Pedal Past the Pumps

An analysis of the variables contributing to the demand for commuter cycling

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Abstract

This paper analyzes the substitution effects between commuter bicycling and the price of gasoline. A multiple regression analysis is conducted to determine the elasticity of demand for bicycles from gasoline as well as other relevant variables, availability of bike sharing, population density, bike paths, median income, days below zero degrees Celsius, precipitation, and the CPI for recreational vehicles (including bicycles) and public transportation. Data was collected primarily through Government of Canada resources such as Statistics Canada, Environment Canada, as well as numerous local and provincial governments and news agencies. The analysis is conducted using both pooled average and random effects regression models. The modelling revealed that there is indeed a substitution effect on the demand for commuter cycling due to the price of gasoline. The study also shows asymmetrical results for male and female cyclists, showing that male and female cycling habits are influenced by different variables. This analysis suggests that policy makers can influence rates of cycling by manipulating the cost of its alternatives as well as the opportunity costs of cycling itself.

Introduction

Combustion vehicle use is abundant across Canada and contributes heavily to the nation's greenhouse gas (GHG) emissions. Worldwide, roughly 95% of the energy used for transportation comes from petroleum-based fuels (gasoline and diesel), which accounts for 14% of global GHG emissions (EPA, 2010). In Canada, the percentage of GHG emissions associated with the transportation industry was 24.5% in 2010, much higher than the global average of 14% in the same year (Natural Resources Canada, 2016).

Since 1984, Canada has reduced its energy intensity across all sectors through improved energy efficiency and technological advancement. However, these effects have been offset by increased activity in energy-intensive sectors such as oil, mining and transportation (Moshiri & Duah, 2016). While public transportation, electric vehicles, and improved roadway efficiencies offer to reduce GHG emissions in the transportation sector, another option exists.

In terms of urban transportation solutions, the humble bicycle provides an efficient mode of transportation that is virtually emission-free and uses only the energy of the human body. The habitual use of bicycles as a mode of transportation has the potential to greatly reduce the environmental impacts of the individuals using them. Although cycling does have limitations with respect to distances, carrying capacity and weather protection, it offers a wide range of benefits to the environment such as reduced road congestion and shortened commuting times in urban centres. In addition, cycling promotes fitness and weight loss while also reducing stress, which may create externality benefits for individuals and society (Lusk et al., 2011; Chen, 2015).

As the global demand for energy has risen over the past century, so too has the immense strain that it places on the environment. The recent Paris Climate Accord saw

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representatives of 195 nations reach an agreement that commits nearly every country to lowering GHG emissions and other significant pollutants to prevent the most drastic effects of climate change (Davenport, 2015). As the battle against climate change continues, political leaders and policymakers are scrambling to find the most effective solutions while maintaining economic stability in an emission-dependant world. Many leaders and policy makers view transportation as an area in which significant changes can and will be made to meet the demands of international regulation.

The focus of this study is to view cycling as a form of transportation energy use and to discuss which factors influence commuters to choose the bicycle over other forms of transportation energy. As such, it is hypothesized that the energy used by the person riding a bicycle is a substitute for the energy produced by the gasoline that powers a combustion engine. This study seeks to prove the notion that human transportation energy (via bicycle) is an alternative to gasoline by determining the rate of substitution between the energy used for bicycles and the energy used for vehicles (primarily gasoline) in Canada.

Thus, the primary goal of the study is to find the elasticity between the price of gasoline and the demand for commuting by bike, or in layman's terms, to determine how much a change in the price of gasoline will affect the number of people commuting primarily by bike. To determine an accurate elasticity between gasoline price and rates of consumer cycling, this study seeks to create a model of the demand for commuting by bike that includes the elasticities of all other relevant variables on the rates of commuter cycling. This allows for the secondary goal of identifying the weights of other key variables that have the potential to inform policymakers and city planners in making decisions that affect the number of cyclists in urban centers. Policymakers and city planners in Canada have a significant impact on the viability of clean transportation in cities, and knowledge of the variables that contribute to the use of clean alternatives is key to making informed decisions.

Literature Review

There is an abundance of survey-based research on the demand for cycling and the factors that influence its uptake. Perhaps unsurprisingly, quantitative analysis on the demand for commuter cycling is far less common. Alternatively, most of the research on cycling demand is largely focused on qualitative behavioral choice, using surveys and trip data to analyze the use of bicycles and public infrastructure. This is likely due to a lack of available data necessary for extensive modelling. It may also be that discussions of alternative transportation strategies, policy, and spending choices are a recent development. Researchers respond to the demands of their time, and the call to action on climate change has only recently entered mainstream discussion.

The bulk of cycling-related research focuses on health benefits and infrastructure, including that of Lusk et al. (2011) and Chen (2015), who discuss many of the potential benefits and challenges of bicycle commuting and infrastructure. A handful of papers have been particularly influential in determining the relevant variables in the consumer's choice to cycle. By showing that 27% of commuter trips in the Netherlands are done by bike, compared to just 2% in Canada and 1% in the USA, Pucher and Buehler (2008) reveal that there is room for substantial improvement in terms of bicycle use in North America. Pucher and Buehler emphasize the need for "carrot and stick" policies that both incentivize cycling and reduce the benefits of driving. Such measures or policies target factors such as: access to bikes, trip planning, public awareness (particularly health and community programs including competitions), public participation in planning, automobile speed limitations, road and parking capacity limitations, taxation of automobiles (including purchase, ownership, petrol sales, parking rates), and strict land-use planning policies (Pucher & Buehler, 2008).

