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Incentive Elasticity of Demand for Bike/Walk Program

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Disclaimer

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1. Introduction

The primary objective of this research is to estimate the "incentive" (price) elasticity of demand for using non-motorized transportation (specifically walking and bicycling) to work. Results can be used directly in the formation of local policies to encourage these activities. Benefits include improved environmental quality (Higgens 2005), and decreased incidence of overweight (Higgens 2005; Wen et al. 2006; Merom et al. 2005).

A secondary objective is to develop profiles of "heavy," "medium," and "light" users of the program in terms of demographic characteristics, behaviors associated with the program, and seasonality.

This study uses the Bike/Walk Bucks program data available from the Campus Area Transportation Management Association (CATMA). Coordinating with CAMTA will allow us access to two different data sets: the primary behavioral data set and a secondary data set with more detailed information about individuals and their use/attitudes toward the Bike/Walk Bucks program.

Winston (1985) provides a rather large review of the seminal economic literature related to transportation. Each commuting mode consists of a bundle of characteristics including time, space and cost. The Lancastrian approach to consumer theory addresses these choice bundles (Lancaster 1966). Commuting mode has been discussed in terms of the opportunity cost of time, making Becker's (1965) A Theory of the Allocation of Time a relevant reference. Both Lancaster and Becker can start as a point of reference for the development of an economic model of the demand for non-motorized transportation for commuting in that the good produced (transportation) is a function of a combination of time inputs and purchased inputs.

Also included in Winston's (1985) review are empirical methodologies that are as relevant to the analysis of transportation as they are to many other consumer choices. These choices are discrete, not continuous and therefore require adaptations of standard regression analyses. Early developers of these econometric approaches included Amemiya's (1981) Qualitative Response Models: A Survey. Indeed, further development of these types of statistical models by Maddala (1985) and McFadden (1973, 1974) have contributed as much to the estimation of modal choice as they have in other areas of consumer choice.

The above, broad inclusion of applied economists' approaches to consumer transportation choices clearly shows that the estimation of an incentive elasticity of demand for non-motorized commuting is analogous to a variety of consumer choices and the theories and techniques developed for transportation studies have been adapted to study a wide variety of consumer choices.

This project includes an extensive literature review and utilization of the CATMA Bike/Walks Bucks program data. It is possible that the dearth in the literature regarding incentive elasticities of demand are due to the fact that data do not exist that cover a period of the program in which the incentive changed. Elasticity, in an economic sense, is the percentage change in demand given a one percent change in price. If there is no variability on price, then the elasticity for participants can not be calculated. The Bike/Walk Bucks program changed its incentive in January 2007. Therefore we will have both variations in price (incentive) and quantity demanded (biking/walking) measurements and will be able to calculate an elasticity. We will also be able to calculate elasticities for various characteristics of both participants and place. We will calculate incentive elasticities for subgroups of participants and by season to test the null hypothesis:

> H10: The incentive elasticity of demand for walking/biking to work is the same regardless of the individual characteristics of the participant. These characteristics include demographics and seasonality.

This project has the potential to add to the body of transportation literature through the addition of another indicator of "what works" to encourage non-motorized commuting behaviors. While economic approaches have been used to estimate a variety of transportation elasticities, the dearth of available data has made elusive the calculation of "incentive elasticity."

This research was conducted beginning in August 2007 through August 2008, using data from 2006-2007. Appendix A includes a complete literature review.

2. Research Methodology

2.1. Methods

The Campus Area Transportation Management Association (CATMA) in Burlington, Vermont, population 39,000, (US Census 2000) oversees a variety of programs to ensure efficient and equitable transportation solutions for employees of its member organizations, including the University of Vermont and Fletcher Allen Healthcare. One program, the Bike/Walk Bucks Reward Program, has recently undergone several changes. Launched in 2001 as an incentive for commuters to bike or walk to and from work, the program currently has over 700 enrolled participants, with approximately 200 actively participating in any given month. For the first five years of the program, participating employees committed to bike or walk to work at least two days a week for four consecutive weeks. Each participant receives a card to record the dates they bike and/or walk to work. After completing the card, participants were sent a $10 gift card redeemable at stores/restaurants in the Burlington Town Center and the Church Street Marketplace (CATMA 2007).

Beginning in 2007, participants were required to bike/walk at least three times a week and cards are completed in eight-week blocks. Participants have a choice of four rewards, all valued at $15: the original gift card, or a gift card specific to City Market, Merrill's Roxy Cinema, or Borders Bookstore. These changes were made to address the increasing participation in the program (CATMA 2007).

The data for this analysis were collected from participants' completed cards from January 2006 through July 2007, reflecting six months before and six months after the program's incentive change. While the information on the card is self-reported, participants are occasionally contacted to validate the accuracy of the information reported. One hundred sixty participated in the program (by making a least one bike/walk trip before and after the change) during the time period studied and were therefore included in this study.

Those who participate in the bike/walk program are not typical of the CATMA employee community. Only a small proportion of this community are enrolled in the program and those who participate in the program are more likely to live closer to work. Of all the CATMA employees, just fifteen percent (15%) usually bike or walk to work, with approximately seven percent (7%) of CATMA employees enrolled in the Bike/Walk Bucks Reward program and approximately two percent (2%) actively participating in the program at any given time. For comparison, approximately 80% of employees of CATMA member organizations live in Chittenden County, compared to 100% of those in the Bike/Walk program.

