ABSTRACT

Title of Dissertation: JOINT EVALUATION OF TRANSPORTATION REVENUE GENERATION AND INFRASTRUCTURE INVESTMENT POLICIES WITH BENEFITS REDISTRIBUTION CONSIDERATIONS

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The purpose of this dissertation is to guide economic policymaking by providing a comprehensive estimation of the effects that transportation revenue generation and infrastructure investment policies have on users. A 10-level integration framework is proposed to capture the complex research question of ***revenue generation-investment-benefits redistribution***, via the use of activity-based modeling and innovative data integration techniques. Revenue policies are not evaluated based on their first-level impacts on payers alone. On the contrary, they are combined with transportation investment outlooks, and their performance is assessed based on how users eventually benefit from the revenues being invested in transportation projects that facilitate their travel experience. The revenue policies explored include the status quo (fuel tax), a fuel tax increase, a flat VMT fee, an income-based VMT fee, a transportation-dedicated property tax, and a transportation-dedicated sales tax. Subsequently, three alternative transportation investment outlooks

are explored; these outlooks may be adopted by Maryland in the future, in an effort to redefine the state's purpose, perspective and vision with respect to transportation. The selected outlooks capture some of the most popular and widely discussed future transportation vision directions for the U.S. transportation agencies, and include: *(i)* network-wide bottleneck removal projects funded by the state fuel tax increase of 2015 in Maryland, *(ii)* development of a bus-only network funded by a transportation-dedicated property tax that is invested locally, and *(iii)* infrastructure retrofitting projects to accommodate connected and autonomous vehicles, funded by an income-based VMT fee. The policies' performance is evaluated on the basis of tax incidence, travel behavior and revenue generation metrics, while changes in welfare measures are estimated to assess the benefits redistribution due to the proposed revenue-investment dyads. The redistribution analysis shows that investing in bottleneck removal or CAVs will partially alleviate the burden that users will experience due to the fuel tax increase and variable VMT fee policies. However, in a situation where transportation funding shifts from the status quo to a transportation-dedicated property tax, lower income HHs will bear greater burden, and none of the income groups or counties will be able to recuperate part of their losses via the transit-oriented investment.

JOINT EVALUATION OF TRANSPORTATION REVENUE GENERATION AND INFRASTRUCTURE INVESTMENT POLICIES WITH BENEFITS REDISTRIBUTION CONSIDERATIONS

by

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2017

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Dedication

To my mother.

Acknowledgements

I would like to thank my advisor and mentor, Dr. Lei Zhang for his precious guidance, and support of my doctoral studies.

I would like to thank Carlos Carrion for his invaluable help during the long debugging hours.

I would like to thank Marty Milkovits for his round-the-clock availability to provide technical assistance.

I would like to thank my Advisory Committee for their constructive comments on my doctoral research.

I would like to thank my professors at University of Maryland for the scientific and professional knowledge I gained, and my fellow research group members for the excellent collaboration.

I would like to thank my mother Vasiliki, my father Ilias, and my brother Michalis for their endless and selfless love and support.

I would like to thank Angelos for his enduring love and ceaseless encouragement.

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Chapter 1. Introduction

1.1 Background

Currently, the U.S surface transportation spending experiences fiscal weakness, and cannot be fully funded by the Highway Trust Fund, i.e. the accounting mechanism in the federal budget for the surface transportation system. The Highway Trust Fund receives money primarily from a federal 18.4 cent-per-gallon tax on gasoline and 24.4 cent-per-gallon tax on diesel fuels. These taxes were last increased in 1993, and have been maintained until today. If those excise taxes had been indexed based on the consumer price index (CPI), the gasoline tax would be 29.7 cent-per-gallon, and the diesel tax would be 39.4 cent-per-gallon. Put it in another way, the purchasing power of the fuel tax is decreased by about 60% [1].

In the meantime, the vehicle fuel economy has increased, and shows an upward trend due to more restrictive Corporate Average Fuel Economy (CAFE) standards that require the vehicle manufacturers to comply with the gas mileage, or fuel economy standards set by the Department of Transportation (DOT). From 1993 to 2011, the CAFE standards raised the fuel economy by about 3 miles per gallon, and further by 2025 the standards will increase the fuel economy to the equivalent of 54.5 miles per gallon for cars and light trucks, as announced by the Obama administration [2].

The financial situation of the surface transportation system has long been receiving significant attention, mainly due to the aversion of politicians to implement revenue mechanisms that aim to generate additional revenue for the surface transportation system. The necessary funding for the surface transportation system in the U.S. mainly comes from the federal, the state and the local government, with a share that is close to 21% - 43% - 36% respectively [3].

At the federal level, typical sources of revenue are:

- Federal Motor Fuel Taxes: an 18.4 cents-per-gallon tax on gasoline and 24.4 cents-per-gallon tax on diesel, which have not been increased since 1993, are deposited into the Federal Highway Trust Fund with a share between the highway and mass transit accounts of 84%-16% [3].
- Other Federal Taxes: Truck Tire Excise Taxes, Truck and Trailer Sales Taxes, and Heavy Vehicle Use Taxes are also deposited into the Federal Highway Trust Fund [3].
- General Fund: approximately 9% of the federal funding comes from the General Fund to support intercity passenger rail and Amtrak, as well as Capital Investment Grants (e.g. New Starts and Small Starts fixed guideway capital projects) [3].

State funding sources include the following [3] :

- State Motor Fuel Taxes and Fees: each state sets its own fuel tax rates for gasoline and diesel, while state sales taxes on fuel can also be included in the state's fuel excise taxes.
- State Motor Vehicle Registration Fees: these fees are collected by all states from passenger and commercial vehicles based on the vehicles' characteristics. The revenues are typically used for transportation infrastructure improvements, traffic law enforcement, and public safety programs.
- State Motor Vehicle Sales Taxes: these revenues are typically directed to general funds; however, they may be used for transportation-specific purposes.
- Tolls: the provisions of the 1991 ISTEA (Intermodal Surface Transportation Efficiency Act) and 1995 NHS (National Highway System Designation Act) promoted the development of toll roads and the use of toll revenues to close gaps

in transportation projects, in the public-private partnership context. Most recently, SAFETEA-LU (Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users) has encouraged the use of tolling to finance infrastructure projects, and not merely for congestion mitigation purposes.

- Other Sources of State Revenue: these may include property taxes, motor vehicle operator license fees, general fund appropriations, and bond proceeds.

Local funding sources are becoming more popular as they are necessary to cover the declining funds from the federal and state governments. Local governments implement local taxes for transportation, which are levied and spent within their jurisdictions, however a voter referendum is required. Such taxes may include:

- Local Motor Fuel Taxes: their purpose is complementary to federal and state fuel taxes, therefore they tend to be of lower magnitude. Moreover, they tend to be lower than state and federal taxes to prevent users from purchasing fuel in neighboring local jurisdictions that do not levy local motor fuel taxes.
- Local Motor Vehicle Registration Fees: some counties and municipalities are allowed to levy these fees, which are then spent locally for maintenance or operations projects.
- Local Option Sales Taxes: such taxes are increasingly popular to fund transportation projects at the local level. The use of these revenues varies: some states may collect it as general revenue, while others are required to earmark the revenue to specific projects.
- Local Income and Payroll/Employer Taxes: such taxes are levied at the place of residence or the place of employment, respectively. They are typically deposited into the general funds.

- Local Severance Taxes: these taxes are levied on operators of natural resource extraction activities, and the revenues are used towards road improvements in rural road facilities that experience damage due to these activities.
- Value Capture: this type of financing allows the public sector to recover some or all the value that a transportation project (e.g. transit project) creates for private landowners and businesses.
- Fares: transit fares are exclusively collected at the local level and the revenues are used almost entirely for operational needs. Typically, capital investment needs are supported from federal funding.

At the federal level, several multi-year transportation bills have passed in a bid to govern the United States federal surface transportation spending, with the most recent being:

- Transportation Equity Act for the 21st Century (TEA-21), 1998: A $217.89 billion 6-year bill.
- Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU), 2005: A $286.4 billion 5-year bill.
- Moving Ahead for Progress in the 21st Century Act, 2012: A $105 billion 2-year bill that did not propose any increase in the user fees.
- Fixing America's Surface Transportation Act (FAST), 2015: A $305 billion 5-year bill for the transportation system without any increase in user fees.

Section 6020 of FAST [4] introduces a program to provide grants to states that wish to explore alternative, user-based revenue mechanism to fund the surface transportation system. Among others, the objectives of this program focus on designing and implementing user-based schemes of high functionality and low administrative cost that will have received the public's acceptance through proper outreach efforts. The states receiving funds under this program *shall address* a number of issues, including the following, which is explored in this dissertation: *equity concerns, including the impacts of the user-based alternative revenue mechanism on differing income groups, various geographic areas, and the relative burdens on rural and urban drivers.*

Additionally, Title IX of FAST outlines the details of the establishment of a National Surface Transportation and Innovative Finance Bureau in the U.S. Department of Transportation. This Bureau will work with modal administrations, and will be responsible for innovative financing programs and P3s, and their application on infrastructure finance programs, railroad rehabilitation and improvement financing programs, and nationally significant freight and highway projects [4].

The United States surface transportation system has been facing numerous challenges in the last years: the infrastructure has been aging and deteriorating, the levels of congestion have been increasing, the high number of traffic fatalities and major injuries continues and population, along with its subsequent oil dependency, has been continuously growing. The need for an effective, self-sustained investment plan is imperative. Inaction in terms of sufficing revenue generation has led (and will continue leading) to a series of negative consequences including deterioration of the surface transportation system, increase in traffic accidents, exacerbation of congestion, and issues with people and freight movements.

However, it should be emphasized that good investment practice requires securing the necessary funds to be used towards the investment plan. This strong relationship between revenue generation and investment is particularly important for agencies that aim for a change in their vision, as dedicated transportation funds allows for higher levels of experimentation in their investment practices.

On the other hand, achieving equity in transportation decision-making has long been discussed by researchers, policymakers, and human rights advocates. The Leadership Conference on Civil and Human Rights [5] defines transportation equity in a very comprehensive way that illustrates the need to make it a priority in transportation decision-making, if we want a society that prospers economically:

"Transportation equity is a civil and human rights priority. Access to affordable and reliable transportation widens opportunity and is essential to addressing poverty, unemployment, and other equal opportunity goals such as access to schools and health care services. However, current transportation spending programs do not equally benefit all communities and populations. And the negative effects of some transportation decisions- such as the disruption of low-income neighborhoods – are broadly felt and have long-lasting effects. Providing equal access to transportation means providing all individuals living in the United States with an equal opportunity to succeed. [5] "

1.2 Research Objective and Conceptual Model

The purpose of this dissertation is to guide economic policymaking by providing a comprehensive estimation of the effects that revenue and investment policies have on users. The value of the approach lies in the fact that revenue policies are not evaluated based on their first-level impacts on payers alone. On the contrary, they are combined with transportation investment outlooks, and their performance is assessed on the basis of how users eventually benefit from the revenues being invested on transportation projects that facilitate their travel experience (benefits redistribution). Policymakers at the state level can significantly benefit from the results of this work as they can draw useful conclusions as to what are the expected costs and benefits for the population from a combined revenue-investment set of policies.

This dissertation is organized into 3 main parts:

Part I: Alternative revenue policies to the status quo (fuel tax) are explored and evaluated in terms of their revenue potential and travel behavior implications. Proper statistical and network-based techniques are employed to identify the tax-paying population and their travel behavior under each revenue policy. The analysis results of this part will allow for a first-level evaluation of the revenue mechanisms based on their population-wide distributional effects.

Part II: The second part focuses on alternative transportation investment processes that Maryland may adopt in the future, in an effort to redefine the state's purpose, perspective and vision with respect to transportation. Alternative agency investment outlooks are explored, and are differentiated on the basis of resource allocation mechanism and project selection mechanism, while the resources used are closely linked to the revenue generated in Part I, resulting in a comprehensive evaluation of the joint ***revenue-investment*** process.

Part III: The benefits stemming from transportation infrastructure investment, throughout the full revenue-investment cycle, are analyzed across different socioeconomic and geographic population groups. This allows us to revisit the conclusions drawn in Part I regarding the performance of each revenue policy, by accounting for the combination of revenue – investment outlooks and for the redistribution of project benefits among the population groups that were originally affected. This last part of the dissertation compiles the findings of Part I and Part II in a bid to perform a comprehensive ***revenue-investment-redistribution*** analysis.

Figure 1 illustrates these interactions among the 3 parts of the dissertation at the higher conceptual level. A detailed figure of the comprehensive framework used in this dissertation is included in the Appendix.

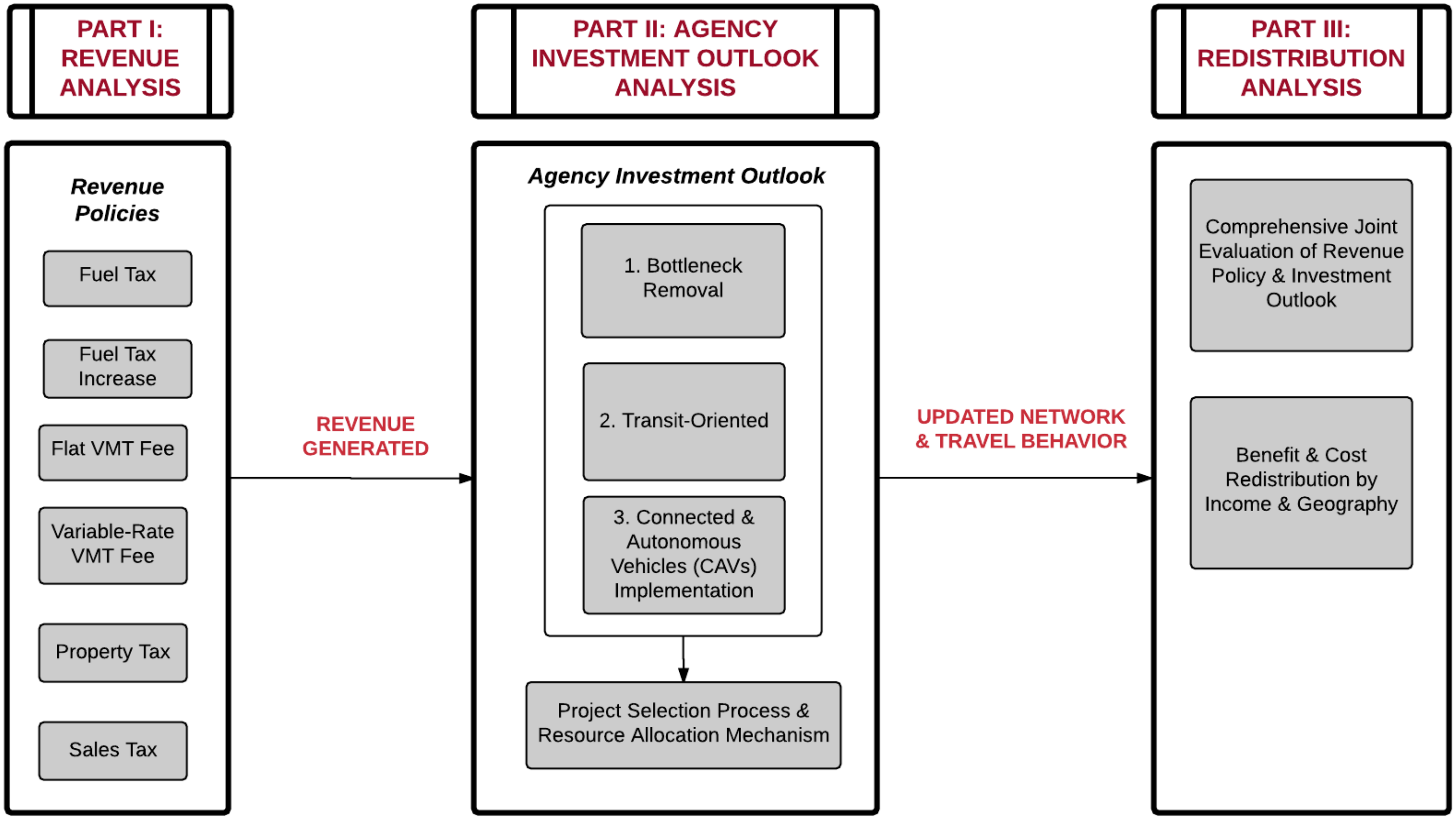


Figure 1 High-Level Conceptual Model

1.3 Research Contribution

The research contribution of this dissertation is multi-level.

Policy-wise:

- The performance of the revenue policies is evaluated not only based on the economic burden they impose on the taxpayers, but based on a comprehensive analysis that accounts for the redistribution of benefits of projects that are funded by the specific revenue mechanisms, and that aim to enhance the travel experience of the payers.
- Alternative investment outlooks are proposed and explored in a bid to showcase how a change in vision can lead to different investment decisions with respect to project selection and benefits redistribution. These alternative investment scenarios focus on bottleneck removal, transit, as well as connected and automated vehicles, and they capture some of the most popular and widely discussed future transportation vision directions for the U.S. transportation agencies.

Methodology-wise:

- Data sets from different research fields are integrated and used in order to accurately model the proposed revenue generation policies. The integration of said data sets requires the use of statistical matching, a methodological approach which has not been extensively used in the transportation research field.
- The use of activity-based models to capture the complex research question of ***revenue-investment-redistribution*** is innovative and past research has not fully exploited the significant advantages that such models offer in terms of *(i)* understanding the changes in the users' travel behavior due to different revenue mechanisms, *(ii)* reshaping the

transportation network supply according to the respective investment decisions and *(iii)* estimating and illustrating the results in a geographic context.

- A 10-level framework is proposed to allow for revenue and investment integration, in order to fully capture the total distributional effects at both the revenue generation and redistribution/investment stages.

Chapter 2. Revenue Generation Analysis

2.1 Background

Due to the declining purchasing power, more restrictive CAFE standards, as well as the emergence of hybrid and electric vehicles, the funding gap will increase if the fuel tax is still the primary source of the Highway Trust Fund. Faced with such fiscal deficit, policy makers and researchers are exploring a number of innovative funding policies to increase the revenue and reduce the deficit. In this section, the main relevant past research that has been conducted in the alternative revenue policies field is presented, in a bid to showcase the extent to which such policies have been studied, and whether/how they have been implemented in the real world.

New financing policies such as mileage-based user fees, fuel tax increase, tax replaced with a transportation-targeted increase in the sales tax [6], etc., have been put forward in the last few years. Past research has found that fuel taxes are regressive [7] [8], and even more regressive than a general sales tax [8], due to the income elasticity of gasoline being lower than 1 [9] [10]. West and Williams [11] explored the distributional effects of a gas tax increase, under different revenue recycling scenarios. They found that a gas tax increase is overall regressive, but they suggest that proper revenue recycling mechanisms may alleviate the tax's regressivity, and even make it progressive. Such mechanisms include lump-sum transfers to households, or using the revenue to lower taxes on labor. They also found that incorporating demand responses to tax changes is essential in order to obtain a realistic view of the progressivity/regressivity of the tax.

Researchers and planners have explored the use of mileage-based user fees (MBUFs) or vehicle-miles-traveled (VMT) fees as a either a supplement or a substitute for the fuel tax, that could also address critical issues such as traffic congestion and pollution. The structure of such fees, where the per-mile charges are proportional to the level of the road usage, has been very appealing to researchers, as this per mile structure creates a direct linkage between infrastructure usage, road damage, and driving cost.

A fair number of mileage-based user fee pilot studies have been conducted both in the U.S. and internationally. In the U.S., Oregon [12] [13], Minnesota [14] [15], and Iowa [16] have been the leading U.S. states in the field of MBUFs because of the pilot studies that have been administered there. For reference, Oregon and Iowa are presented next; however, other states that have been exploring VMT taxation include Alabama [17], California, Indiana, Kentucky, Michigan, Utah, and Washington State. Internationally, VMT studies have been conducted in Canada, Denmark, U.K., and Germany. Interested readers may refer to Boos and Moruza [18] for a complete list of publications on VMT pilot studies administered both domestically and internationally.

In a bid to identify alternative funding sources to the fuel tax, the Oregon Road User Fee Task Force recommended the conduct a 12-month pilot study under the name Oregon Mileage Fee concept [12] [13]. The pilot study had a two-fold objective: to study the technical feasibility of replacing the fuel tax with a VMT fee that will be collected at the pump, and to study the feasibility of using the same scheme to implement and collect congestion fees. The program recruited 285 volunteer vehicles, 299 drivers, and 2 fuel stations in Portland. The main findings of the study were that collecting the fees at the pump allows for a gradual integration of the new scheme with the old state of practice, i.e. users of both schemes can be simultaneously serviced at the pump, till the MBUF scheme gains complete market penetration. Regarding privacy, the report found that different levels of privacy can be achieved, depending on the level of information that will be collected to allow for enforcement and dispute resolution. The report also found that a MBUF would have low administrative costs of approximately $1M per year.

The University of Iowa Public Center conducted a 2-year field study on Mileage-Based Road User Charges [16] [19]. The 2-year program (December 2008 - June 2010) was funded under the 2005 SAFETEA-LU transportation reauthorization to explore the technical feasibility and the public's level of acceptance of switching from fuel taxes to MBUFs. The program recruited 2,650 volunteers in 12 states, and on-board units (OBUs) were installed in all participating vehicles. The GPS-equipped OBUs provided information on the jurisdiction where driving occurred, so as to allow linkage of infrastructure use and fee payment at the geographical level. Regarding the public's privacy concerns, Hanley and Kuhl [16] found that participants preferred audit ability instead of maximum privacy protection.

Setting a proper fee is challenging, and it heavily depends on the objective of the policy, as this has been decided by the decision makers. There has been an increasing number of research studies on this topic, including Zhang [20] [21], West [22], Parry and Small [23], Zhang and Methipara [24], Weatherford [25], Zhang and Lu [26] [27], Larsen et al. [28], and McMullen et al. [29]. Rufolo [30] studied the cost associated with fee collection under a MBUF revenue policy. Comparing 3 alternative VMT fee collection systems to fuel tax, he found that paying at the pump (similar to the Oregon pilot study) has the lowest cost at $1.79 per 1,000VMT, while the corresponding cost for fuel tax is $0.10. He found that, although the technology-related cost can be reduced, the administration and enforcement costs are still high. Deakin et al. [31] performed a comprehensive study of five alternative policies to the fuel tax for California, in a bid to understand their effects on congestion, emissions, energy, and equity. Among others, they explored fuel tax increases, VMT fees and emission fees.

The effect on equity is particularly important. In the discussion on the transportation financing policies, five equity concepts including benefits received, ability to pay, return to source, costs imposed, and process or participation are confronted [32]. Among all these concepts, the benefits received and ability to pay are the most traditional and familiar concepts when people debate the transportation financing policies [33]. Equity across income groups refers to the ability to pay and the cost imposed on people across the economic spectrum. The concept of ability to pay indicates that people who are wealthy should pay more, while the cost imposed on people mainly means the out-of-pocket cost most of the time. Consideration of income equity in revenue policy design encourages more progressive funding structures instead of regressive schemes which place a disproportionate burden on lower-income groups [8].

Local option transportation taxes have been viewed as a funding alterative to the current fuel tax practice. Local option transportation taxes vary and may include fuel taxes (e.g. local option motor fuel taxes), vehicle taxes (e.g. local vehicle license tax), property, or sales taxes. They are typically administered and collected at the local level, in a bid to move away from planning bureaucracies and towards mechanisms of direct democracy [34]. Therefore, they provide the local government with a greater flexibility in terms of investing in projects of local significance.

This flexibility in administration and collection has motivated us to explore whether property taxes are a form of local option taxes that could be effectively used for transportation purposes in a dedicated fashion. Unfortunately, it is very hard to collect completely accurate data regarding the level of property taxes that state and local governments dedicate to transportation-related projects, mainly due the lack of such detailed documentation. Goldman et al. [35] [36] have collected the most comprehensive information up-to-date on road- and transit-dedicated property taxes for selected states, along with information on vote requirement, taxpaying population, and annual per capita revenue. All such information is presented in Table 1 and Table 2.

Table 1 Selected States with Dedicated Property Taxes for Roads [36]

State	Vote Required?	Areas Imposing Tax	% of Population Taxed	Annual Per Capita Revenues
Alabama	No	All counties	100%	$28.80
Arizona	Some	5 districts, 3 cities	>18%	$15.30
Arkansas	Yes	All counties, 18 districts	100%	>$18.50
Colorado	Some	Nearly all counties, 18 districts	100%	$25.90
Idaho	No	113 cities, 26 counties, 51 districts	64%	$63.20
Indiana	No	88 of 92 counties	85%	$2.70
Iowa	Some	All counties	100%	$38.60
Kansas	Yes	99 of 105 counties	84%	$48.40
Michigan	Some	28 of 83 counties	56%	$2.70
Minnesota	No	85 of 87 counties, 1 district, most towns	100%	$76.60
Nevada	No	1 county, 2 cities, 10 districts	14%	$82.60
North Dakota	Some	All counties	100%	$32.00
Ohio	Some	5 counties, 568 townships, 52 cities	100%	$10.10
Oregon	Some	19 counties, 16 cities	65%	$16.70
Texas	Some	156 of 254 counties, 22 districts	38%	$19.80
Washington	Some	All counties	100%	$106.40
Wyoming	No	3 counties	10%	$68.10

Table 2 Selected States with Dedicated Property Taxes for Transit [36]

State	Vote Required?	Areas Imposing Tax	% of Population Taxed	Annual per Capita Revenues
California	Yes	7 districts	21%	$14.90
Florida	Yes	5 district	23%	$8.60
Georgia	No	3 districts	6%	$15.20
Indiana	No	7 cities, 8 districts	29%	$30.20
Iowa	Some	15 cities	32%	$16.20
Kansas	Yes	2 cities	7%	$17.30
Louisiana	Yes	1 parish	10%	$8.30

State	Vote Required?	Areas Imposing Tax	% of Population Taxed	Annual per Capita Revenues
Massachusetts	No	17 districts	92%	$26.90
Michigan	Some	7 districts	56%	$5.10
Minnesota	No	4 districts	54%	$3.00
Nebraska	Some	1 RR safety district, 1 transit district	37%	$14.30
North Dakota	Some	4 cities	26%	$3.40
Ohio	Some	6 districts	11%	$8.50
Oregon	Some	7 districts	42%	$14.10

The estimation of property taxes is not uniform, but follows a similar process in all local jurisdictions. The local government obtains the market value of each property as well as the assessed home value (% of the market value as defined determined by each local government's tax authority). Based on the financial needs of each tax district within the state (e.g. financial support for school districts and local government offices), property taxes are calculated so as to cover the budget deficiency [37].

From the government's perspective, property taxes have a few advantages that are worth mentioning [38]:

(i) they can be collected in a consistent fashion, and they grow in line with population and inflation;

(ii) they are easily administered and collected;

(iii) they are consistent with accountability, in terms of raising revenues and spending.

However, the public's opinion on property taxes is undoubtedly not highly favorable, mainly due to the following reasons, as discussed in [38]:

(i) property taxes are paid in lump-sums, therefore are more noticeable than taxes that are paid in a more continuous fashion (e.g. sales tax);

(ii) voters do not trust the tax administration process which fairly often leads to similar properties having completely different property tax evaluations; and

(iii) property taxes are not representative of the payer's income level.

Therefore, while property taxes are easy to administer and collect as the process is already in place, using property taxes to fund the transportation system may not necessarily find a great number of advocates. However, herein, it is worth exploring such a revenue policy, as the investment scenarios and benefits redistribution mechanisms that are implemented in Part II and Part III of this dissertation shall show whether there is margin for benefit redistribution that will alleviate the property tax payers.

This is particularly important and interesting to explore, as property tax has been found to be regressive for the most part. Netzer [39] found that the residential component of the property tax is indeed regressive (contrary to property tax on the combination of the residential and non-residential components). Musgrave [40] challenged the Harberger-Mieszkowski model and concluded that property tax is regressive, under the majority of tax burden distribution scenarios (allocation by capital income, allocation by capital income with excise effect, mixed allocation, full allocation by housing consumption). Zodrow's findings [41] were mixed: he found property tax to be progressive under the capital tax view (i.e. the property tax is a tax on capital with a distortionary effect on the use of the capital), but regressive under the benefit view (i.e. the property tax is a user charge for local public services). Suits [42] found personal property taxes to be progressive, although their progressivity decreased from 1966 to 1970, and Aaron [43] emphasized that property taxes should be considered progressive until proven regressive, and not the other way around.

Sales taxes on fuel and other transportation-related purchases have been used to fund transportation infrastructure in various states [44]. In Los Angeles County, a 0.5% dedicated sales tax increment passed in 2008 for 30 years, with the revenues dedicated to transit and freeway projects in the area [44]. In addition, in Virginia, there was a 0.3% statewide retail and sales tax rate increase in July 2013; 0.125% of the 0.3% was dedicated to transportation [44].

Table 3 Local Option Sales Tax for Transportation Capital Projects [36]

State	Vote Required	Areas Imposing Tax	% of Population Taxed	Annual Per Capita Revenue
Alabama	No	Roads: 3 counties	3%	$22.80
Alaska	No	None	-	-
Arizona	Yes	Roads: 4 counties, 3 cities	68%	$77.10
Arkansas	Yes	Roads: 34 counties, 17 cities	35%	Not Available
California	Yes	Multimodal: 13 counties Roads: 3 counties, 1 town	49% 3%	$59.50 $41.50
Colorado	Yes	Roads: 15 counties, 10 cities	>46%	$58.20
Florida	Yes	Multimodal: 6+ counties	>23%	$41.80
Georgia	Yes	Roads: more than ¼ of the counties	>25%	$112.00
Iowa	Yes	Roads: 21 of 99 counties?	23%	$50.00
Kansas	Yes	Roads: 2 counties, 8+ cities	>13%	Not Available
Louisiana	Yes	Roads: 7 parishes, 1 city	29%	$60.50
Minnesota	Yes	Roads: 1 city	2%	$32.60
Missouri	Yes	Roads: 40+ counties, 8 cities	32%	$96.20
Montana	No	None	-	-
Nebraska	Yes	Roads: 1+ cities	>1%	Not Available
Nevada	Yes	Roads: 4 counties Railroads: 2 counties	6% 18%	$29.50 $18.40
New Mexico	Yes	Roads: 8+ counties, 20 cities	40%	$6.60
New York	No	Roads: 1 county	<1%	$15.40

State	Vote Required	Areas Imposing Tax	% of Population Taxed	Annual Per Capita Revenue
North Dakota	No	Not Available	Not Available	Not Available
Ohio	Yes	Roads: 5+ counties	>3%	$59.30
Oklahoma	Yes	Roads: 17 counties	Not Available	Not Available
Pennsylvania	Yes	None	-	-
South Carolina	Yes	Roads: 2 counties	7%	$150.60
South Dakota	No	Not Available	Not Available	Not Available
Tennessee	Yes	Roads: 9 counties	21%	$7.40
Texas	Yes	Not Available	Not Available	Not Available
Utah	Yes	Roads: 19 cities	8%	$13.10
Vermont	Yes	None	-	-
Washington	Yes	None	-	-
Wyoming	Yes	Roads: 3 counties	14%	Not Available

Table 4 Local Option Sales Taxes for Transit [36]

State	Vote Required	Areas Imposing Tax for Transit	% of Population Taxed	Annual Per Capita Revenue
Alabama	Yes	1 district	15%	$6.10
Arizona	Yes	2 cities	30%	Not Available
Arkansas	No	None	-	-
California	Yes	7 counties	46%	$85.80
Colorado	Yes	3 counties, 1 city, and 1 district	59%	$81.60
Georgia	Yes	1 district	17%	$182.60
Illinois	Yes	2 districts	69%	$58.90
Louisiana	Yes	1 district	11%	$98.90
Missouri	Yes	1 county 3 cities	34%	$67.40
Nebraska	Yes	Not Available	?	Not Available
Nevada	Yes	3 counties	85%	$39.60
New Jersey		None	-	-
New Mexico	Yes	2 cities	28%	$129.30
New York	No	1 county, 1 district	71%	$24.90
North Carolina	Yes	1 county	8%	84.00
Ohio	Yes	6 districts	36%	$62.10
Oklahoma	Yes	1 county	Not Available	Not Available
Texas	Yes	Transit: 8 districts	40%	$108.30
Utah	Yes	Transit: 4 counties and 22 cities	84%	$33.90
Washington	Yes	Transit: 10 counties and 14 districts	87%	$82.60

Evidence so far has shown that sales taxes are not necessarily a good idea for transportation funding, as they have been found to be regressive when compared to congestion pricing [45] [46]. For instance, Schweitzer and Taylor [45] compared the distributional effects of the cost burden of Orange County's local option transportation sales tax (Measure M) to those of a value-priced road, State Route 91 (SR91) in Orange County, California. Based on their analysis, they concluded that moving from congestion pricing to a local option sales tax would shift the cost burden from the boundaries of the income range (low- and high-income households) to the middle-income households. They also found that the cost burden transfers from regular SR91 users to occasional and non-users. They found that sales taxes are regressively distributed among a larger number of consumers (compared to other revenue strategies), and they emphasized the importance of proper cost burden redistribution mechanisms to alleviate lower-income households and users (i.e. tax-funded transit service or affordable housing). Among other alternative transportation financing strategies, Rosenbloom [47] discussed the effect of sales taxes on older and retired people, emphasizing the fact that such taxes do not successfully meet the traditionally-defined equity criteria of "user-pays" and "ability-to-pay". Goldman et al. [36] have thoroughly reviewed the existence of local option taxes in various states. In Maryland, the state government has a strong presence when it comes to transportation funding at both the state and the local level [36], and the existence of local option taxes is very small (although not non-existing).

The majority of past research has found sales tax to be regressive. In 2006, Slemrod [48] discussed the misconception surrounding the progressivity of sales taxes: he claimed that fewer people would support sales taxes if they were aware of its regressive performance. Suits [42] explored the progressivity of a variety of U.S. taxes, including sales and excise taxes, payroll taxes, etc. Using data from 1966 and 1970, he confirmed the sales tax's regressivity, and he actually found sales and excise taxes to be the most regressive of all the taxes explored in that research work. Davies [49] found sales tax to be regressive across all income groups, regardless of the income variable that was used (gross or net) to estimate the effective tax rate. However, he also found that exempting food from sales tax decreases the tax's regressivity, particularly for the middle income class groups. However, using a more aggregate metric for wealth (including assets, liabilities etc.) instead of income makes the sales tax overall progressive. Schaefer [50] reached similar conclusions regarding the effect of the exemption of food for home consumption on the sales tax (its regressivity is reduced), while the tax becomes progressive when total consumption is used to measure the ability to pay. He concludes that the tax's regressivity can be significantly reduced if policymakers implement proper category exemptions. Caspersen and Metcalf [51] reached similar conclusions as Davies [49] regarding the effect of the metric of wealth on the progressivity/regressivity categorization. They found that, using lifetime income as welfare metric, the sales tax becomes progressive, contrary to using annual income which makes the tax regressive. However in 1997, Metcalf argued that sales taxes are regressive, regardless of the metric of welfare used. He did mention, though, that the tax's regressivity is emphasized when annual income metrics are used instead of lifetime ones. Derrick and Scott [52] explored the variation in the incidence measures of sales tax using data for Maryland. They found that the conclusion depends heavily on the pass forward/backward specification: sales tax is found to be regressive if it is assumed that consumers bear the burden, whereas it is found to be less regressive if capital owners bear the tax. More information on tax incidence analysis can be found in Fullerton and Metcalf [53].

Sales taxes, although for the most part they are found to be regressive, they are often preferred by taxpayers, due to their incremental (instead of lump-sum) nature, while they have good revenue potential due to their broad payers base [35] [34]. When evaluated in terms of equity, they perform well, mainly because they pass the horizontal equity test, but also because expenditures are considered a better representation of ability to pay than income [35] [34]. Crabbe et al. [54] identified the four key elements that make voters favorable towards local transportation sales taxes (LTSTs): (i) the need for direct voter approval, (ii) local use of the collected revenues, (iii) explicit expiration date, and (iv) pre-defined list of transportation projects to be financed.

Prompted by these findings, the objective of Part I is to explore how different revenue policies may affect the taxpaying population and their travel behavior. The revenue policies explored have received great research and political attention, are fairly easy to implement, and their charges are/can be differentiated across different socioeconomic and geographic groups. The objective of this analysis is to identify which socioeconomic groups will most likely be affected under each revenue scenario, compared to the status-quo base case, as well as quantify the effects of each scenario on the population's travel behavior. The analysis results of this part will allow for a first-level evaluation of the revenue mechanisms based on their population-wide distributional effects. The conclusions shall prove helpful to policymakers who wish to understand how the candidate revenue schemes may affect the population if they are implemented alone, without accounting for benefits redistribution via informed project investment decisions (Parts II and III).

2.2 Policy Design

Six revenue policies are explored so as to cover a wide range of proposed schemes found in the literature. Each policy is defined by two parameters: the level of the fee, and the revenue generated. Since the purpose of this research part is exploratory, for each policy either the fee or the revenue level is pre-defined, as it will be discussed in more detail in the following sections. Once the details of each revenue scheme are set, the different scenarios are run using the BMC region network, and their performance is quantified and discussed.

2.2.1 Fuel Tax per Gallon - Status Quo

The purpose of this scenario is to estimate the total revenue generated under the current level of federal and state fuel tax in the Baltimore Metropolitan Council (BMC) region, as well as the distributional effects of the current policy on different socioeconomic and geographic groups. The current federal and state taxes of $0.184 per gallon and $0.235 per gallon respectively are implemented on all agents driving on the BMC region network and residing within the BMC region boundaries (assuming that refueling will occur within the BMC region boundaries as well). The assumptions that are in place in the estimation of the vehicle operating cost are the following:

- Average gas price in MD in 2012: $3.60 per gallon [55]
- State gas tax in MD in 2012: 23.5 cents per gallon
- Federal gas tax in MD in 2012: 18.4 cents per gallon
- Maintenance: 5.0 cents per mile [56]
- Tires: 1.0 cents per mile [56]

In addition to the aforementioned costs and assumptions, the per-mile cost of operating a light-duty vehicle also depends on the vehicle's fuel efficiency. As it will be discussed in more detail in the following sections, the activity-based model used in this analysis is heavily revised to allow for a vehicle-specific operating cost (contrary to the original model configuration which assumed the same operating cost for all agents). This revision in the model configuration was deemed essential in order to capture travel behavior more realistically.

2.2.2 Maryland-Approved State Fuel Tax Increase

This scenario models the $0.018 per gallon increase in the state's fuel taxes, according to the 2013 law which went into effect in July 2015. The purpose of this increase is to generate additional funds for transportation projects [57]. This increase applies to all agents driving on the BMC region network and residing within the BMC region boundaries (assuming that refueling will occur within the BMC region boundaries as well). This scenario uses the same assumptions and same modeling configuration as the status quo scenario.

2.2.3 Flat-Rate Vehicle-Miles-Traveled (VMT) Fee

Flat-rate VMT fees have been the focus of extensive research in terms of their equity performance and revenue generation potential. They have been particularly popular among researchers as they directly link infrastructure usage to user cost. This scenario assumes a flat VMT fee of $0.22755 per mile on all users driving on the BMC region network. The selection of the fee is based on the original model configuration of the activity-based model used in this analysis. The same assumptions hold as in the status-quo scenario in terms of average gas price in MD ($3.60 per gallon), state gas tax in MD (23.5 cents per gallon), federal gas tax in MD (18.4 cents per gallon), maintenance (5.0 cents per mile), and tires (1.0 cents per mile). The fee is estimated assuming an average fuel efficiency of 21mpg for all vehicles driving on the network [58]. The flat-rate VMT fee applies to all agents driving on the BMC region network.

2.2.4 Variable Rate Vehicle-Miles-Traveled (VMT) Fee

This revenue scenario attempts to generate the same level of revenue as the flat-rate VMT fee, but accounting for the income level of the user. In order to address the multi-cited regressivity of flat-rate VMT fees, this policy design charges higher-income users a higher VMT fee than their lower-income counterparts. Such a policy design does not only link transportation fees to transportation infrastructure usage, but also accounts for the user's ability to pay. The scheme based on which the fee for each income group is defined follows the fixed-incremental fee structure, as it has been found to be progressive across all income groups [59]. This scheme is simple to design, easy for the public to comprehend and does not require additional socioeconomic data from the drivers [59] . The variable-rate VMT fee applies to all agents driving on the BMC region network, and the state fuel tax (SFT) component varies as follows:

$$SFT_{INCi} = SFT_{INC(i-1)} * 1.05$$

for i = 0, 1, 2, 3, 4, and $SFTI_{INC4}$ = \$0.22755 per mile.

2.2.5 Transportation-Dedicated Property Tax

Property taxes could be used as an alternative source of revenue for the transportation system. Property taxes in Maryland are administered and enforced by the Maryland Department of Assessment and Taxation, are based on property assessments, and cover the 23 Maryland counties, Baltimore City and 155 incorporated cities [60]. Property taxes are a form of local tax, in the sense that property tax revenues are collected by local agencies, and could be partially invested in transportation projects of local interest.

Herein, conclusions will be drawn at the household level regarding the composition of the taxpaying population and the level of taxes paid. Once the taxpaying population is identified, a 9.4% increase in property tax is implemented to all agents owning property in a specific county.[1] The level of this local option property tax increase is set equal to 9.4% in order to generate comparable revenue to the status-quo scenario. This approach allows us to explore how the same level of revenue can be generated from different policies, and what are the distributional effects of the property tax vs. the status-quo. The property tax increase will be applied to all agents owning property within the model area.

2.2.6 Transportation-Dedicated Sales Tax

Another alternative source of revenue for the transportation system is sales taxes. State sales taxes of 6% (or 9% for alcoholic beverages) apply to purchases made in Maryland, whereas use taxes refer to taxes on goods that have been purchased out of state. The objective of a use tax is to protect Maryland business from unfair competition [61]. We use the 2009 Consumer Expenditure Data (Interview Files) to estimate the level of sales taxes collected by the state of Maryland from the household’s taxable purchases. Sales taxes are statewide taxes that are collected from state agencies and could be partially invested in projects of statewide interest.

Using data from multiple sources, conclusions will be drawn at the household level regarding the composition of the taxpaying population and the level of taxes paid. Once the taxpaying population is identified, a 21.5% increase in sales taxes is implemented to all agents residing in a specific county. The level of this local option sales tax increase is set equal to 21.5% in order to generate comparable revenue to the status-quo scenario. This approach allows

[1] Property taxes are paid by property owners only. However, it is assumed that part of the burden is borne by renters, as it is assumed that 15% of each renter’s occupancy rent goes towards the payment of property taxes [93]. Therefore, it is acknowledged that both property owners and renters would experience additional economic burden from a transportation-dedicated property tax increase.

us to explore how the same level of revenue can be generated from different policies, and what are the distributional effects of the sales tax vs. the status-quo. The sales tax increase will be applied to all agents residing within the model area.

2.3 Data

The data used in the first part of this dissertation comes from 3 distinct sources that are used cooperatively to model the 6 policies. Modeling the property and sales tax policies is more complex, and requires merging two datasets. The first dataset is obtained from the activity-based model InSITE, is the product of the post population synthesizer processor, and contains socioeconomic and vehicle ownership related information at the household level, such as income class, number of children, number of full-time and part-time workers, number of vehicles owned, etc. Despite the large amount of information that this dataset contains for the synthetic population, there is no information on the household's expenditures behavior.

2.3.1 Activity-Based Model Data (InSITE)

The primary data source used in the first part of this dissertation is the data used in the activity-based model developed for the BMC region, InSITE. The InSITE datasets are created using the following inputs [62]:

(i) Synthetic population: produced by the synthetic population generator PopGen, the synthetic population represents every person and household in the model region.

(ii) Land use parcel database: includes land use type and size information for all land parcels in the model region.

(iii) Zone level socioeconomic and other data: the model region is divided into 2919 transportation analysis zones (TAZs)

(iv) Highway and transit networks: the static highway and transit networks are used to create the initial travel time, distance and cost skims that are used as inputs to the demand model components.

Table 5 and Table 6 present the descriptive statistics of the main variables in the InSITE HH and person datasets.

Table 5 Variable List and Descriptive Statistics for the InSITE HH dataset

Variable Mnemonic	Variable Description	Mean	Std. Dev.	Min.	Max.
HHINC5S	Zero-based, 5-segment income class (<15K, 15-30K, 30-50K, 50-100K, >100K)	2.57	1.37	0	4.00
HCHILD1	Number of Child1 in HH	0.16	0.52	0	5.00
HCHILD2	Number of Child2 in HH	0.34	0.78	0	8.00
HCHILD3	Number of Child3 in HH	0.07	0.30	0	6.00
HSTUD	Number of Adult Student in HH	0.13	0.50	0	5.00
HFTW	Number of Full time worker in HH	1.07	0.92	0	7.00
HPTW	Number of Part time worker in HH	0.16	0.40	0	4.00
HNWA	Number of non-working adult in HH	0.28	0.51	0	5.00
HSEN	Number of senior in HH	0.22	0.46	0	8.00
HHSIZE	Household size	2.42	1.35	1	12.00
GRPQRTR	Gross Regional Product	0.09	0.41	0	2.00
HCHILDREN	Number of children	0.56	0.97	0	9.00
HNOCHILDREN	Zero children in household	0.69	0.46	0	1.00
HWORKERS	Number of workers	1.23	0.95	0	7.00
HADULTS	Number of adults	1.86	0.98	0	8.00
ADULT1KIDS	Single adult with 1+ children	0.08	0.26	0	1.00
HH1PERSON	1 Person in HH	0.32	0.47	0	1.00
HH2PERSON	2 People in HH	0.28	0.45	0	1.00
WORKVOT	Work tour value of time (cents/minute)	13.78	14.05	0.15	566.03
NONWORKVOT	Non-work tour value of time (cents/minute)	9.19	9.37	0.10	377.35

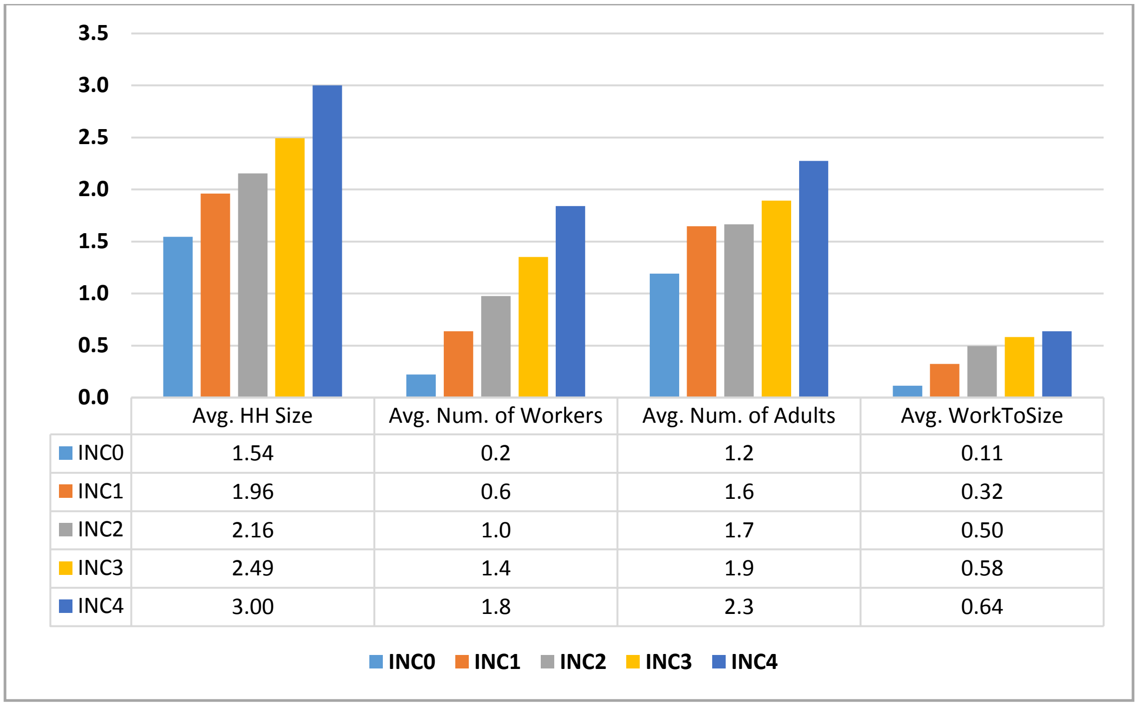
Variable Mnemonic	Variable Description	Mean	Std. Dev.	Min.	Max.
WORKTC	Work tour time coefficient	-0.02	0.02	-0.65	0.00
NONWORKTC	Non-work tour time coefficient	-0.02	0.01	-0.44	0.00
INTDEN05	Intersection density within 1/2 mile buffer	120.21	75.54	0	436.94
LNEMPDEN05	LN(1 + Employment density) within 1/2 mile buffer	4.05	2.08	0	10.77
LNHHDEN05	LN(1 + Household density) within 1/2 mile buffer	1.06	0.86	0	7.25

Table 6 Variable List and Descriptive Statistics for the InSITE Person dataset

Variable Mnemonic	Variable Description	Mean	Std. Dev.	Min.	Max.
HHINC5S	Zero based, 5 segment income class (<15K, 15-30K, 30-50K, 50-100K, > 100K)	2.84	1.26	0.00	4.00
AGE	Age in years	36.79	22.04	0.00	95.00
GENDER	Gender (1 = male, 2 = female)	1.52	0.50	1.00	2.00
EmpStatus	Employment status (1 = worker)	0.51	0.50	0.00	1.00
SchStatus	School status (1 = student)	0.23	0.42	0.00	1.00
female	1 if female	0.52	0.50	0.00	1.00
HCHILD1	Number of Child1 in HH	0.26	0.67	0.00	5.00
HCHILD2	Number of Child2 in HH	0.57	0.99	0.00	8.00
HCHILD3	Number of Child3 in HH	0.10	0.37	0.00	6.00
HSTUD	Number of Adult Student in HH	0.20	0.64	0.00	5.00
HFTW	Number of Full time worker in HH	1.37	1.01	0.00	7.00
HPTW	Number of Part time worker in HH	0.22	0.48	0.00	4.00
HNWA	Number of non-working adult in HH	0.29	0.54	0.00	5.00
HSEN	Number of senior in HH	0.15	0.42	0.00	8.00

Variable Mnemonic	Variable Description	Mean	Std. Dev.	Min.	Max.
HHSIZE	Household size	3.18	1.40	1.00	12.00
GRPQRTR	Gross Regional Product	0.04	0.26	0.00	2.00
HCHILDREN	Number of children	0.94	1.18	0.00	9.00
HNOCHILDRE	Zero children in household	0.54	0.50	0.00	1.00
HWORKERS	Number of workers	1.59	1.01	0.00	7.00
HADULTS	Number of adults	2.24	1.13	0.00	8.00
ADULT1KIDS	Single adult with 1+ children	0.09	0.29	0.00	1.00
HH1PERSON	1 Person in HH	0.13	0.34	0.00	1.00
HH2PERSON	2 People in HH	0.23	0.42	0.00	1.00
WORKVOT	Work tour value of time (cents/minute)	14.91	14.73	0.15	566.03
NONWORKVOT	Non-work tour value of time (cents/minute)	9.94	9.82	0.10	377.35
WORKTC	Work tour time coefficient	-0.02	0.02	-0.65	0.00
NONWORKTC	Non-work tour time coefficient	-0.02	0.01	-0.44	0.00
INTDEN	Intersection density within 1/2 mile buffer	115.86	73.04	0.00	436.94
EMPDEN	LN(1 + Employment density) within 1/2 mile buffer	4.01	2.00	0.00	10.77
DEN_HH	LN(1 + Household density) within 1/2 mile buffer	1.02	0.83	0.00	7.25

The following figures illustrate the average household characteristics by income group, the number of HHs by income group, and the income distribution by county. Finally, Table 7 presents the main socioeconomic characteristics at the county level.



	Avg. HH Size	Avg. Num. of Workers	Avg. Num. of Adults	Avg. WorkToSize
INC0	1.54	0.2	1.2	0.11
INC1	1.96	0.6	1.6	0.32
INC2	2.16	1.0	1.7	0.50
INC3	2.49	1.4	1.9	0.58
INC4	3.00	1.8	2.3	0.64

Figure 2 InSITE Household Characteristics by Income Group.

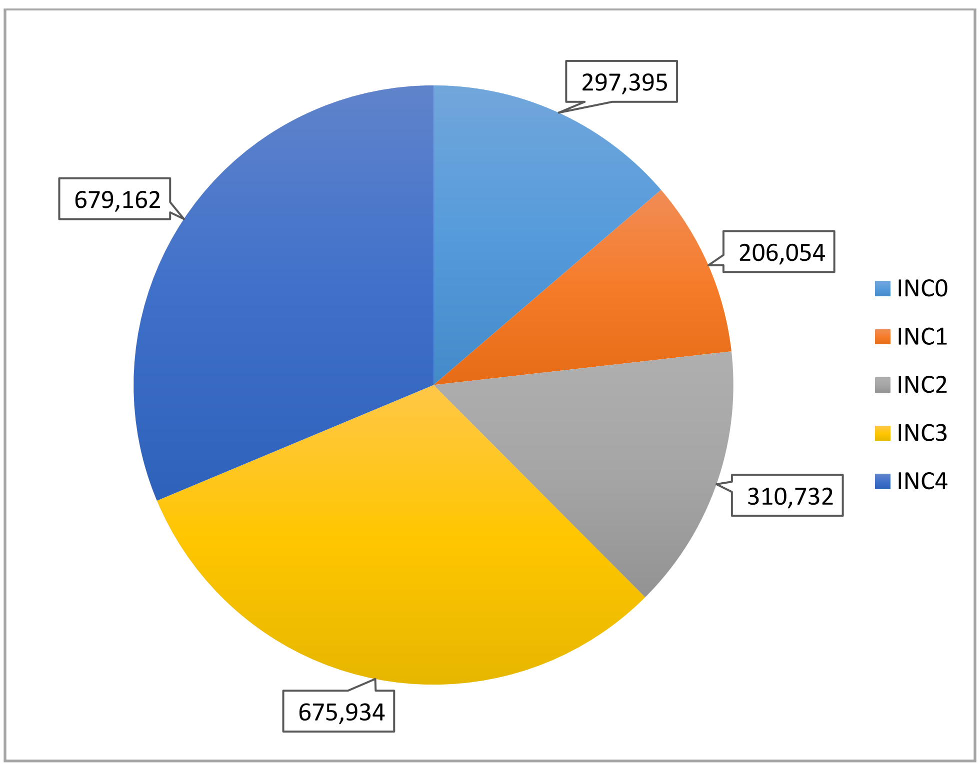


Figure 3 InSITE Number of HHs by Income Group.

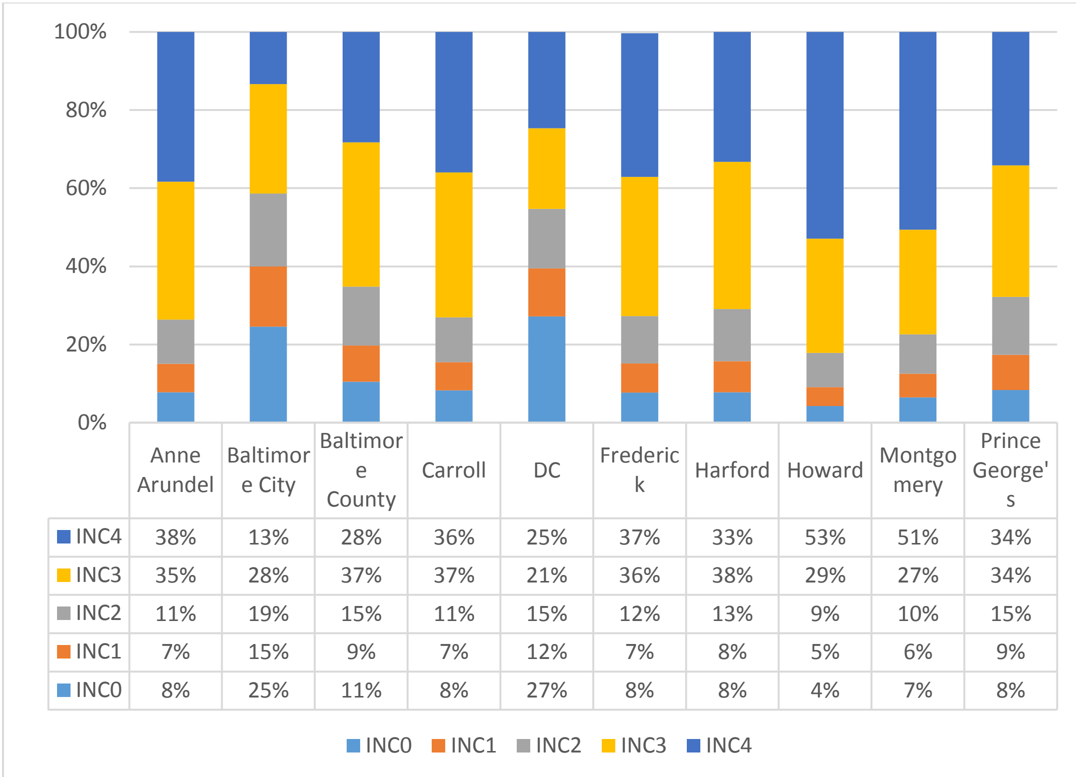


Figure 4 Income Distribution by County.

Table 7 Main SocioEconomic Characteristics at the County Level (InSITE Dataset)

County	Num. of HHs	Avg. HH Size	Avg. Income Level	Avg. Num. of Workers per HH	Avg. Num. of Adults per HH	Avg. Workers-To-Size Ratio per HH
Anne Arundel	208,982	2.6	2.89	1.3	2.0	49%
Baltimore City	267,979	2.3	1.90	1.0	1.8	46%
Baltimore County	331,473	2.5	2.63	1.2	1.9	50%
Carroll	64,457	2.6	2.85	1.4	1.9	49%
DC	307,517	2.0	2.03	0.9	1.6	46%
Frederick	88,547	2.6	2.86	1.4	1.9	49%
Harford	93,214	2.6	2.81	1.3	2.0	50%
Howard	108,223	2.7	3.22	1.5	2.0	54%
Montgomery	371,534	2.6	3.09	1.4	2.0	53%
Prince George's	327,351	2.6	2.76	1.4	2.0	53%

2.3.2 National Household Travel Survey (NHTS)

The second dataset used in the revenue analysis is Version 2.1 of the 2009 National Household Travel Survey (2009 NHTS) [63]. Conducted between March 2008 and March 2009, and updated in February 2011, this dataset complements the InSITE data by providing vehicle-specific information at the HH level. The 2009 NHTS "serves as the nation's inventory of daily travel" and the information provided is aimed "to assist transportation planners and policy makers who need comprehensive data on travel and transportation patterns in the United States" [63]. The 2009 NHTS consists of four dataset files that provide useful information on socioeconomic, and travel-related variables: the Household File, the Person File, the Vehicle File, and the Day-trip File [63].

For the purpose and the scope of this dissertation, the Household and the Vehicle File are merged together on the basis of the HOUSEID variable (HH eight-digit ID number) to produce a dataset that contains detailed vehicle-specific information at the HH level. This information is required to model the status-quo, and fuel tax increase policy scenarios, where data on the fuel efficiency of the vehicle fleet is necessary but not readily available from the InSITE model data. The final dataset contains a single observation per HH, with a dummy vehicle whose characteristics are estimated as the VMT-based weighted average of the characteristics of all the vehicles that the HH owns. The following table provides the descriptive statistics of the main NHTS variables that are used in the analysis.

Table 8 Descriptive Statistics of Selected NHTS Variables

Variable Mnemonic	Variable Description	Mean	Std. Dev.	Min.	Max.	No. Obs.
DRVRCNT	Number of drivers in HH	1.79	0.70	1	5	437
hadults	Number of adults in HH	1.86	0.72	1	6	437
HHFAMINC	Derived total HH income	13.37	5.12	1	18	437
hhinc5s	Total HH income (as	2.85	1.15	0	4	437

Variable Mnemonic	Variable Description	Mean	Std. Dev.	Min.	Max.	No. Obs.
	defined in InSITE)					
hhsize	Count of HH members	2.33	1.27	1	8	437
hworkers	Number of workers in HH	1.08	0.84	0	4	437
ncars	Number of cars in HH	1.87	0.91	1	5	437
OwnAuto	HH owns automobile (1: Yes; 0: No)	0.81	0.39	0	1	437
OwnElect	HH owns electric vehicle (1: Yes; 0: No)	0.00	0.00	0	0	437
OwnHybrid	HH owns hybrid vehicle (1: Yes; 0: No)	0.05	0.22	0	1	437
OwnNG	HH owns natural gas vehicle (1: Yes; 0: No)	0.00	0.05	0	1	437
OwnPUTorTR	HH owns pick-up truck or other truck (1: Yes; 0: No)	0.21	0.40	0	1	437
OwnSUV	HH owns SUV vehicle (1: Yes; 0: No)	0.32	0.47	0	1	437
OwnVan	HH owns van (mini, cargo, passenger) (1: Yes; 0: No)	0.13	0.34	0	1	437
TotVMT	Total annual miles for all vehicles in the HH	19,616.14	15,084.26	300	101,251	437
WAvgFE	Fuel efficiency (weighted average)	22.23	5.87	10	57	437
WAvgMonths	How long vehicles owned in months (weighted average)	61.17	42.94	0	264	437

2.3.3 Consumer Expenditure Survey (CES)

The third data source that is used to model the property and sales tax transportation policies comes from the Consumer Expenditure Program Quarterly Interview Survey Data [64]. The Consumer Expenditure (CE) program is administered by the Bureau of Labor Statistics and collects data on the buying habits of American consumers, along with the respondents' socioeconomic characteristics. The Consumer Expenditure data is collected based on two surveys, the Quarterly Interview Survey and the Diary Survey. During the Quarterly Interview Survey, each respondent is surveyed once every quarter, for five consecutive quarters, and the focus is on large expenditures (e.g. vehicle purchase) or recurring expenses (e.g. rent). During the Diary Survey, which consists of two consecutive one-week periods, each respondent reports information on frequently purchased smaller items [65].