Past research also shows the clear benefits of cycling infrastructure towards both safety and participation rates. The most important factor in bicycle use, according to Pucher and Buehler (2008), is perceived safety; citing a lack of bike lanes and multi-use paths as making large urban centers in the USA "extremely hostile to cycling" (Pucher & Buehler, 2008, p. 524). Research conducted by Ricci (2015) and Dung Tram et. al. (2015) showed the impacts of bicycle sharing programs, suggesting they are used primarily for commuting for both work and university education. Ricci's (2015) meta analysis also suggested that bike sharing offers many community-based benefits that are often associated with cycling, such as health, environment (through a reduction in the overall distance travelled by motor vehicle) and positive effects on the local economy. Ling et al. (2020) further highlight both the benefits and dangers of cycling when performed on shared roadways, as well as the significant impacts of infrastructure and dedicated bike lanes to both perceived and actual safety. Their paper showed that cycling infrastructure benefits not only its users, but it also creates a "halo effect" that reduces cyclist motor vehicle collisions within 151m to 550m of the actual cycle track (Ling et al. 2020).

Surveys conducted in Portland, Oregon identified many of the physical and behavioral barriers to cycling (Dill & Voros, 2006). These researchers found that the most significant barriers were too much traffic, no bike lanes or bike trails, and no safe places to bike nearby (Dill &Voros, 2006), further emphasising the need for bicycle infrastructure and perceptions of safety. The surveys also identified "a relationship between regular cycling and positive perceptions of a neighborhood for cycling" (Dill &

Voros, 2006, p. 16). They also noted that persons with friends, family or coworkers who bicycled had significantly more positive perceptions towards bicycling. This was equally true for persons that lived near bike lanes and other forms of cycling infrastructure.

Economist Michael Everett's 1974 analysis models the demand for commuter cycling in the USA. The model focuses primarily on the relationship between cars and bicycles showing the conditions under which they should be considered substitutable goods. The analysis measured the cost of bicycles, cars, and individual valuation of time per year based on different distances commuted (yearly) and identified a "strong economic motive for bicycle commuting" (Everett, 1974, p. 593). The paper also identified several recommendations for improving cycling rates such as safe and clean bicycle trails, reducing the cost of cycling relative to driving, trails that access universities, colleges, malls and public spaces and finally of educational programs that promote the many individual and social benefits of bicycling (Everett, 1974).

While the studies mentioned above were influential in establishing factors that influence the rate of cycling, they do not determine the weight of these factors. Ivan Rashad's 2009 panel data regression analysis, "Associations of Cycling With Urban Sprawl and the Gasoline Price," revealed the weights of several key variables impacting the rate of cycling within the USA. Rashad also performed a demographic analysis including employment, gender, education, ethnicity, and marital status. Rashad demonstrated that higher gasoline prices are indeed associated with an increased likelihood of cycling, and that there are disproportionate effects on men and women. The data suggests that "an increase of one 1982-1984 dollar in the real gasoline price potentially generated an increase of 4.7 and 3.4 percentage points in the prevalence of cycling for men and women respectively" (Rashad, 2009, p. 27). The analysis also showed that urban sprawl, income, precipitation, sunlight hours, and bicycle culture (a mix of trails, bike shops, and fatalities) all had a significant impact on the rate of cycling (Rashad, 2009). It should be noted that Rashad's analysis was based on recreational cycling and used fixed period effects to account for yearly differences.

Methodology

This study uses panel data from 20 different Census Metropolitan Areas (CMAs) in Canada from the years of 1997, 2006, and 2016, to conduct a regression analysis and estimate the determinants of cycling. The full data set can be found in appendix Table 7. These 20 CMAs were selected from an initial sampling of 37 different locations for which the "main mode of transportation" question was surveyed by the Canadian Census. These 37 CMAs were then reduced to 20 due to the availability of open source data, particularly regarding the availability of bike lanes (deemed an essential variable for measuring infrastructure and some form of safety). Commuter cycling rates were chosen for the dependent variable as it is most representative of a consumer's habitual choice to ride a bike, as opposed to using other forms of transportation energies. The years 1997, 2006, and 2016 correspond to the years in which the long-form Canadian Census produced data on bicycle ridership. Individuals aged 15 and older within the employed labour force were asked to select their "main mode of commuting" (car, truck or van as driver, car, truck or van as a passenger, public transit, walked, bicycled, or other); this data produced a 25% sample of the population.

To reduce the degrees of separation from the initial sampling, the dependent variable was selected to be the actual number of respondents in each CMA that reported commuting primarily by bike. The implications of the data are then aggregated to the share of working age population after the modeling is completed and assumed to be generally representative of how the variables affect the consumer's choice to commute primarily by bike.