2.2. Model

Economists have shown that elasticity of demand must not ignore the cost of time (Becker 1965). Mode choice studies have repeatedly shown the importance of time value on mode choice (Gomez-Ibanez, Tye & Winston 1999). Non-motorized commuting typically requires more time spent in the commute, effectively reducing the wage rate (more hours spent in work activity with no increase in income), and lowering income if additional hours are not spent in labor. When wage rate decreases, a consumer will choose to increase their leisure time, since their work time is less valuable. At the same time, their leisure time decreases as a result of having to spend more time in work for the same income. The net effect depends on the actual wage rate and change in income, as well as time spent commuting. Even when one gets utility (directly or indirectly) from an activity, the price or cost of the activity must be considered along with the opportunity cost of time spent in the activity (Becker 1965).

By implementing an incentive program, CATMA has attempted to mitigate this effect, as the incentive partially compensates for a lower wage rate. Furthermore, CATMA employees who use non-motorized modes may gain utility directly from their commute by realizing health benefits; therefore, they may be more likely to view their commute time as leisure than those commuting by motor vehicle, which would also mitigate the above-described effect.

Demand for bike/walk trips may be affected by two opposing effects. The substitution effect states that, as the wage rate decreases (that is, as the incentive decreases), the value of work time decreases and these commuters will substitute leisure time for work time because leisure has become relatively less expensive. At the same time, the income effect states that for normal goods (those goods for which demand increases as income increases), as the wage rate decreases, demand for trips will also decrease. Since a rise in income (resulting from the incentive) will result in an increase in the opportunity cost of commuting (Becker 1965), an incentive could decrease willingness for a longer commute if no other utility (such as perceived health benefits) results from the longer commute.

As the price of time decreases (that is, as the incentive decreases), the demand for bike/walk trips also decreases. At the same time, the income effect results in a decrease in income which in turn causes a decrease in bike/walk trips. The sign of the trips coefficient will be determined by which effect is stronger in this model. Further, the cross price effect must also be considered; how does the effect of the price of the alternative affect bike/walk trips. In this case, cross price effects might include the price of gas, the price of parking, the amount of traffic congestion, the availability and cost of transit.

Joint production describes now more than one output is produced from one production process and share inputs (Lancaster 1966; Rosenzweig & Schultz 1983). In the case of non-motorized commuting, several outputs may be produced, including the commute itself, exercise/good health, and/or mental health. This joint production capability may result in commuters gaining more utility from non-motorized commuting.

In general, goods and activities like cars and commuting do not have an intrinsic utility (Lancaster 1966), but have characteristics which lead to utility. In the case of commuting, utility is gained from getting to work. On the other hand, due to mental and physical health benefits (utility), commuters may obtain more direct utility from non-motorized forms of commuting in the form of exercise, health benefits, or self-satisfaction and positive contribution to the environment. Therefore, the expected sign of the coefficient for years in the program is positive; the longer someone participates in the bike/walk program the more trips they are likely to make. Season and weather also affect the bike/walk trips and the expected signs are positive in the fall and spring, negative in the winter. The literature suggests that gender is an important variable and men are far more likely than women to rely on non-motorized commute modes. There are many reasons for this, ranging from women's role in childcare responsibilities and household chores (competing demands for time), to social constraints such as dress and image. Therefore, the expected sign for gender is negative.

This study examines the commute behavior of employees who participate in an employer-sponsored incentive program. Demand for commute trips was analyzed controlling for the amount of the incentive, distance traveled, longevity in program, non-motorized mode, gender and season. In addition, the incentive elasticity of demand is calculated to demonstrate the effect of the incentive on the demand for non-motorized commute trips.

3. Results

The data set used for analysis (Table 1) consisted of program participants who made at least 1 bike/walk trip during the 6 months before and after the incentive changed. The data set is time series panel data, as it follows the same 160 commuters over the course of 53 weeks.

This model of the incentive elasticity of demand for bike/walk trips is represented as:

Number of trips/week = F (Incentive Amount, Years in Program, Mode, Town, Season, Gender)

Table 3-1. Variables, definitions and expected signs

Variables	Definition	Expected Signs
Dependent Variable		
Made a bike/walk trip	Yes/No	
Met threshold	Yes/No	
Independent Variables		
Town	Town of residence, either	Positive
Spring	March 21 – June 20	Negative
Winter	December 21 – March 20	Negative
Fall	June 21 – September 20	Positive
Mode-Walk	Walk mode, not bike or both	Unknown
Years in Program	The number of years in	Positive
Incentive Amount	Incentive was $2.50/week	Positive
Gender	Female	Negative

The rationale for the expected signs is as follows:

The dummy variable for town which is a 1 if Burlington and 0 if some other town is expected to be positive because participants are more likely to bike or walk shorter distances than longer distances and all employers are located in Burlington. The dummy variable summer may be positive as well because better weather in the summer could result in more bike/walk trips. The number of years in the program is expected to be positive because commute mode may be habitual, once in the habit participants may find it easier to make more trips.

The incentive amount is expected to be negative, since the incentive decreased over time it may result in fewer bike/walk trips. The dummy variable winter is expected to be negative as the cold winter weather may result in fewer bike/walk commute trips.

The expected signs of employer, mode type and incentive type are unknown, as it is not clear whether these variables will have a positive or negative effect on the number of bike/walk commute trips.