For the purpose and the analysis scope of this dissertation, we use the DC and Maryland FMLY datasets from the 2012 Quarterly Interview Survey Data, which covers up to 95% of total expenditures [65]. Each of these datasets includes 5 quarterly datasets for each one of 4 quarters of 2012 (2012 Q1, Q2, Q3, Q4) and the first quarter of 2013 (2013 Q1), and contains information at the Consumer Unit (CU) level (same as the HH level) on CU characteristics, income and summary level expenditures [65].

It is noted that for each region (DC, MD), all 5 quarterly datasets were used in order to produce a 2012 annual estimate of the expenditures made in the same year. This is essential, as CUs report their expenditures for both the current and the previous quarter, depending on the month that the CU was interviewed. For instance, if a CU is interviewed in the first month of Q4 of 2012 (i.e. October), then it is not feasible to report the expenditures for the entire Q4 of 2012, as the quarter is not over yet. Instead, the expenditures for Q4 of 2012 will be reported as "expenditures in previous quarter" when the CU is interviewed again in Q1 of 2013.

To estimate the level of sales taxes that each CU pays, expenditures from the following taxable categories are considered: alcoholic beverages, telephone services, house furnishing and equipment, apparel, entertainment, and personal care. Property taxes are reported on a quarterly basis, so no major data processing was required to obtain the corresponding annual values. The original CES dataset contains approximately 900 variables; Table 9 shows the descriptive statistics of some of the most significant ones:

Table 9 Descriptive Statistics of Selected 2012 CES Variables

Variable	Variable Mnemonic	Mean	Std. Dev.	Min	Max	No. Obs.

Variable	Variable Mnemonic	Mean	Std. Dev.	Min	Max	No. Obs.
bathrmq	Number of complete bathrooms in the unit	1.86	0.93	1	6	542
bedroomq	Number of bedrooms in the unit	2.93	1.20	0	7	542
built	The year range that the property was built	1,967.07	27.51	1,915	2,011.0	542
fincatax	Amount of CU income after taxes in the past 12 months	81,061.45	98,848.13	0	1,121,017	542
fincbtax	Amount of CU income before taxes in the past 12 months	88,524.17	108,196.50	0	1,121,017	542
hchildren	Number of children less than 18 in CU	0.60	0.98	0	6	542
hhsize	Number of members in CU	2.47	1.39	1	8	542
hlfbathq	Number of half bathrooms in the unit	0.45	0.58	0	3	542
hworkers	Number of earners	1.41	0.93	0	5	542
own	Housing tenure: owned	0.66	0.47	0	1	542
popsize	Population size of the PSU	1.49	0.50	1	2	542
PropTaxAnn	Annual property taxes	1,981.36	2,690.72	0	15,460	542
rent	Housing tenure: rented	0.34	0.47	0	1	542
roomsq	Number of rooms in the unit, including finished living areas and excluding all baths	6.64	2.66	2	16	542
SalesTaxAnn	Annual sales taxes	904.46	998.37	0	8,173.44	542

2.4 Methodology

The proposed revenue policies are implemented in the BMC region using a combination of methodological tools. The main tool is the activity-based model InSITE which allows us to model the changes in travel behavior due to the different forms of fees imposed on the users. Supplementary to InSITE, statistical matching techniques are used to enrich the InSITE data with additional information at the HH level that will allow for a more realistic modeling of property and sales tax policies, as well as any policy that is based on the vehicle’s fuel efficiency (status quo, fuel tax increase).

2.4.1 Activity-Based Model Description (InSITE)

One product of the recent MITAMS effort (Maryland Integrated Travel Analysis Modeling System) is the InSITE activity-based model [62]. This integrated model covers the BMC (Baltimore Metropolitan Council) region, as well as the District of Columbia and the Maryland portion of the MWCOG (Metropolitan Washington council of Governments) model. The modeled area includes 2,919 transportation analysis zones (TAZs), and is displayed in Figure 5:

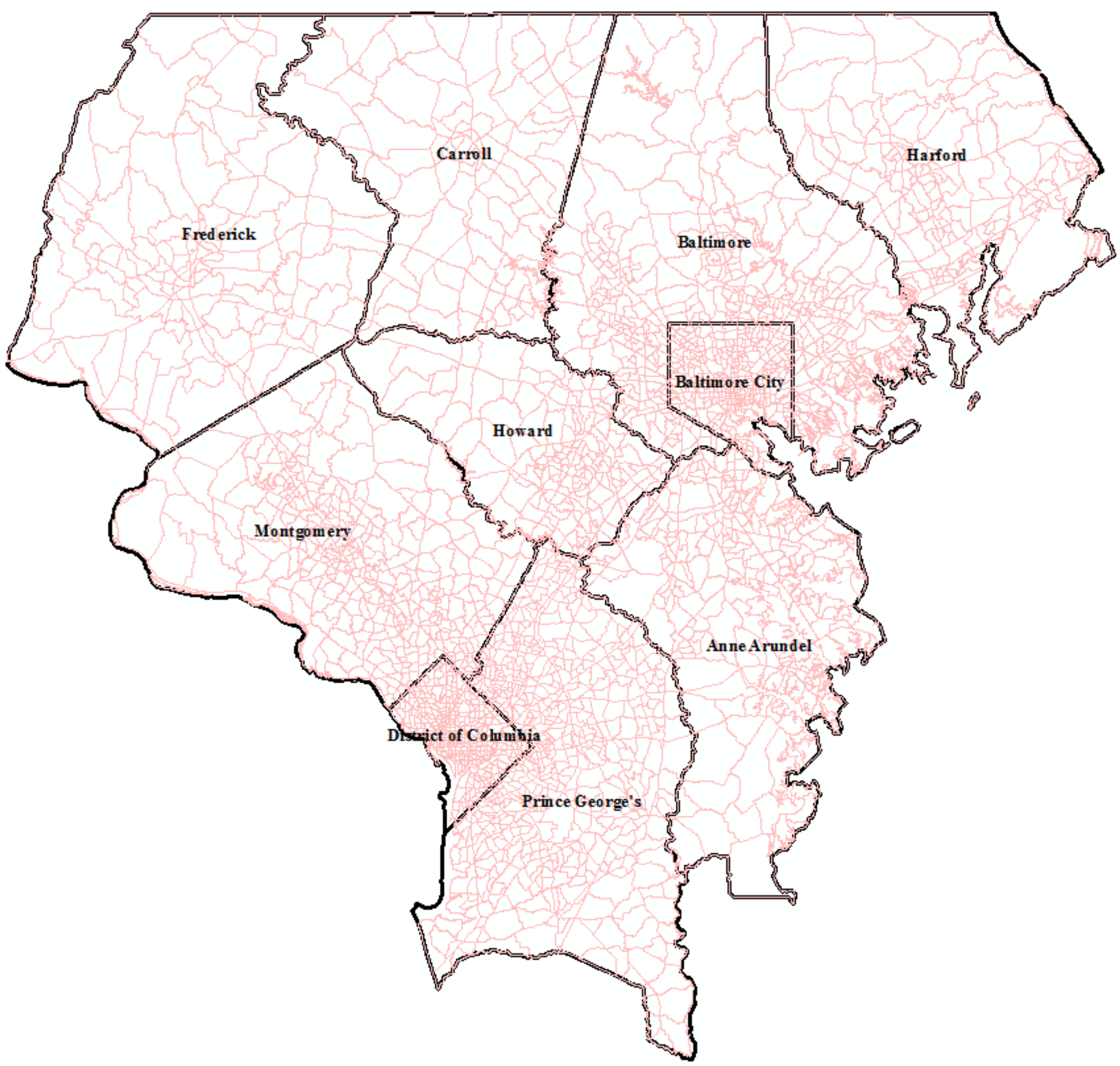


Figure 5 InSITE Model Area Coverage.

InSITE models travel behavior in an activity-based context for a typical weekday, where activities are simulated for a synthetic population, creating schedules of activities and locations. It includes 39 modules which run consecutively, each one generating a different piece of information. Table 10 lists the module components of InSITE in a more condensed form, along with information on the type of data predicted by each module, and at what level of analysis.

Table 10 InSITE Model Components [62]

Model	**Level of Analysis**	**Predicted Information**
Synthetic Population Generator	Households	Household size and composition, household income, person age, gender, employment status, student status
Regular Workplace Location	Workers	Workplace location zone
Regular School Location	Students	School location zone
Auto Ownership	Households	Number of autos owned
Transit Pass Ownership	Households	Whether the household owns a transit pass
E-Z Pass Ownership	Households	Whether the households owns an E-Z pass transponder
Household Class Membership	Households	Class in which household falls, for Daily Activity Pattern Model
Daily Activity Pattern	Person Day	0, 1, or 2 tours for each activity purpose 0, 1, or 2 stops for each activity purpose
Joint Travel	Households	Number of fully joint tours with 2 or more household members Which household members participate in each joint tour
School Escorting	Person (Households) Day	On which half tours a student is escorted to/from school Which household member escorts the student Whether escorting is done on a mandatory tour
Work Tour Destination Choice	Work Tours	For work tours – regular workplace or other work location (and its zone)
Work-Based Sub-tour Generation	Work Tours	Number and purpose of any sub-tours made during a work tour
Work mode choice	Work Tours	Main tour mode
School mode and time-of-day choice	School Tours	Main tour mode, the time period arriving at school, and the time period leaving school (all school tours are to regular school location)
Work time of day choice	Work Tours	The time period arriving at work, and the time period leaving work

Model	Level of Analysis	Predicted Information
Other tour time of day choice	Other Tours	Time period arriving at the primary destination and the time period leaving the primary destination
Other tour mode and destination choice	Other Tours	Primary destination zone and main tour mode
Intermediate stop generation	Half-Tour	Number and activity purpose of any intermediate stops made on the half-tour, conditional on day pattern
Intermediate stop location	Trip	Destination zone of each intermediate stop, conditional on tour origin and destination, and location of any previous stops
Trip mode choice	Trip	Trip mode, conditional on main tour mode
Trip departure time	Trip	Departure time, conditional on time windows remaining from previous choices
Special generators	Zone	Number of trips, trip end location, mode choice
Commercial vehicle	Zone	Number of trips, trip end location
External travel	Zone	Number of trips, trip end location
Highway assignment	Vehicle Trip Table	Link volumes and travel times/speeds
Transit assignment	Person Trip Table	Transit trips/boardings by routes/stop

Figure 6 depicts the model structure of InSITE, which is separated in 5 main structural levels:

Long-term Choices Model: at the upper level, ***long-term choices*** regarding auto ownership, work location, school location, transit pass ownership, and E-ZPass toll transponder ownership are modeled.

Household Class Membership Model: household attributes such as household size and household income help define the class membership of the household, via a multinomial logit model, following Lemp's methodology [66].

Tour-Generation Model: at this level, the daily activity pattern of each person is modeled. First, the mandatory individual tours are modeled (e.g. work tours), followed by the school-escorting tours for persons with children. Following the mandatory and school escorting tours, decisions regarding the joint tours are made at the household level (i.e. fully joint travel).

Finally, after mandatory and joint tours have been scheduled, the individual non-mandatory travel is modeled.

Tour-Level Choices: these choices are made simultaneously with the tour generation model for all mandatory, joint, and non-mandatory travel. They include choices regarding the tour destination and time of day.

Short/Trip-Level Choices: this is the last step in the InSITE model where destination decisions, mode decisions and time decisions are made for each stop and trips between stops.

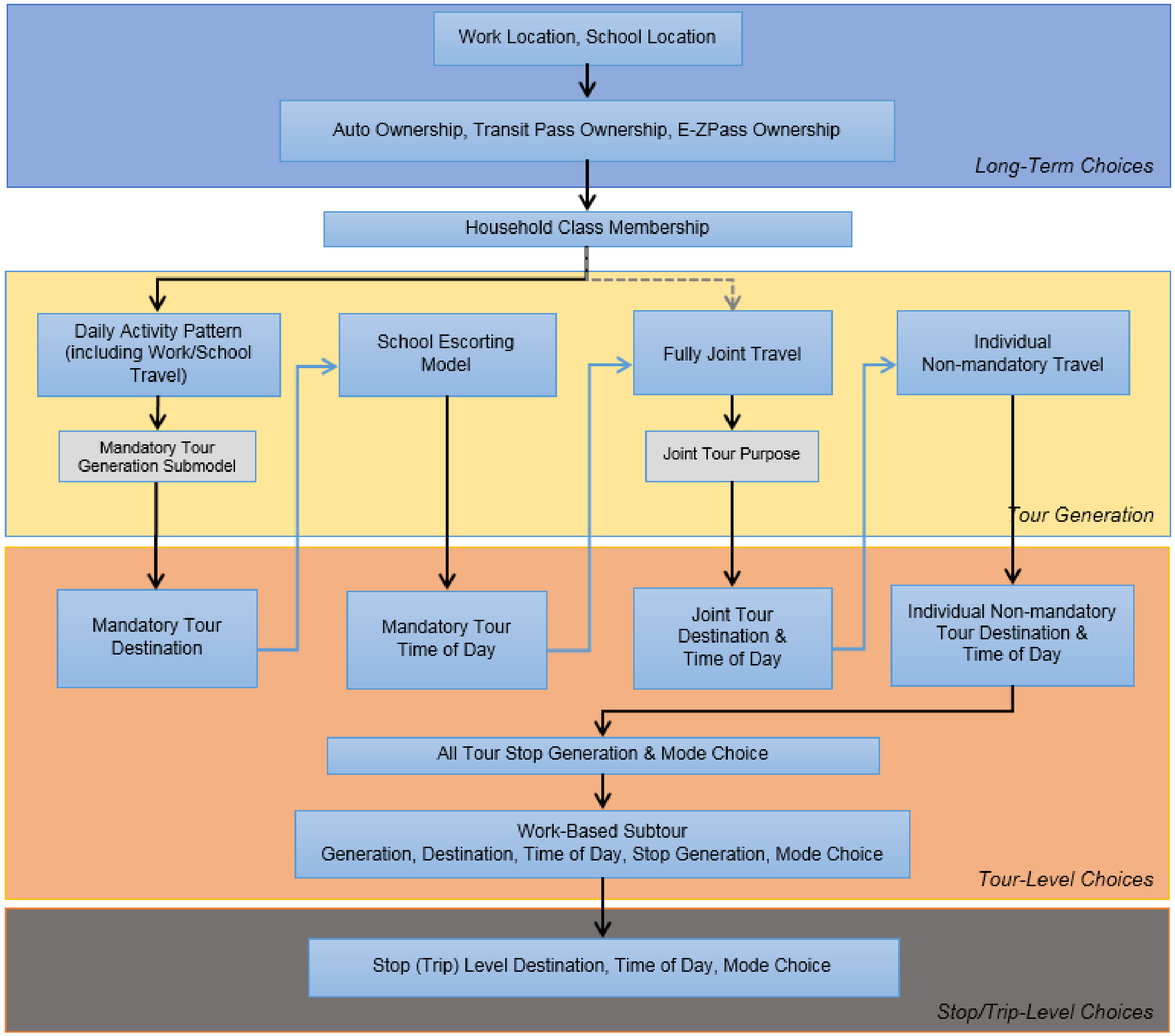


Figure 6 InSITE Model Structure [62]

The literature review has shown that activity-based models have not been very extensively used in the revenue-investment-redistribution research field, despite their significant advantages.

When exploring different ***revenue*** scenarios, activity-based models can provide significant insight with respect to how users of the transportation network (either auto drivers/passengers, or transit users) will change their travel behavior following the implementation of a new revenue policy. This is particularly interesting when implementing policies that have a direct impact on tour generation, tour-level choices, and stop/trip-level choices. Some policies are related to travel behavior changes in a more straightforward way. For instance, increasing fuel tax or implementing a mileage-based user fee is expected to have an effect on how much users travel (the magnitude of the effect though should be modeled analytically), i.e. the effects are expected to be observed at the tour generation, tour-level choices and stop/trip-level choices. However, activity-based models can be employed along with other techniques to model the effect of sales taxes and property taxes on revenue generation. At the ***investment*** level, activity-based models allow for geographically identifying the sources of the collected revenue, and therefore link revenue collection with investment decisions. This is particularly important when the implemented revenue policy is a "local-option tax", where typically it is required that collected revenues are invested locally, to promote access in the local area. The contribution of activity-based models for ***redistribution analysis*** can also be very important. Using synthetic population techniques, activity-based models contain substantial socioeconomic, demographic, geographic, and other information regarding the agents utilizing the system.

2.4.2 Statistical Matching

Some of the policies explored in this dissertation are harder to model in the transportation context due to data availability issues. This is the case with 4 out of the 6 policies: status-quo, Maryland-approved fuel tax increase, property tax, and sales tax. The data needed to model each one of these 5 policies for the BMC region does not come from a single data source, therefore proper methodological tools are required to address this issue. *Statistical matching* (also known as data fusion or synthetical matching) is a data integration modeling technique, which allows for the integration of two or more distinct datasets that contain different information. For statistical matching to be accurate and reliable, it is essential that the original datasets refer to the same population; otherwise the matching is not trustworthy. The process is characterized by the fact that the two datasets contain a set of common variables, variables that are not jointly observed, and disjoint sets of units [67].

In this dissertation, the nonparametric micro approach is used in order to perform statistical matching between the InSITE dataset, and datasets that contain the additional information that is required to model these 4 policies. This approach generates a third, synthetic data file. The approach is ***micro***, in that it contains all necessary information from the original datasets, and ***nonparametric*** in that there is no assumption regarding the family of distributions for the variables of interest [67]. Three hot deck methods have been traditionally used in statistical matching: random hot deck, rank hot deck, and distance hot deck. After testing all three methods to understand which performs better for this research problem, we selected the ***distance hot deck.***

Fuel Tax and Fuel Tax Increase

The model configuration used for the fuel tax, and fuel tax increase is the following:

- The InSITE data was selected as the recipient dataset;
- The NHTS data was selected as the donor dataset;
- HH size, number of workers, and number of cars were selected as the matching variables;
- HH income was used as donation class (it should be noted that, the number of cars was not used as donation class, because the range of the variable is different in the donor and recipient datasets, therefore some classes would have zero observations, making statistical matching impossible);
- The statistical matching was performed using the Gower's distance, to account for the different nature of the matching variables:

$$d_{ab} = \frac{1}{P}\sum_{p=1}^{P} c_p d_{abp}$$

where $x_a, a = 1, \dots, n$ is a set of n P-dimensional records, $c_p = \frac{1}{R_p}$ with $R_p = \max_a\{x_{ap}\} - \min_a\{x_{ap}\}$. The city-block metric is recommended for the Gower-type measure of distance:

$$d_{abp} = |x_{ap} - x_{bp}|$$

- The recipient and donor datasets were divided into 2 sub-samples each (Maryland sample and DC sample), and the statistical matching was performed for each sub-sample independently.

It should be noted that, although the matching variables were used to evaluate the performance of the matching technique, eventually only the fuel efficiency information was added from the NHTS data (donor) to the InSITE data (recipient) in order to develop the final synthetic dataset.

Property and Sales Tax

The model configuration used for property and sales taxes is the following:

- The InSITE data was selected as the recipient dataset;
- The CES data was selected as the donor dataset;
- HH income, HH size, number of workers, and number of children were selected as the matching variables;
- No donation class was used, as it did not improve the matching performance;
- The statistical matching was performed using the Gower's distance, to account for the different nature of the matching variables:

$$d_{ab} = \frac{1}{P}\sum_{p=1}^{P} c_p d_{abp}$$

  where $x_a, a = 1, \ldots, n$ is a set of n P-dimensional records, $c_p = \frac{1}{R_p}$ with $R_p = \max_a\{x_{ap}\} - \min_a\{x_{ap}\}$. The city-block metric is recommended for the Gower-type measure of distance:

$$d_{abp} = |x_{ap} - x_{bp}|$$

- The recipient and donor datasets were divided into 2 sub-samples each (Maryland sample and DC sample), and the statistical matching was performed for each sub-sample independently.

It should be noted that, although the matching variables were used to evaluate the performance of the matching technique, eventually only the sales tax and property tax information was added from the CES data (donor) to the InSITE data (recipient) in order to develop the final synthetic dataset.

Performance Evaluation

The performance of the statistical matching is evaluated on the basis of the following metrics:

- Distribution of the matching variables in the donor, the recipient, and the synthetic datasets;
- Distribution of the non-common variables in the donor and synthetic datasets;
- Correlation matrices in the donor, recipient, and synthetic datasets.

2.4.3 Modified Activity Based Model Modules

The original activity based model modules have been significantly recoded in order to model the proposed policies.

The first modification pertains to the incorporation of vehicle fuel efficiency information in the data, and the definition of the vehicle operating cost on a per gallon basis. This modification is applicable to the status-quo, and Maryland-approved fuel tax increase policies. As previously described, for these scenarios, the original InSITE data is enriched with vehicle fuel efficiency data from the 2009 NHTS dataset. Vehicle fuel efficiency is a continuous variable, which is recoded into a categorical variable, based on the Greenhouse Gas Rating (GHG) Scales for MY2012 [68]. For each level in the GHG Rating scale, a mean fuel efficiency is assigned, which is used to estimate the vehicle operating cost on a per gallon basis. The look-up table for this process is as follows:

Table 11 Corrected Average Fuel Efficiency, GHG Rating, and Mean Fuel Efficiency

Corrected Average Fuel Efficiency Range (mpg)	GHG Rating MY2012	Mean Fuel Efficiency (mpg)
0	0	0
(0,16.4]	1	14.8
[16.5, 17.5)	2	17.5
[17.5, 19.5)	3	19
[19.5, 21.5)	4	21
[21.5, 24.5)	5	23.5
[24.5, 27.5)	6	26.5
[27.5, 32.5)	7	30.5
[32.5, 38.5)	8	36
[38.5, 47.5)	9	43.5
[47.5, ∞)	10	56.2

Subsequently, the FUELINCOME variable is created, which conceptually is the interaction variable between the GHG Rating and the HHINC5S variable for each observation.

Table 12 FUELINCOME Classes

FUELINCOME	GHG Rating	HHINC5S
0	0	0
1	1	0
2	2	0
3	3	0
4	4	0
5	5	0
6	6	0
7	7	0
8	8	0
9	9	0
10	10	0
11	0	1
12	1	1
13	2	1
14	3	1
15	4	1
16	5	1
17	6	1
18	7	1
19	8	1
20	9	1

FUELINCOME	GHG Rating	HHINC5S
21	10	1
22	0	2
23	1	2
24	2	2
25	3	2
26	4	2
27	5	2
28	6	2
29	7	2
30	8	2
31	9	2
32	10	2
33	0	3
34	1	3
35	2	3
36	3	3
37	4	3
38	5	3
39	6	3
40	7	3
41	8	3

FUELINCOME	GHG Rating	HHINC5S
42	9	3
43	10	3
44	0	4
45	1	4
46	2	4
47	3	4
48	4	4
49	5	4

FUELINCOME	GHG Rating	HHINC5S
50	6	4
51	7	4
52	8	4
53	9	4
54	10	4

Finally, each observation in the household dataset includes FUELINCOME information, based on which a different cost coefficient is used when modeling travel behavior. The segmented cost coefficients by FUELINCOME class are used in the following InSITE modules:

- SchoolLocationModeChoiceLogsum
- UsualWorkplaceLocationTourModeChoiceLogsumModel
- TourModeChoiceLogsum_Work
- TourModeChoiceLogsum_WorkBased
- TourModeChoiceLogsum_SchoolUni
- TourModeChoiceLogsum_IndividualNonMandatory_Escort
- TourModeChoiceLogsum_IndividualNonMandatory
- TourModeChoiceLogsum_FullyJoint
- TripModeChoice

In each of these modules, the following modifications are performed:

- The per mile operating cost component is set equal to 0, to ensure that the vehicle operating cost is not modeled on a per mile basis;
- FUELINCOME is added in the list of input variables to be read and used from the revised InSITE datasets;

- An additional segmentation is defined based on the FUELINCOME variable, with 55 classes, ranging from 0 to 54;
- A FUELINCOME-segmented cost coefficient matrix is applied to the round-trip (RT) component of the logsum, in the transient coefficients section of the module. The RT cost is modified to vary by FUELINCOME class, and each FUELINCOME-segmented cost coefficient is equal to the HHINC5S-segmented cost coefficient multiplied by the inverse of the mean fuel efficiency of each fuel class, multiplied by the average gas cost in the BMC region for year 2012 (including other cost components, such as maintenance and tires), and divided by the vehicle occupancy factor (2.0 for shared ride 2p, 3.0 for shared ride 3p+).

The second modification was required in order to accurately model the variable-rate VMT fee policy. A similar approach was pursued, as in the first modification. As the purpose of this policy is to charge higher income drivers a higher VMT fee, the following InSITE modules were recoded:

- SchoolLocationModeChoiceLogsum
- UsualWorkplaceLocationTourModeChoiceLogsumModel
- TourModeChoiceLogsum_Work
- TourModeChoiceLogsum_WorkBased
- TourModeChoiceLogsum_SchoolUni
- TourModeChoiceLogsum_IndividualNonMandatory_Escort
- TourModeChoiceLogsum_IndividualNonMandatory
- TourModeChoiceLogsum_FullyJoint
- TripModeChoice

In each of these modules, the following modifications are performed:

- The per mile operating cost component is set equal to 0, to ensure that we are substituting the flat VMT fee with the variable-rate VMT fee, and not supplementing it;
- The income segmentation is already defined for other model purposes, as follows: 5 classes, ranging from 0 to 4;
- A HHINC5S-segmented cost coefficient matrix is applied to the round-trip (RT) component of the logsum, in the transient coefficients section of the module. The RT cost is modified to vary by HHINC5S class, and each HHINC5S-segmented cost coefficient is equal to the HHINC5S-segmented cost coefficient multiplied by the vehicle operating cost in the BMC region for year 2012 (in cents per mile form, including other cost components, such as maintenance and tires), and divided by the vehicle occupancy factor (2.0 for shared ride 2p, 3.0 for shared ride 3p+).

An example of a revised module script is presented in the Appendix.

2.4.4 Evaluation Metrics

The performance of each policy is evaluated on the basis of a set of metrics, which will allow us to draw comparative conclusions among the different scenarios. We further distinguish the metrics to represent both the taxpayers' and the state's perspective.

<u>Taxpayer's Perspective</u>

Tax Incidence Analysis:

- Taxpaying population by vehicle ownership, income group, and county;
- Tax-to-income ratio by vehicle ownership, income group, and county;
- Annual cost incurred at the HH level by vehicle ownership status, income group, and county.

Travel Behavior:

- Vehicle ownership by income group, and county;
- Mode share by vehicle ownership, income group, and county;
- Average daily travel time at the HH level by mode, vehicle ownership status, income group, and county;
- Average miles traveled daily at the HH level by mode, vehicle ownership status, income group, and county;

State's Perspective

Revenue Potential:

- Revenue generated by vehicle ownership, income group, and county.

2.5 Analysis Results

2.5.1 Statistical Matching Performance

Fuel Tax and Fuel Tax Increase

Upon completion of the statistical matching based on the configuration described previously, an additional step of data processing was taken to ensure that HHs with 0 vehicles were not assigned a non-zero fuel efficiency. This step further improved the model performance, and the affected HHs are now assigned a revised fuel efficiency (WAvgFECorr).

Figure 7 and Table 13 summarize the findings of this evaluation. Each graph of Figure 7 corresponds to a single variable, whose distributions in the donor, recipient, and synthetic datasets are plotted. The good performance of the employed technique can be validated by the almost coinciding distributions of the matching variables in the InSITE dataset (blue line) and the synthetic dataset (red line). Some discrepancies can be observed in the distributions that are caused by the different range of values that can be found in each dataset. For instance, HH size in InSITE ranges from 1 to 12, whereas in NHTS it ranges from 1 to 8; this causes the mismatch in the right tail of the distributions. The same applies to the number of workers variable. It is worth noting that the distributions of the fuel efficiency variable in NHTS is maintained in the synthetic dataset fairly well (the discrepancy in the left tail of the distributions is attributed to the post-statistical matching data processing that zeroed out the non-zero fuel efficiency of HHs with no vehicles). This also validates the good performance of the statistical matching. The distributions of the variables in the NHTS dataset (green line) are presented for reference only. Matching these distributions is not required. However, since both datasets refer to the same population, the distributions should be similar.

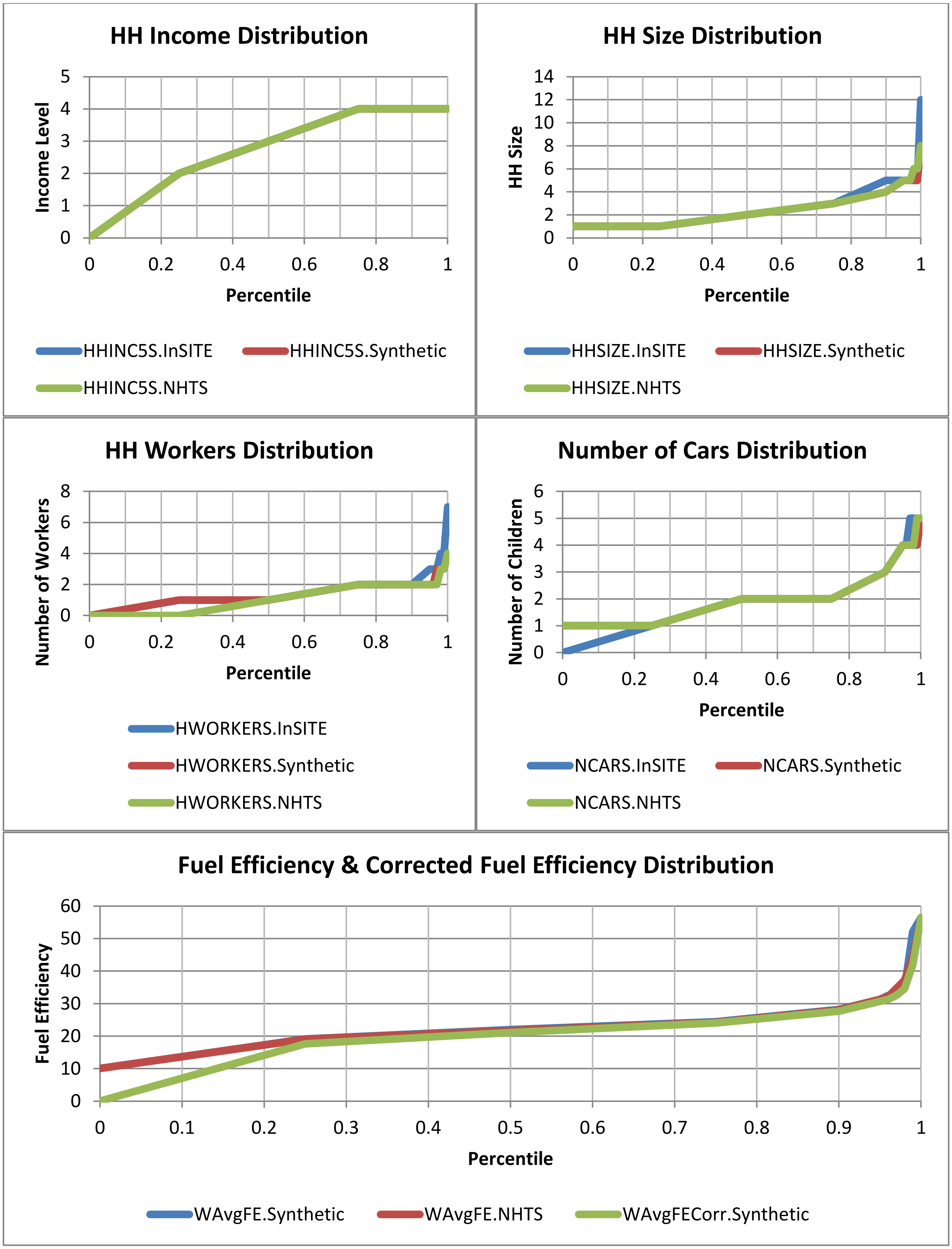


Figure 7 Performance Evaluation of Distance Hot Deck Technique (Gower's Distance).

Table 13 Variable Distributions in Donor (NHTS), Recipient (InSITE), and Synthetic Datasets

Statistic	HHINC5S			HHSIZE			HWORKERS			NCARS			WAVGFE		
	R	**S**	**D**	**R**	**S**	**D**	**R**	**S**	**D**	**R**	**S**	**D**	**D**	**S Original**	**S Corrected**
25th %ile	2	2	2	1	1	1	1	1	0	1	1	1	19.1	19.2	17.6
50th %ile	3	3	3	2	2	2	1	1	1	2	2	2	21.7	22.0	21.1
75th %ile	4	4	4	3	3	3	2	2	2	2	2	2	24.2	24.5	24.0
90th %ile	4	4	4	5	4	4	2	2	2	3	3	3	28.1	28.2	27.7
95th %ile	4	4	4	5	5	5	3	2	2	4	4	4	31.3	31.3	30.7
96th %ile	4	4	4	5	5	5	3	2	2	4	4	4	32.1	32.5	31.3
97th %ile	4	4	4	5	5	5	3	3	2	5	4	4	34.6	32.5	32.5
98th %ile	4	4	4	5	5	6	4	3	3	5	4	4	37.2	34.6	34.6
99th %ile	4	4	4	5	5	6	4	3	3	5	4	5	44.3	52.1	41.9
Mean	2.6	2.6	2.9	2.4	2.3	2.3	1.2	1.2	1.1	1.7	1.8	1.9	22.2	22.4	19.7
Std. Dev.	1.4	1.4	1.1	1.4	1.3	1.3	1.0	0.8	0.8	1.1	0.9	0.9	5.9	5.8	9.1
Min.	0	0	0	1	1	1	0	0	0	0	1	1	10.1	10.1	0.0
Max.	4	4	4	12	8	8	7	4	4	5	5	5	56.5	56.5	56.5

R: Recipient, D: Donor, S: Synthetic

The correlation matrix for the synthetic dataset is presented in Figure 8, in both numerical and graphical form. It is evident that statistical matching has performed extremely well, resulting in correlation values between the InSITE and the donor versions of each variable that are close to 1:

- HHINC5S.InSITE and HHINC5S.Synthetic have a correlation of 1, i.e. perfect match;
- HHSIZE.InSITE and HHSIZE.Synthetic have a correlation of 0.94;
- NCARS.InSITE and NCARS.Synthetic have a correlation of 0.91;
- HWORKERS.InSITE and HWORKERS.Synthetic have a correlation of 0.91.

These high values show that the InSITE observations where matched to NHTS observations who have very similar characteristics in terms of income, HH size, number of workers, and number of cars. Therefore, we feel confident that the property and sales tax information that are added to each HH in the InSITE population are reliable, and the subsequent analysis yields credible results.

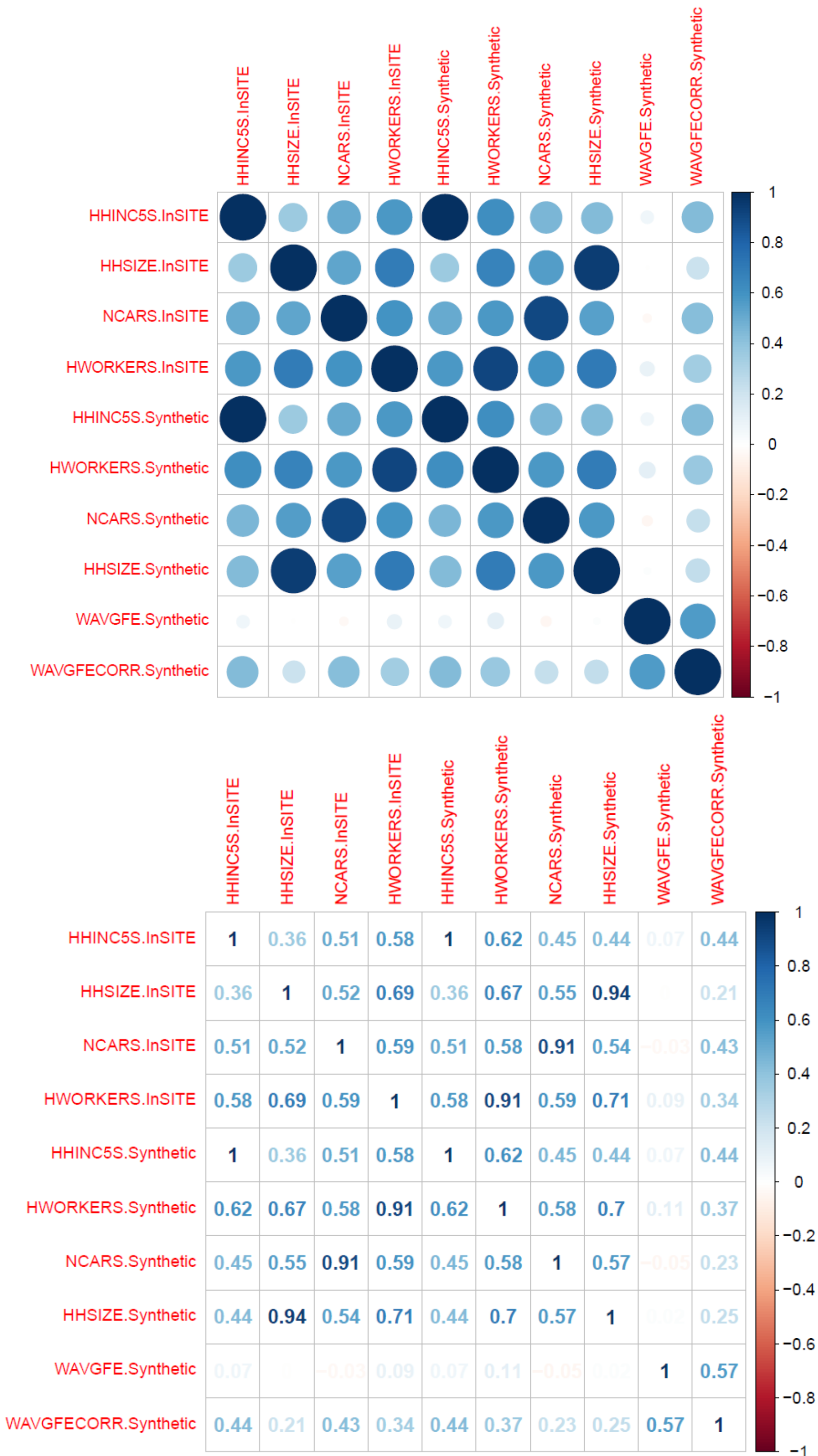


Figure 8 Correlation Matrix for the Synthetic Dataset.

Property and Sales Tax

Figure 9 and Table 14 summarize the findings of the statistical matching evaluation. Each graph of Figure 9 corresponds to a single variable, whose distributions in the donor, recipient, and synthetic datasets are plotted. The good performance of the employed technique can be validated by the almost coinciding distributions of the matching variables in the InSITE dataset (blue line) and the synthetic dataset (red line). Some discrepancies can be observed in the distributions that are caused by the different range of values that can be found in each dataset. For instance, HH size in InSITE ranges from 1 to 12, whereas in CES it ranges from 1 to 8; this causes the mismatch in the right tail of the distributions. The same applies to the number of children and number of workers variables. It is worth noting that the distributions of the sales tax and property tax variables in CES are maintained in the synthetic dataset fairly well. This also validates the good performance of the statistical matching. The distributions of the variables in the CES dataset (green line) are presented for reference only. Matching these distributions is not required. However, since both datasets refer to the same population, the distributions should be similar.

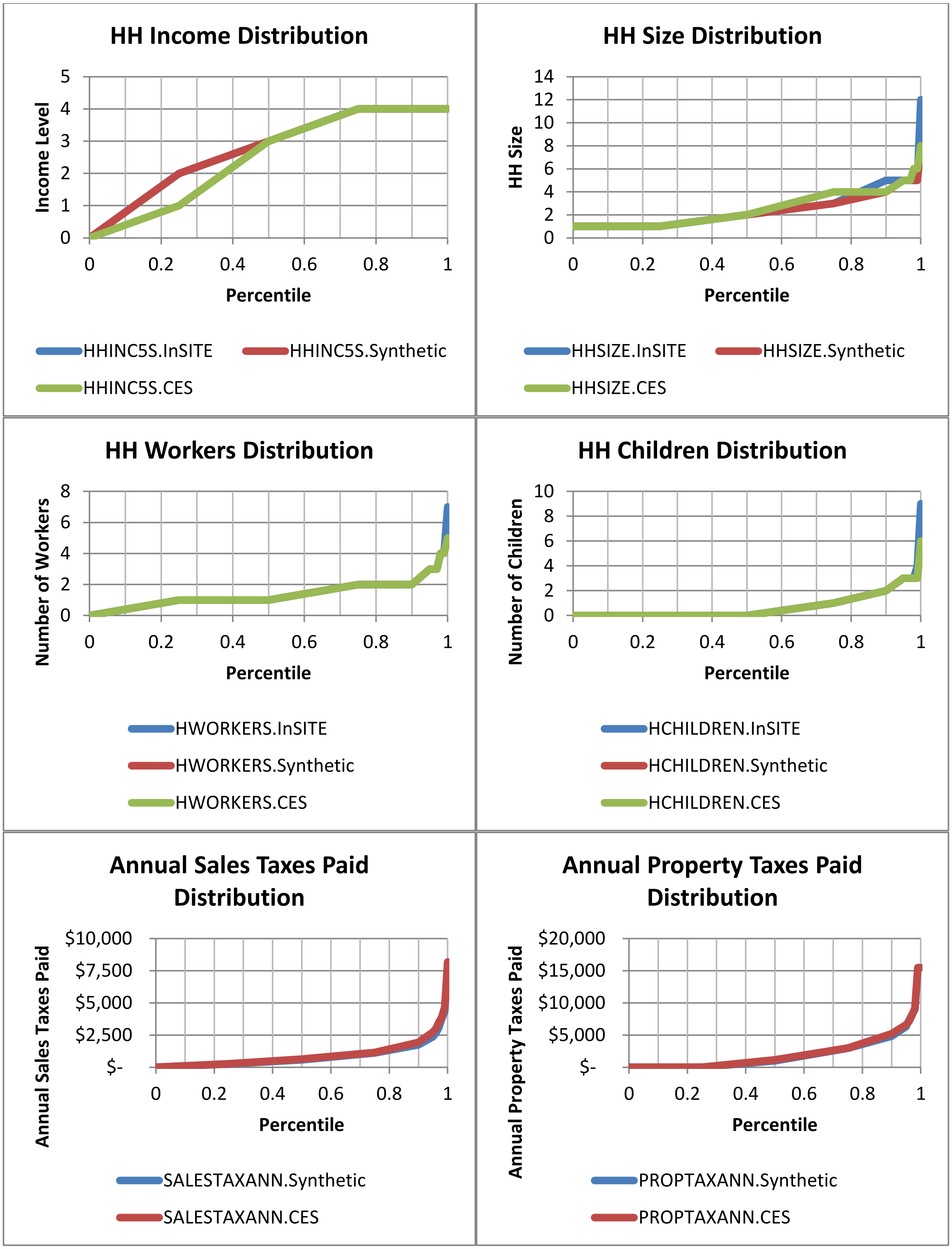


Figure 9 Performance Evaluation of Distance Hot Deck Technique (Gower's Distance).

Table 14 Variable Distributions in Donor (CES), Recipient (InSITE), and Synthetic Datasets

Statistic	HHINC5S			HHSIZE			HWORKERS			HCHILDREN			SALESTAXANN		PROPTAXANN	
	R	S	D	R	S	D	R	S	D	R	S	D	S	D	S	D
25th %ile	2	2	1	1	1	1	1	1	1	0	0	0	246	275	0	0
50th %ile	3	3	3	2	2	2	1	1	1	0	0	0	568	636	1000	1133
75th %ile	4	4	4	3	3	4	2	2	2	1	1	1	1116	1151	2961	3000
90th %ile	4	4	4	5	4	4	2	2	2	2	2	2	1749	1941	4800	5195
95th %ile	4	4	4	5	5	5	3	3	3	3	3	3	2373	2728	6292	6597
96th %ile	4	4	4	5	5	5	3	3	3	3	3	3	2664	3007	7300	7108
97th %ile	4	4	4	5	5	5	3	3	3	3	3	3	3076	3490	8195	8084
98th %ile	4	4	4	5	5	6	4	4	4	3	3	3	3781	3896	9000	9180
99th %ile	4	4	4	5	5	6	4	4	4	4	3	3	4340	4681	15460	15460
Mean	2.6	2.6	2.4	2.4	2.4	2.5	1.2	1.3	1.4	0.7	0.5	0.6	834	904	1907	1981
Std. Dev.	1.4	1.4	1.5	1.4	1.3	1.4	1.0	0.9	0.9	1.0	0.9	1.0	916	998	2638	2691
Min.	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0
Max.	4	4	4	12	8	8	7	5	5	9	6	6	8173	8173	15460	15460

R: Recipient, D: Donor, S: Synthetic

The correlation matrix for the synthetic dataset is presented in Figure 10, in both numerical and graphical form. It is evident that statistical matching has performed extremely well, resulting in correlation values between the InSITE and the values of each variable in the synthetic dataset that are close to 1:

- HHINC5S.InSITE and HHINC5S.Synthetic have a correlation of 1, i.e. perfect match;
- HHSIZE.InSITE and HHSIZE.Synthetic have a correlation of 0.95;
- HCHILDREN.InSITE and HCHILDREN.Synthetic have a correlation of 0.97;
- HWORKERS.InSITE and HWORKERS.Synthetic have a correlation of 0.95.

These high values show that the InSITE observations where matched to CES observations who have very similar characteristics in terms of income, HH size, number of workers, and number of children. Therefore, we feel confident that the property and sales tax information that are added to each HH in the InSITE population are reliable, and the subsequent analysis yield credible results.

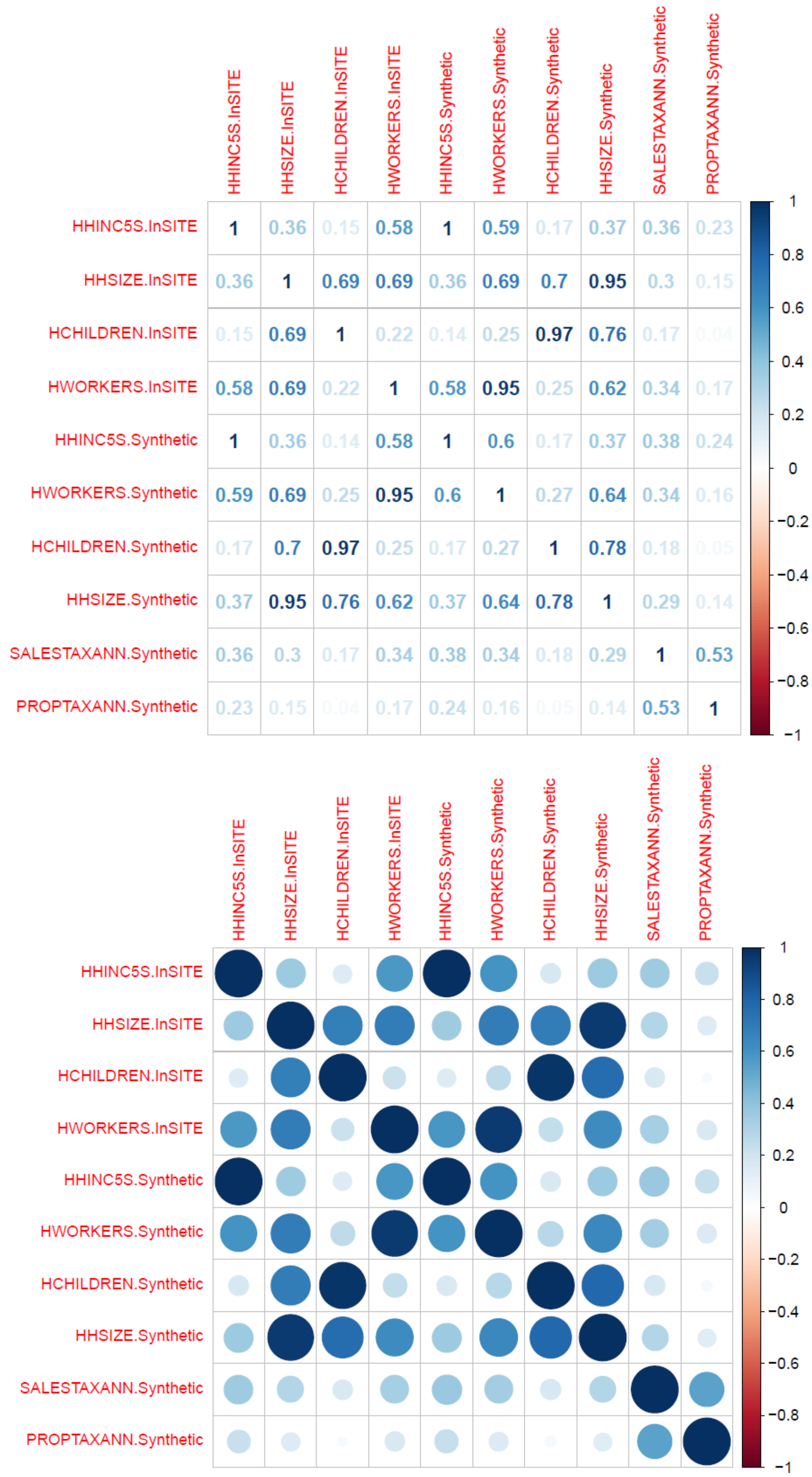


Figure 10 Correlation Matrix for the Synthetic Dataset

2.5.2 Revenue Policy Results

The results for each policy are presented at the income level and at the county level. Such a representation allows us to understand the impacts of each policy across different income groups, as well as across the different counties in the model region, and to also make the linkage among revenue, investment, and benefits redistribution.

Fuel Tax per Gallon – Status Quo

As a reminder, the operating cost for this scenario is at $4.8924 per gallon, and is implemented on all drivers using the InSITE/BMC region network. This cost is on a per gallon basis, thus the final cost that each HH pays depends on the fuel efficiency of their vehicle(s).

<u>Tax Incidence</u>

Under the ***status quo*** revenue policy, households in lower income groups pay lower taxes on a daily basis compared to higher income groups; however, they experience a higher state tax-to-income ratio than their higher income counterparts (1.66% for INC0 vs. 0.30% for INC4), as they have significantly lower income. Additionally, they constitute a smaller percentage of the taxpaying population (5.58% for INC0 vs. 37.8% for INC4). The tax incidence results by income group are presented in Table 15.

Table 15 Tax Incidence by Income Group – *Fuel Tax*

Income Group	Num. of Paying HHs	Daily State Tax Paid (HH level)	State Tax -to-Income (HH level)	Daily Federal Tax Paid (HH level)	Federal Tax-To-Income (HH level)
INC0	92,579	$0.34	1.66%	$0.27	1.30%
INC1	115,932	$0.41	0.66%	$0.32	0.52%
INC2	236,737	$0.51	0.47%	$0.40	0.37%
INC3	587,287	$0.64	0.31%	$0.50	0.25%
INC4	627,855	$0.81	0.30%	$0.64	0.23%
Total	1,660,388	-	-	-	-

The tax incidence results for different counties are presented in Table 16. DC, Baltimore City and Montgomery County experience the lowest tax-to-income ratios (0.20%, 0.28% and 0.30% respectively), while Carroll, Frederick and Harford experience the highest (0.51%, 0.48% and 0.45% respectively). In terms of taxpaying population, Montgomery, Prince George’s and Baltimore counties have the highest number of taxpayers, while Carroll, Frederick and Harford have the lowest.

Table 16 Tax Incidence by County – *Fuel Tax*

County	Num. of Paying HHs	Daily Income of Driving HHs	Daily Tax Paid		Tax to Income Ratios	
			Fed	State	State	Fed
Anne Arundel	175,372	$207	$0.65	$0.83	0.42%	0.33%
Baltimore City	175,051	$153	$0.31	$0.39	0.28%	0.22%
Baltimore	263,346	$192	$0.54	$0.69	0.36%	0.28%
Carroll	53,999	$204	$0.82	$1.04	0.51%	0.40%
District of Columbia	173,222	$169	$0.23	$0.29	0.20%	0.16%
Frederick	73,855	$206	$0.78	$1.00	0.48%	0.38%
Harford	78,290	$201	$0.70	$0.89	0.45%	0.35%
Howard	95,112	$226	$0.65	$0.83	0.37%	0.29%
Montgomery	306,428	$221	$0.51	$0.65	0.30%	0.24%
Prince George's	265,713	$198	$0.59	$0.76	0.39%	0.31%

Travel Behavior

The vehicle ownership model results by income group and by county are presented in Table 17 and Table 18. It is important to note the high percentage of lower income HHs that do not own any vehicle compared to their higher income counterparts (INC0: 52.45% vs. INC4: 0.76%). In terms of counties, Baltimore City and DC have the highest percentages of HHs without vehicles (23.9% and 27% respectively), which is expected as these areas have better transit provision than the other counties in the study area.

Table 17 Vehicle Ownership Model Results by Income Group – *Fuel Tax*

Income Group	Avg. HH Size	Avg. Num. of Workers	Avg. Num. of Adults	Avg. Num. of Cars	% of HHs with Cars < Workers	% of HHs with no Car
INC0	1.54	0.2	1.2	0.60	5.68%	52.45%
INC1	1.96	0.6	1.6	1.22	9.06%	22.24%
INC2	2.16	1.0	1.7	1.51	8.8%	9.56%
INC3	2.49	1.4	1.9	1.89	8.35%	2.93%
INC4	3.00	1.8	2.3	2.35	9.47%	0.76%

The mode share results are shown in Figure 11. The majority of the trips are motorized across all income groups (58% for INC0, 76% for INC1, 83% for INC2, 88% for INC3 and 89% for INC4), while the minority are transit trips (14% for INC0, 7% for INC1, 5% for INC2, 3% for INC3 and 3% for INC4). However, among HHs not owning a vehicle, walking/biking is the prevalent trip mode (40% for INC0, 39% for INC1, 35% for INC2, 39% for INC3 and 42% for INC4), while the minority of the trips are by transit (25% for INC0, 28% for INC1, 31% for INC2, 22% for INC3 and 24% for INC4).

Table 18 Vehicle Ownership Model Results by County – *Fuel Tax*

County	HH Size	Number of HHs	Avg. Income Level	Avg. Num. Workers	Avg. Num. Adults	Avg. Workers-To-Size	Avg. Num. Cars	% HHs with Cars<Workers	% HHs Without Car
Anne Arundel	2.6	208,982	2.89	1.30	2.0	49.4%	2.07	5.2%	4.7%
Baltimore City	2.3	267,979	1.90	1.01	1.8	46.1%	1.32	14.1%	23.9%
Baltimore	2.5	331,473	2.63	1.25	1.9	49.5%	1.87	6.5%	7.7%
Carroll	2.6	64,457	2.85	1.35	1.9	49.4%	2.14	3.8%	3.8%
District of Columbia	2.0	307,517	2.03	0.94	1.6	45.5%	1.22	13.8%	27.0%
Frederick	2.6	88,547	2.86	1.36	1.9	48.9%	2.11	4.1%	3.9%
Harford	2.6	93,214	2.81	1.35	2.0	50.3%	2.08	4.8%	4.7%
Howard	2.7	108,223	3.22	1.47	2.0	54.3%	2.16	5.4%	2.8%
Montgomery	2.6	371,534	3.09	1.41	2.0	53.1%	1.92	8.3%	6.5%
Prince George's	2.6	327,351	2.76	1.40	2.0	53.2%	1.96	7.7%	6.3%

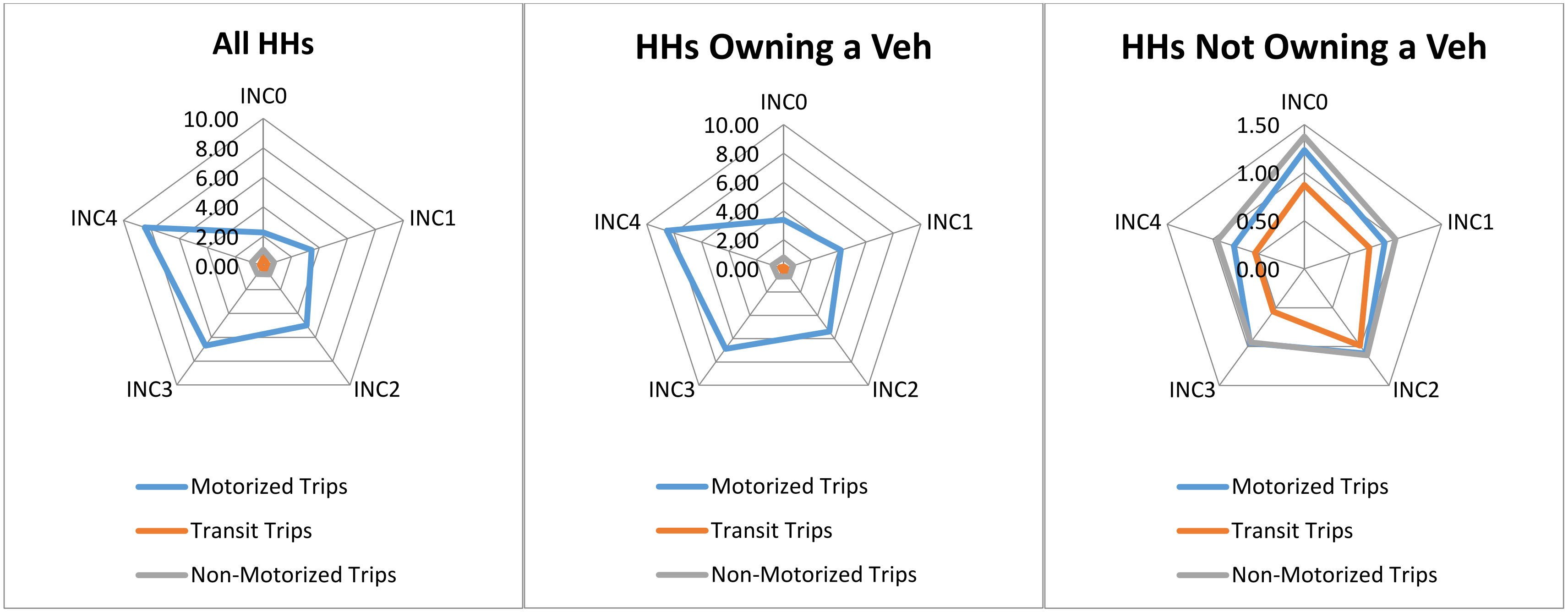
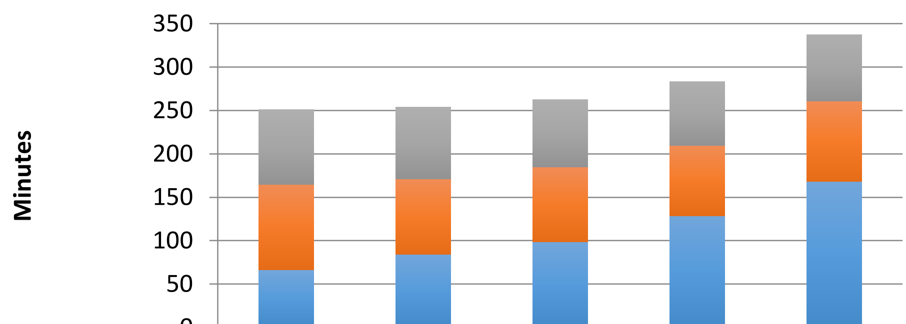


Figure 11 Number of Motorized, Transit, and Non-Motorized Trips by Income Group and Vehicle Ownership Status – *Fuel Tax*

The results in terms of average time spent and average distance traveled daily by mode and income group are presented in Figure 12 and Figure 13. The results show that across all income groups, users travel longer distances driving than using transit (3.24 to 6.19 times), or walking/biking (5.73 to 16.76 times). As income increases, the miles driven increase significantly, while the distance traveled by foot/bike or using transit stays relatively fixed (approximately 5 miles and 9 miles respectively). In terms of time spent traveling by each mode (i.e. driving, transit, walking/biking), it is evident that the time per mile traveled is higher for walking/biking and transit, and this is reflected in the model results. As income increases, the time spent driving also increases, and this is associated with longer distances traveled, while congestion may also play a role in motorized travel modes. The time spent in transit or walking/biking declines as income increases, except for INC4 where a slight increase can be observed.