The standard theory of demand states that the demand for a normal good will depend on its price, and on consumer income. The standard theory of demand is a very simplified approach to what is a complex consumption choice driven not only by cost and income, but also substitutable goods, personal tastes, environment, perceived value, opportunity costs, and a wide variety of externalities.

The calculation of demand within this paper attempts to account for as many of these factors as is possible given the available data. Review of prior literature revealed that cycling rates are primarily influenced by four broad categories: safety, costs, weather, and culture. Costs and weather are easily quantifiable variables while safety and culture can be more difficult to quantify. Safety was a particularly difficult variable to quantify as CMAs tend to report rates of injury, crashing, and fatalities among cyclists in very different ways; some do not report these statistics at all. Nine independent variables were selected to be representative of these broad categories and are hypothesised to be relevant variables in determining the number of commuter cyclists in a city. These variables are population density, availability of bike sharing, kilometers of bike path, temperature, precipitation, real median income, bike price, transit price, and gasoline price.

The matrix formed by the data was not compatible with fixed effects modeling. Instead, fixed effects are controlled for by introducing a tenth independent variable that is representative of the year in which the data was collected. This variable shows the change in tastes and preferences over time. The method of representation for the above variables will be discussed in the "data" subsection of this paper. However, it should be noted here that "bike sharing" is a binary variable and "kilometers of bike path" is taken as a constant value within each area because open-source data was not available outside of current reports. Gasoline was chosen as the primary alternative transportation energy source as it is the most abundantly used source of transportation energy in Canada. Gasoline is also one of the highest emitting forms of transportation energy. Price and income variables are representative of the costs of cycling and its alternatives, while temperature and precipitation quantify the effects of weather. Safety and culture are somewhat combined categories with bike sharing, population density, and kilometers of bike path being representative of both safety and the prevalence of cycling culture.

The modelling contained within this paper is conducted using EViews 11, as published in 2019. The analysis conducted uses a least-squares panel data regression model on 60 data points from 1996, 2006, and 2016. The regression was performed with and without random cross-sectional effects. Random cross-sectional effects are typically applied to the model in order to reduce error between locations. In this analysis, the Pooled Average method of regression is considered more plausible than the random effects model. This is because CMAs across Canada are urban centers that have been grouped into the same classification as census metropolitan areas. As such, it is assumed that there are limited differences between the cities and that metropolitan areas in Canada have similar tastes and are influenced similarly after accounting for other variables such as weather. However, as previously mentioned, both model scenarios will be analyzed. Fixed period effects are accounted for through the time 'dummy variable' (T) represented by a value of 1, 2 or 3. The time variable is used to analyze whether tastes and preferences have changed over time. The model chosen makes use of Log transformations so that the coefficients are interpreted as elasticities. The equation used in this model is:

$$(q) = C + \beta_1 D + \beta_2 T + \beta_2 Log\ (X_1) + \beta_3 Log\ (X_2) + \cdots + \beta_9 Log\ (X_8) + \varepsilon$$

Where q is the number of persons cycling within the metropolitan area, D and T are dummy variables that represent the availability of bike sharing and the time period, respectively. X represents each of the remaining independent variables, C is the intercept, and ε represents the error within the model. The natural logarithm of each term is taken such that β will represent the elasticity of each variable on q. The availability of bike sharing has either a value of 1 (has bike sharing) or 0 (does not have bike sharing); thus,it does not require a Log() transformation.

As previously stated, the "km of bike path" variable does not change within each unit throughout the time periods as the data was not available for this. As such, a second regression is conducted with the bike path distance having an applied arbitrary growth rate of 10% every ten years. This will examine how sensitive the model is towards changes in bike path distance creating a scenario analysis showing how the variables change under the assumption of increased bicycle infrastructure over time. This is a substantial assumption to make given potentially different cultures and spending habits towards cycling infrastructure across Canada. Accurate time series data on the growth of cycling infrastructure is necessary to improve the accuracy of the model.

The model is then individually applied to the male and female cycling populations. The goal of this final scenario is to determine if male and female cycling habits are influenced by the same variables regarding commuting by bike. Furthermore, this analysis should reveal the relative influence that males and females have within the model. Significance within this analysis is determined as being within 5% significance, although it is specified when variables are within the less accurate 10% standard.

Data

The primary source of data for this study is Statistics Canada. The dependent variable for this model, the number of people commuting primarily by bike, came from the 1996, 2006, and 2016 long form Canadian census which is reported online through the Statistics Canada website. The dependent variable was taken as the actual reported number of cyclists within the census. This was done to ensure that the results of the regression can be applied to the entire employed labour force (given that the central limit theorem holds).

Median individual income and population density, as well as the number of male and female commuter cyclists, were also reported through the census. All median incomes were converted to real 2002 dollars in order to account for inflation. This was done by dividing each nominal value by each of the respective province's Consumer Price Index (CPI) for each period. It is important to remember that this median income represents the median income of all employed individuals within the CMA; as such, it shows the typical income of the representative population, not the income of the actual cyclists. Instead, this metric shows the typical level of income within the city. All CPI values were also sourced through the Statistics Canada website and were used to represent the costs of bicycles, gasoline, and transit.

