

UC Irvine

UC Irvine Electronic Theses and Dissertations

Title

The Impact of Weather on Children's School Travel Mode: Evidence from the 2009 National Household Travel Survey

Permalink

<https://escholarship.org/uc/item/22v3p99f>

Author

Han, Yang

Publication Date

2014

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA,
IRVINE

The Impact of Weather Conditions on Children's School Travel Mode:
Evidence from the 2009 National Household Travel Survey

THESIS

submitted in partial satisfaction of the requirements
for the degree of

MASTER OF SCIENCE

in Civil Engineering

by

Yang Han

Thesis Committee:
Professor Jean-Daniel Saphores, Chair
Professor Michael G. McNally
Professor Douglas Houston

2014

DEDICATION

To

My parents, my husband and all my dear friends,

Thanks for your unconditional love and support.

TABLE OF CONTENTS

	Page
LIST OF FIGURES	v
LIST OF TABLES	vi
ACKNOWLEDGEMENTS	vii
ABSTRACT	viii
CHAPTER 1. INTRODUCTION	1
CHAPTER 2. LITERATURE REVIEW	3
CHAPTER 3. DATA	15
3.1 <i>NHTS Data</i>	15
3.2 <i>NOAA Climatic Data</i>	16
3.3 <i>Explanatory Variables</i>	19
CHAPTER 4. METHODOLOGY	24
4.1 <i>Models</i>	24
4.2 <i>Diagnostics</i>	25
CHAPTER 5. RESULTS	27
5.1 <i>Binary Logit Model for Children's To-school Travel</i>	27
5.1.1 <i>Initial To-School Model</i>	27
5.1.2 <i>Revised To-School Model</i>	35
5.2 <i>Binary Logit Model for Children's From-school Travel</i>	39
5.2.1 <i>Initial From-School Model</i>	39
5.2.2 <i>Revised From-School Model</i>	48
CHAPTER 6 CONCLUSIONS	51
6.1 <i>Overview</i>	51
6.2 <i>Limitations and Future Research</i>	52
REFERENCES	54
APPENDIX A: FIGURES	59

LIST OF FIGURES

	Page
Figure 1: Standardized Pearson Residuals for To-School Model	31
Figure 2: Deviance Residual for To-School Model	32
Figure 3: Pregibon Leverage for To-School Model	33
Figure 4: Deviance Residuals	34
Figure 5: Differences of Chi-square	34
Figure 6: Pregibon's dbeta	34
Figure 7: Standard Pearson Residuals for From-School Model	43
Figure 8: Deviance Residuals for From-School Model	44
Figure 9: Pregibon's Leverage for From-School Model.....	45
Figure 10: Difference of Chi-Square for From-School Model	46
Figure 11: Difference of Deviance for From-School Model	46
Figure 12 Pregibon's dbeta for From-School Model	46

LIST OF TABLES

	Page
Table 1: Summary of Selected Papers	11
Table 2: Summary of Weather Data for To-School Model	18
Table 3: Summary of Weather Data for From-School Model.....	18
Table 4: List of Variables	19
Table 5: Summary Statistics.....	22
Table 6: To-School Initial Model Results	28
Table 7: Specification Error Test (Linktest) of To-school Model	30
Table 8: Good of Fitness (fitstat) of To-school Model.....	30
Table 9: Standardized Pearson Residuals for To-School Model.....	31
Table 10: Deviance Residuals for To-School Model	32
Table 11: Leverage for To-School Model	33
Table 12: To-School Best Model Results.....	36
Table 13: From-School Initial Model Results.....	40
Table 14: Specification Error Test (Linktest) for From-School Model.....	42
Table 15: Goodness of Fit (Fitstat) for From-School Model	42
Table 16: Standardized Pearson Residual for From-School Model.....	43
Table 17: Deviance Residuals for From-School Model.....	44
Table 18: Pregibon's Leverage for From-School Model	45
Table 19: From-School Best Model Results	47

ACKNOWLEDGEMENTS

First, I would like to sincerely thank my graduate advisor Professor Jean-Daniel Saphores for his guidance and persistent support. His knowledgeable advice, patience, and encouraging attitude helped me accomplish this work.

Second, I would like to sincerely thank my committee members: Professor Michael G. McNally and Professor Douglas Houston. I learned a lot from you; thank you for your very valuable input.

Lastly, I am grateful to Suman Kumar Mitra, who is a Ph.D. candidate in Transportation Science. He gave me a lot of valuable suggestions. Thank you very much for your support.

ABSTRACT

The Impact of Weather Conditions on Children's School Travel Mode:
Evidence from the 2009 National Household Travel Survey

by

Yang Han

Master of Science in Civil Engineering

University of California, Irvine, 2014

Professor Jean-Daniel Saphores, Chair

Intuitively, weather conditions may prevent people from relying on walking for different trip purposes. However, to-date this topic has not attracted a lot of attention from researchers. The purpose of this thesis is to start filling this gap based on data from the 2009 National Household Travel Survey (NHTS). I estimated binary regression models to analyze trips to and from school for children aged 5 to 16 in several areas of the United States. I found that snowfall and precipitation are statistically significant for to-school trips, but not for from-school trips. The variable that captures parental concerns about poor weather has explanatory power both statistically and practically: parents who consider harsh weather an issue for children's active transportation are less likely let their children walk or bike to school. However, in my from-school model, none of the factors related to the weather are significant.

Future studies could assign weather data at a finer temporal scale (hourly instead of daily). Since parents are concerned about poor weather, cities may consider cleaning sidewalks (removing snow) and building more shelters along school routes to facilitate active travel.

CHAPTER 1. INTRODUCTION

Many variables influence the choice and level of use of transportation, including socio-demographic, geographical and environmental factors. This thesis inquires whether weather should also be considered for trips analyses with a special attention to children's active commuting to school.

The main modes of transportation in the U.S.A. are private vehicles, public transit and walking, which cover 95% of individual trips in the United States. Car trips represent over 80% of all trips; another 10% are walking trips, and 2% involve public transit (NHTS 2009). A number of papers have analyzed the relationship between the weather and transportation (e.g., Arana *et al.*, 2013; Cools *et al.*, 2010; Kilpelainen *et al.*, 2006), but most of these studies are concerned with the relationship between traffic accidents, vehicle speed, traffic volume, road safety and weather conditions. A few papers were also interested in travel mode, especially for children going to school (e.g., see Mitra *et al.*, 2012 and Table 1). Walking and biking are much more sensitive to weather conditions. In this context, the goal of this thesis is to study the influence of weather conditions on school travel mode choice for selected areas in the U.S. where weather is likely a factor.

Active commuting (walking or biking) to school has been advocated by the government to reduce childhood obesity in the U.S. However, a number of studies reveal a decrease in children's active school travels over time (McDonald, 2007, Buliung, Mitra and Faulkner, 2009; Grize *et al.*, 2010). McDonald (2011) in particular pointed out that the U.S. has been experiencing a sharp decline in children using active modes to commute to school. This issue has attracted much research. One common finding is the importance of the distance from home to

school (McDonald, 2007; Yeung, Wearing, and Hills., 2008; Mitra, Buliung, and Roorda., 2010). Some other studies reported that land use characteristics, such as population density, and mixed-use land use impact travel patterns (McMillian 2007; Larsen *et al.*, 2009; Clifton *et al.*, 2011) Several studies point out that parental attitudes and concerns about traffic and safety affect how children travel to schools (Lam 2001, 2005), as well as concerns about gangs and crimes (Meyer and Avi, 2002). I found only one study that considered parental concerns for poor weather (Seraj *et al.*, 2012).

This thesis incorporates several weather variables, such as maximum and minimum temperature, snowfall, precipitation and fog. I hypothesize that children are less likely to walk or bike to and from school in poor weather like heavy rain, snow, high or very low temperatures. Since parental concern have been found to have a strong impact on children's school travel modes (Kerr *et al.*, 2006), I also hypothesize that greater parental concerns about the weather decrease the likelihood that children will walk or bike between home and school.

In Chapter 2, I briefly review some relevant papers on children's travel modes. In Chapter 3, I describe the data used to estimate my models, and Chapter 4 summarizes my modeling methodology. In Chapter 5, I present my results, before concluding and suggesting avenues for future research in Chapter 6.

CHAPTER 2. LITERATURE REVIEW

Children's active travel to and from school has dramatically declined in the past few years in most countries around the world. This phenomenon has been observed in prior studies of children school travel modes. Using multivariate regression applied to data from 1994, 200, and 2005, Grize et al. (2010) conducted a time trend analysis of the relationship between active transportation to school and associated factors among Swiss school children. Results reveal that more than 70% of Swiss children walked or biked to school. However, in urban areas, the percentage of children biking to school went down while motorized transportation increased since 1994. Distance to school, a major factor in the selection of children's school travel mode, did not change significantly over time. Meanwhile, the use of bikes declined and the number of vehicles per household rose. However, the data analyzed only provided limited information about the factors that impacted children's school travel mode choice (Grize *et al.* 2010).

Buliung Mitra and Faulkner (2009) studied active school transportation in the Greater Toronto Area (GTA), Canada, with particular attention to space and time trends. They analyzed data from the Transportation Tomorrow Survey (TTS). They report that the proportion of active school transportation (walking and cycling) across the GTA decreased between 1986 and 2006 while car trips in the morning increased. In addition, more walking takes place in the afternoon, which appears to be more common for younger children.

McDonald (2007) conducted a trends study of active school travel in U.S. schoolchildren from 1969 to 2001 using data from the 1969, 1977, 1983, 1990, 1995 and 2001 National Personal Transportation Survey and National Household Transportation Survey. Her binary logit models (estimated to assess the impacts of individual, household, and trip characteristics) show

that from 1969 to 2001 the steepest decrease in walking and biking affected elementary students, although they had the highest rates of active transportation to school in most years. Both girls and boys equally experienced this decline. Minority students were twice as likely to actively commute to school as Caucasians. Moreover, travel times of children walking to school have remained relatively constant during the study period ranging from a low of 10 minutes in 1990 to a high of 12.7 minutes in 2001. As in other studies, trip distance had the strongest impact on children's active school travels.

In contrast, active transportation in Australia dramatically increased between 2004 and 2006 among children and adolescents (Hume *et al.*, 2009). Most parents were satisfied with neighborhood design and infrastructure, but a large proportion of parents reported concerns about traffic and road safety. Children with many neighborhoods friends were more than twice as likely to engage in active transportation compared with other children. Adolescents of parents concerned about traffic lights and pedestrian crossings were less likely to encourage their children to actively commute. Moreover, children of parents who think it is too dark and cold in the winter and too hot in the summer to spend time outside were less likely to commute actively to and from school. Limitations of this study include a relatively small sample size (121 children and 188 adolescents) and limited variability in some explanatory variables.

More recently, Mitra and Buliung (2014) analyzed the impacts of neighborhood environment and household travel interactions on school travel behavior. Their data came from different sources, including the 2006 Transportation Tomorrow survey, from the Toronto Transit Commission. Their results indicate that the built environment impacts the choice of children's active school travel mode. Neighborhoods with no major streets going directly to schools and higher mixed land-use foster walking, and so do urban areas with safe, attractive and walkable

neighborhoods. This study also found a relationship between a child's school travel mode and travel characteristics of other household members: the availability of an adult at school time encourages chauffeuring to school. However, in this study, some spatial variations in mode-choice behavior were correlated with unobservable characteristics likely shared among neighboring households, so some of these results may not be robust.

Other studies also report that the built environment influences parental attitudes. If their home is located in a neighborhood with lower traffic and better walkability, parents are more likely to let their children bike or walk to school (Napier *et al.*, 2011).

Hsu and Saphores (2013) focused on the effects of parental gender and attitudes on children's school travel modes and parental chauffeuring behavior in their analysis of 2009 National Household Travel Survey add-on data from California. They found that the attitudes of mothers matter more for children's active commuting to school than the attitudes of fathers. Mothers are more likely to have concerns about traffic along school route, which in turn discourage their children to walk or bike to school and increase their chauffeuring behavior. Moreover, even though parental attitudes significantly influence parental chauffeuring behavior, Hsu and Saphores (2013) found "the ability to explain the gender chauffeuring gap is limited" because the data they analyzed had information only about one parent for each household, making it impossible to understand the parental decision-making process regarding how children commute to school and who is responsible for chauffeuring them.

Badri *et al.* (2013) analyzed children's active school travel mode in Abu Dhabi, using data from a survey conducted by the Abu Dhabi Education Council (ADEC), the Department of Transportation – Abu Dhabi (DTAD) and the Health Authority in Abu Dhabi (HAAD). Using ANOVA, they tested 23 hypotheses on their sample of 1,145 students aged 14 to 18 years. They

found that only 9.4 percent of children commute to school by walking or biking and fewer than 15 percent of school children who live within two kilometers of school actively commute to school. Around 45 percent of all school-aged children are chauffeured to school by their parents, many of which appear to be concerned by road safety.

Using the Healthy Neighborhoods dataset, Leslie *et al.* (2010) investigated the impact of gender differences on active commuting to and from school among Australian adolescents. They found that females are generally less active than males (they were more likely to walk or be chauffeured while males were more likely to bike to school). They also point out that both boys and girls were more likely to actively travel to school if they knew there were recreational facilities (playgrounds, parks or gyms) close to home. However, this study used self-reported measures of distance from home to school, and did not collect information about parental attitudes, safety concerns, parental work patterns and work travel mode.

