other Races	0.013**	0.014	0.010	0.180	0.008	0.116	0.021***	0.000	0.013*	0.050	0.020*	0.092
Unexplained												
Age	0.028*	0.072	-0.011	0.600	-0.018	0.290	-0.021	0.208	0.021	0.330	0.063*	0.088
Age^2	0.110	0.364	-0.050	0.718	-0.081	0.570	-0.015	0.902	0.429**	0.032	0.235	0.446
Age^3	-0.041***	0.000	-0.014	0.328	-0.024**	0.042	-0.010	0.234	-0.026**	0.024	-0.056***	0.004
Age^4	-0.225***	0.002	0.014	0.908	-0.089	0.266	-0.130*	0.066	-0.321***	0.006	-0.416**	0.012
Single^N	-0.019	0.454	-0.047	0.196	-0.031	0.316	-0.038	0.168	-0.022	0.544	-0.063	0.324
Married	0.036	0.424	0.015	0.826	0.051	0.382	0.051	0.330	0.036	0.556	0.082	0.444
Prev. Married	0.001	0.874	0.013	0.238	0.003	0.748	0.006	0.584	0.002	0.864	0.010	0.664
Non-Immig.^{N}	-0.080	0.366	-0.186	0.256	-0.334***	0.004	-0.118	0.252	-0.195	0.106	0.313**	0.062
Immg. ≤10 yrs	0.028**	0.018	0.042*	0.080	0.052***	0.000	0.036***	0.000	0.036**	0.012	-0.050**	0.014
Immg. >10 yrs	-0.050***	0.008	-0.061*	0.064	-0.052**	0.038	-0.060**	0.010	-0.044*	0.098	0.051	0.250
Not HS Grad.^{N}	0.015	0.406	-0.030	0.198	-0.032*	0.078	-0.017	0.394	0.017	0.552	0.141***	0.006
HS Graduate	-0.014	0.608	-0.033	0.314	-0.053**	0.046	-0.021	0.494	-0.006	0.868	0.033	0.618
Some Postsec.	0.019	0.118	-0.008	0.622	0.014	0.182	0.010	0.432	0.019	0.210	0.020	0.356
Postsecondary	-0.213***	0.002	-0.252***	0.002	-0.339***	0.000	-0.366***	0.000	-0.112	0.272	-0.080	0.626
Education MV	0.000	0.962	0.016**	0.020	0.014***	0.006	0.011	0.110	-0.004	0.670	-0.024*	0.078
Non-drinker^N	-0.064**	0.018	0.009	0.898	-0.015	0.686	-0.126***	0.002	-0.126***	0.002	-0.030	0.628
Mod. Drinker	-0.020	0.686	0.027	0.828	0.016	0.830	-0.115	0.076	-0.162***	0.036	-0.042	0.746
Drinker	-0.161*	0.088	0.165	0.432	0.015	0.914	-0.332***	0.008	-0.329**	0.018	-0.269	0.130
Drinker MV	0.002*	0.086	-0.001	0.692	0.000	0.988	0.005***	0.002	0.005***	0.008	0.002	0.390
Non-smoker^N	-0.049	0.318	-0.011	0.846	-0.001	0.990	-0.065	0.170	-0.061	0.382	0.199*	0.098
Smoker	0.016	0.312	0.004	0.848	0.000	0.990	0.021	0.166	0.020	0.380	-0.064*	0.096
Eq HH Income	0.022	0.730	-0.076	0.376	-0.079	0.260	-0.027	0.742	0.019	0.850	0.268	0.118
Food Insecure	0.029	0.128	-0.017	0.386	-0.042***	0.006	-0.004	0.762	0.066**	0.012	0.125*	0.058
White^N	0.092	0.362	-0.116	0.488	0.077	0.516	-0.045	0.746	0.300**	0.046	0.127	0.560
Aboriginal	-0.013*	0.070	-0.004	0.572	-0.004	0.614	-0.008	0.326	-0.007	0.548	-0.028	0.170
Afr./ Caribb.	0.005	0.496	-0.007	0.622	-0.003	0.782	0.018*	0.062	0.004	0.764	0.042*	0.086
Asian	0.010	0.426	-0.002	0.918	-0.014	0.432	0.009	0.514	0.018	0.204	0.008	0.764
South Asian	0.000	0.974	0.018	0.382	0.000	0.992	-0.013	0.332	-0.013	0.318	0.006	0.782
Other Races	-0.004	0.774	0.013	0.598	0.028*	0.096	-0.015	0.360	-0.023	0.256	-0.072**	0.012
Constant	1.346***	0.000	0.734*	0.094	1.217***	0.000	2.110***	0.000	1.408***	0.000	0.845*	0.094
N	62311		62311		62311		62311		62311		62311	

Note: * p<0.1, ** p<0.05 and *** p<0.01. ^{N} Denotes reference categories, included in the regression for normalization option. Equivalent household income is a continuous variable in Canada only regressions. All converted to the US dollars using PPP. Other races include mixed races.

Table 3.2B Detailed Over time Decomposition Estimates for Canada / Females: Recent (2013) - Early (2000/01)

CND (FEMALES)	Oaxaca/Blinder	pv	RIFreg Q10	pv	RIFreg Q25	pv	RIFreg Q50	pv	RIFreg Q75	pv	RIFreg Q90	pv
Overall												
Recent Group	25.640***	0.000	19.778***	0.000	21.703***	0.000	24.613***	0.000	28.528***	0.000	32.938***	0.000
Early Group	24.981***	0.000	19.625***	0.000	21.324***	0.000	24.038***	0.000	27.578***	0.000	31.746***	0.000
Difference	0.660***	0.000	0.153***	0.002	0.379***	0.000	0.575***	0.000	0.950***	0.000	1.191***	0.000
Explained	-0.308***	0.000	-0.038	0.114	-0.101***	0.000	-0.223***	0.000	-0.461***	0.000	-0.615***	0.000
Unexplained	0.968***	0.000	0.190***	0.002	0.480***	0.000	0.799***	0.000	1.411***	0.000	1.806***	0.000
Explained												
Age	0.067***	0.000	0.054***	0.000	0.096***	0.000	0.131***	0.000	0.079***	0.000	0.008	0.648
Age^2	-0.021***	0.000	-0.012***	0.000	-0.017***	0.000	-0.018***	0.000	-0.025***	0.002	-0.031***	0.002
Age^3	-0.004	0.126	0.000	0.964	-0.005	0.046	-0.013***	0.000	-0.010**	0.030	-0.002	0.754
Age^4	-0.003	0.268	-0.002	0.362	0.000	0.816	-0.003	0.288	-0.003	0.444	-0.003	0.534
Single[N]	0.002	0.176	-0.006***	0.000	-0.005***	0.000	-0.002	0.298	0.006***	0.008	0.011***	0.000
Married	-0.001	0.240	-0.005***	0.008	-0.006***	0.002	-0.007***	0.000	0.000	0.916	0.012***	0.000
Prev. Married	0.001	0.120	0.000	0.346	0.001	0.100	0.002**	0.062	0.002	0.100	-0.001	0.280
Non-Immig.[N]	-0.013***	0.004	-0.004*	0.080	-0.006**	0.022	-0.011**	0.010	-0.016	0.014	-0.023***	0.008
Immg. ≤10 yrs	-0.011**	0.016	-0.005*	0.084	-0.005*	0.088	-0.010**	0.036	-0.012	0.042	-0.016**	0.034
Immg. >10 yrs	0.004**	0.044	0.003**	0.048	0.002	0.164	0.004**	0.044	0.004	0.066	0.004	0.128
Not HS Grad.[N]	-0.051***	0.000	-0.013	0.186	-0.011	0.138	-0.029***	0.000	-0.082***	0.000	-0.101***	0.000
HS Graduate	0.000	0.764	0.000	0.780	0.000	0.768	0.000	0.780	0.000	0.748	0.000	0.780
Some Postsec.	0.000	0.996	-0.001	0.790	0.000	1.000	0.001	0.792	-0.001	0.872	0.010	0.178
Postsecondary	-0.029***	0.000	0.006	0.662	-0.028***	0.004	-0.050***	0.000	-0.042***	0.002	-0.016	0.348
Education MV	-0.003*	0.078	-0.003	0.364	0.001	0.634	0.001	0.520	-0.005**	0.038	-0.006**	0.036
Non-drinker[N]	0.005	0.250	0.000	0.910	0.001	0.536	0.003	0.334	0.009	0.268	0.014	0.256
Mod. Drinker	-0.045***	0.000	-0.015	0.224	-0.019	0.100	-0.026*	0.072	-0.068***	0.000	-0.085***	0.000
Drinker	-0.034***	0.000	-0.004	0.724	-0.016	0.114	-0.039**	0.012	-0.053***	0.006	-0.063***	0.000
Drinker MV	-0.002**	0.036	0.000	0.782	0.000	0.810	0.000	0.754	-0.003*	0.058	-0.005**	0.036
Non-smoker[N]	0.030***	0.000	0.022***	0.000	0.021***	0.000	0.024***	0.000	0.033***	0.000	0.043***	0.000
Smoker	0.030***	0.000	0.022***	0.000	0.021***	0.000	0.024***	0.000	0.033***	0.000	0.043***	0.000
Eq HH Income	-0.170***	0.000	-0.040**	0.020	-0.100***	0.000	-0.165***	0.000	-0.235***	0.000	-0.293***	0.000
Food Insecure	-0.011***	0.008	-0.008	0.118	-0.008**	0.014	-0.007**	0.054	-0.015***	0.000	-0.012	0.140
White[N]	-0.036***	0.000	-0.020***	0.002	-0.011*	0.060	-0.023***	0.000	-0.040***	0.002	-0.079***	0.000
Aboriginal	0.029***	0.000	0.015***	0.000	0.014***	0.000	0.024***	0.000	0.041***	0.000	0.064***	0.000
Afr./ Caribb.	0.012**	0.026	0.008***	0.006	0.008**	0.012	0.009**	0.018	0.021**	0.018	0.006	0.430
Asian	-0.046***	0.000	-0.035***	0.002	-0.038***	0.000	-0.047***	0.000	-0.055***	0.000	-0.056***	0.000
South Asian	-0.011**	0.028	-0.003	0.212	0.003	0.220	-0.001	0.676	-0.022**	0.028	-0.032**	0.016
Other Races	0.003	0.418	0.010***	0.002	0.007**	0.026	0.004	0.234	-0.003	0.720	-0.004	0.628
Unexplained												
Age	0.025	0.178	0.027	0.134	0.023	0.198	0.010	0.662	-0.002	0.926	0.060	0.190
Age^2	0.267*	0.072	0.281*	0.054	0.494***	0.000	0.312*	0.088	0.034	0.908	-0.345	0.292
Age^3	-0.046***	0.002	-0.032**	0.044	-0.039**	0.016	-0.040**	0.014	-0.027	0.172	-0.062*	0.072
Age^4	-0.209**	0.022	-0.151*	0.096	-0.323***	0.000	-0.246**	0.018	-0.052	0.714	0.012	0.964
Single[N]	0.007	0.756	-0.005	0.862	-0.006	0.820	-0.001	0.964	-0.002	0.972	0.066	0.324
Married	-0.036	0.444	-0.022	0.644	-0.088**	0.044	-0.063	0.270	-0.087	0.220	0.018	0.886
Prev. Married	0.005	0.760	0.011	0.464	0.031*	0.052	0.020	0.384	0.028	0.384	-0.059	0.300
Non-Immig.[N]	0.368***	0.000	0.244*	0.056	0.286**	0.014	0.248**	0.032	0.433***	0.004	0.698***	0.000
Immg. ≤10 yrs	-0.018	0.148	-0.024	0.196	-0.017	0.286	-0.009	0.626	-0.017	0.502	-0.067***	0.008
Immg. >10 yrs	-0.041*	0.056	0.000	1.000	-0.024	0.344	-0.035	0.270	-0.059	0.138	-0.003	0.960
Not HS Grad.[N]	-0.051**	0.022	-0.032	0.162	0.005	0.812	-0.035	0.196	-0.064*	0.058	-0.125**	0.010
HS Graduate	0.028	0.338	-0.032	0.348	0.055*	0.070	0.071*	0.086	0.064	0.188	-0.002	0.968
Some Postsec.	-0.011	0.286	0.012	0.302	0.014	0.234	-0.008	0.502	-0.009	0.588	-0.005	0.864
Postsecondary	-0.058	0.454	-0.126	0.176	0.075	0.382	0.089	0.398	0.097	0.422	-0.155	0.392
Education MV	0.007	0.140	0.004	0.464	-0.008	0.146	-0.001	0.904	0.002	0.728	0.016	0.110
Non-drinker[N]	0.119**	0.040	-0.006	0.918	0.177*	0.054	0.211***	0.000	0.118	0.156	0.122	0.174
Mod. Drinker	0.127	0.192	-0.104	0.376	0.268	0.100	0.378***	0.004	0.066	0.630	0.085	0.494
Drinker	-0.025	0.780	-0.082	0.470	0.130	0.328	0.176	0.116	-0.070	0.534	-0.313***	0.004
Drinker MV	-0.002	0.304	0.001	0.572	-0.005	0.208	-0.007*	0.060	-0.001	0.594	0.000	0.880
Non-smoker[N]	0.001	0.978	-0.115**	0.014	-0.042	0.458	-0.011	0.868	-0.042	0.644	0.003	0.982
Smoker	0.000	0.978	0.026**	0.014	0.010	0.460	0.003	0.868	0.010	0.642	-0.001	0.984
Eq HH Income	0.315***	0.000	0.196***	0.008	0.238***	0.004	0.180*	0.050	0.429***	0.000	0.496***	0.002
Food Insecure	0.171***	0.000	0.036**	0.024	0.074***	0.000	0.135***	0.000	0.162***	0.000	0.373***	0.000
White[N]	0.119	0.314	-0.092	0.484	-0.121	0.322	0.044	0.790	0.076	0.714	0.312	0.330
Aboriginal	-0.003	0.672	-0.003	0.600	-0.005	0.430	0.000	0.990	-0.020	0.130	-0.029	0.226
Afr./ Caribb.	-0.010	0.444	0.010	0.238	0.021**	0.010	0.000	0.958	-0.034	0.152	0.018	0.702
Asian	0.029*	0.052	0.055**	0.012	0.012	0.552	0.026	0.244	0.047	0.174	0.010	0.786
South Asian	0.009	0.494	-0.007	0.686	0.003	0.832	-0.008	0.650	0.047	0.146	0.016	0.520
Other Races	-0.020	0.102	-0.038*	0.058	-0.029**	0.032	-0.012	0.426	-0.013	0.556	-0.025	0.448
Constant	-0.100	0.730	0.155	0.620	-0.728*	0.086	-0.627	0.106	0.297	0.566	0.690	0.220
N	68634		68634		68634		68634		68634		68634	