The prices for gasoline and public transit are reported annually and were taken respectively to each CMAs province and the census year. It is assumed that there is low variation between cities located within the same province. CPI does not report the direct price index for bicycles; instead, they are considered a recreational vehicle and are included within the CPI for 'use and operation of recreational vehicles'. Due to necessity, this was the category used to represent the cost of bicycles as it includes both the fixed cost of the bicycle and the variable costs of its necessary accessories and repairs. It should be noted that the coefficient resulting from the bike price variable (the CPI for 'use and operation of recreational vehicles') is likely to be inflated by the presence of other recreational vehicles and cycling substitutes. This is a potential source of error within the model. However, without an accurate consumer price index specifically for bicycles in Canada, it is impossible to refine this category further. As such, the bike price variable is considered to be the price of bikes and alternatives.

Weather data was taken from the online source "weatherstats.ca". Weatherstats.ca is an online software that interprets and presents the data reported by Environment Canada. This website is updated every five minutes. Several potential weather metrics were initially tested to determine which ones were likely to influence cycling habits. Weather metrics incorporated in the analysis included: average annual temperature (mean of min/max), annual Precipitation, days above 30 degrees Celsius, days below 0 degrees Celsius, and days below -20 degrees Celsius. These were selected as measures of both typical and extreme weather patterns. After the initial tests, it was revealed that only the number of days below 0 degrees had a statistically relevant effect on the number of people cycling. This initial test can be found in Table 4 of the appendix. The Number of days below 0 degrees Celsius was chosen as the temperature variable. Annual precipitation remained in the model as it was proven statistically relevant in Rashad's analysis.

Bike sharing and bike paths proved difficult variables to quantify. The bike sharing variable is based on whether the city had a bike sharing program during the given period. This information was sourced through Kate Hosford and Meghan Winter's (2016) paper, *Who are Public Bicycle Programs Serving? An Evaluation of the Equity of Spatial Access to Bicycle Share Service Areas in Canadian Cities*. The kilometers of bike paths variables were taken as either the 2016 value or the most recent value that is reported depending on availability. There were multiple sources for this information including city transit and public information websites, as well as third party reports from the Pembina Institute, CBC, and local cycling organizations. The variable includes designated bike lanes as well as paved and non-paved multi-use trails. Data on bike path growth and the ability to distinguish between the different types of bike and multi-use trails would improve the accuracy of this model.

Results and Analysis

The 20 CMAs that were selected produced a mean of 5931 persons commuting primarily by bike, with a maximum of 39320 persons (Toronto, ON 2016) and a minimum of 175 persons (St. John's, NL 1996). This wide range of persons cycling is due, in part, to the significant difference in population between CMAs, which is accounted for by the inclusion of the population density within the model. The mean of the employed labour force in CMAs commuting primarily by bike was 1.53%, which is proportional to the population that completed the long-form census. The maximum rate of cycling among the employed labour force was 6.60% (Victoria, BC 2016) and the minimum was 0.20% (St. John's, NL 2016). The sample statistics for this model can be seen below in Table 1.

The rate of commuter cycling was noticeably higher in large metropolitan areas with mild weather, with Victoria, Vancouver, Kelowna, Ottawa, and Montreal having the highest rates of cycling. However, as discussed earlier, only extreme temperatures (days below 0 degrees Celsius) have a significant impact on those who commute by bike. Tables 2 and 3 below present the coefficients and corresponding significance levels for the base model and growing bike paths model, as well as the effects of the variables on males and females, respectively. Table 2 presents a basic pooled average regression without any weights on cross-sectional effects. Table 3 has random cross-sectional effects which is a technique used to account for hidden error within the model; however, the pooled average model is likely more realistic under the assumption that cities within Canada are culturally and institutionally similar, implying that unobserved heterogeneity will not bias our estimations. Standard Error tables can be viewed in appendix Tables 5 and 6.

Table 1: Sample Statistics

	Census riders	Bike sharing	Population density	Bike paths	Median income	Days below zero	Average Precip.	Bike price	Transit Price	Gas price
Mean	5930.917	0.083333	271.4672	257.1000	24882.04	143.9167	880.7383	107.9417	118.0750	122.2633
Median	1687.500	0.000000	155.2404	182.5000	24527.58	149.0000	960.9500	109.9000	111.7000	137.2000
Maximum	39320.00	1.000000	1003.759	1032.000	33693.63	211.0000	1593.600	144.1000	180.5000	169.5000
Minimum	175.0000	0.000000	31.99231	7.000000	17621.23	32.00000	261.6000	83.20000	69.00000	74.70000
Std. Dev.	9038.422	0.278718	273.5704	262.4616	3533.205	43.45748	380.4826	16.55744	32.53764	29.16427
Observations	60	60	60	60	60	60	60	60	60	60

Table 2: Pooled Time Series Estimation of Cycling Demand in Canadian Cities
Periods: 3 Cross Sections:20
Total Observations: 60
Dependent variable: Share of working population commuting primarily by bicyle