According to Seraj *et al.* (2012), older children are more likely to use non-motorized modes of transportation than younger children, and age is more related to bicycle use than to walking. In general, higher household income and vehicle ownership is associated with a greater tendency to use automobiles and a lower utility for walking or biking. Unsurprisingly, students in zero-vehicle households with low family incomes are more likely to actively travel to school (McDonald, 2008; Yarlagaadda and Srinivasan, 2008; Rodriguez and Vogt, 2009; Zhu and Lee, 2009).

In their study of 3,451 US adolescents aged 12 to 17 from the 2005 California Health Interview Survey, Babey *et al.* (2009) reported that males and Latinos from lower-income families were more likely to walk or bike to school. They also found that urban youths attending public school and living closer to school were more likely to actively commute to school.

Students whose parents do not escort them after school and those whose parents have little idea about their whereabouts after school were also more likely to commute actively. According to their results, adolescent active commuting is not related to parental walking and perceived neighborhood safety.

Yoon, Doudnikoff, and Goulias (2011) conducted a spatial analysis of propensity to escort children to school in Southern California using 2001 post-census travel survey data. They included accessibility measures and population density in their binary logit model to account for the effects of spatial characteristics around schools and to identify the spatial distribution of travel mode choices. They found that, although spatial variables are significantly associated with children's independent travel to school, changing just land use and neighborhood accessibility around schools was not very likely to change children's commuting modes. However, children's independent travel by active modes is more related to population density and accessibility than by other modes. Other studies that addressed parental escort behavior also indicate that mothers are more likely than father to escort their children. (Schwanen, 2007; Liu, Murray-Tuite, and Schweitzer. 2012)

A study conducted by Sidharthan *et al.* (2011) in Southern California shows that an accessible neighborhood (terms of retail employment) is negatively associated with school bus mode utility. Spatial interactions statistically influence children's active commuting to school. According to them, households located close to each other may influence each other's behavior and tend to have the same choice of travel mode.

Also in Southern California, He (2011) studied links between school quality and location with school mode choice in Los Angeles based on the 2001 Post Census Regional Household Travel Survey. Results do not show a strong correlation between school quality and

walking and biking. However, they imply a strong relationship between school location and bus mode choice for 7th to 12th grade students.

In an earlier study, Braza, Shoemaker and Seeley (2004) investigated neighborhood design and level of active travel to elementary schools in 34 California communities. Their findings support their hypothesis that walking and biking are more common in denser neighborhoods and for children attending smaller schools, but they do not support the hypothesis that students walk more to schools in neighborhoods with high street network connectivity. Because schools in this study were self-selected, their findings may not be generalized to California schools. Moreover, their sample is relatively small and multicollinearity is a problem.

In Alachua County (Florida), Ewing, Schroeer and Greene (2004) focused on the relationship between school location and student travel modes. They analyzed data from two travel diary surveys conducted by the Gainesville Metropolitan Transportation Planning Organization and the Florida Department of Transportation. Their results indicate that students with shorter walking and biking times to and from school are significantly more likely to walk and bike. In addition, a higher proportion of arterials and collectors with sidewalks foster active commuting to and from school. The more accessible the location, the less attractive the school bus is relative to other modes, including driving.

Only a few studies investigated the impact of weather on children active school commuting. Home-to-school trips by 11-12-year old children in Toronto, Canada, were examined by Mitra and Faulkner (2012) using data from the 2006 Transportation Tomorrow Survey. After estimating binomial logistic regressions to explain non-motorized (walking or biking) versus motorized (i.e., private automobile, transit and school bus) modes for school trips, they found that seasonal climate and weekly weather conditions do not have a significant influence on

children's school travel mode choice in Toronto. As expected, distance between home and school was significant and important as living closer to school encourages students' active school transportation. Mitra and Faulkner (2012) also pointed out that students living in inner suburban neighborhoods walked to school less. One limitation of their study, however, is that they relied on weekly weather data instead of on weather data for the day of each trip.

Although many studies focused on the environment, safety, and cost of the travel, few have examined whether weather factors affect people's travel mode choices. Although policymakers cannot affect whether conditions, these conditions should not be ignored for models to be well specified. Moreover, understanding the relationship between weather and travel mode choice can better help planners and engineers predict public transit ridership, encourage walking or biking to work or school by improving maintenance on walkways and bikeways during cold weather days, and increase highway safety when weather conditions are challenging. However, most of the published studies I found focus on how adverse weather influences traffic volume, vehicle speed, traffic safety, public transit ridership and the transportation infrastructure, and very few examined how weather conditions affect travel mode choice, especially for school children.

One exception is Kilpelainen and Summala (2006), who conducted a study of how harsh weather and traffic weather forecasts impact driver behavior in Finland based on answers from 1437 drivers of passenger cars, vans, and trucks. Using ANOVA and a binary logit model, they found that people who are older, female, have low recent driving experience, and planning a long trip on poor local roads are more likely to acquire weather information. Drivers who acquire this type of information are more like to change their travel plans compared to others. Moreover, daylight and snow conditions significantly influence traffic flow speeds.

In another weather-related study, Arana, Cabezudo and Penalba (2014) studied the association between weather conditions and the number of public bus trips made for leisure, shopping and personal business in Gipuzkoa, Spain. After analyzing 35 million trips using multivariate regression, they found that wind and rain could discourage people from taking trips while a temperature rise would have the opposite effect. In general, more trips happened on days with no rain, gentle wind and warm temperatures.

Finally, a relatively recent study by Sabir, Koestse and Rietveld (2008) analyzes micro-level information from 1996 with a focus on transport behavior and weather conditions in the Netherland. Results from a multinomial logit model show that in extremely low temperatures, people who prefer walking and biking in warm temperatures would switch from biking to driving and public transit. Compared to normal temperatures (between 0°C and 10°C) the probability of using a bicycle decreases by 8.4% when temperatures are very low (below -8°C) and by 5.5% when temperatures are between -8°C and 0°C. Strong winds discourage the use of bicycles and increase car use.

Table 1 presents a summary of selected relevant papers.

Table 1: Summary of Selected Papers

Authors	Data & Location	Method	Main Findings
Arana, Cabezudo, and Penalba. (2014)	35 million trips in Gipuzkoa, Spain	Multiple linear regression	Wind and rain can discourage people from making trips, while a temperature rise could result in an increase in the number of trips; in general, more trips happen on days with no rain, gentle wind and warm temperatures.
Babey <i>et al.</i> (2009)	2005 California Health Interview Survey; 3451 children aged 12-17	logistic regression	Males, Latinos from lower-income families are more likely to commute actively; attending public school, living in urban areas and living closer to school are more likely to encourage students to walk or bike; adolescents without an adult escort after school and those whose parents are not concerned about the whereabouts of their children after school are also more likely to actively commute; adolescent active commuting is not related to parental transportation modes and awareness of neighborhood safety.
Badri <i>et al.</i> (2012)	1145 parents whose children attended K to 12 grades, aged 4 to 18	ANOVA	In Abu Dhabi, only 9.4% of children commute actively to school; less than 15% of students who live within two km from school prefer to walk or bike; ~45% of all school-aged children are chauffeured to school by their parents; parental chauffeuring behavior is encouraged when parents have concern about their children's safety; increasing parental worries about safety is hampering the use of active modes.
Braza, shoemaker and Seeley. (2004)	1990 U.S. census data, 1995 TIGER; 2993 students	Descriptive statistics, pairwise correlations, & multivariate regression	Active commuting to school rates are higher in denser neighborhoods and for smaller schools.
Builiung, Mitra and Faulkner (2009)	Transportation Tomorrow Survey (TTS) Greater Toronto Area, 11,736 - 35,300 school trips of children aged 11 to 15	Cochran – Armitage test, Chi-square test	Active school travel (walking and cycling) across the GTA has decreased between 1986 and 2006, and automobile mode share in the morning has been increased; more walking occurs in the afternoon, and is more common for younger children.

Cools <i>et al.</i> (2010)	586 respondents in Brussels, Belgium	Pearson chi-square independence tests	The type of weather matters and has different degrees of influence on travel mode choices; the influence of different weather conditions is highly dependent on trip purpose.
Ewing, Schoreer, and Greene. (2004)	Gainesville Metropolitan Transportation Planning, Florida Department of Transportation, Alachua Gainesville, Florida; 15,980 trips; 3,815 persons; 2,140 households.	Multinomial logit model, nested logit model.	Students with shorter commute times to and from school are significantly more likely to walk and bike; a higher proportion of arterials and collectors with sidewalks fosters active transportation between home and school.
Grize <i>et al.</i> (2010)	Swiss Microcensus on travel behavior (1994, 2000, 2005); 4244 children aged 6 to 14	Pairwise correlations, Multiple regression	A significant decrease in the proportion of children biking to school appeared with a dramatic increase of the automobile mode share for children commuting between 1994 and 2000; during the same time the numbers of car per household rose while bike use decreased.
He (2011)	2001 Post Census Regional Household Travel Survey (RHTS) of Los Angeles and 2001 academic performance index (API); 2,967 school trips of children aged 5 to 18	Multinomial logit	Travel distance, number of household vehicles and age are the three main factors on non-motorized travel modes to and from school; school quality and residential environment had no significant impact on active transportation modes for children's attending kindergarten to sixth grade; distance from home to the nearest high school significantly raised the likelihood that students who attended seventh to 12th grades go to school by a bus instead of a private vehicle.
Hsu and Saphores (2013)	2009 NHTS California add-on; 1642 observations	Binary logit, multinomial logit, generalized ordered logit.	Female parents are more likely to have higher concerns about traffic amount along the route to school, which in turn decrease the likelihood that their children will commute to school by walking or biking; mothers are more likely than fathers to chauffeur their children.

Hume <i>et al.</i> (2009)	Children living in active neighborhoods (Australia); 188 adolescents and 121 children	t-test, chi-square test, logistic regression	Most parents are satisfied with neighborhood design and infrastructure, but a large proportion of parents report concerns about traffic and road safety; active commuting significantly increased between 2004 and 2006 among children and adolescents; children with many friends in school-home neighborhood are more likely to walk or bike to school compared to other children; parents who express concerns about a lack of traffic lights or crossings availability are only half as likely to encourage their children to actively commute; those with a positive perception of the number of pedestrian crossings in their neighborhood are more likely to let their children walk or bike to school; parents who think it is too dark and cold in the winter and too hot in summer to spend time outside are less likely let their children do travel actively to or from school.
Kilpelaine and Summala (2006)	1437 drivers in Finland, University of Helsinki and the FINNRA	Binary logit , ANOVA	Low recent driving experience, old age, females, a long trip or poor local road conditions encourage drivers to acquire weather information; drivers who acquired information reported more changes to their travel plans; daylight and snow significantly impacts traffic flow speeds
Leslie (2010)	Healthy neighborhoods dataset, Australia; 2961 observations; 483 primary schools	Binary logit	Boys are generally more active than girls; both genders are more likely to walk or bike to school if they are aware of recreational facilities (playgrounds, parks or gyms) in their home neighborhood; females are more likely to walk or be driven to school while males are more likely to bicycle.
McDonald (2007)	6000 households in 1969, 4608 children in 1977, 1670 children in 1983, 4824 children in 1990, 9898 children in 1995 and 14,553 children in 2001 National Personal Transportation Survey; Children aged 5 to 18	Binary logit	Distance from home to school has increased over time, which explains half the decline in active school travel across survey years; distance has the strongest influence on children's school travel mode; active commuting by elementary students significant decreased between 1969 and 2001; the decline in walking to school affected boys and girls equally; minority students are more likely to walk to school; for those who walk, travel times have remained relatively constant during the study period; walking and biking travel times increase slightly with the age of students; students in rural areas are less likely to walk or bike to school.

Mitra and Buliung (2014)	2006 Transportation Tomorrow Survey; 945 observations	Multinomial logit	Built environment near home and school is associated with the decision to have children walk to school; availability of adults may encourage chauffeuring behavior.
Mitra and Faulkner (2012).	2006 Transportation Tomorrow Survey; Environmental Canada customized climate search; 2520 trips of children aged 11 to 12	Logistic regression	Seasonal climate and weekly weather conditions are not significantly associated with choice of school travel modes in Toronto; distance between home and school has the strongest impacts on travel mode; students living outside of urban area are less likely to walk to school.
Sidharthan <i>et al.</i> (2011)	California add-on sample of the 2009 NHTS (LA-Riverside-OC); 1,192 children aged 5 to 15	Probit	Actions and choices of other individuals and households who are living in the same spatial area have a significant influence on children's school travel mode choice.
Yoon, Doudnikoff and Goulias. (2011)	2001 post census travel survey conducted for SCAG, Southern California; 3,483 children under 16	Binary logit	Children's travel by active modes is related to population density and to accessibility; it is also significantly associated with mother's working and with their location.

CHAPTER 3. DATA

The data used in this study come from two sources: travel data come from the 2009 National Household Travel Survey (NHTS) and weather data from the National Oceanic and Atmospheric Administration (NOAA).

3.1 NHTS Data

From the 2009 NHTS data, I obtained travel data as well as household socio-economic characteristics, school travel modes, and parental concerns. This dataset provides a unique opportunity to study parental attitude regarding children's school travel modes and concerns about the weather. I focused on four areas: 1) the Bay area in Northern California; 2) the Dallas-Fort Worth area in Texas; 3) Rochester and Buffalo in New York State; and 4) the New York-Long Island area. I selected these areas because they offer substantial weather variations during the year.

A total of 38,469 households in these four areas participated in the 2009 NHTS. Of these, 3,139 respondents gave information about their to-school travel modes, but I kept only the 1,648 participants whose home is less than 2 miles from school since students who are more than 2 miles away from school are not likely to walk to or from school (Nelson *et al.*, 2008).