Note: * $p<0.1$, ** $p<0.05$ and *** $p<0.01$. [N] Denotes reference categories included in the regression for normalization option. Equivalent household income is a continuous variable in Canada only regressions. All converted to the US dollars using PPP. Other races include mixed races.

Table 3.3A Detailed Over time Decomposition Estimates for the US / Males: Recent (2009/12) - Early (1999/02)

US (MALES)	Oaxaca/Blinder	pv	RIFreg Q10	pv	RIFreg Q25	pv	RIFreg Q50	pv	RIFreg Q75	pv	RIFreg Q90	pv
Overall												
Recent Group	28.675***	0.000	22.304***	0.000	24.703***	0.000	27.807***	0.000	31.691***	0.000	36.152***	0.000
Early Group	27.741***	0.000	21.616***	0.000	24.073***	0.000	26.971***	0.000	30.337***	0.000	34.531***	0.000
Difference	0.934***	0.000	0.688***	0.000	0.630***	0.000	0.836***	0.000	1.354***	0.000	1.621***	0.000
Explained	0.004	0.944	0.307***	0.000	0.192***	0.006	0.126*	0.052	-0.106	0.194	-0.297**	0.018
Unexplained	0.930***	0.000	0.381**	0.010	0.438***	0.000	0.709***	0.000	1.460***	0.000	1.918***	0.000
Explained												
Age	-0.015	0.726	-0.032	0.400	0.045	0.220	0.099***	0.004	0.049	0.320	-0.067	0.432
Age^2	0.020	0.334	-0.047*	0.080	0.010	0.580	0.025	0.256	0.047	0.114	0.047	0.292
Age^3	0.067**	0.036	0.104***	0.004	0.065**	0.018	0.007	0.804	0.013	0.714	0.094	0.136
Age^4	0.091***	0.006	0.114***	0.004	0.072**	0.010	0.063**	0.022	0.069**	0.040	0.127**	0.022
Single^N	0.001	0.802	0.016	0.112	0.007	0.222	0.001	0.762	-0.006	0.252	-0.008	0.350
Married	-0.003	0.436	-0.006	0.410	-0.006	0.396	-0.005	0.414	-0.003	0.410	0.000	0.950
Prev. Married	-0.008	0.174	0.004	0.486	-0.011*	0.088	-0.015**	0.026	-0.018**	0.028	-0.011	0.282
Non-Immig.^{N}	-0.039***	0.000	-0.017*	0.054	-0.019**	0.020	-0.034***	0.000	-0.046***	0.000	-0.074***	0.002
Immg.≤10 yrs	0.003	0.568	0.002	0.592	0.002	0.574	0.003	0.576	0.003	0.568	0.004	0.566
Immg.>10 yrs	0.003	0.568	0.012*	0.074	0.018**	0.012	0.005	0.370	-0.001	0.888	-0.017	0.170
NotHS Grad.^{N}	0.003	0.668	0.022**	0.046	0.003	0.668	0.003	0.738	0.005	0.654	-0.013	0.462
HS Graduate	-0.013*	0.050	-0.010	0.104	-0.011*	0.068	-0.017**	0.018	-0.011	0.120	-0.004	0.676
Some Postsec.	0.005	0.278	0.009	0.100	0.007	0.132	0.008	0.132	0.009	0.164	-0.001	0.946
Postsecondary	-0.025**	0.020	-0.007	0.384	-0.025**	0.028	-0.037**	0.018	-0.027**	0.040	-0.019	0.330
Non-drinker^N	-0.012	0.094	-0.006	0.128	-0.007*	0.092	-0.008	0.128	-0.015	0.100	-0.007	0.378
Mod. Drinker	0.000	0.724	0.000	0.696	0.000	0.696	0.000	0.708	0.000	0.686	0.002	0.756
Drinker	-0.036***	0.006	-0.003	0.526	-0.006	0.238	-0.030***	0.006	-0.053***	0.002	-0.056**	0.016
Drinker MV	-0.007	0.212	0.006	0.184	0.007	0.144	-0.003	0.330	-0.013	0.120	-0.033*	0.094
Non-smoker^N	-0.002	0.840	-0.001	0.832	-0.001	0.840	-0.001	0.836	-0.001	0.822	-0.001	0.816
Smoker	0.037***	0.000	0.041***	0.002	0.036***	0.002	0.030***	0.004	0.025**	0.020	0.034**	0.032
Smoker MV	0.007	0.124	0.019**	0.026	0.013**	0.040	0.008	0.106	-0.002	0.762	0.015	0.178
EqHH Inc.	-0.092*	0.068	0.063	0.330	-0.014	0.812	0.022	0.666	-0.137**	0.048	-0.373***	0.000
Poverty	0.007	0.318	0.005	0.476	0.000	0.948	0.003	0.554	0.005	0.534	0.014	0.384
White^N	0.006	0.278	0.007	0.292	0.000	0.938	0.001	0.808	0.002	0.728	0.036**	0.040
Afr./ Caribb.	-0.003	0.228	-0.004	0.216	-0.004	0.202	-0.002	0.208	-0.002	0.272	0.001	0.698
Mex. Amer.	0.009**	0.018	0.008*	0.062	0.009**	0.036	0.013**	0.014	0.008**	0.052	0.001	0.726
Other Races	-0.001	0.820	0.007	0.192	0.003	0.536	-0.010*	0.072	-0.005	0.372	0.014	0.244
Unexplained												
Age	0.017	0.616	0.017	0.590	0.076**	0.014	0.094***	0.008	0.101**	0.020	-0.051	0.524
Age^2	0.136	0.688	-0.400	0.266	-0.112	0.732	0.401	0.284	0.706	0.178	0.346	0.680
Age^3	-0.008	0.562	-0.018	0.338	-0.034**	0.044	-0.030*	0.066	-0.036*	0.074	0.030	0.388
Age^4	-0.175	0.386	-0.034	0.902	-0.195	0.332	-0.308	0.180	-0.487	0.114	-0.278	0.570
Single^N	-0.095*	0.094	0.101	0.134	-0.079	0.216	-0.160***	0.004	-0.092	0.228	-0.120	0.410
Married	-0.069	0.592	-0.207	0.122	-0.154	0.202	-0.145	0.218	-0.276*	0.070	-0.252	0.366
Prev. Married	0.073**	0.046	-0.021	0.580	0.081**	0.028	0.129***	0.000	0.113***	0.008	0.126	0.134
Non-Immig.^{N}	0.130	0.480	0.148	0.528	0.342*	0.090	0.095	0.640	0.429*	0.088	0.116	0.822
Immg.≤10 yrs	0.023*	0.074	0.026	0.262	0.016	0.390	0.004	0.824	0.011	0.514	0.060**	0.030
Immg.>10 yrs	-0.070***	0.008	-0.080**	0.036	-0.086**	0.010	-0.022	0.532	-0.088**	0.024	-0.150***	0.008
NotHS Grad.^{N}	0.009	0.784	-0.002	0.950	0.037	0.342	0.023	0.554	0.039	0.444	-0.142	0.110
HS Graduate	-0.002	0.956	-0.006	0.894	-0.028	0.504	-0.008	0.878	0.034	0.588	0.178	0.160
Some Postsec.	0.141**	0.012	0.022	0.736	0.027	0.638	0.195***	0.000	0.160**	0.046	0.089	0.540
Postsecondary	-0.157**	0.022	-0.011	0.844	-0.056	0.360	-0.230***	0.002	-0.277***	0.008	-0.077	0.650
Non-drinker^N	-0.070*	0.066	-0.046	0.104	-0.064**	0.036	-0.028	0.450	-0.085	0.102	-0.041	0.636
Mod. Drinker	0.209***	0.000	0.056	0.316	0.146***	0.004	0.073	0.218	0.194***	0.006	0.548***	0.000
Drinker	0.151*	0.078	0.009	0.902	-0.057	0.522	0.181*	0.052	0.289**	0.016	0.050	0.786
Drinker MV	-0.070*	0.080	0.017	0.578	0.013	0.708	-0.057	0.130	-0.087*	0.076	-0.223**	0.020
Non-smoker^N	0.041	0.454	0.045	0.386	0.070	0.180	0.080	0.128	0.079	0.304	0.269**	0.036
Smoker	-0.105**	0.014	-0.004	0.948	-0.116**	0.014	-0.123***	0.008	-0.160***	0.008	-0.341***	0.000
Smoker MV	0.155**	0.032	-0.072	0.336	0.128	0.126	0.126	0.152	0.208*	0.062	0.262	0.148
Eq.HH Inc.	-0.008	0.982	-0.165	0.614	0.107	0.736	-0.297	0.314	0.331	0.382	-0.093	0.888
Food Insecure	-0.176***	0.002	-0.082	0.178	-0.045	0.444	-0.103*	0.050	-0.158**	0.028	-0.417***	0.000
White^N	-0.443***	0.004	-0.149	0.370	-0.289**	0.040	-0.342**	0.014	-0.739***	0.002	-0.318	0.418
Afr./ Caribb.	0.075***	0.002	0.032	0.196	0.034	0.136	0.034	0.138	0.070**	0.018	0.126**	0.030
Mex. Amer.	0.014	0.444	0.073***	0.000	0.052***	0.000	0.007	0.738	0.018	0.494	0.011	0.796
Other Races	-0.036	0.258	-0.121***	0.002	-0.067*	0.066	0.008	0.830	0.018	0.694	-0.117	0.208
Constant	1.238***	0.000	1.255***	0.004	0.690*	0.058	1.112***	0.008	1.146**	0.020	2.328**	0.010
N	8883		8883		8883		8883		8883		8883	