Variables	Base Model	Growing Bike Lanes	Males	Females
Year	0.353*	0.28240	-0.0670**	0.6191
Bike Sharing	1.1364*	1.1412*	-0.0337	1.1817*
Population Density	0.3659*	0.3680*	-0.0166	0.4182*
Bike Paths	0.6101*	0.6050*	-0.0117	0.6616*
Median Income	2.7511*	2.7738*	-0.1831*	3.1139*
Days Below 0° C	-0.7534*	-0.7531*	0.0721*	-0.9291*
Annual Precipitation	-0.1809	-0.1850	0.0493**	-0.3157
Bike Price	-6.624216*	-6.6248*	0.1888	-7.3595*
Transit Price	-0.059444	-0.0576	0.0192	-0.1412
Gasoline Price	2.1444*	2.1469*	0.0346	2.0368**
** significant at 5% ** significant at 10%*	*R-squared: 0.6717*	*R-squared: 0.7673*	*R-squared: 0.5129*	*R-squared: 0.7596*

Table 3: Random Effect Estimation of Cycling Demand in Canadian Cities
Periods: 3 Cross Sections:20
Total Observations: 60
Dependent variable: Share of working population commuting primarily by bicyle

Variables	Base Model	Growing Bike Lanes	Males Only	Females Only
C	-11.695**	-12.038**	0.196	-13.8402
Year	-0.4235*	-0.5206*	-0.0628	-0.2203
Bike Sharing	0.3962*	0.4098*	-0.0188	0.3709*
Population Density	0.0925	0.0897	-0.0264	0.2193*
Bike Paths	0.7749*	0.7607*	-0.0091	0.8026*
Median Income	0.6357	0.7314	-0.1984	1.1013
Days Below 0° C	-0.4809*	-0.4944	0.0714**	-0.6941*
Annual Precipitation	0.1488	0.1297	0.0567**	-0.0327
Bike Price	1.4721**	1.4416**	0.1874	1.0744
Transit Price	0.2327	0.2382	0.0068	0.1515
Gasoline Price	0.5866*	0.5961*	0.0359	0.4555
** significant at 5% ** significant at 10%*	*R-squared: 0.7605*	*R-squared: 0.7584*	*R-squared: 0.6717*	*R-squared: 0.7675*

The first noteworthy observation to make is that both models tend to agree on which factors are significant. Time, availability of bike sharing, population density, bike paths, days below 0 degrees Celsius, bike price (only within 10%), and gasoline price are significant in the base model for both pooled average and random effects modelling. It also appears that the period has a significant effect in the model, suggesting that cycling tastes have changed over time. The coefficient for the year is to be exponentiated (based off the natural logarithm) as 1.423 and 0.655 for the pooled average and random effects models, respectively. This suggests that tastes and perceptions of cycling improved over the period within the model for both the pooled average and random effects. Median Income is shown to be insignificant given random effects, which runs contrary to what would be expected of a normal good. If bicycles are indeed normal goods, the median income as well as the sign change to the bike price coefficient adds further support to the validity of the pooled average model. However, it should be noted that bikes are durable goods with small annual discount costs. As such, bicycles are unlikely to be greatly sensitive to income changes over time. The random effects model also suggests that attitudes towards bikes have deteriorated over time, this result discredits the random effects model given the substantial increases in both sale and demand for bicycles worldwide (National Bicycle Dealers Association, 2015).

Both transit price and precipitation prove to be insignificant within the models. The insignificance of precipitation within the model is surprising as it contradicts the results of Rashad's (2009) model. It appears that there may be some significant correlation between precipitation and male cycling rates; however, the relationship is highly inelastic, with the coefficient suggesting that a 1% change in precipitation resulting in between 0.049 and 0.057 percentage change to the number of men cycling. This could be attributed to the fact that Rashad analyzed recreational cycling and not the most frequent mode of transportation. A recreational cyclist may not ride their bike when it is raining or snowing. However, a person commuting to work may still rely on their bike. The sub-zero degree boundary may also be picking up the effects of rain, as well as cold weather, considering the majority of rain in Canada occurs entering and exiting the winter months.

Assuming now that Table 2 represents a more plausible model, the primary influencers on bicycle commuting trends are bike price, median income, gasoline price, and the presence of bike sharing. Of these factors, the bike price is the most elastic. The model shows that a 1% change in the price for recreational vehicles (including bikes) results in as much as a 6.62% reduction in the number of people using bikes as their main mode of transportation. This is a very significant relationship and suggests that cyclists are highly reactive to price changes. However, as mentioned previously the bike price variable is the CPI for the use and operation of recreational vehicles. As such, a coefficient of -6.62 incorporates not just the cost of bicycles (and its accessories/maintenance) but also recreational alternatives. Median income and gasoline, which is the variable of interest, also have an elastic relationship with cycling rates. A 1% rise in the price of gasoline will result in as much as a 2.14% increase in the number of people cycling. Gasoline is statistically significant in both scenarios, which suggests that there is indeed a relationship between cycling and energy costs.