Among respondents within 2 miles of school, 1,157 filled a travel diary. After removing records with incomplete information and merging in weather data, I was left with 827 observations for the to-school model. Of those, 371 children were driven to school on the survey day, 225 took public transit, and 223 biked or walked to school.

From travel diary data, 3,134 children provided their from-school travel mode; of those, 1665 lived within 2 miles of school. After combining with weather data and removing incomplete observations, I was left with a sample of 838 observations for the from-school travel mode study. On their survey day, 375 children were driven by a parent; 230 children used public transit to get home; 226 children walked or biked home; and 7 used another form of transit.

3.2 NOAA Climatic Data

The National Oceanic and Atmospheric Administration (NOAA) provides comprehensive weather data on its website. Weather data for my study areas were obtained from NOAA and merged with the NHTS travel survey data in my sample. I focused on six weather variables: snowfall, rain, fall, fog, maximum temperature and minimum temperature on the survey day.

All temperatures were measured in degree Celsius (C). I hypothesized that only harsher weather conditions matter for commuting to school so I created new variables to capture daily maximum temperatures above 30 C or below 10 C, and minimum daily temperatures above 20 C or below 0 C.

After cleaning the data, of the 24 observations from the Buffalo area, 11 trips were made during raining days; two trips during snowy days; four days had snow depth; nine trips were made when the maximum temperature was under 10 C and six trips were made when the minimum temperature was under 0 C.

Of 27 trips in Rochester, 14 took place during rainy days, four were made during snowy days, five days had some snow depth, 10 trips were made on days with a maximum temperature under 10 C, 1 trip was made on a day with a minimum temperature over 20 C, 8 trips on days with a minimum temperature under 0 C, and 17 trips had fog.

My dataset had 306 observations from the New York City area. It included 104 trips during rainy days, 22 with snowy conditions, 36 with cumulated snow on the ground, 33 during hot days, 242 trips during cold days (maximum temperature under 10 C or minimum temperature below 0 C), and 112 trips on foggy days.

Dallas did not have snowy days for the 273 observations in my sample; 35 of them occurred on rainy days; 196 trips took place during hot days (maximum temperature above 30 C or minimum temperature above 20 C); 41 trips took place in cold weather (maximum temperature below 10 C or minimum temperature below 0 C); and 30 trips were recorded during foggy days.

Similarly, San Francisco had no snowy day and no day with a minimum temperature above 20 C or below 0 C during the survey period; it had 158 trips on rainy days; 10 trips on hot days, 4 trips on cold days, and 74 trips on foggy days.

Overall, 203 trips were made on rainy days, 28 trips took place in a snowy day, 45 trips happened on a day with cumulated snow on the ground, 240 trips were on hot days (122 with a maximum temperature over 30 C and 118 with a minimum temperature above 20 C), 320 were on cold days (166 with a maximum temperature under 10 C and 154 with a minimum under 0 C). In addition, 246 out of 827 trips took place on foggy days. Data are presented in Table 2.

For the from-school travel mode analysis, I collected weather data for 838 observations. These data are very similar to the to-school travel data. They are summarized in Table 3.

Table 2: Summary of Weather Data for To-School Model

	Obs	PRCP	Snow	SNWD	TMAX>=30	TMAX<=10	TMIN>=20	TMIN<=0	Foggy
SF	197	39	0	0	10	4	0	0	74
NYC	306	104	22	36	12	131	21	111	112
Dallas	273	35	0	0	100	12	96	29	30
Buffalo	24	11	2	4	0	9	0	6	17
Rochester	27	14	4	5	0	10	1	8	13
Total	827	203	28	45	122	166	118	154	246

Table 3: Summary of Weather Data for From-School Model

	Obs	PRCP	Snow	SNWD	TMAX>=30	TMAX<=10	TMIN>=20	TMIN<=0	Foggy
SF	200	40	0	0	10	4	0	0	75
NYC	310	104	22	35	12	133	21	113	113
Dallas	277	35	1	0	101	13	97	30	30
Buffalo	24	11	2	4	0	9	0	6	17
Rochester	27	14	4	5	0	10	1	8	13
Total	838	204	29	44	123	169	119	157	248

3.3 Explanatory Variables

I considered several groups of variable in my to- and from-school models. Given the focus of my study, weather conditions (see above) are my primary independent variables. Children’s variables include age and gender. For land use (Larsen *et al.*, 2009; Mitra *et al.*, 2010; Clifton *et al.*, 2011), I considered density and urbanization. For parental attitudes, I included concerns about traffic volume, vehicle speed and weather (Hsu and Saphores, 2013). My household socio-economic characteristics include parental age, education level, and work status among other variables (Zhu and Lee 2009; Panter *et al.*, 2010). Moreover, I thought that parental travel mode choice may impact children’s travel behavior so I also included variables on parents’ commuting patterns, in addition to standard socio-economic variables.

Table 4: List of Variables

Variable	Meaning
Parental socio-demographic characteristics:	
P_1829	Age of surveyed parent is 18-29
P_3044	Age of surveyed parent: 30–44
P_4559	Age of surveyed parent: 45–59
P_60pl	Age of surveyed parent: >60
P_edulh	Parental education < high school
P_eduh	Parental education: high school
P_edusc	Parental education: some college
P_eduba	Parental education: bachelor degree
P_edugr	Parental education: graduate degree
self_emp	Parent is self-employed
partime	Parent work status: part time
disttowk	One-Way distance to work(mi)
Parental level of active/transit transportation	

P_wkcar	Transit mode to work last week is car
P_wktransit	Transit mode to work last week is public transit
P_wkoth	Transit mode to work last week is other
P_wkwlkbk	Transit mode to work last week is walking or biking
P_nwalktrp0	Walk trips last week: 0
P_nwalktrp1	Walk trips last week: 1-7
P_nwalktrp2	Walk trips last week: >7
P_nbiketrp0	Bike trips last week: 0
P_nbiketrp1	Bike trips last week: 1-2
P_nbiketrp2	Bike trips last week: >2
Parental attitudes	
schdistno	Distance to school: no concern
schdistye	Distance to school: have concern
schspdno	Traffic speed: no concern
schspdye	Traffic speed: have concern
schtrafno	Traffic volume: no concern
schtrafye	Traffic volume: have concern
schwthrno	Poor Weather: no concern
schwthrye	Poor weather: have concerns
Children characteristics	
C_age	Age of children
C_female	Gender of child is girl
School characteristics	
Public	Child attends public school
disttosc1	Distance to school: <1/4 mi
disttosc2	Distance to school: 1/4–1/2 mi
disttosc3	Distance to school: 1/2–1 mi
disttosc0	Distance to school: 1–2 mi
Household characteristics	
vehratio	Vehicles equal or greater than drivers in the household

hhfaminc2	Household annual income
white	Household race is White
black	Household race is African-American
asian	Household race is Asian
hispanic	Household race is Hispanic
others	Household race is others
wkratio	The ratio of workers in a household
Land use characteristics	
htresdn1	Housing density/mi ²
hthtnrnt1	Renter-occupied housing
htppopdn1	Population density/mi ²
Urbansize1	Urban size 50-200k
Urbansize2	Urban size 200-500k
Urbansize3	Urban size 500k-1m
Urbansize4	Urban size > 1m w/o subway/rail
Urbansize5	Urban size > 1m with subway/rail
nonurban	Not in an urban area
Weather characteristics	
tpmaxab30	Maximum temperature is above 30 degrees in Celsius
tpmaxbl10	Maximum temperature is below 10 degrees in Celsius
tpminab20	Minimum temperature is above 20 degrees in Celsius
tpminbl0	Minimum temperature is below 0 degree in Celsius
PRCP	Precipitation (tenths of mm)
SNOW	Snowfall (mm)
SNWD	Snow depth (mm)
Fog	Fog, ice fog or freezing fog

Table 5: Summary Statistics

Name	Minimum	Mean	Median	Maximum	Standard Deviation
Dependent variables					
wkbbk	0.00	0.21	0	1.00	0.41
wkbbkpsc	0.00	0.27	0	1.00	0.44
Explanatory variables					
asian	0.00	0.10	0.00	1.00	0.30
black	0.00	0.07	0.00	1.00	0.25
hisp	0.00	0.04	0.00	1.00	0.20
other	0.00	0.04	0.00	1.00	0.20
disttosc1	0.00	0.17	0.00	1.00	0.38
disttosc2	0.00	0.14	0.00	1.00	0.35
disttosc3	0.00	0.26	0.00	1.00	0.44
C_age	5.00	10.03	10.00	16.00	3.15
C_female	0.00	0.46	0.00	1.00	0.50
schdistye	0.00	0.50	0.00	1.00	0.50
schspdye	0.00	0.71	1.00	1.00	0.46
schtrafye	0.00	0.72	1.00	1.00	0.45
private	0.00	0.10	0.00	1.00	0.30
schwthrye	0.00	0.47	0.00	1.00	0.50
vehratio	0.00	0.88	1.00	1.00	0.33
urbansize1	0.00	0.03	0.00	1.00	0.17
urbansize2	0.00	0.09	0.00	1.00	0.29
urbansize3	0.00	0.09	0.00	1.00	0.28
urbansize4	0.00	0.30	0.00	1.00	0.46
nonurban	0.00	0.13	0.00	1.00	0.33
parttime	0.00	0.21	0.00	1.00	0.41
wrkeratio	0.20	0.85	1.00	2.00	0.26
self_emp	0.00	0.09	0.00	1.00	0.28

P_1829	0.00	0.03	0.00	1.00	0.17
P_4559	0.00	0.42	0.00	1.00	0.49
P_60pl	0.00	0.02	0.00	1.00	0.14
P_edulh	0.00	0.03	0.00	1.00	0.17
P_eduh	0.00	0.13	0.00	1.00	0.33
P_edusc	0.00	0.23	0.00	1.00	0.42
P_eduba	0.00	0.32	0.00	1.00	0.47
disttowk	0.00	14.33	10.00	560.00	25.67
P_wktransit	0.00	0.08	0.00	1.00	0.27
P_wrkwkbbk	0.00	0.04	0.00	1.00	0.19
P_wrkoth	0.00	0.01	0.00	1.00	0.08
P_nbiketrp1	0.00	0.10	0.00	1.00	0.30
P_nbiketrp2	0.00	0.03	0.00	1.00	0.17
P_nwalktrp1	0.00	0.58	1.00	1.00	0.49
P_nwalktrp2	0.00	0.13	0.00	1.00	0.34
htresdn1	0.50	31.56	15.00	300.00	54.56
hthtrnt1	0.00	2.52	2.00	9.50	2.30
htppopdn1	0.05	6.83	3.00	30.00	7.68
hhfaminc2	2.50	31.64	12.50	87.50	28.10
SNOW	0.00	1.36	0.00	109.00	8.93
SNWD	0.00	3.14	0.00	229.00	16.94
PRCP	0.00	21.33	0.00	914.00	77.47
tpminab20	0.00	0.14	0.00	1.00	0.35
tpminbl0	0.00	0.19	0.00	1.00	0.39
tpmaxab30	0.00	0.15	0.00	1.00	0.35
tpmaxbl10	0.00	0.20	0.00	1.00	0.40
Fog	0.00	0.30	0.00	1.00	0.46

CHAPTER 4. METHODOLOGY

4.1 Models

To explore factors associated with children's school travel modes, I estimated some binary logit models. The dependent variable was denoted by y_i : if child "i" walks to school, y_i equals 1 and it equals 0 otherwise. To motivate the binary logit model, I assume that there is a latent continuous variable y_i^* related to a vector of explanatory variables denoted by \mathbf{x}_i via:

$$y_i^* = \mathbf{x}_i \boldsymbol{\beta} + \varepsilon_i, \quad (1)$$

which is connected to the observed dependent variable y_i by

$$y_i = \begin{cases} 1 & \text{if } y_i^* \geq 0, \\ 0 & \text{if } y_i^* < 0. \end{cases} \quad (2)$$

The Probability that child "i" walks to (from) school is then given by

$$\Pr(y_i = 1 | \mathbf{x}_i) = \frac{\exp(\mathbf{x}_i \boldsymbol{\beta})}{1 + \exp(\mathbf{x}_i \boldsymbol{\beta})}, \quad (3)$$

where $\boldsymbol{\beta}$ is a vector of unknown parameters.

The odds of observing $y_i = 1$ versus $y_i = 0$ are:

$$\Omega(\mathbf{x}_i) = \frac{\Pr(y_i = 1 | \mathbf{x}_i)}{\Pr(y_i = 0 | \mathbf{x}_i)} = \exp(\mathbf{x}_i \boldsymbol{\beta}), \quad (4)$$

If we denote by $\Omega(\mathbf{x}_i, x_j + \delta)$ the odds obtained by adding $\delta > 0$ to explanatory variable x_{ij} , the corresponding odds ratios (OR_j) is given by:

$$\frac{\Omega(\mathbf{x}_i, x_{ij} + \delta)}{\Omega(\mathbf{x}_i)} = \exp(\delta \beta_j). \quad (5)$$

Hence, increasing x_{ij} increases the likelihood that a child will walk to school if and only if $\exp(\delta\beta_j) > 1$, which requires $\beta_j > 0$; therefore, we report odds ratios $\exp(\beta_j)$.

4.2 Diagnostics

Diagnostics are important to assess the soundness of statistical models. I conducted a number of standard diagnostics.

First, I tested explanatory variables for multicollinearity using variance inflation factors (VIF). The variance inflation factor for explanatory variable j is $VIF_j \equiv (1 - R_j^2)^{-1}$, where R_j^2 is the coefficient of determination obtained by regressing explanatory variable j on all other explanatory variables. If R_j^2 is close to 1, VIF_j is large; values of VIF above 10 are typically of concern (<http://www.ats.ucla.edu/stat/stata/webbooks/logistic/chapter3/statalog3.htm>).