Note: * p<0.1, ** p<0.05 and *** p<0.01. ^{N} Denotes reference categories included in the regression for normalization option. Equivalent household income is a categorical variable. Other races include, non-White Hispanics and mixed races.

Table 3.3B Detailed Over time Decomposition Estimates for the US / Females: Recent (2009/12) - Early (1999/02)

US (FEMALES)	Oaxaca/Blinder	pv	RIFreg Q10	pv	RIFreg Q25	pv	RIFreg Q50	pv	RIFreg Q75	pv	RIFreg Q90	pv
Overall												
Recent Group	28.852***	0.000	20.955***	0.000	23.479***	0.000	27.391***	0.000	32.883***	0.000	38.771***	0.000
Early Group	28.049***	0.000	20.446***	0.000	22.883***	0.000	26.705***	0.000	31.943***	0.000	37.675***	0.000
Difference	0.803***	0.000	0.509***	0.000	0.596***	0.000	0.687***	0.000	0.940***	0.000	1.096***	0.002
Explained	-0.299***	0.000	-0.001	0.990	-0.137**	0.038	-0.260***	0.000	-0.360***	0.004	-0.520***	0.000
Unexplained	1.102***	0.000	0.511***	0.000	0.733***	0.000	0.947***	0.000	1.300***	0.000	1.617***	0.000
Explained												
Age	0.129***	0.004	0.122***	0.000	0.144***	0.000	0.171***	0.000	0.179**	0.014	0.075	0.464
Age^2	0.041*	0.094	0.003	0.846	0.011	0.440	0.015	0.376	0.066*	0.096	0.101	0.110
Age^3	0.004	0.870	0.013	0.626	0.035	0.202	0.000	0.980	-0.068	0.146	-0.040	0.576
Age^4	0.043*	0.074	0.046*	0.080	0.052*	0.068	0.086**	0.036	0.039	0.336	-0.017	0.754
Single^N	-0.004	0.348	0.001	0.580	-0.002	0.398	-0.001	0.572	-0.003	0.434	-0.007	0.394
Married	0.000	0.970	0.000	0.984	0.000	0.974	0.000	0.956	0.000	0.968	0.000	0.974
Prev. Married	-0.002	0.416	-0.001	0.444	-0.002	0.392	-0.001	0.664	0.000	0.892	-0.005	0.400
Non-Immig.^{N}	-0.050***	0.000	-0.008	0.262	-0.031***	0.004	-0.048***	0.008	-0.074***	0.002	-0.098***	0.008
Immg.≤10 yrs	-0.008	0.180	-0.006	0.240	-0.007	0.212	-0.009	0.192	-0.009	0.208	-0.010	0.170
Immg.>10 yrs	-0.002	0.708	0.023**	0.018	0.009	0.168	0.004	0.524	-0.020**	0.024	-0.032**	0.020
NotHS Grad.^{N}	-0.017**	0.032	-0.014*	0.052	-0.035***	0.006	-0.040***	0.008	-0.002	0.858	0.005	0.774
HS Graduate	-0.019**	0.078	-0.017*	0.090	-0.014	0.170	-0.038**	0.016	-0.020	0.300	-0.004	0.886
Some Postsec.	0.011*	0.094	0.004	0.256	0.004	0.278	0.012	0.116	0.016	0.126	0.021	0.162
Postsecondary	-0.106***	0.000	-0.070***	0.002	-0.110***	0.000	-0.182***	0.000	-0.098***	0.004	-0.084**	0.032
Non-drinker^N	-0.018*	0.052	0.005	0.222	-0.003	0.330	-0.019*	0.062	-0.029*	0.054	-0.051*	0.052
Mod. Drinker	-0.009	0.150	-0.021**	0.028	-0.013*	0.072	-0.012	0.138	0.001	0.938	0.003	0.826
Drinker	-0.092***	0.000	-0.016	0.190	-0.042**	0.020	-0.101***	0.000	-0.149***	0.000	-0.189***	0.002
Drinker MV	0.000	0.664	0.000	0.710	-0.001	0.494	-0.001	0.580	-0.004	0.394	0.002	0.588
Non-smoker^N	0.010*	0.090	0.005	0.226	0.010*	0.094	0.004	0.360	0.014	0.140	0.033*	0.064
Smoker	0.035***	0.004	0.029**	0.012	0.026**	0.018	0.029**	0.014	0.049***	0.008	0.068**	0.014
Smoker MV	0.007	0.148	0.010	0.108	0.002	0.518	0.011	0.130	0.010	0.196	-0.002	0.830
EqHH Inc.	-0.301***	0.000	-0.135**	0.024	-0.226***	0.000	-0.191***	0.002	-0.304***	0.002	-0.354**	0.010
Poverty	0.000	0.820	0.000	0.604	-0.003	0.558	0.000	0.710	0.003	0.568	0.006	0.592
White^N	0.041***	0.006	0.021**	0.012	0.045***	0.000	0.040**	0.014	0.038**	0.036	0.051**	0.038
Afr./ Caribb.	0.015**	0.024	0.006*	0.056	0.006*	0.062	0.009*	0.078	0.020**	0.046	0.027**	0.046
Mex. Amer.	0.006**	0.044	0.004	0.122	0.010**	0.012	0.008**	0.036	0.006	0.150	-0.006	0.296
Other Races	-0.013*	0.094	-0.005	0.268	-0.003	0.434	-0.006	0.252	-0.021	0.112	-0.010	0.360
Unexplained												
Age	0.007	0.626	0.019	0.190	0.001	0.904	-0.005	0.792	0.004	0.860	0.005	0.886
Age^2	1.984***	0.000	1.149***	0.004	1.290***	0.006	1.329***	0.008	3.022***	0.000	4.528***	0.000
Age^3	0.005	0.486	0.007	0.300	-0.001	0.774	0.000	0.912	0.006	0.612	0.015	0.356
Age^4	-1.351***	0.000	-0.962***	0.000	-0.934***	0.002	-0.962***	0.002	-1.990***	0.000	-3.069***	0.000
Single^N	-0.031	0.572	-0.038	0.456	-0.079	0.130	0.013	0.828	0.049	0.570	0.036	0.812
Married	0.035	0.764	-0.146	0.238	0.050	0.694	0.008	0.962	0.084	0.666	-0.071	0.832
Prev. Married	0.030	0.618	0.114**	0.032	0.092	0.120	-0.022	0.772	-0.103	0.316	-0.022	0.898
Non-Immig.^{N}	-0.212	0.310	-0.030	0.924	-0.677**	0.012	-0.153	0.636	-0.266	0.518	-0.154	0.728
Immg.≤10 yrs	0.004	0.838	0.020	0.336	0.035*	0.080	0.023	0.250	-0.022	0.374	-0.032	0.154
Immg.>10 yrs	0.019	0.534	-0.048	0.140	-0.001	0.984	-0.042	0.360	0.094*	0.066	0.107*	0.090
NotHS Grad.^{N}	-0.005	0.912	0.004	0.902	-0.064	0.120	-0.095*	0.084	0.047	0.542	0.149	0.186
HS Graduate	0.032	0.492	-0.011	0.800	0.026	0.542	-0.052	0.372	0.203**	0.024	-0.044	0.738
Some Postsec.	-0.093	0.200	-0.025	0.732	0.013	0.842	-0.109	0.208	-0.296**	0.022	-0.275	0.164
Postsecondary	0.047	0.558	0.031	0.698	0.065	0.508	0.348***	0.002	-0.117	0.404	0.050	0.818
Non-drinker^N	-0.037	0.394	0.103***	0.004	0.022	0.528	-0.046	0.314	0.001	0.992	-0.243*	0.050
Mod. Drinker	0.054	0.484	-0.195***	0.004	-0.008	0.898	-0.034	0.724	0.177	0.198	0.338*	0.096
Drinker	0.182***	0.004	0.122	0.124	0.175**	0.016	0.190**	0.026	0.196*	0.082	0.434***	0.006
Drinker MV	-0.126**	0.022	-0.153***	0.008	-0.182***	0.002	-0.056	0.428	-0.294***	0.002	-0.172	0.244
Non-smoker^N	0.007	0.886	0.044	0.360	-0.011	0.828	0.091	0.138	0.032	0.752	-0.259*	0.058
Smoker	-0.072	0.110	0.008	0.894	-0.057	0.242	-0.112**	0.040	-0.117	0.116	-0.026	0.820
Smoker MV	0.226*	0.072	-0.154	0.160	0.228*	0.056	0.125	0.412	0.308	0.144	0.823**	0.014
EqHH Inc.	-0.046	0.872	0.355	0.258	0.024	0.948	-0.518	0.214	-0.511	0.332	-0.883	0.276
Food Insecure	0.068	0.326	-0.013	0.844	0.136*	0.058	0.108	0.218	-0.007	0.962	-0.197	0.268
White^N	0.082	0.672	-0.070	0.622	0.444***	0.000	-0.109	0.582	0.029	0.914	0.165	0.716
Afr./ Caribb.	0.091**	0.022	0.019	0.432	0.096***	0.000	0.153***	0.000	0.092	0.136	0.169**	0.078
Mex. Amer.	-0.020	0.276	0.024	0.158	-0.020	0.250	0.000	0.988	-0.015	0.638	-0.076**	0.088
Other Races	-0.075*	0.056	-0.052	0.190	-0.148***	0.000	-0.143***	0.000	-0.076	0.278	-0.070	0.498
Constant	0.298	0.444	0.388	0.402	0.219	0.598	1.014*	0.054	0.771	0.274	0.393	0.718
N	8719		8719		8719		8719		8719		8719	