The availability of bike sharing, a variable that policymakers have a significant influence over, has a slightly different and potentially more impactful interpretation. Bike sharing is not logarithmically transformed;as such, the given coefficient is exponentiated based on a natural log to become 3.115 in the pooled average model and 1.486 for the random effects model. As a dichotomous variable, the coefficient of bike sharing suggests that the number of people cycling will be up to 3.11% higher if a bike sharing program is made available. This is a massively significant improvement to the rates of commuter cycling; the variable may be capturing some of the impacts of improved infrastructure, safety and perceptions towards cycling that often accompany the installment of a bicycle sharing program (Ricci, 2015). Regardless, introducing a bike sharing program, and creating policy to encourage its use, is a highly effective way of improving the rate of bicycle commuting. The remaining variables within the model are all statistically significant and inelastic, with a 1% change in the variable producing a less than 1% change in the number of people commuting by bike.

The initial scenario analysis of increasing bike lanes over time did not create significant changes within the model. As discussed previously, real growth rates must be made available in order to improve the accuracy of this metric. Furthermore, there is almost no difference in the relative fit of the base model and growing bike lanes model, with R^2values rounded to 0.77 in both scenarios (pooled model). This suggests that more than ¾ of the variation in the model is accounted for, the remaining amount can likely be attributed to external or unquantifiable factors such as tastes, culture, and perceived safety.

The random effects modeling in table 3 essentially reduces the impacts of all independent variables. The only variable that remains elastic within the base model is the bike price; however, bike price drops from the 5% significance level to 10%, which is not typically considered to be a significant outcome. Other variables such as the year, bike sharing, bike paths, days below 0 and gasoline price, remain significant at 5% but their coefficients are reduced when compared to the pooled average model. Although the elasticity falls greatly, it remains significant and positive, supporting the hypothesis that bicycles are a substitute gasoline. Similar to pooled average modeling, there was no significant change to the results when an arbitrary growth rate was applied to the bike lanes.

Male and Female scenarios proved to offer surprising results and most certainly warrant more research. The models affect males and females differently, not just in scale but also in the factors that contribute to consumer choice. Within both models male and female cyclists appear to have very different variables contributing to the choice of commuting by bike. In the pooled average model (Table 2) Male results were significantly dependent on Median Income and Days Below 0. Time and Precipitation are possible factors, being that they are significant at the lower accuracy metric of 10%. Females on the other hand, have many factors within the model contributing to their choice. Population Density, Bike Sharing, Bike Paths, Median Income, Days Below 0, Bike Price and Gasoline Price (within 10%) remaining significant. This suggests that females are perhaps more influenced by safety and infrastructure than their male counterparts.

The Median Income coefficients are particularly interesting, as a 1% increase in the cities mean income results in a highly elastic increase to the number of female cyclists (3.11%) and an inelastic decrease in the number of male cyclists (-0.18%). This shows that growing wealth within a city has inverse effects on men and women. As mentioned previously, this study considers pooled variance to be a more accurate model of bicycle demand across Canadian metropolitan areas. However, it is important to note that both models show discrepancies in the significance of variables on males and females. The random effects model in Table 3 shows that only days below 0 and annual precipitation are significant for male cyclists, and only at the 10% significance level. Female cyclists continue to have their choices influenced by bike sharing, population density, bike paths and days below 0; all other variables are insignificant given random effects.

The R^2 values between males and females reveal that the model used in this paper fits for females far better than it fits for males. R^2 for men is 0.51 (pooled average), showing that almost half of the variation within male cycling trends is not shown within the model. This variation may be attributable to social norms, perceived safety, culture, or other unquantifiable variables, this warrants further research. The female model has a much stronger R^2 value of 0.76 (pooled average), which is a much better fit for the model. Census responses showed that cycling commuters tend to be about 2/3 male and 1/3 female, however, the R^2 values suggest that most of the variation within the model comes from women.

Conclusion

This study consistently demonstrated that policymakers could have a significant influence on cycling rates through the independent variables within the model. It was also revealed that most of the variation in the number of cyclists in Canadian CMAs comes from women. The variables contributing to the male choice to commute by bike are not reflected well within this model and the asymmetric influences on male and female cycling once again warrants more research. Female-oriented policies towards cycling, bicycle infrastructure, and costs may be essential in order to effectively increase the number of people commuting by bike.

The model shows that elastic variables such as the price of gasoline and the price of bicycles, as represented by the price of recreational vehicles and accessories, have the potential to drastically affect the number of people cycling. Rising price for recreational vehicles was the most elastic negative variable and therefore has likely reduced the positive effects of the variables that are increasing cycling rates over time. A reduction to the opportunity costs of cycling can be influenced by business and policy through increased bicycle infrastructure, parking (bike racks), route mapping services, the availability of bike-sharing, and by increasing the cost of its alternatives through emissions taxes or quotas. The availability of bike sharing is a highly impactful variable that policymakers have a large influence on. By regulating for, and developing the infrastructure required by bike-sharing companies, policymakers can create an environment that allows for increased bike commuting. Bike-sharing companies are also likely to bring positive externalities with them, such as fitness, convenience, reduced congestion, and employment.

The primary goal of this paper was to demonstrate the existence of an energy-based relationship between cycling and gasoline. Regression modelling has shown that there is an elastic relationship between the price of gasoline and the consumer choice to commute primarily by bike. This shows that the human energy needed to power a bicycle is indeed a substitute for the energy produced by gasoline for other modes of transportation. It also suggests that gasoline pricing policies have a significant effect on consumers' transportation energy choices. This relationship may also extend to other forms of between different transportation energies.