As shown in Table 2, the average number of bike/walk trips per week is 2.23. Since in the first six months studied the program requires at least two trips per week during participating weeks and the second six months required three trips per week, this mean is somewhat lower than expected. The average incentive of $2.20 reflects an incentive of $2.50 from July 2006 through December 2006 and $1.88 from January 2007 through June 2007.

Table 3-2. Descriptive Statistics, N=160

Variable	Mean
# of Trips	2.23
Incentive Amt	$2.20
Mode (Walk)	0.58
Town (Burlington)	0.86
Years in Program	4.19
Winter	0.25
Spring	0.25
Fall	0.25
Female	0.61

The mode mean of 0.56 reflects a slight propensity of the program participants to walk rather than bike or use both modes. The timeframe for this study was one calendar year, so the equal distribution among each season is not surprising. As shown in Table 2, program participants are more likely to be women than men, and the majority of participants commute from within the city of Burlington, Vermont.

The simplest calculation of the elasticity of the number of trips made in response to a change in incentive

$$\frac{\text{Change in number of trips}}{\text{Change in incentive}} \quad X \quad \frac{\text{Incentive}}{\text{Number of trips}}$$

results in an elasticity of 0.182, meaning that the number of trips increases as the incentive increases, but at a much lower rate than the incentive (inelastic demand). In this simple model, all values are calculated at the mean. While this simple elasticity is a good starting point, it does not control for other variables that may affect the elasticity. A regression model would control for the other variables. However, simply using the Ordinary Least Squares regression model resulted in an unexpected negative coefficient for the incentive variable. The dependent variable, number of commute trips, has a limited number of possible values. Most people commute to work no more than five days per week, with a maximum number of seven weekly commute days. While it is possible to make more than one trip per day, realistically commuters only commute from home once each day. A standard regression model assumes that the dependent variable is truly continuous. Therefore, the most appropriate model to use is one of a limited dependent variable. Further confounding these results, simultaneous to the change in incentive the number of trips required to meet the threshold was increased. While the decrease in incentive results in fewer trips, the increased threshold results in more trips, and so the best fit model accounts for both of these decisions separately.

To account for limited values of the dependent variable and the change in required number of trips, a binomial probit model was constructed using Limdep 9.0, Econometric Software Inc. Plainview, NY (Greene 2007a; Greene 2007b). Tobit (with and without Cragg's model) (Tobin 1958; Cragg 1971; Greene 2007a; Greene 2007b) and bivariate probit models were also considered but the binomial probit model fit the results best. The binomial probit was used to determine what effect, if any, the increase in the trip threshold had on the model. By using a binomial model, the probability for making a trip was determined separately from the probability of meeting the threshold of required trips, to account for any effect the increased requirement might have. But the decision to make a trip nearly always resulted in meeting the required threshold for number of trips (both before and after the threshold changed) so only the model predicting whether to make a trip is reported here. In probit models, the function used is the inverse of the standard normal cumulative distribution. After observing consistent results regardless of the number of Halton draws specified, for simplicity and speed, the final model used 2 draws.

All of the results where significant show that demand is relatively inelastic with respect to the incentive. The coefficients for incentive, while positive, show that incentive has very little effect on the probability that a trip is made in any particular week, all other variables being held constant.

Table 3-3. Binomial probit model of probability of making a trip

	Probability of making at least one trip
Incentive Coefficient	0.035**
Elasticity	*0.13***
Years in Program	-0.010
Winter	-0.033***
Spring	-0.062***
Fall	0.082***
Gender	-0.118***
Town	0.012
Mode	-0.003

N=160
*p<.1
**p<.05
***p<.01

Although none of the variables individually have a large impact on the decision to make a trip, gender has a relatively large effect on the decision to make a trip with the probability of being female decreasing the likelihood of making a trip, as shown in Table 3. Surprisingly, the number of years someone participates in the program has very little (or no significant) effect on the decision to make a trip. Also somewhat surprising, living in Burlington (which is a proxy for distance) does not significantly increase the probability of making a trip, suggesting that, within a range, shorter commute distances have little effect on the likelihood of walking or biking, though no commuters living outside of the county participate in the program so the distance under consideration are only those within the county.

The effect of seasons is also not surprising. Winter and spring (from December 21 to June 20) have a generally negative effect on the decision to walk or bike to work. In some climates, the negative effects of spring might be surprising but in northern Vermont where the last frost may be as late as mid-May, the weather can be inclement through most of spring. Fall (defined as September 21 through December 20), however, has a positive effect on the decision to commute by bike or foot.

In summary, the increase in the required number of trips concurrent with the decrease in the incentive amount effectively kept the overall number of trips from declining. The change in the incentive did not result in a significant change in the probability of making a trip.

4. Implementation/Tech Transfer

The results of this research were included in the Master's Thesis titled "Individual Investment In Health: An Evaluation Of Policies And Programs". In addition, the results were presented as "Will Financial Incentives Effectively Increase Demand for Non-Motorized Commuting?" at the Transportation Research Board 2009 Annual Meeting. The results have also been submitted for possible inclusion at the Marketing & Public Policy Conference and the Transport Research Foundation Conference.

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Several limitations have been noted about this research. This study does not include employees who chose not to participate in the bike/walk program, or those who may have ceased to participate in the program after the incentive changed. Among the participants, because this study relies on revealed preference data not survey data, there is a lack of demographic variables which may have added robustness to the model. Lastly, this model does not account for environmental factors, such as sidewalks, bike lanes and other infrastructure factors, which have been shown to influence non-motorized commute rates in other studies.