Note: * p<0.1, ** p<0.05 and *** p<0.01. [N] Denotes reference categories included in the regression for normalization option. Equivalent household income is a categorical variable. Other races include non-White Hispanics and mixed races.

Table 3.4A Detailed Cross-country Decomposition Estimates for Early Era / Males: US (1999/02) – Canada (2000/01)

(EARLY) MALES	Oaxaca/Blinder	pv	RIFreg Q10	pv	RIFreg Q25	pv	RIFreg Q50	pv	RIFreg Q75	pv	RIFreg Q90	pv
Overall												
US	26.398***	0.000	20.959***	0.000	22.816***	0.000	25.576***	0.000	28.848***	0.000	32.439***	0.000
Canada	26.130***	0.000	21.369***	0.000	23.411***	0.000	25.687***	0.000	28.487***	0.000	31.446***	0.000
Difference	0.268***	0.002	-0.410***	0.000	-0.594***	0.000	-0.111	0.160	0.361***	0.000	0.993***	0.000
Explained	-0.264***	0.000	-0.342	0.162	-0.053	0.654	-0.300***	0.010	-0.295***	0.002	-0.415***	0.000
Unexplained	0.532***	0.000	-0.068	0.772	-0.541***	0.000	0.189	0.164	0.657***	0.000	1.409***	0.000
Explained												
Age	-0.002	0.292	0.015**	0.010	0.007*	0.068	-0.003	0.234	-0.009*	0.062	-0.009	0.112
Age^2	-0.050***	0.000	-0.015**	0.040	-0.028***	0.004	-0.041***	0.000	-0.071***	0.000	-0.078***	0.000
Age^3	-0.014**	0.016	-0.043***	0.000	-0.030***	0.004	-0.014**	0.022	0.000	0.918	0.002	0.774
Age^4	-0.016***	0.008	-0.051***	0.000	-0.035***	0.000	-0.017**	0.012	0.006	0.286	0.005	0.410
Single^N	0.001	0.510	0.002	0.532	0.002	0.534	0.002	0.516	0.001	0.490	0.000	0.996
Married	-0.005**	0.022	-0.008***	0.008	-0.008**	0.012	-0.007**	0.012	-0.006**	0.032	0.002	0.370
Prev. Married	0.001	0.620	0.000	0.840	0.002	0.184	0.001	0.586	-0.001	0.758	0.002	0.482
Non-Immig.^{N}	0.047***	0.000	0.045***	0.000	0.040***	0.000	0.044***	0.000	0.052***	0.000	0.055***	0.000
Immg. ≤10 yrs	0.010***	0.000	0.011***	0.004	0.009***	0.004	0.010***	0.000	0.010***	0.002	0.007**	0.014
Immg. >10 yrs	-0.014***	0.000	-0.022***	0.000	-0.017***	0.000	-0.017***	0.000	-0.012***	0.008	0.006	0.412
Not HS Grad.^{N}	0.001	0.658	0.000	0.632	0.000	0.658	0.001	0.658	0.001	0.664	0.001	0.672
HS Graduate	0.007*	0.060	0.009**	0.046	0.009**	0.010	0.008**	0.022	0.007	0.120	0.004	0.622
Some Postsec.	-0.024**	0.014	-0.033**	0.048	-0.019	0.156	-0.016	0.166	-0.041***	0.006	-0.041*	0.056
Postsecondary	0.062***	0.000	-0.001	0.940	0.036***	0.000	0.071***	0.000	0.097***	0.000	0.085***	0.000
Non-drinker^N	0.001	0.622	0.000	0.712	-0.001	0.586	0.001	0.628	0.001	0.614	0.002	0.608
Mod. Drinker	-0.033***	0.000	-0.025	0.212	-0.009	0.362	-0.031**	0.012	-0.043***	0.000	-0.052***	0.000
Drinker	-0.013	0.186	-0.051	0.192	-0.004	0.874	-0.032*	0.062	0.002	0.928	0.020*	0.070
Drinker MV	-0.151***	0.002	-0.135	0.404	0.014	0.874	-0.198**	0.012	-0.196***	0.002	-0.251***	0.000
Non-smoker^N	-0.132***	0.000	-0.101***	0.000	-0.125***	0.000	-0.125***	0.000	-0.136***	0.000	-0.123***	0.000
Smoker	0.023***	0.000	0.017***	0.000	0.022***	0.000	0.021***	0.000	0.023***	0.000	0.021***	0.000
Smoker MV	0.144***	0.000	0.110***	0.000	0.136***	0.000	0.135***	0.000	0.148***	0.000	0.134***	0.000
Eq HH Income	0.002	0.110	0.011***	0.004	0.009***	0.008	0.004*	0.070	0.000	0.908	-0.005*	0.066
Pov./F. Inscr	0.003	0.498	0.000	0.976	0.009*	0.070	0.004	0.390	-0.006	0.300	0.010	0.304
White^N	-0.078***	0.000	-0.062***	0.002	-0.058***	0.000	-0.068***	0.000	-0.084***	0.000	-0.135***	0.000
Afr./ Caribb.	0.000	0.976	0.024	0.216	0.026*	0.052	-0.007	0.612	-0.016	0.242	-0.065***	0.000
Other Races	-0.031***	0.000	-0.040***	0.000	-0.040***	0.000	-0.022***	0.002	-0.023***	0.002	-0.011**	0.046
Unexplained												
Age	0.034	0.366	0.016	0.678	-0.055*	0.086	-0.070**	0.034	0.019	0.684	0.154**	0.028
Age^2	0.131	0.538	0.557***	0.008	0.214	0.252	0.106	0.622	0.238	0.406	0.147	0.708
Age^3	-0.006	0.292	0.000	0.942	0.004	0.426	0.002	0.604	-0.008	0.312	-0.020	0.198
Age^4	-0.334***	0.004	-0.235	0.150	-0.167	0.210	-0.201	0.138	-0.534***	0.002	-0.648***	0.008
Single^N	0.058	0.212	-0.028	0.636	0.031	0.492	0.128***	0.000	0.108**	0.040	0.049	0.558
Married	0.068	0.530	0.250***	0.006	0.314***	0.000	0.131	0.122	0.072	0.528	0.018	0.926
Prev. Married	-0.039	0.110	-0.028	0.254	-0.067***	0.000	-0.083***	0.000	-0.064**	0.010	-0.027	0.510
Non-Immig.^{N}	0.593***	0.000	0.040	0.838	0.050	0.722	0.442***	0.000	0.744***	0.000	1.548***	0.000
Immg. ≤10 yrs	-0.018	0.128	-0.004	0.806	-0.008	0.554	-0.027**	0.014	-0.029**	0.034	-0.064***	0.004
Immg. >10 yrs	-0.031	0.034	0.002	0.924	0.009	0.660	-0.001	0.968	-0.029	0.212	-0.053*	0.090
Not HS Grad.^{N}	-0.041	0.266	-0.111***	0.002	-0.033	0.316	0.034	0.284	-0.030	0.528	-0.062	0.398
HS Graduate	0.064*	0.098	0.012	0.760	-0.006	0.860	0.065*	0.066	0.108**	0.038	0.030	0.678
Some Postsec.	0.041	0.258	0.116***	0.002	0.063*	0.072	0.035	0.374	0.049	0.350	-0.031	0.696
Postsecondary	-0.053	0.220	0.007	0.844	-0.016	0.664	-0.134***	0.002	-0.115*	0.056	0.071	0.382
Non-drinker^N	0.063*	0.056	0.038	0.474	0.085**	0.018	0.004	0.930	0.049	0.280	0.104	0.114
Mod. Drinker	-0.202***	0.000	-0.161	0.144	-0.031	0.634	-0.093	0.106	-0.273***	0.000	-0.484***	0.000
Drinker	-0.410***	0.000	-0.221	0.148	-0.095	0.298	-0.372***	0.000	-0.509***	0.000	-0.591***	0.000
Drinker MV	0.199***	0.000	0.131	0.410	-0.035	0.720	0.186**	0.016	0.290***	0.000	0.379***	0.000
Non-smoker^N	0.099**	0.018	0.047	0.124	0.013	0.716	0.060*	0.080	0.110**	0.016	0.074	0.330
Smoker	-0.064*	0.066	-0.037	0.308	-0.017	0.644	-0.026	0.450	-0.077*	0.080	-0.117*	0.062
Smoker MV	-0.050	0.316	-0.013	0.794	0.008	0.856	-0.052	0.278	-0.047	0.510	0.083	0.426
Eq HH Income	-0.549***	0.000	-0.290	0.130	-0.557***	0.002	-0.084	0.588	-0.723***	0.000	-1.216***	0.000
Pov./F. Inscr	0.032	0.406	-0.003	0.936	-0.028	0.370	-0.013	0.640	0.017	0.688	0.064	0.432
White^N	-0.534***	0.000	-0.448***	0.000	-0.285***	0.006	-0.533***	0.000	-0.522***	0.000	-1.398***	0.000
Afr./ Caribb.	-0.025	0.128	-0.062	0.022	-0.056***	0.004	-0.015	0.454	0.005	0.828	0.093***	0.006
Other Races	0.171***	0.000	0.218***	0.000	0.170***	0.000	0.153***	0.000	0.113**	0.012	0.160**	0.022
Constant	1.335***	0.000	0.136	0.756	-0.045	0.894	0.547*	0.082	1.694***	0.000	3.143***	0.000
N	47072		47072		47072		47072		47072		47072	

Note: * $p<0.1$, ** $p<0.05$ and *** $p<0.01$. ^{N} Denotes reference categories included in the regression for normalization option. Equivalent household income is a categorical variable. Other races include, non-White Hispanics and mixed races.