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Appendix

Table 4: Weather test

Dependent Variable: LOG(CENSUSRIDERS)
Method: Panel Least Squares
Date: 03/24/20 Time: 17:17
Sample (adjusted): 1996 2016
Periods included: 3
Cross-sections included: 16
Total panel (unbalanced) observations: 42

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(AVGTEMP)	-0.007013	0.182302	-0.038471	0.9695
LOG(PRECIP)	-0.195321	0.535957	-0.364434	0.7176
LOG(ABOVE_30)	-0.088815	0.221463	-0.401038	0.6907
LOG(BELOW_0)	1.968739	0.846546	2.325616	0.0256
LOG(BELOW_20NEG)	-0.412486	0.361095	-1.142318	0.2607

Root MSE	1.360231	R-squared	-0.00893
Mean dependent var	7.526639	Adjusted R-squared	-0.11800
S.D. dependent var	1.370610	S.E. of regression	1.44922
Akaike info criterion	3.691281	Sum squared resid	77.7095
Schwarz criterion	3.898146	Log likelihood	-72.5169
Hannan-Quinn criter.	3.767105	Durbin-Watson stat	0.07421

Table 5: Standard Deviation, Pooled Average

Unspecified effects	Base Model	Growing Bike Lanes	Males only	Females only
Year	0.4087	0.4079	0.0375	0.4677
Bike Sharing	0.4600	0.4597	0.0422	0.5263
Population Density	0.1497	0.1495	0.0137	0.1713
Bike Paths	0.0983	0.0974	0.0090	0.1125
Median Income	0.8261	0.8256	0.0758	0.9452
Days below 0° C	0.2805	0.2805	0.0257	0.3210
Annual Precipitation	0.2769	0.2765	0.0254	0.3168
Bike Price	2.5696	2.5687	0.2358	2.9403
Transit Price	1.2365	1.2361	0.1135	1.4149
Gasoline Price	1.0053	1.0050	0.0923	1.1504

Table 6: Standard Deviation, Random Effects

Random Effect	Base Model	Growing Bike Lanes	Males only	Females only
C	6.1901	6.2788	1.7561	8.6737
Year	0.1867	0.1890	0.0590	0.2625
Bike Sharing	0.1100	0.1116	0.0377	0.1563
Population Density	0.0642	0.0652	0.0169	0.0903
Bike Paths	0.1486	0.1469	0.0139	0.1771
Median Income	0.4892	0.4948	0.1265	0.6868
Days below 0° C	0.2151	0.2176	0.0372	0.2915
Annual Precipitation	0.1579	0.1595	0.0336	0.2178
Bike Price	0.8374	0.8502	0.2914	1.1904
Transit Price	0.2960	0.3003	0.0993	0.4183
Gasoline Price	0.2384	0.2418	0.0796	0.3367

Table 6: Data Set

year	Location (CMA)	Number of Cyclists	dummy year	Bike Sharing	Population Density	Bike Path	Median Income	Days Below 0	Precipitation	Bike Price	Transit Price	Gasoline Price
1996	Toronto, ON	13075	1	0	726.6447161	640	24596.37	144	969.8	86.2	84.5	84.3
2006	Toronto, ON	24690	2	0	866.1025505	640	24586.4	112	865.7	111	111.7	137.2
2016	Toronto, ON	39320	3	1	1003.758991	640	24444.87	119	630.6	125.1	154.3	145.3
1996	Vancouver, BC	12750	1	0	649.3746145	289	22110.39	60	1462.8	89	73.5	82.2
2006	Vancouver, BC	16585	2	0	735.5982567	289	23156.34	32	1224.2	109.3	109.9	145.2
2016	Vancouver, BC	27240	3	1	854.562768	289	26643.79	33	1356.8	128	159.4	159.4
1996	Montreal, QB	13800	1	0	826.6243561	648	20363.13	148	1067.1	89.4	88.9	86
2006	Montreal, QB	27400	2	0	853.6268159	648	23147.19	132	1343.1	107.2	123.4	139.7
2016	Montreal, QB	38060	3	1	890.2466412	648	26305.73	147	1038.2	144.1	121.6	169.5
1996	Ottawa-Gatineau	9075	1	0	177.7022571	480	26338.74	169	916.8	86.2	84.5	84.3
2006	Ottawa-Gatineau	11640	2	0	197.8238279	480	29804.81	141	1112.3	111	111.7	137.2
2016	Ottawa-Gatineau	14895	3	1	195.6114673	480	33693.63	164	796.2	125.1	154.3	145.3
1996	Calgary, AB	3970	1	0	161.633827	1032	24703.7	202	376.4	83.2	82.1	80
2006	Calgary, AB	7560	2	0	211.3215453	1032	27454.14	190	419.6	109.9	115.6	142.1
2016	Calgary, AB	10285	3	0	272.5150238	1032	32525.15	171	521.5	129.6	171.4	136.3
1996	Edmonton, AB	4130	1	0	90.45123906	390	23064.81	184	482.1	83.2	82.1	80
2006	Edmonton, AB	6230	2	0	109.8915042	390	25997.33	173	442.5	109.9	115.6	142.1
2016	Edmonton, AB	6440	3	0	139.9984744	390	32470.41	161	489.5	129.6	171.4	136.3
1996	Hamilton, ON	1960	1	0	459.5951417	103	23857.14	149	1114.8	86.2	84.5	84.3
2006	Hamilton, ON	2900	2	0	505.0776666	103	26117.65	116	1033.3	111	111.7	137.2
2016	Hamilton, ON	3020	3	1	544.9015592	103	27231.3	134	838.8	125.1	154.3	145.3
1996	Victoria, BC	6300	1	0	480.3769891	190	23690.48	53	1120.3	89	73.5	82.2
2006	Victoria, BC	8955	2	0	474.7077012	190	26402.41	39	1049.5	109.3	109.9	145.2
2016	Victoria, BC	11245	3	0	528.2913165	190	30621.73	33	1027.7	128	159.4	159.4
1996	Halifax, NS	1520	1	0	132.8412768	80	22736.96	122	1508	92.6	98.5	74.7