5. Conclusions

Transportation and obesity are two of this decade's largest public policy challenges, with non-motorized commuting at the nexus of the two issues. Economists and transportation planners have long studied mode choice and predicting demand for motorized alternatives. This research represents a preliminary investigation into demand for non-motorized commute modes and the role policy generally, and incentives specifically, may play in promoting these modes.

With the price of gasoline expected to increase over the long term, commuters are more motivated than ever to reevaluate mode choice. The media reports increases in transit trips as well as creative alternatives to solo driving. By linking cost savings and health benefits of non-motorized commuting, policymakers and proponents of alternative commute modes may be able to affect change in mode choice.

While this research has shown that economic incentives may not greatly increase demand for non-motorized commute trips, the literature and economic models show that policy solutions do affect demand for commute modes. Policy solutions must be carefully considered and evaluated for likely impact before being implemented, as this research shows that a small incentive may be treated more as a reward for existing behavior than as an impetus to change commute behavior. By using a binomial probit model, this research analyzes not only the impact of the incentive and the change in the incentive, but other factors that may influence mode choice decision among those who have committed to bike/walk. Further research is needed to determine the appropriate mix of policy solutions (economic, land use, social) to encourage non-motorized commuting, as well as to size the potential market for non-motorized commuting. Even with supportive policies, non-motorized commuting may not be feasible for the majority of commuters.

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Appendix A

Literature Review

Economic policy tools and transportation

Prevailing policies and investments in the latter half of the twentieth century have resulted in infrastructure development favoring automobiles at the cost of all non-motorized transport (Sallis et al. 2004). While incentives and other subsidies may help achieve some level of market equilibrium, they may also diminish the promotion of social good. The first risk in providing incentives is that they may simply maintain or increase usage by those already using the desired mode, resulting in very little behavior change (or additional cars off the road) despite programmatic and financial investments in the incentives. This could result in no affect on commute behavior while incurring a financial cost. Even worse, the financial incentive could result in fewer commuters using the desired mode because commuters may cease to consider their non-motorized commute choice a social good.

Some literature suggests that financial incentives may undermine efforts when the desired behavior is a social good. For example, offering to pay blood donors seems to negatively impact their willingness to donate blood (Frey & Oberholzer-Gee 1997). The underlying theory is that financial incentives may reduce the “intrinsic motivation” one has to behave altruistically (Gneezy & Rustichini 2000). Because some commuters may consider walking and biking to be a social good, the use of financial incentives to promote non-motorized transportation should be reviewed with this consequence in mind. In future, it may be useful to determine if non-motorized commuting is perceived as primarily a self-serving or community-serving activity.

Economic incentives produce behavior change when the benefit is primarily self-interested, not altruistic, such as health benefits (Kane et al. 2004). Evidence suggests that short trips will shift to non-motorized modes when incentives are combined with vehicle restrictions, at least in the U.K. and Canada (Litman 2004). However, the level of incentive required to obtain long-term behavior change is unclear. In addition, the importance of internal motivation should not be overlooked (Frey & Oberholzer-Gee 1997). While an incentive may result in a short-term, finite behavior change, it is unlikely to sustain long-term behavior modification without internal motivation (Kane et al. 2004).

Recognizing the importance of the environmental, health and other effects of commute mode, Metropolitan Planning Organizations (MPOs) must now plan for pedestrian and bicycle traffic (Plaut 2005). Communities are encouraged to develop programs that will make alternatives more attractive and subsequently reduce demand for car trips (Harrington et al 2001). In addition, larger companies in many communities have mandates to reduce the number of their employees who commute alone each day (Balsas 2003). These pressures to reduce car trips and encourage alternate mode use have resulted in increased research and testing of various policy tools to reduce congestion and driving alone, and promote use of alternate modes.

Another policy area that researchers believe contributes to the likelihood of non-motorized mode use is urban design (Pucher & Dijkstra 2003; Cervero 1996; Moudon 2005; Lumsdon &

Mitchell 1999). Some urban areas have invested in high density development, partly in hope that it will encourage more non-motorized mode use and/or fewer car trips (Plaut 2005). Individuals rely on automobiles because land uses are separated (Khattak & Rodriguez 2005), and non-motorized trips increase in mixed land use areas, especially those with high population densities and employment at trip origin and destination (Cervero 1996; Frank & Pivo 1994; Handy 1996; Kitamura et al. 1997). Community features like sidewalks, public transit, along with land use and density are related to mode choice, but even more important in predicting mode choice is the traveler's attitude toward modes (Kitamura et al. 1997). Moudon et al. (2005) further conclude that proximity to offices, medical facilities, and restaurants significantly affect the choice to make non-motorized trips. Spending on bicycle infrastructure, such as bike lanes, has increased and communities that made larger investments have experienced higher levels of bicycle commuting (Dill & Carr 2003). Another factor that positively affects the likelihood of using an alternative commute mode is a mixed-use work setting – one that combines service, restaurant, and traditional commercial space (Cervero 2002). Most of this research, however, examines leisure use, or does not distinguish between trip purpose; limited research suggests that environmental factors such as sidewalks and traffic volume are correlated to utilitarian physical activity like commuting (Troped et al. 2003).