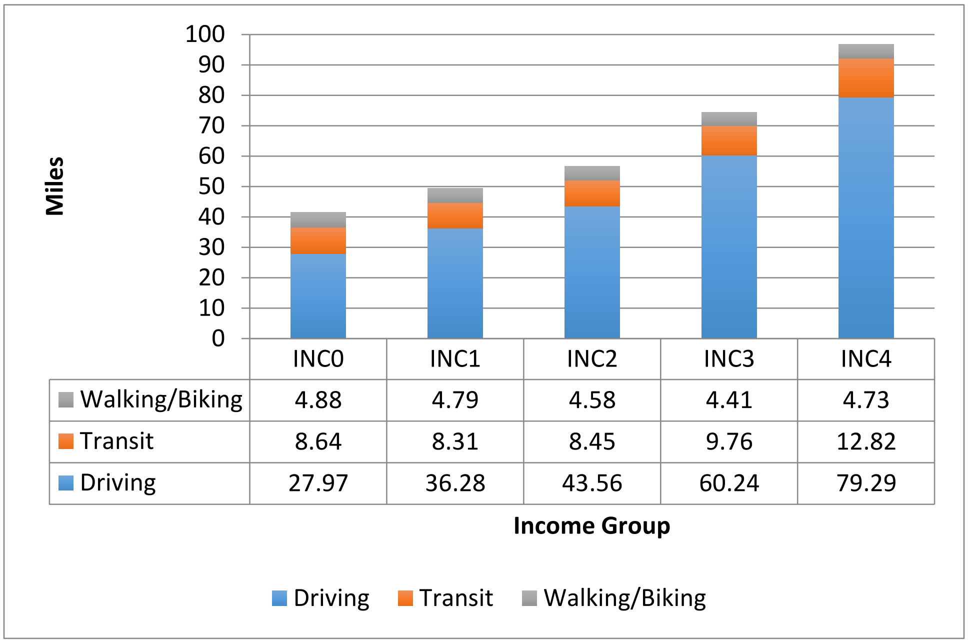


	INC0	INC1	INC2	INC3	INC4
Walking/Biking	85.98	82.60	77.45	73.50	76.52
Transit	98.58	87.28	86.23	81.18	92.86
Driving	66.37	83.97	98.65	128.72	168.06

Income Group

Driving Transit Walking/Biking

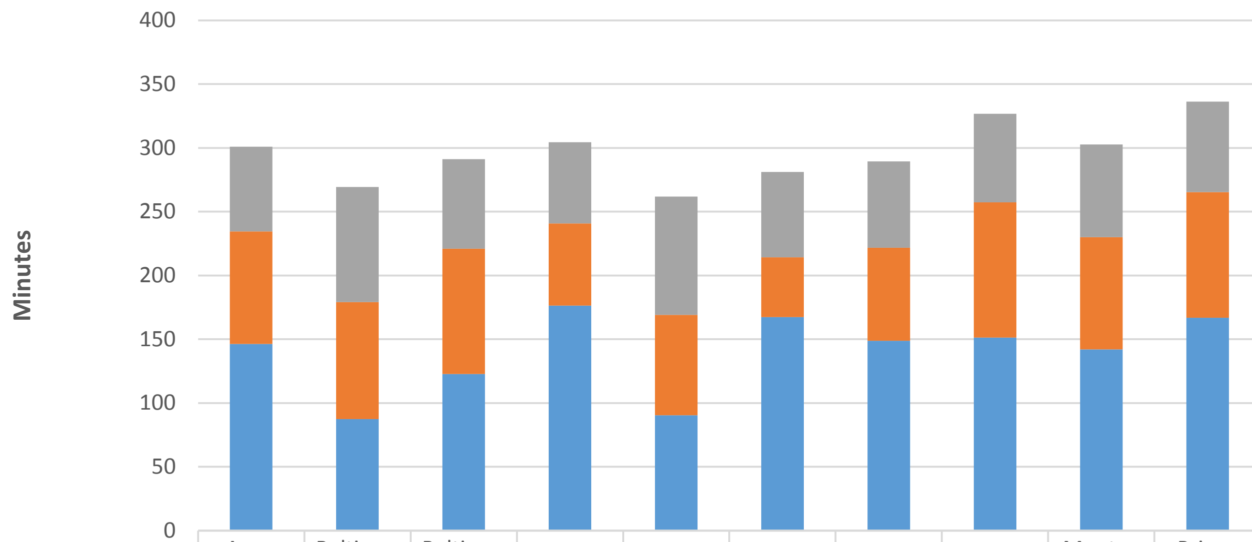
Figure 12 Average Time Spent Daily at the HH level by Mode and Income Group – *Fuel Tax*



	INC0	INC1	INC2	INC3	INC4
Walking/Biking	4.88	4.79	4.58	4.41	4.73
Transit	8.64	8.31	8.45	9.76	12.82
Driving	27.97	36.28	43.56	60.24	79.29

Figure 13 Average Miles Traveled Daily at the HH level by Mode and Income Group – *Fuel Tax*

The results in terms of average time spent and average distance traveled daily by mode and county are presented in Figure 14 and Figure 15. DC and Baltimore City residents drive the least (24.82 miles and 35.07 respectively), while Carroll and Frederick residents drive the most (94.11 miles and 98.85 miles respectively). Baltimore City and DC residents walk the most (5.32 miles and 5.61 miles respectively), while residents of Carroll and Frederick walk the least (2.82 miles and 2.76 miles respectively).

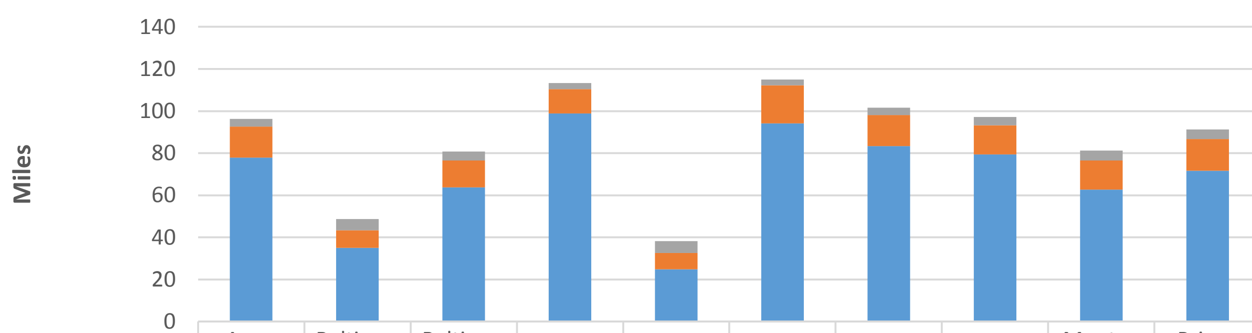


	Anne Arundel	Baltimore City	Baltimore County	Carroll	DC	Frederick	Harford	Howard	Montgomery	Prince George's
Walking/Biking	66.49	90.15	70.12	63.76	92.80	67.10	67.51	69.45	72.84	70.99
Transit	88.35	91.74	98.23	64.36	78.57	46.83	73.04	106.09	87.94	98.51
Driving	146.16	87.41	122.75	176.42	90.42	167.24	148.75	151.27	141.94	166.85

County

Driving Transit Walking/Biking

Figure 14 Average Time Spent Daily at the HH level by Mode and Income Group – *Fuel Tax*



	Anne Arundel	Baltimore City	Baltimore County	Carroll	DC	Frederick	Harford	Howard	Montgomery	Prince George's
Walking/Biking	3.76	5.32	4.25	2.82	5.61	2.76	3.52	4.08	4.64	4.57
Transit	14.74	8.38	12.68	11.65	7.81	18.18	14.73	13.72	13.84	15.05
Driving	77.86	35.07	63.79	98.85	24.82	94.11	83.43	79.46	62.69	71.67

County

Driving Transit Walking/Biking

Figure 15 Average Miles Traveled Daily at the HH level by Mode and County – *Fuel Tax*

Revenue Potential

Under the ***status quo*** revenue policy, more revenue is generated from users of higher income groups, following an ascending trend, as depicted in Table 19. The results at the county level are presented in Table 20: Montgomery, Prince George's, and Baltimore counties generate the highest revenue ($189,878, $183,318, and $177,998 respectively), while DC, Carroll and Frederick generate the lowest ($51,903, $56,157 and $63,927, respectively).

Table 19 Daily Revenue Generation by Income Group – *Fuel Tax*

Income Group	Num. of Paying HHs	Revenue Generated from State Fuel Tax	Revenue Generated from Federal Fuel Tax
INC0	92,579	$31,594	$24,737
INC1	115,932	$47,106	$36,883
INC2	236,737	$121,179	$94,881
INC3	587,287	$378,636	$296,464
INC4	627,855	$509,758	$399,130
Total	**1,660,388**	**$1,088,272**	**$852,094**

Table 20 Daily Revenue Generation by County – *Fuel Tax*

County	Num. of Paying HHs	Revenues	
		Federal Fuel Tax	State Fuel Tax
Anne Arundel	175,372	$114,486	$146,219
Baltimore City	175,051	$57,216	$73,075
Baltimore	263,346	$139,369	$177,998
Carroll	53,999	$43,970	$56,157
District of Columbia	173,222	$40,639	$51,903
Frederick	73,855	$50,053	$63,927
Harford	78,290	$53,446	$68,260
Howard	95,112	$60,781	$77,628
Montgomery	306,428	$148,599	$189,787
Prince George's	265,713	$143,534	$183,318

Maryland-Approved State Fuel Tax Increase

As a reminder, the operating cost for this scenario is at $4.9104 per gallon, including the $0.018 per gallon fuel tax increase, and is implemented on all drivers using the InSITE/BMC region network. Similar to the status quo scenario, this cost is on a per gallon basis, thus the final cost that each HH pays depends to the fuel efficiency of their vehicle(s).

<u>Tax Incidence</u>

The structure of the tax incidence results for the ***fuel tax increase*** is the same as the structure of the status quo tax incidence results; the level of tax burden though is slightly higher for each group, which is expected due to the increase in the state fuel tax. Households in lower income groups pay lower taxes on a daily basis compared to higher income groups; however, they experience a higher state tax-to-income ratio than their higher income counterparts (1.79% for INC0 vs. 0.87% for INC4), as they have significantly lower income. Additionally, they constitute a smaller percentage of the taxpaying population (5.58% for INC0 vs. 37.8% for INC4). The tax incidence results by income group are presented in Table 21.

Table 21 Tax Incidence by Income Group – *Fuel Tax Increase*

Income Group	Num. of Paying HHs	Daily State Tax Paid (HH level)	State Tax -to-Income (HH level)	Daily Federal Tax Paid (HH level)	Federal Tax-To-Income (HH level)
INC0	92,581	$0.37	1.79%	$0.27	1.30%
INC1	115,927	$0.44	0.44%	$0.32	0.52%
INC2	236,733	$0.55	0.55%	$0.40	0.37%
INC3	587,310	$0.69	0.69%	$0.50	0.25%
INC4	627,867	$0.87	0.87%	$0.64	0.23%
Total	**1,660,418**	**-**	**-**	**-**	**-**

The tax incidence results for different counties are presented in Table 22. DC, Baltimore City and Montgomery County experience the lowest tax-to-income ratios (0.22%, 0.30% and 0.32% respectively), while Carroll, Frederick and Harford experience the highest (0.55%, 0.52%

and 0.48% respectively). In terms of taxpaying population, Montgomery, Prince George's and Baltimore counties have the highest number of taxpayers, while Carroll, Frederick and Harford have the lowest.

Table 22 Tax Incidence by County – *Fuel Tax Increase*

County	Num. of Paying HHs	Daily Income of Driving HHs	Daily Tax Paid		Tax to Income Ratios	
			Fed	State	State	Fed
Anne Arundel	175,371	$207	$0.65	$0.90	0.45%	0.33%
Baltimore City	175,051	$153	$0.31	$0.42	0.30%	0.22%
Baltimore	263,349	$192	$0.54	$0.74	0.39%	0.28%
Carroll	53,998	$204	$0.82	$1.12	0.55%	0.40%
District of Columbia	173,219	$169	$0.23	$0.31	0.22%	0.16%
Frederick	73,858	$206	$0.78	$1.07	0.52%	0.38%
Harford	78,292	$201	$0.69	$0.95	0.48%	0.35%
Howard	95,114	$226	$0.65	$0.90	0.40%	0.29%
Montgomery	306,441	$221	$0.51	$0.70	0.32%	0.24%
Prince George's	265,725	$198	$0.59	$0.82	0.42%	0.31%

Travel Behavior

The vehicle ownership model results by income group and by county are presented in Table 23 and Table 24. It is important to note the high percentage of lower income HHs that do not own any vehicle compared to their higher income counterparts (INC0: 52.45% vs. INC4: 0.76%). In terms of counties, Baltimore City and DC have the highest percentages of HHs without vehicles (23.9% and 27% respectively), which is expected as these areas have better transit provision that the other counties in the study area.

Table 23 Vehicle Ownership Model Results by Income Group – *Fuel Tax Increase*

Income Group	Avg. HH Size	Avg. Num. of Workers	Avg. Num. of Adults	Avg. Num. of Cars	% of HHs with Cars < Workers	% of HHs with no Car
INC0	1.54	0.2	1.2	0.60	5.68%	52.45%
INC1	1.96	0.6	1.6	1.22	9.06%	22.24%
INC2	2.16	1.0	1.7	1.51	8.8%	9.56%

Income Group	Avg. HH Size	Avg. Num. of Workers	Avg. Num. of Adults	Avg. Num. of Cars	% of HHs with Cars < Workers	% of HHs with no Car
INC3	2.49	1.4	1.9	1.89	8.35%	2.93%
INC4	3.00	1.8	2.3	2.35	9.47%	0.76%

The mode share results are shown in Figure 16. The majority of the trips are motorized across all income groups (58% for INC0, 76% for INC1, 83% for INC2, 88% for INC3 and 89% for INC4), while the minority are transit trips (14% for INC0, 7% for INC1, 5% for INC2, 3% for INC3 and 3% for INC4). However, among HHs not owning a vehicle, walking/biking is the prevalent trip mode (40% for INC0, 39% for INC1, 35% for INC2, 39% for INC3 and 42% for INC4), while the minority of the trips are by transit (25% for INC0, 28% for INC1, 31% for INC2, 22% for INC3 and 24% for INC4).

Table 24 Socioeconomic and Vehicle Ownership Characteristics by County - *Fuel Tax Increase*

County	HH Size	Number of HHs	Avg. Income Level	Avg. Num. Workers	Avg. Num. Adults	Avg. Workers-To-Size	Avg. Num. Cars	% HHs with Cars<Workers	% HHs Without Car
Anne Arundel	2.6	208,982	2.89	1.30	2.0	49.4%	2.07	5.2%	4.7%
Baltimore City	2.3	267,979	1.90	1.01	1.8	46.1%	1.32	14.1%	23.9%
Baltimore	2.5	331,473	2.63	1.25	1.9	49.5%	1.87	6.5%	7.7%
Carroll	2.6	64,457	2.85	1.35	1.9	49.4%	2.14	3.8%	3.8%
District of Columbia	2.0	307,517	2.03	0.94	1.6	45.5%	1.22	13.8%	27.0%
Frederick	2.6	88,547	2.86	1.36	1.9	48.9%	2.11	4.1%	3.9%
Harford	2.6	93,214	2.81	1.35	2.0	50.3%	2.08	4.8%	4.7%
Howard	2.7	108,223	3.22	1.47	2.0	54.3%	2.16	5.4%	2.8%
Montgomery	2.6	371,534	3.09	1.41	2.0	53.1%	1.92	8.3%	6.5%
Prince George's	2.6	327,351	2.76	1.40	2.0	53.2%	1.96	7.7%	6.3%

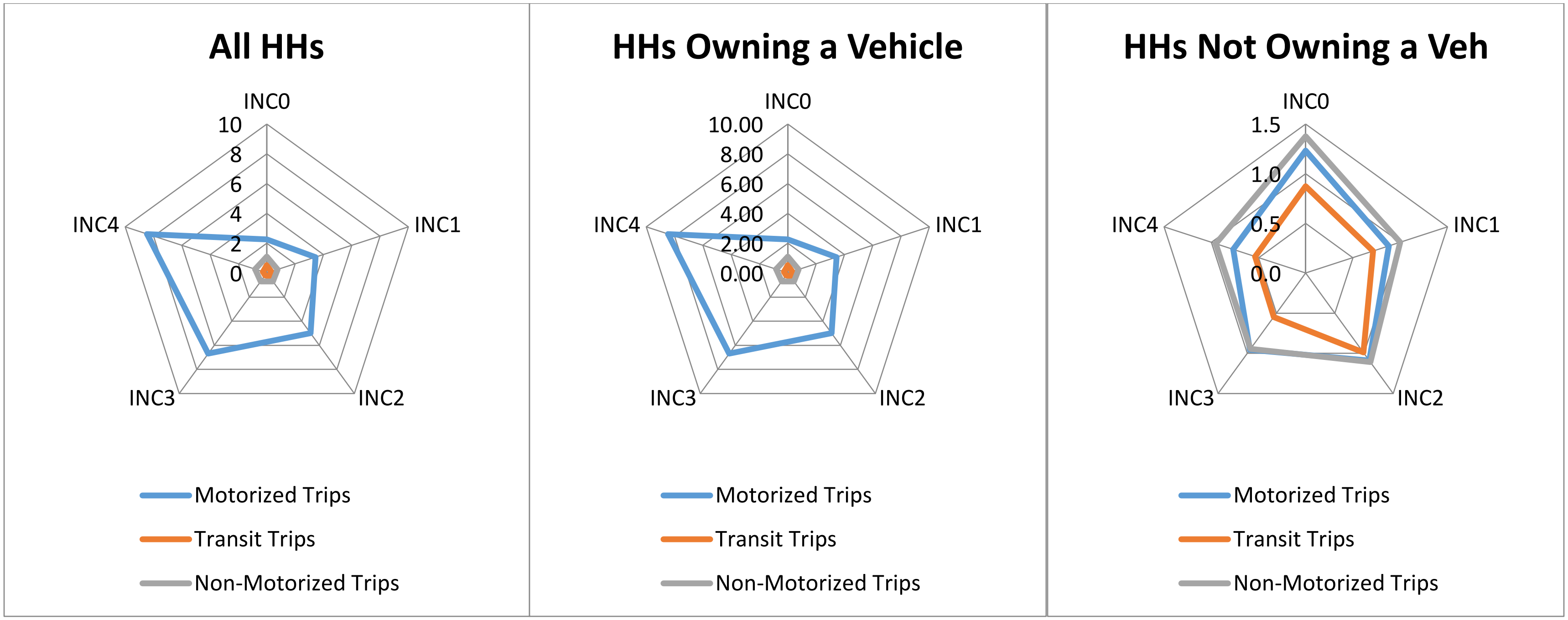
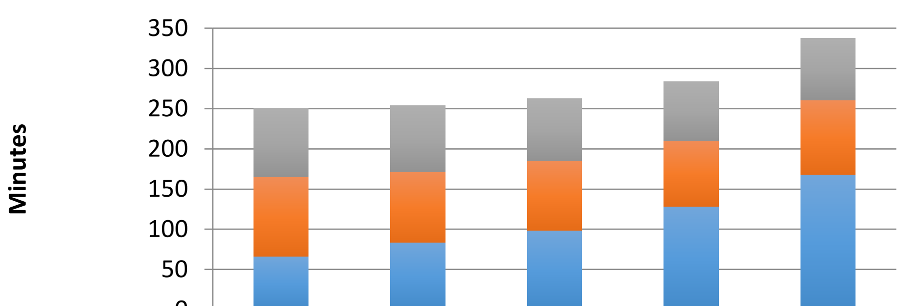


Figure 16 Number of Motorized, Transit, and Non-Motorized Trips by Income Group and Vehicle Ownership Status – *Fuel Tax Increase*

The results in terms of average time spent and average distance traveled daily by mode and income group (Figure 17 and Figure 19) are almost identical to the status quo, proving that a very small fuel tax increase does not affect travel behavior significantly. Across all income groups, users travel longer distances driving than using transit (3.23 to 6.18 times), or walking/biking (5.72 to 16.76 times). As income increases, the miles driven increase significantly, while the distance traveled by foot/bike or using transit stays relatively fixed (approximately 5 miles and 9 miles respectively). In terms of time spent traveling by each mode (i.e. driving, transit, walking/biking), it is evident that the time per mile traveled is higher for walking/biking and transit, and this is reflected in the model results. As income increases, the time spent driving also increases, and this is associated with longer distances traveled, while congestion may also play a role in motorized travel modes. The time spent in transit or walking/biking declines as income increases, except for INC4 where a slight increase can be observed.

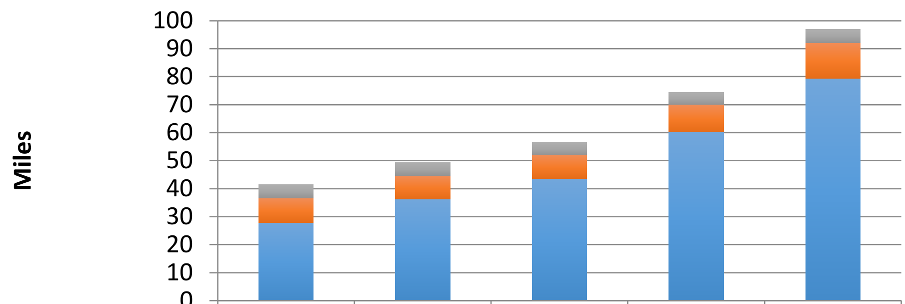


	INC0	INC1	INC2	INC3	INC4
Walking/Biking	86.00	82.60	77.46	73.50	76.52
Transit	98.59	87.28	86.13	81.19	92.81
Driving	66.36	83.99	98.66	128.71	168.07

Income Group

Driving Transit Walking/Biking

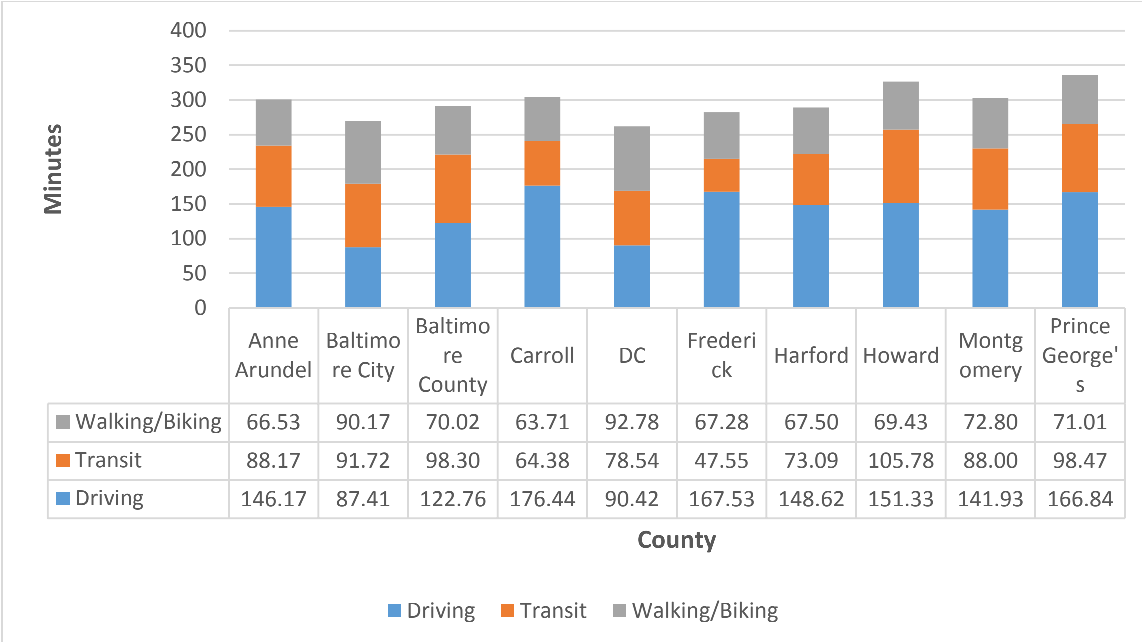
Figure 17 Average Time Spent Daily at the HH level by Mode and Income Group – *Fuel Tax Increase*



	INC0	INC1	INC2	INC3	INC4
Walking/Biking	4.88	4.79	4.58	4.41	4.73
Transit	8.64	8.31	8.44	9.76	12.82
Driving	27.96	36.29	43.56	60.23	79.30

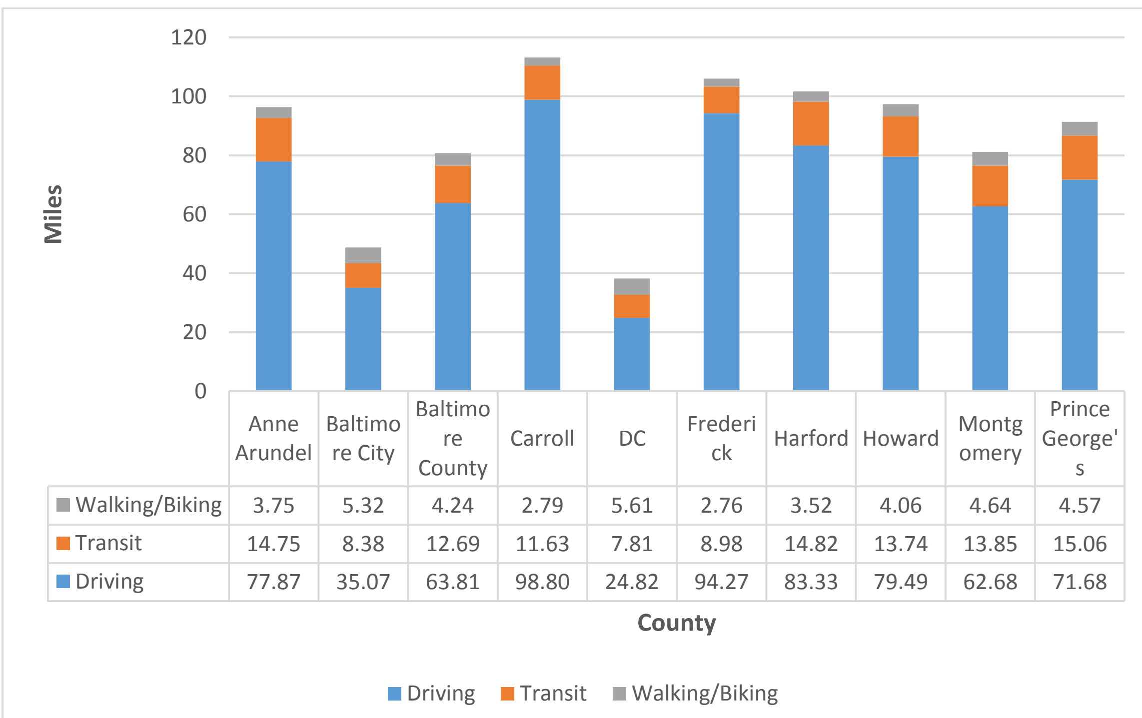
Figure 18 Average Miles Traveled Daily at the HH level by Mode and Income Group – *Fuel Tax Increase*

The results in terms of average time spent and average distance traveled daily by mode and county are presented in Figure 19 and Figure 20. DC and Baltimore City residents drive the least (24.82 miles and 35.07 respectively) while Carroll and Frederick residents drive the most (98.80 miles and 94.27 miles respectively). Baltimore City and DC residents walk the most (5.32 miles and 5.61 miles respectively), while residents of Carroll and Frederick walk the least (2.79 miles and 2.76 miles respectively).



	Anne Arundel	Baltimore City	Baltimore County	Carroll	DC	Frederick	Harford	Howard	Montgomery	Prince George's
Walking/Biking	66.53	90.17	70.02	63.71	92.78	67.28	67.50	69.43	72.80	71.01
Transit	88.17	91.72	98.30	64.38	78.54	47.55	73.09	105.78	88.00	98.47
Driving	146.17	87.41	122.76	176.44	90.42	167.53	148.62	151.33	141.93	166.84

Figure 19 Average Time Spent Daily at the HH level by Mode and Income Group – *Fuel Tax Increase*



	Anne Arundel	Baltimore City	Baltimore County	Carroll	DC	Frederick	Harford	Howard	Montgomery	Prince George's
Walking/Biking	3.75	5.32	4.24	2.79	5.61	2.76	3.52	4.06	4.64	4.57
Transit	14.75	8.38	12.69	11.63	7.81	8.98	14.82	13.74	13.85	15.06
Driving	77.87	35.07	63.81	98.80	24.82	94.27	83.33	79.49	62.68	71.68

Figure 20 Average Miles Traveled Daily at the HH level by Mode and County – *Fuel Tax Increase*

Revenue Potential

The ***fuel tax increase*** policy generates approximately an additional $100,000 revenue on a daily basis compared to the other policies. Similar to the status quo policy, more revenue is generated from users of higher income groups, following an ascending trend, as depicted in Table 25. The results at the county level are presented in Table 26: under the fuel tax increase policy, Montgomery, Prince George's, and Baltimore counties generate the highest revenue ($204,311, $197,370, and $191,689 respectively), while DC, Carroll and Frederick generate the lowest ($55,884, $60,425, $68,865 respectively).

Table 25 Daily Revenue Generation by Income Group – *Fuel Tax Increase*

Income Group	Num. of Paying HHs	Revenue Generated from State Fuel Tax	Revenue Generated from Federal Fuel Tax
INC0	92,581	$34,008	$24,733
INC1	115,927	$50,731	$36,895
INC2	236,733	$130,463	$94,882
INC3	587,310	$407,623	$296,453
INC4	627,867	$548,863	$399,173
Total	**1,660,418**	**$1,171,687**	**$852,136**

Table 26 Daily Revenue Generation by County – *Fuel Tax Increase*

County	Num. of Paying HHs	Revenues	
		Federal Fuel Tax	State Fuel Tax
Anne Arundel	175,371	$114,499	$157,436
Baltimore City	175,051	$57,210	$78,663
Baltimore	263,349	$139,410	$191,689
Carroll	53,998	$43,945	$60,425
District of Columbia	173,219	$40,643	$55,884
Frederick	73,858	$50,084	$68,865
Harford	78,292	$53,414	$73,444
Howard	95,114	$60,799	$83,599
Montgomery	306,441	$148,590	$204,311
Prince George's	265,725	$143,542	$197,370

Flat-Rate Vehicle-Miles-Traveled (VMT) Fee

As a reminder, a flat-rate VMT fee of $0.22755 per mile was implemented on all drivers using the InSITE/BMC region network.

<u>Tax Incidence</u>

The structure of the tax incidence results for the ***flat VMT fee*** is the same as the structure of the status quo tax incidence results. Households in lower income groups pay lower taxes on a daily basis compared to higher income groups; however, they experience a higher state tax-to-income ratio than their higher income counterparts (1.87% for INC0 vs. 0.30% for INC4), as they have significantly lower income. Additionally, they constitute a smaller percentage of the taxpaying population (5.35% for INC0 vs. 38.1% for INC4). The tax incidence results by income group are presented in Table 27.

Table 27 Tax Incidence by Income Group – *Flat VMT Fee*

Income Group	Num. of Paying HHs	Daily State Tax Paid (HH level)	State Tax -to-Income (HH level)	Daily Federal Tax Paid (HH level)	Federal Tax-To-Income (HH level)
INC0	87,858	$0.39	1.87%	$0.30	1.46%
INC1	112,950	$0.38	0.62%	$0.30	0.48%
INC2	233,188	$0.44	0.41%	$0.35	0.32%
INC3	583,306	$0.60	0.29%	$0.47	0.23%
INC4	625,823	$0.81	0.30%	$0.63	0.23%
Total	**1,643,125**	-	-	-	-

The tax incidence results for different counties are presented in Table 28. DC, Baltimore City and Montgomery County experience the lowest tax-to-income ratios (0.21%, 0.30% and 0.30% respectively), while Carroll, Frederick and Harford experience the highest (0.46%, 0.44% and 0.42% respectively). In terms of taxpaying population, Montgomery, Prince George’s and Baltimore counties have the highest number of taxpayers, while Carroll, Frederick and Harford have the lowest.

Table 28 Tax Incidence by County – *Flat VMT Fee*

County	Num. of Paying HHs	Daily Income of Driving HHs	Daily Tax Paid		Tax to Income Ratios	
			Fed	State	State	Fed
Anne Arundel	174,032	$207	$0.61	$0.79	0.40%	0.31%
Baltimore City	171,540	$154	$0.31	$0.40	0.30%	0.23%
Baltimore	260,896	$193	$0.51	$0.65	0.34%	0.27%
Carroll	53,606	$205	$0.75	$0.96	0.46%	0.36%
District of Columbia	169,681	$170	$0.22	$0.29	0.21%	0.16%
Frederick	73,329	$206	$0.71	$0.91	0.44%	0.34%
Harford	77,831	$202	$0.65	$0.83	0.42%	0.33%
Howard	94,568	$226	$0.64	$0.81	0.36%	0.28%
Montgomery	304,109	$221	$0.51	$0.65	0.30%	0.23%
Prince George's	263,533	$198	$0.58	$0.74	0.38%	0.30%

Travel Behavior

The vehicle ownership model results by income group and by county are presented in Table 29 and Table 30. It is important to note the high percentage of lower income HHs that do not own any vehicle compared to their higher income counterparts (INC0: 53.29% vs. INC4: 0.81%). In terms of counties, Baltimore City and DC have the highest percentages of HHs without vehicles (24.5% and 27.5% respectively), which is expected as these areas have better transit provision that the other counties in the study area.

Table 29 Vehicle Ownership Model Results by Income Group – *Flat VMT Fee*

Income Group	Avg. HH Size	Avg. Num. of Workers	Avg. Num. of Adults	Avg. Num. of Cars	% of HHs with Cars < Workers	% of HHs with no Car
INC0	1.54	0.2	1.2	0.59	6.53%	53.29%
INC1	1.96	0.6	1.6	1.20	10.00%	23.08%
INC2	2.16	1.0	1.7	1.49	9.55%	10.11%
INC3	2.49	1.4	1.9	1.87	8.88%	3.14%
INC4	3.00	1.8	2.3	2.35	9.78%	0.81%

The mode share results are shown in Figure 21. The majority of the trips are motorized across all income groups (52% for INC0, 73% for INC1, 81% for INC2, 87% for INC3 and 88% for INC4), while the minority are transit trips (16% for INC0, 8% for INC1, 6% for INC2, 3% for INC3 and 3% for INC4). However, among HHs not owning a vehicle, walking/biking is the prevalent trip mode (43% for INC0, 41% for INC1, 36% for INC2, 40% for INC3 and 43% for INC4), while the minority of the trips are by transit (28% for INC0, 29% for INC1, 32% for INC2, 24% for INC3 and 24% for INC4).

Table 30 Socioeconomic and Vehicle Ownership Characteristics by County – *Flat VMT Fee*

County	HH Size	Number of HHs	Avg. Income Level	Avg. Num. Workers	Avg. Num. Adults	Avg. Workers-To-Size	Avg. Num. Cars	% HHs with Cars<Workers	% HHs Without Car
Anne Arundel	2.6	208,982	2.89	1.30	2.0	49.4%	2.06	5.4%	4.8%
Baltimore City	2.3	267,979	1.90	1.01	1.8	46.1%	1.30	15.1%	24.7%
Baltimore	2.5	331,473	2.63	1.25	1.9	49.5%	1.85	7.1%	8.0%
Carroll	2.6	64,457	2.85	1.35	1.9	49.4%	2.14	3.8%	3.8%
District of Columbia	2.0	307,517	2.03	0.94	1.6	45.5%	1.20	14.5%	27.5%
Frederick	2.6	88,547	2.86	1.36	1.9	48.9%	2.11	4.1%	3.9%
Harford	2.6	93,214	2.81	1.35	2.0	50.3%	2.08	5.0%	4.8%
Howard	2.7	108,223	3.22	1.47	2.0	54.3%	2.15	5.7%	2.9%
Montgomery	2.6	371,534	3.09	1.41	2.0	53.1%	1.91	8.8%	6.8%
Prince George's	2.6	327,351	2.76	1.40	2.0	53.2%	1.95	8.2%	6.5%

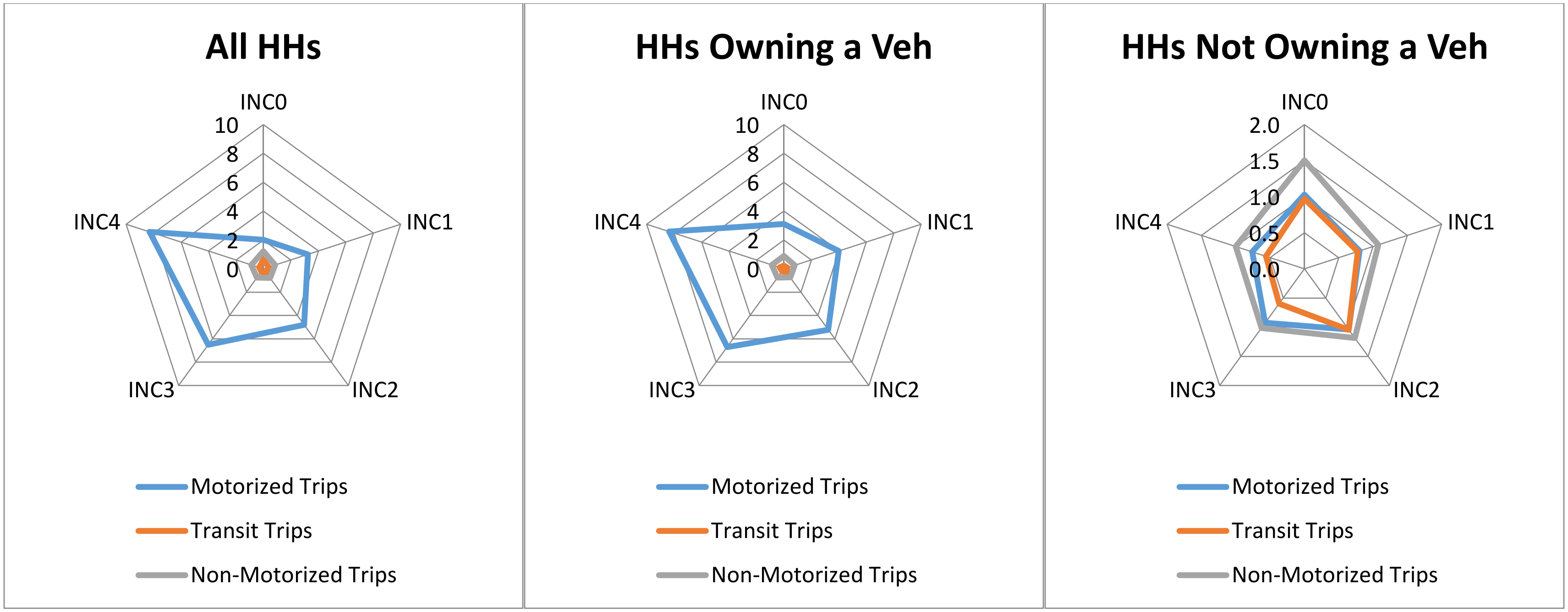


Figure 21 Number of Motorized, Transit, and Non-Motorized Trips by Income Group and Vehicle Ownership Status – *Flat VMT Fee*

The results in terms of average time spent and average distance traveled daily by mode and income group (Figure 22 and Figure 23) are comparable to the fuel tax policies results. Across all income groups, users travel longer distances driving than using transit (2.41 to 5.42 times), or walking/biking (4.43 to 15.08 times). As income increases, the miles driven increase significantly, while the distance traveled by foot/bike or using transit stays relatively fixed (approximately 5 miles and 9 miles respectively). In terms of time spent traveling by each mode (i.e. driving, transit, walking/biking), it is evident that the time per mile traveled is higher for walking/biking and transit, and this is reflected in the model results. As income increases, the time spent driving also increases, and this is associated with longer distances traveled, while congestion may also play a role in motorized travel modes. The time spent in transit or walking/biking declines as income increases, except for INC4 where a slight increase can be observed.

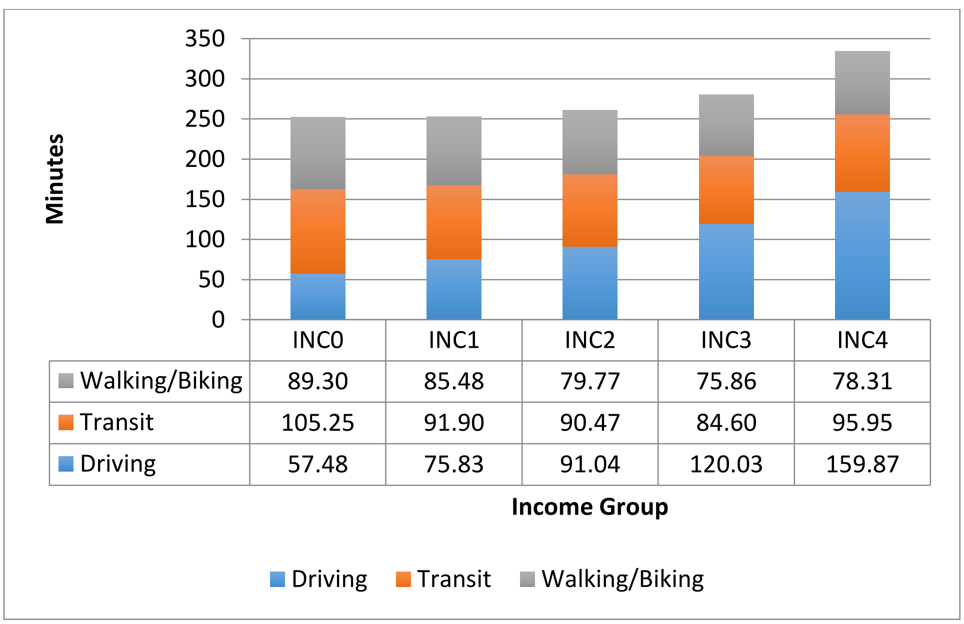
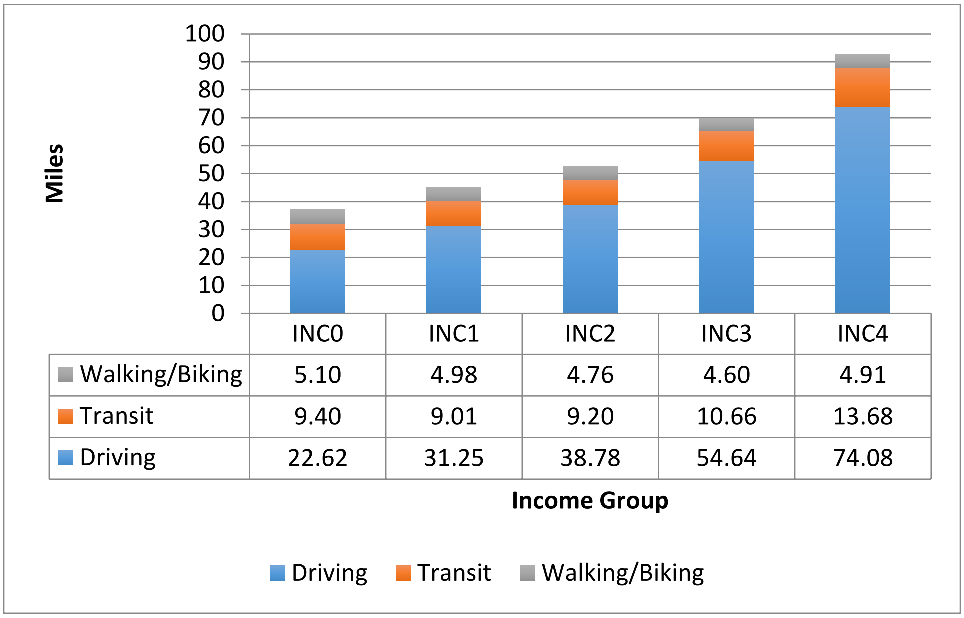


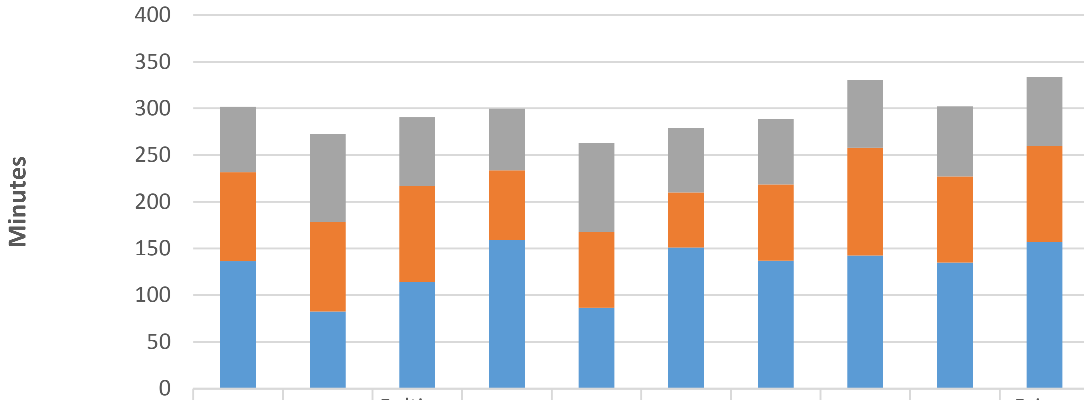
Figure 22 Average Time Spent Daily at the HH level by Mode and Income Group – *Flat VMT Fee*



	INC0	INC1	INC2	INC3	INC4
Walking/Biking	5.10	4.98	4.76	4.60	4.91
Transit	9.40	9.01	9.20	10.66	13.68
Driving	22.62	31.25	38.78	54.64	74.08

Figure 23 Average Miles Traveled Daily at the HH level by Mode and Income Group – *Flat VMT Fee*

The results in terms of average time spent and average distance traveled daily by mode and county are presented in Figure 24 and Figure 25. DC and Baltimore City residents drive the least (22.96 miles and 31.97 respectively) while Carroll and Frederick residents drive the most (86.99 miles and 82.54 miles respectively). Baltimore City and DC residents walk the most (4.53 miles and 5.76 miles respectively), while residents of Carroll and Frederick walk the least (2.97 miles and 2.85 miles respectively).

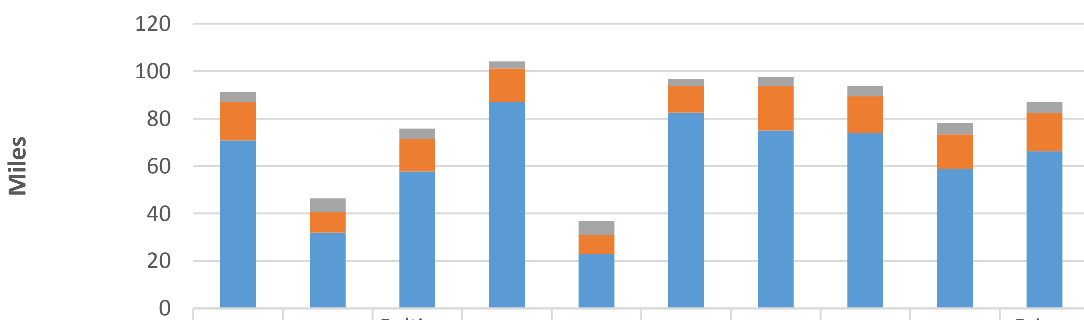


	Anne Arundel	Baltimore City	Baltimore County	Carroll	DC	Frederick	Harford	Howard	Montgomery	Prince George's
Walking/Biking	70.42	94.07	73.76	66.34	95.00	68.97	70.26	72.38	75.13	73.42
Transit	95.28	95.70	102.89	74.82	81.36	58.99	81.67	115.66	92.09	103.09
Driving	136.25	82.57	114.01	158.77	86.53	151.03	137.05	142.32	134.98	157.09

County

Driving Transit Walking/Biking

Figure 24 Average Time Spent Daily at the HH level by Mode and Income Group – *Flat VMT Fee*



	Anne Arundel	Baltimore City	Baltimore County	Carroll	DC	Frederick	Harford	Howard	Montgomery	Prince George's
Walking/Biking	4.06	5.63	4.53	2.97	5.76	2.85	3.75	4.29	4.89	4.82
Transit	16.29	8.83	13.63	14.14	8.10	11.23	18.68	15.42	14.69	15.93
Driving	70.85	31.97	57.66	86.99	22.96	82.54	75.04	73.94	58.66	66.27

County

Driving Transit Walking/Biking

Figure 25 Average Miles Traveled Daily at the HH level by Mode and County – *Flat VMT Fee*

Revenue Potential

Similar to the fuel tax policies, under the ***flat VMT fee*** policy, more revenue is generated from users of higher income groups, following an ascending trend, as depicted in Table 31. The results at the county level are presented in Table 32 under the flat VMT fee policy, Montgomery, Prince George's, and Baltimore counties generate the highest revenue ($187,631, $178,216, and $166,602 respectively), while DC, Carroll and Frederick generate the lowest ($50,189, $51,139, $57,675 respectively).

Table 31 Daily Revenue Generation by Income Group – *Flat VMT Fee*

Income Group	Num. of Paying HHs	Revenue Generated from State Fuel Tax	Revenue Generated from Federal Fuel Tax
INC0	87,858	$33,835	$26,385
INC1	112,950	$42,989	$33,523
INC2	233,188	$103,652	$80,830
INC3	583,306	$351,947	$274,454
INC4	625,823	$506,888	$395,280
Total	**1,643,125**	$1,039,311	$810,472

Table 32 Daily Revenue Generation by County – *Flat VMT Fee*

County	Num. of Paying HHs	Revenues	
		Federal Fuel Tax	State Fuel Tax
Anne Arundel	174,032	$107,116	$137,360
Baltimore City	171,540	$55,486	$71,152
Baltimore	260,896	$129,919	$166,602
Carroll	53,606	$39,879	$51,139
District of Columbia	169,681	$39,138	$50,189
Frederick	73,329	$44,976	$57,675
Harford	77,831	$49,913	$64,007
Howard	94,568	$58,751	$75,340
Montgomery	304,109	$146,318	$187,631
Prince George's	263,533	$138,976	$178,216

Variable-Rate Vehicle-Miles-Traveled (VMT) Fee

As a reminder, a variable-rate VMT fee of $0.22755 per mile for INC4 with a 5% decrease for each subsequent income group was implemented on all drivers using the InSITE/BMC region network.

<u>Tax Incidence</u>

The structure of the tax incidence results for the ***variable VMT fee*** is the same as the structure of the status quo tax incidence results. Households in lower income groups pay lower taxes on a daily basis compared to higher income groups; however, they experience a higher state tax-to-income ratio than their higher income counterparts (1.89% for INC0 vs. 0.31% for INC4), as they have significantly lower income. Additionally, they constitute a smaller percentage of the taxpaying population (5.56% for INC0 vs. 37.83% for INC4). The tax incidence results by income group are presented in Table 33.

Table 33 Tax Incidence by Income Group - *Variable VMT Fee*

Income Group	Num. of Paying HHs	Daily State Tax Paid (HH level)	State Tax -to-Income (HH level)	Daily Federal Tax Paid (HH level)	Federal Tax-To-Income (HH level)
INC0	92322	$0.39	1.89%	$0.37	1.79%
INC1	115764	$0.37	0.61%	$0.34	0.55%
INC2	236425	$0.45	0.41%	$0.38	0.35%
INC3	587116	$0.63	0.30%	$0.51	0.25%
INC4	627773	$0.86	0.31%	$0.67	0.25%
Total	**1,659,400**	**-**	**-**	**-**	**-**

The tax incidence results for different counties are presented in Table 34. DC, Baltimore City and Montgomery County experience the lowest tax-to-income ratios (0.21%, 0.30% and 0.31% respectively), while Carroll, Frederick and Harford experience the highest (0.50%, 0.48% and 0.44% respectively). In terms of taxpaying population, Montgomery, Prince George's and

Baltimore counties have the highest number of taxpayers, while Carroll, Frederick and Harford have the lowest.

Table 34 Tax Incidence by County - *Variable VMT Fee*

County	Num. of Paying HHs	Daily Income of Driving HHs	Daily Tax Paid		Tax to Income Ratios	
			Fed	State	State	Fed
Anne Arundel	175,311	$207	$0.67	$0.83	0.42%	0.34%
Baltimore City	174,818	$154	$0.34	$0.40	0.30%	0.26%
Baltimore	263,192	$193	$0.55	$0.68	0.36%	0.30%
Carroll	53,981	$205	$0.83	$1.03	0.50%	0.41%
District of Columbia	173,006	$170	$0.24	$0.29	0.21%	0.18%
Frederick	73,821	$206	$0.80	$0.99	0.48%	0.39%
Harford	78,272	$202	$0.72	$0.88	0.44%	0.36%
Howard	95,089	$226	$0.68	$0.85	0.37%	0.30%
Montgomery	306,310	$221	$0.54	$0.68	0.31%	0.25%
Prince George's	265,600	$198	$0.62	$0.76	0.39%	0.32%

Travel Behavior

The vehicle ownership model results by income group and by county are presented in Table 35 and Table 36. It is important to note the high percentage of lower income HHs that do not own any vehicle compared to their higher income counterparts (INC0: 52.49% vs. INC4: 0.76%). In terms of counties, Baltimore City and DC have the highest percentages of HHs without vehicles (24% and 27% respectively), which is expected as these areas have better transit provision that the other counties in the study area.

Table 35 Vehicle Ownership Model Results by Income Group – *Variable VMT Fee*

Income Group	Avg. HH Size	Avg. Num. of Workers	Avg. Num. of Adults	Avg. Num. of Cars	% of HHs with Cars < Workers	% of HHs with no Car
INC0	1.54	0.2	1.2	0.60	5.71%	52.49%
INC1	1.96	0.6	1.6	1.22	9.10%	22.26%
INC2	2.16	1.0	1.7	1.51	8.82%	9.58%
INC3	2.49	1.4	1.9	1.89	8.37%	2.94%
INC4	3.00	1.8	2.3	2.35	9.48%	0.76%

The mode share results are shown in Figure 26. The majority of the trips are motorized across all income groups (57% for INC0, 76% for INC1, 83% for INC2, 88% for INC3 and 88% for INC4), while the minority are transit trips (14% for INC0, 7% for INC1, 5% for INC2, 3% for INC3 and 3% for INC4). However, among HHs not owning a vehicle, walking/biking is the prevalent trip mode while the minority of the trips are by transit.

Table 36 Socioeconomic and Vehicle Ownership Characteristics by County – *Variable VMT Fee*

County	HH Size	Number of HHs	Avg. Income Level	Avg. Num. Workers	Avg. Num. Adults	Avg. Workers-To-Size	Avg. Num. Cars	% HHs with Cars<Workers	% HHs Without Car
Anne Arundel	2.6	208,982	2.89	1.30	2.0	49.4%	2.07	5.2%	4.7%
Baltimore City	2.3	267,979	1.90	1.01	1.8	46.1%	1.32	14.1%	24.0%
Baltimore	2.5	331,473	2.63	1.25	1.9	49.5%	1.87	6.6%	7.8%
Carroll	2.6	64,457	2.85	1.35	1.9	49.4%	2.14	3.8%	3.8%
District of Columbia	2.0	307,517	2.03	0.94	1.6	45.5%	1.22	13.8%	27.0%
Frederick	2.6	88,547	2.86	1.36	1.9	48.9%	2.11	4.1%	3.9%
Harford	2.6	93,214	2.81	1.35	2.0	50.3%	2.08	4.8%	4.7%
Howard	2.7	108,223	3.22	1.47	2.0	54.3%	2.16	5.4%	2.8%
Montgomery	2.6	371,534	3.09	1.41	2.0	53.1%	1.92	8.3%	6.5%
Prince George's	2.6	327,351	2.76	1.40	2.0	53.2%	1.96	7.7%	6.3%

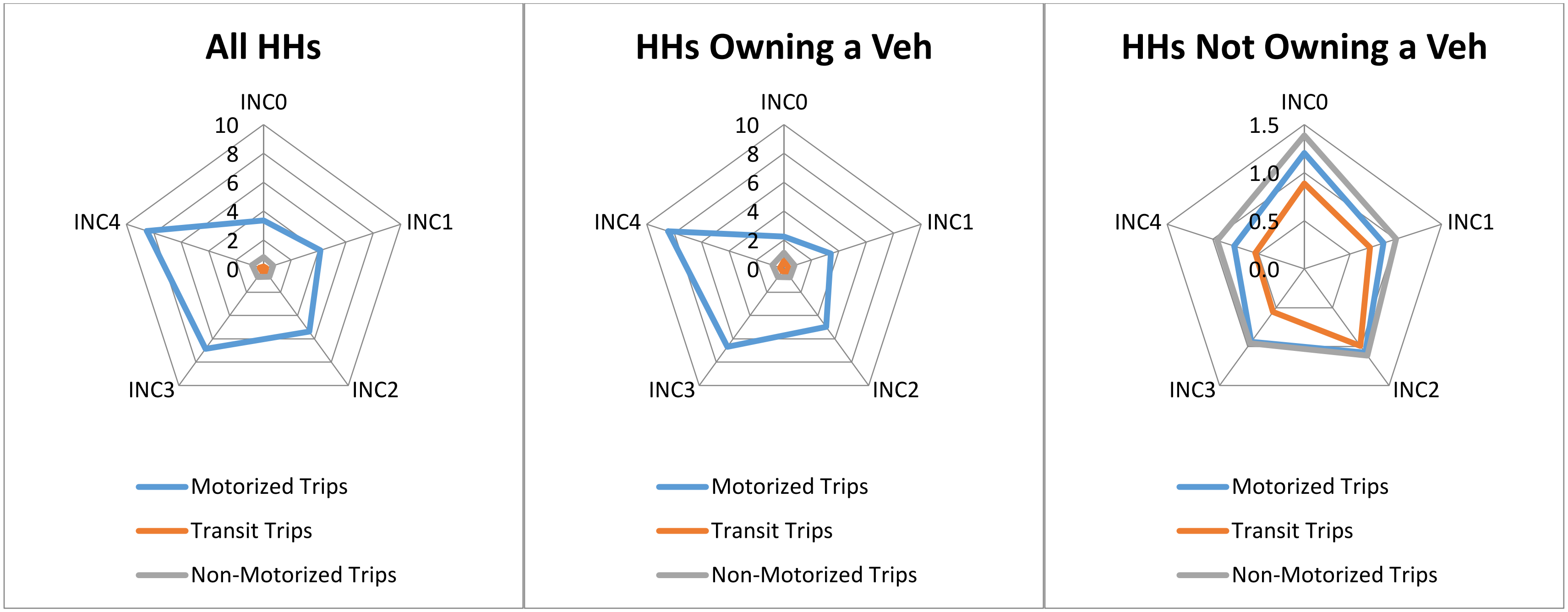


Figure 26 Number of Motorized, Transit, and Non-Motorized Trips by Income Group and Vehicle Ownership Status – *Variable VMT Fee*

The results in terms of average time spent and average distance traveled daily by mode and income group (Figure 27 and Figure 28) are comparable to the fuel tax policies results. Across all income groups, users travel longer distances driving than using transit (3.11 to 6.12 times), or walking/biking (5.54 to 16.54 times). As income increases, the miles driven increase significantly, while the distance traveled by foot/bike or using transit stays relatively fixed (approximately 5 miles and 9 miles respectively). In terms of time spent traveling by each mode (i.e. driving, transit, walking/biking), it is evident that the time per mile traveled is higher for walking/biking and transit, and this is reflected in the model results. As income increases, the time spent driving also increases, and this is associated with longer distances traveled, while congestion may also play a role in motorized travel modes. The time spent in transit or walking/biking declines as income increases, except for INC4 where a slight increase can be observed.

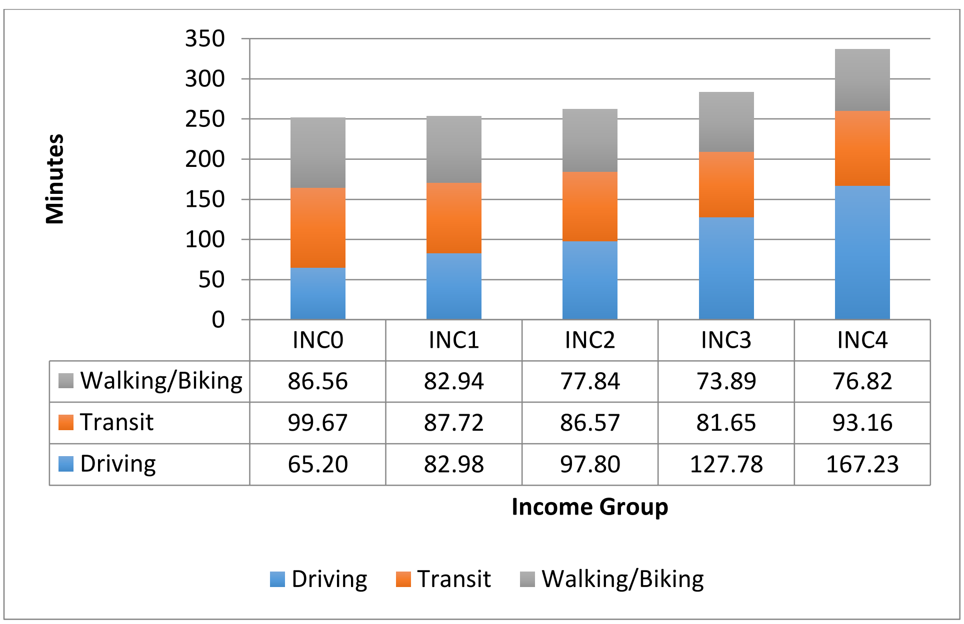


Figure 27 Average Time Spent Daily at the HH level by Mode and Income Group - *Variable VMT Fee*

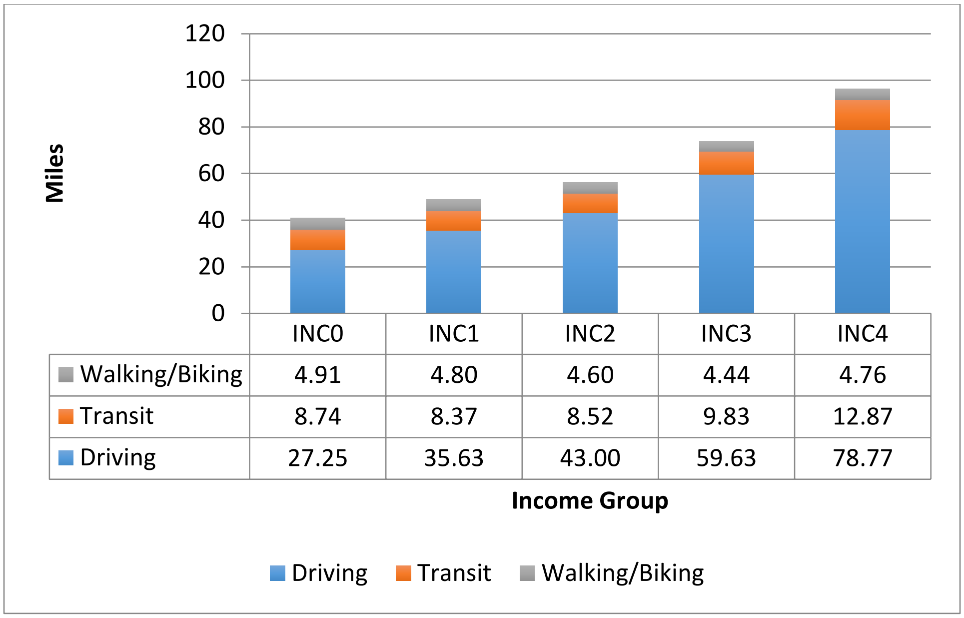
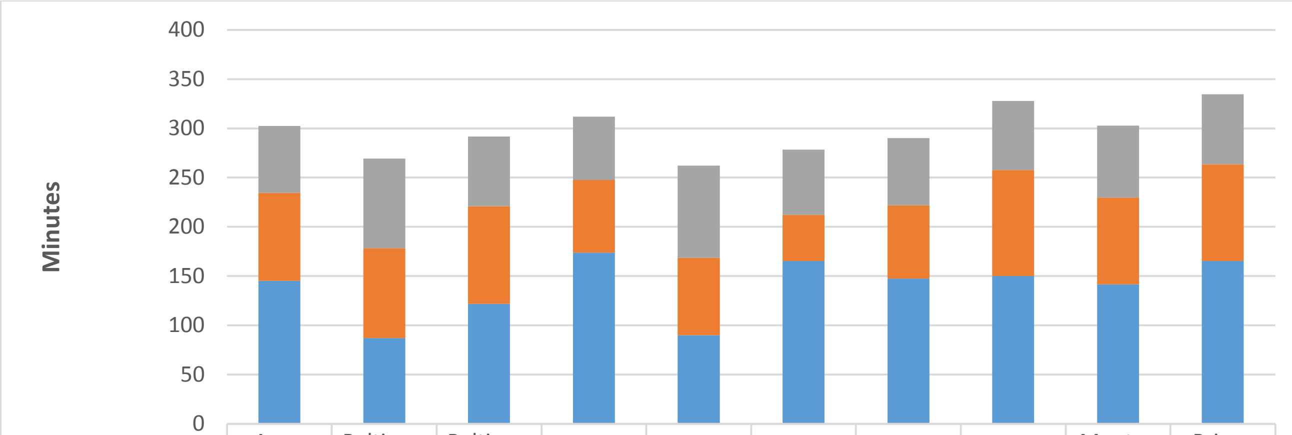


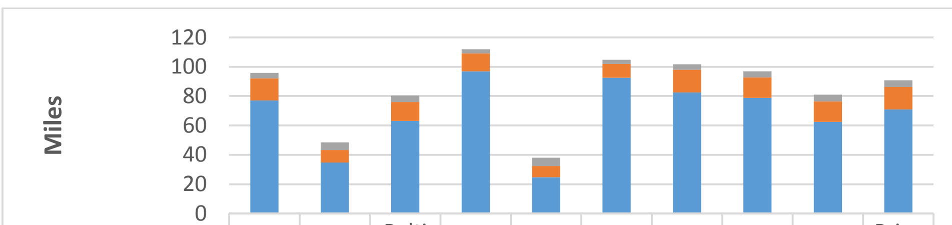
Figure 28 Average Miles Traveled Daily at the HH level by Mode and Income Group - *Variable VMT Fee*

The results in terms of average time spent and average distance traveled daily by mode and county are presented in Figure 29 and Figure 30. DC and Baltimore City residents drive the least (24.62 miles and 34.76 respectively) while Carroll and Frederick residents drive the most (96.99 miles and 92.55 miles respectively). Baltimore City and DC residents walk the most (5.37 miles and 5.66 miles respectively), while residents of Carroll and Frederick walk the least (2.87 miles and 2.74 miles respectively).