Table 3.4B Detailed Cross-country Decomposition Estimates for Early Era / Females: US (1999/02) – Canada (2000/01)

(EARLY) FEMALES	Oaxaca/Blinder	pv	RIFreg Q10	pv	RIFreg Q25	pv	RIFreg Q50	pv	RIFreg Q75	pv	RIFreg Q90	pv
Overall												
US	26.211***	0.000	19.422***	0.000	21.566***	0.000	24.850***	0.000	29.731***	0.000	34.918***	0.000
Canada	24.983***	0.000	19.628***	0.000	21.322***	0.000	24.036***	0.000	27.576***	0.000	31.753***	0.000
Difference	1.228***	0.000	-0.206**	0.018	0.243***	0.004	0.814***	0.000	2.155***	0.000	3.165***	0.000
Explained	-0.277**	0.012	-0.029	0.882	0.023	0.886	0.001	0.998	-0.386	0.126	-0.879***	0.000
Unexplained	1.505***	0.000	-0.178	0.438	0.221	0.230	0.813***	0.006	2.541***	0.000	4.044***	0.000
Explained												
Age	-0.008	0.438	-0.006	0.434	-0.010	0.446	-0.013	0.444	-0.010	0.442	-0.004	0.434
Age^2	-0.031**	0.012	-0.016**	0.020	-0.023**	0.014	-0.025**	0.010	-0.036***	0.008	-0.046**	0.016
Age^3	0.001	0.398	0.000	0.714	0.002	0.282	0.004	0.244	0.003	0.328	0.000	0.962
Age^4	-0.001	0.406	-0.002	0.368	0.000	0.820	-0.001	0.422	-0.001	0.460	-0.001	0.542
$Single^N$	-0.001	0.266	0.003*	0.070	0.003*	0.064	0.001	0.254	-0.003*	0.090	-0.006*	0.052
Married	-0.002	0.144	-0.008***	0.008	-0.010***	0.000	-0.010***	0.000	-0.001	0.706	0.017***	0.008
Prev. Married	-0.005**	0.016	-0.002	0.500	-0.005***	0.006	-0.011***	0.000	-0.011***	0.000	0.007	0.232
Non-Immig.^N	0.054***	0.000	0.023***	0.000	0.027***	0.000	0.046***	0.000	0.071***	0.000	0.099***	0.000
Immg. ≤10 yrs	0.021***	0.000	0.010***	0.004	0.010***	0.002	0.019***	0.000	0.025***	0.000	0.033***	0.000
Immg. >10 yrs	-0.017***	0.000	-0.012***	0.008	-0.007*	0.090	-0.018***	0.000	-0.016***	0.006	-0.018*	0.052
Not HS Grad.^N	-0.007**	0.036	-0.001	0.168	-0.003*	0.074	-0.006**	0.036	-0.010**	0.040	-0.013**	0.034
HS Graduate	-0.003	0.300	0.002	0.374	0.000	0.848	-0.003	0.272	-0.005	0.282	-0.003	0.614
Some Postsec.	-0.022	0.112	-0.016	0.298	0.006	0.628	0.005	0.758	-0.032	0.220	-0.107***	0.000
Postsecondary	0.093***	0.000	0.018*	0.092	0.056***	0.000	0.099***	0.000	0.143***	0.000	0.102***	0.000
Non-drinker^N	-0.059***	0.000	0.006	0.706	-0.005	0.680	-0.033*	0.076	-0.099***	0.000	-0.151***	0.000
Mod. Drinker	-0.064***	0.000	-0.019	0.376	-0.024	0.146	-0.035	0.136	-0.095***	0.000	-0.123***	0.000
Drinker	0.054***	0.000	0.009	0.610	0.027*	0.084	0.061**	0.018	0.085***	0.002	0.101***	0.000
Drinker MV	-0.217**	0.010	-0.002	0.994	-0.002	0.992	-0.031	0.886	-0.350	0.104	-0.560***	0.000
Non-smoker^N	-0.133***	0.000	-0.098***	0.000	-0.094***	0.000	-0.106***	0.000	-0.140***	0.000	-0.184***	0.000
Smoker	0.020***	0.000	0.015***	0.000	0.014***	0.000	0.016***	0.000	0.021***	0.000	0.028***	0.002
Smoker MV	0.143***	0.000	0.105***	0.000	0.101***	0.000	0.114***	0.000	0.151***	0.000	0.198***	0.000
Eq HH Income	-0.034***	0.000	-0.005*	0.092	-0.017***	0.006	-0.031***	0.000	-0.048***	0.000	-0.061***	0.000
Pov./F. Inscr	-0.052***	0.000	-0.039*	0.084	-0.041**	0.012	-0.036**	0.028	-0.073***	0.000	-0.066**	0.044
$White^N$	-0.030**	0.046	-0.014	0.234	-0.005	0.674	-0.024	0.102	-0.009	0.726	-0.104***	0.002
Afr./ Caribb.	0.080***	0.000	0.057***	0.000	0.060***	0.000	0.067***	0.000	0.137***	0.000	0.053	0.218
Other Races	-0.057***	0.000	-0.038***	0.000	-0.037***	0.000	-0.047***	0.000	-0.082***	0.000	-0.069***	0.000
Unexplained												
Age	0.011	0.756	-0.019	0.552	0.026	0.440	-0.001	0.988	0.093	0.118	-0.020	0.812
Age^2	-0.317	0.238	0.261	0.308	0.432*	0.082	0.259	0.414	-1.045**	0.018	-1.368*	0.056
Age^3	-0.003	0.462	-0.002	0.564	-0.006	0.370	-0.004	0.408	-0.003	0.538	-0.001	0.796
Age^4	-0.166	0.292	-0.269	0.136	-0.449***	0.006	-0.549***	0.008	0.143	0.630	0.355	0.428
$Single^N$	0.065	0.114	0.053	0.156	0.032	0.354	0.031	0.488	-0.019	0.784	0.172*	0.074
Married	-0.130	0.130	0.048	0.594	-0.050	0.544	-0.140	0.166	-0.195	0.196	-0.007	0.988
Prev. Married	-0.036	0.476	-0.091***	0.008	-0.023	0.544	0.015	0.776	0.104	0.144	-0.229**	0.046
Non-Immig.^N	0.694***	0.000	0.365*	0.080	0.288	0.118	0.924***	0.000	1.005***	0.002	1.523***	0.000
Immg. ≤10 yrs	-0.020**	0.026	-0.041**	0.014	-0.021*	0.062	-0.026**	0.018	0.009	0.578	-0.022*	0.090
Immg. >10 yrs	-0.017	0.366	0.074***	0.000	0.027	0.212	-0.023	0.380	-0.129***	0.000	-0.097***	0.002
Not HS Grad.^N	0.009	0.824	0.013	0.684	0.081***	0.008	0.077*	0.062	-0.033	0.604	-0.175*	0.056
HS Graduate	0.057	0.202	0.002	0.962	0.045	0.260	0.137***	0.008	0.079	0.292	-0.097	0.422
Some Postsec.	0.159***	0.004	0.085**	0.054	0.017	0.726	0.118*	0.038	0.209**	0.020	0.566***	0.000
Postsecondary	-0.170***	0.000	-0.077**	0.058	-0.137***	0.000	-0.282***	0.000	-0.180**	0.024	-0.135	0.198
Non-drinker^N	0.089**	0.030	-0.047	0.244	0.043	0.206	0.083*	0.096	0.093	0.150	0.216**	0.030
Mod. Drinker	-0.173***	0.008	0.099	0.300	0.046	0.570	-0.033	0.762	-0.269**	0.026	-0.558***	0.000
Drinker	-0.225***	0.000	-0.011	0.876	-0.088	0.124	-0.180***	0.008	-0.327***	0.000	-0.468***	0.000
Drinker MV	0.225**	0.014	0.027	0.846	-0.005	0.954	0.085	0.690	0.402**	0.048	0.550***	0.000
Non-smoker^N	0.038	0.230	0.006	0.836	-0.002	0.968	-0.015	0.666	0.076	0.150	0.287***	0.002
Smoker	-0.059	0.130	-0.026	0.514	-0.056	0.140	0.000	0.992	-0.112*	0.078	-0.144	0.148
Smoker MV	0.045	0.590	0.051	0.460	0.154**	0.022	0.044	0.602	0.075	0.532	-0.467**	0.032
Eq HH Income	-0.218	0.214	-0.167	0.370	-0.436**	0.012	-0.120	0.562	0.053	0.858	-0.374	0.420
Pov./F. Inscr	0.073	0.226	0.102	0.070	0.039	0.498	-0.036	0.598	0.232**	0.014	0.113	0.414
$White^N$	-0.946***	0.000	-0.568***	0.000	-0.553***	0.000	-1.077***	0.000	-0.875***	0.000	-1.510***	0.000
Afr./ Caribb.	0.074***	0.002	-0.007	0.704	0.021	0.286	0.053**	0.038	0.043	0.370	0.213***	0.002
Other Races	0.106***	0.002	0.143***	0.000	0.097***	0.000	0.170***	0.000	0.138**	0.018	0.025	0.756
Constant	2.339***	0.000	-0.183	0.658	0.700*	0.060	1.303***	0.002	2.974***	0.000	5.696***	0.000
N	49342		49342		49342		49342		49342		49342	

Note: * p<0.1, ** p<0.05 and *** p<0.01. [N] Denotes reference categories included in the regression for normalization option. Equivalent household income is a categorical variable. Other races include, non-White Hispanics and mixed races.