One important issue in urban transportation today is congestion (Small 2006). It is easy to see why congestion is a top priority when between 1980 and 1996, total highway miles increased by 15% while vehicle use of highways increased by 75% in the same time period (FHWA 1998). Several policy tools are available to address the problem of congestion but, despite the elasticity models developed in the 1970s and 1980s, many economists believe that commuter behavior will change if the price of single car commuting increases. This belief is primarily motivated by the fact that rush hour commuting is currently priced below its real cost, both through subsidization of infrastructure and parking as well as by not accounting for the environmental and health costs of motorized commuting. Anecdotally, media reports of increasing transit usage as gas prices exceed four dollars per gallon lend support to this belief. Direct increases to the price of commuting are politically difficult to implement (as exemplified by recent political proposals to roll back the gas tax to lower the cost of fuel) so most policies try to address the price disparity by providing incentives to commuters using alternative modes (Small 2006). As with MPOs and large corporations, many universities have been testing a variety of solutions to alleviate congestion for campus users. Transportation Demand Management (TDM) has resulted in solutions like market pricing for parking, better transit access for campus users, rideshare programs, and bicycle and pedestrian programs and facilities (Balsas 2003). Further influencing university priorities has been the Talloires Declaration which details actions to be taken by universities to create a more sustainable future, which has been signed by over 275 universities worldwide (Balsas 2003).

While the likely effectiveness of price-related policies is questionable, other policy tools, both economic and otherwise, may help to promote a bike and pedestrian friendly community. Two important hurdles to overcome are the social stigma and perceived safety; policies that address either or both of these issues will promote bike and pedestrian modes. Since most federal transportation funding programs permit expenditures to improve walking and biking

(Pucher Komanoff & Schimek 1999), especially as it relates to safety, there is funding available for policies and programs such as better facilities for walking and cycling (such as sidewalks and bike lanes), traffic calming, education of both motorists and non-motorists, and enforcement of existing traffic regulations which promote safety (Pucher & Dijkstra 2003). To this point, however, few communities have promoted awareness and education of non-motorist safety and rules of the road among non-motorists and motorists (Pucher Komanoff & Schimek 1999). Interestingly, some research has shown that supposed safety features such as bike lanes and traffic speed are insignificant in predicting bicycle use (Moudon et al. 2005).

Not only are non-motorized modes better for health and the environment, but they promote social equity (Sallis et al. 2004). Walking and biking are the cheapest commute modes, available to nearly everyone (Pucher Komanoff & Schimek 1999). Policymakers, especially in areas of great socio-economic disparity, could rely on the social equity issue to justify investment in non-motorized commute modes.

Obesity is another policy issue being addressed by many communities. Most communities have chosen to address obesity through policies designed to affect food consumption, but non-motorized transportation policies could also be used to promote more active, healthy lifestyles (Dora 1999). With 65% of Americans overweight, and some 30% considered obese, policymakers anxiously seek solutions. Most proposed solutions entail telling Americans what they can (or can't) eat, but to address a problem of this magnitude solutions should encourage energy expenditure, as well as limiting energy intake. Benefits of moderate, daily physical activity are numerous and should not be undercounted (Oja, Vuori & Paronen 1998; HHS 1996) and some studies suggest that not engaging in regular daily activity may contribute to the obesity trend in America and the Surgeon General recommends walking and cycling for utilitarian travel as a way to increase regular daily activity levels (Pucher & Dijkstra 2003). Neighborhood environment and travel mode are both predictors of obesity (Frank et al. 2004) and some research suggests that walking and cycling as part of daily travel is an affordable way for Americans in achieve recommended levels of daily activity (Dora 1999; Koplan & Dietz 1999; Carnall 2000), though the direct connection between walking and reducing obesity is less clear (Berke, et al. 2007). Increasing physical activity must be a tactic in any strategy to reduce obesity and reducing short car trips should be a part of increasing levels of physical activity (Koplan & Dietz 1999). A variety of approaches have been tested and met with varying success in efforts to determine the best strategy for increasing physical activity (Kahn et al. 2002), but health promotion and transportation naturally overlap (Lumsdon & Mitchell 1999) and joint solutions and strategies may better serve both goals. Bike/walk commuting offers one way to incorporate physical activity into everyday routines (Oja, Vuori & Paronen 1998) to address goals set forth to increase physical activity among Americans (HHS 1996).

Trends in non-motorized transportation

Prior to the mid-1800s, walking was the primary mode of commuting. The availability of motorized modes, and government subsidization of these modes, such as transit and automobiles, particularly since World War II, resulted in a rapid decline of non-motorized modes. Today, non-motorized transport options are not typically included in commute mode models. Cycling makes up less than 1% of all commute trips (Pucher, Komanoff & Schimek 1999), but policies that encourage cycling could increase the number of cycling commute trips, particularly by improving environmental conditions, both real and perceived (Moudon et al 2005). Though adult walking trips have increased in recent years they still lag below U.S. goals (Ham et al. 2005; USHHS 2001). University communities make for particularly effective laboratory environments for testing these policies (Balsas 2003) since residents of these communities typically fit the demographic profiles of alternative commuters. Additionally, many universities need to address parking and traffic demands for infrastructure, but lack the will, funds, or land to accommodate increased demand.

Many factors contribute to the very low incidence of non-motorized commute modes, ranging from weather and geography, low costs of autos, to land use and infrastructure, travel time, safety, and lack of social acceptance of the mode (Cervero 1996; Plaut 2005; Bergstrom and Magnusson 2003). The average commuter using non-motorized transportation is male, white, well-educated, low/middle income, does not own a car, and lives close to the city center (Plaut 2005; Moudon et al. 2005). Women are less likely to use non-motorized commute modes, which may be due to their need for 'chaining trips,' especially those involving children (e.g., dropping the kids off at day care on the way to work) (Cervero 2002), safety concerns, or possibly the image of cyclists as rebels or renegades (Pucher, Komanoff & Schimek 1999).