	Anne Arundel	Baltimore City	Baltimore County	Carroll	DC	Frederick	Harford	Howard	Montgomery	Prince George's
Walking/Biking	67.93	90.66	70.81	64.23	93.41	66.40	68.20	70.18	73.08	71.05
Transit	89.39	91.57	98.97	73.80	78.78	46.68	74.44	107.30	88.23	98.09
Driving	145.17	86.93	121.80	173.82	89.90	165.33	147.44	150.18	141.49	165.43

Figure 29 Average Time Spent Daily at the HH level by Mode and Income Group – *Variable VMT Fee*



	Anne Arundel	Baltimore City	Baltimore County	Carroll	DC	Frederick	Harford	Howard	Montgomery	Prince George's
Walking/Biking	3.83	5.37	4.31	2.87	5.66	2.74	3.56	4.14	4.68	4.59
Transit	14.91	8.38	12.88	12.13	7.83	9.39	15.58	14.00	13.91	15.11
Driving	77.06	34.76	63.13	96.99	24.62	92.55	82.45	78.80	62.42	71.00

Figure 30 Average Miles Traveled Daily at the HH level by Mode and County – *Variable VMT Fee*

Revenue Potential

Similar to the fuel tax policies, under the ***variable VMT fee*** policy, more revenue is generated from users of higher income groups, following an ascending trend, as depicted in Table 37. The results at the county level are presented in Table 38: under the variable VMT fee policy, Montgomery, Prince George's, and Baltimore counties generate the highest revenue ($195,784, $184,033, and $176,159 respectively), while DC, Carroll and Frederick generate the lowest ($51,332, $55,615, $63,424 respectively).

Table 37 Daily Revenue Generation by Income Group – *Variable VMT Fee*

Income Group	Num. of Paying HHs	Revenue Generated from State Fuel Tax	Revenue Generated from Federal Fuel Tax
INC0	92322	35,784	33,920
INC1	115764	43,272	39,062
INC2	236425	105,420	90,632
INC3	587116	367,787	$301,145
INC4	627773	540,472	$421,469
Total	**1,659,400**	$1,092,735	$886,228

Table 38 Daily Revenue Generation by County – *Variable VMT Fee*

County	Num. of Paying HHs	Revenues	
		Federal Fuel Tax	State Fuel Tax
Anne Arundel	175,311	$117,653	$146,007
Baltimore City	174,818	$61,550	$73,550
Baltimore	263,192	$143,569	$176,159
Carroll	53,981	$44,780	$55,615
District of Columbia	173,006	$42,859	$51,332
Frederick	73,821	$51,223	$63,424
Harford	78,272	$54,996	$67,933
Howard	95,089	$63,050	$78,899
Montgomery	306,310	$156,909	$195,784
Prince George's	265,600	$149,639	$184,033

Transportation-Dedicated Property Tax

As a reminder, an increase of 9.4% in the property tax paid by all users residing within the BMC region will be implemented, so as to generate comparable revenue to the state fuel taxes raised under the status-quo policy.

Tax Incidence

The tax incidence results for the transportation-dedicated ***property tax*** have a slightly different structure. Households in lower income groups experience a significantly higher tax-to-income ratio than their higher income counterparts (3.88% for INC0 vs. 0.35% for INC4). However, as far as the taxpaying population is concerned, the pattern is very interesting: the three income groups that have the highest taxpaying populations are INC4, INC3 and INC1 (594,385, 361,763 and 142,029 respectively).

Table 39 Tax Incidence by Income Group and Vehicle Availability Status - *Transportation-Dedicated Property Tax*

Income Group	Num. of Paying HHs	% of HHs Paying Property Tax	Annual Transportation Dedicated Property Tax Paid (HH level)	Transportation Dedicated Property Tax -to-Income (HH level)
All HHs				
INC0	142,029	48%	$3,093	3.8761%
INC1	97,032	47%	$3,319	1.3866%
INC2	105,812	34%	$2,301	0.5408%
INC3	361,763	54%	$2,581	0.3235%
INC4	594,385	88%	$3,698	0.3476%
Total	**1,301,021**			
HHs without vehicle				
INC0	74,627	25%	$3,059	3.8343%
INC1	19,325	9%	$3,555	1.4850%
INC2	10,056	3%	$2,094	0.4922%
INC3	10,833	2%	$2,129	0.2669%
INC4	4,806	1%	$3,209	0.3016%
Total	**119,647**			
HHs with vehicle				
INC0	67,402	23%	$3,129	3.9223%
INC1	77,707	38%	$3,260	1.3621%

Income Group	Num. of Paying HHs	% of HHs Paying Property Tax	Annual Transportation Dedicated Property Tax Paid (HH level)	Transportation Dedicated Property Tax -to-Income (HH level)
INC2	95,756	31%	$2,323	0.5459%
INC3	350,930	52%	$2,595	0.3253%
INC4	589,579	87%	$3,702	0.3480%
Total	**1,181,374**			

County-wise, Howard, Anne Arundel and Harford counties experience the lowest tax-to-income ratios (0.40%, 0.46% and 0.46% respectively), while Baltimore City, DC and Baltimore county experience the highest (0.82%, 0.56% and 0.53% respectively). In terms of taxpaying population, Montgomery, Prince George's and Baltimore counties have the highest number of taxpayers, while Carroll, Frederick and Harford have the lowest.

Table 40 Tax Incidence by County - *Transportation-Dedicated Property Tax*

County	Num. of Paying HHs	% of HHs Paying Property Tax	Annual Transportation Dedicated Property Tax Paid (HH level)	Transportation Dedicated Property Tax -to-Income (HH level)
Anne Arundel	137,589	65%	$310.89	0.46%
Baltimore City	146,410	55%	$293.10	0.82%
Baltimore County	200,336	62%	$303.97	0.53%
Carroll	41,366	64%	$306.00	0.47%
DC	132,097	44%	$238.86	0.56%
Frederick	55,236	63%	$308.03	0.46%
Harford	59,297	64%	$305.40	0.46%
Howard	75,215	71%	$313.46	0.40%
Montgomery	251,427	69%	$307.90	0.49%
Prince George's	202,048	63%	$306.55	0.48%
Total	**1,301,021**	**61%**		**0.53%**

Revenue Potential

The transportation-dedicated property tax policy exhibits a more interesting behavior. Among the 5 income groups, the lowest revenue is generated from INC2, INC1 and INC0 ($62,711, $82,938, and $113,119 respectively). County-wise, Montgomery, Prince George's, and Baltimore counties generate the highest revenue ($212,097, $169,695, and $166,839 respectively), while Carroll, Frederick and Harford generate the lowest ($34,680, $46,614, $49,614 respectively).

Table 41 Annual Revenue Generation by Income Group and Vehicle Availability Status – *Transportation Dedicated Property Tax*

Income Group	Num. of Paying HHs	% of HHs Paying Property Tax	Revenue Generation from Transportation Dedicated Property Taxes
All HHs			
INC0	142,029	48%	$41,288,519
INC1	97,032	47%	$30,272,509
INC2	105,812	34%	$22,889,693
INC3	361,763	54%	$87,775,815
INC4	594,385	88%	$206,624,856
Total	**1,301,021**		$388,851,391
HHs without vehicle			
INC0	74,627	25%	$21,460,936
INC1	19,325	9%	$6,456,995
INC2	10,056	3%	$1,979,685
INC3	10,833	2%	$2,168,464
INC4	4,806	1%	$1,449,711
Total	**119,647**		$33,515,791
HHs with vehicle			
INC0	67,402	23%	$19,827,583
INC1	77,707	38%	$23,815,514
INC2	95,756	31%	$20,910,008
INC3	350,930	52%	$85,607,351
INC4	589,579	87%	$205,175,145
Total	**1,181,374**		$355,335,601

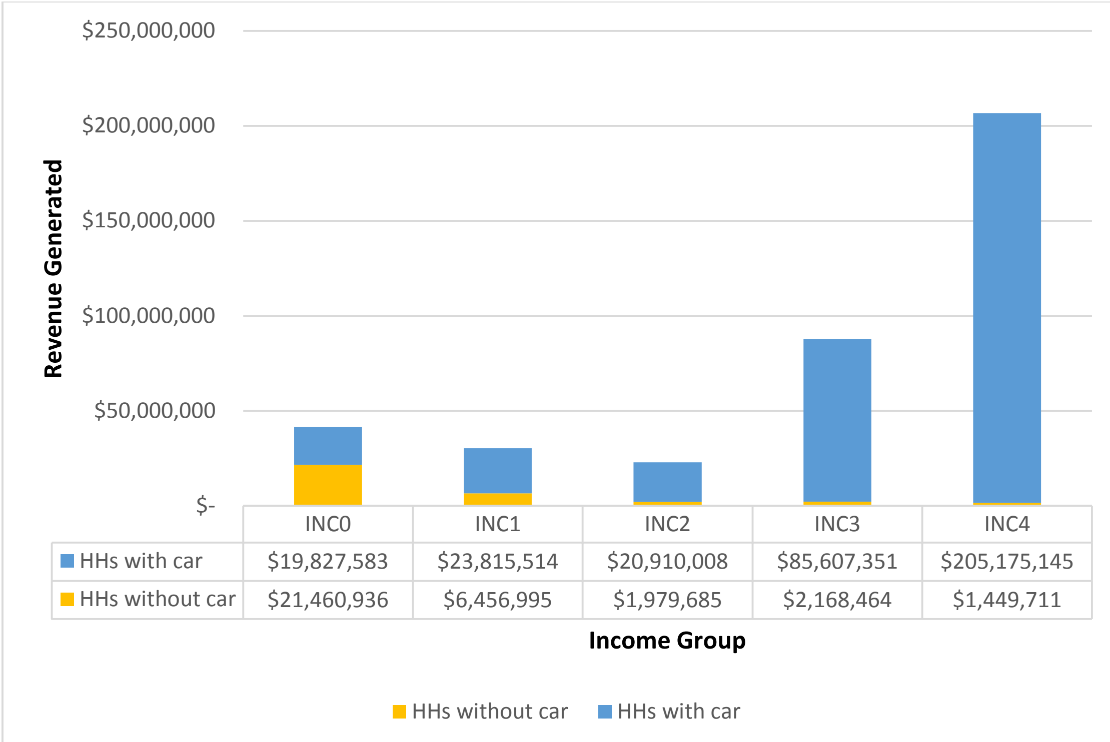


Figure 31 Revenue Generated by Income Group and Vehicle Ownership Status - ***Transportation Dedicated Property Taxes***

Table 42 Annual Revenue Generation by County – ***Transportation Dedicated Property Tax***

County	Num. of Paying HHs	% of HHs Paying Property Tax	Revenue Generation from Transportation Dedicated Property Taxes
Anne Arundel	137,589	65%	$42,775,418
Baltimore City	146,410	55%	$42,913,407
Baltimore County	200,336	62%	$60,896,361
Carroll	41,366	64%	$12,658,082
DC	132,097	44%	$31,553,283
Frederick	55,236	63%	$17,014,264
Harford	59,297	64%	$18,109,154
Howard	75,215	71%	$23,577,048
Montgomery	251,427	69%	$77,415,584
Prince George's	202,048	63%	$61,938,791
Total	**1,301,021**	61%	$388,851,391

Transportation-Dedicated Sales Tax

As a reminder, an increase of 21.5% in the sales tax paid by all users making taxable purchases within the BMC region is implemented. This increase will result in a new sales tax of 7.29%, and will generate comparable revenue to the state fuel taxes raised under the status-quo policy.

<u>Tax Incidence</u>

The tax incidence results for the transportation-dedicated ***sales tax*** have a similar structure to the property tax results. Households in lower income groups experience a higher tax-to-income ratio than their higher income counterparts (1.35% for INC0 vs. 0.31% for INC4). However, as far as the taxpaying population is concerned, the pattern is very interesting: the three income groups that have the highest taxpaying populations are INC4, INC3 and INC1 (649,981, 631,015, and 288,150 respectively).

Table 43 Tax Incidence by Income Group and Vehicle Availability Status - *Transportation-Dedicated Sales Tax*

Income Group	Num. of Paying HHs	% of HHs Paying Sales Tax	Annual Transportation Dedicated Sales Tax Paid (HH level)	Transportation Dedicated Sales Tax -to-Income (HH level)
All HHs				
INC0	288,150	97%	$472	1.3526%
INC1	176,462	86%	$532	0.5088%
INC2	275,559	89%	$465	0.2498%
INC3	631,015	93%	$827	0.2372%
INC4	649,981	96%	$1,426	0.3067%
Total	**2,021,167**			
HHs without vehicle				
INC0	153,727	52%	$471	1.3511%
INC1	38,815	19%	$489	0.4673%
INC2	28,226	9%	$501	0.2695%
INC3	18,591	3%	$767	0.2200%
INC4	5,331	1%	$1,573	0.3381%
Total	**244,690**			
HHs with vehicle				

Income Group	Num. of Paying HHs	% of HHs Paying Sales Tax	Annual Transportation Dedicated Sales Tax Paid (HH level)	Transportation Dedicated Sales Tax - to-Income (HH level)
INC0	134,423	45%	$472	1.3544%
INC1	137,647	67%	$545	0.5205%
INC2	247,333	80%	$461	0.2476%
INC3	612,424	91%	$829	0.2377%
INC4	644,650	95%	$1,425	0.3064%
Total	**1,776,477**			

County-wise, Carroll, Anne Arundel and Baltimore City experience the highest tax-to-income ratios (0.54%, 0.36% and 0.30% respectively), while Frederick, Prince George's and Montgomery county experience the lowest (0.28%). In terms of taxpaying population, Harford, Prince George's and Frederick counties have the highest number of taxpayers, while Baltimore County, Anne Arundel and DC have the lowest.

Table 44 Tax Incidence by County - *Transportation-Dedicated Sales Tax*

County	Num. of Paying HHs	% of HHs Paying Sales Tax	Annual Transportation Dedicated Sales Tax Paid (HH level)	Transportation Dedicated Sales Tax - to-Income (HH level)
Anne Arundel	194,265	93%	$198.72	0.29%
Baltimore City	248,088	93%	$151.76	0.36%
Baltimore County	306,212	92%	$176.11	0.29%
Carroll	59,738	93%	$190.29	0.28%
DC	294,488	96%	$222.31	0.54%
Frederick	82,160	93%	$187.89	0.28%
Harford	86,768	93%	$190.71	0.28%
Howard	100,964	94%	$217.27	0.28%
Montgomery	344,369	93%	$203.68	0.28%
Prince George's	304,115	93%	$188.94	0.30%
Total	**2,021,167**	93%		0.33%

Revenue Potential

The transportation-dedicated sales tax policy exhibits an interesting behavior, as well. Among the 5 income groups, the lowest revenue is generated from INC1, INC2 and INC0 ($55,347, $75,444, $80,086 respectively).

Table 45 Annual Revenue Generation by Income Group and Vehicle Availability Status - ***Transportation-Dedicated Sales Tax***

Income Group	Num. of Paying HHs	% of HHs Paying Sales Tax	Revenue Generation from Transportation Dedicated Sales Taxes
All HHs			
INC0	288,150	97%	$29,231,609
INC1	176,462	86%	$20,201,872
INC2	275,559	89%	$27,537,117
INC3	631,015	93%	$112,246,818
INC4	649,981	96%	$199,318,019
Total	**2,021,167**		$388,535,434
HHs without vehicle			
INC0	153,727	52%	$15,577,155
INC1	38,815	19%	$4,081,026
INC2	28,226	9%	$3,042,921
INC3	18,591	3%	$3,066,872
INC4	5,331	1%	$1,802,417
Total	**244,690**		$27,570,392
HHs with vehicle			
INC0	134,423	45%	$13,654,453
INC1	137,647	67%	$16,120,846
INC2	247,333	80%	$24,494,196
INC3	612,424	91%	$109,179,945
INC4	644,650	95%	$197,515,602
Total	**1,776,477**		$360,965,042

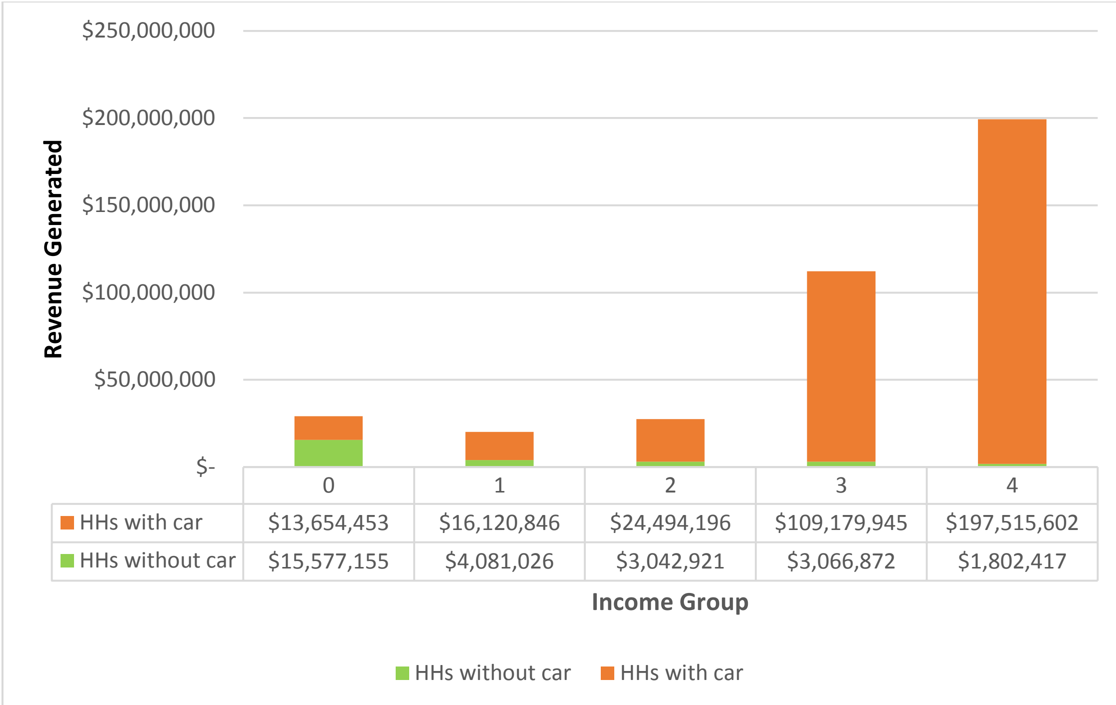


Figure 32 Revenue Generated by Income Group and Vehicle Ownership Status - *Transportation-Dedicated Sales Tax*

County-wise, Montgomery, DC and Prince George's counties generate the highest revenue ($192,165, $179,360, and $157,423 respectively), while Carroll, Frederick and Harford generate the lowest ($31,145, $42,293, $45,336 respectively).

Table 46 Annual Revenue Generation by County - *Transportation-Dedicated Sales Tax*

County	Num. of Paying HHs	% of HHs Paying Sales Tax	Revenue Generation from Transportation Dedicated Sales Taxes
Anne Arundel	194,265	93%	$38,603,740
Baltimore City	248,088	93%	$37,649,710
Baltimore County	306,212	92%	$53,927,111
Carroll	59,738	93%	$11,367,787
DC	294,488	96%	$65,466,228
Frederick	82,160	93%	$15,436,803
Harford	86,768	93%	$16,547,777
Howard	100,964	94%	$21,936,767
Montgomery	344,369	93%	$70,140,088
Prince George's	304,115	93%	$57,459,424

County	Num. of Paying HHs	% of HHs Paying Sales Tax	Revenue Generation from Transportation Dedicated Sales Taxes
Total	**2,021,167**	**93%**	**$388,535,434**

2.6 Implications of Findings

Policy-wise:

- The fuel tax and VMT fee policies result in similar paying patterns: users of lower-income groups experience higher tax-to-income ratios, and this burden decreases progressively as income increases. However, property and sales taxes result in different patterns, which seem to favor the middle income users but put disproportionately bigger burden on the lower income HHs.
- Herein, tax incidence is defined by two metrics that provide complementary information. As expected, the larger the taxpaying population is, the lower is the tax burden that is associated with the policy. Decision makers shall find the analysis results useful in order to understand the magnitude of the effect of a candidate policy and to make an educated decision.
- In terms of revenue generation, all policies (except for the fuel tax increase policy) were designed to generate similar level of revenue as the state tax revenue of the status quo revenue policy (fuel tax per gallon). The fuel tax increase revenue policy appears to be effective in generating additional revenue (approximately $100,000 on a daily basis) without affecting the behavior of travelers or the tax incidence structure of the status quo policy. The revenue analysis shows that alternative policies can be implemented, while the revenue goal can be still met; however, the same level of revenue can be generated from different socioeconomic and geographic groups. This piece of information is

particularly interesting when revenue generation is paired with investment, especially when there is a spatial constraint.

- It is important to consider the vehicle ownership factor in the revenue policies. By design, fuel tax, and VMT fees impose charges on vehicle owners only. Property and sales taxes have a different taxpaying population which consists of payers who do not necessarily own a vehicle (119,647 HHs and 244,690 HHs respectively). This may raise public acceptance issues, unless an effective political point is made in terms of investment of revenues in a local context.

Methodology-wise:

- Activity-based models prove to be successful in modeling the proposed revenue policies that vary by agent. This is very important for policymakers who want to reach specific revenue goals via policies that target or alleviate specific socio-economic and geographic groups.
- The incorporation of fuel efficiency information allows for a more realistic depiction of the travel decisions that users make, along with their implications on revenue generation. The depiction is more realistic in the sense that travelers typically account for their vehicle's fuel consumption prior to their travel decision, most likely in a subconscious fashion.
- The statistical matching performance shows that the distribution of the matching variables in the donor, recipient and synthetic datasets is very good. The good performance of the employed technique can be validated by the almost coinciding distributions of the matching variables in the InSITE dataset and the synthetic dataset. Some discrepancies can be observed in the distributions that are caused by the different

range of values that can be found in each dataset. Additionally, the correlation matrices show a close-to-1 correlation between corresponding variables in the donor, recipient and synthetic datasets. These findings suggest that statistical matching should be considered to be an effective approach to address data availability issues.

Chapter 3. Agency Investment Outlook Analysis

3.1 Background

The surface transportation system has been facing numerous challenges in the last years. For 2013, the ASCE Report Card gave bridges a C+, while transit and roads were given a D [69]. Aging bridges is a concern, as more than 30% of the Nation's bridges exceed the 50-year design life, while almost 25% of the bridges are functionally obsolete or structurally deficient [69]. To understand the funding needs for the bridge system, it is worth noting that $76 billion are needed to repair or replace just the deficient bridges [69]. As far as roads are concerned, 32% of the major roads are in poor or mediocre condition, requiring additional $91 billion annually for capital investments in order to maintain the system at a State of Good Repair. Transit also received a low grade. It is worth noting that only 55% of households have access to transit, which raises issues of transportation equity. Investment-wise, the percentage of newer transit vehicles has increased since 2010 and under the State of Good Repair Initiative, the Federal Transit Administration gave $48 million to 31 transit agencies. However, the number of agencies receiving this funding was significantly lower than the total number of transit agencies in the Nation (approximately 650), and the needs persist.

A high-level analysis of the long-term capital investment needs was prepared by the National Surface Transportation Policy & Revenue Study Commission [70]. Under a high investment scenario, where maximum level of investment of high benefit-cost potential is pursued, the Commission found that transit investment needs in 2035 (compared to a hypothetical 2007 base case scenario where the transit service is already sustainable) would range between $10 and $21 billion. The corresponding numbers for highway are $115 and $182 million.

Based on these figures, it is essential to identify viable investment solutions that can improve the current problematic state of the transportation infrastructure. The focus of Part II is the alternative transportation investment processes that Maryland may adopt in the future, in an effort to redefine the state's purpose, perspective and vision with respect to transportation. The selection of the alternative investment processes was made based on the need to explore how investment scenarios that are inherently different in terms of objective, resource allocation mechanism and project selection mechanism, may change the outcome of the joint ***revenue-investment*** process. The analysis in Part II is an essential extension of Part I in order to link revenue to investment. This connection shall prove useful to policymakers in three directions:

(i) it will illustrate how the transportation investment process can be modified to successfully address a change of transportation vision on behalf of the state,

(ii) it will shed light on the nature of projects that can be funded by each revenue policy, and

(iii) it will showcase how project selection occurs under each investment scenario.

The benefits redistribution of each investment revenue-investment pair are evaluated in Part III.

3.2 Agency Investment Outlooks - Status Quo

The starting point for defining the resource allocation mechanism of each investment outlook will be the current state of practice. Yusufzyanova [71] conducted interviews at the agency level in order to understand the 2 critical processes: the flow-of-funds process, and the use-of-funds process. The hierarchy of and interactions between the different Maryland - Washington DC agencies are illustrated in Figure 33.

The Maryland Department of Transportation (MDOT) consists of the following agencies:

- The State Highway Administration (SHA): is responsible for the planning, design, construction and maintenance of the numbered highways (Interstate and state) in Maryland;
- The Maryland Transit Administration (MTA): is responsible for the public transportation system in Maryland, including the Maryland Rail Commuter (MARC) service among DC, Baltimore, Montgomery and Frederick counties and West Virginia, and the commuter and local busses in the Washington-Baltimore Metropolitan area;
- The Maryland Aviation Administration (MAA): owns and operates Baltimore/Washington International Thurgood Marshall Airport (BWI) and Martin State Airport;
- The Maryland Transportation Authority (MdTA): is responsible for financing, constructing, operating, and maintaining the toll facilities in Maryland [72];
- The Maryland Port Administration (MPA): oversees operations for the Port of Baltimore;
- The Maryland Motor Vehicle Administration (MVA): administers vehicle registration and driver licensing in Maryland.

Each agency has a modal focus; in this dissertation, the focus will be solely on highway and transit. The process behind the funding allocation is illustrated in Figure 33. The state's Transportation Trust Fund (TTF) is first divided among 3 "needs" categories with the following allocation shares: *i.* capital expansion needs (39%), *ii.* maintenance and preservation (42%), and *iii.* other needs, including regional needs (19%). Within each "needs" category, the following allocation scheme occurs:

- For capital expansion needs, SHA receives 52% of the TTF, MTA and WMATA receives 33%, while the remaining 15% is directed towards other modes.

- For maintenance and preservation needs, 14% is allocated to SHA, 52% to MTA and WMATA, while the remaining 34% is directed towards other modes.

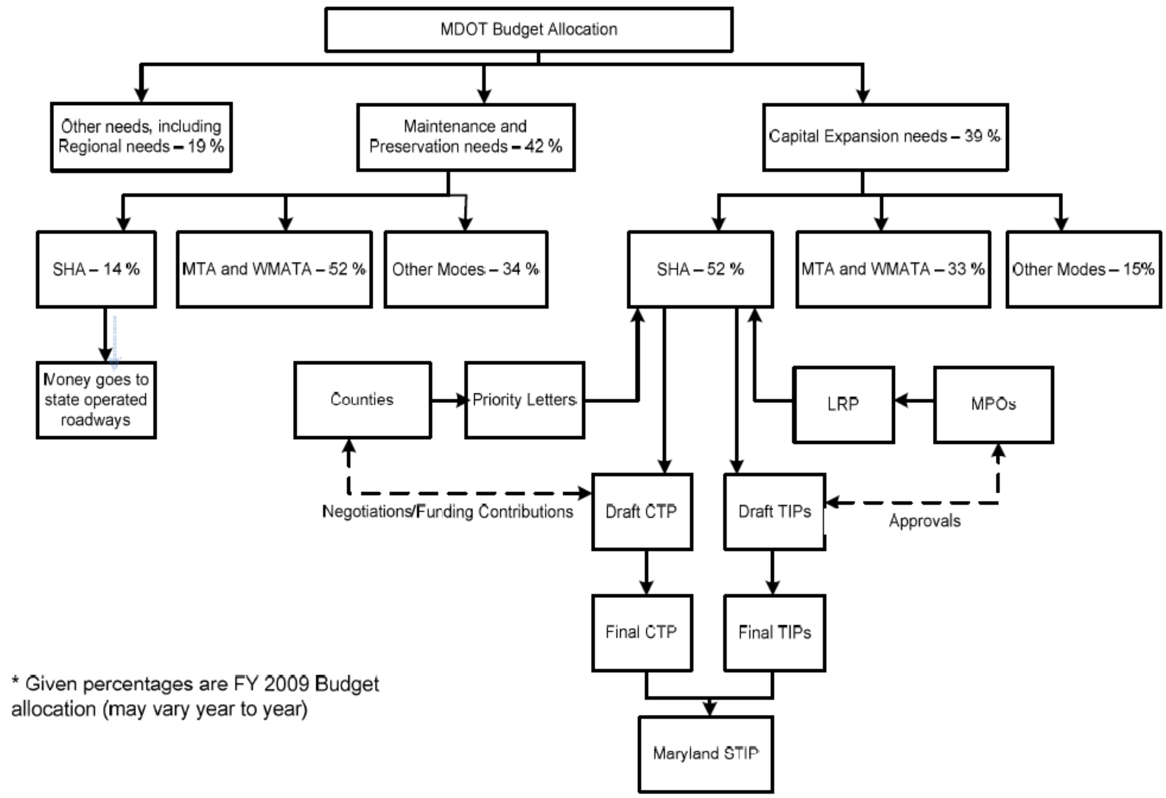


Figure 33 Maryland Statewide Planning Process [71].

The modal focus of this dissertation is highway and transit, therefore this section briefly presents the current SHA and MTA investment processes. For more detailed information, readers are referred to Yusufzyanova [71].

- Within Maryland Transit Administration (MTA), 50% off the MDOT-allocated funds are allotted to operating and maintenance expenditures, including maintenance, preservation, and personnel, while 30% of the funds are directed towards capital improvement expenditures, including construction, equipment, vehicles, fuel, stations. Particularly, for capital improvement projects, 20% of the cost is covered by the state while the remaining

80% is covered by federal grants if project is eligible). For other capital needs such as bus fleet expansion and new local routes, there is no federal matching available and the state covers the entire project cost.

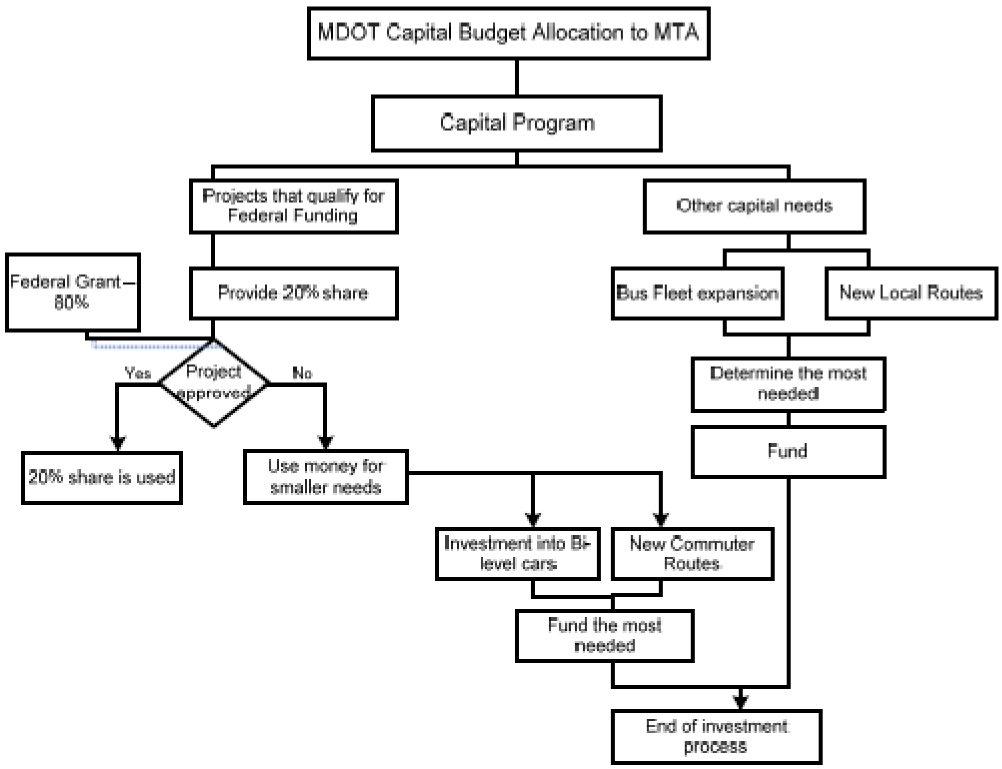


Figure 34 MTA Budget Allocation Process [71].

- Maryland State Highway Administration (MSHA) focuses more on preservation projects as a result of the aging transportation infrastructure. There are no specific shares that MSHA abided by in terms of allocation between capacity and maintenance projects. Investment decisions are guided by the MPO-level Transportation Improvement Programs (TIPs), the statewide Consolidated Transportation Program (CTP), the Highway Needs Inventory (HNI), priority letters and the Fall county tours.

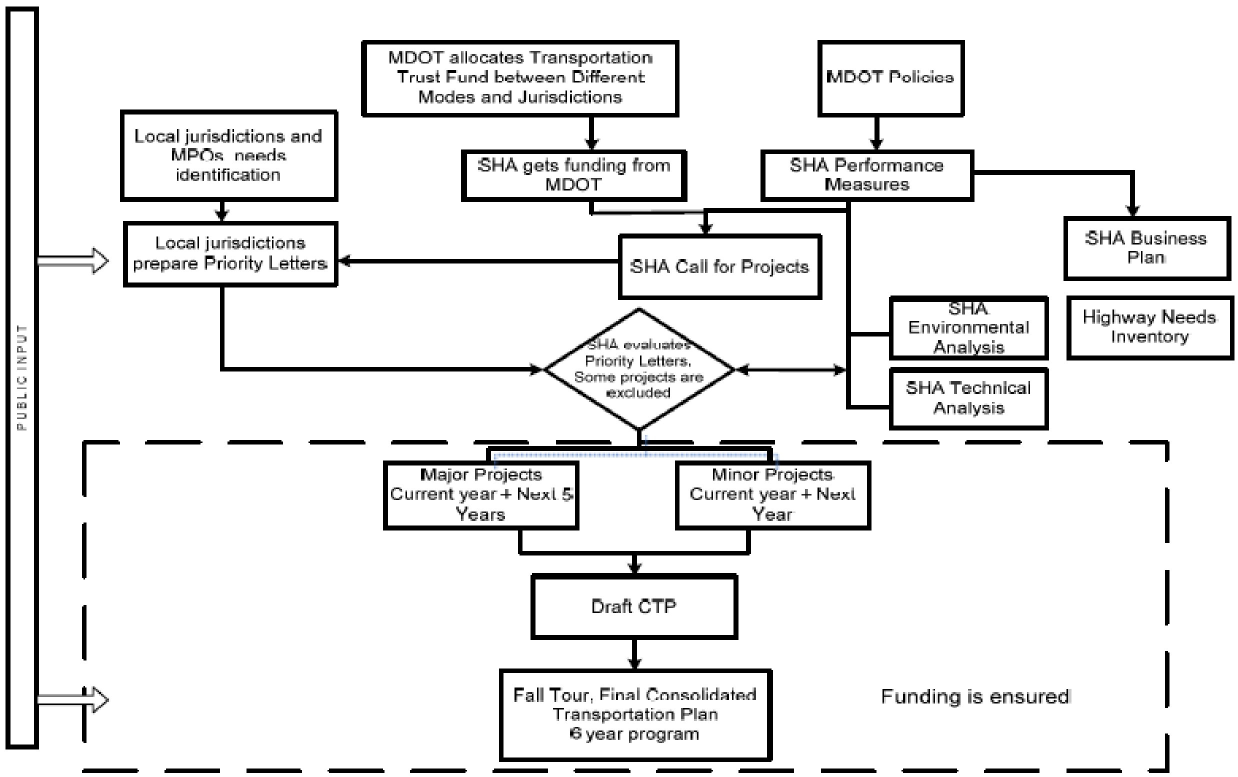


Figure 35 MSHA Investment Process [71].

3.3 Alternative Investment Outlooks

In this part, 3 joint revenue policy-investment outlook dyads are being modeled and evaluated. Each investment outlook is fully defined by its *objective*, the *investment model & cost estimates*, the *revenue generation policy & resource allocation mechanism*, and the *network performance implications.* For all investment outlooks, the following assumptions hold:

- The analysis period is 2012-2035, to estimate the long-term impacts of joint revenue generation and investment decisions;
- Model-wise, each outlook is modeled for 4 cycles, where each cycle represents 6 years;
- Investment occurs annually, at the end of the year and project completion occurs instantaneously (duration = 0);

- Projects are selected from a priority list which depends on the investment outlook priority scheme, and within each year, investment stops when the available budget is exhausted;
- Unused budget does not roll over to the following investment cycle;
- Total population is assumed to be fixed – no population growth is considered for the analysis period.

3.3.1 Proposed 10-Level Integration Framework

The following revenue-investment integration framework is proposed for the analysis period (herein 24 years, i.e. 2012-2035).

Level 1: The integrated revenue-investment evaluation process starts.

Level 2: A joint revenue generation-investment outlook decision is made; herein, one of the proposed dyads is selected.

Level 3: At this step, the program decides whether it will implement the revenue policy – investment outlook combination and continue to Level 4, or if it will terminate the process and skip to Level 10. At this level, the decision is solely based on the analysis year and how it compares with the analysis horizon (herein 4 Iterations).

Level 4: The revenue policy is modeled in InSITE using the original network (if this is the first Iteration of the process) or the updated network from Level 8 (if it is a subsequent Iteration). Upon successful implementation of the revenue policy, the generated revenue by income group and geographic area is estimated at this level.

Level 5: Following the generation of revenue in Level 4, the decision to invest is subject to the available budget, based on the Investment Model and Resource Allocation Mechanism of the implemented investment outlook. If investment can occur (i.e. if the budget and other investment criteria are met), then the program continues to Level 6, otherwise it continues to level 8.

Level 6: At this level, the investment model for the specific investment outlook is implemented, providing all the necessary information to obtain the revised network in Level 7.

Level 7: The revised network is obtained for the current round of investment, and the model returns to Level 5 to identify if the criteria are met to continue with the next round of investment. If yes, then the same process between Levels 5 and 7 is followed; if not, then the latest version of the revised network is fed to Level 8.

Level 8: The revised network is finalized to reflect the new investment, and the transit service data files are processed (if the investment outlook is transit-focused) to reflect any changes in the transit provision as a result of the investment outlook. Both types of files are fed into Level 9.

Level 9: Using the updated network and transit service files, static assignment is run in Cube to obtain the new highway and transit skim matrices for the new network. The new skim matrices, along with the updated network and the transit service files from Level 8, are fed to Level 3.

Level 10: The program reaches Level 10 when the analysis horizon is reached.

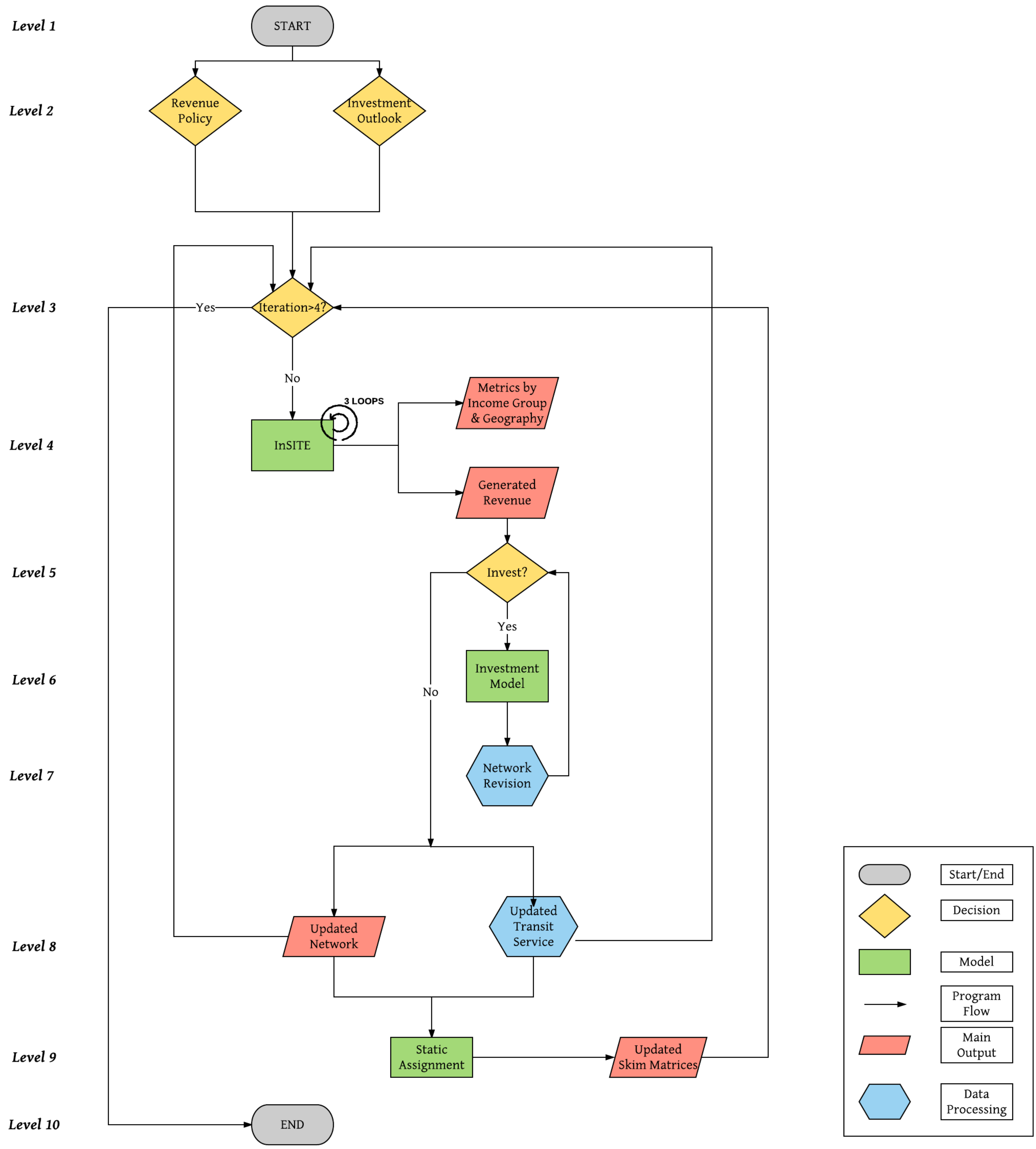


Figure 36 Proposed 10-Level Integration Framework

3.3.2 Bottleneck Removal & Mobility

Objective

The objective of this outlook is to promote mobility and reduce bottlenecks by providing additional capacity along congested roadway facilities.

Investment Model & Cost Estimates

The investment action associated with this investment outlook pertains to the widening of existing roadway facilities that experience congestion. The available revenue is used to remove bottlenecks from the existing network, by widening roadway links that operate near or over capacity, based on the volume-to-capacity ratio. Since the objective of this outlook is to address congestion and improve mobility across the network, only facilities that promote mobility are eligible for investment, as those are presented in Table 48. Such facilities have fewer access points and allow for higher speeds and larger throughputs. In this outlook, highway capacity expansion comes in the form of widening the existing mobility-promoting road facilities in a descending v/c order that is estimated over the entire day.

The cost associated with widening an existing roadway facility varies depending on the type of environment (rural, urban, or mixed), the state, the facility type, etc. Based on the available estimates in the literature, the average cost to widen an existing roadway in an urban environment is considered to be approximately $3,450,000 per lane-mile.

Revenue Generation Model & Resource Allocation Mechanism

The bottleneck removal investment outlook, with the proposed project selection process and resource allocation configuration, resembles the current state of investment practice well. Therefore, combining this investment outlook with a revenue policy whose structure and fee are currently in place is evidently an effective way to model a situation that for all practical purposes is similar to the status quo. Thus, for this scenario, the Maryland-approved ***fuel tax increase*** revenue policy is implemented in conjunction with the ***bottleneck removal & mobility*** investment outlook. Under this revenue policy, users pay $3.62 per gallon for fuel, plus 5.0 and 1.0 cents per mile for maintenance and tires respectively.

Based on the resource allocation mechanism that is currently in place and being used by the Maryland transportation agencies, thirty-nine percent (39%) of the collected state fuel tax revenue is allocated to capital expansion across all modes, while fifty-two percent (52%) of this revenue is allocated to SHA for highway projects. These shares are in effect during all modeling cycles of this revenue policy-investment outlook dyad.

Network Performance Implications

Investment in link widening occurs if there is available budget, and the functional type criterion is met. At the link level, widening results in an additional lane of the same capacity class as of the existing link. New lanes maintain the facility characteristics of the pre-existing lanes. This type of investment is expected to impact the generalized travel cost for both personal vehicle and transit users; these impacts are expected to be captured in the corresponding travel skims. However, induced demand effects may be observed due to the additional capacity availability.

3.3.3 Transit-Oriented & Accessibility

Objective

The objective of this outlook is to promote accessibility via improved transit service provision in a locally-funded context.

Investment Model & Cost Estimates

In this outlook, transit service provision improvement comes in the form of constructing new bus-only lanes. The funds allocated to SHA for highway projects are used to improve accessibility by adding dedicated, bus only-lanes along roadway links that operate near capacity. Only facilities that are currently served by transit are eligible for investment. The average construction cost of a bus-only lane in an urban environment is assumed to be approximately $3,450,000 per lane-mile.

Revenue Generation Model & Resource Allocation Mechanism

The transit-oriented investment outlook focuses on the improvement of transit service provision. However, the proper use of funds for transit has been a highly controversial topic amongst taxpayers, who frequently do not consider the use of tax dollars for transit to be an effective investment decision. It has been found that public is more favorable towards the investment of local option taxes (property or sales taxes) in local transit projects, as the benefits are attained locally. Based on strong local component of this investment outlook, it is proposed that the ***transit-oriented & accessibility*** investment outlook is paired with a transportation-dedicated ***property tax***[2] revenue policy, subject to the constraint that revenue collection and investment are geographically linked (i.e. revenue generated in county *A* can be only invested in projects of county *A*). A 9.4% increase in property taxes is implemented, according to the rationale described in Part I.

Based on the resource allocation mechanism that is currently in place and being used by the Maryland transportation agencies, thirty-nine percent (39%) of the collected revenue is allocated to capital expansion. Fifty-two percent (52%) of this revenue is allocated to SHA for highway

[2] Alternatively, a transportation-dedicated sales tax policy may be implemented in conjunction with the transit-oriented outlook, as such policy also has a fairly strong local component.

projects while thirty-three percent (33%) of this revenue is allocated to MTA and WMATA for transit-related investment. The MTA and WMATA capital expansion funds can be used to improve the existing transit service by adding more frequent service, however this is not in the scope of this outlook.

Network Performance Implications

Investing in dedicated, bus-only lanes is expected to impact the generalized travel cost for both personal vehicle and transit users. New bus lanes maintain the facility characteristics of the conventional lanes but are only open to buses. Along the bus-only lanes, transit users will be experiencing close to free-flow travel times, while users on the conventional lanes will benefit as well from the absence of bus competition. These impacts are expected to be captured in the corresponding travel skims. However, induced demand effects may be observed due to the additional capacity availability.

3.3.4 CAV Implementation & Safety

Objective

This investment outlook scenario aspires to understand the infrastructure-specific challenges that agencies will encounter in their effort to accommodate a future scenario where Connected and Automated Vehicles (CAVs) have a high market share and constitute a significant fraction of the road users. Infrastructure-wise, the main challenge that agencies will face with respect to CAVs will relate to constructing new CAV-enabled lanes (or retrofitting old lanes to accommodate the CAV fleet) versus opting for non-CAV-enabled infrastructure. The objective of this outlook is to use the generated revenue to retrofit the existing infrastructure to accommodate CAV technologies in a bid to promote safety and improve mobility.

Investment Model & Cost Estimates

The available revenue is used to retrofit existing road infrastructure in order to accommodate CAVs. All roadway links in the network are eligible for CAV retrofitting (Table 48), and the CAV-related investment strategies considered in this analysis are Red Light Violation Warning System, Stop Sign Gap Assist, Stop Sign Violation Warning, Smart Intersections, and Clearer Lane Markings. Investment starts by retrofitting the existing road facilities in a descending v/c order, till the available budget is exhausted. Once a link is retrofitted to accommodate CAVs, then the start and end nodes of the links are retrofitted as well, if they are categorized as road intersections in InSITE.

- Red Light Violation Warning System: this technology warns drivers whether their path will result in red light violation, based on their speed and the configuration of the upcoming intersection (i.e. traffic signal timing). The associated cost is estimated at $3,000 per intersection for the hardware, $1,000 per intersection for the installation, and $400 per intersection for the operation and maintenance.
- Stop Sign Gap Assist: this technology helps CAV drivers at a stop sign identify whether there is a sufficient gap to safely make a left turn, right turn, or through movement, based on the ongoing traffic. The associated cost is estimated at $30,000 per intersection for the hardware and installation, and $3,000 per intersection for the annual maintenance.
- Stop Sign Violation Warning: this technology warns drivers whether their path will result in stop sign violation, based on their speed and the configuration of the upcoming intersection (i.e. STOP sign). The associated cost is estimated at $3,000 per intersection for the hardware, $1,000 per intersection for the installation, and $400 per intersection for the operation and maintenance.

- Clearer Lane Markings: clear lane markings are essential for CAVs in order to successfully perceive the road infrastructure and the surrounding environment. It is assumed that maintaining clear lane markings is a key investment strategy, especially during the initial CAV deployment phase, when other advanced technologies may not necessarily be available (e.g. advanced in-vehicle GPS systems that will allow precise location identification, based on high-accuracy maps). In this context, proper maintenance of the lane markings is essential, especially in order to overcome weather-related limitations. The associated cost are as follows:
    - Two-lane highways with AADT<10,000: $1,219 per mile
    - Multilane highways with AADT<10,000: $2,483 per mile
    - Two-lane highways with AADT>10,000: $1,828 per mile
    - Multilane highways with AADT>10,000: $3,724 per mile
- Smart Intersections:
    - Installation: $5,000 per module (one per intersection)
    - Equipment: $5000 per module
    - Operation & Maintenance: $500 per module

  All cost information has been obtained from [73].

Revenue Generation Model & Resource Allocation Mechanism

The investment outlook that focuses on the implementation of CAVs aims to improve safety and promote the efficient use of the infrastructure by increasing existing highway capacity via reduced headways between following vehicles. The focus of this investment outlook on efficiency can be substantially supported by a revenue policy that links driving cost to usage in a proportional fashion. Following this rationale, the ***CAV implementation & safety*** investment outlook is evaluated in conjunction with a ***variable VMT fee*** revenue policy[3]. Such a policy links cost to usage in a proportional fashion, while it also places less burden on lower-income users as a result of its variable-rate structure. In this outlook, users in INC4 have the highest operating cost at $0.22755 per mile, while a 5% decrease is implemented for each subsequent income group (income groups listed from highest to lowest income). For more information, please refer to Section 2.2.

In terms of resource allocation, since this investment outlook explores the feasibility of improving mobility and safety via CAV-enabled infrastructure versus conventional capacity expansion (e.g. road widening, new road construction, etc.), it is assumed that a similar percentage is available to the agencies to pursue CAV-related investment. Therefore, thirty-nine percent (39%) of the collected revenue is allocated to CAV-related infrastructure investment, and these funds will also cover the maintenance of the CAV-related investment, i.e. operations and maintenance of the intersections and remarking of the retrofitted facilities on an annual basis.

Network Performance Implications

Link and intersection retrofitting occurs as long as there is available budget. At the link level, retrofitting to allow for CAV technologies results in improved capacity that is subject to the CAV fleet market share on the network. Intersection retrofitting is expected to improve safety and throughput, however such effects cannot be captured by the current model (due to its macroscopic nature). Predicting the future CAV market share is a challenging task; based on the limited available literature on this topic, the assumptions for market penetration and capacity improvement are as follows:

[3] Alternatively, a flat-rate VMT fee policy may be also implemented in conjunction with the CAV Implementation outlook if the progressivity/regressivity of the revenue policy is not of immediate concern to the policymakers.

Table 47 Future CAV Market Share and Associated Capacity Improvement ([73], [74], [75])

Year	Market Share	Capacity Improvement
2017	5%	8%
2023	10%	16%
2029	15%	24%
2035	20%	32%
2041	25%	40%

This type of investment is expected to impact the generalized travel cost for both personal vehicle and transit users, and these impacts are expected to be captured in the corresponding travel skims.

Table 48 Eligibility of Functional Classes by Investment Outlook

Code	Functional Type	Number of Links	% of Total Links	A	B[4]	C
1	Interstate	1204	3.01%	✓	✓	✓
2	Freeway	753	1.88%	✓	✓	✓
3	Primary Arterial	7645	19.12%	✓	✓	✓
4	Minor Arterial	9212	23.04%	✓	✓	✓
5	Collector	7380	18.46%		✓	✓
6	Interstate High Speed Ramp	185	0.46%	✓	✓	✓
7	Interstate Medium Speed Ramp	548	1.37%	✓	✓	✓
8	Interstate Low Speed Ramp	270	0.68%	✓	✓	✓
9	Freeway Medium Speed Ramp	350	0.88%	✓	✓	✓
10	Freeway Low Speed Ramp	310	0.78%	✓	✓	✓
11	Centroid Connector	11103	27.77%			
12	B-W Parkway & I-895	190	0.48%	✓	✓	✓
13	Drive Access to Transit Connectors	446	1.12%		✓	
14	Business Routes	48	0.12%		✓	✓
34	Light Rail	74	0.19%			
35	METRO	162	0.41%			
36	MARC	106	0.27%			

[4] All roadway links, despite their functional class, are eligible. However, investment occurs only along the links that are already served by transit.

3.4 Network Description

The characteristics of the current transportation network are provided in Table 49 - Table 51. Table 52 and Figure 37 describe the transit provision in the base case. This information about the network will prove useful in order to identify the candidate project list for each revenue – investment dyad.

Table 49 Number of Links by Functional Class

Code	Functional Type	Number of Links
1	Interstate	1,204
2	Freeway	753
3	Primary Arterial	7,645
4	Minor Arterial	9,212
5	Collector	7,380
6	Interstate High Speed Ramp	185
7	Interstate Medium Speed Ramp	548
8	Interstate Low Speed Ramp	270
9	Freeway Medium Speed Ramp	350
10	Freeway Low Speed Ramp	310
11	Centroid Connector	11,103
12	B-W Parkway & I-895	190
13	Drive Access to Transit Connectors	446
14	Business Routes	48
34	Light Rail	74
35	METRO	162
36	MARC	106

Table 50 Number of Links by Jurisdiction

Jurisdiction	Number of Links
Baltimore City	5,879
Anne Arundel County	3,674
Baltimore County	6,260
Carroll County	1,534
Harford County	2,080
Howard County	2,535
District of Columbia	6,065
Montgomery County	4,570

Jurisdiction	Number of Links
Prince Georges County	5,982
Frederick County	1,324
External Stations	83
Grand Total	**40,009**

Table 51 Network Categorization by Functional Type and Jurisdiction (miles)

	Interstate	Freeway	Primary Arterial	Minor Arterial	Collector	Interstate Ramps	Freeway Ramps	Light Rail	METRO	MARC
Baltimore City	36.1	9.1	293.3	301.3	62.8	33.5	11.2	21.2	16.9	27.3
Anne Arundel	67.3	90.5	220.2	341.6	279.2	55.7	38.8	12.6		39.2
Baltimore	171.3	34.0	317.1	593.2	651.0	83.8	18.1	23.9	12.2	37.3
Carroll	3.3		156.9	191.7	444.0	1.0	2.3			
Harford	36.2	0.6	142.0	239.7	346.3	10.1	5.6			37.4
Howard	62.0	58.0	113.4	212.2	303.7	26.7	41.2			17.0
DC	22.3	24.0	166.1	288.3	235.7	4.0	9.8		67.2	26.1
Montgomery	145.5	15.9	384.0	564.7	400.4	37.8	4.6		36.7	54.4
Prince Georges	108.2	51.0	376.5	368.3	609.6	46.1	25.6		38.7	55.1
Frederick	78.9	94.7	126.2	328.7	369.9	16.0	4.5			52.6

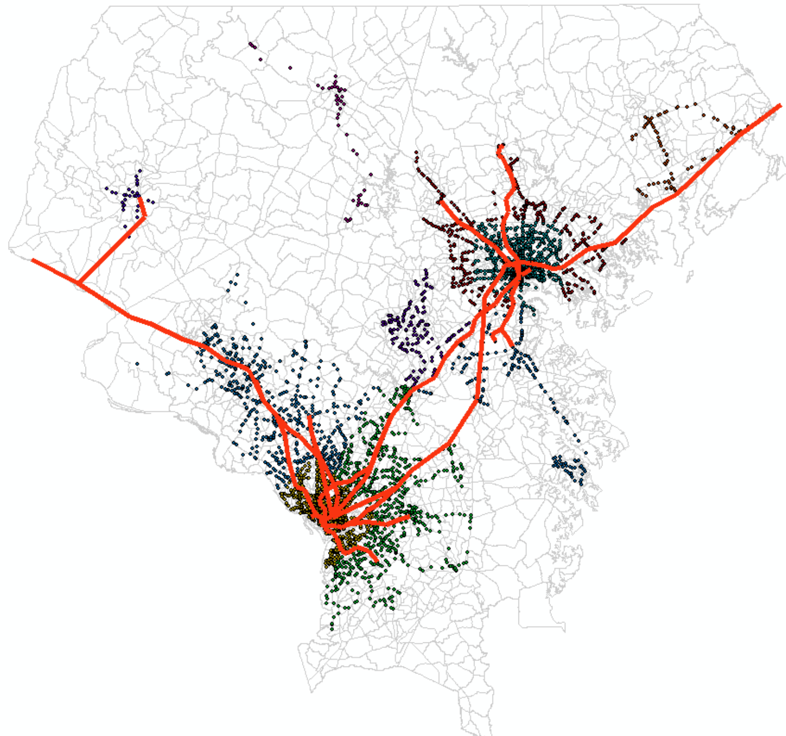


Figure 37 Transit Provision by County.

Table 52 Number of Transit Stops by County

Jurisdiction	Number of Transit Stops
DC	1808
Anne Arundel	179
Baltimore County	388
Carroll	48
Harford	83
Howard	164
Frederick	29
Montgomery	593
Prince George’s	737
Baltimore City	849

3.5 Integrated Model Configuration

The integrated model is run for 4 iterations, to capture the long-term effects of a joint revenue generation-investment policy scheme. Prior to investment, the activity-based model is run for 3 full feedback loops, with a previous iteration weight of 0.5 and a 10% convergence link volume error threshold. At convergence, the allowable percentage of links exceeding link volume is set at 1%. The relative average absolute volume difference based upon successive iterations is set to 0.0001, the gap for each iteration is equal to 0.000001, the relative gap is 0.0001, and the average absolute volume difference is 0.01. The method to combine the results of iteration volumes is equilibrium assignment, where a lambda (λ) is computed for each iteration to be applied to obtain the factor to combine the volume (V) of the current iteration with the previous combined volume (CVOL):

$$V = V * \lambda + CVOL * (1 - \lambda)$$

This method is an implementation of the Frank-Wolfe algorithm.

In Outlook A (Bottleneck Removal), the revenue generated is based on a $3.62 per gallon fuel cost. Users driving vehicles of different fuel efficiency experience different travel costs. In Outlook B, the operating cost is implemented on a per mile basis as a flat-rate mileage-based user fee at $0.22755 per mile. Travel behavior is affected by said operating cost; however, the available revenue to be used for investment comes from a transportation-dedicated property tax (9.4% increase). In Outlook C, the operating cost is implemented on a per mile basis as a variable-rate mileage-based user fee, at $0.22755 per mile for INC4 and a 5% decrease for the subsequent groups.