Second, I performed a linktest (known as Tukey's one-degree-of-freedom test for non-additivity) to detect specification problems. It tests the null hypothesis that the effects of covariates are additive against alternatives where they are not (the introduction of the square of the linear predictor to the model captures a range of such alternatives). Failing to reject the null hypothesis suggests that a model is not badly specified.

To assess goodness of fit, I ran “fitstat” in Stata, which provides a range of goodness of fit measures. In particular, I relied on the count R-squared. To calculate the count R-squared, predicted probabilities are transformed into binary variables on the same scale as the outcome variable (0-1) and the correctness of predictions is assessed (see http://www.ats.ucla.edu/stat/mult_pkg/faq/general/Psuedo_RSquareds.htm). Higher count R-squared values (closer to 1) indicate a better fit.

In order to detect potential problems, it is also good practice to examine model residuals.

There are different types of residuals. Pearson residuals measure the relative deviations between observed and fitted values. Deviance residuals measure the disagreement between the maxima of the observed and the fitted log likelihood functions. Another statistic, sometimes called the hat diagonal (it is the diagonal of the hat matrix) or Pregibon leverage, measures the leverage of an observation (an observation for a variable has leverage if it is “far” from the mean of that variable). These three statistics, Pearson residual, deviance residual and Pregibon leverage are the basic building blocks for logistic regression diagnostics.

There is no hard-and-fast rule for what is considered as a “large” residual. Hosmer and Lemeshow (2000, 176) point out that it is impossible to provide any absolute standard: “in practice, an assessment of ‘large’ is, of necessity, a judgment call based on experience and the particular set of data being analyzed”. However, normally the absolute value of deviance residual should not exceed two.

Finally, I investigated the presence of influential observations (observations that greatly influence the value of estimated parameters). Influential observations may result from data errors or from a distinct sub-population that should be modeled separately.

CHAPTER 5. RESULTS

5.1 Binary Logit Model for Children's To-school Travel

Results for children's active commuting to school, estimated by STATA, are presented below.

5.1.1 Initial To-School Model

Results of the initial to-school model are presented in Table 6. Before discussing the result, let us go over model diagnostics (see Tables 7 to 11, and Figures 1 to 6). First, results indicate that multicollinearity is not a problem because the largest VIF is under 5. Second, the linktest failed to reject the null hypothesis that my model is well specified. Third, the value of the count R-squared (0.837) suggests that fit is adequate.

In this dataset, some observations are far away from others. For example, observations number 434, 369, 223, 644, 29, 224, 768 and 97 have relative large Pearson residual and deviance residuals (Figures 1 and 2, and Table 8). Moreover, observations number 154, 185, 127 and 158 are far away from others (they have leverage).

The difference of chi-squares and the difference of deviance tests were used to identify observations with substantial impact on either the chi-square fit statistic or the deviance statistic (Figures 4 and 5). Results indicate that observations 369, 434, 223, 644, 29, 224, 43, 97, 125 and 768 deserve further examination. Meanwhile, Pregibon's dbeta provides summary information about influence on parameter estimates of each individual observation. Figure 6 indicates that observations 43, 91, 351, 223, 224, 306, 596, 184 and 521 need further attention.

Table 6: To-School Initial Model Results

Variable	Name	Coefficient	Odds Ratio
Ethnicity is Asian	asian	0.513	1.670
Ethnicity is African-American	black	0.301	1.351
Ethnicity is Hispanic	hisp	-0.770	0.463
Ethnicity is others	other	-0.175	0.840
Distance to school: <1/4 mi	disttosc1	3.702***	40.546***
Distance to school: 1/4–1/2 mi	disttosc2	2.668***	14.405***
Distance to school: 1/2–1 mi	disttosc3	1.681***	5.369***
Age of child	C_age	0.178***	1.195***
Gender of child is girl	C_female	0.109	1.116
Distance to school: have concern	schdistye	-0.087	0.917
Traffic speed: have concern	schspdye	-0.250	0.779
Traffic volume: have concern	schtrafye	-0.238	0.788
Child attends private school	private	-1.727***	0.178***
Poor weather: have concern	schwthrye	-0.374	0.688
Vehicles equal or greater than drivers in the household	vehratio	0.078	1.081
Urban size 50-200k	urbansize1	-0.646	0.524
Urban size 200-500k	urbansize2	-0.334	0.716
Urban size 500k-1m	urbansize3	-0.462	0.630
Urban size > 1m w/o subway/rail	urbansize4	-0.396	0.673
Not in an urban area	nonurban	-0.552	0.576
Parent work status: part time	parttime	0.096	1.101
The ratio of workers in a household	wrkeratio	0.303	1.354
Parent is self-employed	self_emp	0.215	1.240
Age of surveyed parent is 18-29	P_1829	-0.231	0.793
Age of surveyed parent: 45-59	P_4559	-0.282	0.754
Age of surveyed parent:>60	P_60pl	0.010	1.010
Parental education < high school	P_edulh	-1.100	0.333

Parental education: high school	P_eduh	0.124	1.132
Parental education: some college	P_edusc	-0.133	0.876
Parental education: bachelor degree	P_eduba	0.026	1.026
One-Way distance to work (mi)	disttowk	0.007	1.007
Transit mode to work last week is transit	P_wktransit	0.658*	1.930*
Transit mode to work last week is walking or biking	P_wrkwkbbk	1.262**	3.532**
Transit mode to work last week is other	P_wrkoth	1.310*	3.705*
Bike trips last week: 1-2	P_nbiketrp1	0.863**	2.371**
Bike trips last week: >2	P_nbiketrp2	1.157**	3.180**
Walk trips last week: 1-7	P_nwalktrp1	0.468*	1.597*
Walk trips last week: >7	P_nwalktrp2	0.320	1.377
Housing density/mi ²	htresdn1	0.007*	1.007*
Renter-occupied housing	hthtnrnt1	-0.021	0.980
Population density/mi ²	htppopdn1	0.036	1.036
Household annual income	hhfaminc2	-0.006	0.994
Snowfall (mm)	SNOW	0.004	1.004
Snow depth (mm)	SNWD	-0.007	0.993
Precipitation (tenths of mm)	PRCP	0.000	1.000
Minimum temperature is above 20 degrees in Celsius	tpminab20	0.279	1.321
Minimum temperature is below 0 degrees in Celsius	tpminbl0	-0.066	0.936
Maximum temperature is above 30 degrees in Celsius	tpmaxab30	-0.038	0.963
Maximum temperature is below 10 degrees in Celsius	tpmaxbl10	-0.335	0.716
Fog, ice fog or freezing fog	fog	0.113	1.120
--	constant	-5.331***	--

Table 7: Specification Error Test (Linktest) of To-school Model

Logistic regression	Number of obs	=	827.000
	LR chi2(2)	=	287.670
	Prob > chi2	=	0.000
Log likelihood = -285.58125	Pseudo R2	=	0.335

wkblk	Coef.	Std. Err.	z	P>z	[95% Conf.Interval]	
_hat	0.975	0.110	8.860	0.000	0.759	1.190
_hatsq	-0.013	0.041	-0.320	0.746	-0.093	0.067
_cons	0.011	0.130	0.090	0.932	-0.244	0.266

Table 8: Good of Fitness (fitstat) of To-school Model

Log-Lik Intercept Only:	-429.414	Log-Lik Full Model:	-285.634
D(776):	571.268	LR(50):	287.56
		Prob > LR:	0
McFadden's R2:	0.335	McFadden's Adj R2:	0.216
Maximum Likelihood R2:	0.294	Cragg & Uhler's R2:	0.455
McKelvey and Zavoina's R2:	0.531	Efron's R2:	0.362
Variance of y*:	7.016	Variance of error:	3.29
Count R2:	0.837	Adj Count R2:	0.237
AIC:	0.814	AIC*n:	673.268
BIC:	-4641.749	BIC':	48.33

Table 9: Standardized Pearson Residuals for To-School Model

	Percentiles	Smallest		
1%	-1.891	-4.477		
5%	-1.052	-4.379		
10%	-0.734	-2.574	Obs	827
25%	-0.406	-2.181	Sum of Wgt.	827
50%	-0.201		Mean	0.001
		Largest	Std. Dev.	1.072
75%	-0.073	7.176		
90%	1.216	7.494	Variance	1.148
95%	1.690	8.158	Skewness	3.079
99%	3.915	8.290	Kurtosis	21.245

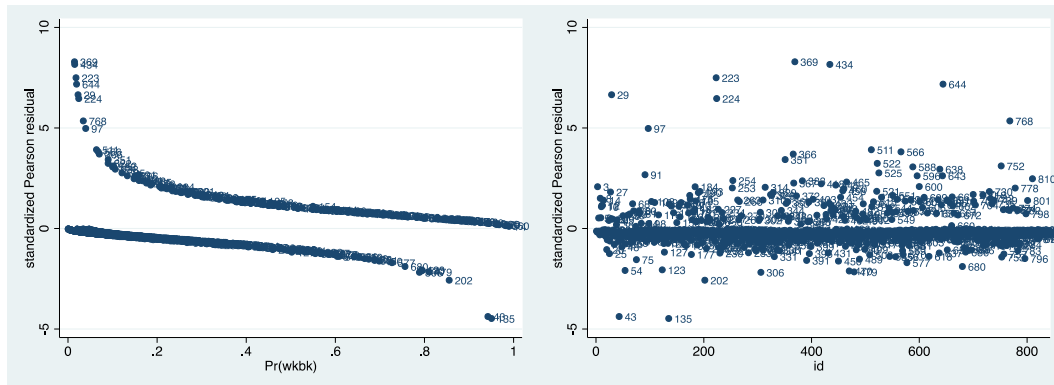


Figure 1: Standardized Pearson Residuals for To-School Model

Table 10: Deviance Residuals for To-School Model

	Percentiles	Smallest		
1%	-1.680	-2.451		
5%	-1.174	-2.388		
10%	-0.884	-1.967	Obs	827
25%	-0.538	-1.822	Sum of Wgt.	827
50%	-0.278		Mean	-0.109
		Largest	Std. Dev.	0.824
75%	-0.102	2.810		
90%	1.264	2.835	Variance	0.680
95%	1.602	2.896	Skewness	1.152
99%	2.345	2.907	Kurtosis	4.462

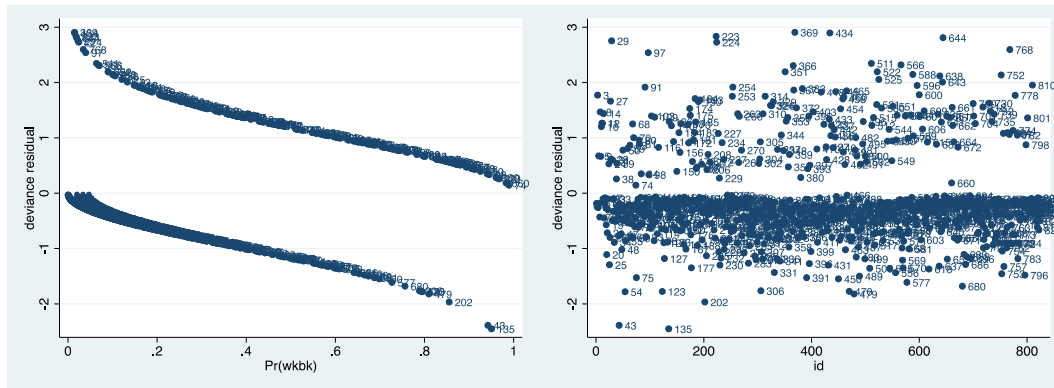


Figure 2: Deviance Residual for To-School Model

Table 11: Leverage for To-School Model

	Percentiles	Smallest		
1%	0.002024	0.005501		
5%	0.0036759	0.0018247		
10%	0.0056634	0.0010454	Obs	827
25%	0.015312	0.0010525	Sum of Wgt.	827
50%	0.028044		Mean	0.0595707
		Largest	Std. Dev.	0.0557059
75%	0.0899543	0.2733901		
90%	0.1361716	0.2735806	Variance	0.0031031
95%	0.1697267	0.3083784	Skewness	1.370873
99%	0.2410017	0.323008	Kurtosis	4.962613