2006	Halifax, NS	1825	2	0	67.84639404	80	24631.34	90	1358.2	109.6	110.3	139.5
2016	Halifax, NS	1965	3	0	73.39287631	80	27569.9	130	1508.6	124.5	136.4	134.1
1996	Saskatoon, SK	1940	1	0	41.15958204	175	20822.93	210	446.4	86.1	69	84.9
2006	Saskatoon, SK	2860	2	0	42.56535204	175	23934.01	191	488.8	108.9	124.7	138.1
2016	Saskatoon, SK	2850	3	0	50.09498006	175	30742.06	196	345.1	121.3	180.5	128.2
1996	Regina, SK	870	1	0	56.59812134	59	23363.22	211	395.1	86.1	69	84.9
2006	Regina, SK	1365	2	0	57.2054362	59	26863.43	196	507.9	108.9	124.7	138.1
2016	Regina, SK	1305	3	0	54.68540072	59	32854.77	194	437.1	121.3	180.5	128.2
1996	St. John's, NL	175	1	0	220.4113163	208	19046.46	143	1460.7	98.7	97.6	81.3
2006	St. John's, NL	240	2	0	225.0857526	208	22197.26	150	1530.3	110.5	116.6	137.9
2016	St. John's, NL	195	3	0	255.91148	208	29108.68	162	1593.6	127.9	131.5	149.2
1996	Belleville, ON	540	1	0	99.61091568	28	22143.99	152	1047.2	86.2	84.5	84.3
2006	Belleville, ON	680	2	0	123.5711103	28	23153.49	132	1097.3	111	111.7	137.2
2016	Belleville, ON	445	3	0	77.41896866	28	24436.39	148	767.1	125.1	154.3	145.3
1996	Trois Rivieres, QB	620	1	0	160.5154202	49	17621.23	146	1105.6	89.4	88.9	86
2006	Trois Rivieres, QB	875	2	0	160.7626426	49	20398.34	124	1085.5	107.2	123.4	139.7
2016	Trois Rivieres, QB	555	3	0	149.9654019	49	24617.83	176	1179.8	121.6	169.5	144.1
1996	Moncton, NB	335	1	0	52.72057491	100	19725.42	160	1271.8	88.1	74.9	76.4
2006	Moncton, NB	635	2	0	52.54768466	100	22908.42	152	1204.2	104.9	115.4	138.8
2016	Moncton, NB	400	3	0	56.58740548	100	26198.91	166	994.6	125.1	150	133.3
1996	Kelowna, BC	1015	1	0	45.41251754	335	19787.88	139	483.4	89	73.5	82.2
2006	Kelowna, BC	1550	2	0	55.87962851	335	23162.81	112	341	109.3	109.9	145.2
2016	Kelowna, BC	2315	3	0	67.08825899	335	28193.63	111	261.6	128	159.4	159.4
1996	Lethbridge, AB	490	1	0	525.8965805	234	20626.16	184	345.9	83.2	82.1	80
2006	Lethbridge, AB	660	2	0	31.99231077	234	21845.06	188	337.5	109.9	115.6	142.1
2016	Lethbridge, AB	750	3	0	39.45910698	234	27440.09	142	285.6	129.6	171.4	136.3
1996	Peterborough, ON	655	1	0	86.07448134	70	20697.28	173	952.1	86.2	84.5	84.3
2006	Peterborough, ON	1215	2	0	77.4263397	70	23006.43	157	879.8	111	111.7	137.2
2016	Peterborough, ON	815	3	0	91.72195976	70	24511.95	178	419.9	125.1	154.3	145.3
1996	Barrie	295	1	0	132.30524	7	23863.95	158	699	86.2	84.5	84.3
2006	Barrie	500	2	0	197.2890459	7	26714.15	163	1056.9	111	111.7	137.2
2016	Barrie	390	3	0	219.4372063	7	26652.27	168	824.3	125.1	154.3	145.3
1996	Brantford	345	1	0	308.9191605	25	21803.85	149	1114.8	86.2	84.5	84.3
2006	Brantford	630	2	0	116.1403672	25	24543.2	116	1033.3	111	111.7	137.2
2016	Brantford	510	3	0	125.0552113	25	25670.78	140	776.7	125.1	154.3	145.3