“Transit Makes you Short”: On Health Impact Assessment of Transportation and the Built Environment

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Abstract

The current research provides a test framework to understand whether and to what extent increasing public transit use and accessibility by transit affect health. To this end, the effect of transit mode share and accessibility by transit on general health, body mass index, and height are investigated, while controlling for socioeconomic, demographic, and physical activity factors. The coefficient-p-value-sample-size chart is created and effect size analysis are conducted to explore whether the transit use is practically significant. Building on the results of the analysis, we found that the transit mode share and accessibility by transit are not practically significant, and the power of large-sample misrepresents the effect of transit on public health. The results, also, highlight the importance of data and variable selection by portraying a significant correlation between transit use and height in a multivariate regression analysis. What becomes clear from this study is that in spite of the mushrooming interdisciplinary studies in the nexus of transportation and health arena, researchers often propose short- and long-term policies blindly, while failing to report the inherent explanatory power of variables. We show that there is a thin line between false positive and true negative results. From the weakness of p-values perspective, further, we strove to alert both researchers and practitioners to the dangerous pitfall deriving from the power of large-samples. Building the results on just significance and sign of the parameter of interest is worthless, unless the magnitude of effect size is carefully quantified post analysis.

Keywords: Public transit; BRFSS data; ACS data; Accessibility to jobs; p-hacking

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1 Introduction

Motor vehicle use has been associated with numerous transportation externalities, including congestion (Anas and Lindsey 2011), crashes (Edlin and Karaca-Mandic 2006), and air pollution (Kunzli et al. 2000). Increased motor vehicle use is logically (given time constraints) significantly associated with reduced travel by active modes of transportation (Leyden 2003; Frank et al. 2004; Sallis et al. 2004). Fall in active travel use has aroused concerns among transportation and public health officials.

Numerous research has suggested that providing access to public transit reduces vehicle use, and encourages active transportation (Ewing and Cervero 2010; Lund et al. 2004). From the public health viewpoint, many tend to consider public transit as an active mode of travel (Rissel et al. 2012), and thereby to recommend transit use as a gateway for improving physical activity (Sallis et al. 2004; Wener and Evans 2007; Julien 2015). Wasfi et al. (2013) emphasize that public transit users, particularly train users, can meet the daily recommended minutes of physical activity by just walking to and from transit stops.

Although there appears to be promising evidence that transit can reduce transportation externalities and increase physical activity, the question which has attracted the attention of the scholars is whether the increased physical activity can be reflected into improved health measures (Frank et al. 2006). Two school of thoughts have emerged in this manner. The first hypothesizes that increasing transit use has beneficial health impacts, if only because the average distance between origins and destinations and the vehicle is longer for transit than for the typical automobile, requiring more walking. Research trying to substantiate this hypothesis is numerous. For instance, Besser and Dannenberg (2005) conducted a descriptive analysis of the data acquired from the 2001 US National Household Travel Survey (NHTS) to determine the physical activity of Americans in terms of walking to and from public transit. They concluded that boosting accessibility to public transit stations increases the share of transit, and consequently improves the level of physical activity. Lachapelle and Frank (2009), employed a multinominal logit regression on a travel survey in Metropolitan Atlanta between 2001 and 2002. The results of the study demonstrate that transit users are more likely to meet physical activity recommendation, i.e. walking more than 1.5 miles (2.5 km) a day, compared to those who used a private vehicle. The conducted studies, further, tend to link transit use to health benefits due to increased physical activity.

The other school of thought, however, look from the other side and professes that transit might not be as beneficial as hypothesized in the majority of research. Transit may substitute for cycling and walking trips, leading to reduced health benefits. For instance, Jones et al. (2012) in a study of young people aged between 12 and 18 in London with free bus passes concluded that many young people tend to substitute short distance walking trips with transit, when buses are freely available and accessible. Further transit may be self-selected by people who are already healthier or already have greater physical activity in their lifestyle, which may offset some of the reported correlations.

Examining this question requires more than a simple regression and reporting of the statistical significance of p-values. The second of half of this paper looks at the interpretability of the results in more detail, conducting a similar regression on height using an otherwise identical set of independent variables. There is no theory as to why transit use or accessibility affects height, yet the significance is similar to that of BMI. This raises doubts.

This paper does not take a prejudiced side on the two school of thoughts, but it does attempt to analyze, to the extent possible, the effect of transit access and mode share on measures of general health and Body Mass Index (BMI), while controlling for socioeconomic and demographic variables. The rest of the paper is structured as follows. First, the literature of the effect of active transportation and health measures is reviewed in the following section. In the review, we focus on those studies which investigated the effect of transit on health. A discussion on the data used for the analysis, then, is represented followed by the framework of the study. A section is dedicated to assessing the impact of the public transit mode share and accessibility by transit on both general health and BMI. Finally, in the discussion section, remarkable findings are mentioned and unpacked and potential pathways are suggested for the future research.