Physical surroundings (both constructed and natural) also influence a commuter's mode choice. Those who live near commercial areas and green spaces are more likely to walk or bike to work (Plaut 2005). Plaut (2005) also found that non-motorized commuters are more likely to live on the West Coast, which may be due to factors of weather, geography, and/or attitudes towards "green" commuting. Destination type also influences mode choice. Leisure destinations are less associated with walking than more utilitarian destinations (Lee & Moudon 2006).

Recent research has studied walking and biking in different types of residential neighborhoods, comparing conventional suburban neighborhoods with "neotraditional" urban villages. Khattak & Rodriguez (2005) found that households in the urban-village/mixed-use communities substituted non-motorized trips for driving trips, though not necessarily for commute trips and specifically communities that are "sprawling" result in fewer minutes walked and higher likelihood of obesity among residents (Ewing et al. 2003). Specifically, urban village households make 20% fewer auto trips than those in conventional suburban neighborhoods (Khattak & Rodriguez 2005). One study of similar communities found that residents of a mixed-use community made 10% fewer non-work trips by car, and they had higher rates of non-work walk trips (Cervero & Radisch 1996). Other studies have found that residents of mixed-use communities make more walk or bike trips per week (Handy 1993; Saelens, Sallis & Frank 2003; Frank et al. 2007), but the modes used for work commuting do not differ based on land-use. Residential density and connectivity is positively correlated with walking (Lee & Moudon 2006; Saelens, Sallis & Frank 2003).

Bergstrom & Magnusson (2003) found that car trips increased by nearly one-third and bike trips decreased by nearly half from summer to winter in this study of Scandanavian commuters. In addition, they found that distance was a more significant variable in commute mode in the winter than in the summer (Bergstrom & Magnusson 2003) and bikeways/sidewalks free of snow was important in selecting travel mode. Weather aside, it is unclear that distance plays as significant a role in commuter's mode choice. Two out of five car trips in the United States travel less than two miles (Pucher & Renne 2005) and nearly 30% were shorter than one mile (Pucher & Dijkstra 2003). Similar to the general driving statistics, one in five work trips are less than one mile, and two in five work trips are less than two miles (Moudon et al 2005). Even with such short commuting distances, only 15% of the population bike at least once a week (HHS 1996) including both leisure and commute trips. Pucher & Renne (2005) found that cars are used for two-thirds of all trips up to one mile long, and 89% of trips between one and two miles. While commute distance negatively affects likelihood of non-motorized travel (Cervero 1996), even short distances are most likely to be traveled by car.

Despite reports that the number of bicycle trips made in the United States has doubled over the past 20 years, the vast majority of trips are still made by car in both urban (86%) and rural (91%) areas, while non-motorized modes are used in just ten percent and six percent of trips, respectively (Pucher & Renne 2005). In rural communities especially, walking/biking are no substitute for a car, even when the household doesn't own a car. In rural households without a car, only one-quarter of all trips are made by non-motorized modes (Pucher & Renne 2005). Density plays a role, as in urban households nearly half of all trips are made by non-motorized modes, compared to just 9% of trips for those households owning a motor vehicle (Pucher & Renne 2005). Household car ownership significantly affects the percent of trips made by walking or biking, but even without owning a car, the majority of trips made by a household are by car (Pucher & Renne 2005).

Economics of mode choice

Traditional microeconomics dictates that to affect demand, price must change due to either a supply shift or an economic regulation. Economic regulations can be positive or negative incentives (taxes vs. subsidization). Many economists believe that increasing the cost of traditional motorized commuting may encourage the use of non-motorized transportation for commuting. However, for such a shift in transportation mode to succeed, viable alternative transportation options must exist.

With single occupant commuting currently priced below its real cost (Small 2006), an alternative to taxes may be needed to provide a positive incentive for public transit and/or non-motorized commuting. Small (2006) argues that incentives could be used to adjust the price of driving to better reflect its real cost. Balsas (2003) found that university communities often lead the way in providing incentives to use non-single occupant modes through such means as subsidized or free transit passes. Down's law states that congestion will rise to meet the maximum available capacity as commuters shift commute patterns to reflect preferred routes and times (Winston 1991). The idea that infrastructure spending should increase to reduce congestion is not based on efficient pricing models. Rather efficient infrastructure investment should maximize the difference between social good provided by the infrastructure and the costs of using the infrastructure. Commuters may ignore their personal contribution to congestion and resource use, resulting in the social costs exceeding the social goods, unless these external costs are internalized to the commuter. The gasoline tax is one way to internalize some of the infrastructure costs, though it makes up an increasingly small portion of the costs, as infrastructure costs and congestion increase, while the tax rate remains unchanged.