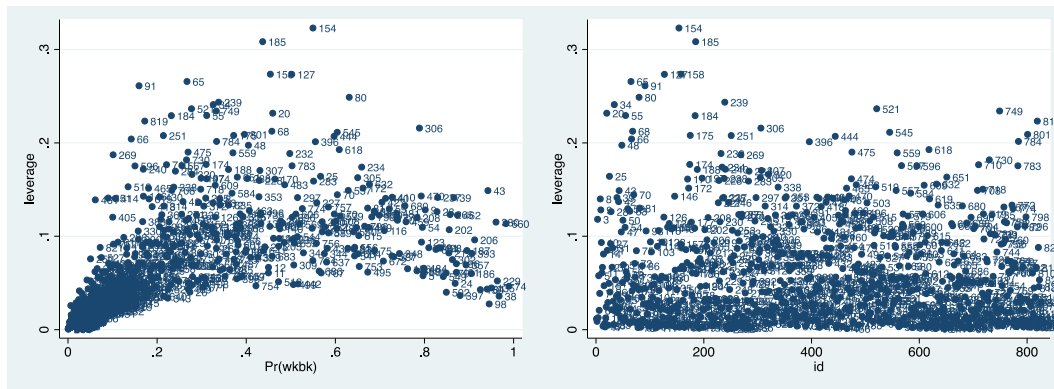


Figure 3: Pregibon Leverage for To-School Model

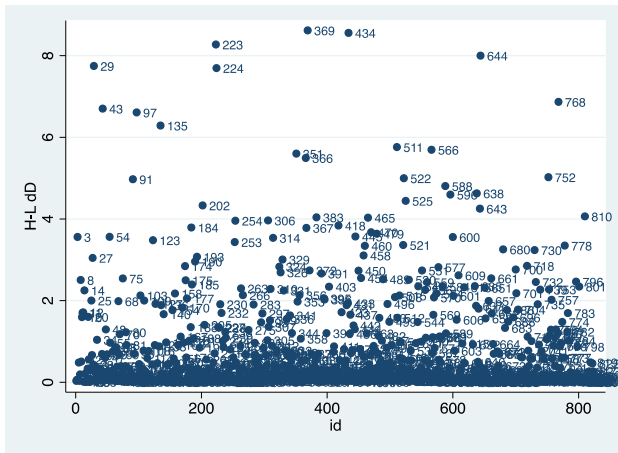


Figure 4: Deviance Residuals

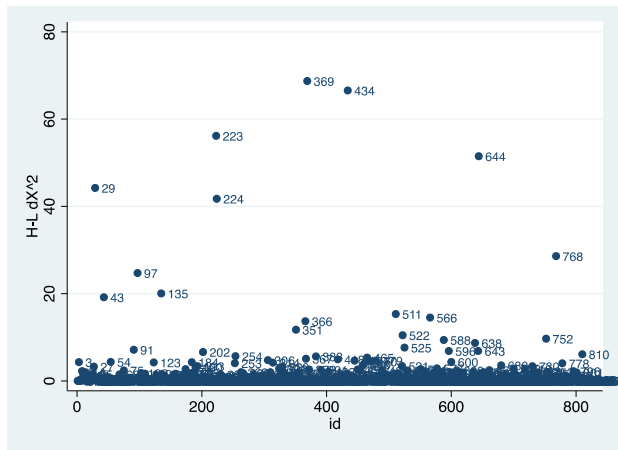


Figure 5: Differences of Chi-square

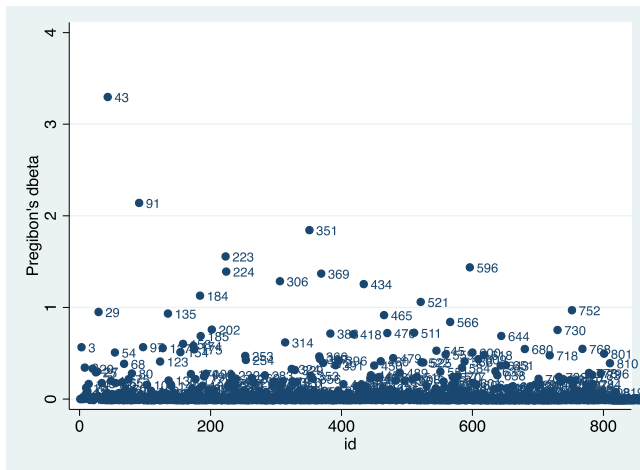


Figure 6: Pregibon's dbeta

5.1.2 Revised To-School Model

After conducting the above diagnostics, I removed 37 influential observations (434, 369, 223, 644, 29, 224, 768, 97, 135, 154, 185, 158, 43, 91, 351, 596, 306, 184, 521, 566, 174, 202, 269, 680, 819, 740, 511, 366, 277, 522, 588, 470, 450, 479, 68, 55, and 752) from the dataset, which left me with 790 observations. Results are displayed in Table 7.

Diagnostics conducted for the new model suggest it is statistically sound. Multicollinearity diagnostics show that there is no multicollinear relationship between explanatory variables in this model. Linktest (Appendix A Table A) fails to reject that the model is specified correctly. The count R-squared increased slightly (0.884). Although several observations still appear to be somewhat influential (Appendix B Figures A-F), omitting those observations does not change the model dramatically. Therefore, this is my final model.

As is common for binary logit models, I discuss odds ratios (OR) of statistically significant explanatory variables to understand results. Variables with odds ratios larger from 1.0 have more influence in changing the probability of an outcome than variables with OR closer to 1.0.

As in previous studies, I find that distance is the main factor driving parents' decision to have their children rely on an active mode to school. When distance decreases, children are more likely to walk or bike to school. Distance between home and school under 0.25 miles highly encourages children to actively commute (OR= 1649.3). Children who live between 0.25 miles and 0.5 miles are also more likely to walk or bike to school (OR= 342.9). Compared to children who live 1 to 2 miles away from school 1 to 2 miles, children whose home are 0.5 to 1 mile away are more likely to actively commute to school (OR= 55.1).

Table 12: To-School Best Model Results

Variable	Name	Coefficient	Odds Ratio
Ethnicity is Asian	asian	1.210**	3.353**
Ethnicity is African-American	black	1.155**	3.174**
Ethnicity is Hispanic	hisp	-1.654**	0.191**
Ethnicity is others	other	-0.672	0.511
Distance to school: <1/4 mi	disttosc1	7.408***	1649.343***
Distance to school: 1/4–1/2 mi	disttosc2	5.838***	342.942***
Distance to school: 1/2–1 mi	disttosc3	4.008***	55.062***
Age of child	C_age	0.328***	1.388***
Gender of child is girl	C_female	0.140	1.150
Distance to school: have concern	schdistye	0.170	1.186
Traffic speed: have concern	schspdye	-1.029***	0.357***
Traffic volume: have concern	schtrafye	0.135	1.145
Child attends private school	private	-4.474***	0.011***
Poor weather: have concern	schwthrye	-0.671**	0.511**
Vehicles equal or greater than drivers in the household	vehratio	0.201	1.223
Urban size 50-200k	urbansize1	-1.956*	0.141*
Urban size 200-500k	urbansize2	-1.450***	0.235***
Urban size 500k-1m	urbansize3	-0.538	0.584
Urban size > 1m w/o subway/rail	urbansize4	-1.026**	0.358**
Not in an urban area	nonurban	-1.909***	0.148***
Parent work status: part time	parttime	0.449	1.567
The ratio of workers in a household	wrkeratio	0.859*	2.361*
Parent is self-employed	self_emp	0.455	1.575
Age of surveyed parent is 18-29	P_1829	0.744	2.104
Age of surveyed parent: 45-59	P_4559	-0.190	0.827
Age of surveyed parent:>60	P_60pl	-1.002	0.367
Parental education < high school	P_edulh	-2.195***	0.111***

Parental education: high school	P_eduh	0.163	1.177
Parental education: some college	P_edusc	0.239	1.271
Parental education: bachelor degree	P_eduba	-0.080	0.923
One-Way distance to work (mi)	disttowk	0.013	1.013
Transit mode to work last week is transit	P_wktransit	1.146**	3.146**
Transit mode to work last week is walking or biking	P_wrkwk bk	4.098***	60.250***
Transit mode to work last week is other	P_wrkoth	2.667***	14.390***
Bike trips last week: 1-2	P_nbiketrp1	1.712***	5.541***
Bike trips last week: >2	P_nbiketrp2	1.902**	6.698**
Walk trips last week: 1-7	P_nwalktrp1	0.193	1.213
Walk trips last week: >7	P_nwalktrp2	0.168	1.183
Housing density/mi ²	htresdn1	0.016**	1.016**
Renter-occupied housing	hthtnrnt1	-0.032	0.969
Population density/mi ²	htppopdn1	0.062*	1.064*
Household annual income	hhfaminc2	-0.021***	0.979***
Snowfall (mm)	SNOW	-0.059	0.943
Snow depth (mm)	SNWD	0.016	1.016
Precipitation (tenths of mm)	PRCP	-0.010***	0.990***
Minimum temperature is above 20 C	tpminab20	0.042	1.043
Minimum temperature is below 0 C	tpminbl0	-0.541	0.582
Maximum temperature is above 30 C	tpmaxab30	-0.260	0.771
Maximum temperature is below 10 C	tpmaxbl10	-0.866	0.421
Fog, ice fog or freezing fog	fog	0.020	1.020
--	constant	-9.572	--

Age also matters, with OR= 1.39. This indicates that older children are more likely to walk or bike to school. Asian (OR=3.35) and African-American (OR=3.17) children are also more likely to walk or bike to school compared to white children. However, Hispanic children are much less likely to go to school by active commuting (OR=0.19). Results also indicate that in

households with a higher worker ratio, children are more likely walk or bike to school (OR=2.36).

Parental concerns about the weather matter: more concern about poor weather decreases the odds parents will let their children walk or bike to school (OR=0.51). Traffic speed along the route is also a major concern for parents, as parents who are more concerned about traffic speed are less likely to allow their children to walk or bike to school (OR=0.36). Parent who do not have a high school level education are also less likely to have their children walk or bike to school (OR=0.11). Meanwhile, children who are attending a private school are highly unlikely to go to school by active commuting, compared to public school children (OR=0.01).

In addition, results show that parents' travel modes have a noticeable influence on children's school travel mode choices. Compared to driving to workplace, if parents take public transit to work, their children are more likely to walk or bike to school (OR= 3.15); if parents actively commute to their workplace, their children are much more likely to actively commute to school as well (OR=60.25); if parents go to work by other travel modes (other than active commuting, public transit and driving), their children also highly likely to walk or bike to school (OR=14.39). In addition, the number of walking or biking trips parents make on average during a week has an effect on their children's school travel mode as well. Therefore, parental attitudes toward active commuting for themselves influences the decision making for their children's school travel modes. Hence, to encourage children's active transportation, walking and biking by parents should be encouraged.

Of the land use variables I considered, compared to residents of big urban areas (1 million or more) with subway or rail, people who live in a nonurban area are less likely to let their children go to school by walking or biking (OR=0.15); likewise, children who live in a

small size urban area are rarely allowed to walk or bike to school (OR=0.14). Similarly people who live in a small to middle size urban area (20k-50k) are less likely to let their children actively commute to school (OR=0.23). Moreover, people living in a large urban area that does not have subway or rail are less likely to let their children walk or bike to school (OR=0.36). This suggests that size is not everything and that public transit encourages active commuting to school. Although housing and population density are significant, their practical impacts are very small. However, it still indicates that the children who are living in the area with high housing and population density are slightly more likely to actively travel to school.

I hypothesized that harsh weather would have a negative impact on children's active commuting to school. Results of the to-school model show that children are less likely to walk or bike when it rains (OR=0.99) and snows (OR=0.94) more; however, the corresponding practical impact is quite small. Other weather factors are not statistically significant. However, my starting hypothesis that parental concerns about the weather matter is supported by my results.

5.2 Binary Logit Model for Children's From-School Travel

In order to better understand children's school travel modes and uncover the factors that may significantly influence children's school travel modes, I also estimated a binary logit model for from-school travel.

5.2.1 Initial From-School Model

Results of the initial from-school model are presented in Table 11. As before, we first consider model diagnostics. First, multicollinearity diagnostics based on VIF indicate that there is no multicollinearity problem in my explanatory variables (all VIF values are under 5). Second, the

linktest again failed to reject the null hypothesis that my model is well specified. Third, the value of the R-squared (0.808) suggests an adequate fit.

However, this model is not perfect. From Figures 9 and 12, observations 219, 613, 679, 659, and 84 have high leverages and need extra evaluation. Deviances show that points 277, 527, 55, 790 and 335 may have a substantial impact on either the chi-square fit statistic or on the deviance statistic. Pregibon’s dbeta indicates that observation 221 may have a powerful influence on parameter estimates.

Table 13: From-School Initial Model Results

Variable	Name	Coefficient	Odds Ratio
Ethnicity is Asian	asian	0.519*	1.680*
Ethnicity is African-American	black	-0.332	0.718
Ethnicity is Hispanic	hisp	-0.882	0.414
Ethnicity is others	other	-0.196	0.822
Distance to school: <1/4 mi	disttosc1	3.497***	33.023***
Distance to school: 1/4–1/2 mi	disttosc2	2.487***	12.020***
Distance to school: 1/2–1 mi	disttosc3	1.849***	6.353***
Age of child	C_age	0.240***	1.271***
Gender of child is girl	C_female	-0.022	0.978
Distance to school: have concern	schdistye	0.049	1.051
Traffic speed: have concern	schspdye	-0.147	0.863
Traffic volume: have concern	schtrafye	-0.506*	0.603*
Child attends private school	private	-2.077***	0.125***
Poor weather: have concern	schwthrye	0.074	1.077
Vehicles equal or greater than drivers in the household	vehratio	-0.219	0.803
Urban size 50-200k	urbansize1	-0.036	0.965
Urban size 200-500k	urbansize2	-0.410	0.663