2 Previous Studies

This section reviews the past studies on the effect of public transit on the health measures of the public. From the method of analysis, previous studies might be divided into two main categories, namely descriptive and statistical analyses. Descriptive analysis is usually employed to find the relationship between the health outcomes, and some variables of interest, by looking at the distribution of the data. Rundle et al. (2007), for instance, used a cross-sectional analysis to measure the effect of built environment on BMI. The authors analyzed the BMI of 13,102 volunteers from the five boroughs of New York City through January 2000 and December 2002. The results of the study show that the individuals living in areas with higher density of both subway and bus stops, have significantly lower BMI. Analytical methods, on the other hand, attempt to build a mathematical relationship driven from the evidence that relates the health outcomes to independent variables. A recent study (Langerudi et al., 2014), for instance, used a binary probit model on a sample of 2,500 individuals living in Chicago Metropolitan Area to find the link between travel behavior and health outcomes. The authors found out that an increase in average transit use in a census tract is associated with better general health, lower BMI, and lower prevalence of Asthma and heart attack.

We reviewed the studies in the past two decades which analyzed the direct effect of transit on health measures. These studies are outlined in Table 1. In the review of the literature, we found several gaps and attempt to address them to the extent possible. First, many studies presuppose that people who use public transit are more physically active than personal car users. Hence, they suggest that using transit is an escape from the unhealthy travel behavior -use of personal vehicles- which has been dominating over the past decades. These studies, however, fail to provide strong and convincing evidence to support health benefits associated with transit use. Although people who use transit might be more active than average population, this cannot be translated into improved health measures. Using transit might be a more stressful mode of transportation. People who use transit might eat more (due to increased physical activity and stress) unhealthy fast-foods (due to less available time to eat/make healthy foods). Higher travel time by transit might also prevent users from active social behaviors, and other forms of physical activities.

There are also many possible confounding factors, as transit use and access are highly localized in urban areas, which are also associated with particular socio-economic and demographic distributions, built and natural environment conditions, and are used by people with particular attitudes.

3 Measures and Data Collection

This study is built on three major data sources, namely 1) share of public transit use, 2) accessibility to jobs by transit, and 3) obesity and health condition characteristics in 46 of the 50 largest metropolitan areas by population.

The first is derived from the American Community Survey (ACS) one year of 2013. The ACS is an ongoing mail-based survey collected by the US Census Bureau which targets a sample of about 250,000 addresses per month. The survey gathers information about the household socioeconomic and demographic variables, along with travel information of workers.

The Accessibility Observatory at the University of Minnesota estimated the second information in 2014. To achieve this, the average accessibility to jobs by walking directly and by walking to transit and taking transit (cumulative opportunities) for each census block over 7:00 to 9:00 morning period was calculated for ten minutes thresholds.

The third set of information, finally, is extracted from the Behavioral Risk Factor Surveillance System (BRFSS) health survey conducted in 2013 (US Centers for Disease Control and Prevention 2013). The BRFSS is a database of the largest health survey in the United States. Each year, the system conducts telephone surveys on more than 400,000 adults from residents nationally on health-related behaviors and conditions. Table 2 shows the explanation of variables used in the analysis.

4 Framework and Hypotheses

The conceptual framework that underpins our research is a potential relationship among health and public transportation. This framework tests whether and to what extent increasing public transit share promotes general health and BMI. Pursuant to previous studies in the discipline of health, heredity, nutrition, and physical exercise play a pivotal role in general health and controlling BMI. It is also well known that regular physical activity has health benefits, and walking is the most common form of physical activity. Hence, encouraging walking in routine activities has been recommended, and encompassed in intervention programs.

Following findings of positive correlation between walking and physical activity, many are shifting to investigate how the environmental factors such as urban form and travel behavior affect physical activity, and thereby general health. In light of the recent evidence on the physical activity promotion derived from taking public transit, health scientists contend that promoting public transit has a positive effect on health outcomes. Little is known, however, whether that derived conclusion is generalizable or even reliable. The current framework attempts to shed light on the influence of public transit and accessibility by transit on both general health and BMI. In this vein, a number of hypotheses are considered as the backbone of the analysis.