The revenue that is available at each investment cycle is estimated based on the state fuel tax (or state fuel tax equivalent, i.e. transportation-dedicated property tax in Outlook B) revenues generated at each 6-year iteration, assuming that said revenues constitute approximately 22% of the total funds available at the state level to pursue transportation projects [76]. For Outlooks A and C, there are no spatial limitations with respect to spending; however, for Outlook B, the transportation-dedicated property taxes that are collected within county A can only be invested locally within the same county.

In terms of investment eligibility, for Outlook A (Bottleneck Removal), from the 39,816 links of the original network, widening may be pursued for the following links: interstates, freeways, primary arterials, minor arterials, interstate ramps (high, medium, and low speed), freeway ramps (medium and low speed), B-W Parkway and I-895. In Outlook B, bus-only lanes may be constructed adjacent to existing links that already have transit service and operate near capacity. Since the transit network is not comprehensively defined via a set of links and nodes similar to the highway network, the transit network was extracted from the list of transit routes that are running through the system, using the information on transit stops and transit routes. Since investment occurs only on links served by bus, only the following lines were revised to reflect the use of the bus-only network:

- Maryland Transit Administration-Bus
- Howard Transit
- Harford County Transit Services
- Annapolis Transit
- Carroll Transit
- WMATA Metro Bus

- BWI-MARC Shuttle
- Baltimore City DoT
- Montgomery County RideOn
- Prince George's County The Bus
- Frederick County TransIT
- DC Circulator

For modeling purposes, the bus only lanes are introduced to the network as new links, parallel to the corresponding conventional lanes, with start (-A) and end (-B) nodes that have slightly different coordinates than the original start (A) and end (B) nodes. The bus-only lane (-A-B) is connected to the existing network through 2 new, artificial links of minimal distance (A-A and -BB). The new nodes are used to redirect the buses from the conventional to the bus-only lanes, and do not serve as bus stops, hence the (-) sign in the node ID.

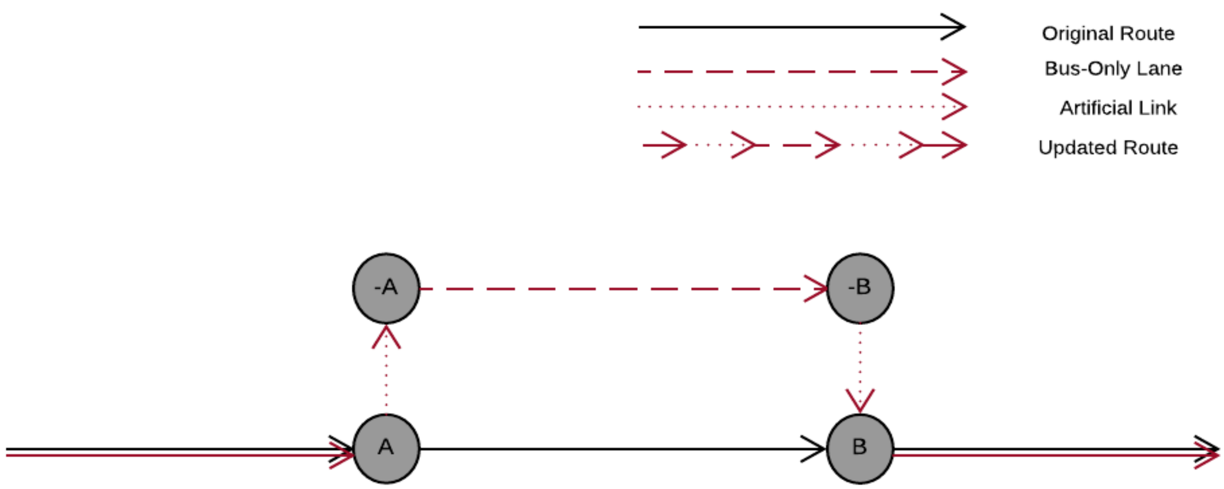


Figure 38 Network Revision for Bus-Only Lanes.

All other characteristics of the transit lines are maintained (i.e. direction, fare, stops, headway, and dwell time). In Outlook C, from the 39,816 links of the original network, retrofitting may be pursued for links of the following functional types: interstates, freeways, primary arterials, minor arterials, collectors, interstate ramps (high, medium, and low speed), freeway ramps (medium and low speed), business routes, and B-W Parkway & I-895. At the node level, nodes of road intersection (RI) type are eligible to be retrofitted to accommodate CAV technologies.

Changes in capacity are captured differently for each Outlook. For Outlook A, investment in additional lanes affects (i.e. increases) the total number of AM, PM, and off-peak lanes of the link in the revised network. The link maintains its capacity classification and InSITE dynamically estimates the capacity of the link during the model run based on its capacity classification and number of lanes. In Outlook C, the new capacity of the link is estimated internally based on the current capacity of the link (which is not directly available/reported, but is intermediately estimated through the assignment scripts based on the capacity classification and number of lanes of the link) multiplied by the expected increase in capacity associated with the assumed CAV market share. In Outlook B, any new bus-only lane that is constructed maintains the characteristics of the corresponding conventional lanes between the same pair of nodes.

In terms of initial-cycle versus subsequent-cycle investment, the investment decisions are modeled differently for each outlook. For Outlook A, previous investment does not prevent subsequent investment along the same link, if the investment criterion is met. However, for Outlook B, during each subsequent investment cycle, new bus-only lanes can only be added along links that do not already have a bus-only lane. For Outlook C, initial investment along a link requires maintenance of the link during the subsequent investment cycles, while a retrofitted intersection cannot be re-retrofitted during the next cycle, but should be maintained.

3.6 Analysis Results

This section summarizes the details of the investment cycle for each revenue policy-investment outlook dyad, in terms of the actual investment decisions as well as the impacts of the investment on the network performance.

3.6.1 Outlook A: Bottleneck Removal

Overall, approximately $5B were invested in the network, resulting in the widening of 1,440 miles. The investment resulted in an observable improvement in the v/c ratio, as this is presented in Figure 39 and Figure 108. Additionally, Figure 109 shows that the total volume at the end of the 4 iterations increased for most of the links (distance-weighted average increase in volume: 2.76%), while Table 55 presents the changes in v/c and volume by functional type.

Table 53 Investment Summary per Investment Cycle – Outlook A

	Investment Cycle 1	Investment Cycle 2	Investment Cycle 3
Available Revenue ($)	1,610,279,412.89	1,629,169,039.96	1,730,433,154.75
Unused Funds ($)	8,127.89	5,692.96	4,614.25
Number of Links Widened	1,608	1,462	1,587
Total Length Widened (mi)	466.75	472.22	501.57

Table 54 V/C Frequency per Model Iteration – Outlook A

	ITER1	ITER2	ITER3	ITER4
Bin	***Frequency***	***Frequency***	***Frequency***	***Frequency***
0.1	12,967	13,007	12,884	12,927
0.2	3,967	4,703	4,485	4,832
0.3	6,888	8,280	8,141	8,817
0.4	7,454	8,029	8,520	8,216
0.5	5,343	3,669	3,631	3,265
0.6	1,810	1,048	1,180	863
0.7	576	439	333	319
0.8	240	137	180	152
0.9	89	66	76	62
1	47	32	30	15
>1	92	61	11	3

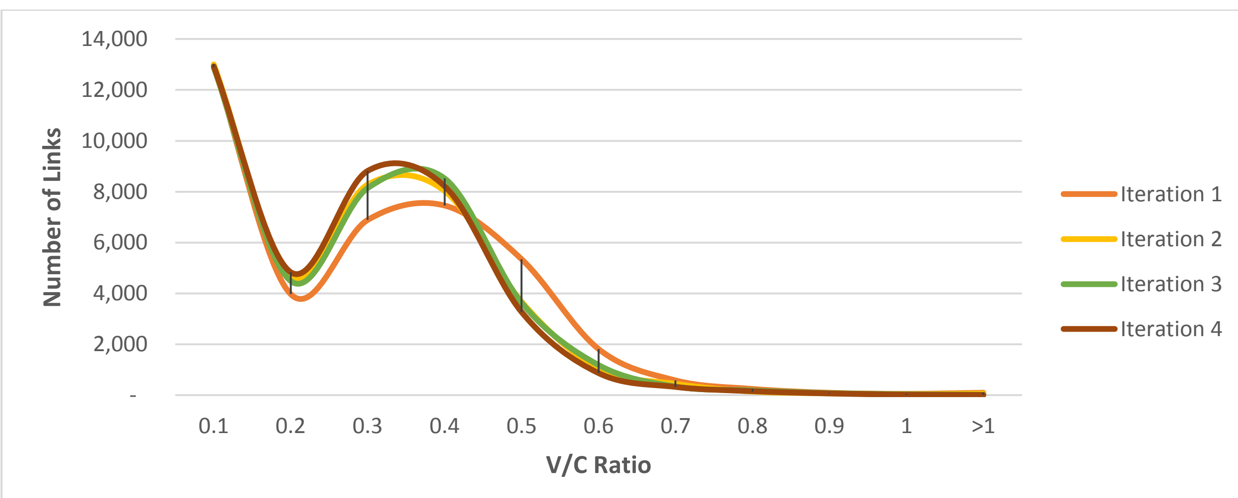


Figure 39 V/C Frequency per Model Iteration – Outlook A

Table 55 Percent Change in V/C and Volume by Functional Type – Outlook A

FT	Δ(V/C)	FT	Δ(VOL24)
Interstate	-18.04%	Interstate	13.49%
Freeway	-9.64%	Freeway	3.66%
Primary Arterial	-9.45%	Primary Arterial	3.51%
Minor Arterial	-7.07%	Minor Arterial	1.35%
Collector	-6.79%	Collector	-1.61%
Interstate High Speed Ramp	74.43%	Interstate High Speed Ramp	76.25%
Interstate Medium Speed Ramp	73.56%	Interstate Medium Speed Ramp	60.82%
Interstate Low Speed Ramp	22.11%	Interstate Low Speed Ramp	22.67%
Freeway Medium Speed Ramp	17.35%	Freeway Medium Speed Ramp	17.36%
Freeway Low Speed Ramp	11.02%	Freeway Low Speed Ramp	12.62%
Centroid Connector	2.66%	Centroid Connector	6.19%
B-W Parkway & I-895	-13.66%	B-W Parkway & I-895	2.29%
Drive Access to Transit Connectors	45.73%	Drive Access to Transit Connectors	50.79%
Business Routes	8.33%	Business Routes	12.26%
Avg. Δ(V/C)	**-3.05%**	**Avg. Δ(VOL24)**	**4.59%**
W. Avg. Δ(V/C)	**-3.70%**	**W. Avg. Δ(VOL24)**	**2.76%**

3.6.2 Outlook B: Transit-Oriented

Overall, approximately $6B were invested in the network, resulting in the widening of 1,306 miles of bus-only lanes. The investment did not result in any significant improvement in the v/c ratio, as this is presented in Figure 41 and Figure 112. Additionally, Figure 110 shows that the total volume at the end of the 4 iterations decreased by 1.44%, while Table 57 presents the changes in v/c and volume by functional type.

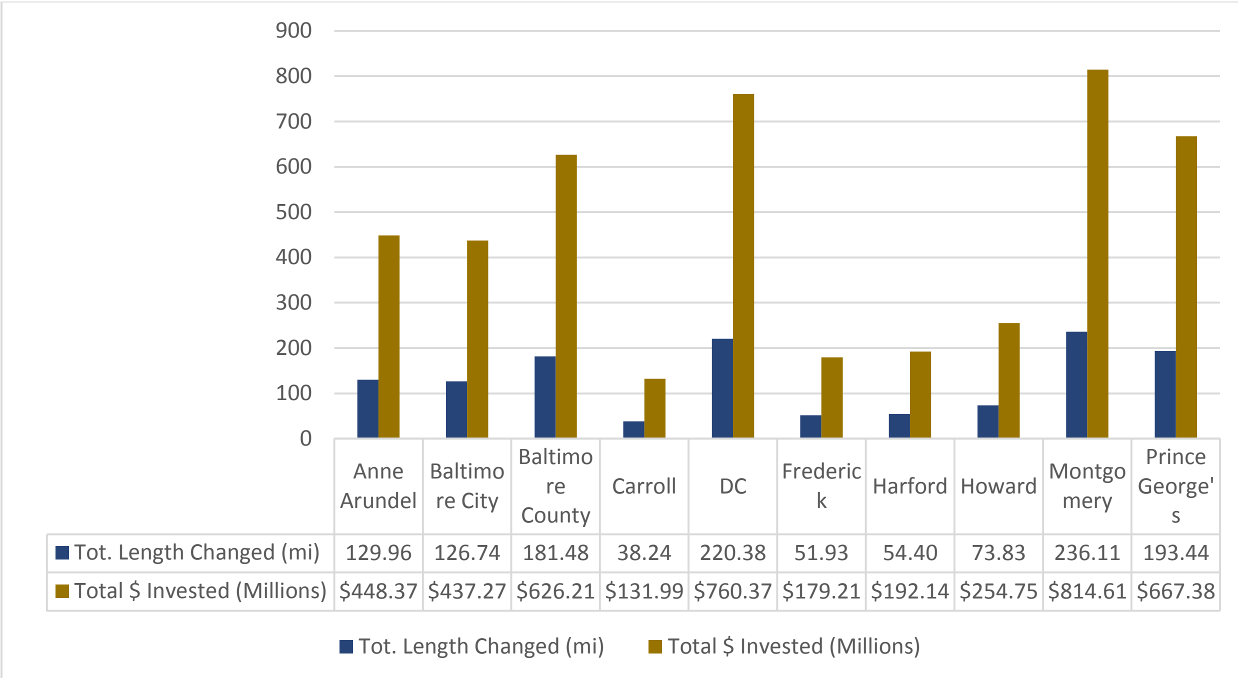


Figure 40 Investment Summary per Investment Cycle – Outlook B

Table 56 V/C Frequency per Model Iteration – Outlook B

	ITER1	**ITER2**	**ITER3**	**ITER4**
Bin	***Frequency***	***Frequency***	***Frequency***	***Frequency***
0.1	13,589	13,298	13,220	12,926
0.2	4,835	4,035	4,096	4,178
0.3	8,205	7,384	7,612	7,610
0.4	8,241	8,281	8,435	8,379
0.5	3,512	4,600	4,409	4,379
0.6	904	1,372	1,274	1,243
0.7	280	436	407	406
0.8	116	189	166	164
0.9	48	89	79	72
1	26	46	39	39
>1	59	85	78	77

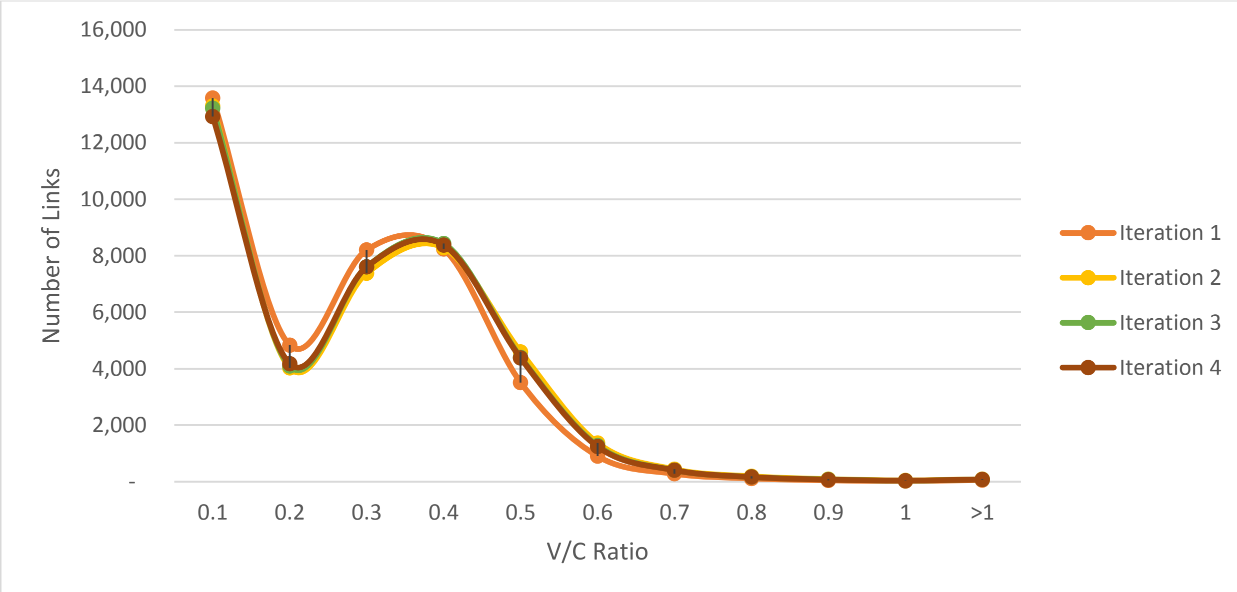


Figure 41 V/C Frequency per Model Iteration – Outlook B

Table 57 Percent Change in V/C and Volume by Functional Type – Outlook B

FT	Δ(v/c)	FT	Δ(VOL24)
Interstate	0.5%	Interstate	0.27%
Freeway	-0.6%	Freeway	-0.68%
Primary Arterial	-1.2%	Primary Arterial	-1.37%
Minor Arterial	-1.5%	Minor Arterial	-1.88%
Collector	-0.4%	Collector	-0.79%
Interstate High Speed Ramp	4.9%	Interstate High Speed Ramp	3.27%
Interstate Medium Speed Ramp	11.3%	Interstate Medium Speed Ramp	9.25%
Interstate Low Speed Ramp	10.0%	Interstate Low Speed Ramp	8.88%
Freeway Medium Speed Ramp	8.6%	Freeway Medium Speed Ramp	8.73%
Freeway Low Speed Ramp	13.5%	Freeway Low Speed Ramp	10.04%
Centroid Connector	-1.7%	Centroid Connector	-2.87%
B-W Parkway & I-895	0.2%	B-W Parkway & I-895	0.17%
Drive Access to Transit Connectors	-1.3%	Drive Access to Transit Connectors	-0.05%
Business Routes	0.4%	Business Routes	-0.60%
Avg. Δ(V/C)	**-0.70%**	**Avg. Δ(VOL24)**	**-1.30%**
W. Avg. Δ(V/C)	**-0.52%**	**W. Avg. Δ(VOL24)**	**-1.44%**

3.6.3 Outlook C: CAV Implementation

Overall, less than $1B were invested in the network, resulting in the retrofitting of 7,400 miles. The investment resulted in an observable improvement in the v/c ratio, as this is presented in Figure 42 and **Error! Reference source not found.**. Additionally, **Error! Reference source not found.** shows that the total volume at the end of the 4 iterations increased for most of the links (distance-weighted average increase in volume: 4.47%), while Table 60 presents the changes in v/c and volume by functional type.

Table 58 Investment Summary per Investment Cycle – Outlook C

Investment Summary	**After Inv. 1**	**After Inv. 2**	**After Inv. 3**
Available Revenue ($)	1,537,644,054	1,668,055,680	1,788,701,508
Unused Funds ($)	1,270,455,589	1,312,783,615	1,433,429,443
Number of links Retrofitted	20720	20720	20720

Total Length Retrofitted (mi)	7407.01	7407.01	7407.01
Number of Intersections Retrofitted	6673	6673	6673

Table 59 V/C Frequency per Model Iteration – Outlook C

	ITER1	**ITER2**	**ITER3**	**ITER4**
Bin	*Frequency*	*Frequency*	*Frequency*	*Frequency*
0.1	12,820	12,955	12,888	13,316
0.2	3,640	4,338	4,783	7,479
0.3	6,476	7,917	8,982	11,018
0.4	7,518	8,151	8,214	5,239
0.5	5,722	4,225	3,165	1,632
0.6	2,103	1,138	846	473
0.7	628	414	310	156
0.8	292	153	121	69
0.9	109	69	74	45
1	61	36	24	17
>1	104	77	66	29

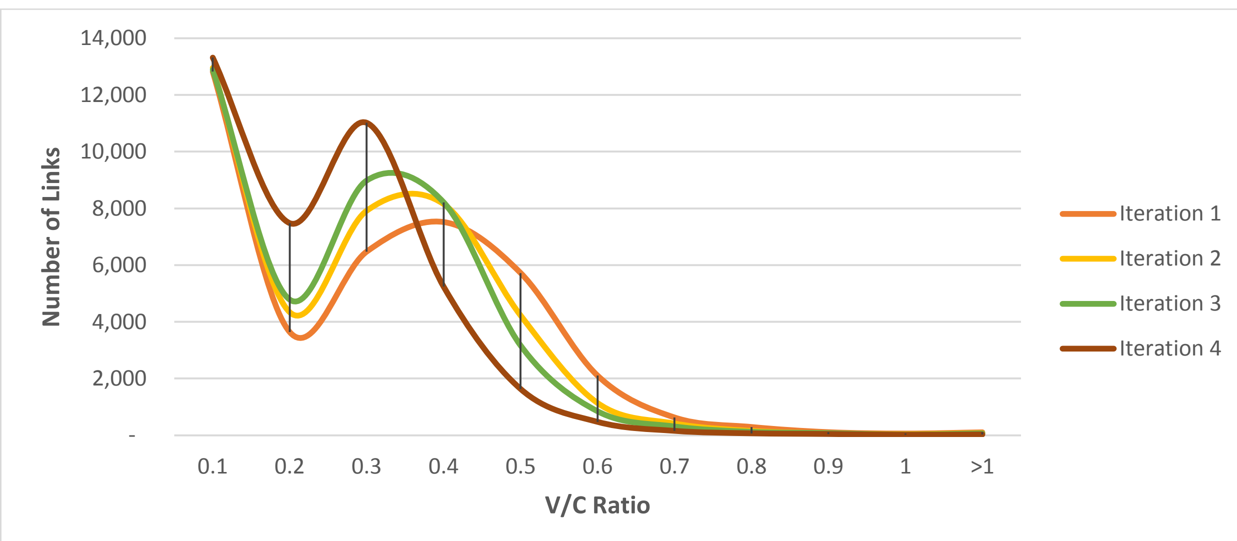


Figure 42 V/C Frequency per Model Iteration – Outlook C

Table 60 Percent Change in V/C and Volume by Functional Type – Outlook C

FT	Δ(v/c)	FT	Δ(VOL24)
Interstate	-37.10%	Interstate	1.88%
Freeway	-36.58%	Freeway	2.82%
Primary Arterial	-34.93%	Primary Arterial	7.13%
Minor Arterial	-34.28%	Minor Arterial	6.05%
Collector	3.12%	Collector	6.30%
Interstate High Speed Ramp	-1.70%	Interstate High Speed Ramp	2.69%
Interstate Medium Speed Ramp	-1.96%	Interstate Medium Speed Ramp	1.80%
Interstate Low Speed Ramp	1.41%	Interstate Low Speed Ramp	5.03%
Freeway Medium Speed Ramp	16.14%	Freeway Medium Speed Ramp	19.72%
Freeway Low Speed Ramp	0.86%	Freeway Low Speed Ramp	4.70%
Centroid Connector	-0.08%	Centroid Connector	3.93%
B-W Parkway & I-895	-36.77%	B-W Parkway & I-895	2.77%
Drive Access to Transit Connectors	1.85%	Drive Access to Transit Connectors	5.14%
Business Routes	47.43%	Business Routes	50.83%
Avg. Δ(V/C)	**-16.16%**	**Avg. Δ(VOL24)**	**5.59%**
W. Avg. Δ(V/C)	**-13.54%**	**W. Avg. Δ(VOL24)**	**4.47%**

3.6.4 Outlook Comparison

It is valuable to compare the three investment outlooks with each other, in order to draw useful conclusions regarding the level of investment and the associated improvement in the network. The largest network-wide v/c improvement is observed in the CAV scenario (13.54%) with only a fraction of cost compared to the other two scenarios. The high v/c improvement of outlook C can be attributed to the fairly lower change in volume both at the modified lanes and across the entire network (approximately 4.4% for both cases). However, the corresponding values for Outlook A are significantly different. A $5B investment resulted in only 3.70% improvement in network wide v/c which can be attributed to a significantly larger volume increase (12.94% in the modified lanes, and 2.76% across the network). Outlook B also yields some interesting results: the cost is comparable to Outlook A, since this investment outlook also requires the construction of physical infrastructure (bus-only lanes). The v/c ratio is only slightly improved since the non-transit volumes do not significantly decrease.

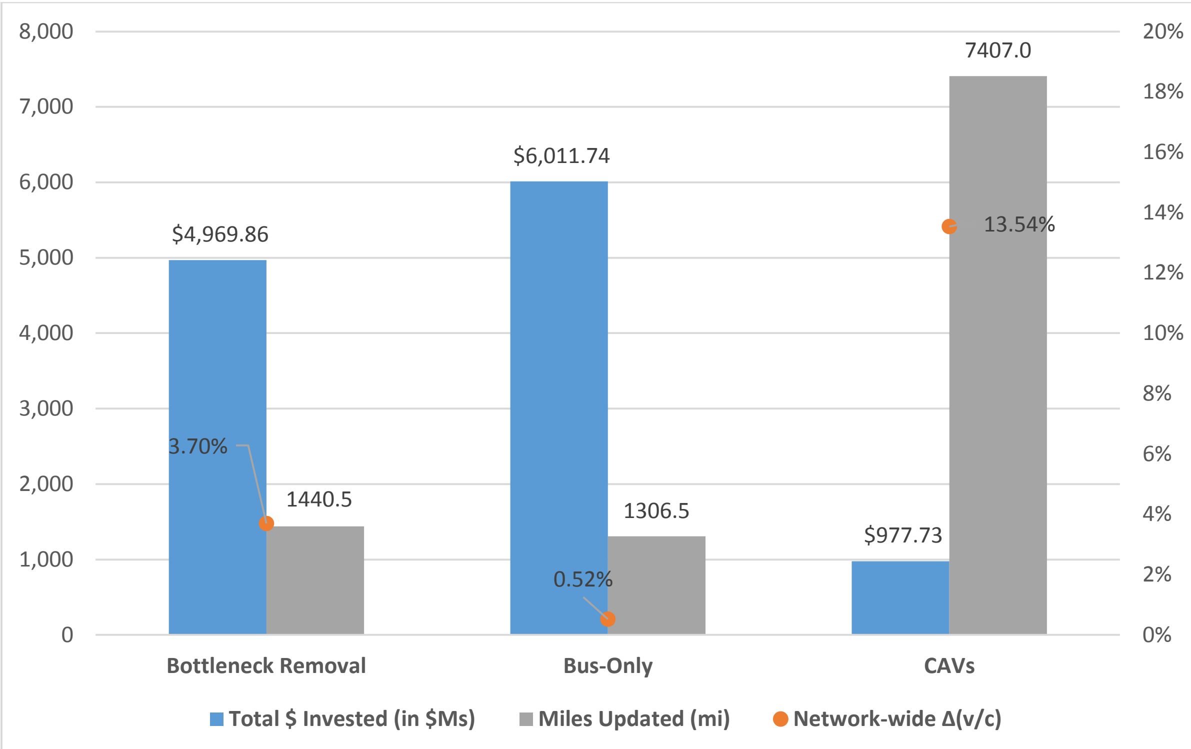


Figure 43 Investment Outlook Comparison (Year 2035)

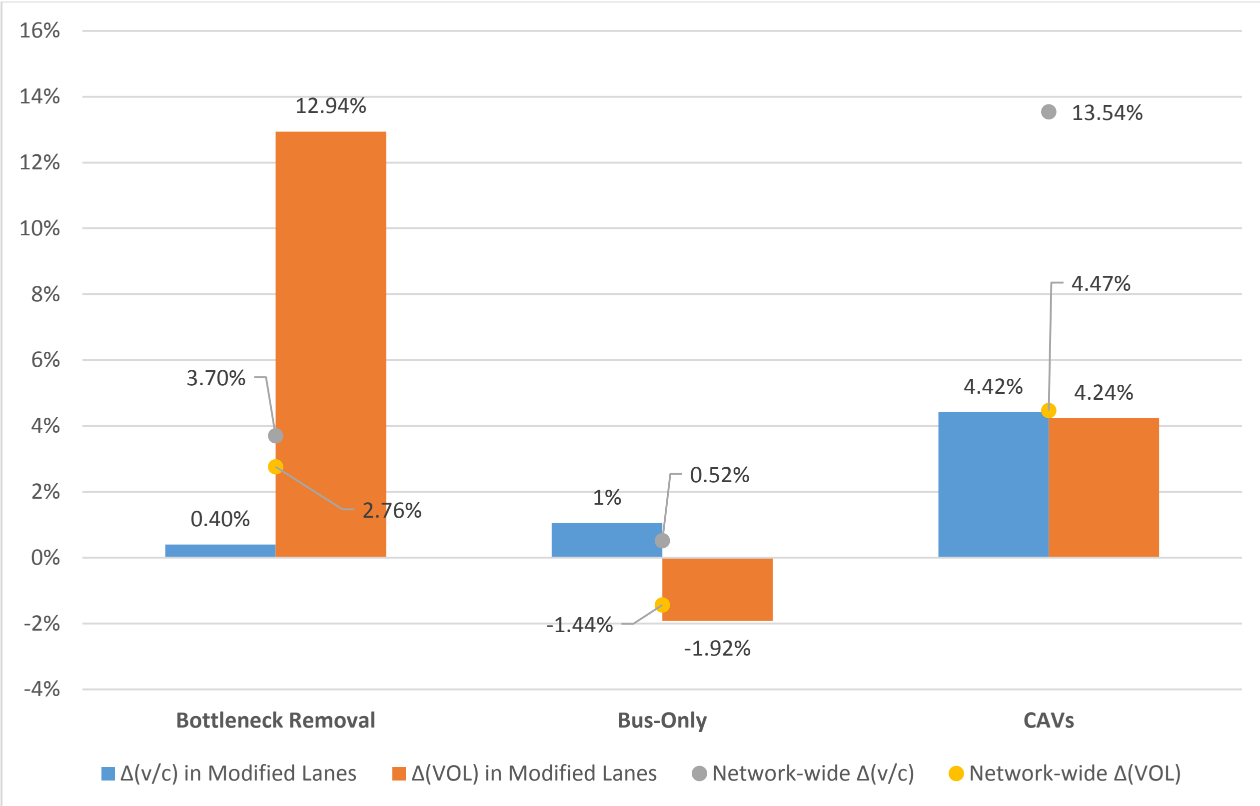


Figure 44 Investment Outlook Comparison (Year 2035)

Chapter 4. Benefits Redistribution Analysis

Following the implementation of the revenue policy and investment outlook dyads in Chapter 3, this last part of the dissertation focuses on the benefits redistribution analysis. In order to evaluate the redistribution effects of the revenue and investment dyads, the following meaningful metrics are presented and discussed:

- Tax Incidence:
  - Taxpaying population by income group, and county;
  - Tax-to-income ratio by income group, and county;
- Travel Behavior:
  - Mode share by income group, and county;
  - Average daily travel time at the HH level by mode, income group, and county;
  - Average miles traveled daily at the HH level by mode, income group, and county;
- Revenue Potential:
  - Revenue generated by income group, and county.

These metrics are selected from the list of metrics presented in Part I as being the most meaningful ones when evaluating the dyads' long-term performance. They are presented both in absolute terms and in terms of percent change across the 4 iterations, with Iteration 1 providing the base values for all estimated percentage changes.

4.1 Outlook A: Bottleneck Removal

4.1.1 Tax Incidence

It is evident that a long-term implementation of the fuel tax increase and bottleneck removal dyad will result in an increase in the taxpaying population. Taxpayers in INC0 will increase by 10.29%, which is the highest increase among all income groups, while the number of INC4 taxpayers will increase by only 0.92%. The fact that an increase is observed across all income groups is interesting, and shows that more users will be opting for motorized transportation modes, therefore contributing to the fuel tax revenue generated. Such a choice is intuitive as users now have access to a better-performing highway network that reduces their overall travel time. The fact that the percent change for lower income groups is higher than the corresponding change for higher income groups can be attributed to the actual percentage of users in each income bin driving. Only 19% of the INC0 users were paying fuel taxes in Iteration 1 versus 89% of INC4 users. The corresponding numbers for Iteration 4 are 21% and 90% respectively. It is therefore evident that INC0 provided larger margins for improvement.

Table 61 Taxpaying Population by Income Group (Bottleneck Removal)

	ITER1	**ITER2**	**ITER3**	**ITER4**
INC0	55,690	57,444	61,212	61,412
INC1	90,773	92,316	96,095	96,075
INC2	205,942	207,967	213,803	213,427
INC3	544,477	547,100	555,625	555,420
INC4	606,662	607,786	612,760	612,240

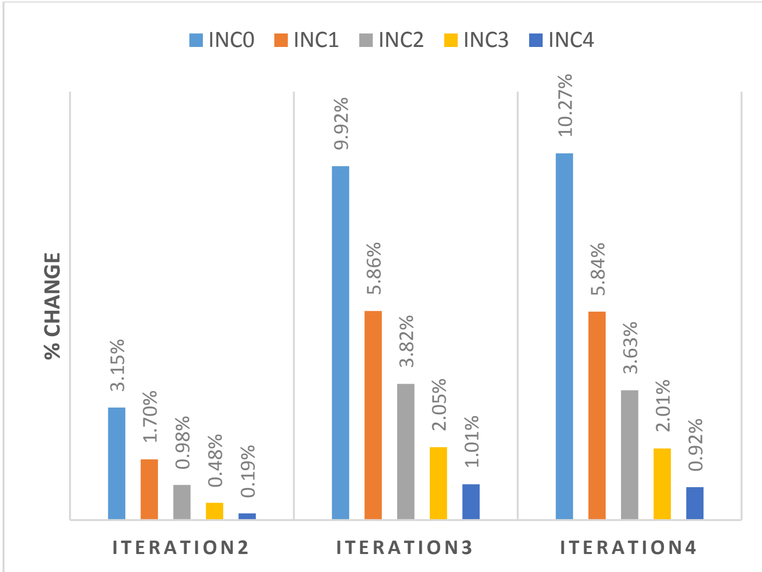


Figure 45 Change in Taxpaying Population by Income Group (Bottleneck Removal)

The results at the county level follow a similar rationale. A long-term implementation of the fuel tax increase and bottleneck removal dyad will result in an increase in the taxpaying population. Taxpayers in DC and Baltimore City will increase by 5.42% and 7.30% respectively, which are the highest increases among all counties, while the number of taxpayers in Frederick and Harford will increase by only 0.39% and 0.37% respectively. Similar to the income-based discussion, the fact that an increase is observed across all counties is interesting, and shows that more users will be opting for motorized transportation modes, therefore contributing to the fuel tax revenue generated. Such a choice is intuitive as users now have access to a better-performing highway network that reduces their overall travel time. The fact that the percent change for some counties is higher than others can be attributed to the actual percentage of users in each county driving. Only 43% of users in DC and 72.9% of users in Baltimore County were paying fuel taxes in Iteration 1 versus 80.1% and 82.2 of users in Frederick and Harford respectively. The corresponding numbers for Iteration 4 are 46.17% (DC), 74.17% (Baltimore County), 80.39% (Frederick) and 82.51% (Harford). It is therefore evident that DC and Baltimore County provided larger margins for improvement. It is also important to acknowledge the income distribution in each county, and interpret the county results in conjunction with the income-based results.

Table 62 Taxpaying Population by County (Bottleneck Removal)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	153,086	154,352	161,778	161,389
Anne Arundel	165,247	165,620	166,634	166,581
Baltimore County	241,542	242,636	246,099	245,845
Carroll	53,524	53,736	53,883	53,867
Harford	76,626	76,677	76,915	76,907
Howard	90,749	91,011	91,836	91,823
DC	132,327	135,135	141,922	141,991
Montgomery	280,285	281,669	284,695	284,511
Prince George's	239,249	240,812	244,523	244,473
Frederick	70,909	70,965	71,210	71,187

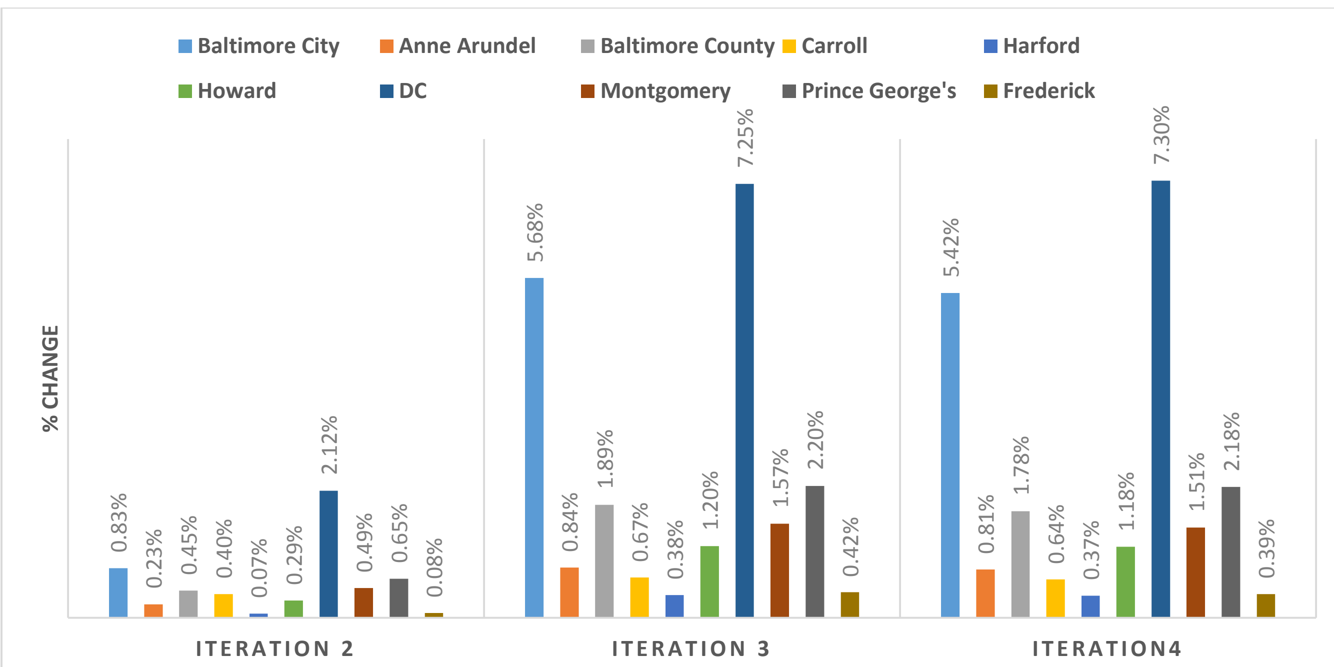


Figure 46 Change in Taxpaying Population by County (Bottleneck Removal)

Estimating the tax-to-income ratio as another measure of tax-incidence is important in order to understand how users will be financially affected by the implement revenue and investment policies in the long run. Since the focus of this dissertation is state-level revenue and investment policies, and only the state component of the implemented revenue strategies were subject to regulation, the discussion focuses on the state fuel tax-to-income ratios by income group and county.

A long-term implementation of the fuel tax increase and bottleneck removal dyad will result in an increase in the state fuel tax-to-income ratios for all income groups except for INC0 (INC0: -1.06%; INC1: 2.07%; INC2: 3.73%; INC3: 4.81%; INC4: 5.52%). These results indicate that as income increases, users bear a larger financial burden, most likely because their travel behavior changes at a faster pace. However, it should be noted that these changes are minor and, although they suggest a pattern, they do not seem to capture significant changes in the financial situation of the users.

Table 63 State Fuel Tax-to-Income by Income Group (Bottleneck Removal)

	ITER1	**ITER2**	**ITER3**	**ITER4**
INC0	1.715%	1.686%	1.71%	1.70%
INC1	0.600%	0.599%	0.62%	0.61%
INC2	0.396%	0.398%	0.41%	0.41%
INC3	0.248%	0.250%	0.26%	0.26%
INC4	0.227%	0.229%	0.24%	0.24%

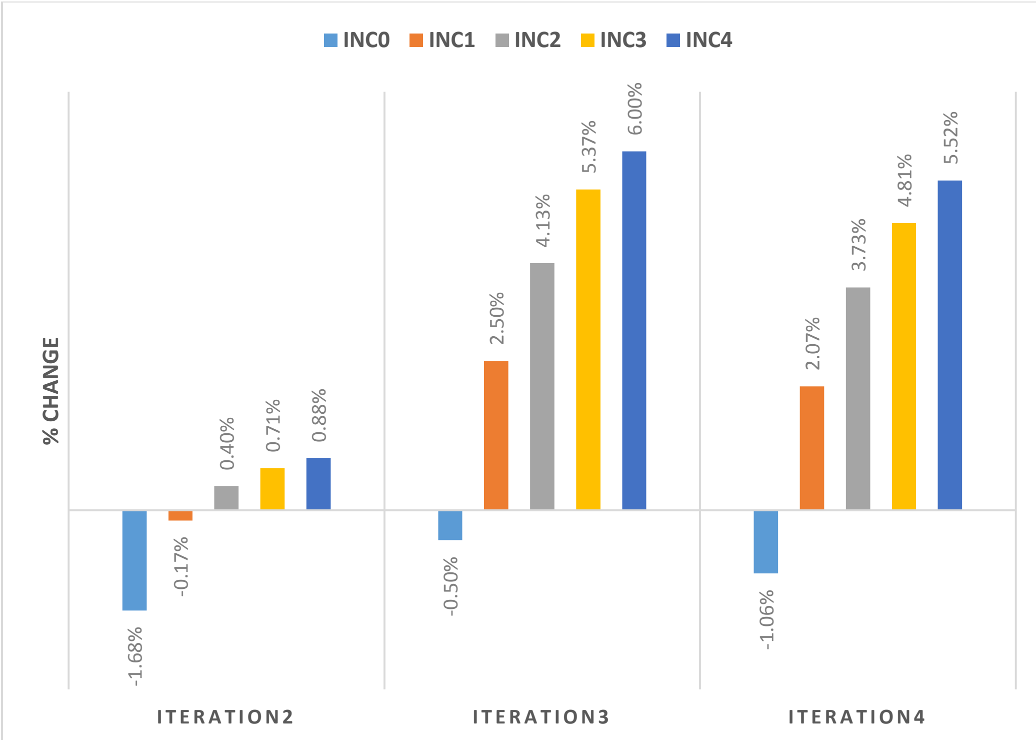


Figure 47 Change in State Fuel Tax-to-Income by Income Group (Bottleneck Removal)

At the county level, a long-term implementation of the fuel tax increase and bottleneck removal dyad will result in an increase in the state fuel tax-to-income ratios for all counties. This increase is most likely due to the increased travel activity that users undertake. The biggest increases are observed for Howard and Carroll counties at 7.30% and 6.44% respectively. On the other hand, the smallest increases are observed for HHs in Harford and Frederick at 3.65% and 4.41% respectively.

Table 64 State Fuel Tax-to-Income by County (Bottleneck Removal)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	0.221%	0.223%	0.233%	0.232%
Anne Arundel	0.288%	0.289%	0.306%	0.303%
Baltimore County	0.276%	0.278%	0.292%	0.291%
Carroll	0.360%	0.363%	0.386%	0.383%
Harford	0.335%	0.337%	0.349%	0.348%
Howard	0.268%	0.271%	0.288%	0.287%
DC	0.152%	0.153%	0.160%	0.159%
Montgomery	0.217%	0.220%	0.229%	0.229%

	ITER1	ITER2	ITER3	ITER4
Prince George's	0.280%	0.284%	0.298%	0.297%
Frederick	0.332%	0.334%	0.349%	0.347%

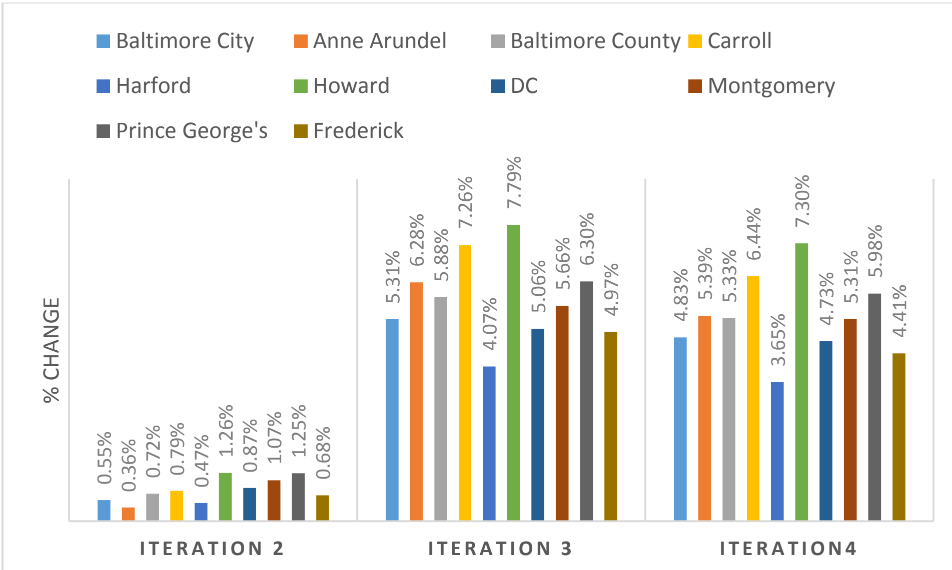


Figure 48 Change in State Fuel Tax-to-Income by County (Bottleneck Removal)

4.1.2 Travel Behavior

Aside from the financial implications of the fuel tax increase and bottleneck removal dyad, it is important to understand its long-term effects on travel behavior.

The largest increase in motorized trips is observed for INC0 at 7.03%, which, as expected, also has the lowest absolute number of daily motorized trips at 1.72. On the other hand, INC4 has the largest number of daily motorized trips (7.74 trips per day) and experiences the smallest increase at 2.23%.

The largest decrease in transit trips is observed for INC3 at 15.84%, which as expected, also has the lowest absolute numbers of daily transit trips at 0.42 transit trips per day. On the other hand, INC0 and INC4 have the largest number of daily transit trips and experience moderate decreases, at 7.10% and 13.12% respectively. However, when observing the transit trip changes, caution is recommended: despite the fact that some percentages may seem high, the absolute numbers remain fairly steady for all practical considerations.

Table 65 Number of Motorized Trips at the HH Level by Income Group (Bottleneck Removal)

	ITER1	ITER2	ITER3	ITER4
INC0	1.60	1.63	1.72	1.72
INC1	2.81	2.84	2.96	2.95
INC2	4.32	4.36	4.50	4.49
INC3	5.91	5.94	6.08	6.07
INC4	7.57	7.60	7.76	7.74

Table 66 Number of Transit Trips at the HH Level by Income Group (Bottleneck Removal)

	ITER1	ITER2	ITER3	ITER4
INC0	0.80	0.79	0.75	0.75
INC1	0.60	0.58	0.52	0.52
INC2	0.64	0.62	0.55	0.55
INC3	0.50	0.49	0.42	0.42
INC4	0.64	0.62	0.55	0.56

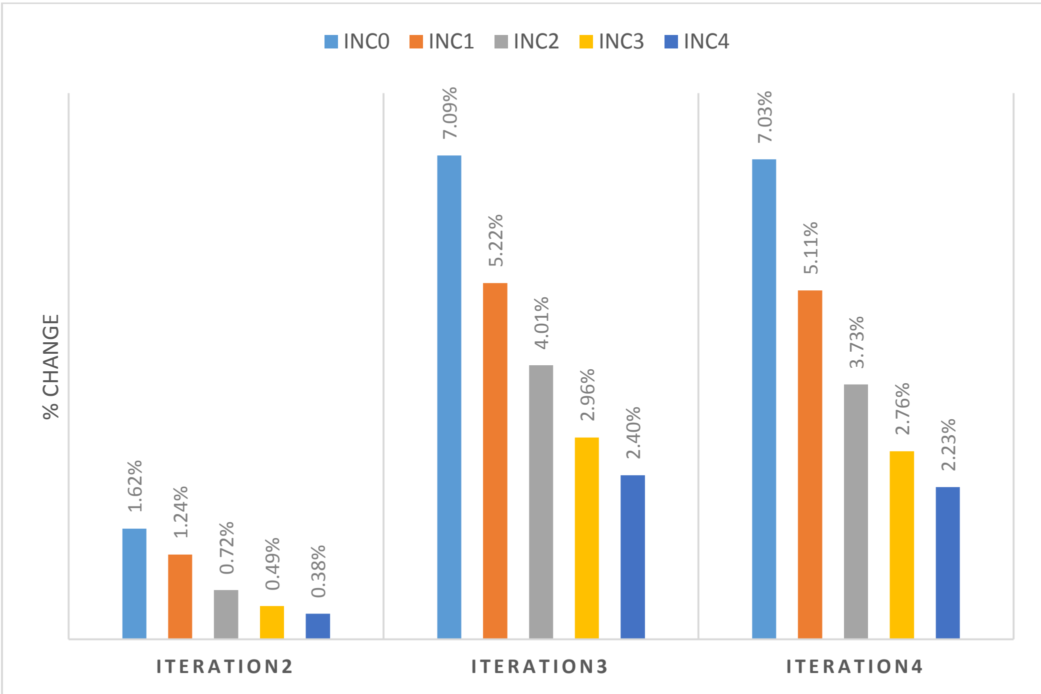


Figure 49 Change in Number of Motorized Trips at the HH Level by Income Group (Bottleneck Removal)

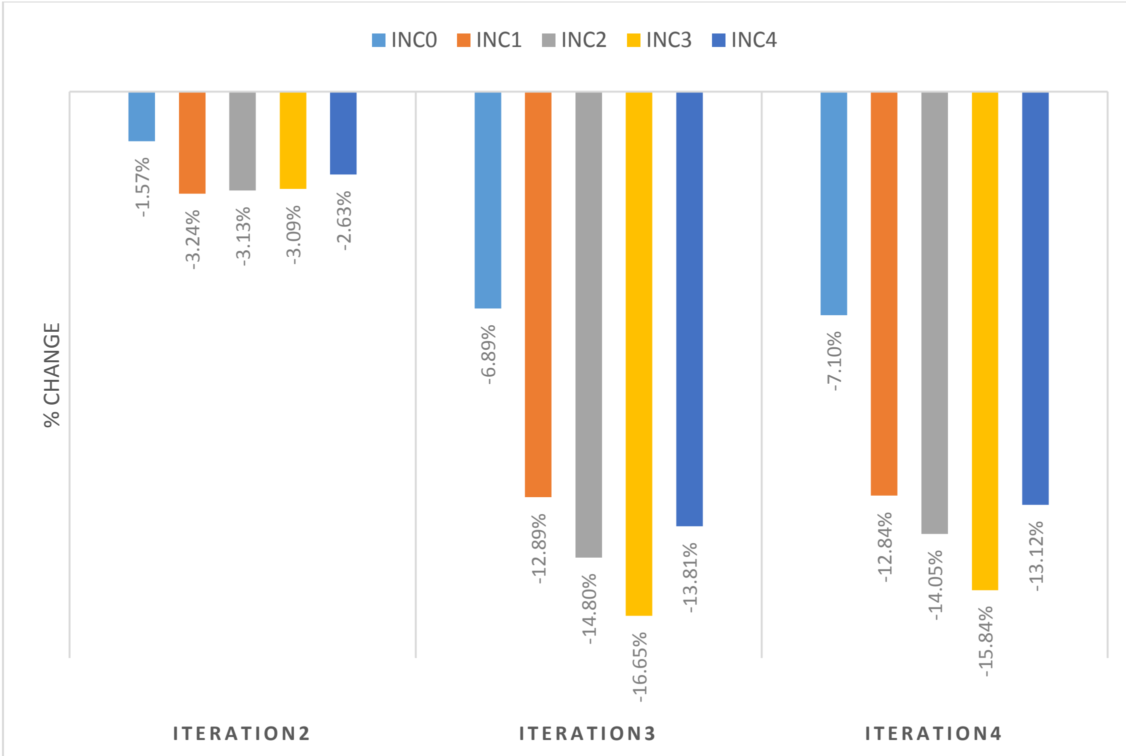


Figure 50 Change in Number of Transit Trips at the HH Level by Income Group (Bottleneck Removal)

The largest increases in motorized trips are observed for DC and Baltimore City at 8.30% and 5.57% respectively which, as expected, also have the lowest absolute numbers of daily motorized trips at 2.8 and 4.46 respectively. On the other hand, Carroll and Howard counties have the largest number of daily motorized trips and experience some of the smallest increases in the model, at 0.9% and 0.52% respectively.

The largest decreases in transit trips are observed for Carroll and Howard counties at 20.1% and 18.9% respectively which, as expected, also have the lowest absolute numbers of daily transit trips at 0.06 and 0.12 respectively. On the other hand, DC and Baltimore City have the largest number of daily transit trips (as expected for cities with well-developed transit networks) and experience moderate decreases, at 11.27% and 12.53% respectively.

Table 67 Number of Motorized Trips at the HH Level by County (Bottleneck Removal)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	4.228	4.2545	4.4823	4.4637
Anne Arundel	6.316	6.3298	6.4242	6.4152
Baltimore County	5.6433	5.6632	5.788	5.7771
Carroll	6.9736	6.9915	7.051	7.0366
Harford	6.889	6.8884	6.9321	6.9248
Howard	6.9133	6.9339	7.0831	7.0711
DC	2.593	2.648	2.8127	2.8081
Montgomery	5.7681	5.802	5.9242	5.9139
Prince George's	5.6385	5.6807	5.8319	5.8246
Frederick	6.6321	6.6346	6.6864	6.6784

Table 68 Number of Transit Trips at the HH Level by County (Bottleneck Removal)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	0.8339	0.8206	0.7221	0.7294
Anne Arundel	0.3209	0.3055	0.2589	0.2627
Baltimore County	0.4152	0.407	0.3544	0.3574
Carroll	0.0766	0.0748	0.0593	0.0612
Harford	0.1461	0.1428	0.1256	0.1271
Howard	0.3062	0.2955	0.2431	0.2483
DC	1.2142	1.180	1.077	1.0774
Montgomery	0.6668	0.6482	0.5885	0.5925
Prince George's	0.6882	0.666	0.5868	0.5885
Frederick	0.1143	0.1131	0.1027	0.1029

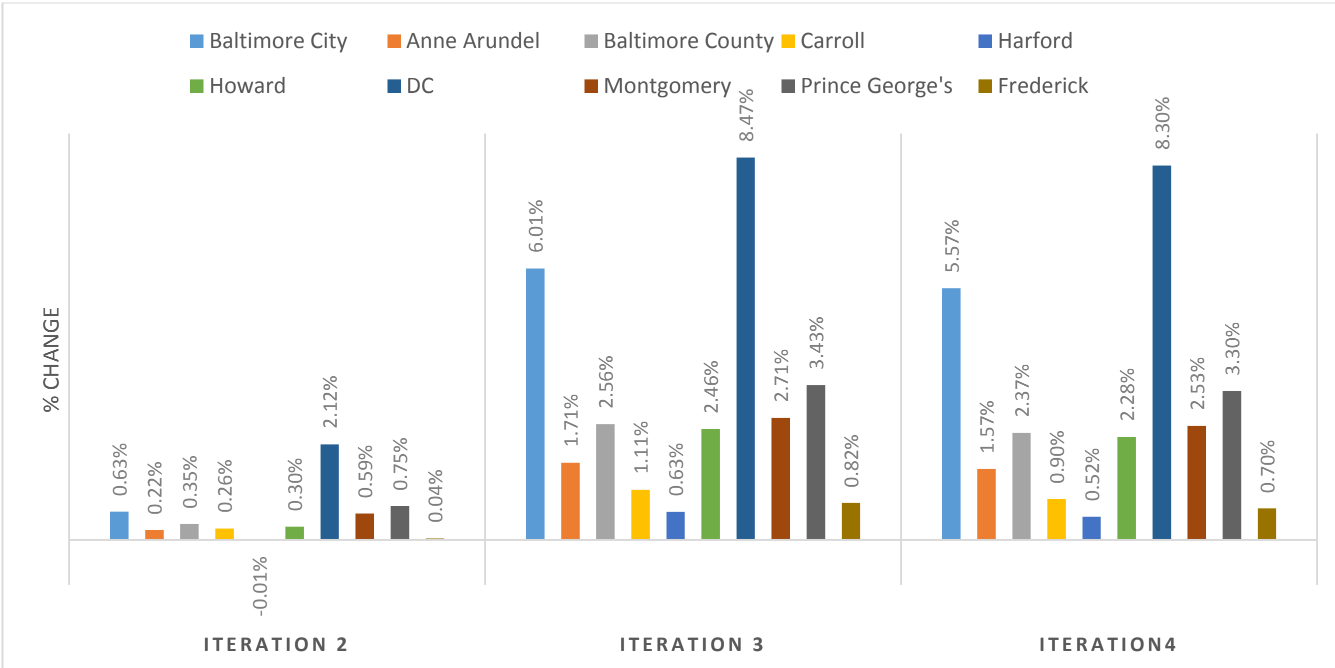


Figure 51 Change in Number of Daily Motorized Trips at the HH Level by Income Group (Bottleneck Removal)

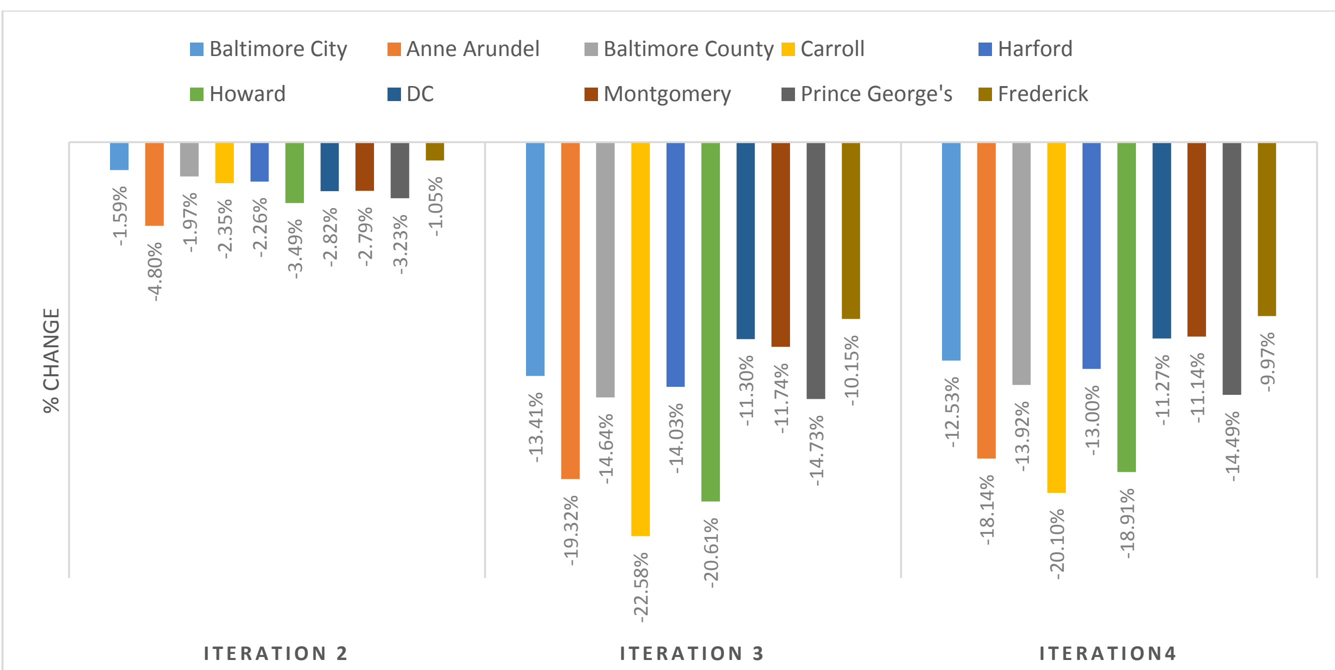


Figure 52 Change in Number of Daily Transit Trips at the HH Level by Income Group (Bottleneck Removal)

Understanding the mode share results requires a simultaneous evaluation of the corresponding travel time and travel distance findings. The increase in the number of motorized trips across all income groups is associated with an increase in the average daily miles traveled. Users of INC0 experience the smallest increase at 4.31% versus a 6.04% decrease for users of INC4 (smallest change). In absolute terms, HHs of higher income have are associated with longer driving distances, since they generate more trips. The findings regarding the number of motorized trips and the daily miles traveled combined with the travel time results will shed more light on the effect of the revenue-investment dyad on travel behavior.