Urban size 500k-1m	urbansize3	-0.252	0.777
Urban size > 1m w/o subway/rail	urbansize4	-0.194	0.824
Not in an urban area	nonurban	-0.289	0.749
Parent work status: part time	parttime	0.140	1.150
The ratio of workers in a household	wrkeratio	0.513	1.670
Parent is self-employed	self_emp	-0.083	0.921
Age of surveyed parent is 18-29	P_1829	0.339	1.403
Age of surveyed parent: 45-59	P_4559	-0.039	0.962
Age of surveyed parent:>60	P_60pl	1.120*	3.066*
Parental education < high school	P_edulh	-1.217*	0.296*
Parental education: high school	P_eduh	-0.143	0.867
Parental education: some college	P_edusc	-0.511*	0.600*
Parental education: bachelor degree	P_eduba	-0.270	0.763
One-Way distance to work (mi)	disttowk	0.005*	1.005*
Transit mode to work last week is transit	P_wktransit	0.326	1.385
Transit mode to work last week is walking or biking	P_wrkwkbbk	1.935***	6.925***
Transit mode to work last week is other	P_wrkoth	0.286	1.330
Bike trips last week: 1-2	P_nbiketrp1	0.716**	2.046**
Bike trips last week: >2	P_nbiketrp2	1.076*	2.933*
Walk trips last week: 1-7	P_nwalktrp1	0.445**	1.561**
Walk trips last week: >7	P_nwalktrp2	0.395	1.484
Housing density/mi ²	htresdn1	0.007*	1.007*
Renter-occupied housing	hthtrnt1	0.014	1.014
Population density/mi ²	htppopdn1	0.010	1.010
Household annual income	hhfaminc2	-0.001	0.999
Snowfall (mm)	SNOW	-0.002	0.998
Snow depth (mm)	SNWD	-0.007	0.993
Precipitation (tenths of mm)	PRCP	0.002	1.002
Minimum temperature is above 20 C	tpminab20	0.103	1.108

Minimum temperature is below 0 C	tpminbl0	-0.212	0.809
Maximum temperature is above 30 C	tpmaxab30	-0.069	0.933
Maximum temperature is below 10 C	tpmaxbl10	0.006	1.006
Fog, ice fog or freezing fog	fog	-0.136	0.873
--	constant	-5.405	--

Table 14: Specification Error Test (Linktest) for From-School Model

Logistic regression	Number of obs	=	838
	LR chi2(2)	=	301.920
	Prob > chi2	=	0.000
Log likelihood = -337.554	Pseudo R2	=	0.309

wkbbk	Coef.	Std. Err.	z	P>z	[95% Conf.Interval]	
_hat	0.996	0.099	10.070	0.000	0.803	1.190
_hatsq	-0.002	0.041	-0.060	0.954	-0.082	0.078
_cons	0.002	0.116	0.020	0.984	-0.226	0.231

Table 15: Goodness of Fit (Fitstat) for From-School Model

Log-Lik Intercept Only:	-488.512	Log-Lik Full Model:	-337.555
D(776):	675.111	LR(50):	301.914
		Prob > LR:	0.000
McFadden's R2:	0.309	McFadden's Adj R2:	0.205
Maximum Likelihood R2:	0.303	Cragg & Uhler's R2:	0.439
McKelvey and Zavoina's R2:	0.518	Efron's R2:	0.344
Variance of y*:	6.822	Variance of error:	3.290
Count R2:	0.808	Adj Count R2:	0.288
AIC:	0.927	AIC*n:	777.111
BIC:	-4622.201	BIC':	-34.637

Table 16: Standardized Pearson Residual for From-School Model

	Percentiles	Smallest		
1%	-2.101	-3.235		
5%	-1.081	-2.744		
10%	-0.862	-2.705	Obs	838
25%	-0.484	-2.382	Sum of Wgt.	838
50%	-0.236		Mean	0.003
		Largest	Std. Dev.	1.070
75%	0.331	7.226		
90%	1.324	7.966	Variance	1.146
95%	1.783	7.994	Skewness	2.801
99%	3.301	9.392	Kurtosis	20.037

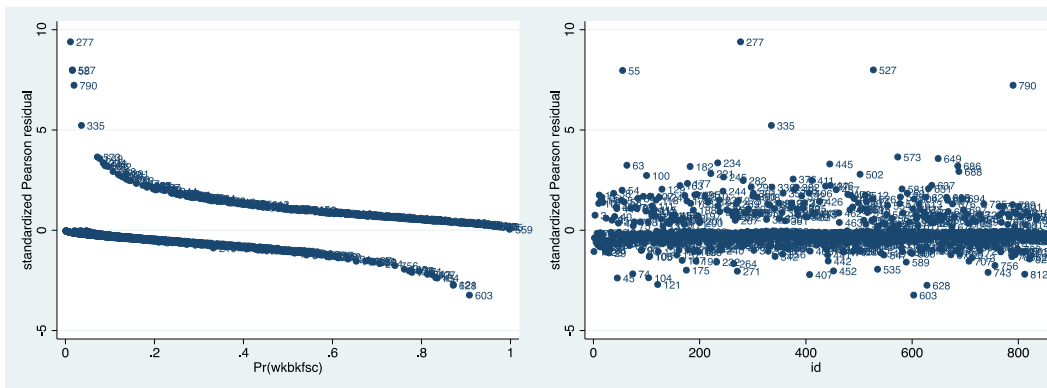


Figure 7: Standard Pearson Residuals for From-School Model

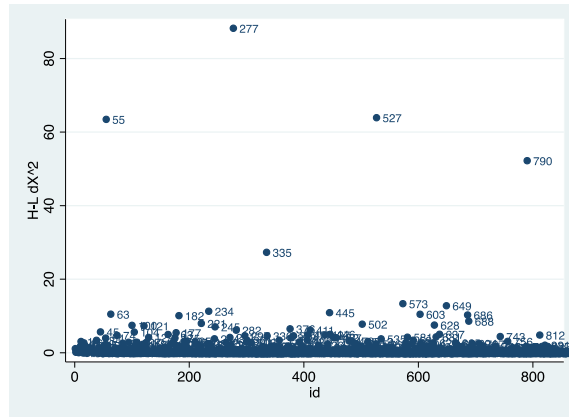


Figure 10: Difference of Chi-Square for From-School Model

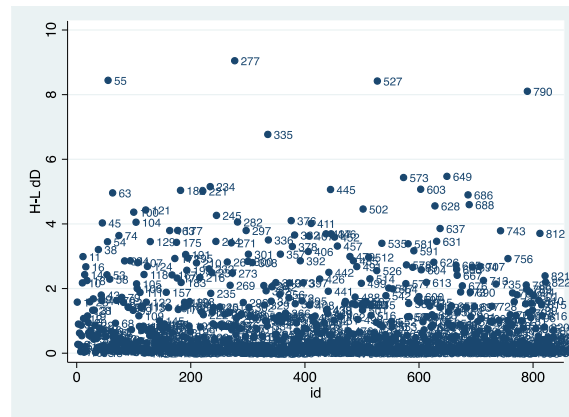


Figure 11: Difference of Deviance for From-School Model

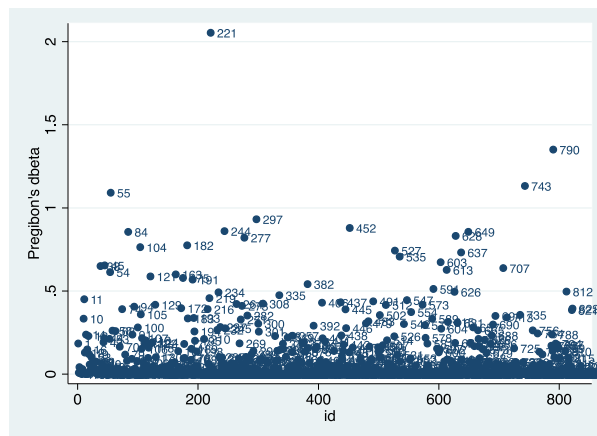


Figure 12 Pregibon's dbeta for From-School Model

Table 19: From-School Best Model Results

Variable	Name	Coefficient	Odds Ratio
Ethnicity is Asian	asian	0.564*	1.757*
Ethnicity is African-American	black	-0.530	0.588
Ethnicity is Hispanic	hisp	-1.487***	0.226***
Ethnicity is others	other	-0.454	0.635
Distance to school: <1/4 mi	disttosc1	4.233***	68.947***
Distance to school: 1/4–1/2 mi	disttosc2	3.059***	21.308***
Distance to school: 1/2–1 mi	disttosc3	2.245***	9.444***
Age of child	C_age	0.297***	1.346***
Gender of child is girl	C_female	-0.028	0.972
Distance to school: have concern	schdistye	0.185	1.203
Traffic speed: have concern	schspdye	-0.139	0.870
Traffic volume: have concern	schtrafy	-0.582*	0.559*
Child attends private school	private	-2.968***	0.051***
Poor weather: have concern	schwthrye	0.086	1.090
Vehicles equal or greater than drivers in the household	vehratio	-0.132	0.876
Urban size 50-200k	urbansize1	0.211	1.234
Urban size 200-500k	urbansize2	-0.724*	0.485*
Urban size 500k-1m	urbansize3	-0.301	0.740
Urban size > 1m w/o subway/rail	urbansize4	-0.240	0.786
Not in an urban area	nonurban	-0.396	0.673
Parent work status: part time	parttime	0.114	1.121
The ratio of workers in a household	wrkeratio	0.783*	2.188*
Parent is self-employed	self_emp	0.070	1.072
Age of surveyed parent is 18-29	P_1829	0.590	1.804
Age of surveyed parent: 45-59	P_4559	0.084	1.087
Age of surveyed parent:>60	P_60pl	1.423*	4.149*
Parental education < high school	P_edulh	-1.960***	0.141***

Parental education: high school	P_eduh	-3.850	0.680
Parental education: some college	P_edusc	-0.722**	0.486**
Parental education: bachelor degree	P_eduba	-0.489*	0.613*
One-Way distance to work (mi)	disttowk	0.006*	1.006*
Transit mode to work last week is transit	P_wktransit	0.661*	1.936*
Transit mode to work last week is walking or biking	P_wrkwkbbk	2.437***	11.438***
Transit mode to work last week is other	P_wrkoth	0.218	1.243
Bike trips last week: 1-2	P_nbiketrp1	1.055***	2.872***
Bike trips last week: >2	P_nbiketrp2	1.416**	4.121**
Walk trips last week: 1-7	P_nwalktrp1	0.509**	1.663**
Walk trips last week: >7	P_nwalktrp2	0.394	1.483
Housing density/mi ²	htresdn1	0.011***	1.011***
Renter-occupied housing	hthtrnt1	0.003	1.003
Population density/mi ²	htppopdn1	-0.003	0.997
Household annual income	hhfaminc2	-0.006*	0.994*
Snowfall (mm)	SNOW	-0.006	0.994
Snow depth (mm)	SNWD	-0.005	0.995
Precipitation (tenths of mm)	PRCP	0.002	1.002
Minimum temperature is above 20 C	tpminab20	0.229	1.257
Minimum temperature is below 0 C	tpminbl0	-0.338	0.713
Maximum temperature is above 30 C	tpmaxab30	-0.295	0.745
Maximum temperature is below 10 C	tpmaxbl10	-0.043	0.958
Fog, ice fog or freezing fog	fog	-0.271	0.762
--	constant	-6.137	--

5.2.2 Revised From-School Model

According to diagnostic results, the following 13 observations were omitted from my revised from-school model: 121, 407, 628, 603, 55, 277, 527, 79, 335, 219, 221, 790, 743. The revised

model was estimated with 825 observations; results are shown in Table 17.

For this model, multicollinearity is not an issue (all VIF values are under 10). Linktest again fails to reject the null hypothesis that the model is well specified (Appendix A Table F), and the model fits observations slightly better (Appendix A Table G). Other diagnostics are also satisfactory (Appendix B Figure H-J). It is therefore my best model for travel from school.

As in my to-school travel mode analysis, distance from school to home has the largest influence on children's from-school travel modes. Compared to children who live between 1 mile and 2 miles away from school, children who live within a quarter of a mile or between a quarter mile and half a mile are more likely to walk or bike to school (OR=68.95, OR=21.31). Children who live between half a mile and a mile also are quite likely to go to school by active modes (OR=9.44).

As expected, Asian children are also more likely to commute to school by walking or biking than white children (OR=1.76). Likewise, older children are relatively more likely to resort to active commuting from school to home (OR=1.35). Moreover, children who are attending private schools are less likely to use active modes to return home from school (OR=0.05)

Parents who have great concerns with traffic volume along the route to school do not encourage their children to walk or bike to home from school (OR=0.56). Moreover, parents without a high school degree or with some college, or a bachelor's degree are significantly less likely to choose walking or biking for their children's school travel modes (OR=0.14, 0.49, 0.61). Compared to younger parents, older parents (60 or over) are more likely to make their children walk or bike from school (OR=4.15). In addition, when parents' workplace is far away from home, they are lightly more willing to encourage their children walk or bike home from school

(OR=1.01).

Parental use of active transportation or public transit is statistically associated with parental attitudes (Hsu and Saphores, 2013). As for the to-school model, parental travel patterns have a powerful impact on their children's from-school travel behavior. If parents take public transit to work, it increases the likelihood that their children walk or bike home after school (OR=1.94). Parents, who commute to work normally by walking or biking, are extremely likely to encourage their children to actively commute back home from school (OR=4.15). Meanwhile, parents with more biking or walking trips the week before the survey day, are more open to letting their kids walk or bike home from school (ORP_nbiketrip1=2.87, ORP_nbiketrip2=4.12, ORP_nwalktrip1=1.48).

A few land use variables also influence parental attitudes and children's from-school travel mode choices. Children who live in a relative small urban area are less likely to walk or bike after school (OR=0.48).

Unfortunately, weather variables are not statistically significant here. Even parental concerns about poor weather are not statistically significant.

CHAPTER 6 CONCLUSIONS

6.1 Overview

In this thesis, I analyzed the impact of weather variables on children's travel mode choice to and from school using data from selected areas in the 2009 NHTS. Results from the to-school model show that precipitation levels and snowfall statistically influence parental decisions regarding children's to-school travel mode choice, but their practical effects are quite small ($OR_{PRCP}=0.99$, $OR_{SNOW}=0.94$). However, weather variables are not statistically significant in the from-school model. These results show that the data we analyzed do not support our starting hypothesis that weather characteristics substantially impact children's travel mode choices.