Table 1: Summary of previous studies

Study	Place	Sample Size	Analysis Method	Health Measures	Main Findings
Langerudi et al. (2014)	Chicago Metropolitan Area	>2,500	Binary probit model	General Health, BMI, Asthma, and Heart Attack	Increase in average transit use in a census tract is associated with better general health, lower BMI, and lower prevalence of Asthma and heart attack
MacDonald et al. (2010)	Charlotte	660	Multivariate analysis	BMI	The use of LRT to commute to work was associated with reduction in BMI
Samimi et al. (2009a)	Nationwide	>300,000	Binary probit model	General Health, BMI	Increase in average transit use in a census tract is associates with better general health and lower BMI
Samimi and Mohammadian (2009b)	Nationwide	>300,000	Binary probit model	General Health and Asthma	Increase in average transit use in a census tract is associated with better general health and lower prevalence of asthma
Brown and Werner (2008)	Salt Lake City	51	Analysis of variance	BMI	Obesity is lower in light rail users than non-users
Rundle et al. (2007)	New York City	13,102	Cross-sectional analysis	BMI	Individuals living in,areas with higher density of both,subway and bus stops had significantly lower BMI
Gordon et al. (2005)	Nationwide	10, 771	Multivariate analysis	-	Individuals using transit were not found to have a significant lower or higher BMI than non-transit users
Wener et al. (2003)	New Jersey and New York	29	Analysis of covariance	Perceived stress	The level of stress for those transit commuters who used new route with a lower travel time decreases compared to those who used the old route with higher travel time
Evans et al. (2002)	New Jersey and New York	56	Linear regression	Perceived stress	Increase in the unpredictability of commute to work by train increase the levels of stress experienced by commuters

Table 2: Definition of explanatory variables used in the analysis

Variable	Definition	Mean	Std. Dev.	Min	Max
Transit Share	Average transit use in work trips at the county level	7.06	9.29	0.41	61.05
A_5	Transit accessibility to jobs by transit in 5 minutes threshold at the county level	12281	79576	33	581629
A_{15}	Transit accessibility to jobs by transit in 15 minutes threshold at the county level	4492	6865	137	27798
A_{30}	Transit accessibility to jobs by transit in 30 minutes threshold at the county level	36233	61702	283	317884
General Health	1: If the general health is good or excellent/ 0: otherwise	0.53	0.49	0	1
Physical Activity	1: If the person has done any physical activity other than regular job in the past 30 days/ 0: otherwise	0.77	0.41	0	1
Age	Age in years	53.16	18.28	7	99
Married	1: If a person is married/ 0: otherwise	0.48	0.49	0	1
No. Children	Number of children in the household	0.54	1.05	0	15
Education	1: Education higher than college or technical school/ 0: otherwise	0.68	0.46	0	1
Income	8 Categories of income from BRFSS (1 to 8)	5.86		1	8
Male	Gender of the respondent	0.40	0.49	0	1
Hispanic	1: If the ethnicity of person is hispanic/ 0: otherwise	0.09	0.29	0	1
Height	Height in centimeter	169.13	10.52	91	234
BMI	Body Mass Index (kg/m^2)	27.40	5.94	12.03	93.97
Smoker	1: Smoke cigarette/ 0: otherwise	0.14	0.35	0	1

Hypothesis 1: Taking public transit has two contradictory effects on general health:

- From the positive point of view, people who choose routinely active modes of travel for the access and egress, accomplish a portion of recommended physical activity in a day. Given the physical activity has a positive correlation with public health, public transit use in this way improves general health.

- From the negative view point, two fundamental questions are raised: (1) does public transit mode include a significant amount of physical activity, when park and ride or kiss and ride modes of travel is used for the access and egress of a trip? and (2) what if a public transit system discourages people from walking and biking? Indeed, the main incentive behind promoting both transit and transit-oriented development is to encourage people to shift from driving private vehicles to taking public transit. It is plausible, however, that the high level of accessibility in a neighborhood induces residents to take public transit not only for long-distance trips, but for short-distance trips. Consequently, the level of physical activity related to walking mode of travel may diminish in that area.

Hypothesis 2: Boosting accessibility by transit to valued destinations has a contradictory influence on public health in different time thresholds.

- The authors posit that if a transit system performs impressively in providing access to nearby destinations, active transportation is superseded by transit. Accessibility changes behavior. Hence, frequent use of public transit for short-distance trips might be epidemic and consequently spread laziness.

- For the long-distance trips, in contrast, we hypothesize that the high level of accessibility may encourage people to shift from private vehicle to public transit, and thereby boosts physical activity.

Hypothesis 3: Adding more data to the sample diminishes the size of the p-value significantly. As a result, a question is raised whether a particular variable is inherently significant or adding more observation begets this reduction. Transportation researchers have commonly borrowed three datasets from the field of health, namely BRFSS, NHIS, and NHANES. These datasets are gathered randomly at the individual based level and contain more than 80,000 observations. We postulate that many reported significant correlation between transportation variables and health outcomes are the results of large samples in the analyses.