Table 69 Driving Distance at the HH Level by Income Group (Bottleneck Removal)

	ITER1	**ITER2**	**ITER3**	**ITER4**
INC0	20.66	20.71	21.66	21.56
INC1	26.69	26.94	28.30	28.18
INC2	31.71	32.02	33.76	33.60
INC3	42.49	42.92	45.35	45.11
INC4	55.54	56.10	59.19	58.90

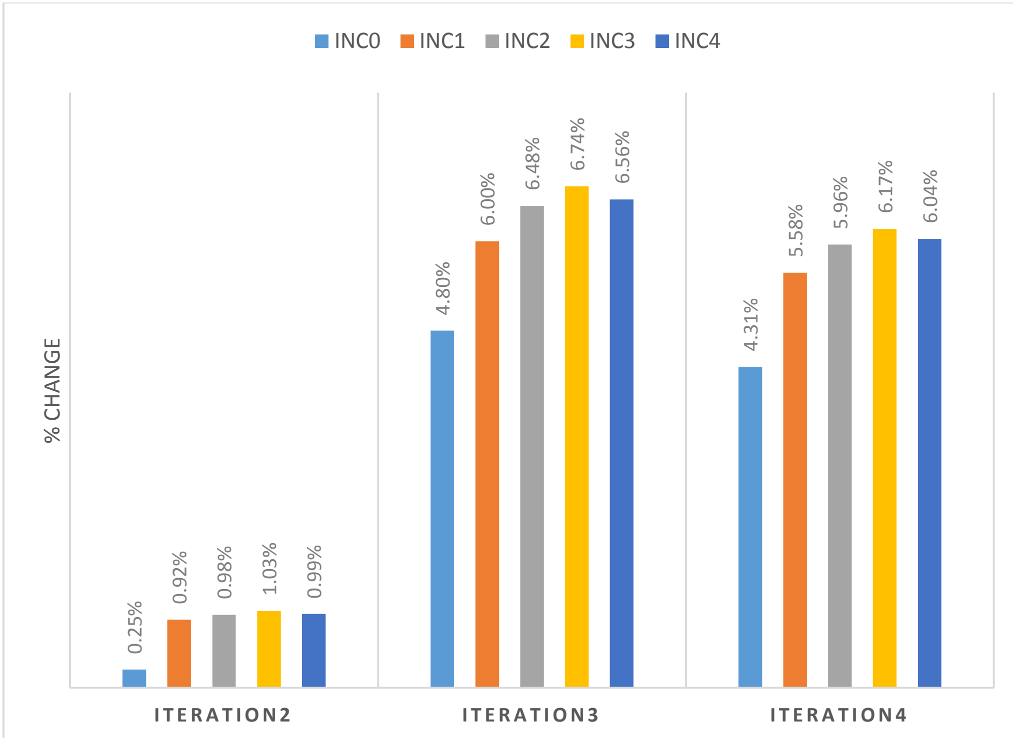


Figure 53 Change in Driving Distance at the HH Level by Income Group (Bottleneck Removal)

At the county level, the driving distance results capture the effects of the revenue policy-investment outlook dyad on travel behavior. Carroll and Frederick are the top 2 counties in terms of daily distance traveled at the HH level, at 69.2mi and 61.66mi respectively. The urban and land use planning characteristics of these two counties support the results, as they encourage users to rely more on driving for their everyday trips. On the other hand, the shortest distances are observed for DC and Baltimore City. This is expected based on the characteristics of the DC and Baltimore City transportation networks, which discourage driving (compared to using public transit). The percent changes due the revenue policy-investment outlook dyad suggest that Howard county and DC experience the largest increases in miles driven at 7.54% and 7.35% respectively, while Harford and Frederick experience the smallest increases at 3.73% and 4.44% respectively.

Table 70 Driving Distance at the HH Level by County (miles) (Bottleneck Removal)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	28.33	28.56	30.36	30.21
Anne Arundel	52.22	52.47	55.68	55.22
Baltimore County	44.63	45.00	47.45	47.19
Carroll	65.20	65.62	69.78	69.23
Harford	58.96	59.25	61.41	61.16
Howard	52.68	53.37	56.90	56.66
DC	19.41	19.70	20.94	20.84
Montgomery	41.70	42.21	44.36	44.20
Prince George's	46.65	47.29	49.89	49.73
Frederick	59.03	59.46	61.99	61.66

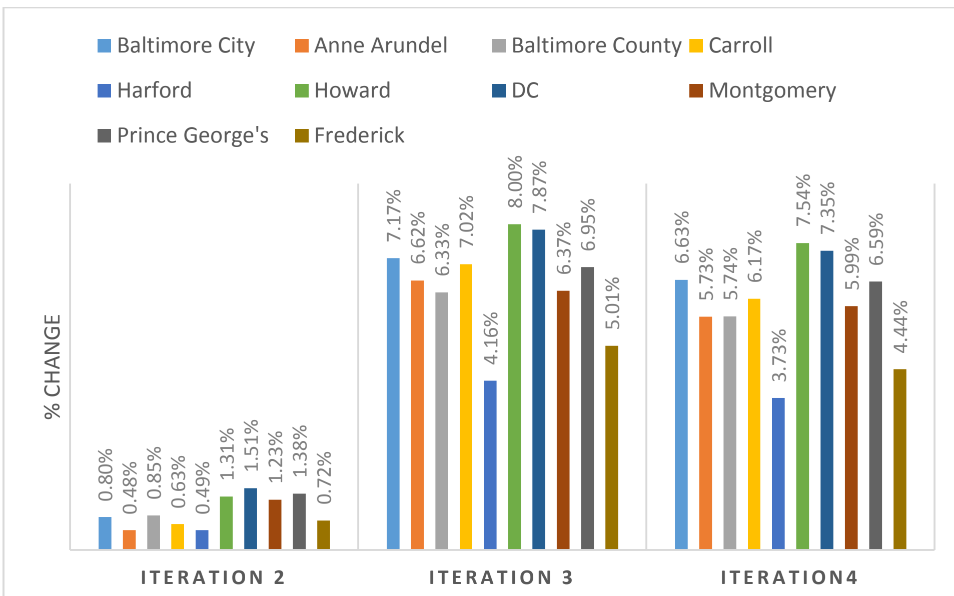


Figure 54 Change in Driving Distance at the HH Level by County (Bottleneck Removal)

Despite the increase in the number of motorized trips and the miles traveled across all income groups, the corresponding changes are negative, i.e. users experience reduced travel times. Users of INC0 experience the largest change at 19.9% versus a 16.17% decrease for users of INC4 (smallest change). It can be inferred that these two phenomena can simultaneously occur under the implemented investment outlook, i.e. the additional lanes reduce congestion and subsequently attract more trips. As expected, in absolute terms, higher-income HHs have higher daily travel times as they generate more trips, and the relationship between travel time (as a result of the number of motorized trips) and income is positively correlated.

Table 71 Driving Time at the HH Level by Income Group (minutes) (Bottleneck Removal)

	ITER1	ITER2	ITER3	ITER4
INC0	155.52	149.38	122.75	124.57
INC1	197.92	191.76	158.76	161.42
INC2	233.73	226.68	188.86	191.71
INC3	303.98	296.12	248.85	252.93
INC4	405.55	395.31	334.87	339.97

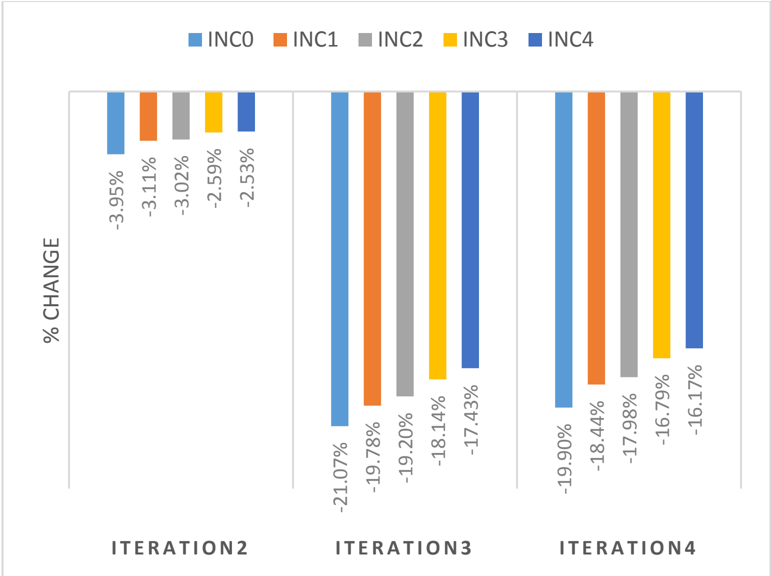


Figure 55 Change in Driving Time at the HH Level by Income Group (Bottleneck Removal)

At the county level, the results follow similar patterns. Despite the increase in the number of motorized trips across all counties, the corresponding changes are negative, i.e. users experience reduced travel times. Users in Baltimore City experience the largest change at 19.95% versus a 9.96% decrease for users in Frederick (smallest change). It can be inferred that these two phenomena can simultaneously occur under the implemented investment outlook, i.e. the additional lanes reduce congestion and subsequently attract more trips. As expected, in absolute terms, HHs in areas with well-developed transit networks (DC and Baltimore City) have lower daily travel times as they generate less motorized trips, whereas HHs in relatively remote areas, that rely primarily on the highway network experience higher travel times (e.g. Anne Arundel, Frederick, etc.). However, as discussed before, another crucial factor that should always be accounted for when interpreting the county-level results is the income distribution for each county.

Table 72 Driving Time at the HH Level by County (minutes) (Bottleneck Removal)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	238.71	232.57	185.16	191.07
Anne Arundel	366.98	353.08	294.65	297.68
Baltimore County	292.99	287.15	235.26	241.97
Carroll	333.01	329.26	285.79	291.44
Harford	325.92	321.39	281.29	285.24
Howard	361.36	350.34	288.44	294.22
DC	225.03	217.76	183.01	184.29
Montgomery	322.05	313.52	265.45	269.17
Prince George's	377.82	365.21	312.02	314.41
Frederick	318.47	314.66	284.91	286.75

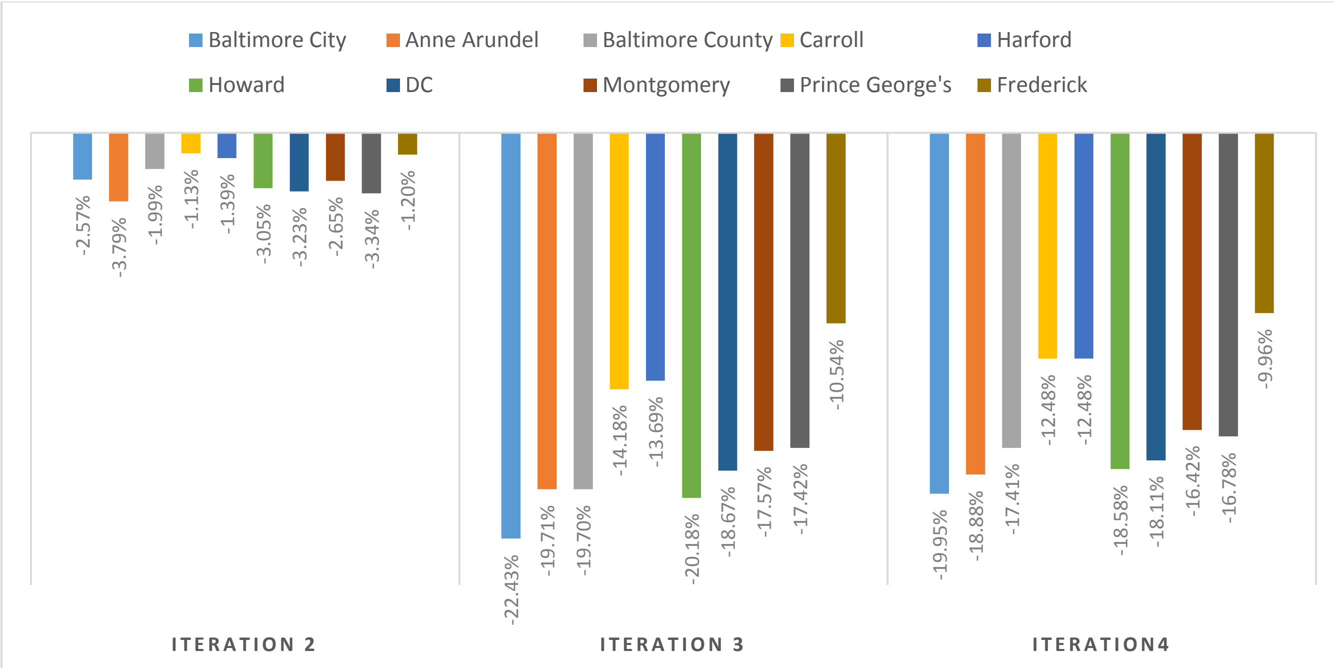


Figure 56 Change in Driving Time at the HH Level by County (Bottleneck Removal)

The transit results suggest that the revenue-investment dyad will affect the transit-related metrics in an expected fashion. While all income groups experience a decrease in daily distance traveled by transit, users of INC0 and INC4 experience the smallest percentage changes (-3.85% and -3.67% respectively). For both income groups, the small percentages can be attributed to the corresponding small decreases observed in the number of transit trips. It is also noteworthy that daily transit distance increases with income. Given the fact that the number of transit trips is fairly similar across all income groups, the difference in distance suggests that geography (place of residence, place of employment, etc.) plays a significant role.

Table 73 Transit Distance at the HH Level by Income Group (miles) (Bottleneck Removal)

	ITER1	ITER2	ITER3	ITER4
INC0	9.63	9.54	9.29	9.26
INC1	10.33	10.18	9.79	9.75
INC2	10.87	10.72	10.25	10.27
INC3	12.71	12.57	12.14	12.15
INC4	15.85	15.72	15.27	15.27

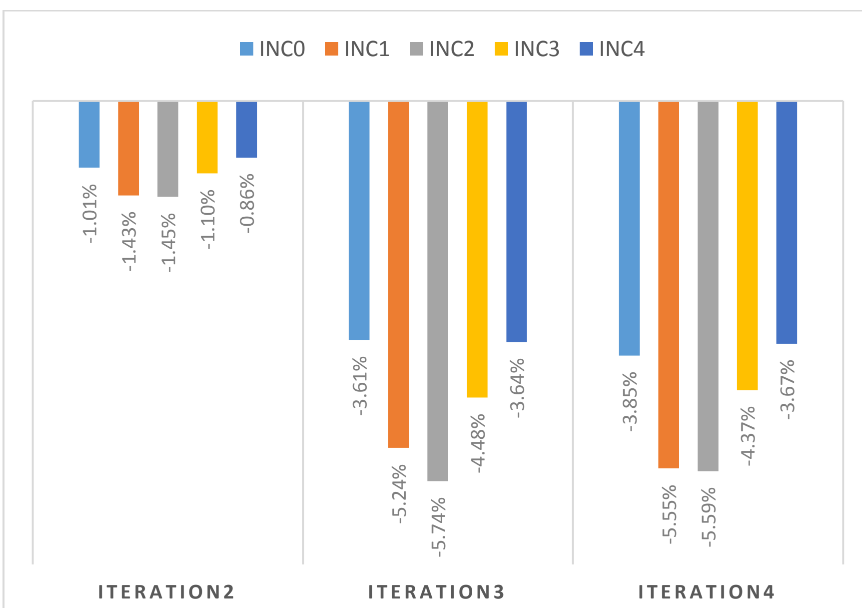


Figure 57 Change in Transit Distance at the HH Level by Income Group (Bottleneck Removal)

The county level results lead to similar conclusions but with a stronger focus on geography. HHs in Carroll and Harford have the highest distance traveled by transit, most likely due to the urban planning and land use characteristics of the county. On the other hand, DC and Baltimore City HHs have the shortest transit distances, despite a heavier use of transit. Harford and Anne Arundel will experience the largest decrease at 10.72 and 7.79% respectively, while Carroll will experience the smallest, at 1.63%. DC and Baltimore City will experience decreases of average magnitude, at 4.57% and 2.94% respectively.

Table 74 Transit Distance at the HH Level by County (miles) (Bottleneck Removal)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	9.59	9.55	9.27	9.31
Anne Arundel	18.76	17.90	17.44	17.30
Baltimore County	13.95	13.93	13.62	13.61
Carroll	21.65	21.91	21.19	21.30
Harford	24.45	24.30	22.92	23.36
Howard	17.55	17.46	16.92	16.98
DC	8.96	8.89	8.57	8.55
Montgomery	13.28	13.19	12.89	12.89
Prince George's	15.26	15.14	14.74	14.71
Frederick	15.42	15.26	13.98	13.76

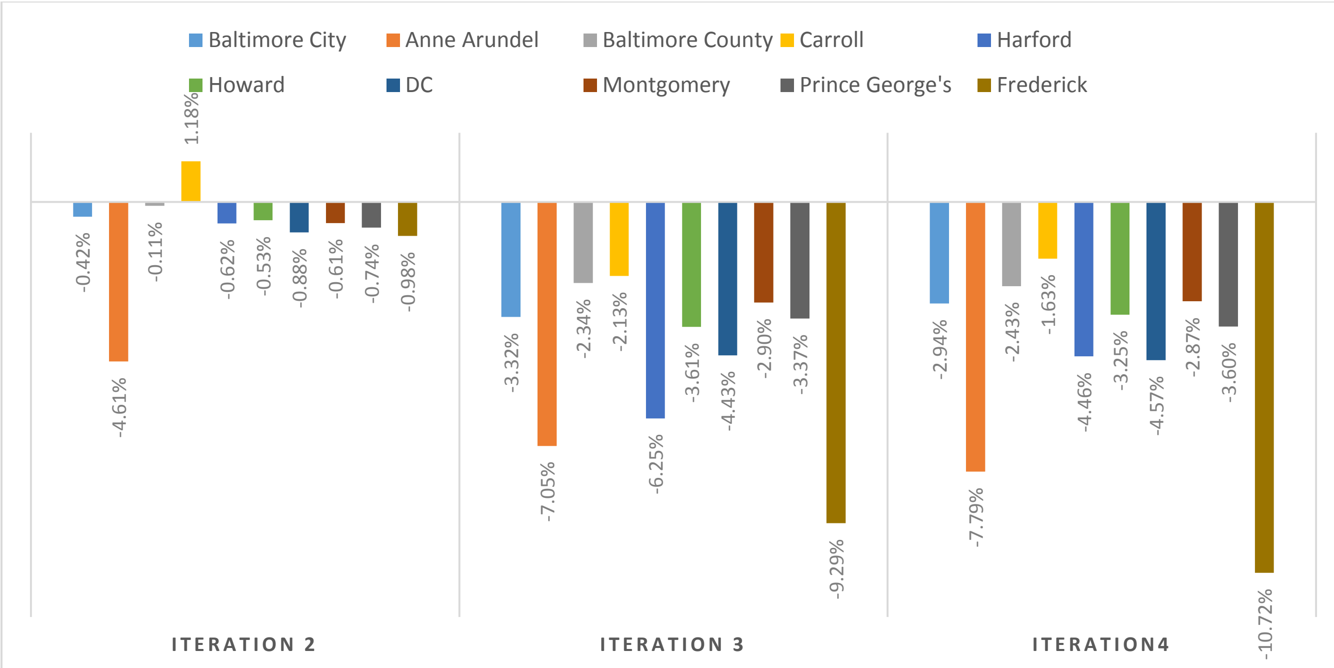


Figure 58 Change in Transit Distance at the HH Level by County (Bottleneck Removal)

As expected, HHs of lower income spend more time on transit trips (a direct effect of the number of transit trips generated by income group). It is also worth noting that HHs of INC4 have similar transit travel times as HHs of INC0, which is in turn a direct effect of the number of transit trips generated by HHs in INC4.

Table 75 Transit Travel Time at the HH Level by Income Group (minutes) (Bottleneck Removal)

	ITER1	ITER2	ITER3	ITER4
INC0	136.15	134.34	127.47	127.62
INC1	130.26	127.72	120.66	120.68
INC2	127.70	125.33	118.49	118.59
INC3	116.90	115.04	109.48	109.66
INC4	131.77	129.83	124.69	124.67

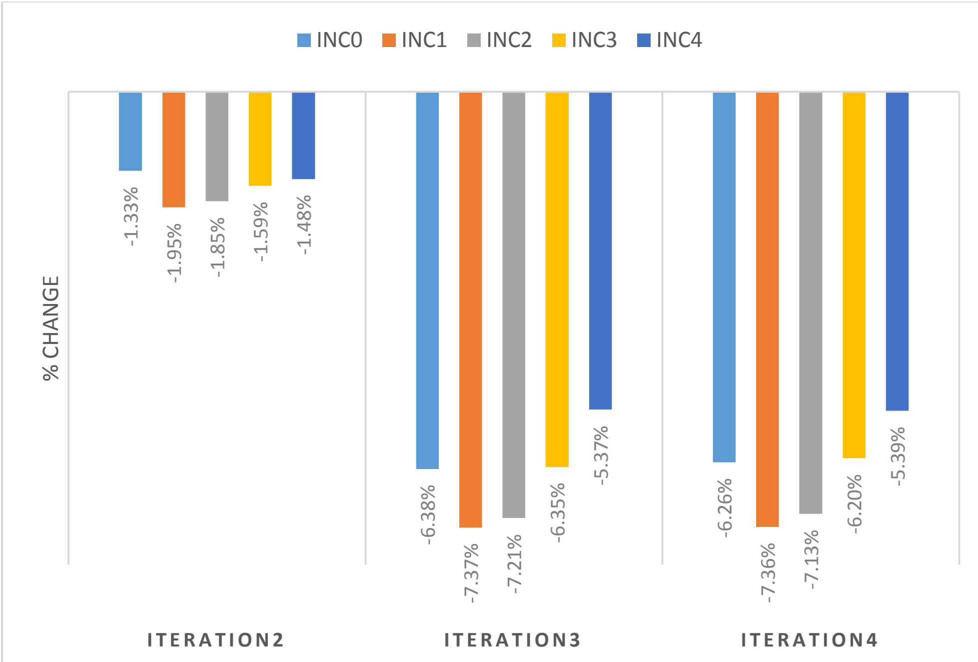


Figure 59 Change in Transit Travel Time at the HH Level by Income Group (Bottleneck Removal)

At the county level, the longest transit travel times are observed for HHs in Prince George's county (139.58 min) and Howard County (151.88 min). On the other hand, the shortest transit travel times are observed for HHs in Carroll County (67.95 min) and Frederick County (79.16 min). All counties but Carroll experience a decrease in transit travel times.

Table 76 Transit Travel Time at the HH Level by County (minutes) (Bottleneck Removal)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	129.32	128.00	119.50	120.40
Anne Arundel	130.58	124.03	127.29	125.06
Baltimore County	134.47	133.70	128.28	128.55
Carroll	63.46	63.16	66.04	67.94
Harford	96.32	94.24	94.88	94.96
Howard	159.74	158.36	151.16	151.87
DC	109.99	108.52	103.26	103.13
Montgomery	125.17	123.37	117.61	117.83
Prince George's	149.20	146.40	139.76	139.57
Frederick	81.82	80.73	80.14	79.16

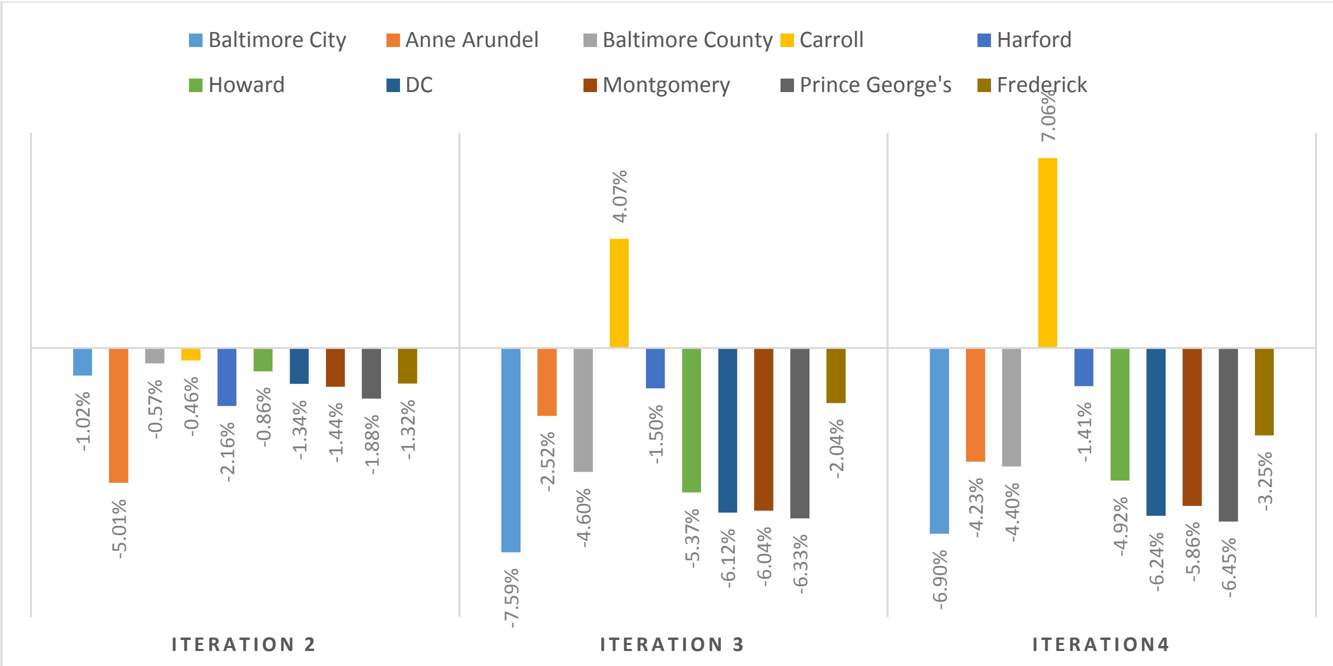


Figure 60 Change in Transit Travel Time at the HH Level by County (Bottleneck Removal)

4.1.3 Revenue Potential

The revenue generated from state fuel taxes is an important metric that summarizes the impact of the revenue policy-investment outlook dyad on travel behavior and ultimately on the state's spending/investment capacity. The results show that, in the long-run, state fuel tax revenues will increase across all income groups in a descending rate (i.e. INC0 by 9% vs. INC4 by 6%). The overall increase in state fuel taxes collected is expected as the implemented revenue-investment dyad improves the travel conditions on the network, therefore encourages users to travel more.

Table 77 Daily State Fuel Tax Revenue Generated by Income Group ($) (Bottleneck Removal)

	ITER1	ITER2	ITER3	ITER4
INC0	19,626	19,905	21,464	21,413
INC1	33,576	34,088	36,433	36,274
INC2	89,455	90,699	96,709	96,163
INC3	277,771	281,079	298,680	296,970
INC4	377,218	381,233	403,879	401,692

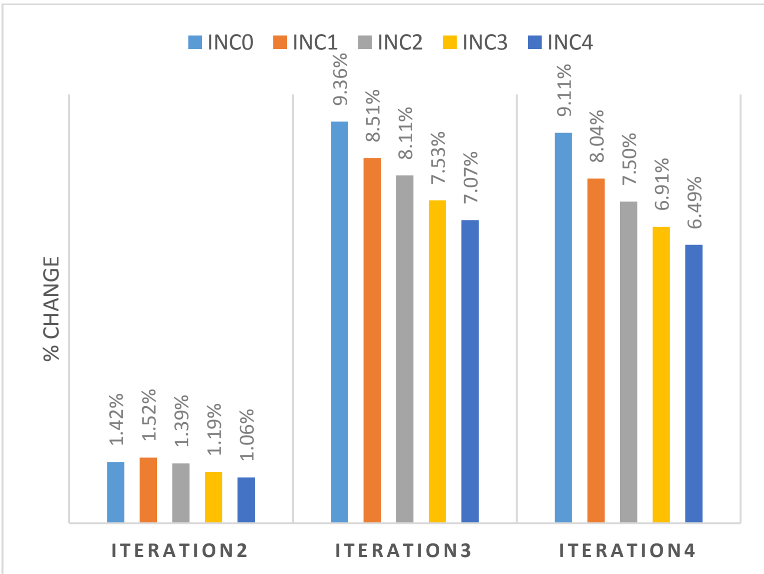


Figure 61 Change in Daily State Fuel Tax Revenue Generated by Income Group (Bottleneck Removal)

At the county level, Montgomery and Prince George's counties generate the highest amounts of state fuel tax revenues, while Carroll and DC generate the lowest. In terms of percentage changes, DC and Baltimore City experience the largest increases at 11% and 9% respectively, while Harford and Frederick experience the lowest increases at 5% and 4% respectively. In addition to travel behavior changes, the revenue-specific results may be also affected by the income distribution, the population size, and the urban and land use planning characteristics of each county. It should be noted that, from the state's perspective, the absolute values of revenues may be of primary interest. However, from a social equity point of view, the revenue information should be evaluated in conjunction with the metrics discussed before, in order to obtain a clear view of the effects of the revenue-investment dyad on users.

Table 78 Daily State Fuel Tax Revenue Generated ($) by County (Bottleneck Removal)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	56,809	57,440	62,299	61,888
Anne Arundel	102,034	102,525	109,103	108,137
Baltimore County	131,592	132,890	141,113	140,228
Carroll	39,839	40,180	42,871	42,528
Harford	52,408	52,668	54,679	54,454
Howard	55,209	55,992	59,997	59,709
DC	37,626	38,601	41,950	41,797
Montgomery	137,810	139,791	147,554	146,967
Prince George's	135,627	137,869	146,329	145,827
Frederick	48,690	49,044	51,267	50,972

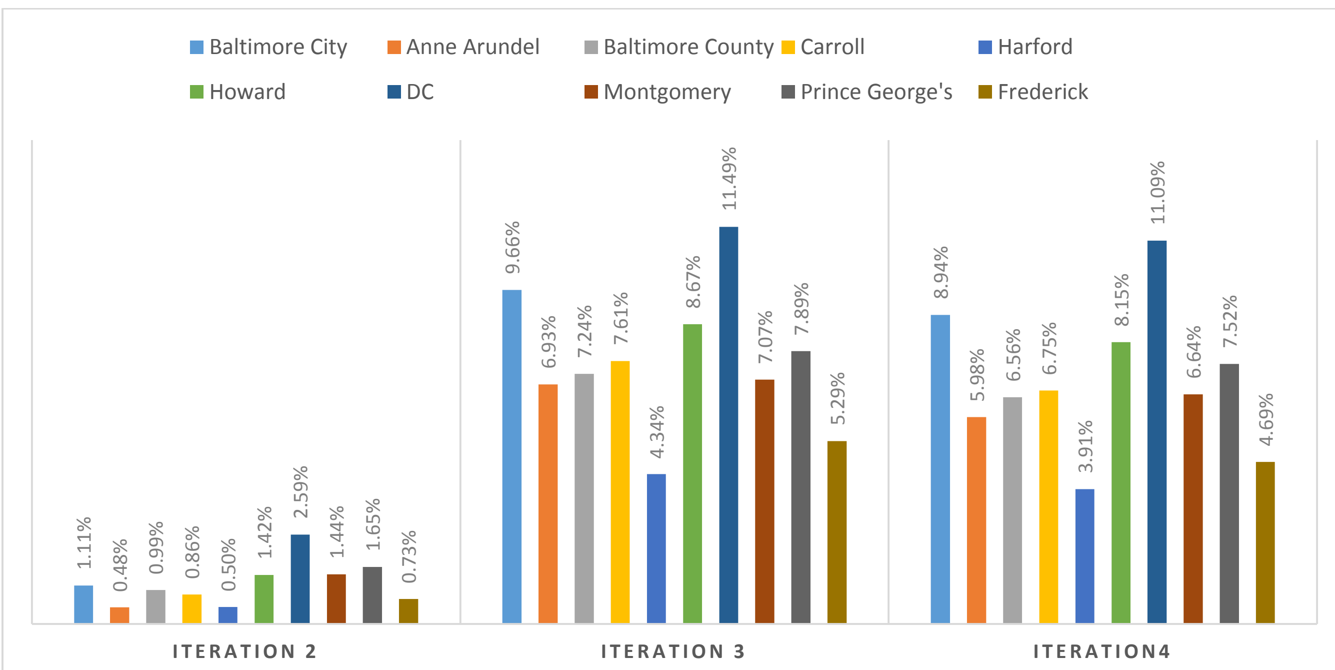


Figure 62 Change in Daily State Fuel Tax Revenue Generated by County (Bottleneck Removal)

4.2 Outlook B: Transit-Oriented

4.2.1 Tax Incidence

The taxpaying population remains constant throughout the analysis period, with the following characteristics at the income and county level:

Table 79 Tax Incidence and Taxpaying Population by Income Group (Transit-Oriented)

	Transp. Dedicated PT/Income	Number of Paying HHs	% of Income Population
INC0	3.8761%	142,029	48%
INC1	1.3866%	97,032	47%
INC2	0.5408%	105,812	34%
INC3	0.3235%	361,763	54%
INC4	0.3476%	594,385	88%

Table 80 Tax Incidence and Taxpaying Population by County (Transit-Oriented)

	Number of Paying HHs	% of County Population	Transp. Dedicated PT/Income
Carroll	41,366	64%	0.47%
Frederick	55,236	63%	0.46%
Harford	59,297	64%	0.46%
Howard	75,215	71%	0.40%
Anne Arundel	137,589	65%	0.46%
Baltimore City	146,410	55%	0.82%
DC (Maryland side)	132,097	44%	0.56%
Prince George's	202,048	63%	0.48%
Baltimore County	200,336	62%	0.53%
Montgomery	251,427	69%	0.49%

The tax incidence results for the transportation-dedicated property tax have an interesting structure. Households in lower income groups experience a significantly higher tax-to-income ratio than their higher income counterparts (3.88% for INC0 vs. 0.35% for INC4). However, as far as the taxpaying population is concerned, the pattern is very interesting: the three income groups that have the highest taxpaying populations are INC4, INC3 and INC1 (594,385, 361,763 and 142,029 respectively).

County-wise, Howard, Anne Arundel and Harford counties experience the lowest tax-to-income ratios (0.40%, 0.46% and 0.46% respectively), while Baltimore City, DC and Baltimore county experience the highest (0.82%, 0.56% and 0.53% respectively). In terms of taxpaying population, Montgomery, Prince George's and Baltimore counties have the highest number of taxpayers, while Carroll, Frederick and Harford have the lowest.

4.2.2 Travel Behavior

Aside from the financial implications of the property tax and transit-oriented dyad, it is important to understand its long-term effects on travel behavior.

The construction of bus-only lanes is expected to decrease the number of motorized trips and increase the number of transit trips especially for those income groups that rely heavily on transit, and for counties that invested significant funds in the transit network. The largest decrease in motorized trips is observed for INC0 at 5.50%, which, as expected, also has the lowest absolute number of daily motorized trips at 1.72. On the other hand, INC4 has the largest number of daily motorized trips (7.77 trips per day) and experiences the smallest decrease at 1.44%.

The largest increase in transit trips is observed for INC3 at 16.74%, which as expected, also has the lowest absolute numbers of daily transit trips at 0.43 transit trips per day. On the other hand, INC0 has the largest number of daily transit trips and experiences the smallest decrease at 5.69%. This relatively small increase can be attributed to the fact the INC0 users already had the highest number of transit trips compared to the other income groups, therefore there was a smaller margin for improvement.

Table 81 Motorized Trips at the HH Level by Income Group (Transit-Oriented)

	ITER1	ITER2	ITER3	ITER4
INC0	1.82	1.76	1.74	1.72
INC1	3.07	3.00	2.97	2.94
INC2	4.61	4.52	4.51	4.48
INC3	6.20	6.13	6.10	6.07
INC4	7.88	7.81	7.78	7.77

Table 82 Transit Trips at the HH Level by Income Group (Transit-Oriented)

	ITER1	ITER2	ITER3	ITER4
INC0	0.70	0.71	0.74	0.74
INC1	0.48	0.50	0.53	0.54
INC2	0.50	0.52	0.55	0.56
INC3	0.37	0.40	0.41	0.43
INC4	0.50	0.53	0.55	0.56

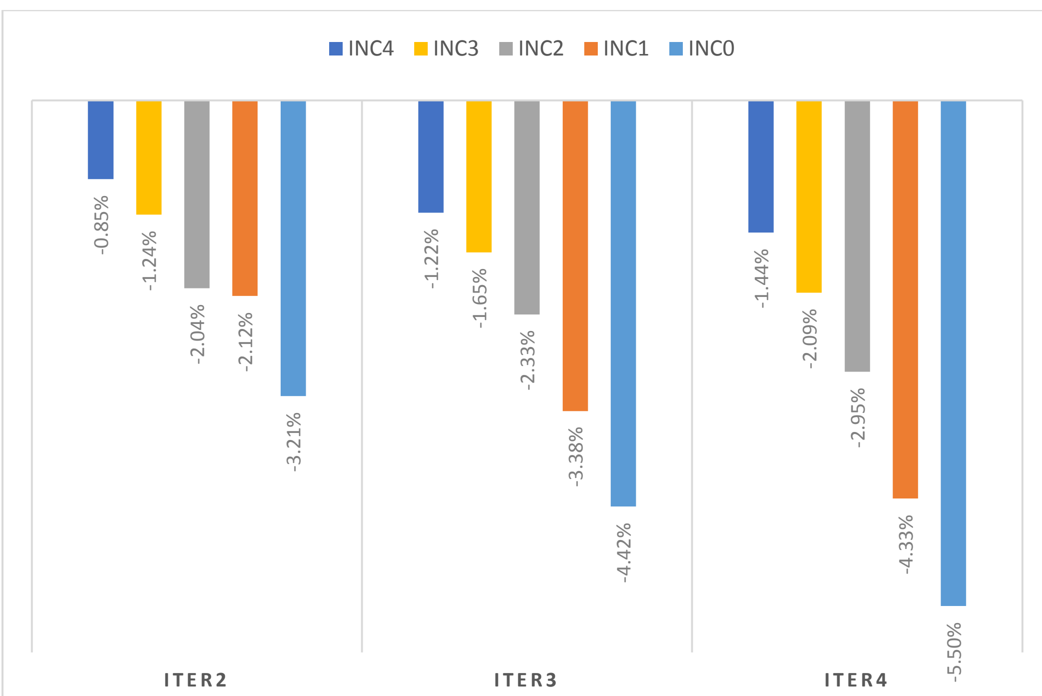


Figure 63 Change in Motorized Trips at the HH Level by Income Group (Transit-Oriented)

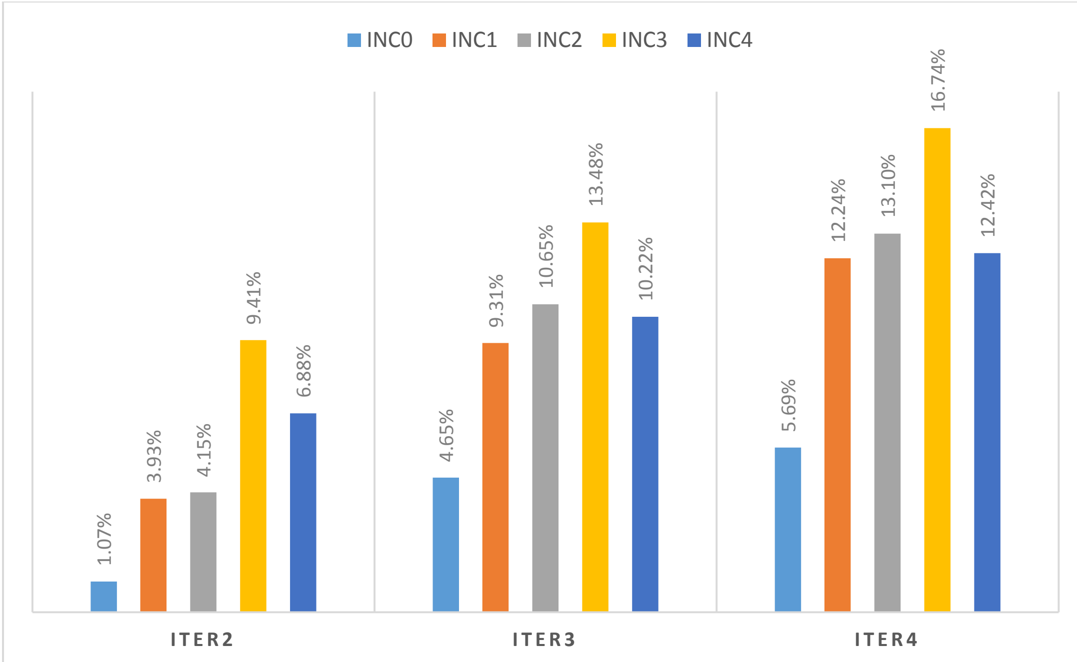


Figure 64 Change in Transit Trips at the HH Level by Income Group (Transit-Oriented)

At the county level, the largest decrease in motorized trips are observed for DC and Baltimore City at 6.07% and 4.54% respectively which, already had the lowest absolute numbers of daily motorized trips at 2.9 and 4.7 respectively (i.e. lower car dependency). On the other hand, Carroll and Harford counties have the largest number of daily motorized trips and experience some of the smallest decreases in the model.

The largest increases in transit trips are observed for Baltimore City and Howard counties. For Baltimore City, the large increase can be attributed to the already higher transit dependency of users. On the other hand, Howard County experiences such a large decrease mainly due to the high percentage of links modified. DC and Baltimore City have the largest number of daily transit trips (as expected for cities with well-developed transit networks) and experience increases of 9.65% and 16.72% respectively.

Table 83 Motorized Trips at the HH Level by County (Transit-Oriented)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	4.675	4.590	4.535	4.463

Anne Arundel	6.583	6.530	6.513	6.509
Baltimore County	5.971	5.920	5.916	5.882
Carroll	7.082	7.075	7.076	7.061
Harford	6.954	6.943	6.947	6.959
Howard	7.008	6.964	6.960	6.933
DC	2.876	2.810	2.715	2.701
Montgomery	6.075	6.010	5.948	5.933
Prince George's	5.956	5.890	5.838	5.817
Frederick	6.665	6.658	6.654	6.655

Table 84 Transit Trips at the HH Level by County (Transit-Oriented)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	0.593	0.635	0.659	0.692
Anne Arundel	0.180	0.200	0.204	0.204
Baltimore County	0.256	0.274	0.278	0.292
Carroll	0.033	0.033	0.033	0.032
Harford	0.108	0.107	0.107	0.099
Howard	0.263	0.274	0.288	0.307
DC	1.073	1.120	1.170	1.177
Montgomery	0.547	0.570	0.608	0.620
Prince George's	0.558	0.578	0.614	0.622
Frederick	0.105	0.105	0.106	0.108

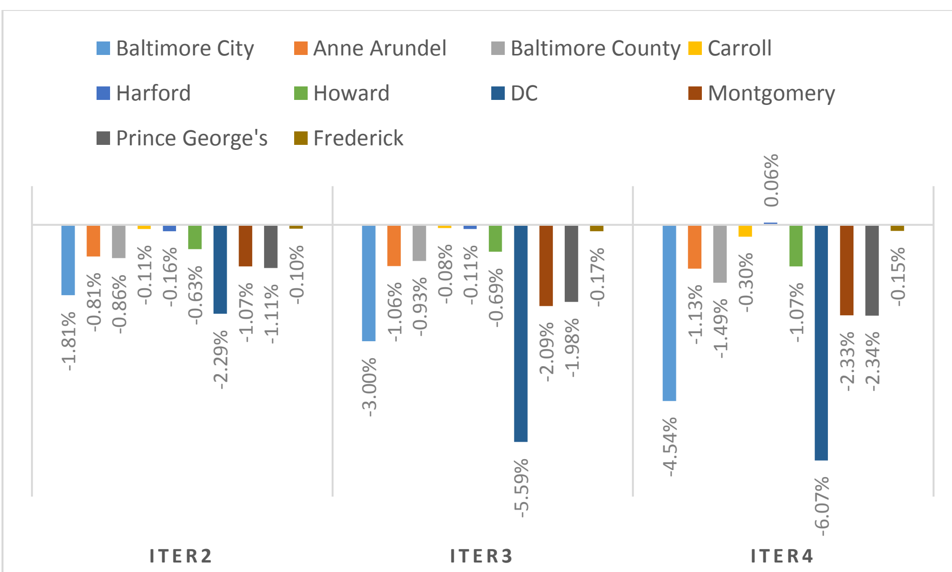


Figure 65 Change in Motorized Trips at the HH Level by Income Group (Transit-Oriented)

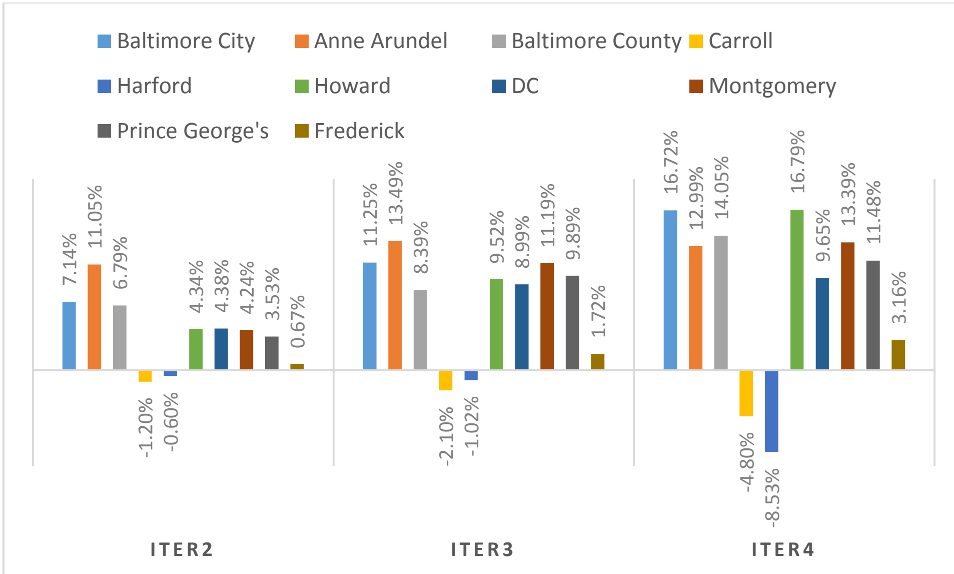


Figure 66 Change in Transit Trips at the HH Level by Income Group (Transit-Oriented)

To provide context for the results of this section, more information on the number of driving HHs is provided. Driving HHs in INC0 will decrease by 0.92%, while the number of INC4 drivers will increase by 0.37%. The fact that an increase is observed for most income groups is interesting, and may suggest that more users will be opting for motorized transportation modes (induced demand due to the overall network performance improvement). However, the results at the county level provide a slightly different narrative. Driving HHs in all counties (except for Harford) will decrease, as a result of investing in bus-only lanes. This is intuitive and suggests that the combination of the income distribution as well as the degree of transit dependency within each county are the two key drivers of the travel behavior changes.

Table 85 Number of Driving HHs by Income Group (Transit-Oriented)

	ITER1	ITER2	ITER3	ITER4
INC0	57,444	58,343	58,762	56,913
INC1	92,316	93,433	93,914	91,959
INC2	207,967	209,117	210,951	208,861
INC3	547,100	550,199	551,433	549,190
INC4	607,786	610,435	610,628	610,060

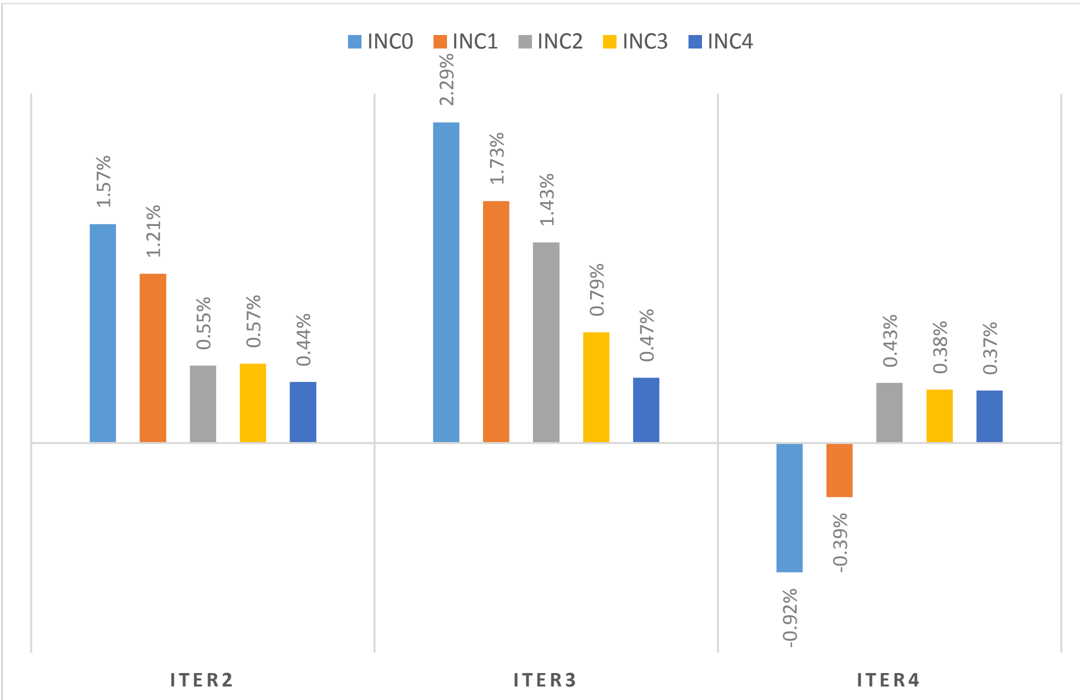


Figure 67 Change in Number of Driving HHs by Income Group (Transit-Oriented)

Table 86 Number of Driving HHs by County (Transit-Oriented)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	164,187	161,235	158,293	154,509
Anne Arundel	169,738	168,591	167,374	167,283
Baltimore County	248,392	247,521	245,961	244,088
Carroll	53,866	53,841	53,852	53,819
Harford	76,869	76,876	76,801	76,882
Howard	90,424	90,151	89,877	89,359
DC	145,780	140,475	135,170	134,339
Montgomery	289,045	286,107	283,168	282,391
Prince George's	249,861	247,031	244,200	243,319
Frederick	71,100	71,046	70,992	70,994

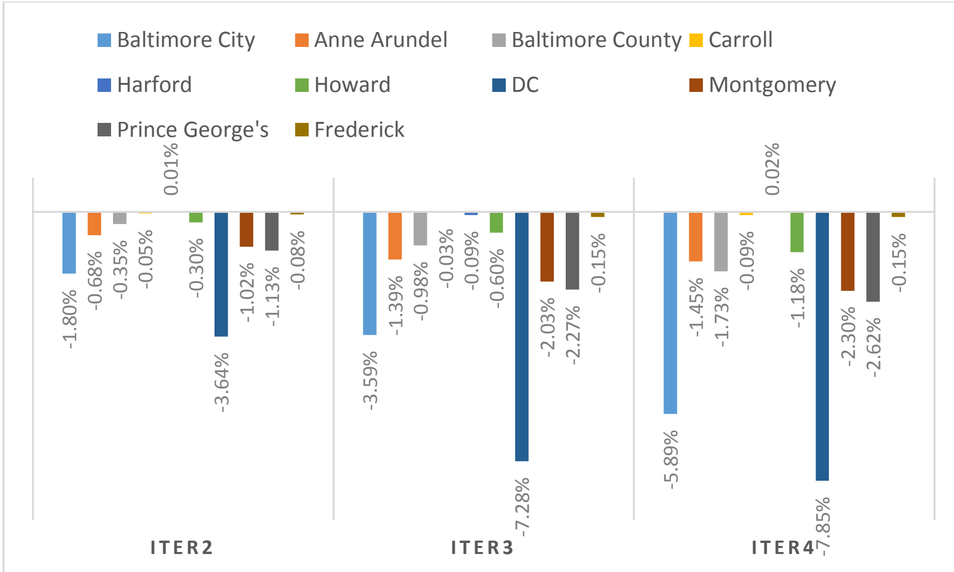


Figure 68 Change in Number of Driving HHs by County (Transit-Oriented)

Understanding the mode share results requires a simultaneous evaluation of the corresponding travel time and travel distance findings. The decrease in the number of motorized trips across all income groups is associated with a decrease in the average daily miles traveled. Users of INC0 and INC1 experience a slight increase at 1.64% and 0.33% respectively, but all other users experience a decrease ranging from 0.99% to 1.13%. In absolute terms, HHs of higher income are associated with longer driving distances, since they generate more trips. The findings regarding the number of motorized trips and the daily miles traveled, combined with the travel time results will shed more light on the effect of the revenue-investment dyad on travel behavior.

Table 87 Driving Distance at the HH Level by Income Group (miles) (Transit-Oriented)

	ITER1	ITER2	ITER3	ITER4
INC0	22.93	23.11	23.17	23.31
INC1	29.08	29.05	29.06	29.18
INC2	34.52	34.46	34.19	34.18
INC3	45.81	45.31	45.26	45.24
INC4	59.58	58.35	58.88	58.91

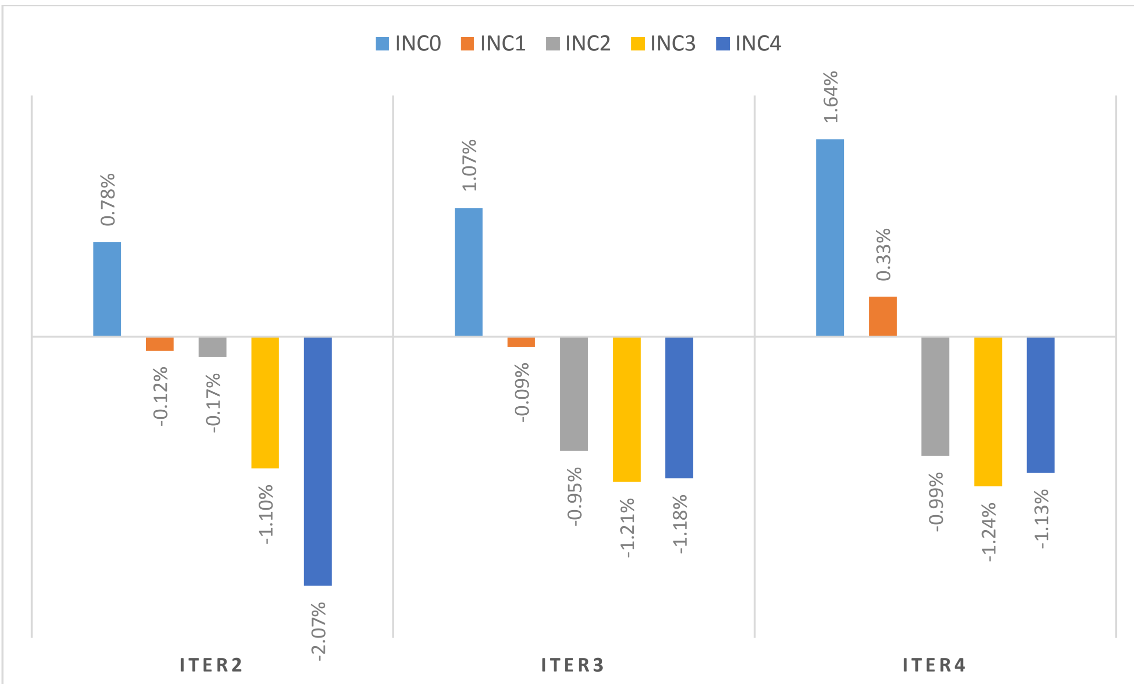


Figure 69 Change in Driving Distance at the HH Level by Income Group (Transit-Oriented)

At the county level, the driving distance results capture the effects of the revenue policy-investment outlook dyad on travel behavior. Carroll and Harford are the top 2 counties in terms of daily distance traveled at the HH level, at 70.4mi and 63.01 mi respectively. The urban and land use planning characteristics of these two counties support the results, as they encourage users to rely more on driving for their everyday trips. On the other hand, the shortest distances are observed for DC and Baltimore City. This is expected based on the characteristics of the DC and Baltimore City transportation networks, which discourage driving (compared to using public transit). The percent changes due the revenue policy-investment outlook dyad suggest that Baltimore City and Carroll county experience the largest decrease in miles driven at 1.97% and 1.50% respectively, while DC and Frederick experience the smallest decreases at 0.30% and 0.22% respectively.

Table 88 Driving Distance at the HH Level by County (miles) (Transit-Oriented)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	33.01	32.40	32.37	32.36
Anne Arundel	55.29	54.78	54.69	54.66
Baltimore County	49.82	49.39	49.19	49.14
Carroll	71.47	70.96	70.64	70.40
Harford	63.34	63.18	63.06	63.01
Howard	57.00	56.71	56.58	56.58
DC	20.68	20.62	20.60	20.62
Montgomery	44.18	43.90	43.75	43.87
Prince George's	49.09	48.75	48.71	48.72
Frederick	59.49	59.00	58.86	59.35

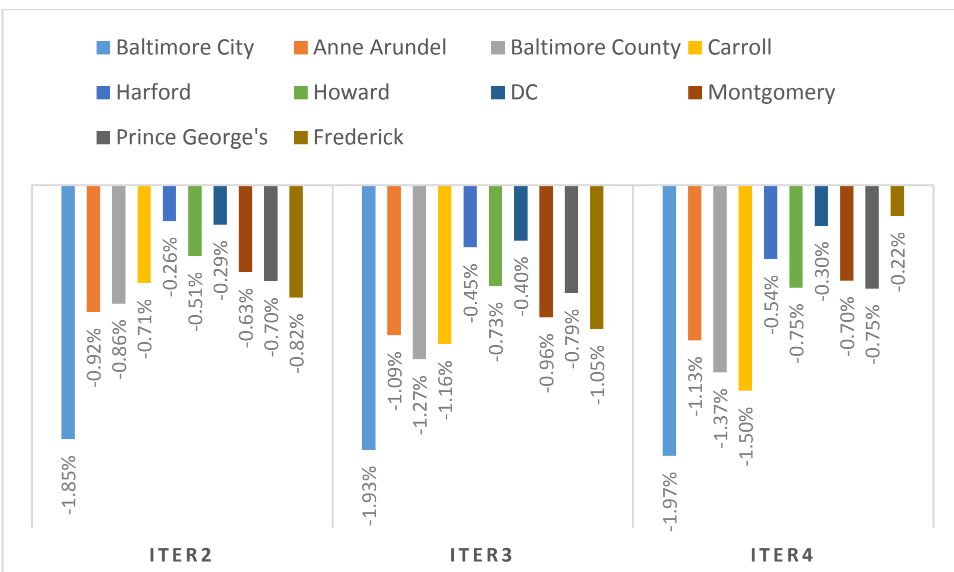


Figure 70 Change in Driving Distance at the HH Level by County (Transit-Oriented)

Despite the decrease in the number of motorized trips and the miles traveled across all income groups, the corresponding changes in travel times are positive, i.e. users experience increased travel times. Users of INC0 experience the largest increase at 7.33% versus a 3.98% increase for users of INC4 (smallest change). It can be inferred that these two phenomena can simultaneously occur under the implemented investment outlook, i.e. the bus lanes encourage shifting from driving to transit, however the fraction of the network modified is not big enough to induce network-wide travel time reduction. As expected, in absolute terms, HHs of higher income have higher daily travel times as they generate more trips, and the relationship between travel time (as a result of the number of motorized trips) and income is positively correlated.

Table 89 Driving Time at the HH Level by Income Group (minutes) (Transit-Oriented)

	ITER1	ITER2	ITER3	ITER4
INC0	136.56	142.58	146.46	146.57
INC1	172.44	177.90	182.37	182.26
INC2	203.30	211.18	213.17	212.36
INC3	263.38	272.59	275.10	274.50
INC4	352.00	364.26	366.41	366.00

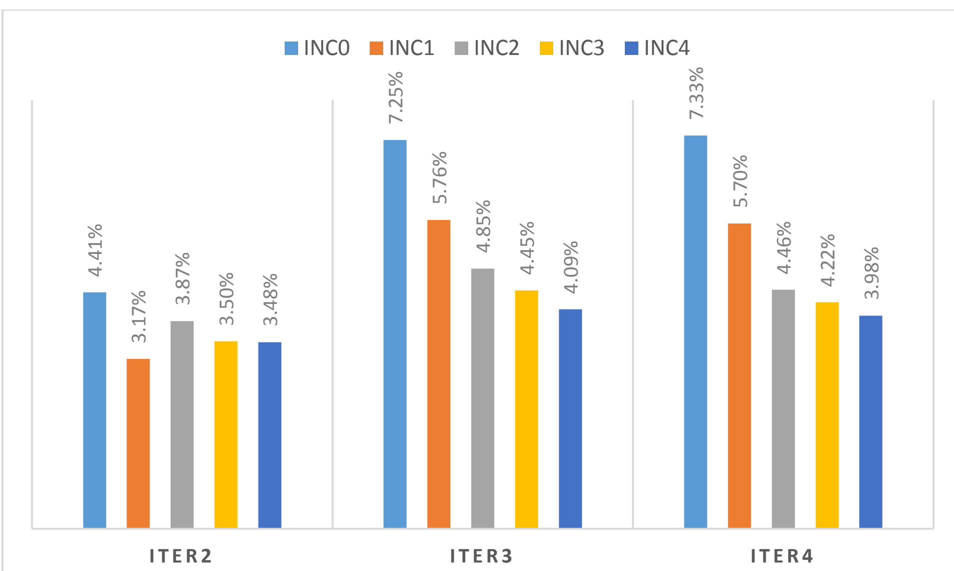


Figure 71 Change in Driving Time at the HH Level by Income Group (Transit-Oriented)

At the county level, the results follow similar patterns. Despite the decrease in the number of motorized trips across all counties (except for Carroll), the corresponding changes in travel time are positive, i.e. users experience increased travel times. Users in Baltimore County and Baltimore City experience the largest increases at 6.71% and 6.51% respectively. It can be inferred that these two phenomena can simultaneously occur under the implemented investment outlook, i.e. the bus lanes encourage shifting from driving to transit, however the fraction of the network modified is not big enough to induce network-wide travel time reduction. As expected, in absolute terms, HHs in areas with well-developed transit networks (DC and Baltimore City) have lower daily travel times as they generate less motorized trips, whereas HHs in relatively remote areas, that rely primarily on the highway network experience higher travel times (e.g. Anne Arundel, Frederick, etc.). However, as discussed before, another crucial factor that should always be accounted for when interpreting the county-level results is the income distribution for each county. Additionally, the level of investment in each county as part of the investment outlook is also a contributing factor that explains the model results.