Optimal, or first-best, pricing occurs when the market sets the price based on equilibrium of supply and demand. In certain markets, however, due to regulations or other externalities, optimal pricing is not attainable. In that case, policymakers and regulators may rely on a “second-best” solution to ensure prices are closer to optimal than could otherwise be attained in that market (Verhoef, Nijkamp & Rietvald 1996; Verhoef 2002; Small & Yan 2001). Second-best theory states that if optimal conditions cannot be achieved then the next best conditions (second best) can be achieved by departing from all other market conditions. In general, second-best pricing addresses taxes, tariffs and other sub-optimal conditions (Lipsey & Lancaster 1956). In the case of transportation, the price of roads is based on the cost of supply and demand is estimated indirectly through collection of fuel and other taxes. But for any given road, the price of usage does not reflect the demand for that road (congestion). Optimal pricing would set a toll equal to the marginal cost of each road segment that would vary based on congestion (Verhoef 2002). Optimal pricing is not a practical or equitable solution for roads, so regulators rely on second-best solutions such as tolled express lanes (Small & Winston 1999). Subsidies and incentives may provide the “second-best” alternative to provide an equal playing field among commute modes. Incentives to reduce car commuting are seen as a way to accomplish a variety of social goods, including health and environmental benefits of reduced congestion, reduced air and noise pollution, and increased walking (Plaut 2005).

Further contributing to the underpricing of commuting, the vast majority of parking is provided free of charge to the driver, and usage and consumption fees (tolls, taxes, etc.) are relatively low; the use of commute modes can hardly be said to be market driven (Pucher & Dijkstra 2003). Yet there is much reluctance to increase any of these fees. Parking subsidies greatly increase solo driving (Willson & Shoup 1990) and when commuters must pay for parking, fewer drive alone. When employers reduce or remove parking subsidies, a significant number of solo drivers shift to carpools and/or transit. Because 90% of American commuters who drive to work receive employer-paid parking (Willson & Shoup 1990), these findings are significant for designing transportation policies to reduce air pollution, traffic congestion, and energy consumption.

Discrete choice models have been widely used to predict transportation mode choice for the past forty years. During this time, the basic analytical methods of logit and probit analysis have remained, but have been refined to allow stronger confidence in their predictive power by supporting more complex models. Many improvements were enabled by the concurrent improvements to computing power. In addition, researchers have recognized the difference between using “stated” preference data (what people say) and ”revealed” preference data (what people do) in the predictive capability of these models; making the same models more accurately predictive of actual behavior. Lastly, the context of travel in the models has changed from assuming primarily trip-based motivation to assuming activity-based travel motivation (or a hybrid of the two) resulting in models that acknowledge the importance of trip purpose and interconnections between trips in predicting mode choice.

Discrete choice models are often used to predict transportation mode choice because such choice incorporates many different types of variables into a single decision (FHWA 1998; Ben-Akiva & Bierlaire 1999). Some variables are individual characteristics such as age or gender, other variables in the model describe common factors of each alternative choice such as cost of trip or duration of trip, while still other variables may describe the trip itself or even the activity which motivates the trip (e.g., work versus recreation) (FHWA 1998). Discrete choice models rely on the economic basis of random utility. Discrete choice models can use either revealed preference data, such as direct observations, or stated preference data from a survey.

While discrete choice models encompass a variety of analytical methods, researchers most commonly use a binary analysis such as probit or logit analysis to predict whether an individual will choose a given mode or not. Discrete choice is valuable for transportation because it predicts individual choices, not choices of the aggregate. In addition to the basic logit and probit forms, other analytic forms have emerged over time in an effort to better predict mode choice and other consumer behaviors. These include nested logit, multinomial logit, generalized extreme values, mixed logit, among others (Small & Winston 1999).

In 1973, McFadden used a logit model to predict mode choice. Since then, economic and transportation researchers have endeavored to improve upon the prediction capabilities of discrete choice models and to predict a variety of transportation mode choices and scenarios (Small & Winston 1999). Most research on modal choice has looked at cars, buses, and rail (Plaut 2005), typically in conjunction with a community considering an investment in a new mode, such as rail. In the earliest studies of mode choice, Lisco in 1969 and Lave in 1970 used a probit analysis to create a choice model based on commuters' value of travel time. Not surprisingly, their research concluded that the value of travel time is strongly related to the individual's ability to earn money in the labor market (Small & Winston 1999). Building on this model, McFadden et al. (1973) developed a multinomial logit model to predict commute mode choice for urban work trips in the San Francisco area prior to the launching of Bay Area Rapid Transit (BART). This model included four mode choices instead of two, and also distinguished between in-vehicle time and out-of-vehicle time. The model found that out-of-vehicle time was valued well above the wage rate, while in-vehicle time was valued at one-half the wage rate; these values were independent of whether the vehicle was a car, bus, or train (Small & Winston 1999). More recently, economists and transportation planners have used multinomial logit discrete choice models to determine elasticities (Taplin, Hensher & Smit 1999). As Train (1980) points out, it is useful to understand how a policy will change demand for autos before implementing the policy.

Since the early transportation mode choice models, research has expanded in two primary directions – refining and evolving the basic models largely due to the increases in computing power to support increasingly complex econometric models and the underlying assumptions about travel demand. Both directions have been undertaken with an eye toward increasing flexibility and realistic modeling capabilities (Bhat 2003).

First, modelers have sought to improve the predictive capabilities of discrete choice models by refining the basic logit and probit models. Some of the new models can account for more variables simultaneously, such as nested multinomial logit and probit or flexible discrete choice and dynamic discrete models. These models offer additional predictive power by making the models more realistic with regard to how transportation consumers make choices. These new models also enhance predictive capabilities and internal validity of the models themselves by reducing the influence of the error term (Brownstone 2001) and stochastic variables on the model, as well as the assumptions made by the analyst (Greene & Hensher 2003).