5 Positive health impact of public transit: Myth or Reality?

To give the reader a flavor for some of the misleading possibilities, we developed three different models in this section under the umbrella of three tales.

5.1 Story 1: Does public transit use diminish BMI?

To understand the impact of public transit use on BMI, we developed a multiple linear regression model. As noted previously, heredity, nutrition, and physical activity are the accepted factors influencing BMI. A model is developed that includes socioeconomic, demographic, and physical activity parameters to the extent of data availability. This approach helps to control the effect of other influential variables and reduce misspecification in the model. The base model includes gender, age, level of income, education, number of children, physical activity, and smoking. Given public transit use and accessibility by transit are highly correlated (Owen and Levinson, 2015), to avoid the multicollinearity issue, the influence of each of them is tested separately. As per Table 3, public transit mode share has a negative correlation with BMI. It means, increasing the share of public transit diminishes the BMI. To investigate the effect of accessibility by transit to jobs, as an index of accessibility to valued destinations, different accessibility time thresholds are included separately in the model. The results of accessibility to jobs by transit in five minutes threshold reveal that increasing the amount of accessibility increases the BMI. It might be rooted in the hypothesis that in this time threshold, walking is replaced by public transit. Interestingly, the accessibility to jobs by transit at the 30 minutes threshold has a negative correlation with BMI. In other words, a simplistic interpretation might imply boosting accessibility to jobs by transit for long-distance trips encourages people to shift from private cars to public transit. From the modeling side, other possible transformation technique and modeling structures were investigated, with Table 3 presenting the best model. The best model was determined based on the model selection criteria that include goodness-of-fit measures and significance and rationality of the estimates. From the general fit of models side, further, it worth mentioning that the low magnitude of the Adjusted R^2 is rooted deeply in the large sample. These amounts, however, are in the range of previous studies with this scope. Nevertheless, we emphasize that the main aim of the current research is not to represent the best model encompassing all significant variables or every conceivable specification.

5.2 Story 2: Does public transit use improve general health?

To test the hypothesis that taking public transit improves general health, we employed a binary logit model. To control the socioeconomic, demographic, and physical activity factors, a base model is developed at the first stage. The public transit factors, then, are added to the base model. High correlation between transit variables prevents them being simultaneously present. As a result, variables are tested individually in the analysis. As shown in Table 4, public transit share has an statistically insignificant effect on general health.

5.3 Story 3: Does public transit use beget short stature?

In our third tale, we test whether that people who use public transit are taller or shorter than other people. Much literature is associated with weight (or BMI). The natural analog to individual weight is height, so we use that as a control of the interpretability of the regression. We have no particular physical model of why height should be associated with built environment, though we can develop speculative "just-so" stories about differences in

Table 3: Regression analysis for dependent variable: Body Mass Index

Variable	Base (BMI-0)		Model BMI-1		Model BMI-2		Model BMI-3		Model BMI-4	
	Coef	t-test	Coef	t-test	Coef	t-test	Coef	t-test	Coef	t-test
Constant	29.922	264.44	30.030	262.02	29.905	263.63	29.934	261.97	29.960	262.45
Age	0.007	5.98	0.007	5.76	0.007	6.00	0.007	5.97	0.007	5.92
Male	0.664	15.90	0.663	15.88	0.665	15.91	0.664	15.90	0.663	15.88
Hispanic	0.032	1.43	0.043	1.57	0.036	1.49	0.031	1.42	0.034	1.45
Children	0.173	8.31	0.168	8.04	0.173	8.32	0.173	8.28	0.171	8.21
Income	-0.182	-17.17	-0.182	-17.21	-0.181	-17.05	-0.182	-17.18	-0.183	-17.24
Education	-0.600	-12.12	-0.592	-11.97	-0.598	-12.09	-0.599	-12.10	-0.596	-12.04
Smoker	-0.999	-16.96	-1.003	-17.03	-1.000	-16.97	-0.999	-16.97	-1.000	-16.98
Physical Activity	-1.943	-36.85	-1.945	-36.89	-1.942	-36.83	-1.943	-36.85	-1.943	
Transit Share	-	-	-0.013	-5.88	-	-	-	-	-	-
A_5	-	-	-	-	5.57e-07	2.15	-	-	-	-
A_{15}	-	-	-	-	-	-	-2.23e-06	-0.75	-	-
A_{30}			-	-	-	-	-	-	-8.40e-07	-2.52
No. Observations:	81,886		81,886		81,886		81,886		81,886	
Adj R^2:	0.035		0.035		0.035		0.035		0.035	

Table 4: Logit analysis for dependent variable: General Health (1: Excellent and very good health/ 0: Otherwise)