Table 3.5A Detailed Cross-country Decomposition Estimates for Recent Era / Males: US (2009/12) – Canada (2013)

(RECENT) MALES	Oaxaca/Blinder	pv	RIFreg Q10	pv	RIFreg Q25	pv	RIFreg Q50	pv	RIFreg Q75	pv	RIFreg Q90	pv
Overall												
US	27.087***	0.000	21.413***	0.000	23.494***	0.000	26.323***	0.000	29.815***	0.000	33.893***	0.000
Canada	26.824***	0.000	21.539***	0.000	23.573***	0.000	26.376***	0.000	29.210***	0.000	32.545***	0.000
Difference	0.263***	0.000	-0.126	0.144	-0.079	0.388	-0.053	0.616	0.605***	0.000	1.348***	0.000
Explained	0.522***	0.000	0.324***	0.000	0.450***	0.000	0.582***	0.000	0.511***	0.000	0.701***	0.002
Unexplained	-0.260**	0.034	-0.450***	0.000	-0.529***	0.000	-0.636***	0.000	0.094	0.540	0.647**	0.014
Explained												
Age	-0.012	0.792	-0.008	0.102	-0.005	0.196	-0.005	0.182	-0.010	0.114	-0.016	0.112
Age^2	0.019	0.328	-0.011	0.384	0.003	0.772	0.025**	0.012	0.021	0.112	0.049**	0.034
Age^3	0.030	0.200	0.037***	0.000	0.030***	0.004	0.017**	0.020	0.015**	0.040	0.023**	0.036
Age^4	0.091	0.998	0.110***	0.000	0.103***	0.000	0.079***	0.000	0.072***	0.000	0.075**	0.016
Single^N	0.016	0.590	0.029***	0.000	0.028***	0.000	0.026***	0.000	0.016***	0.008	-0.001	0.888
Married	0.002	0.556	0.003	0.316	0.003	0.314	0.004	0.332	0.002	0.332	0.000	0.686
Prev. Married	-0.001	1.000	0.007	0.170	0.005	0.232	-0.001	0.800	0.001	0.790	0.001	0.920
Non-Immig.^{N}	0.042	0.786	0.027**	0.020	0.023***	0.002	0.039***	0.000	0.037***	0.000	0.066***	0.000
Immg. ≤10 yrs	0.010***	0.000	0.007	0.228	0.006	0.176	0.010**	0.032	0.007**	0.042	0.019***	0.008
Immg. >10 yrs	0.006	0.266	0.003	0.660	0.003	0.584	0.004	0.362	0.009*	0.080	0.002	0.844
Not HS Grad.^{N}	0.013	0.676	-0.001	0.734	0.006*	0.054	0.009***	0.008	0.019***	0.006	0.031***	0.000
HS Graduate	0.002	0.390	0.004	0.218	0.003	0.174	0.005*	0.078	0.001	0.656	0.000	0.914
Some Postsec.	0.033	1.000	0.028	0.548	0.028	0.396	0.038	0.214	0.006	0.902	-0.008	0.918
Postsecondary	0.178	1.000	0.073***	0.002	0.133***	0.000	0.203***	0.000	0.194***	0.000	0.271***	0.000
Non-drinker^N	0.004	0.544	0.008***	0.032	0.007**	0.034	0.006*	0.072	0.003	0.270	-0.007	0.116
Mod. Drinker	-0.006	0.794	0.000	0.862	-0.001	0.366	-0.003	0.246	-0.006	0.136	-0.010	0.104
Drinker	0.021**	0.044	-0.021***	0.026	0.005	0.602	0.021*	0.056	0.037***	0.006	0.050***	0.006
Drinker MV	0.005	1.000	0.027	0.352	0.046	0.114	0.045	0.268	0.015	0.744	-0.075*	0.086
Non-smoker^N	-0.129	1.000	-0.105***	0.000	-0.118***	0.000	-0.102***	0.000	-0.124***	0.000	-0.212***	0.000
Smoker	0.006	1.000	0.005*	0.070	0.006*	0.082	0.005*	0.066	0.006*	0.076	0.010*	0.072
Smoker MV	0.132	1.000	0.108***	0.000	0.121***	0.000	0.104***	0.000	0.127***	0.000	0.217***	0.000
Eq HH Income	0.003	0.736	0.008	0.174	0.008	0.164	0.003	0.242	0.001	0.648	-0.002	0.504
Pov./F. Inscr	0.067	1.000	-0.008	0.790	-0.003	0.894	0.026	0.258	0.101**	0.016	0.194*	0.068
White^N	-0.019**	0.034	-0.008	0.376	-0.009	0.206	-0.006	0.396	-0.033***	0.000	-0.021	0.210
Afr./ Caribb.	0.002	0.940	-0.001	0.976	0.012	0.530	0.021	0.214	-0.015	0.518	0.027	0.534
Other Races	0.009**	0.044	0.003	0.456	0.008	0.102	0.009*	0.086	0.010	0.120	0.017	0.130
Unexplained												
Age	-0.054	1.000	-0.062	0.228	0.072	0.186	-0.034	0.606	0.073	0.436	-0.088	0.490
Age^2	0.143	0.978	0.461	0.144	0.312	0.268	0.322	0.278	0.179	0.686	0.067	0.926
Age^3	0.170	0.862	0.149**	0.022	0.059	0.264	0.156***	0.006	0.071	0.410	0.210*	0.076
Age^4	-0.317	0.818	-0.502**	0.034	-0.381**	0.018	-0.372*	0.092	-0.432	0.114	-0.367	0.378
Single^N	-0.043	0.914	0.037	0.358	-0.053	0.162	-0.040	0.266	0.027	0.676	-0.062	0.482
Married	-0.013	1.000	-0.010	0.904	0.113	0.164	-0.113	0.200	-0.143	0.216	-0.087	0.648
Prev. Married	0.030	0.992	-0.022	0.402	0.010	0.624	0.048**	0.034	0.012	0.724	0.056	0.360
Non-Immig.^{N}	0.571	1.000	0.324*	0.082	0.531***	0.000	0.541***	0.000	0.920***	0.000	0.657**	0.024
Immg. ≤10 yrs	-0.024**	0.010	-0.020	0.264	-0.032**	0.020	-0.032***	0.008	-0.048***	0.000	0.014	0.536
Immg. >10 yrs	-0.026	0.736	-0.001	0.972	-0.002	0.942	-0.003	0.886	-0.021	0.476	-0.127***	0.000
Not HS Grad.^{N}	-0.032	0.734	-0.006	0.818	-0.004	0.836	0.035	0.256	-0.075**	0.046	-0.188***	0.000
HS Graduate	0.067	0.964	0.057	0.130	0.049	0.154	0.025	0.506	0.122**	0.022	0.124	0.158
Some Postsec.	0.098	0.302	0.000	0.998	0.026	0.656	0.078	0.174	0.214***	0.006	0.223*	0.080
Postsecondary	-0.132	0.394	-0.064	0.186	-0.084*	0.068	-0.176***	0.000	-0.244***	0.000	-0.049	0.680
Non-drinker^N	0.054	0.294	0.028	0.324	0.031	0.232	0.072***	0.006	0.061	0.114	-0.011	0.838
Mod. Drinker	0.041	0.830	0.125***	0.002	0.124***	0.002	0.069	0.194	0.101	0.134	-0.076	0.462
Drinker	-0.082	1.000	-0.059	0.438	0.034	0.630	0.007	0.932	-0.144	0.144	-0.151	0.286
Drinker MV	-0.047	0.920	-0.066*	0.076	-0.095**	0.010	-0.103**	0.038	-0.064	0.232	0.087	0.180
Non-smoker^N	0.158***	0.000	0.114***	0.000	0.112***	0.000	0.135***	0.002	0.190***	0.002	0.206**	0.018
Smoker	-0.156***	0.000	-0.053	0.116	-0.121***	0.002	-0.151***	0.000	-0.171***	0.000	-0.311***	0.000
Smoker MV	0.062	1.000	-0.085*	0.086	0.066	0.168	0.091	0.112	0.038	0.648	0.316***	0.006
Eq HH Income	-0.559**	0.010	-0.374**	0.046	-0.643***	0.000	-0.337*	0.052	-0.460*	0.080	-1.271***	0.000
Pov./F. Inscr	-0.196	0.986	-0.032	0.550	-0.002	0.958	-0.081*	0.082	-0.285***	0.000	-0.540***	0.000
White^N	-0.756	1.000	-0.287**	0.038	-0.315***	0.006	-0.455***	0.000	-1.122***	0.000	-1.159***	0.000
Afr./ Caribb.	0.040	0.500	-0.002	0.940	-0.015	0.566	-0.019	0.440	0.080***	0.006	0.099	0.138
Other Races	0.136	1.000	0.087**	0.044	0.120***	0.004	0.168***	0.000	0.160***	0.000	0.131	0.154
Constant	0.609	1.000	-0.187	0.590	-0.442	0.114	-0.468	0.132	1.056**	0.016	2.944***	0.000
N	29480		29480		29480		29480		29480		29480	

Note: * p<0.1, ** p<0.05 and *** p<0.01. ^{N} Denotes reference categories included in the regression for normalization option. Equivalent household income is a categorical variable. Other races include, non-White Hispanics and mixed races.

Table 3.5B Detailed Cross-country Decomposition Estimates for Recent Era / Females: US (2009/12) – Canada (2013)