Results of the binary logit models for children's school travel mode draw a clear picture of what factors have the strongest influence on children's travel behavior. As expected, distance between home and school is the most powerful explanatory variable of travel mode, which is consistent with previous research (Mitra, Buliung, and Roorda 2010; Yeung, Wearing, and Hills, 2008). I also found that when most drivers in a household have jobs, children are more likely to resort to active transportation modes between school and home, possibly because working adults have less time to chauffeur their children.

Asian children are more likely to walk or bike, whereas Hispanic children have less likely to take active modes to and from school. Meanwhile, children of parents who do not have a high school degree are less likely to travel between home and school via walking or biking.

My results also indicate that when parents are physically active, their children are more likely to actively commute to and from school to home. This highlights that parents have a key role to play in inspiring children to be use active modes to commute to and from schools.

The type of school children attend has a significant and practical impact on school travel mode. Children who study in a private school are less likely to walk or bike, which agrees with Babey's (2009) results (i.e., children who attend public school are more likely to walk or bike to school). This suggest that to encourage children to do more walking or biking and to reduce the obesity rate among children and youth, schools play a key role in advocating active commuting. Planners and city officials may also want to ensure that a network of safe sidewalks and bike lanes connects neighborhoods with local schools.

6.2 Limitations and Future Research

This study has several limitations. First, since the NHTS is designed to inform policymakers, planners, and transportation engineers about nationwide travel trends, it may not provide large samples in areas that I would have liked to study or during periods of extreme weather events. A larger sample with broad variations in the weather experienced by travelers would be useful to take another look at the impact of weather conditions on travel behavior.

Second, I included the New York City area in my sample, even though it has a well-developed transit system and specific land use patterns. This may somewhat protect travelers from rough weather conditions (at least by California standards).

Third, each study area in my study was identified by an MSA code, but it included several cities from different adjacent counties, even different states. However, my weather data were collected from only one station for each study area. I also used daily instead of hourly weather data in my models. The spatial and temporal coarseness of my weather data may also explain the lack of statistical significance of some weather variables. Future studies would benefit from using weather data that are more representative of where travel is taking place.

Having a better understanding of the impact of weather conditions on travel would help operate our transportation systems more effectively, especially as weather events are likely to play an increasing role as climatic changes settle in.

REFERENCES

1. Arana, P., Cabezudo, S., & Peñalba, M.. Influence of weather conditions on transit ridership: A statistical study using data from Smartcards. *Transportation research part A: policy and practice*, 59, 1-12. (2014)
2. Babey, S., Hastert, T., Huang, W., Brown, E.R.: Sociodemographic, family, and environmental factors associated with active commuting to school among US adolescents. *J. Public Health Policy* 30, S203– S220 (2009)
3. Badri, M., Ustadi, M., Pierson, L., Dramaki, M.: Mode of travel and the decision to allow children to walk or bike to schools – The Abu Dhabi experience. *Open Journal of Preventive Medicine* Vol.2, No.4, 514-527 (2012)
4. Braza, M., Shoemaker, W., Seeley, A.: Neighborhood design and rates of walking and biking to elementary school in 34 California communities. *Am. J. Health Promot.* 19(2), 128–136 (2004)
5. Buliung, R., Mitra, R., Faulkner, G.: Active school transportation in Greater Toronto Area, Canada: an exploration of trends in space and time (1986–2006). *Prev. Med.* 48, 507–512 (2009)
6. Clifton, K., Akar, G., Livi-Smith, A., Voorhees, C.: Gender differences in adolescent travel to school: exploring the links with physical activity and health. In: *Women’s Issues in Transportation: Summary of the 4th International Conference, Technical Papers, TRB Conference Proceeding 46, vol. 2, pp. 203–212. National Research Council, Washington DC* (2011)
7. Cools, M., Moons, E., Creemers, L., & Wets, G. Changes in travel behavior in response to weather conditions. *Transportation Research Record: Journal of the Transportation Research*

- Board, 2157(1), 22-28. (2010)
8. Ewing, R., Schroeder, W., Greene, W.: School location and student travel: analysis of factors affecting mode choice. *Transp. Res. Rec.* 1895, 55–63 (2004)
 9. Grize, L., Bringolf-Isler, B., Martin, E., Braun-Fahrlander, C.: Trend in active transportation to school among Swiss school children and its associated factors: three cross-sectional surveys 1994, 2000 and 2005. *Int. J. Behav. Nutr. Phys. Act.* 7, 28 (2010)
 10. He, S.: Effect of school quality and residential environment on mode choice of school trips. *Transp. Res. Rec.* 2213, 96–104 (2011)
 11. Hume, C., Timperio, A., Salmon, J., Carver, A., Giles-Corti, B., Crawford, D.: Walking and cycling to school: predictors of increases among children and adolescents. *Am. J. Prev. Med.* 36(3), 195–200 (2009)
 12. Hosmer Jr, D. W., & Lemeshow, S. *Applied logistic regression*. John Wiley & Sons. (2004)
 13. Hsu, H., Saphores, J. : Impacts of parental gender and attitudes on children’s school travel mode and parental chauffeuring behavior: results for California based on the 2009 National Household Travel Survey. *Transportation*, DOI 10.1007/s11116-013-9500-7. Springer Science +Business Media New York (2013)
 14. Kerr, J., Rosenberg, D., Sallis, J., Saelens, B., Frank, L., Conway, T.: Active commuting to school: associations with environment and parental concerns. *Med. Sci. Sports Exerc.* 38(4), 787–794 (2006)
 15. Kilpeläinen, M., & Summala, H. Effects of weather and weather forecasts on driver behaviour. *Transportation Research Part F: Traffic Psychology and Behaviour*, 10(4), 288-299. (2007)
 16. Lam, L.: Parental risk perceptions of childhood pedestrian road safety. *J. Saf. Res.* 32, 465–

478 (2001)

17. Lam, L.: Parental risk perceptions of childhood pedestrian road safety: a cross-cultural comparison. *J. Saf. Res.* 36, 181–187 (2005)
18. Larsen, K., Gilliland, J., Hess, P., Tucker, P., Irwin, J., He, M.: The influence of the physical environment and sociodemographic characteristics on children's mode of travel to and from school. *Am. J. Public Health* 99(3), 520–526 (2009)
19. Leslie, E., Kremer, P., Toumbourou, J., Williams, J.: Gender differences in personal, social, and environmental influences on active travel to and from school for Australian adolescents. *J. Sci. Med. Sport* 13, 597–601 (2010)
20. Liu, S., Murray-Tuite, P., Schweitzer, L.: Analysis of child pick-up during daily routines and for daytime no-notice evacuations. *Transp. Res. A* 46, 48–67 (2012)
21. McDonald, N.: Active transportation to school: trends among U.S. school children, 1969–2001. *Am. J. Prev. Med.* 32(6), 509–516 (2007)
22. McDonald, N.: Critical factors for active transportation to school among low-income and minority students: evidence from the 2001 National Household Travel Survey. *Am. J. Prev. Med.* 34(4), 341–344 (2008)
23. McDonald, N., Brown, A., Marchetti, L., Pedroso, M.: U.S. school travel, 2009: an assessment of trends. *Am. J. Prev. Med.* 41(2), 146–151 (2011)
24. McMillan, T.: The relative influence of urban form on a child's travel mode to school. *Transp. Res. A* 41, 69–79 (2007)
25. Meyer, H., Avi Astor, R.: Child and parent perspectives on routes to and from school in high crime neighborhoods. *J. Sch. Violence* 1(4), 101–128 (2002)
26. Mitra, R., Buliung, R.: The influence of neighborhood environment and household travel

- interactions on school travel behavior: an exploration using geographically-weighted models. *Journal of Transportation Geography*, volume 36, pp. 69-78 (2014)
27. Mitra, R., Buliung, R., Roorda, M.: Built environment and school travel mode choice in Toronto, Canada. *Transp. Res. Rec.* 2156, 150–159 (2010)
 28. Mitra, R., Faulkner, G.: There's no such thing as bad weather, just the wrong clothing: Climate, weather and Active School Transportation in Toronto, Canada. *Canadian Journal of Public Health* November/December 2012 pp s35-s41. Canadian Public Health Association, 2012.
 29. Napier, M., Brown, B., Werner, C., Gallimore, J.: Walking to school: community design and child and parent barriers. *J. Environ. Psychol.* 31, 45–51 (2011)
 30. Rodríguez, A., Vogt, C.: Demographic, environmental, access, and attitude factors that influence walking to school by elementary school-aged children. *J. Sch. Health* 79(6), 255–261 (2009)
 31. Sabir, M., Koetse, M. J., & Rietveld, P. The impact of weather conditions on mode choice: empirical evidence for the Netherlands. Department of Spatial Economics, VU University, Amsterdam. (2008)
 32. Schwanen, T.: Gender differences in chauffeuring children among dual-earner families. *Prof. Geogr.* 59(4), 447–462 (2007)
 33. Seraj, S., Sidharthan, R., Bhat, C., Pendyala, R., Goulias, K.: Parental attitudes towards children walking and bicycling to school: multivariate ordered response analysis. *Transp. Res. Rec.* 2323, 46–55 (2012)
 34. Sidharthan, R., Bhat, C., Pendyala, R., Goulias, K.: Model for children's school travel mode choice—Accounting for effects of spatial and social interaction. *Transportation Research*

- Record: Journal of the Transportation Research Board, No.2213 pp. 78-86, Transportation Research Board of the National Academies, Washington D.C., (2011)
35. Yarlagadda, A., Srinivasan, S.: Modeling children's school travel mode and parental escort decisions. *Transportation* 35(2), 201–218 (2008)
 36. Yeung, J., Wearing, S., Hills, A.: Child transport practices and perceived barriers in active commuting to school. *Transp. Res. A* 42, 895–900 (2008)
 37. Yoon, S.Y., Doudnikoff, M., Goulias, K.: Spatial analysis of propensity to escort children to school in southern California. *Transp. Res. Rec.* 2230, 132–142 (2011)
 38. Zhu, X., Lee, C.: Correlates of walking to school and implications for public policies: survey results from parents of elementary school children in Austin, Texas. *J. Public Health Policy* 30, S177–S202 (2009)

APPENDIX A: FIGURES

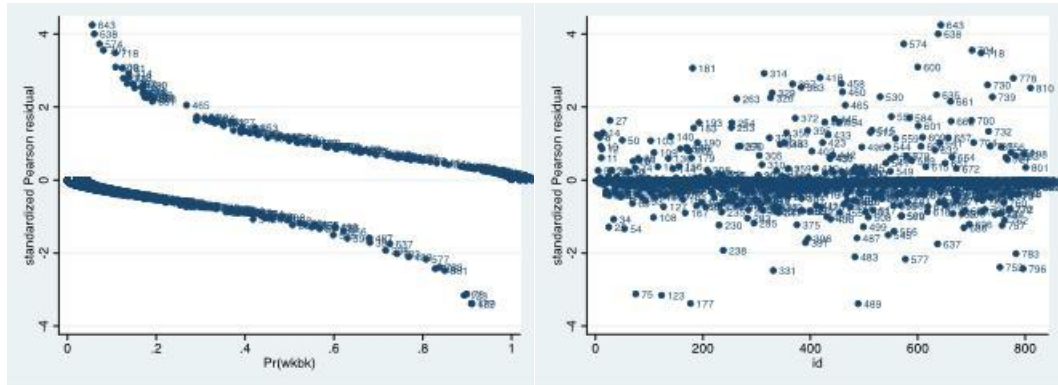


Figure A: Standardized Residual of To-school Model (revised model)

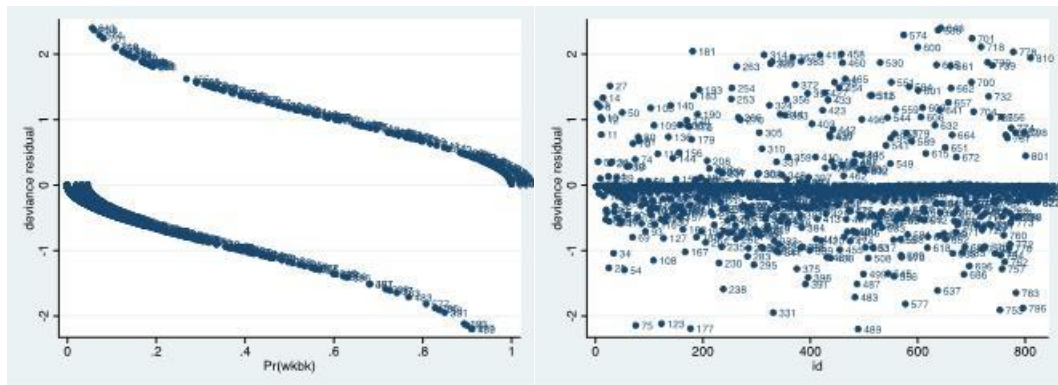


Figure B: Deviance Residual of To-school Model (revised model)

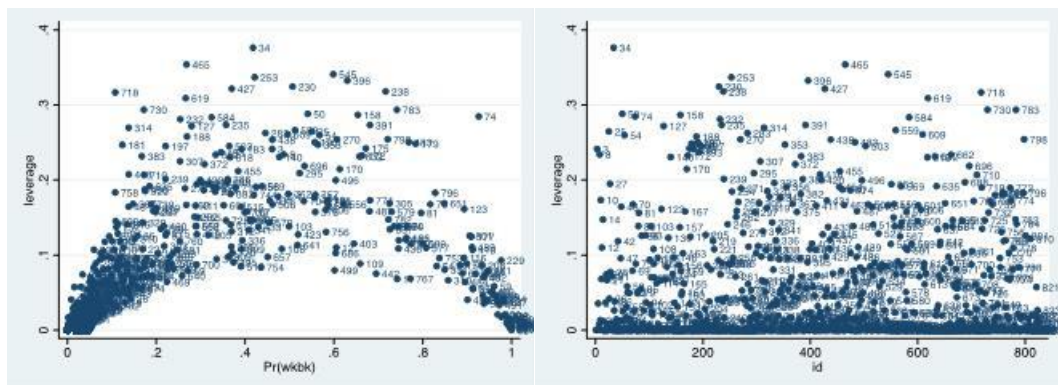


Figure C: Leverage of To-school Model (revised model)