Variable	Base (GH-0)		Model GH-1		Model GH-2		Model GH-3		Model GH-4	
	Coef	t-test	Coef	t-test	Coef	t-test	Coef	t-test	Coef	t-test
Constant	-1.087	-26.51	-1.088	-26.21	-1.080	-26.28	-1.085	-26.21	-1.085	-26.24
Age	-0.016	-35.16	-0.016	-35.14	-0.016	-35.19	-0.016	-35.16	-0.016	-35.16
Male	-0.117	-7.67	-0.117	-7.67	-0.117	-7.67	-0.117	-7.67	-0.117	-7.67
Hispanic	-0.474	-17.19	-0.474	-17.19	-0.476	-17.25	-0.474	-17.19	-0.474	-17.18
Children	0.007	1.92	0.007	1.93	0.007	1.92	0.006	1.91	0.006	1.91
Income	0.228	58.83	0.228	58.83	0.227	58.66	0.228	58.81	0.228	58.80
Education	0.380	21.55	0.380	21.53	0.380	21.51	0.381	21.55	0.381	21.55
Smoker	-0.431	-19.98	-0.431	-19.98	-0.430	-19.97	-0.431	-19.98	-0.431	-19.99
Physical Activity	0.871	45.19	0.871	45.19	0.871	45.18	0.871	45.19	0.871	45.19
Transit Share	-	-	0.001	0.17	-	-	-	-	-	-
A_5	-	-	-	-	-2.52e-07	-2.64	-	-	-	-
A_{15}	-	-	-	-	-	-	-4.01e-07	-0.37	-	-
A_{30}			-	-	-	-	-	-	-4.82e-08	-0.39
No. Observations:	85,149		85,149		85,149		85,149		85,149	
Adj R^2:	0.121		0.121		0.121		0.121		0.121	

Table 5: Regression analysis for dependent variable: Height (cm)

Variable	Model H-1		Model H-2	
	Coefficient	t-test	Coefficient	t-test
Constant	163.730	1169.47	163.717	1174.25
Age	-0.0558	-34.68	-0.0557	-34.65
Male	14.3754	278.80	14.3750	278.79
Hispanic	-4.3196	-46.39	-4.3241	-46.45
Children	0.0015	2.06	0.0020	2.08
Income	0.3090	23.68	0.3081	23.60
Education	1.1872	19.49	1.1878	19.49
Smoker	0.4210	5.80	0.4220	5.81
Physical Activity	0.4351	6.74	0.4359	6.75
Transit Share	-0.0083	-3.04	-	-
A_{30}	-	-	-1.21e-06	-2.95
No. Observations:	84,670		84,670	
Adj R^2:	0.510		0.510	

ethno-demographic or socio-economic conditions of the city (where access and transit share is higher) versus suburbs, small towns, and rural areas. The regressions imply both increasing transit use and the related variable transit accessibility to jobs are negatively correlated with height. The results of the multivariate linear regression analysis are outlined in Table 5. We do not believe this is causal.

We could further engage in data-mining and test other seemingly unrelated phenomenon, and then cherry pick results. We prefer not to do that.

6 Nondiscriminatory Discussion

The student's t-test is widely conducted to show a statistically significant effect of explanatory variables in statistical and econometrics modeling. This test compares the coefficient of an explanatory variable with the null hypothesis that is commonly zero. To understand the probability that the coefficient is exactly zero over the entire sample, then, the p-value is used generally. The amount of p-value fluctuates between zero and one. It is generally interpreted that the smaller the value, the more significant the coefficient. The p-value, by definition, has a inverse relationship with the sample size. In other words, by increasing the sample size, the size of p significantly approaches the zero.

It is generally known that evidently, the estimated coefficient is not zero with a sufficiently high confidence interval. Statisticians, throughout the recent years, have frequently criticized this school of thought. Anderson et al. (2000), for instance, criticized the practicality of p-value in null hypothesis testing by investigating the 347 sampled articles in ecology. They concluded that the p-value test is not a fundamental aspect of the scientific method. Studies concluded that the p-value test is uninformative in which no estimates of effect sizes and their precision are mentioned in analyses.

In recent decades, however, the publication of inflated effect sizes has mushroomed across a broad range of disciplines. Researchers in many realms are attempting to avoid representing the crisis of replication and reliability for several reasons, including conflicts of interest, misaligned incentives, and questionable research practices. Simmons et al. (2011) discuss the p-hacking phenomena in recent publications. Pursuant to p-hacking phenomena, a researcher struggles to falsely represent a hypothesis that support existing evidence or new hypotheses, while concealing the results that disprove their agenda. Consequently, the overwhelming occurrence of p-hacking in recent research studies seems sobering.