(RECENT) FEMALES	Oaxaca/Blinder	pv	RIFreg Q10	pv	RIFreg Q25	pv	RIFreg Q50	pv	RIFreg Q75	pv	RIFreg Q90	pv
Overall												
US	26.800***	0.000	19.829***	0.000	21.994***	0.000	25.536***	0.000	30.325***	0.000	35.568***	0.000
Canada	25.526***	0.000	19.698***	0.000	21.646***	0.000	24.439***	0.000	28.234***	0.000	32.785***	0.000
Difference	1.274***	0.000	0.130	0.140	0.348***	0.000	1.096***	0.000	2.091***	0.000	2.783***	0.000
Explained	0.545***	0.000	0.358	0.168	0.531***	0.004	0.522***	0.000	0.483**	0.020	0.588**	0.018
Unexplained	0.729***	0.000	-0.227	0.338	-0.183	0.282	0.574***	0.002	1.608***	0.000	2.195***	0.000
Explained												
Age	0.002	0.396	0.002	0.396	0.006	0.380	0.009	0.376	0.003	0.406	-0.006	0.400
Age^2	0.041***	0.004	0.007	0.536	0.010	0.372	0.026**	0.040	0.073**	0.014	0.114***	0.002
Age^3	0.003	0.240	0.006*	0.092	-0.001	0.678	-0.006*	0.086	-0.002	0.474	0.008	0.210
Age^4	0.064***	0.000	0.052***	0.004	0.071***	0.000	0.077***	0.000	0.039	0.100	0.030	0.348
Single^N	-0.005	0.232	0.008*	0.054	0.008***	0.034	0.003	0.600	-0.009	0.148	-0.021*	0.050
Married	0.000	0.658	-0.002	0.256	-0.001	0.288	-0.001	0.316	0.001	0.512	0.004	0.310
Prev. Married	-0.005	0.358	-0.002	0.670	0.001	0.882	-0.006	0.288	-0.007	0.420	0.000	1.000
Non-Immig.^{N}	0.116***	0.000	0.058***	0.000	0.065***	0.000	0.100***	0.000	0.140***	0.000	0.194***	0.000
Immg. ≤10 yrs	0.037***	0.000	0.028***	0.004	0.020**	0.014	0.036***	0.000	0.039***	0.000	0.065***	0.002
Immg. >10 yrs	0.007	0.238	-0.014*	0.062	0.006	0.390	-0.001	0.898	0.018	0.150	0.007	0.584
Not HS Grad.^{N}	0.013***	0.008	0.001	0.720	0.005	0.106	0.008*	0.062	0.015**	0.022	0.027**	0.010
HS Graduate	-0.002	0.194	0.000	0.974	-0.001	0.458	-0.003	0.216	-0.003	0.284	-0.002	0.538
Some Postsec.	-0.043	0.222	0.051	0.184	0.044	0.252	-0.032	0.448	-0.060	0.284	-0.112	0.174
Postsecondary	0.133***	0.000	0.067***	0.002	0.119***	0.000	0.115***	0.000	0.152***	0.000	0.186***	0.002
Non-drinker^N	-0.067***	0.000	-0.004	0.876	-0.025	0.142	-0.047**	0.012	-0.113***	0.000	-0.193***	0.000
Mod. Drinker	-0.032***	0.000	-0.009	0.520	-0.021*	0.068	-0.029***	0.006	-0.043***	0.000	-0.078***	0.000
Drinker	0.077***	0.000	0.003	0.844	0.033***	0.008	0.065***	0.000	0.105***	0.000	0.152***	0.000
Drinker MV	-0.053	0.544	-0.036	0.826	-0.044	0.674	-0.027	0.768	-0.119	0.338	-0.305***	0.004
Non-smoker^N	-0.143***	0.000	-0.069***	0.006	-0.075***	0.000	-0.109***	0.000	-0.124***	0.000	-0.224***	0.000
Smoker	0.000	0.898	0.000	0.890	0.000	0.900	0.000	0.902	0.000	0.894	0.001	0.898
Smoker MV	0.143***	0.000	0.069***	0.004	0.075***	0.000	0.109***	0.000	0.124***	0.000	0.225***	0.000
Eq HH Income	-0.023**	0.012	0.006	0.188	0.001	0.802	-0.029***	0.004	-0.041***	0.004	-0.050**	0.018
Pov./F. Inscr	0.214***	0.000	0.034**	0.044	0.089***	0.000	0.165***	0.000	0.198***	0.000	0.461***	0.000
White^N	-0.015**	0.034	0.006	0.248	0.016***	0.004	0.001	0.884	-0.012	0.376	-0.035	0.182
Afr./ Caribb.	0.053**	0.016	0.072***	0.000	0.101***	0.000	0.072**	0.018	0.075	0.100	0.088	0.292
Other Races	0.029***	0.002	0.023***	0.002	0.029***	0.002	0.026***	0.008	0.036**	0.024	0.055*	0.060
Unexplained												
Age	-0.222***	0.002	-0.160**	0.016	-0.277***	0.002	-0.080	0.414	-0.364**	0.010	-0.373*	0.078
Age^2	1.154***	0.002	0.815**	0.016	0.849***	0.008	0.450	0.260	1.668***	0.002	2.906***	0.000
Age^3	0.613***	0.000	0.367***	0.000	0.593***	0.000	0.503***	0.000	0.964***	0.000	0.923***	0.000
Age^4	-1.522***	0.000	-1.019***	0.000	-1.265***	0.000	-1.097***	0.000	-2.223***	0.000	-2.931***	0.000
Single^N	0.051	0.132	-0.001	0.990	0.051*	0.078	0.001	0.980	0.059	0.258	0.185**	0.048
Married	-0.096	0.244	-0.075	0.318	-0.094	0.220	-0.040	0.674	-0.156	0.204	-0.135	0.538
Prev. Married	-0.034	0.422	0.031	0.346	-0.035	0.364	0.014	0.772	-0.021	0.740	-0.211*	0.090
Non-Immig.^{N}	0.284**	0.048	0.058	0.758	0.116	0.478	0.606***	0.002	0.329	0.180	0.565*	0.086
Immg. ≤10 yrs	-0.021**	0.014	-0.025	0.118	-0.016	0.172	-0.026*	0.056	-0.024	0.146	-0.014	0.434
Immg. >10 yrs	0.022	0.282	0.062***	0.006	0.029	0.216	-0.008	0.768	0.025	0.566	-0.036	0.458
Not HS Grad.^{N}	0.023	0.422	0.020	0.526	0.086***	0.000	0.074*	0.038	-0.006	0.908	-0.024	0.758
HS Graduate	0.009	0.800	0.042	0.164	0.047	0.130	-0.032	0.434	0.108*	0.064	-0.087	0.342
Some Postsec.	0.127**	0.020	-0.020	0.760	-0.107*	0.080	0.087	0.196	0.121	0.216	0.410**	0.012
Postsecondary	-0.175***	0.000	-0.083	0.100	-0.138***	0.004	-0.173***	0.006	-0.266***	0.004	-0.199	0.176
Non-drinker^N	0.042	0.186	0.029	0.430	0.014	0.666	0.082**	0.022	0.090*	0.078	0.059	0.514
Mod. Drinker	-0.053	0.432	-0.007	0.946	-0.029	0.716	-0.090	0.224	-0.047	0.650	-0.266*	0.086
Drinker	0.034	0.520	0.082	0.250	0.096	0.110	-0.017	0.820	-0.158*	0.064	-0.073	0.536
Drinker MV	-0.067	0.466	-0.117	0.532	-0.085	0.456	-0.068	0.554	0.007	0.952	0.143	0.246
Non-smoker^N	0.071**	0.022	0.056*	0.060	0.085***	0.004	0.115***	0.004	0.106**	0.028	0.061	0.444
Smoker	-0.121***	0.000	-0.071**	0.046	-0.149***	0.000	-0.182***	0.000	-0.163***	0.000	-0.137**	0.044
Smoker MV	0.210***	0.004	0.085	0.236	0.265***	0.000	0.290***	0.002	0.252**	0.042	0.291	0.158
Eq HH Income	-1.022***	0.000	-0.554***	0.002	-1.081***	0.000	-0.882***	0.000	-0.949***	0.000	-1.497***	0.006
Pov./F. Inscr	-0.293***	0.000	-0.092**	0.056	-0.155***	0.004	-0.210***	0.000	-0.222***	0.008	-0.732***	0.000
White^N	-0.866***	0.000	-0.263**	0.012	-0.182*	0.082	-0.833***	0.000	-0.988***	0.000	-1.325***	0.000
Afr./ Caribb.	0.133***	0.000	-0.013	0.516	-0.005	0.832	0.132***	0.004	0.157**	0.016	0.266**	0.044
Other Races	0.023	0.518	0.092***	0.008	0.057*	0.068	0.016	0.708	0.019	0.784	-0.063	0.596
Constant	2.425***	0.000	0.535	0.168	1.148***	0.000	1.941***	0.000	3.291***	0.000	4.488***	0.000
N	34449		34449		34449		34449		34449		34449	

Note: * p<0.1, ** p<0.05 and *** p<0.01. ^{N} Denotes reference categories included in the regression for normalization option. Equivalent household income is a categorical variable. Other races include, non-White Hispanics and mixed races.

Table 3.6 CDECO Decomposition Estimates

	MALES					FEMALES				
	Q10	Q25	Q50	Q75	Q90	Q10	Q25	Q50	Q75	Q90
Canada										
Over time										
Overall Difference	0.23	0.46	0.71	0.82	1.14	-0.01	0.33	0.54	0.87	1.38
	[0.04,0.42]	[0.32,0.60]	[0.59,0.83]	[0.62,1.02]	[0.80,1.48]	[-0.23,0.20]	[0.19,0.47]	[0.37,0.71]	[0.66,1.08]	[1.03,1.74]
Explained	-0.06	-0.04	-0.09	-0.26	-0.32	-0.09	-0.04	-0.15	-0.23	-0.33
	[-0.15,0.03]	[-0.12,0.04]	[-0.18,-0.00]	[-0.38,-0.15]	[-0.48,-0.16]	[-0.17,-0.01]	[-0.13,0.05]	[-0.25,-0.05]	[-0.36,-0.11]	[-0.49,-0.17]
Unexplained	0.30	0.50	0.80	1.09	1.46	0.08	0.38	0.69	1.11	1.72
	[0.12,0.47]	[0.37,0.63]	[0.66,0.95]	[0.86,1.32]	[1.08,1.84]	[-0.15,0.30]	[0.22,0.53]	[0.52,0.85]	[0.88,1.33]	[1.32,2.11]
N	62311					68634				
US										
Over time										
Overall Difference	0.66	0.71	0.83	1.28	1.55	0.49	0.59	0.74	0.83	1.06
	[0.15,1.18]	[0.20,1.21]	[0.34,1.31]	[0.57,1.99]	[0.55,2.55]	[-0.06,0.99]	[0.08,1.10]	[0.11,1.37]	[0.07,1.59]	[-0.06,2.18]
Explained	0.38	0.24	0.1	-0.11	-0.21	0.16	0.04	-0.11	-0.29	-0.48
	[0.13,0.62]	[0.05,0.42]	[-0.09,0.28]	[-0.34,0.12]	[-0.55,0.13]	[-0.08,0.41]	[-0.21,0.28]	[-0.37,0.16]	[-0.57,-0.01]	[-0.89,-0.08]
Unexplained	0.29	0.47	0.73	1.39	1.77	0.33	0.56	0.85	1.12	1.54
	[-0.23,0.81]	[-0.02,0.96]	[0.23,1.24]	[0.64,2.14]	[0.72,2.81]	[-0.17,0.82]	[0.07,1.04]	[0.29,1.41]	[0.45,1.79]	[0.51,2.58]
N	8883					8719				
Cross-country										
Early										
Overall Difference	-0.44	-0.3	-0.02	0.51	1.08	0.02	0.28	0.86	1.96	3.14
	[-0.68,-0.21]	[-0.52,-0.08]	[-0.26,0.23]	[0.17,0.85]	[0.50,1.66]	[-0.29,0.33]	[0.00,0.55]	[0.50,1.22]	[1.47,2.46]	[2.45,3.82]
Explained	0.05	0.05	0.1	0.16	0.31	0.29	0.5	0.66	0.72	0.79
	[-0.26,0.37]	[-0.28,0.37]	[-0.27,0.47]	[-0.31,0.63]	[-0.39,1.01]	[-0.14,0.73]	[-0.01,1.00]	[0.06,1.26]	[-0.13,1.57]	[-0.20,1.77]
Unexplained	-0.5	-0.34	-0.11	0.35	0.77	-0.27	-0.22	0.20	1.25	2.35
	[-0.93,-0.06]	[-0.75,0.06]	[-0.59,0.36]	[-0.27,0.97]	[-0.18,1.73]	[-0.77,0.22]	[-0.78,0.34]	[-0.40,0.80]	[0.33,2.16]	[1.27,3.43]
N	47072					49342				
Cross-country Recent										
Overall Difference	-0.06	-0.21	-0.04	0.64	1.38	0.47	0.48	1.09	1.98	2.68
	[-0.38,0.26]	[-0.49,0.08]	[-0.32,0.24]	[0.21,1.06]	[0.74,2.02]	[0.08,0.85]	[0.16,0.80]	[0.69,1.50]	[1.42,2.54]	[1.81,3.55]
Explained	0.29	0.43	0.56	0.58	0.46	0.48	0.59	0.75	0.73	1.15
	[-0.06,0.64]	[0.13,0.73]	[0.21,0.91]	[0.01,1.15]	[-0.53,1.45]	[0.08,0.87]	[0.11,1.06]	[0.19,1.31]	[-0.02,1.49]	[0.18,2.13]
Unexplained	-0.35	-0.64	-0.60	0.06	0.92	-0.01	-0.11	0.35	1.25	1.52
	[-0.80,-0.10]	[-1.00,-0.27]	[-1.03,-0.17]	[-0.68,0.80]	[0.28,2.12]	[-0.57,0.55]	[-0.66,0.45]	[-0.30,0.99]	[0.34,2.16]	[0.29,2.76]
N	29480					34449				