Table 90 Driving Time at the HH Level by County (minutes) (Transit-Oriented)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	206.70	218.46	220.48	220.16
Anne Arundel	306.62	321.13	321.31	322.27
Baltimore County	254.59	268.21	270.77	271.69
Carroll	304.52	311.25	313.94	314.78
Harford	303.21	313.29	314.20	314.55
Howard	304.95	317.39	321.12	323.69
DC	195.63	200.12	202.81	199.39
Montgomery	276.35	286.39	288.65	287.16
Prince George's	326.57	336.72	338.99	336.85
Frederick	282.82	286.36	286.46	290.16

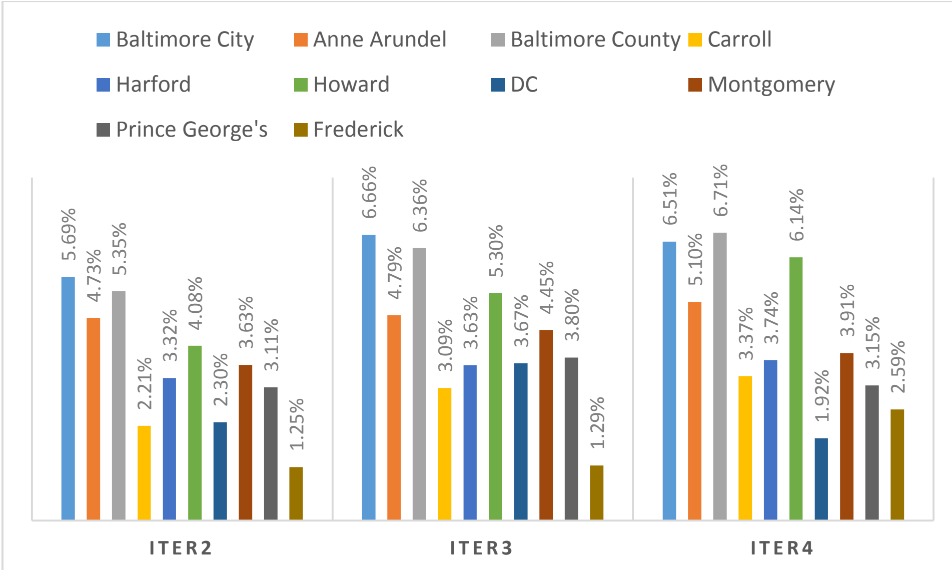


Figure 72 Change in Driving Time at the HH Level by County (Transit-Oriented)

The transit results suggest that the revenue-investment dyad will affect the transit-related metrics in an expected fashion. All income groups experience an increase in daily distance traveled by transit. It is also noteworthy that daily transit distance increases with income. Given the fact that the number of transit trips is fairly similar across all income groups, the difference in distance suggests that geography (place of residence, place of employment, etc.) plays a significant role.

Table 91 Transit Distance at the HH Level by Income Group (miles) (Transit-Oriented)

	ITER1	ITER2	ITER3	ITER4
INC0	9.20	9.27	9.36	9.43
INC1	9.74	9.90	9.96	10.00
INC2	10.20	10.38	10.48	10.51
INC3	11.92	12.03	12.11	12.16
INC4	14.86	14.98	15.05	15.09

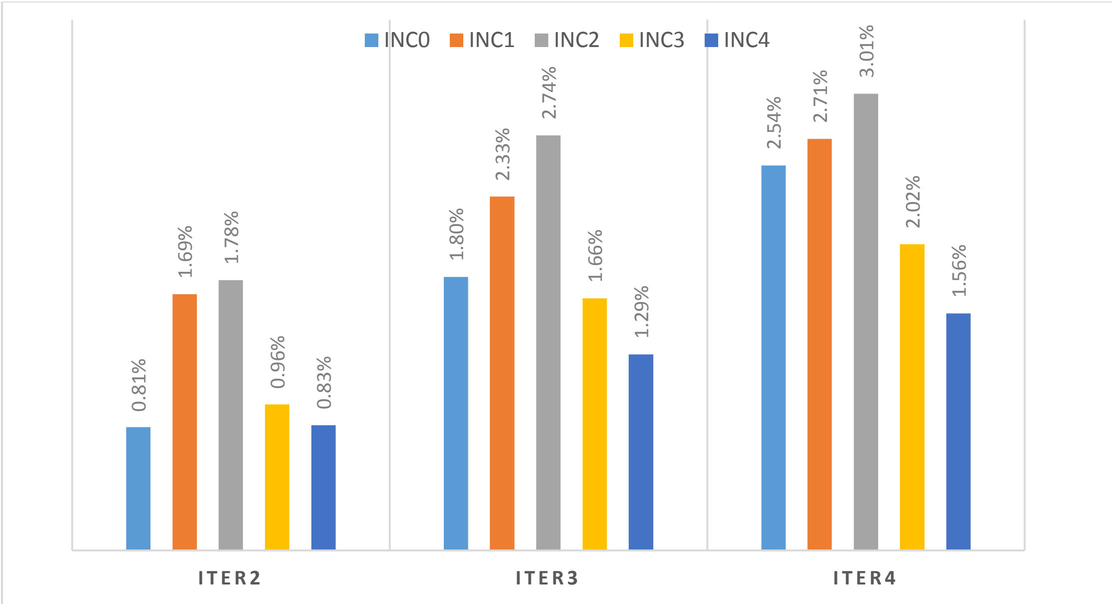


Figure 73 Change in Transit Distance at the HH Level by Income Group (Transit-Oriented)

The county level results lead to similar conclusions but with a stronger focus on geography. HHs in Carroll and Harford have the highest distance traveled by transit, most likely due to the urban planning and land use characteristics of the county. On the other hand, DC and Baltimore City HHs have the shortest transit distances, despite a heavier use of transit. Harford and Carroll will experience the largest increase at 7.68% and 4.35% respectively, while Anne Arundel will experience the smallest, at only 0.2%. DC and Baltimore City will experience increases of moderate magnitude, at 2.60% and 3.36% respectively.

Table 92 Transit Distance at the HH Level by County (miles) (Transit-Oriented)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	9.48	9.63	9.67	9.80
Anne Arundel	17.84	17.81	17.81	17.88
Baltimore County	14.04	14.15	14.19	14.24
Carroll	18.15	19.00	19.03	18.93
Harford	21.26	22.35	22.29	22.89
Howard	16.68	17.11	17.08	17.24
DC	8.45	8.67	8.69	8.67
Montgomery	12.64	12.84	12.83	12.86
Prince George's	14.23	14.50	14.47	14.46

Frederick	13.96	13.76	13.77	14.56

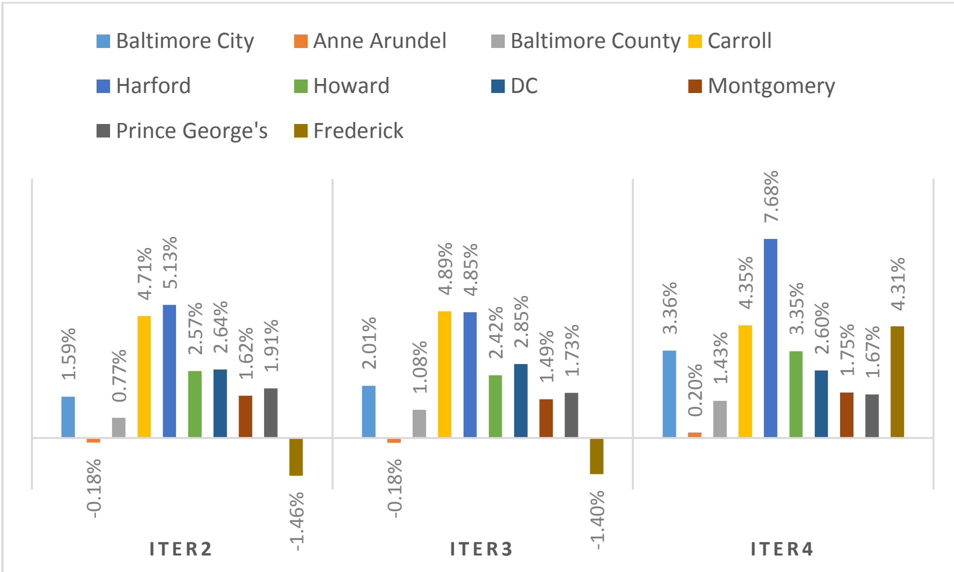


Figure 74 Change in Transit Distance at the HH Level by County (Transit-Oriented)

As expected, HHs of lower income spent more time on transit trips (a direct effect of the number of transit trips generated by income group). All income groups except for INC0 experience an increase in the daily transit travel time, which can be attributed to the fact that they make the highest number of transit trips among all income groups.

Table 93 Transit Travel Time at the HH Level by Income Group (minutes) (Transit-Oriented)

	ITER1	ITER2	ITER3	ITER4
INC0	132.08	132.05	132.04	130.84
INC1	124.71	125.14	126.02	125.23
INC2	121.09	121.50	123.42	122.53
INC3	111.34	111.94	113.55	113.03
INC4	124.63	125.48	126.91	125.70

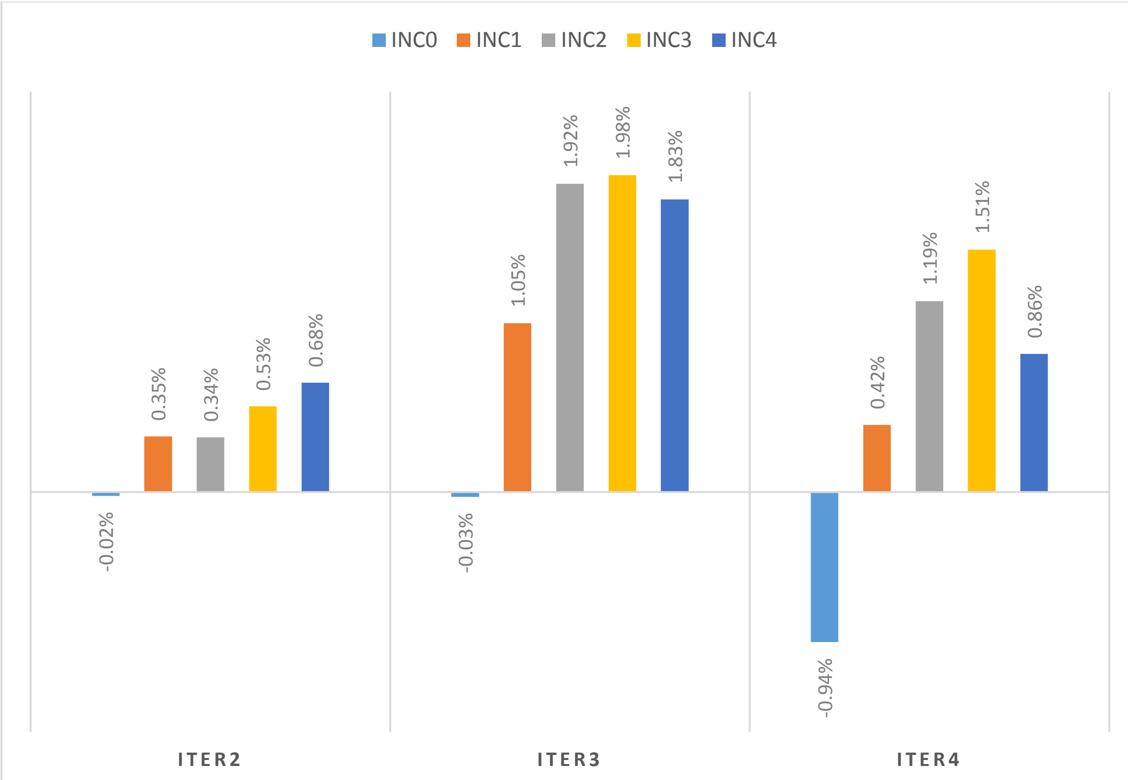


Figure 75 Change in Transit Travel Time at the HH Level by Income Group (Transit-Oriented)

At the county level, the longest transit travel times are observed for HHs in Prince George's county (137.42 min) and Howard County (172.89 min). On the other hand, the shortest transit travel times are observed for HHs in Carroll County (70.78 min) and Frederick County (78.01 min). All counties but Anne Arundel, Baltimore County, Montgomery County and Prince George's County experience a decrease in transit travel times.

Table 94 Transit Travel Time at the HH Level by County (minutes) (Transit-Oriented)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	135.22	133.98	133.85	132.97
Anne Arundel	128.95	134.10	135.45	134.20
Baltimore County	133.09	134.55	134.54	135.67
Carroll	77.08	73.80	75.43	70.78
Harford	96.22	94.26	97.28	92.67
Howard	177.27	172.15	172.64	172.89
DC	102.27	102.98	103.89	102.07
Montgomery	115.01	116.58	117.63	116.43
Prince George's	136.74	138.50	139.06	137.42

	ITER1	ITER2	ITER3	ITER4
Frederick	80.22	79.21	78.54	78.01

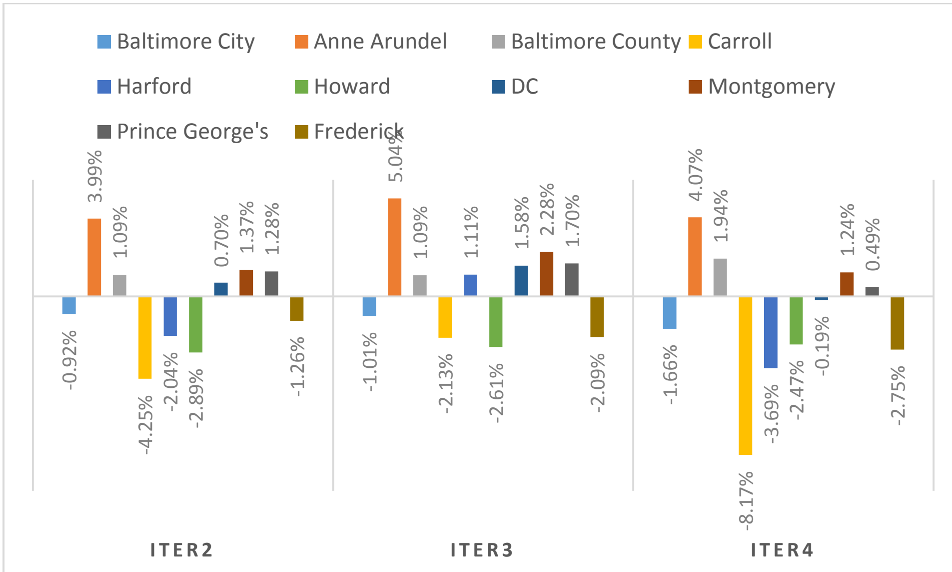


Figure 76 Change in Transit Travel Time at the HH Level by County (Transit-Oriented)

4.2.3 Revenue Potential

The transportation-dedicated property tax policy exhibits a more interesting behavior. Among the 5 income groups, the lowest revenue is generated from INC2, INC1 and INC0 ($62,711, $82,938, and $113,119 respectively). County-wise, Montgomery, Prince George's, and Baltimore counties generate the highest revenue ($212,097, $169,695, and $166,839 respectively), while Carroll, Frederick and Harford generate the lowest ($34,680, $46,614, $49,614 respectively).

Table 95 Annual Revenue Generation by Income Group (Transit-Oriented)

Income Group	Num. of Paying HHs	% of HHs Paying Property Tax	Revenue Generation from Transportation Dedicated Property Taxes
INC0	142,029	48%	$41,288,519
INC1	97,032	47%	$30,272,509
INC2	105,812	34%	$22,889,693

Income Group	Num. of Paying HHs	% of HHs Paying Property Tax	Revenue Generation from Transportation Dedicated Property Taxes
INC3	361,763	54%	$87,775,815
INC4	594,385	88%	$206,624,856
Total	**1,301,021**		**$388,851,391**

Table 96 Annual Revenue Generation by County (Transit-Oriented)

County	Num. of Paying HHs	% of HHs Paying Property Tax	Revenue Generation from Transportation Dedicated Property Taxes
Anne Arundel	137,589	65%	$42,775,418
Baltimore City	146,410	55%	$42,913,407
Baltimore County	200,336	62%	$60,896,361
Carroll	41,366	64%	$12,658,082
DC	132,097	44%	$31,553,283
Frederick	55,236	63%	$17,014,264
Harford	59,297	64%	$18,109,154
Howard	75,215	71%	$23,577,048
Montgomery	251,427	69%	$77,415,584
Prince George's	202,048	63%	$61,938,791
Total	**1,301,021**	**61%**	**$388,851,391**

4.3 Outlook C: CAV Implementation

4.3.1 Taxpaying Incidence

It is evident that, a long-term implementation of the variable-rate VMT fee and CAV implementation dyad will result in an increase in the taxpaying population. Taxpayers in INC0 will increase by 6.91%, which is the highest increase among all income groups, while the number of INC4 taxpayers will increase by only 0.73%. The fact that an increase is observed across all income groups is interesting, and shows that more users will be opting for motorized transportation modes, therefore contributing to the revenue generated. Such a choice is intuitive as users now have access to a better-performing highway network that reduces their overall travel time. The fact that the percent change for lower income groups is higher than the corresponding change for higher income groups can be attributed to the actual percentage of users in each income bin driving.

Table 97 Taxpaying Population by Income Group (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4
INC0	57,444	57,655	61,212	61,412
INC1	92,316	92,267	96,095	96,075
INC2	207,967	207,824	213,803	213,427
INC3	547,100	546,300	555,625	555,420
INC4	607,786	607,425	612,760	612,240

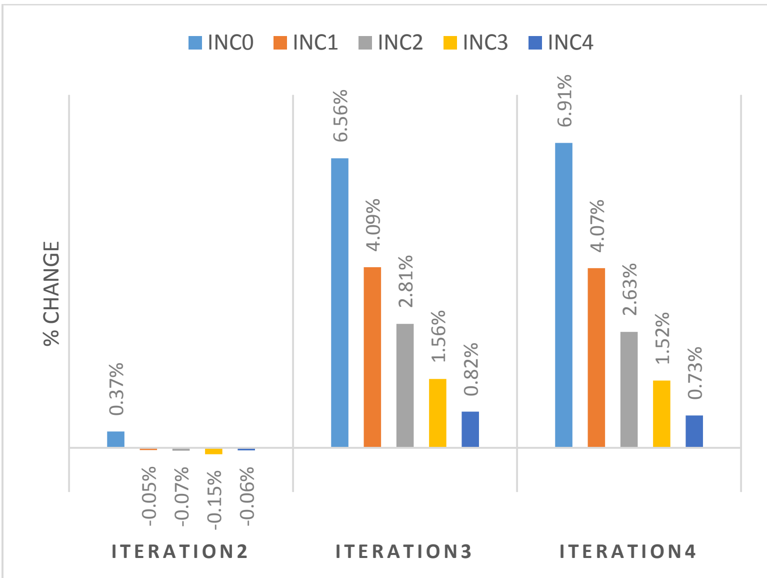


Figure 77 Change in Taxpaying Population by Income Group (CAV Implementation)

The results at the county level follow a similar rationale. A long-term implementation of the revenue-investment dyad will result in an increase in the taxpaying population. Taxpayers in DC and Baltimore City will increase by 5.07% and 4.56 % respectively, which is the highest increase among all counties, while the number of taxpayers in Frederick and Harford will increase by only 0.31% and 0.3% respectively. Similar to the income-based discussion, the fact that an increase is observed across all counties is interesting, and shows that more users will be opting for motorized transportation modes, therefore contributing to the revenue generated. Such a choice is intuitive as users now have access to a better-performing highway network that reduces their overall travel time. The fact that the percent change for some counties is higher than others can be attributed to the actual percentage of users in each county driving. It is therefore evident that DC and Baltimore County provided larger margins for improvement. It is also important to acknowledge the income distribution in each county, and interpret the county results in conjunction with the income-based results.

Table 98 Taxpaying Population by County (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	154,352	153,901	161,778	161,389
Anne Arundel	165,620	166,043	166,634	166,581
Baltimore County	242,636	242,367	246,099	245,845
Carroll	53,736	53,903	53,883	53,867
Harford	76,677	76,926	76,915	76,907
Howard	91,011	90,897	91,836	91,823
DC	135,135	134,109	141,922	141,991
Montgomery	281,669	281,717	284,695	284,511
Prince George's	240,812	240,445	244,523	244,473
Frederick	70,965	71,163	71,210	71,187

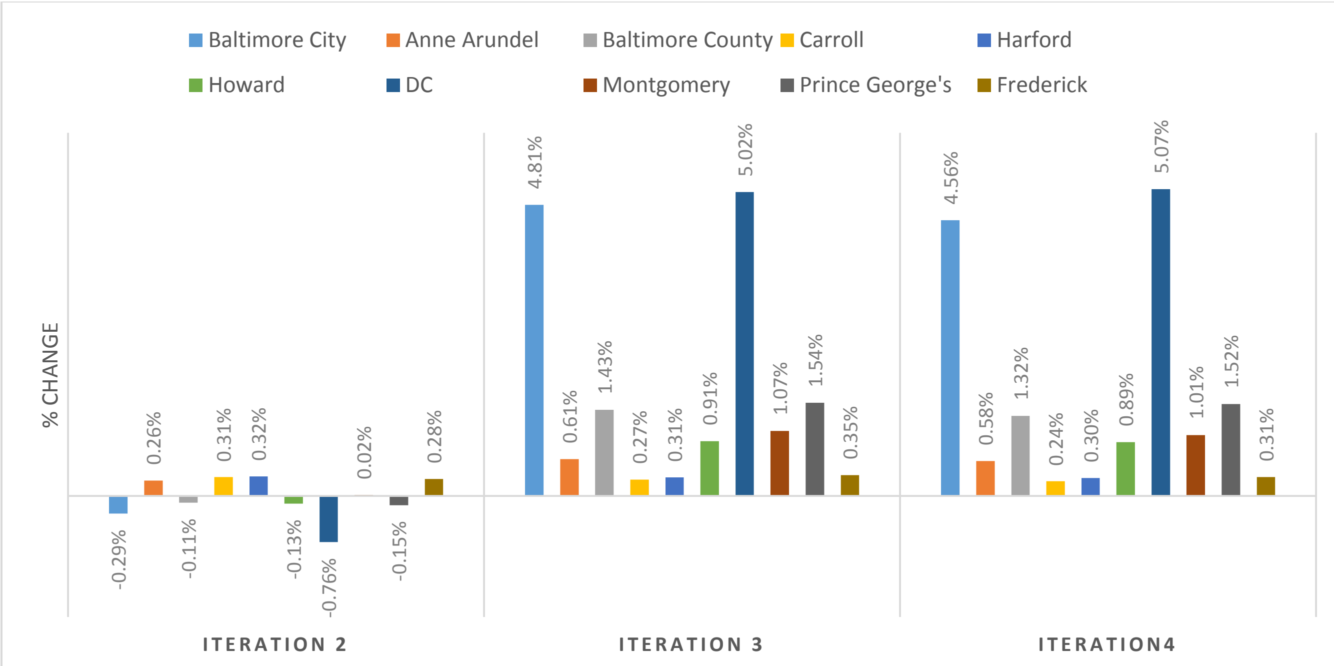


Figure 78 Change in Taxpaying Population by County (CAV Implementation)

Estimating the tax-to-income ratio as another measure of tax incidence is important in order to understand how users will be financially affected by the implemented revenue and investment policies in the long run. Since the focus of this dissertation is state-level revenue and investment policies, and only the state component of the implemented revenue strategies were subject to regulation, the discussion focuses on the state tax-to-income ratios by income group and county.

A long-term implementation of revenue-investment dyad will result in an increase in the state tax-to-income ratios for all income groups. These results indicate that as income increases, users bear a larger financial burden, most likely because their travel behavior changes at a faster pace. However, it should be noted that these changes are minor and, although they suggest a pattern, they do not seem to capture significant changes in the financial situation of the users.

Table 99 State Tax-to-Income by Income Group (%) (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4

INC0	2.076	2.042	2.10	2.08
INC1	0.547	0.546	0.57	0.56
INC2	0.335	0.337	0.35	0.35
INC3	0.231	0.232	0.25	0.24
INC4	0.226	0.228	0.24	0.24

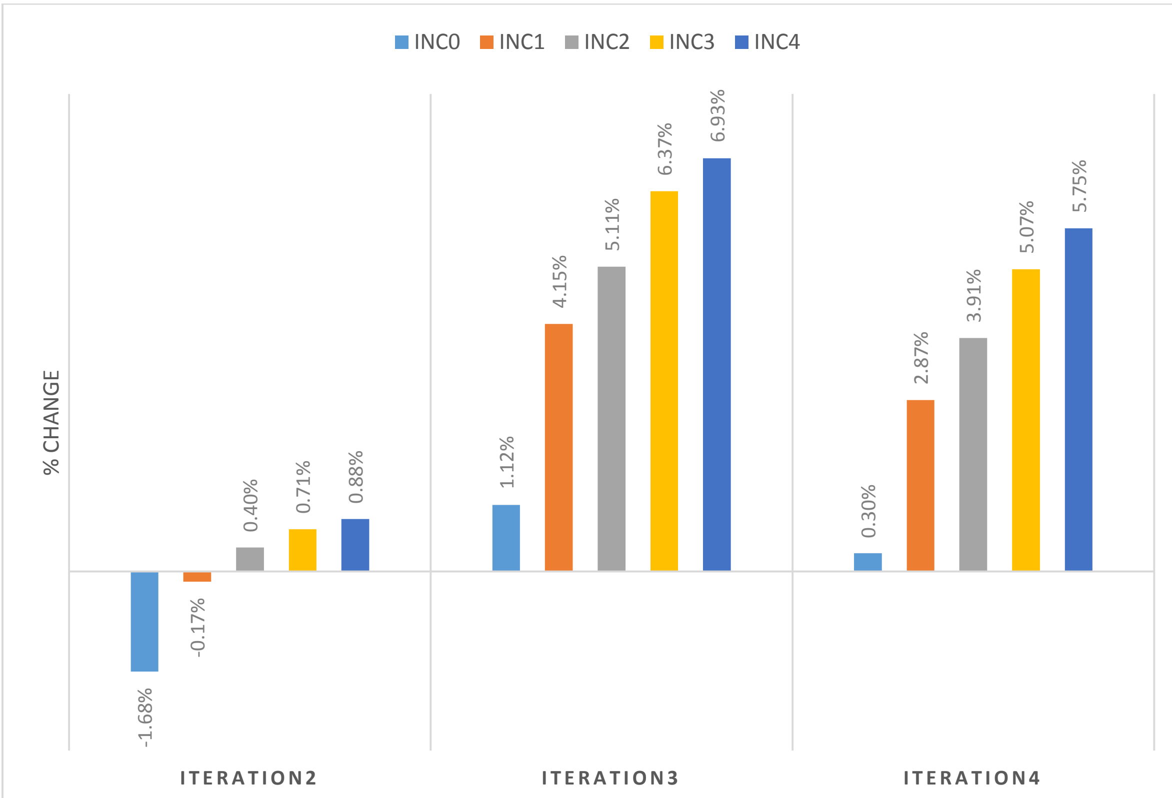


Figure 79 Change in State Tax-to-Income by Income Group (CAV Implementation)

At the county level, the revenue-investment dyad will result in an increase in the state fuel tax-to-income ratios for all counties. This increase is most likely due to the increased travel activity that users undertake. The biggest increases are observed for Howard and Carroll counties, while the smallest increases are observed for HHs in Harford and DC.

Table 100 State Tax-to-Income by County (%) (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	0.213%	0.215%	0.228%	0.225%
Anne Arundel	0.276%	0.277%	0.296%	0.292%
Baltimore County	0.261%	0.263%	0.279%	0.276%
Carroll	0.348%	0.351%	0.380%	0.375%

Harford	0.319%	0.320%	0.334%	0.331%
Howard	0.257%	0.260%	0.279%	0.275%
DC	0.142%	0.144%	0.151%	0.149%
Montgomery	0.212%	0.214%	0.225%	0.224%
Prince George's	0.267%	0.270%	0.286%	0.282%
Frederick	0.317%	0.319%	0.337%	0.332%

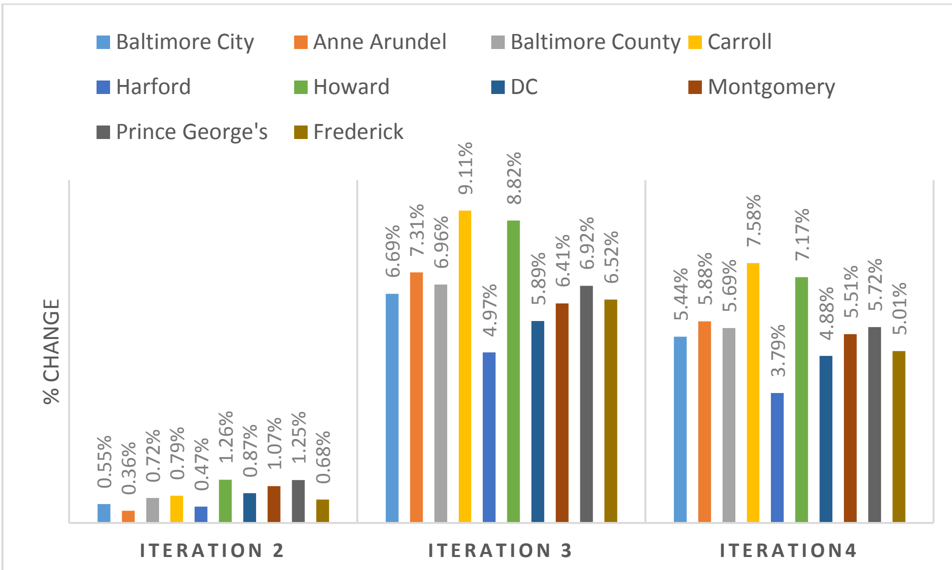


Figure 80 Change in State Tax-to-Income by County (CAV Implementation)

4.3.2 Travel Behavior

The largest increase in motorized trips is observed for INC0 at 6.67%, which, as expected, also has the lowest absolute number of daily motorized trips at 1.78. On the other hand, INC4 has the largest number of daily motorized trips (7.80 trips per day) and experiences the smallest increase at 2.40%.

The largest decrease in transit trips is observed for INC3 at 17.02%, which as expected, also has the lowest absolute numbers of daily transit trips at 0.39 transit trips per day. On the other hand, INC0 and INC4 have the largest number of daily transit trips and experience decreases, at 6.5% and 14.67% respectively.

Table 101 Motorized Trips at the HH Level by Income Group (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4
INC0	1.67	1.70	1.80	1.78
INC1	2.86	2.90	3.02	3.01
INC2	4.39	4.42	4.57	4.56
INC3	5.97	6.00	6.15	6.14
INC4	7.61	7.64	7.81	7.80

Table 102 Transit Trips at the HH Level by Income Group (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4
INC0	0.77	0.76	0.72	0.72
INC1	0.58	0.56	0.50	0.50
INC2	0.61	0.59	0.52	0.52
INC3	0.47	0.46	0.39	0.39
INC4	0.61	0.60	0.52	0.52

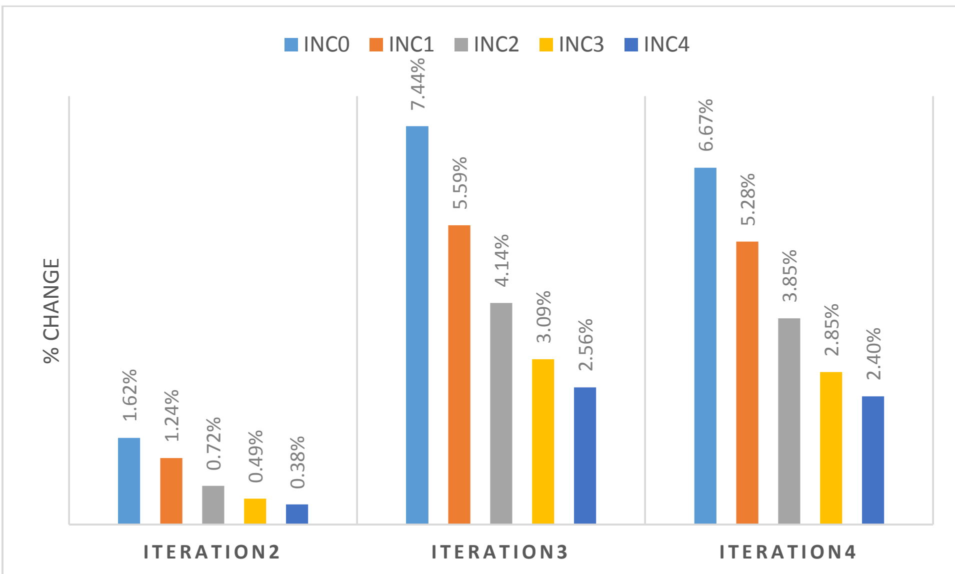


Figure 81 Change in Motorized Trips at the HH Level by Income Group (CAV Implementation)

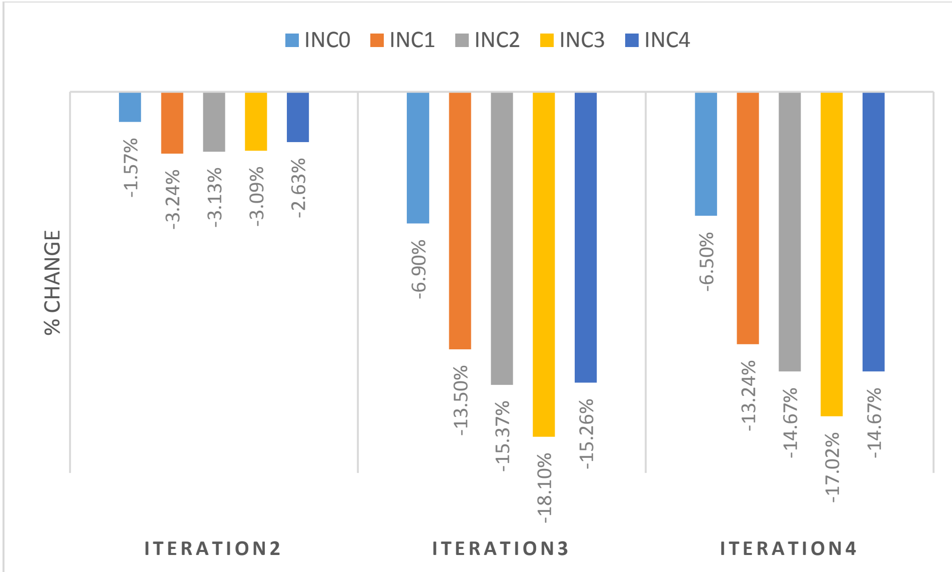


Figure 82 Change in Transit Trips at the HH Level by County (CAV Implementation)

The largest increases in motorized trips are observed for DC and Baltimore City at 8.20% and 5.60% respectively which, as expected, also have the lowest absolute numbers of daily motorized trips at 2.81 and 4.51 respectively. On the other hand, Carroll and Howard counties have the largest number of daily motorized trips and experience some of the smallest increases in the model, at 1.06% and 2.19% respectively.

The largest decreases in transit trips are observed for Carroll and Howard counties at 25.24% and 22.18% respectively which, as expected, also have very low absolute numbers of daily transit trips at 0.04 and 0.21 respectively. On the other hand, DC and Baltimore City have the largest number of daily transit trips (as expected for cities with well-developed transit networks) and experience average level decreases, at 10.53% and 13.16% respectively. However, when observing the transit trip changes, caution is recommended: despite the fact that some percentages may seem very high, the absolute numbers remain fairly steady for all practical considerations.

Table 103 Motorized Trips at the HH Level by County (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	4.2687	4.2955	4.5429	4.5078
Anne Arundel	6.4089	6.423	6.5181	6.5064
Baltimore County	5.7067	5.7269	5.8707	5.8597
Carroll	7.052	7.0711	7.1477	7.1275
Harford	6.9799	6.9793	7.0214	7.0186
Howard	6.9769	6.9977	7.152	7.1296
DC	2.5956	2.6507	2.8257	2.8085
Montgomery	5.8189	5.8531	5.9885	5.994
Prince George's	5.7022	5.7449	5.8996	5.8872
Frederick	6.7094	6.712	6.7683	6.7588

Table 104 Transit Trips at the HH Level by County (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	0.8096	0.7967	0.6895	0.7031
Anne Arundel	0.2838	0.2702	0.2245	0.2283
Baltimore County	0.3781	0.3707	0.3126	0.3158
Carroll	0.0559	0.0546	0.0404	0.0418
Harford	0.1166	0.114	0.0952	0.0972
Howard	0.2717	0.2623	0.2069	0.2115
DC	1.2149	1.1807	1.08	1.087
Montgomery	0.6339	0.6163	0.5497	0.5477
Prince George's	0.6482	0.6273	0.5493	0.5515
Frederick	0.0937	0.0928	0.0838	0.0843

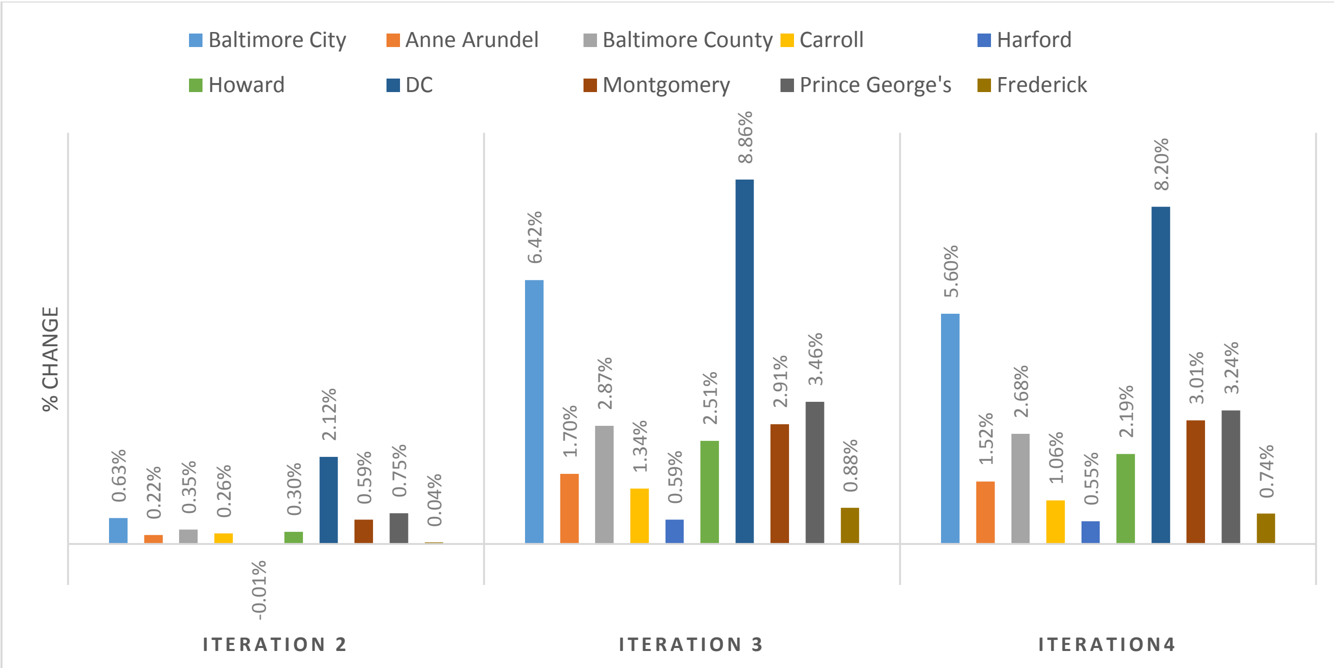


Figure 83 Change in Motorized Trips at the HH Level by County (CAV Implementation)

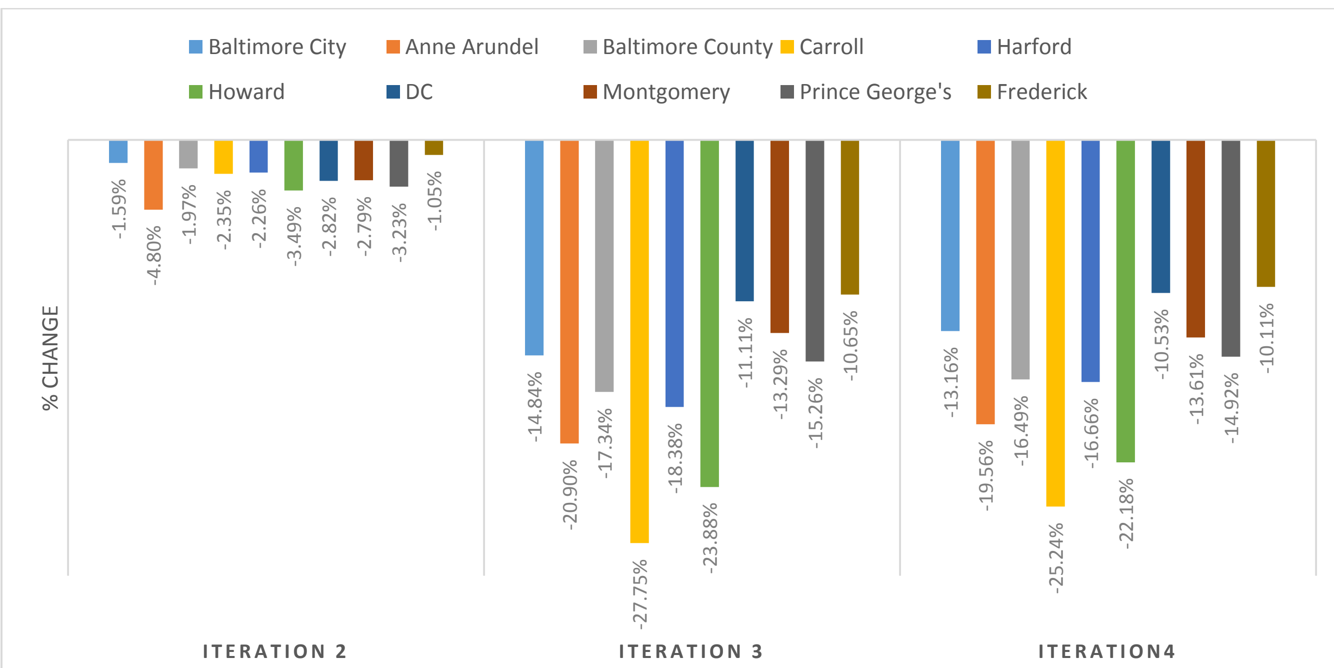


Figure 84 Change in Transit Trips at the HH Level by County (CAV Implementation)

Understanding the mode share results requires a simultaneous evaluation of the corresponding travel time and travel distance findings. The increase in the number of motorized trips across all income groups is associated with an increase in the average daily miles traveled. Users of INC0 experience the smallest increase at 4.9% versus a 6.39% increase for users of INC3. In absolute terms, HHs of higher income are associated with longer driving distances, since they generate more trips. The findings regarding the number of motorized trips and the daily miles traveled, combined with the travel time results will shed more light on the effect of the revenue-investment dyad on travel behavior.

Table 105 Driving Distance at the HH Level by Income Group (miles) (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4
INC0	22.22	22.28	23.55	23.31
INC1	27.88	28.13	29.91	29.57
INC2	32.63	32.95	35.07	34.69
INC3	43.21	43.66	46.54	45.98
INC4	55.79	56.34	59.96	59.29

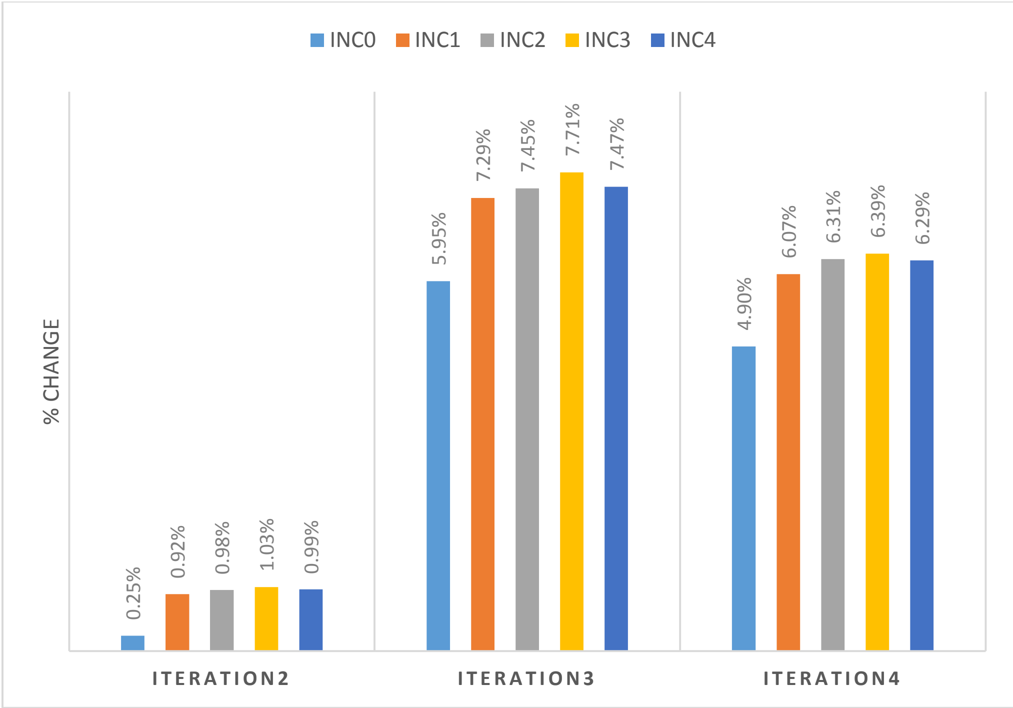


Figure 85 Change in Driving Distance at the HH Level by Income Group (CAV Implementation)

At the county level, the driving distance results capture the effects of the revenue policy-investment outlook dyad on travel behavior. Carroll and Frederick are the top 2 counties in terms of daily distance traveled at the HH level, at 72.34mi and 63.07mi respectively. The urban and land use planning characteristics of these two counties support the results, as they encourage users to rely more on driving for their everyday trips. On the other hand, the shortest distances are observed for DC and Baltimore City. This is expected based on the characteristics of the DC and Baltimore City transportation networks, which discourage driving (compared to using public transit). The percent changes due to the revenue policy-investment outlook dyad suggest that Howard and Carroll experience the largest increase in miles driven at 7.46% and 7.63% respectively, while Harford and Frederick experience the smallest increases at 3.81% and 4.99% respectively.

Table 106 Driving Distance at the HH Level by County (miles) (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	28.71	28.94	31.18	30.79
Anne Arundel	53.34	53.60	57.39	56.63
Baltimore County	45.33	45.71	48.73	48.19
Carroll	67.21	67.64	73.21	72.34
Harford	59.92	60.21	62.93	62.20
Howard	53.01	53.70	57.85	56.96
DC	19.58	19.87	21.22	21.01
Montgomery	42.06	42.58	45.03	44.66
Prince George's	47.14	47.79	50.65	50.12
Frederick	60.07	60.51	63.98	63.07

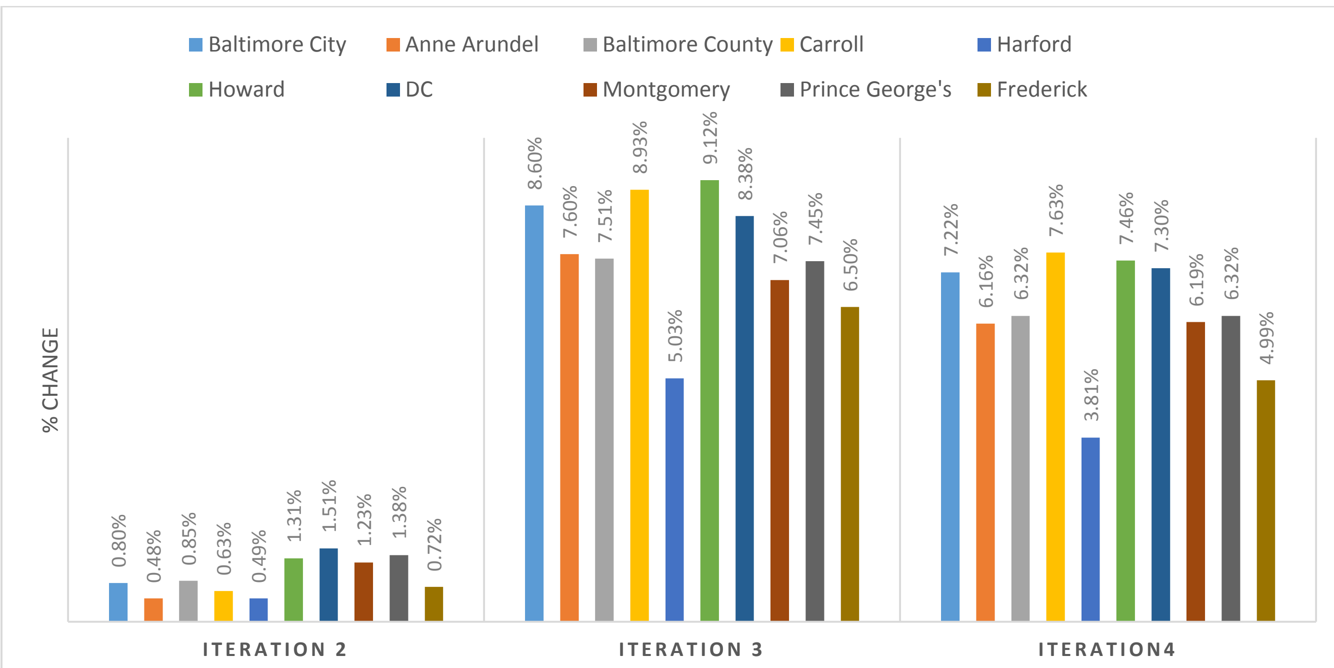


Figure 86 Change in Driving Distance at the HH Level by County (CAV Implementation)

Despite the increase in the number of motorized trips and the miles traveled across all income groups, the corresponding changes are negative, i.e. users experience reduced travel times. Users of INC0 experience the largest change at 18.49% versus a 15.18% decrease for users of INC4 (smallest change), suggesting that the additional capacity reduces congestion and subsequently attracts more trips. As expected, in absolute terms, HHs of higher income have higher daily travel times as they generate more trips, and the relationship between travel time (as a result of the number of motorized trips) and income is positively correlated.

Table 107 Driving Time at the HH Level by Income Group (minutes) (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4
INC0	184.69	177.40	146.31	150.54
INC1	229.31	222.17	184.95	190.29
INC2	266.26	258.22	215.87	221.80
INC3	340.95	332.13	279.93	286.79
INC4	446.63	435.35	370.42	378.82

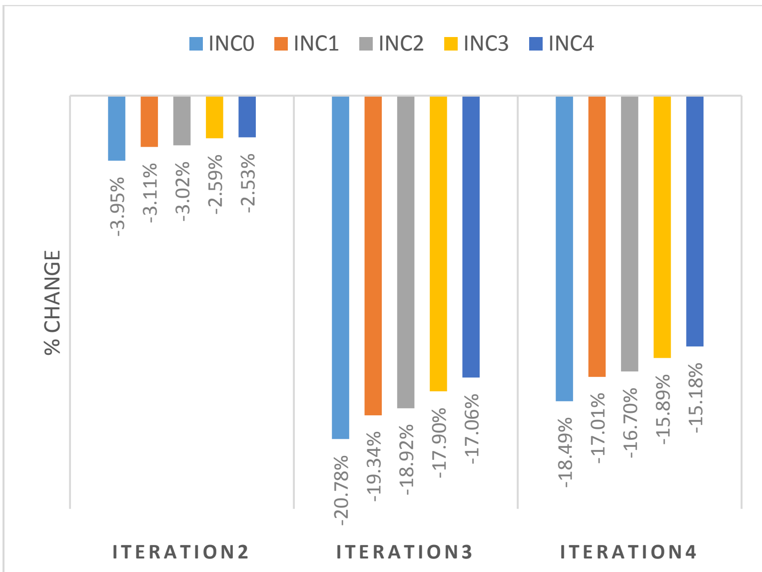


Figure 87 Change in Driving Time at the HH Level by Income Group (CAV Implementation)

At the county level, the results follow similar patterns. Despite the increase in the number of motorized trips across all counties, the corresponding changes are negative, i.e. users experience reduced travel times. Users in Baltimore City experience the largest change at 19.82% versus a 10.37% decrease for users in Frederick (smallest change). As expected, in absolute terms, HHs in areas with well-developed transit networks (DC and Baltimore City) have lower daily travel times as they generate less motorized trips, whereas HHs in relatively remote areas, that rely primarily on the highway network experience higher travel times (e.g. Anne Arundel, Frederick, etc.). However, as discussed before, another crucial factor that should always be accounted for when interpreting the county-level results is the income distribution for each county.

Table 108 Driving Time at the HH Level by County (minutes) (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	270.67	263.71	208.43	217.04
Anne Arundel	415.95	400.19	335.84	343.21
Baltimore County	329.35	322.79	263.90	272.72
Carroll	376.95	372.70	322.44	330.19
Harford	353.75	348.84	309.23	312.84
Howard	408.14	395.70	324.13	333.99
DC	248.17	240.15	206.02	210.73
Montgomery	354.73	345.33	294.51	301.91
Prince George's	422.23	408.13	351.13	357.20
Frederick	348.66	344.49	310.29	312.50

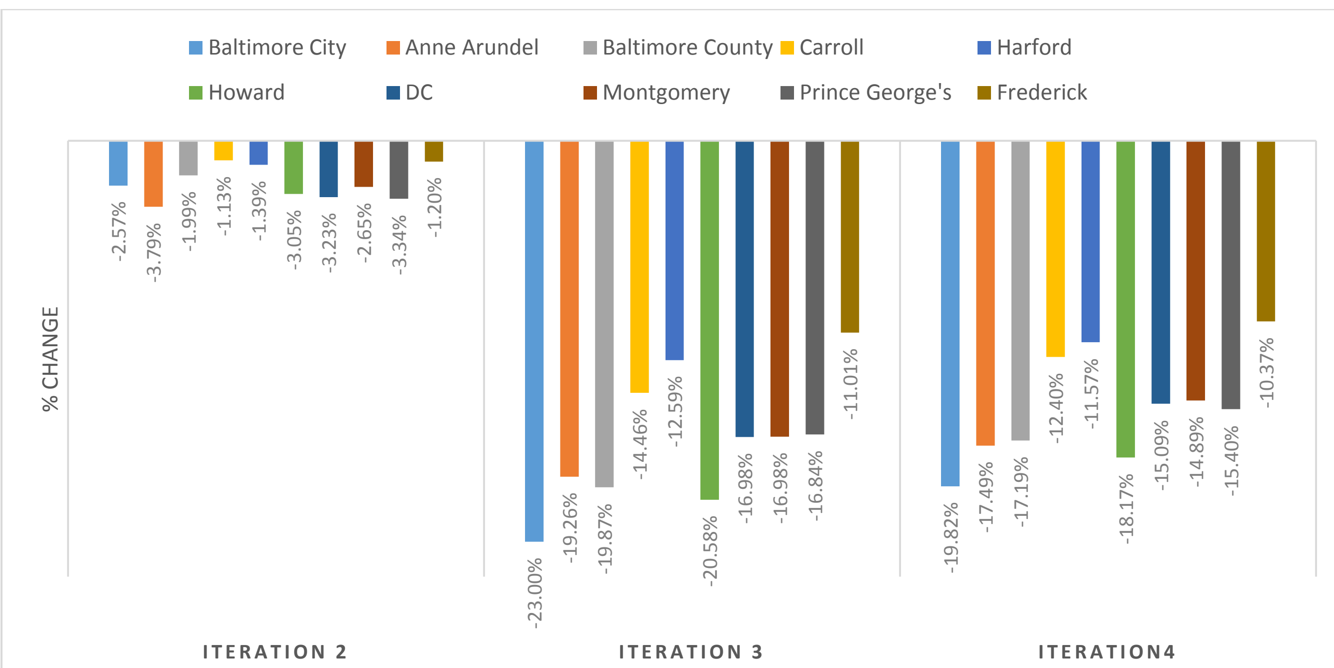


Figure 88 Change in Driving Time at the HH Level by County (CAV Implementation)

The transit results suggest that the revenue-investment dyad will affect the transit-related metrics in an expected fashion. While all income groups experience a decrease in daily distance traveled by transit, users of INC0 and INC4 experience the smallest percentage changes (-3.98% and -4.75% respectively). For both income groups, the small percentages can be attributed to the corresponding small decreases observed in the number of transit trips. It is also noteworthy that daily transit distance increases with income. Given the fact that the number of transit trips is fairly similar across all income groups, the difference in distance suggests that geography (place of residence, place of employment, etc.) plays a significant role.

Table 109 Transit Distance at the HH Level by Income Group (miles) (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4
INC0	9.38	9.28	9.03	9.00
INC1	10.00	9.86	9.38	9.40
INC2	10.49	10.33	9.80	9.79
INC3	12.10	11.96	11.36	11.41
INC4	15.25	15.12	14.52	14.53

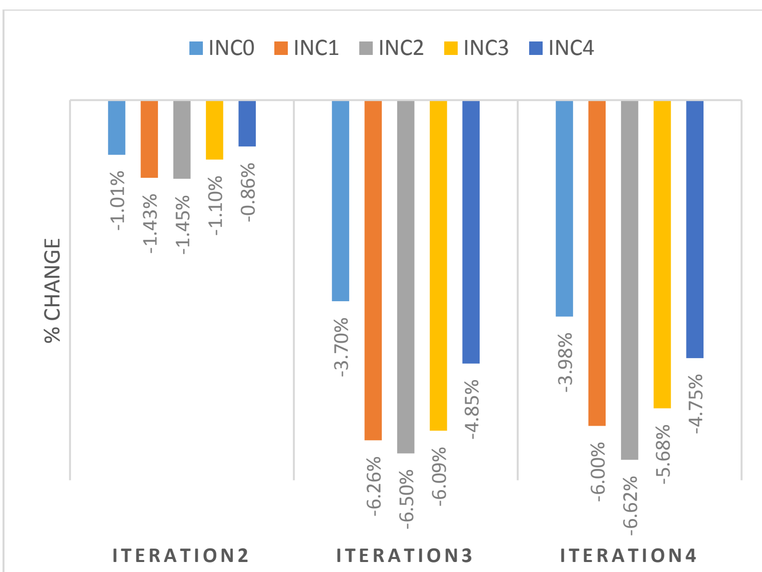


Figure 89 Change in Transit Distance at the HH Level by Income Group (CAV Implementation)

The county level results lead to similar conclusions but with a stronger focus on geography. HHs in Carroll and Harford have the highest distance traveled by transit, most likely due to the urban planning and land use characteristics of the county. On the other hand, DC and Baltimore City HHs have the shortest transit distances, despite a heavier use of transit. Harford and Frederick will experience the largest decrease at 9.14% and 12.02% respectively, while Baltimore County will experience the smallest, at 3.28%. DC and Baltimore City will experience decreases of average magnitude, at 4.66% and 4.00% respectively.

Table 110 Transit Distance at the HH Level by County (miles) (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	9.38	9.35	8.98	9.01
Anne Arundel	18.47	17.62	16.81	16.81
Baltimore County	13.25	13.24	12.72	12.82
Carroll	18.78	19.00	18.11	17.80
Harford	23.29	23.14	21.10	21.16
Howard	16.95	16.86	15.93	16.06
DC	8.89	8.82	8.48	8.48
Montgomery	12.89	12.81	12.41	12.40
Prince George's	14.82	14.71	14.23	14.20
Frederick	13.13	13.01	11.72	11.55

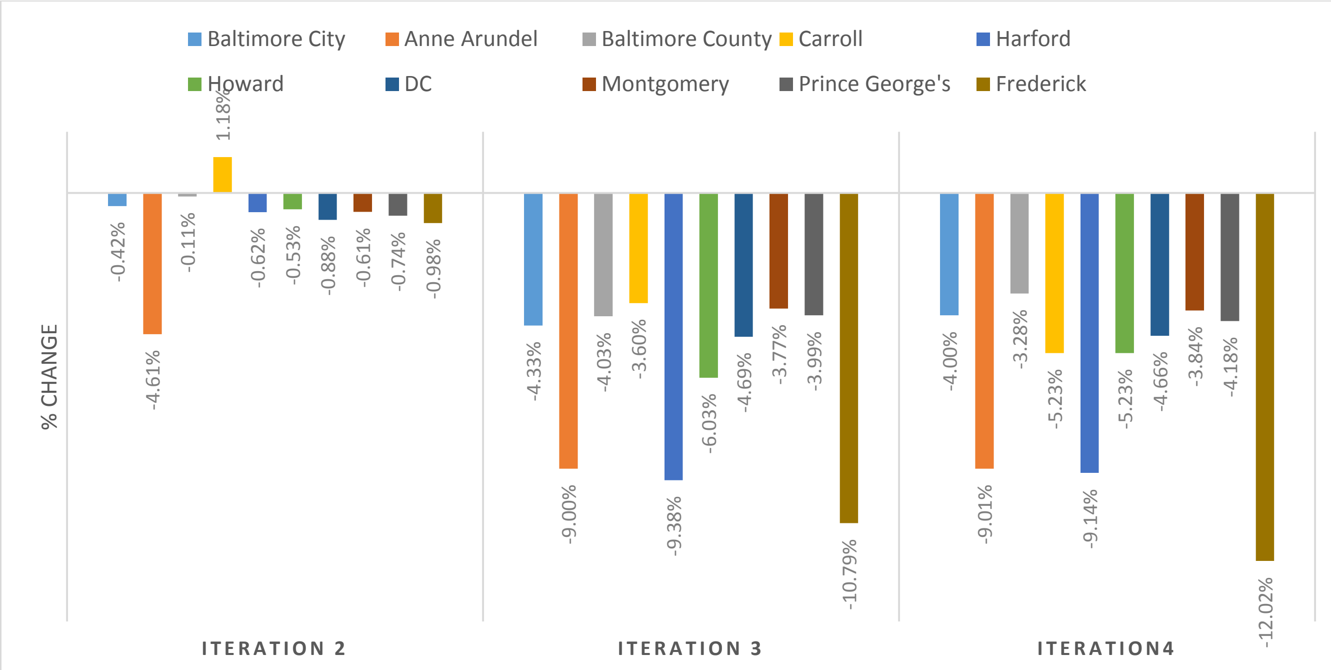


Figure 90 Change in Transit Distance at the HH Level by County (CAV Implementation)

As expected, HHs of lower income spent more time on transit trips (a direct effect of the number of transit trips generated by income group). It is also worth noting that HHs of INC4 have similar transit travel times as HHs of INC0, which is in turn a direct effect of the number of transit trips generated by HHs in INC4.