While this paper does not repudiate any particular paper or researcher, we believe with our simple demonstration that the p-hacking phenomenon is alive and well in the realm of health and transportation, with the aim of supporting particular conclusions. The following section is dedicated to give both researchers and practitioners a real insight into the causes of the present crisis by conducting an in-depth analysis on the effect of a large sample size.

6.1 Too large to Fail

Throughout recent years, many studies in transportation and health literature have been conducted on large data sets, and in an era of "big data", that trend will only increase. Some sample used encompassed hundred of thousands of observations. Samimi and Mohammadian (2009), for instance, extracted over 300,000 observations from BRFSS data to investigate the effect of built environment on public health. Following the pervasiveness of large-sample studies, some scholars are scrutinizing the consequences of employing large samples. A key issue that raises the concern of researchers is known as "p-value problem" in such studies. The issue is rooted deeply in the weakness of p-value for interpretability when the power of large samples begets even minuscule effects become statistically significant. A prolific literature has grown in both challenging and defending the use of p-value. We do not have any intention to sympathize with the two main currents of thoughts. This part of the study, however, is an attempt to explore whether the impact of the transit use on BMI is statistically significant or is the result of the large-sample. To achieve this, two methods of analysis, namely coefficient-p-value-sample-size (CPS) and effect size are employed that shed light on whether the transit use is practically significant. The former displays the fluctuation of both p-value and coefficient of interest when the sample size ranging from small to large. The latter method, on the other hand, simply compares the marginal effect of the independent variables, pursuant to the notion of elasticity in the linear regression analysis. Elasticity in the linear regression model, by definition, represents how much the dependent variable is changed on average, followed by a unit change in an independent variable. In the binary logit model, however, elasticity represents the change in the probability of dependent variable as a function of increasing variable of interest by a unit, while all of the other variables are held at their median.

Lin et al. (2013) introduced a six-step algorithm to generate the CPS chart, including 5,000 random drawing samples of increasing sizes, rerunning the regression model on each sample, computing the coefficient and p-value of independent variable, and plotting them on a chart. The result of the CPS chart is shown in Figures 6.1 and 6.1 that highlight the p-value problem. As per Figure 6.1, the transit use variable is not significant for the small sample sizes. By increasing the sample size, however, the p-value approaches zero. In our particular example, the p-value for share of transit drops suddenly when the sample