Note: Quantile effects are shown, with functional 95% confidence intervals under them. Functional refers to the calculation of these confidence intervals, where bootstrap is used to estimate the distribution of the test statistics in their calculation. Overall differences are those between the observable distributions, based on the conditional model.

Conclusion

This thesis investigates three distinct issues on BMI for the purposes of health economics and health policy. It provides a direction towards the use of the self-reported data on BMI, demonstrates the association between BMI and long-term physician costs and analyzes the gap between BMI distributions of Canada and the US both over time and compared to each other. All three chapters have particular policy relevance on the investigated issues. They are valuable contributions to the literature, and they are currently being prepared to be submitted to high-ranking peer-review journals.

The measurement error in self-reported BMI is a well-known issue to researchers. On the premise of inevitability of using self-reported data on BMI, every quantitative researcher in obesity studies face with the same endeavor to correct for it. Most of studies adopt the simple correction method based on ordinary least squares. Courtemanche et al.(2015) propose a new method that could potentially tackle the applicability of correction equations across different datasets better than the simple correction method. Unlike Courtemanche et al.(2015), who could use only one survey in the US to generate their correction equations, we set up to test the performance of this new method over the simple correction method using the Canadian Community Health Survey and the Canadian Health Measures Survey. We compare reduction in mean-squared error, as well as results of sensitivity and specificity analysis to draw our conclusions. We also look at the consequences of correction BMI, when it is used as an explanatory variable. We find that simple correction perform better than the proposed new method in almost every avenue. As for the consequences of correcting BMI when used as an explanatory variable, we find corrections to be unnecessary.

To further pursue this issue, before its submission to a journal, we are planning to conduct some sensitivity analyses in the near future. These sensitivity analyses will demonstrate how to handle outliers in the data before generating correction equations, whether or not the treatment for outliers is necessary or will the untreated data be more favourable to the more recent method.

Our investigation on Chapter 1 led us contemplate certain policy questions that aim to recommend making improvements in health data collection in survey data. While correction equations aim to correct measurement error in SR data, there are also ways to improve the quality of SR data and reduce (if not eliminate) measurement error before the data collection process. First of all, the studies that use DM data often point out the exact brand of the scale used in measurements when describing their data. We see this as an attempt to disclose the precision of the measurements used and compatibility of these precise measurements with any other similar survey data. However, even between the CCHS and the CHMS different models of scales were used by Statistics Canada (Shields, Connor Gorber, Janssen, & Tremblay, 2011). Without knowing the importance of the differences between these scales, we believe that it is unreasonable to expect comparable precise measurements in common household bathroom scales that most respondents obtain their SR responses. Considering that research evidence, (Brennan, Henry, Nicholson, Kotowicz, & Pasco, 2009; Colhoun, Hemingway, & Poulter, 1998; Everson, Maty, Lynch, & Kaplan, 2002; McLaren, 2007; Sobal & Stunkard, 1989), associates lower socio economic status with obesity, a good quality household scale may not be a priority in poorer households. A standard for the household scales can be recommended for the public or enforced in the market. More importantly, surveys do not ask when the individual last measured his /her height or weight, which leaves SR data prone to not only reporting but also recall bias. Hypothesizing that normal weight individuals have much more interest in keeping their form, they might be measuring their weight more often than an obese individual. Public can be informed to frequently measure and record their body measurements. One can also associate social and psychological factors with why an obese individual would avoid scales. Finally, surveys do not consider the fluctuations in an individual's weight throughout the day. Information on the time of the day when the individual usually weights himself/herself and when the measurements are taken by the interviewer should be provided in these surveys. We believe that these additional improvements in survey design would reduce bias in SR data.

Chapter 2 makes use of data in the McMaster Pilot Project to link administrative health care records from Ontario with certain health survey datasets of the Statistics Canada. It builds on three earlier studies which were able to have similar privileges to use the linked datasets to investigate the cost of obesity for Ontario's health care system at individual level. The limitation of these earlier studies has been the limited access to administrative records and therefore focusing on only the short term costs associated with obesity.

The dataset that we use in this study enables us to investigate the physician costs of individuals one year before and ten years after the year of the survey. Using the survey, we observe individuals' personal characteristics, including BMI, and sociodemographic attributes one point in time, but access to long-term administrative records gives us the opportunity to make our cost analysis longitudinal. Basically, the question that this study answers is regardless of changes in individuals' BMI over time, how do the physician costs differ for a person given that he or she had a certain BMI ten years ago. We first look at the relationship between BMI and the average of annual physician costs over these eleven years (AAPC), with and without controlling for age, sociodemographic variables and existing health conditions. Without controlling for any of these potentially endogenous variables gives us a raw picture of the relationship that we are interested in.

By controlling for them, we let the data to tell us how and if the relationship between BMI and the AAPC changes once we account for these endogenous variables. Since we cannot observe the changes in the individuals' BMI throughout these years, we test if the relationship between physician costs and those we categorize as normal weight, overweight and obese is consistent in each of these years. We do this by applying two-part model regression analysis for each year that we have the cost data for. Our results show that higher BMIs are associated with higher long-term physician costs only for aging population and morbidly obese individuals. Our annual cost analysis show that obese females have statistically significant higher costs than overweight females in almost all eleven years, but the same conclusion cannot be drawn for males.

This study employs also novel microeconometric techniques that are not commonly used in this literature. These result in easier to understand relationships between BMI and long-term physician costs through visual representations. We also adopt the two-part model, but provide a small contribution by testing *a priori* assumptions of the model. Generally, two-part model is used with the same model specification in almost all cost of disease studies. We check the adequacy of these priori assumptions by replicating the two-part model using semi-parametric version of the GLM method (Basu and Rathouz, 2005). This method allows for simultaneous identification of link function and flexible variance structure, and therefore eliminates the need for having priori assumptions. In the end, we confirm that log link and gamma distribution specification in GLM regression in two-part model is adequate for health care cost modelling.

The results of this study suggest that being overweight or moderately obese is not necessarily associated with higher long-term physician costs than the normal weights. The 95% confidence intervals in Figures 2.1A and 2.1B show that physician costs corresponding to a higher

BMI levels are not necessarily different from those associated with lower BMI levels, except in females ages 46 to 65. Among males, ages between 30 and 45, we see an increase in the long-term physician costs with the increase in BMI after overweight threshold and among those with ages between 46 and 65 we see the same after the obesity threshold. Even so, the difference in cost seems to be less $100 in average over 11 years in both cases. On the other hand, it is evident that morbid obesity is associated with higher physician costs in both sexes, but the BMI distribution of the population show that these are relatively very small groups in the population.

The results of this chapter have policy relevance in terms how physicians are being paid to provide service to obese females or morbidly obese individuals. Especially relevant for the remuneration of general practitioners, the interaction between obesity and sex and severity of obesity can be included as extra dimensions to provide weight in adjusting how physicians are paid for the patients in their rosters.

The last chapter is on decomposition of BMI distributions of Canada and the US at mean and selected quantiles. We use nationally representative survey data from each country that span roughly the first decade of 2000s. Given the increasing interest in trying to understand what is associated with the observed increase in BMI in recent times, we choose this setting to look at the differences in BMI distributions both over time within each country and across Canada and the US at two time periods.

We adopt two relatively recent distributional decomposition methods (Chernozhukov, Fernandez-Val, & Melly, 2013; Firpo, Fortin, & Lemieux, 2009), which are - to our knowledge - not used in conjunction in this literature before. The comparison of the results of the two methods increases the validity of our results, along with the attention to detail we paid in calculation of associated statistical inferences.

We find that, in over time analysis the difference that we observe between the groups is mainly contributable to the unexplained part of the decomposition; meaning related to the differences in returns that each group receives from endowments towards their BMI. In males, this is mostly due to omitted variables that we do not control in the models. In females, age, immigration status, equivalent household income and experiencing food-insecurity or living below poverty line are the main covariates in this unexplained part. In cross-country analysis, we find both explained and unexplained parts to be at play in contributing to the overall difference between the US and Canadian populations at different parts of their BMI distributions. At mid to the lower end of the tail, differences can be explained by differences in distribution of endowments, but in higher end of the distribution the differences are mainly coming from the unexplained part. We find evidence that immigration status, race and aging are contributing factors among males. Among females, there is more evidence for the role of socioeconomic inequalities as education and living below poverty or experiencing food-insecurity are the main culprits among the covariates that we control for in the models.

The results of chapter 3 indicate that changes in covariates are not associated with the increase in BMI levels that we observe both over time in each country and between the US and Canada. Instead, these differences are related to the returns from both controlled and omitted covariates. The pathway of how these covariates are related to BMI is a question for future studies.

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