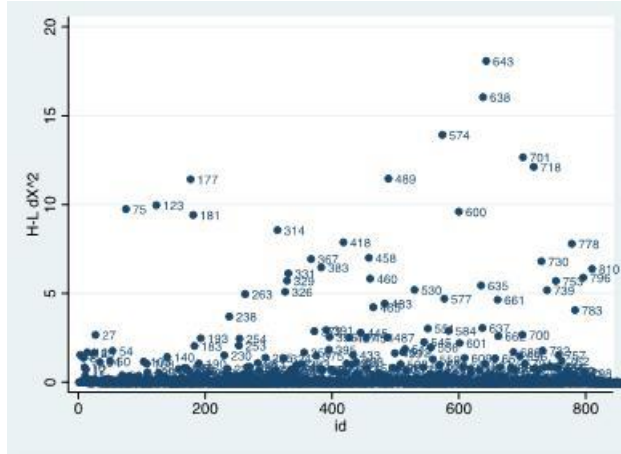


Figure D: Difference of Deviance of To-school Model (revised model)

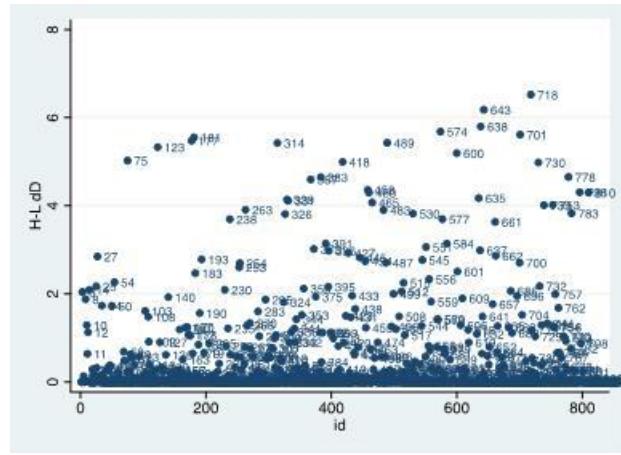


Figure E: Differenced of Chi-squared (revised model)

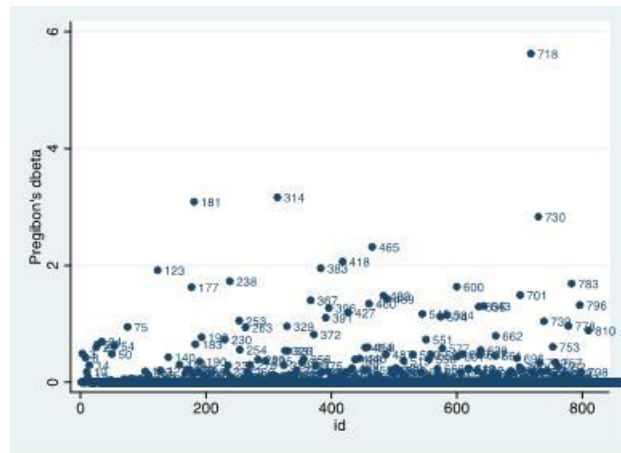


Figure F: Pregibon's dbeta of To-school Model (revised model)

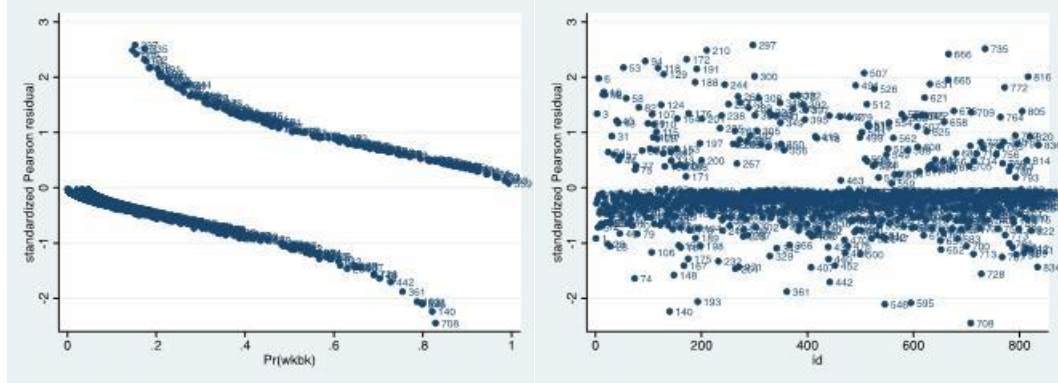


Figure G: Standardized Residual of From-school Model (revised model)

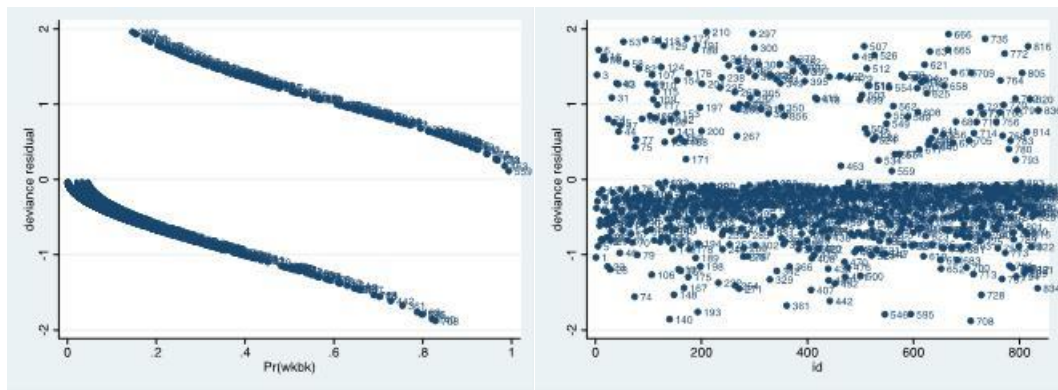


Figure H: Deviance Residual of From-school Model (revised model)

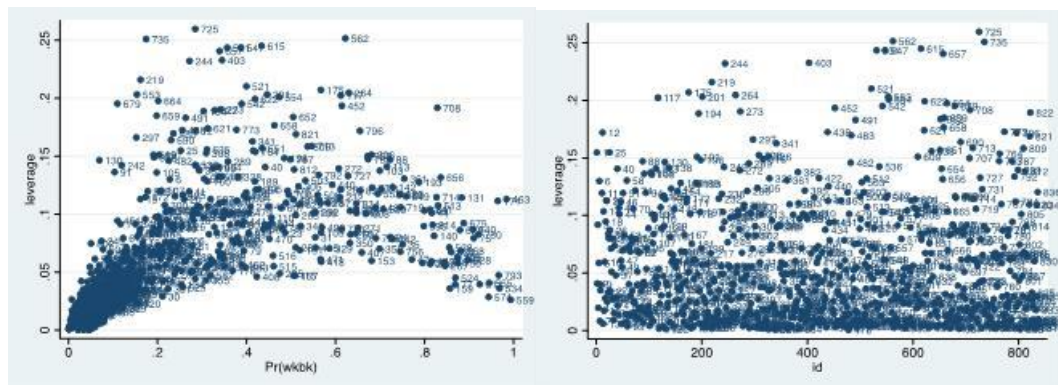


Figure I: Leverage of From-school Model (revised model)

APPENDIX B: TABLES

Table A: Linktest for To-School Best Model

Logistic regression	Number of obs	=	790.000
	LR chi2(2)	=	429.920
	Prob > chi2	=	0.000
Log likelihood = -171.898	Pseudo R2	=	0.556

wkbk	Coef.	Std. Err.	z	P>z	[95% Conf.Interval]	
_hat	0.954	0.091	10.470	0.000	0.775	1.133
_hatsq	-0.046	0.031	-1.470	0.141	-0.108	0.015
_cons	0.089	0.160	0.560	0.578	-0.226	0.404

Table B: Good of Fitness (Fitstat) for To-School Best Model

Log-Lik Intercept Only:	-386.856	Log-Lik Full Model:	-172.873
D(776):	345.746	LR(50):	427.967
		Prob > LR:	0.000
McFadden's R2:	0.553	McFadden's Adj R2:	0.421
Maximum Likelihood R2:	0.418	Cragg & Uhler's R2:	0.670
McKelvey and Zavoina's R2:	0.834	Efron's R2:	0.545
Variance of y*:	19.872	Variance of error:	3.290
Count R2:	0.901	Adj Count R2:	0.487
AIC:	0.567	AIC*n:	447.746
BIC:	-4584.886	BIC':	-94.365

Table C: Standardized Pearson Residual for To-School Best Model

	Percentiles	Smallest		
1%	-2.169	-3.385		
5%	-8.990	-3.380		
10%	-0.610	-3.157	Obs	790
25%	-0.245	-3.123	Sum of Wgt.	790
50%	-0.050		Mean	-0.019
		Largest	Std. Dev.	0.756
75%	-0.006	3.559		
90%	0.682	3.732	Variance	0.572
95%	1.357	4.006	Skewness	1.281
99%	2.926	4.251	Kurtosis	11.025

Table D: Deviance Residual for To-School Best Model

	Percentiles	Smallest		
1%	-1.815	-2.198		
5%	-1.024	-2.190		
10%	-0.746	-2.141	Obs	790
25%	-0.336	-2.115	Sum of Wgt.	790
50%	-0.070		Mean	-0.063
		Largest	Std. Dev.	0.659
75%	-0.009	2.241		
90%	0.807	2.936	Variance	0.434
95%	1.369	2.368	Skewness	0.833
99%	2.036	2.401	Kurtosis	5.669

Table E: Leverage for To-school Best Model

	Percentiles	Smallest		
1%	6.22e-06	2.63e-07		
5%	0.000055	8.03e-07		
10%	0.0001594	2.38e-06	Obs	790
25%	0.0012086	3.97e-06	Sum of Wgt.	790
50%	0.0178571		Mean	0.0591953
		Largest	Std. Dev.	0.0788808
75%	0.931067	0.3368979		
90%	0.1810676	0.3409161	Variance	0.0062222
95%	0.2411279	0.3538955	Skewness	1.519521
99%	0.3180158	0.3762646	Kurtosis	4.628662

Table F: Linktest for From-School Best Model

Logistic regression	Number of obs	=	825
	LR chi2(2)	=	359.540
	Prob > chi2	=	0.000
Log likelihood = -297.644	Pseudo R2	=	0.377

wkbk	Coef.	Std. Err.	z	P>z	[95% Conf.Interval]	
_hat	0.951	0.086	11.060	0.000	0.783	1.120
_hatsq	-0.038	0.036	-1.040	0.299	-0.110	0.034
_cons	0.052	0.123	0.430	0.670	-0.189	0.294

Table G: Goodness of Fit (Fitstat) for From-School Model (revised Model)

Log-Lik Intercept Only:	-477.415	Log-Lik Full Model:	-298.178
D(776):	596.356	LR(50):	358.475
		Prob > LR:	0.000
McFadden's R2:	0.375	McFadden's Adj R2:	0.269
Maximum Likelihood R2:	0.352	Cragg & Uhler's R2:	0.514
McKelvey and Zavoina's R2:	0.624	Efron's R2:	0.394
Variance of y*:	8.741	Variance of error:	3.290
Count R2:	0.821	Adj Count R2:	0.324
AIC:	0.846	AIC*n:	698.356
BIC:	-4601.351	BIC':	-22.706

Table H: Standardized Pearson Residual for From-School Best Model

	Percentiles	Smallest		
1%	-1.736	-2.468		
5%	-1.101	-2.274		
10%	-0.848	-2.244	Obs	825
25%	-0.471	-2.236	Sum of Wgt.	825
50%	-0.242		Mean	-0.030
			Std. Dev.	0.862
		Largest		
75%	0.290	3.102		
90%	1.241	3.351	Variance	0.743
95%	1.712	3.472	Skewness	1.169
99%	2.714	3.552	Kurtosis	4.975

Table I: Deviance Residuals for From-School Best Model

	Percentiles	Smallest		
1%	-1.624	-1.951		
5%	-1.199	-1.858		
10%	-1.015	-1.837	Obs	825
25%	-0.618	-1.833	Sum of Wgt.	825
50%	-0.333		Mean	-0.103
		Largest	Std. Dev.	0.852
75%	0.394	2.164		
90%	1.325	2.209	Variance	0.726
95%	1.601	2.254	Skewness	0.844
99%	2.042	2.276	Kurtosis	3.009

Table J: Leverage of From-School Best Model

	Percentiles	Smallest		
1%	0.0017793	0.0005726		
5%	0.0039659	0.0007026		
10%	0.0065622	0.000901	Obs	825
25%	0.0198783	0.0009396	Sum of Wgt.	825
50%	0.0478182		Mean	0.0586535
		Largest	Std. Dev.	0.0492289
75%	0.0833237	0.2460265		
90%	0.1292141	0.2524080	Variance	0.0024235
95%	0.1563440	0.2739516	Skewness	1.231475
99%	0.2129599	0.2812689	Kurtosis	4.577643