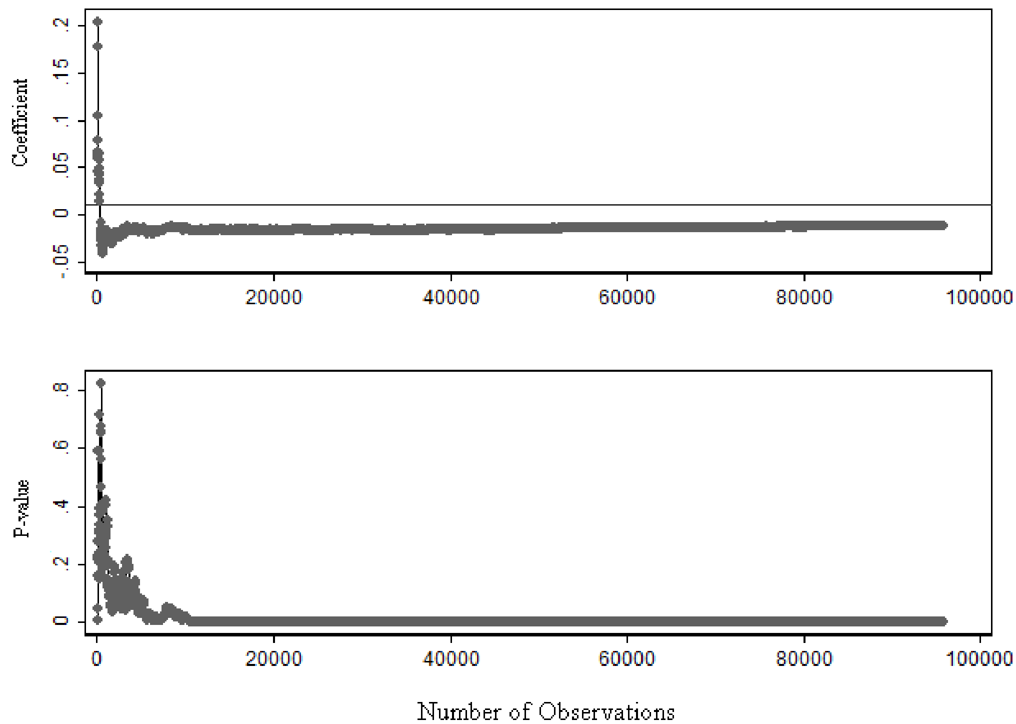

Figure 1: CPS chart for Transit Share variable

size is greater than 12,000. Figure 6.1, also, shows the power of large sample in changing an insignificant variable to a significant one. As per Figure 6.1, the p-value for variable of accessibility by transit in 30 minutes threshold is not significant when the sample is less than 20,000. Increasing the sample size inflates the standard metric of statistical significance of the A_{30}. This is a direct consequence of large sample and p-value issue, which may mislead researchers and policymakers. Hence, the increased power of large-sample in this case triggers the smaller or more complex effect of transit use on BMI deceives policymakers and researchers about practical significance. It worth mentioning that there is not a particular sample size threshold, which raises the p-value issue. To avoid the power of large sample size, therefore, we recommend that researchers present the CPS charts for the variable of interest.

To understand the effect size of transit use variable, the elasticity of the share of transit use and amount of access to destinations by transit is also measured, and the final results are outlined in Table 6. As we expected, the public transit share and accessibility by transit at the county level have a practical significant effect on neither BMI nor general health. At a deeper level, for instance, a one percent increase in the share of transit at the county level diminishes the BMI by only 0.0035 percent on average. The elasticity of transit share, further, indicates that every percent increase in transit use would escalate the chance of having excellent or very good general health by 0.003 percent. Samimi et al. (2010) also mentioned that a one percent increase in public transit use increases the chance of having excellent, very good, or good general health by 0.002 percent.

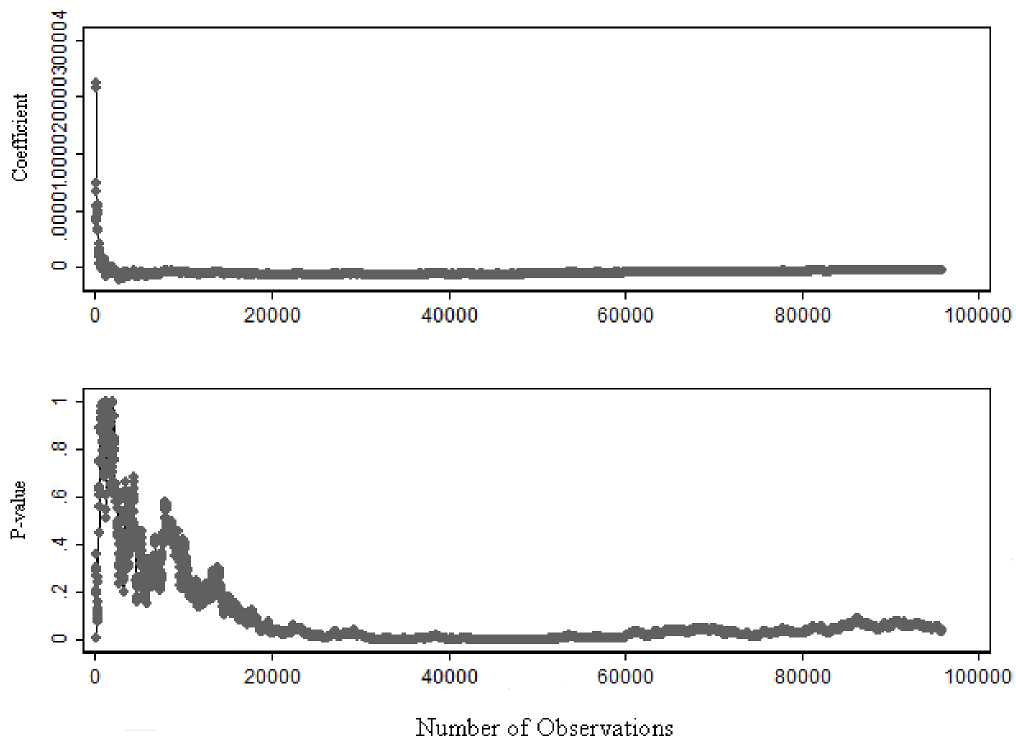

Figure 2: CPS chart for A_{30} variable (Jobs accessible by transit in 30 minutes)

Table 6: Results of the elasticity analysis

Variable	Elasticity		
	BMI	*General Health*	*Height*
Transit Share	-0.0035	0.003	-0.0003
A_5	0.0002	0.000	-0.00004
A_{15}	-0.0003	0.000	-0.0002
A_{30}	-0.0011	0.000	-0.0002

7 Closing Remarks

To date, transport researchers engage in diverse with issues of public health, including, obesity, cardiovascular diseases, and asthma, to name but a few. Indeed, the thought of incorporating physical activity in daily routines by using active travel modes conjoins transportation and health realms to some extent. A number of studies, consequently, identified a positive correlation between transit use and physical activity in light of the fact that typical mode of access and egress is either walking or biking. Despite the recognized potential health benefit of public transit, the impact of transit use on public health remains the most understudied and least understood issue.