One specific concern with the original logit models is the assumption of Independence from Irrelevant Alternatives (Brownstone 2001; Greene & Hensher 2003). Many of the recent model improvements have been undertaken as a way to develop a model that does not rely on this assumption or at least minimizes its effect on the model. The mixed logit model was developed to address the IIA challenge (Greene & Hensher 2003). By utilizing pseudo-random (Brownstone 2001), and later quasi-random (Bhat 2001; Sandor & Train 2004), variables into the model, and by further refining these through techniques such as Halton draws (Bhat 2003; Sandor & Train 2004), the models can better account for heterogeneity among the population (Bhat 2001). Another development moves from parametric models to non-parametric and semi-parametric models, which make fewer assumptions about how the model's parameters are distributed across individuals (Greene & Hensher 2003; Fosgerau & Bierlaire 2007). Most recently, Bhat (2008) has attempted to account for situations where there is simultaneous demand for multiple alternatives that are not perfect substitutes using a multiple discrete-continuous extreme value model.

Improvements like these, however, could only be realized due to the superior computing power that is enjoyed by modelers in the 21st century. Even so, modelers still recognize a need to make the ratio of computer time to accuracy more efficient (Sandor & Train 2004). The other challenge of the more flexible discrete choice models is the vast amount of data required to identify and address error correlation (Brownstone 2001), which also necessitates computing power to accommodate the volume of data.

In addition, discrete choice models have evolved in the basic premise of mode choice motivation. Initially in mode choice models, a transportation consumer was assumed to be motivated by the trip itself. More recent research recognizes that demand for trips is typically derived demand; that is, demand for a trip is not motivated by the trip itself but by the activity prompting the trip (Bhat & Singh 2000; Bhat & Koppelmann 1999). Such prompting may include activities like work, soccer practice, or shopping (Doherty & Miller 2000). By accepting activity-based demand as a premise, researchers have found that different activities result in different mode choices. Building on the activity-based model, a tour-based model was recently proposed which takes into consideration trips based on both activities and trips themselves (Miller, Roorda & Carrasco 2005).

Two primary factors affect why non-motorized modes are rarely included in discrete choice models of transportation mode choice. First, since so few travelers employ non-motorized modes, it is very difficult (time consuming and expensive) to obtain a sizable enough sample to model. While researchers already use stratified sampling to ensure they have a suitable size sample of the modes being studied, these represent modes that are used more frequently and by a larger segment of the population. Second, because so few people use non-motorized modes, they are not seen as a viable substitute for motorized modes. Discrete choice models compare the probability of selecting alternatives and incorrectly assume that all alternatives are substitutable. Further, because non-motorized modes are not considered viable economic substitutes for motorized modes, researchers do not consider non-motorized modes to be in the same choice set with motorized modes.

As gas prices and pressure to reduce greenhouse gas emissions continue to rise, not to mention increases in rates of traffic congestion and obesity-related illnesses, interest in predicting non-motorized mode choice may grow beyond simple cost concerns. Further, sample size may not be as much of a problem, as data can come from a broader geographic area. Bhat's (2008) recently proposed multiple discrete-continuous extreme value model may also facilitate non-motorized mode choice models, as non-motorized modes may be considered simultaneously to motorized modes despite being imperfect substitutes.

Building on the work of McFadden and others, discrete choice models are a powerful way for transportation planners to predict demand for specific modes of transport under increasingly complex decision conditions. Models have become more flexible and their predictive capabilities stronger, especially as increased computing power has enabled more data and variables to be represented.

Many economists have applied consumer choice theory to predict commute mode choice, expecting that consumers will make a rational choice in order to maximize their utility (Small & Winston 1999). The wage rate measures the marginal value of an hour, and non-working travel time has value because time is a scarce resource (Cherlow 1981). However, this model does not take into account any utility that may be gained from the travel itself, as utility is not expected in the motorized commute modes. Commuters using non-motorized modes may gain some utility in the form of health and well-being, or social good from their travel time.

The rational choice model effectively predicts mode choice when the choices are limited to motorized modes. Studies have shown that the longer the commute and higher the costs of ride-sharing compared to driving alone, the more likely the commuter is to drive alone (Cervero 2002). Additionally, when transit fees cost more than the cost to drive, commuters will drive (Cervero 2002). Some recent studies have shown that drivers will pay tolls in order to avoid traffic congestion (Brownstone et al. 2003). But it is less clear how accurate the rational choice model is in predicting mode choice when the alternative to driving is a non-motorized mode.

Economists have also studied the elasticity of demand for transportation modes. For urban commuting, all vehicle modes have an elasticity of less than one, suggesting that policies which increase the cost of commuting by car (or decrease the cost of an alternative mode) will have little effect on mode choice (Gomez-Ibanez, Tye & Winston 1999). Despite this, some economists believe that free transit or other incentives promoting alternate modes will increase usage as a result of the second-best pricing (Storchmann 2003). The question remains as to how non-motorized choices might be affected by price changes in auto commuting. While motorized commute mode choice is inelastic, it is possible that the unique characteristics of non-motorized commuting (social good, health benefits, etc.) may cause commuters to be more responsive to price changes.

Despite all of the research into commute mode choice, there are not adequate models to forecast either demand or the likely effects of policies, especially for non-motorized modes. With gas prices the most volatile they've been in a generation, concerns about global warming finally reaching the mainstream, and public health interest in active living, now is the time to delve into non-motorized commute modes.