Following the remarkable investment in public transit projects, city officials, on the one hand, are willing to understand the returns of transit projects such as transit-oriented developments and transitway programs. What, de facto, stakeholders ultimately tend to know is whether costs of a particular project or program will return in short- or long-terms. Academic circles, on the other hand, have strived to shed light on the benefits of projects at the request of city officials for economic justification of lunching transit projects. It is crystal clear that both groups are sympathetic towards finding "positive results". One to has justification for investment, and the other to get the city officials' hopes up. This destructive trend in science has triggered the "p-hacking" phenomena to the extent that Pereira and Ioannidis (2011) indicated that 16-37 percent of the statistically significant meta-analyses are false positive. Head et al. (2015), further, notify that there is a strong evidence for p-hacking in results of the studies. In other words, reporting positive effects gives researchers an incentive to select data or analysis method until insignificant results become significant. Ironically, p-values have been bashed in some analysis. Establishing such results not only misleads policies and has substantial economic burden to the government, but it also forms the cornerstone of future studies mistakenly. Analyses show that most researchers frequently follow the path of least resistance, and thereby sidestep the crisis of replication. Editors seeking high impact factors, further, show more tendencies to publish false positive than true negative, which ultimately begets publication bias issue. We label this stream "dragon of compromise." The aim of science is to discover truth about phenomena. In contrast, disciplinary incentives and publication bias encourage and support analyses that bring out the false positives and ignore negative results. Once false positives appear in the literature, they becomes tenacious. A study (Tweedie et al., 1996) shows that 45 percent of an observed association is rooted in publication bias. Fanelli (2011), further, investigated the trend of reporting positive results among more than 4,600 published papers in all disciplines between 1990 and 2007. The final analysis reveals that the interest in reporting the false positive results in the field of engineering have increased linearly with the slope of 0.75. This alarming trend is rooted deeply in the growing competition for publication and citations.

This systematic trend not only disgraces science (even if one assumes the truth will eventually win out), but it also inspires policymakers to implement short- and long-term ineffective policies, draining resources and efforts that could be better spent with more effective strategies, harming the causes it purports to help.

The current study was an attempt to conduct an in-depth analysis to give policymakers and practitioners a flavor for the possibilities of erroneous results in the efficacy of transit use. To this end, the effect of transit mode share and accessibility by transit on general health and

BMI is investigated, while controlling for socioeconomic, demographic, and physical activity factors. The coefficient-p-value-sample-size (CPS) chart and effect size analysis are conducted to explore whether the transit use is practically significant. Building on the results of the analysis, we found that the transit mode share and accessibility by transit are not practically significant, and the power of large-sample misrepresents the effect of transit on public health. The results, also, highlight the importance of data and variable selection by portraying a significant correlation between transit use and height in a bivariate regression analysis. What becomes clear from this study is that in spite of the mushrooming interdisciplinary studies in the nexus of transportation and health arena, researchers often propose short- and long-term policies blindly, while ignoring reporting the lack of inherent explanatory power of variables or their inherent inability to introduce a unique solution for a problem. There is a thin line between false positive and true negative results and researchers should be encouraged to report the truths about the phenomena.

From the weakness of p-values perspective, we strove to alert both researchers and practitioners to the dangerous pitfall deriving from the power of large-samples. In a linear regression model, for instance, a p-value measures the distance between the parameter of interest and zero in units of standard error. Increasing the sample size shrinks the standard error remarkably, and thereby minuscule distances become statistically significant. Researchers, hence, should specify whether or not the small p-value is just an artifact of the power of large-sample. Building the results on just significance and sign of the parameter of interest is worthless, unless the magnitude of effect size is carefully quantified as a post analysis. Although assessing the large-sample and small p-values issue is scant in literature, a few studies suggest: (1) reporting the p-value for small samples (Gefen and Carmel 2008), emphasizing on practical significance instead of statistical significance (Mithas and Lucas 2010), and reducing the significance level threshold for large samples (Greene 2003, Leamer 1978). Having a better understanding of the effects that cause an insignificant variable becomes significant will lead to better modeling accuracy, model suitability, and conclusion in practice. Albeit the current study provides a real insight into the effect of transit use on public health, it has some limitations which is recommended to address in further studies:

- This study only collected public transit use and accessibility by transit information and assessed the connection between transit use and public health. Other built environment variables, including, land use, block size, road density, and intersection density are recommended to assess in this framework.
- Since the lowest level of geography available for individuals is county in the BRFSS data, the aggregated built environment variables were used in this research. Disaggregate information, however, may provide more robust response behavior model.

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