Table 111 Transit Travel Time at the HH Level by Income Group (minutes) (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4
INC0	136.42	134.60	128.11	128.54
INC1	131.63	129.07	121.10	121.60
INC2	128.91	126.52	119.50	119.80
INC3	117.39	115.52	109.43	110.27
INC4	133.23	131.27	125.47	125.78

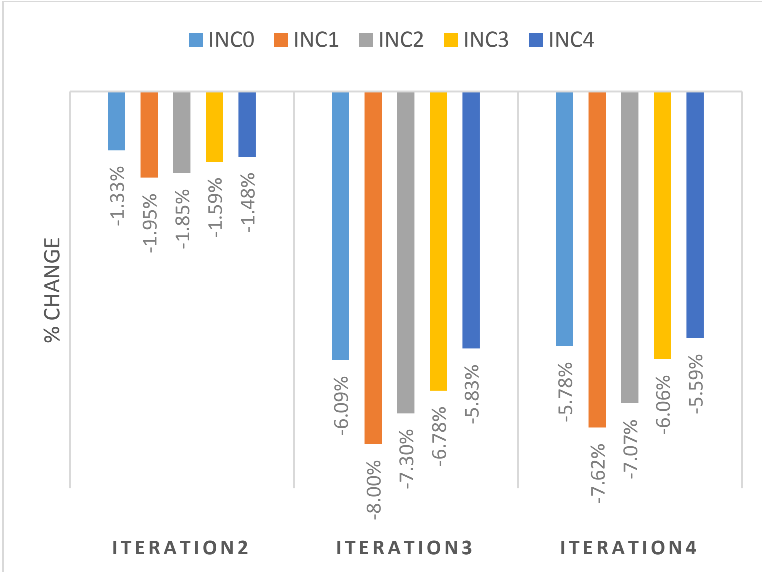


Figure 91 Change in Transit Travel Time at the HH Level by Income Group (CAV Implementation)

At the county level, the longest transit travel times are observed for HHs in Prince George's county (140.4 min) and Howard County (154.2 min). On the other hand, the shortest transit travel times are observed for HHs in Carroll County (70.66 min) and Frederick County (81.81 min). All counties but Carroll experience a decrease in transit travel times.

Table 112 Transit Travel Time at the HH Level by County (minutes) (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	131.60	130.26	120.51	122.03
Anne Arundel	135.18	128.40	131.69	132.05
Baltimore County	135.18	134.41	129.45	130.03
Carroll	62.00	61.71	70.18	70.66
Harford	95.24	93.19	92.17	92.77
Howard	161.67	160.27	152.80	154.20
DC	110.55	109.07	104.30	104.52
Montgomery	125.79	123.98	117.24	117.35
Prince George's	149.82	147.01	140.34	140.39
Frederick	84.09	82.98	82.34	81.81

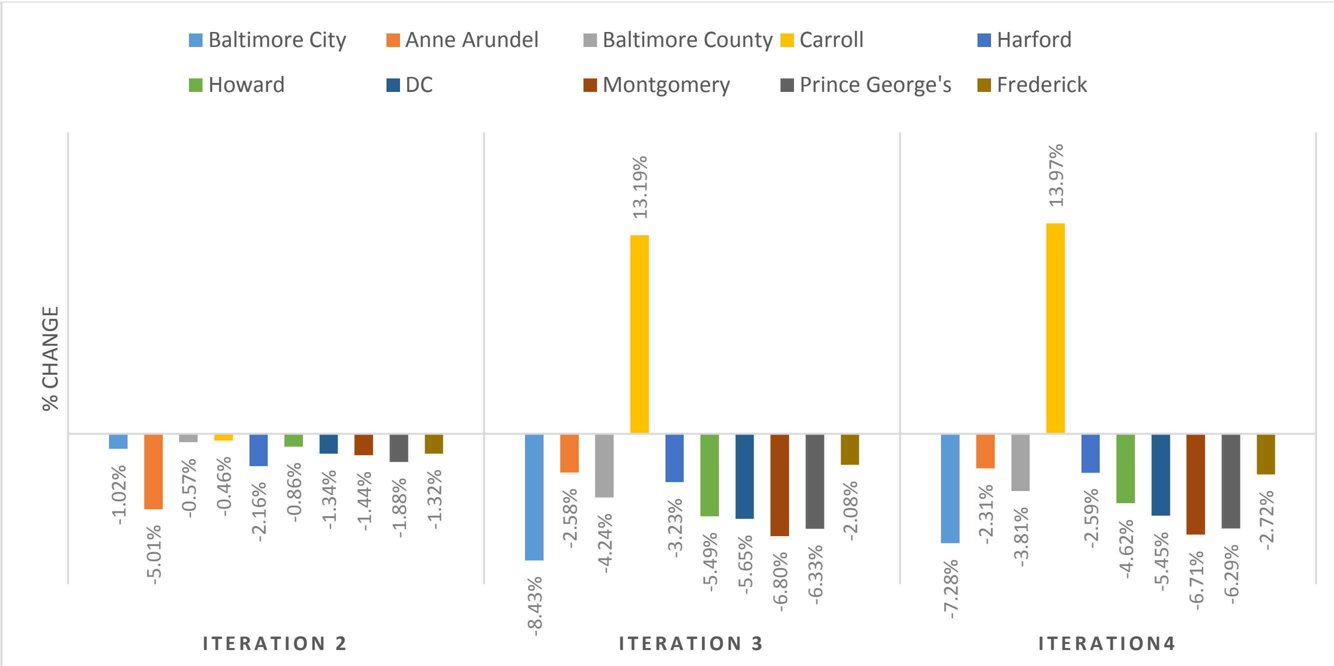


Figure 92 Change in Avg. Daily Transit Travel Time at the HH Level by County (Base: Iteration 1) – (CAV Implementation)

4.3.3 Revenue Potential

The revenue generated from state taxes is an important metric that summarizes the impact of the revenue policy-investment outlook dyad on travel behavior and ultimately on the state's spending/investment capacity. The results show that, in the long-run, state tax revenues will increase across all income groups in a descending rate (i.e. INC0 by 9.19% vs. INC4 by 6.72%). The overall increase in state taxes collected is expected as the implemented revenue-investment dyad improves the travel conditions on the network, therefore encourages users to travel more.

Table 113 Daily Revenue Generated by Income Group (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4
INC0	23,848	24,186	26,406	26,040
INC1	30,596	31,062	33,708	33,285
INC2	75,653	76,704	82,617	81,630
INC3	257,773	260,843	279,984	276,429
INC4	375,455	379,451	405,387	400,693

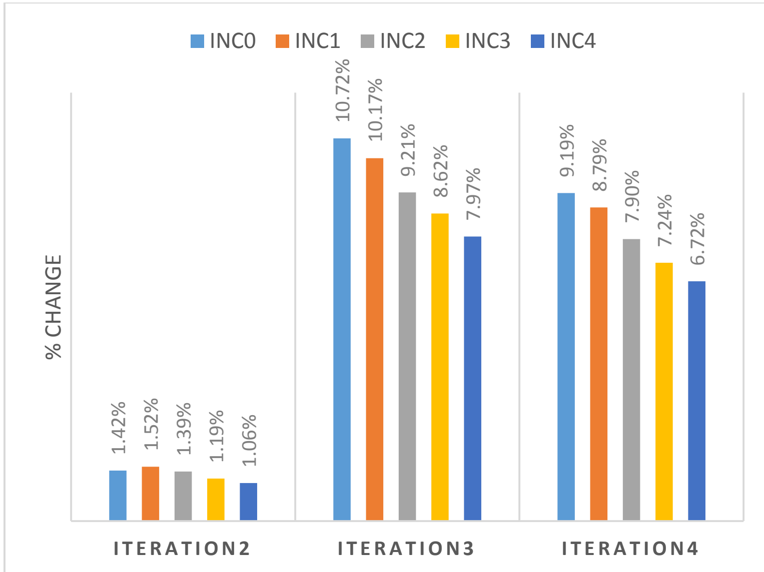


Figure 93 Change in Daily Revenue Generated by Income Group (CAV Implementation)

At the county level, Montgomery and Prince George's counties generate the highest amounts of revenue, while Carroll and DC generate the lowest. In terms of percentage changes, DC and Baltimore City experience the largest increases at 10.88% and 9.66% respectively, while Harford and Frederick experience the lowest increases at 4.06% and 5.32% respectively. In addition to travel behavior changes, the revenue-specific results may be also affected by the income distribution, the population size, and the urban and land use planning characteristics of each county. It should be noted that, from the state's perspective, the absolute values of revenues may be of primary interest. However, from a social equity point of view, the revenue information should be evaluated in conjunction with the metrics discussed before, in order to obtain a clear view of the effects of the revenue-investment dyad on users.

Table 114 Daily Revenue Generated by County ($) (CAV Implementation)

	ITER1	ITER2	ITER3	ITER4
Baltimore City	54,505	55,111	60,732	59,772
Anne Arundel	97,902	98,373	105,602	104,121
Baltimore County	124,431	125,659	134,925	133,347
Carroll	38,636	38,966	42,327	41,694
Harford	49,921	50,169	52,544	51,950

Howard	52,940	53,690	58,117	57,188
DC	34,920	35,825	39,201	38,721
Montgomery	134,372	136,303	144,850	143,733
Prince George's	129,177	131,312	140,111	138,579
Frederick	46,496	46,835	49,689	48,968

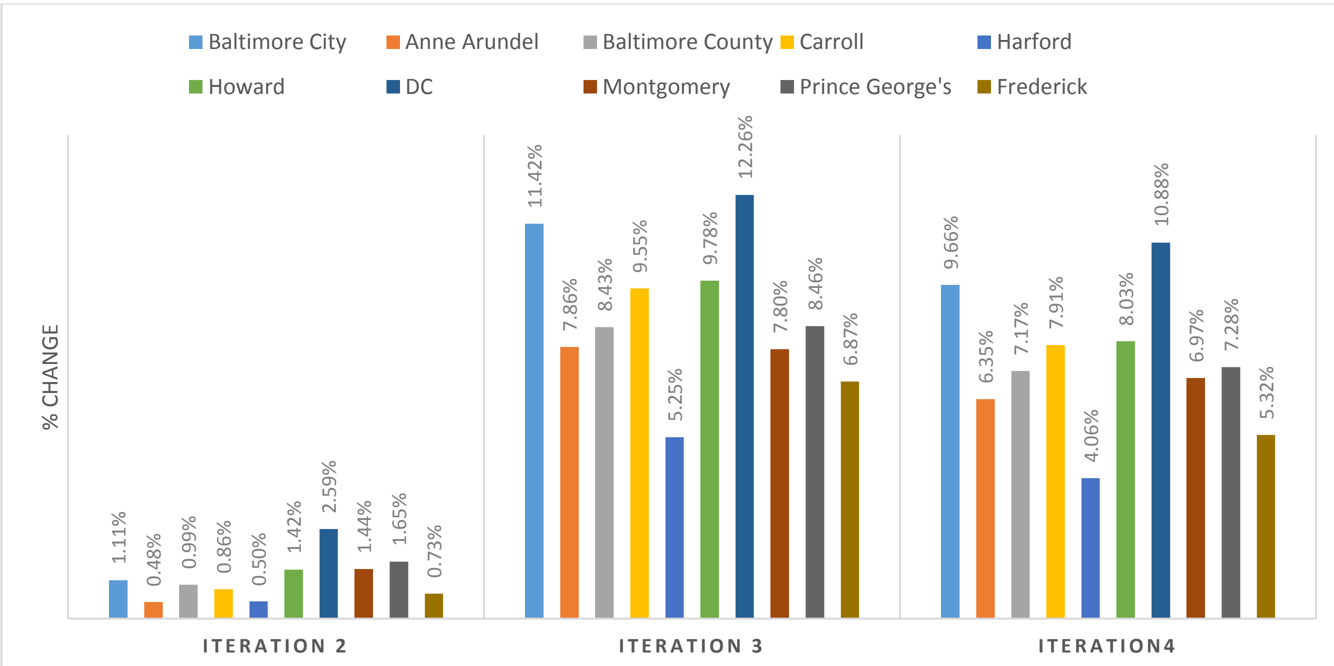
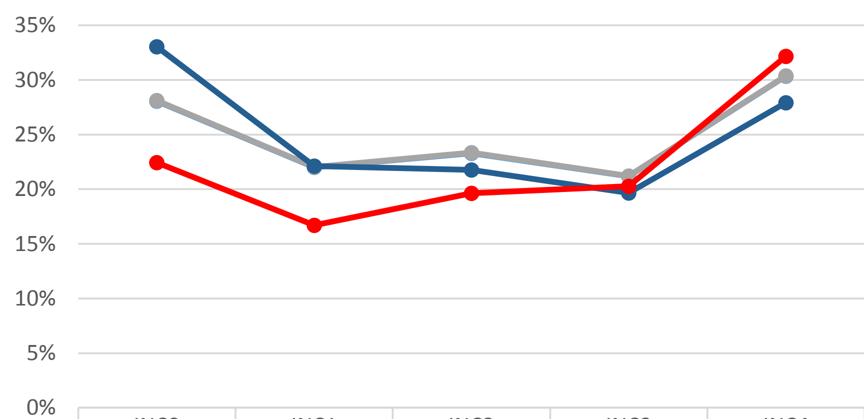


Figure 94 Change in Daily Revenue Generated by County (CAV Implementation)

4.4 Investment Outlook Comparison

In this section, the distribution effects of the different revenue and investment policies are summarized.

In Figure 95, the fuel tax increase (revenue policy of Bottleneck Removal Outlook), the property tax (revenue policy of the Transit-Oriented Outlook) and the variable VMT fee (revenue policy for the CAV Implementation Outlook) are compared against the base case revenue policy, which is the fuel tax, at the income level. As expected, the state fuel tax increase increases the cost-to-income ratio for all income groups, but does not change the distribution effects of the policy, since the increase is negligible. Shifting from fuel tax to a transportation-dedicated property tax will increase the daily cost-to-income ratio for INC0 and INC1, while it will decrease it for all other income groups. The variable VMT fee will decrease the cost-to-income ratio for all income groups except for INC4, as expected based on the policy design.

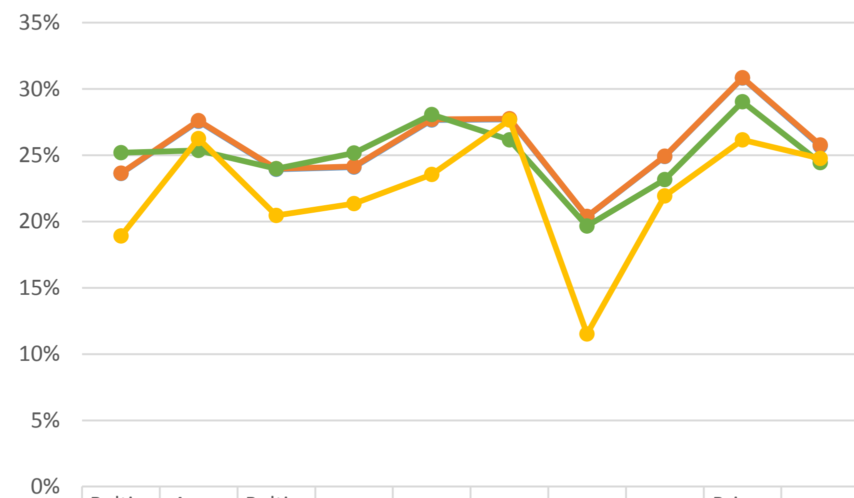


	INC0	INC1	INC2	INC3	INC4
Fuel Tax (Base Case)	28.06%	21.99%	23.30%	21.19%	30.34%
Fuel Tax Increase (Revenue A)	28.11%	22.03%	23.34%	21.22%	30.38%
Property Tax (Revenue B)	33.05%	22.12%	21.77%	19.66%	27.91%
Variable VMT Fee (Revenue C)	22.43%	16.70%	19.62%	20.27%	32.15%

Fuel Tax (Base Case) Fuel Tax Increase (Revenue A)
Property Tax (Revenue B) Variable VMT Fee (Revenue C)

Figure 95 Daily Cost-to-Income Policy Comparison by Income Group

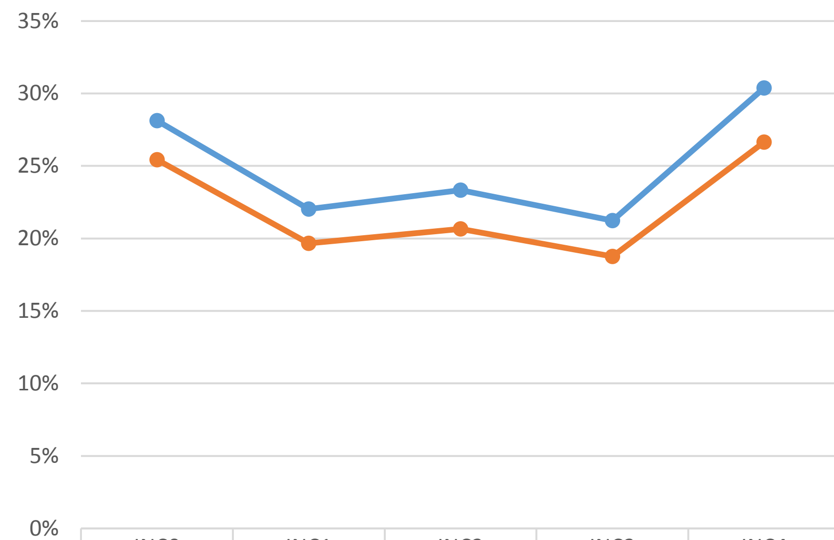
In Figure 96, the fuel tax increase (revenue policy of Bottleneck Removal Outlook), the property tax (revenue policy of the Transit-Oriented Outlook) and the variable VMT fee (revenue policy for the CAV Implementation Outlook) are compared against the base case revenue policy, which is the fuel tax at the county level. Similar to the income-level results, the state fuel tax increase increases the cost-to-income ratio for all counties, but does not change the distribution effects of the policy, since the increase is negligible. Shifting from fuel tax to a transportation-dedicated property tax will decrease the daily cost-to-income ratio for all counties except for Baltimore City, Carroll and Harford. The variable VMT fee will decrease the cost-to-income ratio for all counties, with Howard and Frederick experiencing the smallest changes.



	Baltimore City	Anne Arundel	Baltimore County	Carroll	Harford	Howard	DC	Montgomery	Prince George's	Frederick
Fuel Tax (Base Case)	23.62%	27.57%	23.95%	24.12%	27.66%	27.70%	20.36%	24.91%	30.82%	25.72%
Fuel Tax Increase (Revenue A)	23.65%	27.62%	24.00%	24.15%	27.70%	27.76%	20.39%	24.94%	30.86%	25.77%
Property Tax (Revenue B)	25.20%	25.36%	23.99%	25.17%	28.07%	26.16%	19.66%	23.17%	29.03%	24.46%
Variable VMT Fee (Revenue C)	18.91%	26.25%	20.46%	21.36%	23.55%	27.66%	11.52%	21.94%	26.17%	24.77%

Figure 96 Daily Cost-to-Income Policy Comparison by County

In addition to the comparison of the different revenue policies among each other and against the base, the following figures illustrate the change in the daily cost-to-income ratio that can be attributed to the investment. For Outlooks A and C, it is evident that the investment (Bottleneck Removal and CAV Implementation respectively) reduce the cost-to-income ratio across all income groups. On the other hand, the investment of Outlook B results in an increase in the cost-to-income across all income groups.



	INC0	INC1	INC2	INC3	INC4
Fuel Tax Increase (Revenue A)	28.11%	22.03%	23.34%	21.22%	30.38%
Bottleneck Removal (Investment A)	25.42%	19.66%	20.65%	18.75%	26.63%

Fuel Tax Increase (Revenue A) — Bottleneck Removal (Investment A)

Figure 97 Cost-to-Income Comparison Before and After investment (Outlook A)

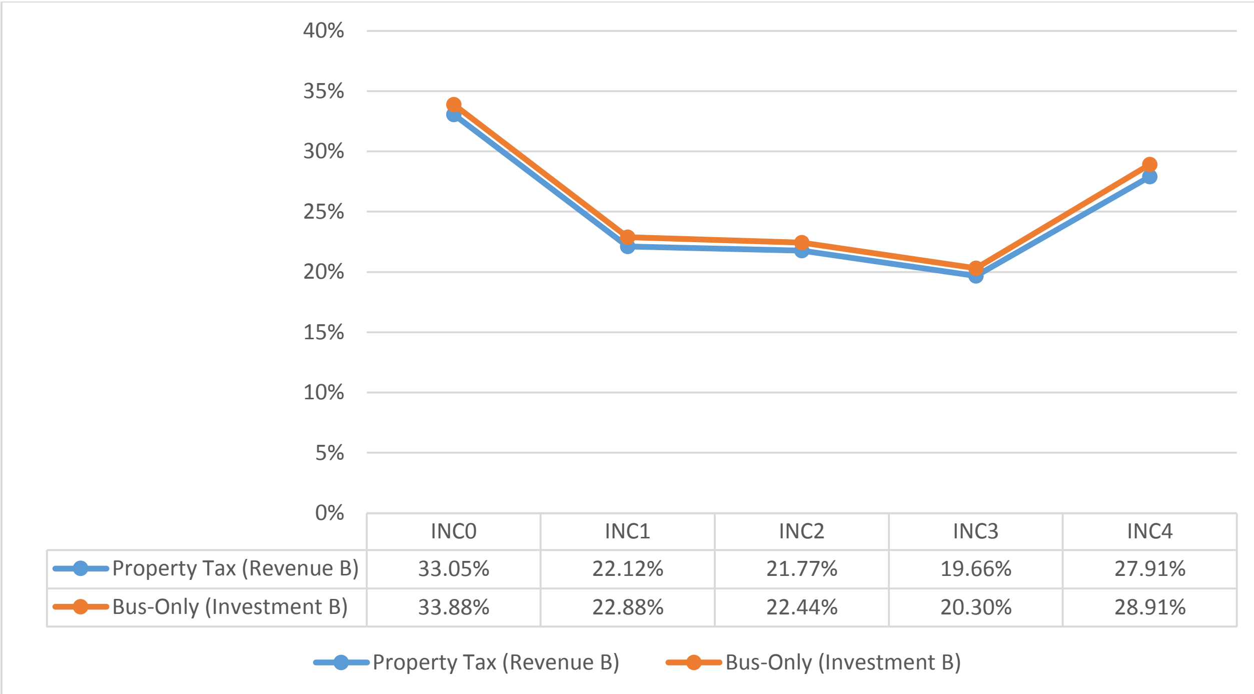


Figure 98 Cost-to-Income Comparison Before and After investment (Outlook B)

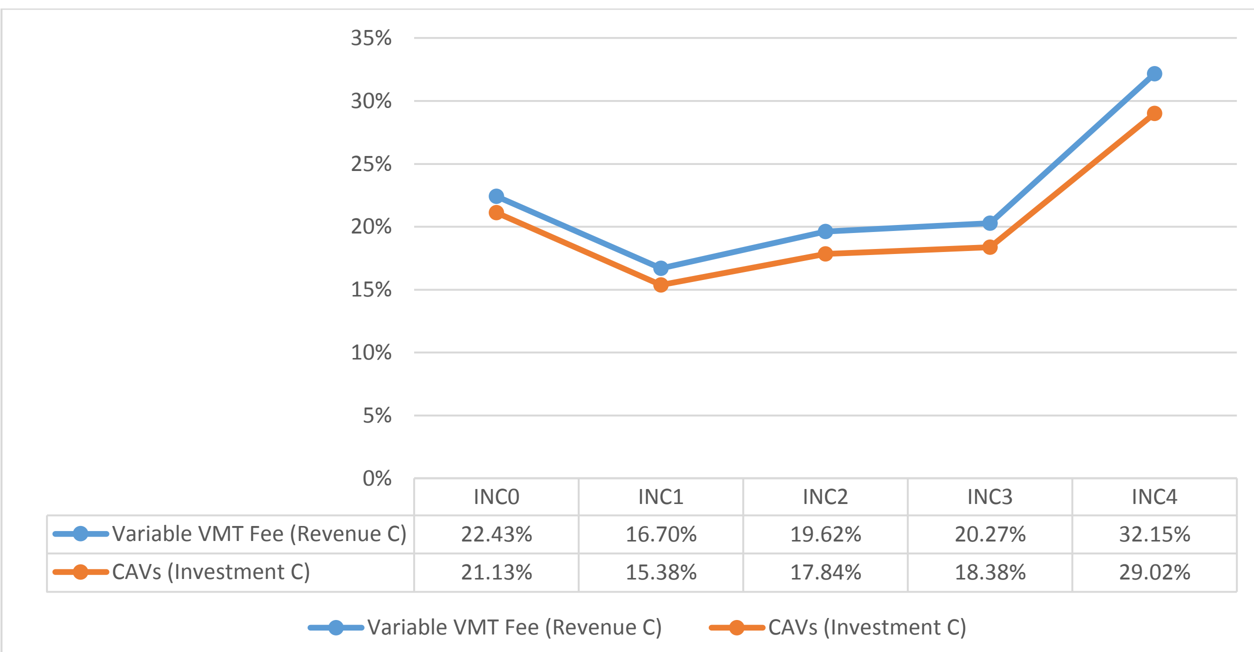
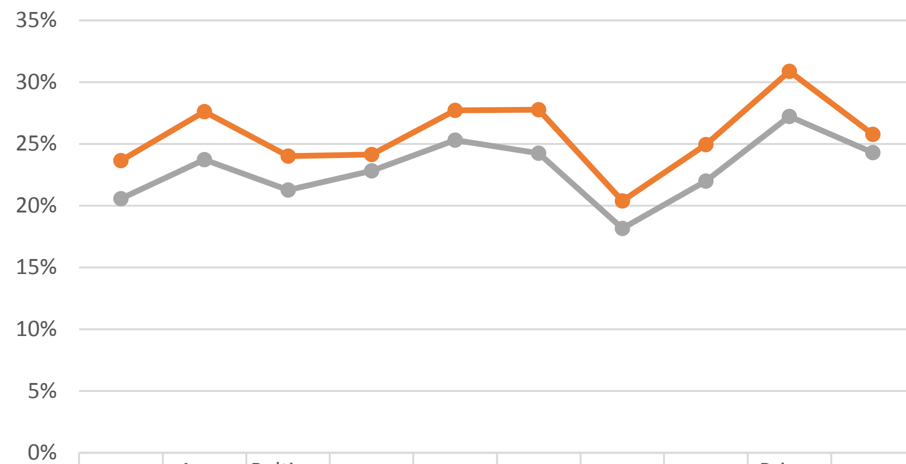


Figure 99 Cost-to-Income Comparison Before and After Investment (Outlook C)

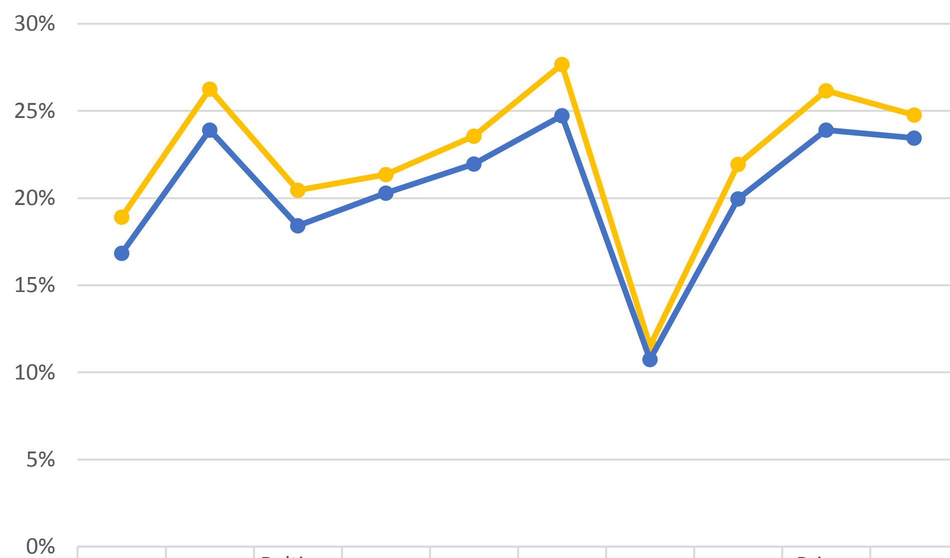
The results are similar at the county level: investment in Outlooks A and C reduce the cost-to-income ratio across all counties, but investment in Outlook B results in an increase.



	Baltimore City	Anne Arundel	Baltimore County	Carroll	Harford	Howard	DC	Montgomery	Prince George's	Frederick
Fuel Tax Increase (Revenue A)	23.65%	27.62%	24.00%	24.15%	27.70%	27.76%	20.39%	24.94%	30.86%	25.77%
Bottleneck Removal (Investment A)	20.57%	23.74%	21.26%	22.82%	25.30%	24.24%	18.17%	22.00%	27.21%	24.29%

Fuel Tax Increase (Revenue A) Bottleneck Removal (Investment A)

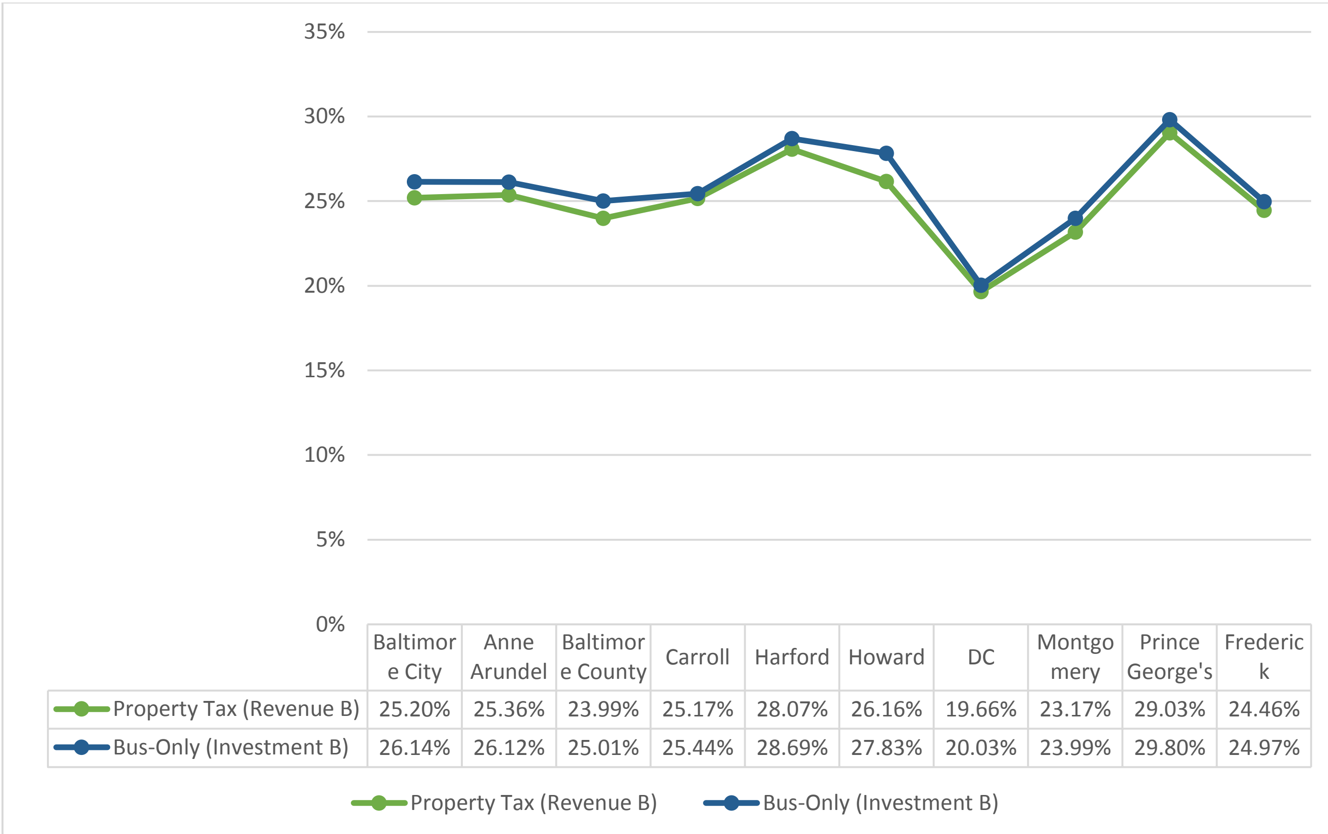
Figure 100 Cost-to-Income Comparison Before and After investment (Outlook A)



	Baltimore City	Anne Arundel	Baltimore County	Carroll	Harford	Howard	DC	Montgomery	Prince George's	Frederick
Variable VMT Fee (Revenue C)	18.91%	26.25%	20.46%	21.36%	23.55%	27.66%	11.52%	21.94%	26.17%	24.77%
CAVs (Investment C)	16.84%	23.91%	18.42%	20.29%	21.96%	24.73%	10.74%	19.96%	23.91%	23.45%

Variable VMT Fee (Revenue C) CAVs (Investment C)

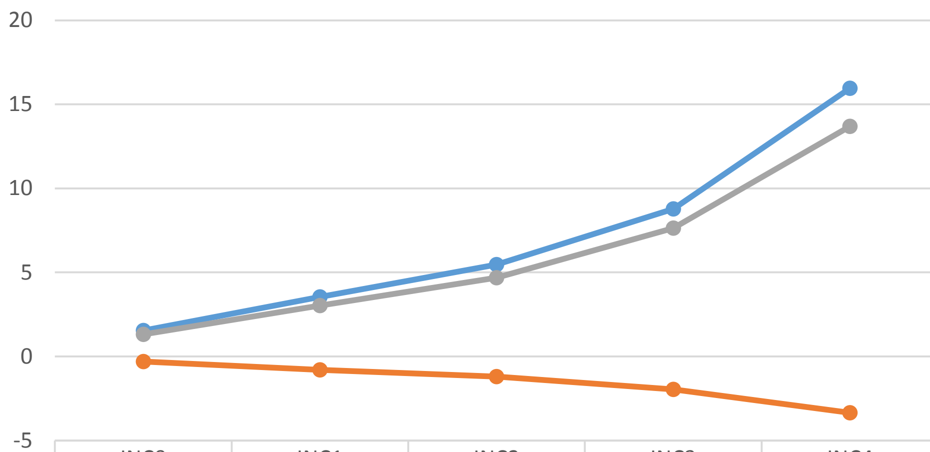
Figure 101 Cost-to-Income Comparison Before and After investment (Outlook C)



	Baltimore City	Anne Arundel	Baltimore County	Carroll	Harford	Howard	DC	Montgomery	Prince George's	Frederick
Property Tax (Revenue B)	25.20%	25.36%	23.99%	25.17%	28.07%	26.16%	19.66%	23.17%	29.03%	24.46%
Bus-Only (Investment B)	26.14%	26.12%	25.01%	25.44%	28.69%	27.83%	20.03%	23.99%	29.80%	24.97%

Figure 102 Cost-to-Income Comparison Before and After investment (Outlook B)

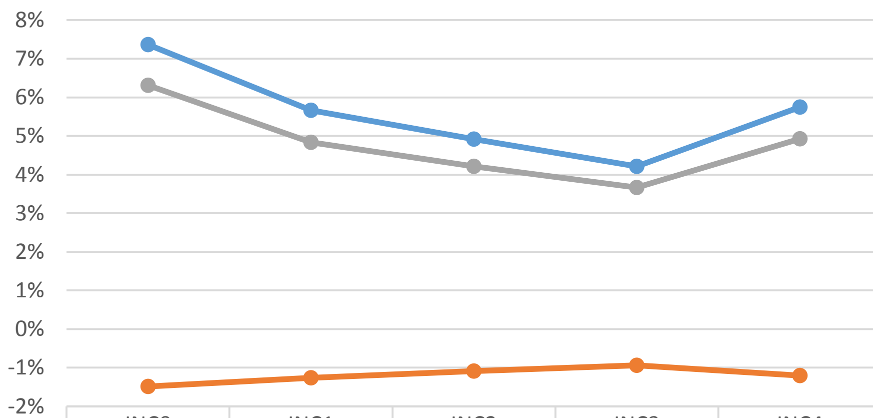
In addition to the cost-to-income comparison across the different revenue policies, the following figures present the change in consumer surplus (both in absolute terms and as a percent of the income) that is observed following the investment. Outlooks A and C result in a consumer surplus increase across all income groups and all counties, whereas Outlook B results in a decrease.



	INC0	INC1	INC2	INC3	INC4
Change in CS - A	1.54	3.54	5.47	8.78	15.96
Change in CS - B	-0.31	-0.79	-1.21	-1.96	-3.34
Change in CS - C	1.31	3.02	4.68	7.64	13.68

Change in CS - A   Change in CS - B   Change in CS - C

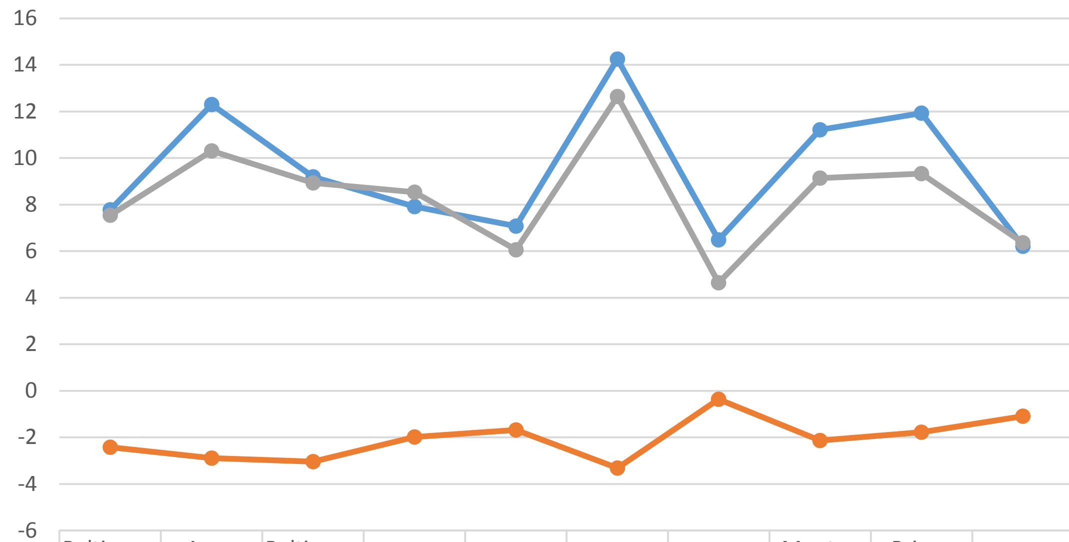
Figure 103 Absolute Change in Consumer Surplus due to Investment



	INC0	INC1	INC2	INC3	INC4
Change in CS/Income A	7.37%	5.66%	4.92%	4.21%	5.75%
Change in CS/Income B	-1.49%	-1.26%	-1.09%	-0.94%	-1.20%
Change in CS/Income C	6.31%	4.84%	4.22%	3.67%	4.93%

Change in CS/Income A   Change in CS/Income B   Change in CS/Income C

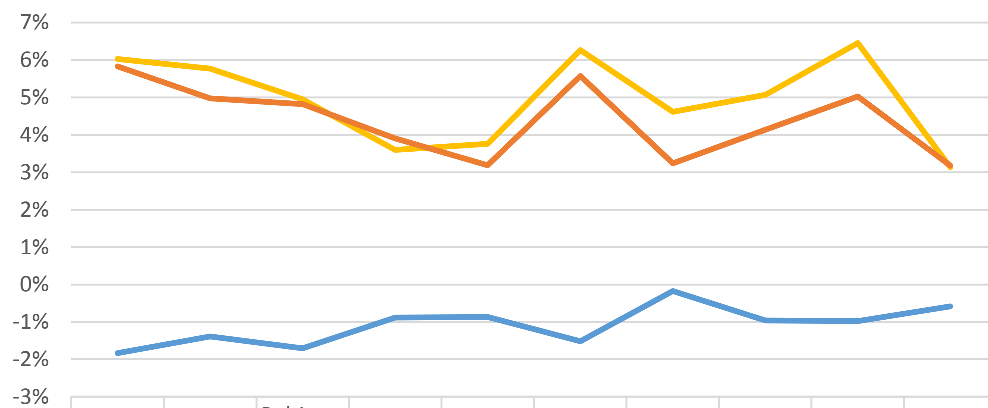
Figure 104 Change in Consumer Surplus as % of Income due to Investment



	Baltimore City	Anne Arundel	Baltimore County	Carroll	Harford	Howard	DC	Montgomery	Prince George's	Frederick
Change in CS - A	7.78	12.29	9.19	7.91	7.07	14.25	6.49	11.21	11.92	6.20
Change in CS - B	-2.43	-2.89	-3.04	-1.98	-1.69	-3.32	-0.37	-2.13	-1.78	-1.09
Change in CS - C	7.54	10.31	8.93	8.53	6.06	12.64	4.64	9.14	9.32	6.36

Change in CS - A   Change in CS - B   Change in CS - C

Figure 105 Absolute Change in Consumer Surplus due to Investment



	Baltimore City	Anne Arundel	Baltimore County	Carroll	Harford	Howard	DC	Montgomery	Prince George's	Frederick
Change in CS/Income A	6.03%	5.77%	4.95%	3.59%	3.76%	6.26%	4.61%	5.06%	6.45%	3.14%
Change in CS/Income B	-1.84%	-1.39%	-1.71%	-0.88%	-0.87%	-1.51%	-0.18%	-0.96%	-0.98%	-0.58%
Change in CS/Income C	5.83%	4.98%	4.82%	3.90%	3.18%	5.57%	3.24%	4.14%	5.03%	3.18%

Change in CS/Income A   Change in CS/Income B   Change in CS/Income C

Figure 106 Change in Consumer Surplus as % of Income due to Investment

Chapter 5. Conclusions

5.1 Summary of Findings

The purpose of this dissertation is to guide economic policymaking by providing a comprehensive estimation of the effects that revenue and investment policies have on users. The value of the approach lies in the fact that revenue policies are not evaluated based on their first-level impacts on payers alone. On the contrary, they are combined with transportation investment outlooks, and their performance is assessed on the basis of benefits redistribution, i.e. how users eventually benefit from the revenues being invested in transportation projects that facilitate their travel experience.

The objective of Part I is to explore how different revenue policies may affect the taxpaying population and their travel behavior. The revenue policies explored include fuel tax, fuel tax increase, flat VMT fee, variable VMT fee, property tax, and sales tax, and the objective of this analysis is to identify which socioeconomic groups will most likely be affected under each revenue scenario, as well as quantify the effects of each scenario on the population's travel behavior. Fuel tax and VMT fee policies result in similar paying patterns, where users of lower-income groups experience higher tax-to-income ratios, and this burden decreases progressively as income increases. However, property and sales taxes result in different patterns, which seem to favor the middle income users but put disproportionately bigger burden on the lower income HHs. In terms of revenue generation, the fuel tax increase revenue policy appears to be effective in generating additional revenue (approximately $100,000 on a daily basis) without affecting the behavior of travelers or the tax incidence structure of the status quo policy. The revenue analysis shows that alternative policies can be implemented, while the revenue goal can be still met. Finally, it is important to consider the vehicle ownership factor in the revenue policies. By design, fuel tax, and VMT fees impose charges on vehicle owners only. Property and sales taxes have a different taxpaying population which consists of payers who do not necessarily own a vehicle. This may raise public acceptance issues, unless an effective political point is made in terms of investment of revenues in a local context.

In Part II, alternative transportation investment outlooks that Maryland may adopt in the future are explored, in an effort to redefine the state's purpose, perspective and vision with respect to transportation. The first outlook is a bottleneck removal investment process funded by an increase in state fuel tax, the second is the construction of a bus-only network funded by transportation-dedicated property taxes, and the last outlook is retrofitting of the existing network to accommodate CAVs, funded by a variable VMT fee. The largest network-wide v/c improvement is observed in the CAV scenario (13.54%) with only a fraction of cost compared to the other two scenarios. This is expected as the CAV outlook can be also considered an operational improvement rather than an infrastructural one. The high v/c improvement of the CAV outlook can be attributed to the fairly lower change in volume both at the modified lanes and across the entire network (approximately 4.4% for both cases). However, the corresponding values for the Bottleneck Removal Outlook are significantly different. A $5B investment resulted in only 3.70% improvement in network wide v/c which can be attributed to a significantly larger volume increase (12.94% in the modified lanes, and 2.76% across the network). The Transit-Oriented (bus-only) Outlook also yields some interesting results: the cost is comparable to the Bottleneck Removal Outlook, since this investment outlook also requires the construction of physical infrastructure (bus-only lanes). However, the v/c ratio is only slightly improved since the non-transit volumes do not significantly decrease.

The redistribution analysis is summarized based on the changes in the cost-to-income and consumer surplus for different income groups and counties. It is evident that investing in bottleneck removal or CAVs will alleviate some of the burden that users will experience due to the fuel tax increase and variable VMT fee policies. However, in a situation where transportation funding shifts from the status quo to a transportation dedicated property tax, the lower income HHs will bear greater burden, and none of the income groups or counties will be able to recuperate part of their losses via the transit-oriented investment. Construction of bus-only lanes increases transit demand; however, infrastructure changes do not seem to be sufficient to provide additional benefits to the users, compared to the revenue policy alone. Changes in transit service characteristics should be explored in future research.

Methodology-wise, activity-based models prove to be successful in modeling policies that vary by agent, since they allow for better market segmentation. This is very important for policymakers who want to reach specific revenue goals via policies that target or alleviate specific socio-economic and geographic groups. Additionally, they provide the necessary platform to evaluate different investment scenarios, by altering the network characteristics based on the investment outlook employed. In terms of the statistical matching methodological approach, its performance shows that the distribution of the matching variables in the donor, recipient and synthetic datasets is good, and its good performance can be further validated by the almost coinciding distributions of the matching variables in the InSITE dataset and the synthetic dataset, as well as the correlation matrices. These findings suggest that statistical matching is an effective approach to address data availability issues.

5.2 Limitations

This dissertation explores the topic of revenue generation and investment in a comprehensive way by accounting for benefits redistribution across the population. Despite the fact that it is the first piece of research to comprehensively explore the topics of revenue generation, investment, and benefits redistribution, it should be acknowledged that there is a number of factors that may influence the results.

Most importantly, the investment and benefits redistribution results strongly depend on the travel behavior assumptions of the activity-based model. Among others, such behavioral assumptions may refer to the operating cost and income elasticities of vehicle ownership, destination, mode and route choice, etc. However, it should be emphasized that, although the absolute values of the results depend on the model assumptions, the results of the comparative analysis among different revenue and investment policies are still trustworthy. Also, due to the large scale of this research approach, the results should be interpreted with caution, since they depend on the employed assumptions. The available information on the market share, investment actions, and cost estimate assumptions in the CAV Implementation Outlook is limited, therefore the results of this outlook should be interpreted within the context of limited information availability. Another limitation pertains to the assumption of fixed population size across the 4 investment iterations. This limitation should affect the results as travel demand (in terms of HHs in the model area) is fixed, therefore the benefits of the investment may be overrepresented. Along the same lines, changes in property and sales taxes are not captured, therefore the long-term revenue potential may be under- or over-estimated. Additionally, based on publicly available sources [94], an estimated 15% of the total property taxes collected comes from renters; however there is no available data to allow for more accurate estimation of the economic burden that renters bear due to property taxes they indirectly pay. Another limitation that pertains to the long term is that no changes in land use patterns have been considered in this analysis. Finally, infrastructure retrofitting to accommodate CAVs and the associated levels of market penetration will result in individual technology costs borne by the users that currently are not captured in this analysis.

5.3 Future Research Directions

There are a few different directions for future research. First, it would be very interesting to explore the implications of on-demand transit service, such as UBER and Lyft, and compare the findings against these of fixed transit route service provision. Such a scenario should be very interesting for policymakers, especially when taking into consideration the millennials' well-documented lower vehicle ownership compared to previous generations, and their dependence on on-demand transit and car-sharing services. In terms of revenue and investment analysis, a few additional scenarios may be explored. These may include emission-related revenue policies, health-oriented/non-motorized investment outlooks, or infrastructure retirement/disinvestment outlooks. Additionally, it would be interesting to incorporate P3 considerations as innovative funding mechanism for transportation investment. Based on the comparative results of the three outlooks explored in this dissertation, and the conclusions drawn regarding the level of investment and the observed network performance improvement, it is suggested that future research explores the effects of traffic management and operations investment versus fixed, inflexible infrastructure investment. Finally, in the benefits redistribution area, it would be interesting to estimate the wider economic effects of transportation infrastructure investment, such as changes in market accessibility and travel time reliability.

Appendix A. Comprehensive Dissertation Framework

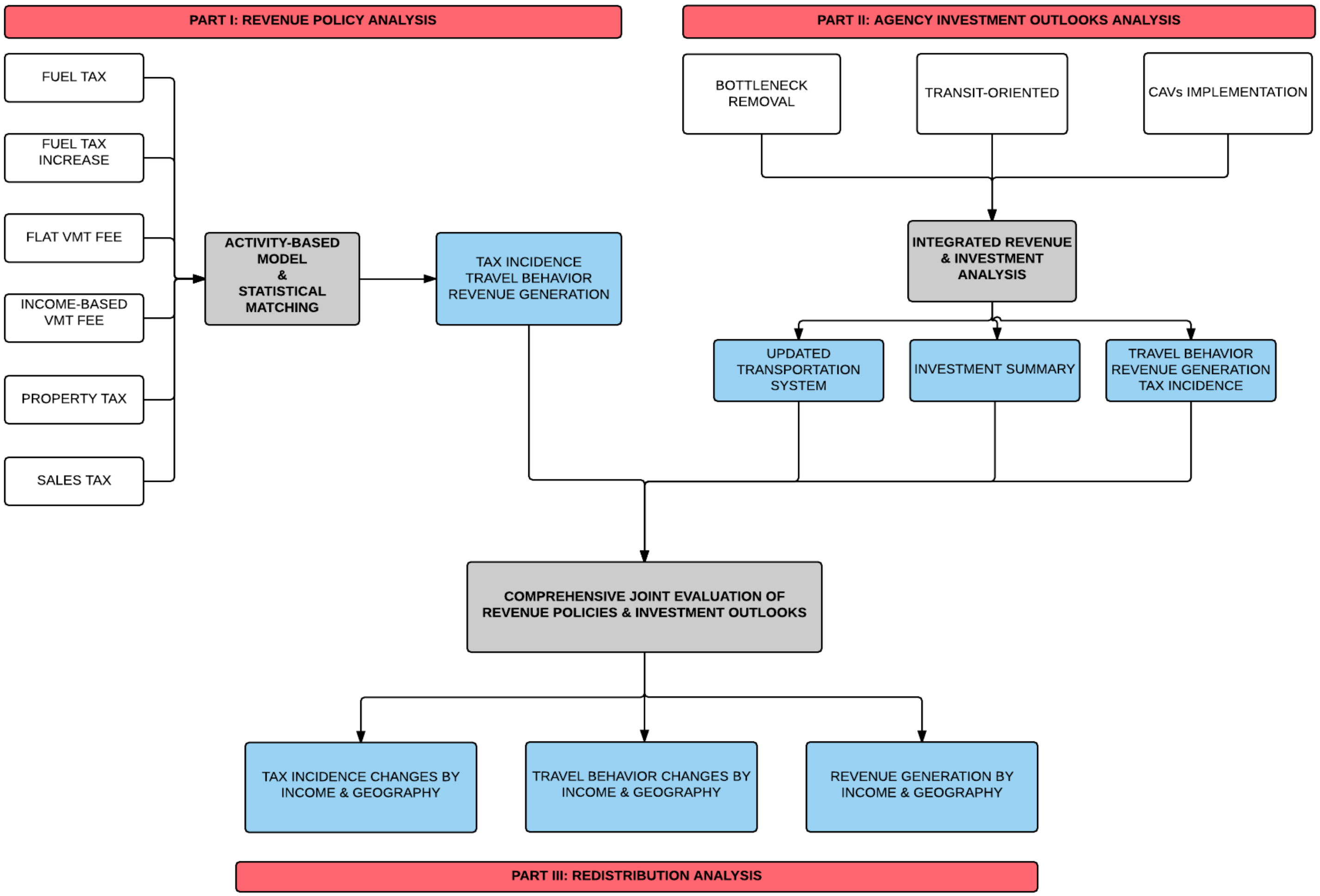


Figure 107 Comprehensive Dissertation Framework

Appendix B. InSITE Component Description

Table 115 InSITE Component Description [62]

Component	Description	Type	Alternatives	Output
Post PopGen Processor	1. Simulates household work and non-work time coefficients and parcel 2. Determines person type and pre-calculates useful household and person attributes	Post processor with sampling	Parcels within the household zone Lognormal distribution of time coefficients	VOT (continuous distribution) and parcels within a zone
School Location	School location for each child in the household This is the destination of every school tour for this child	Destination Choice	Zones	Table of each child and their school location
Usual Workplace Type	Simulates workplace type for every FTW and PTW	MNL	Usual workplace, work at home, external workplace, no usual workplace	Adults with usual workplace type
Usual Workplace Destination	Simulates usual workplace location, if exists	Destination Choice	Zones	Persons with usual workplace, or -1 if none
Pre-Vehicle Availability Processor	Rolls up usual workplace outputs to household level attributes	Data Assembly Component	N/A	Household records with usual workplace attributes
Vehicle Availability	Household model simulating number of vehicles	MNL	0,1,2,3,4,5+	Vehicles per household

Component	Description	Type	Alternatives	Output
Pass Models	Transit and toll Transponder ownership models	MNL	No pass, own pass (either transit or toll transponder)	Household transit and toll transponder ownership
Household Class	Simulates the class of each household	MNL	Household class	Households with class defined
Daily Activity Pattern	Simulates DAP for each person in the household	MNL	Stay at home, mandatory DAP, non-mandatory DAP	Persons with DAP (stay at home, mandatory pattern, non-mandatory pattern)
Mandatory Tour Generation Data Assembly	Summarizes household DAP for each person	Data assembly component	N/A	Persons with household level DAP data
Mandatory Tour Generation	Simulates number and type of mandatory tours for each person with mandatory DAP	MNL	Stay at home, mandatory DAP, non-mandatory DAP	Mandatory Tours
Mandatory Tour Destination	Simulates work and university tour destination	Destination Choice	Zones	Work/university tour with destination zone
School Escort Preprocessor	Assembles the school tours from mandatory tour generation with the work and university tours with destinations from mandatory tour destination. Note that the school tours already had a destination from school location (i.e. all school tours for the same child go to the same place)	Data assembly	N/A	School, work and university tours for school escort simulation

Component	Description	Type	Alternatives	Output
School Escort	Simulates school escort on each half-tour	Nested Logit	Escort by mandatory or standalone tour or no escort	Mandatory tours with escort chosen
	Bundles children going to same destination		For outbound and inbound half-tour	Standalone escort tours
	Simulates escort on mandatory tours and standalone tours		For outbound and inbound half-tour	Escort stops on mandatory tours
			$(3 * 2 + 1)^2 =$ 49 alternatives	
Mandatory tour TOD Data Assembly	Assembles data from school escorting with second work/university tours (that are not available for school escorting) for the tour TOD component.	Data Assembly	N/A	School, work and university tours for TOD
Mandatory Tour TOD	Tour TOD for School, Work and University Tours	MNL Time of Day	1,176 30-minute arrival/departure pairs	School/work/university tour with time of day
				Includes dependencies for school escorting
Post Mandatory Tour TOD Data Assembly	Attaches time of day choice to the school escort stops	Data Assembly	N/A	School escort stops with time of day
Fully Joint Generation and Participation	Generates fully joint tours and models person participation	MNL	0, 1, 2 tours by purpose (meal, shop, personal business, social recreation) Participation of each person in any generated	Fully joint tours

Component	Description	Type	Alternatives	Output
			tours in the household	Persons participating in each fully joint tour
Fully Joint Destination	Models the destination for each fully joint tour	Destination choice	Zones	Fully joint tours with destinations
Fully Joint Tour TOD	Models the time of day for each Fully Joint tour	Time of Day Choice	1,176 30-minute arrival/departure pairs	Fully joint tours with arrival / departure / duration
Individual Non-Mandatory Generation Preprocessor	Assembles data from fully joint and school escort	Data assembly component	N/A	Person-level tours, DAP, and TOD
Individual Non-Mandatory Generation	Generates individual non-mandatory tours	Tour Generation	0, 1, 2, 3 tours by purpose (meal, shop, personal business, social recreation, escort)	Individual non-mandatory tours
Individual Non-Mandatory Destination	Models the destination for each INM tour	Destination choice	Zones	INM tours with destinations
Individual Non-Mandatory Tour TOD	Models the time of day for each Individual Non-Mandatory tour Note that the INM escort tours are modeled after the INM tours	Time of Day Choice	1,176 30-minute arrival/departure pairs	Individual Non-Mandatory tours with arrival/departure/ duration Person schedules with INM tours included
Home-Based Tour Intermediate Stop Generation	Generates stops on each half-tour for mandatory, school escort, FJ and INM tours	Intermediate stop generation	1, 2, 3 stops by purpose and half-tour	Tours with intermediate stop information Intermediate stops
Home-Based Tour Mode Choice	Models tour mode choice	Mode choice	"DA", "S2", "S3", "TW", "TD", "BK", "WK", "SB"	Tours with selected mode

Component	Description	Type	Alternatives	Output
Pre-Work-Based Tour Generation	Data assembly for work based tour generation	Data Assembly	0, 1 tours by purpose (work, university, meal, shop, personal bus, social recreation, escort)	Work-based sub-Tours
Work-Based Tour Generation	Generates work-based tours	Tour Generation	0, 1 tours by purpose (work, university, meal, shop, personal business, social recreation, escort)	Work-based sub-tours
Work-Based Tour Destination Choice	Destination choice for work based sub-tours	Destination choice	Zones	Work-based tours with destinations
Work-Based Tour TOD	Time of day choice for work based sub-tours	Time of Day Choice	30-minute arrival/departure pairs	Work-based tours with arrival / departure / duration
Work-Based Stop Generation	Generates stops on each half-tour for Work-Based sub-tours	Intermediate stop generation	1, 2 stops by purpose and half-tour	Intermediate stops
Work-Based Tour Mode Choice	Models tour mode choice for work based sub-tours	Mode choice	"DA", "S2", "S3", "TW", "BK", "WK"	Tours with selected mode
Pre-Intermediate Stop Destination Choice	Data assembly for intermediate stop models	Data Assembly	N/A	Intermediate stops with person/household data attached
Intermediate Stop Destination Choice	Models destination zone for intermediate stops	Destination Choice	Zones	Intermediate stops with destination zone
Intermediate Stop TOD	Models TOD period for intermediate stops	Time of day choice	time period offset from tour arrival departure and other intermediate stop times	Intermediate stops with time

Component	Description	Type	Alternatives	Output
				Trips with time of day
Trip Mode Choice	Models trip-level mode choice	Mode choice	"DA", "S2", "S3", "TW", "TD", "BK", "WK", "SB"	Trips with mode choice
				Aggregate trip tables for assignment

Appendix C. InSITE Code Revisions

The following example illustrates how InSITE was revised in order to accommodate variable operating cost by FUELINCOME class. The revisions are demonstrated on the TourModeChoiceLogsum_Work.py file.

1. By default, the parameters used in the component are read directly from the Globals.py file where they are originally defined. However, in order to accommodate a variable rate operating cost, the OperatingCostCentsPerMile variable is set equal to 0, and this will be corrected for further down in the process.

```
parameters={
"OutOfVehicleFactor": ovtIvtRatio,
                "OperatingCostCentsPerMile": 0,
                "WalkModeFactor": walkModeFactor,
                "BikeModeFactor": bikeModeFactor,
                "WalkSpeed": walkSpeed,
                "BikeSpeed": bikeSpeed,
"TransitLongWaitFactor": transitLongWaitFactor, #for long transit waits, adjust out of vehicle factor by this amount
"TransitLongWaitThreshold": transitLongWaitThreshold   # Long transit waits are any time greater than this factor (in minutes)
}
```

2. The FUELINCOME variable which was added to the households.dbf file via statistical matching is read into memory. This is essential as the operating cost will vary by FUELINCOME class:

```
dataReferences = [
   {"type" : "memory",
    "dataType" : "double",
    "name" : "HouseholdBaseData",
```

```
"columns" : [
        "HHZON",     # 0
        "HHID",      # 1
        "HHINC5S",   # 2
        "HHSIZE",    # 3
        "HH1PERSON", # 4
        "HH2PERSON", # 5
        "WORKVOT",   # 6
        "WORKTC",    # 7
        "NONWORKVOT",# 8
        "NONWORKTC", # 9
        "PARCELID",  # 10
        "FUELINCOME" #11
         ],
  },
]
```

It is noted that other datasets are also read into memory; however, for simplicity, only the code that reads the household.dbf dataset with the FUELINCOME information is presented herein.

3. Coefficients are divided into two types:

- coefficients whose corresponding values don't change very often ("durable" values)
- coefficients whose values are assumed to change for every iteration ("transient" values)

In the case of logsums, the normal expectations for what is durable and what is transient are reversed because the logsum computations occur over all zones for a fixed person. For logsums, transientCoeffs should contain all skim-related variables, plus all destination-only related variables:

```
transientCoeffs=[
  # DA,       # S2,       # S3,       # TW,       # TD,       # BK        # WK,
[1.00000000]*7, # generalized time - this will be replaced by the variable time coeff
[placeholder]*7, # generalized cost [income segmented]
[0.00000000,0.00000000,0.00000000,-0.05000000,-0.05000000,0.00000000,0.00000000], # transfers (HT count)
[0.00000000,0.00000000,0.00000000,-0.98849466,-0.98849466,0.00000000,0.00000000], # transit path includes local bus
[0.00000000,0.00000000,0.00000000,0.12382195,0.00000000,0.07175289,0.39375325],# Log (1 + Employment Density) at Destination (1/2 mi buffer)
[placeholder]*7 # applied to RT distance, which needs to be referenced through derived durables
]
```

4. Segmentation maps handle cases where the coefficient depends upon some segmentation of the input data, usually household income. In this example, the coefficient depends upon the segmentation based on FUELINCOME. segmentDefinitions is a list, each element of which defines:

   - Name: a friendly name not used elsewhere except maybe in comments in this file;
   - DataRef: which input DataReference contains the segmentation info;
   - Offset: which column in the input has this segmentation info;
   - DataRange: an array of discrete values representing the segmentation range.

In this example, the segmentation of the FUELINCOME variable is defined as follows (again, only the segmentation of this variable is presented herein, for simplicity):

```
segmentDefinitions = [
{'Name': '55 FuelClass Segments', 'DataRef': HouseholdBaseData', 'Offset': 11,
'DataRange': [0, 1, 2, 3, 4, 5 ,6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22,
23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46,
47, 48, 49, 50, 51, 52, 53, 54]
}
]
```

5. segmentCoeffMap is another list. The length of the list is equal to the number of coefficients that are affected by segmentation within the durable and transient vectors of the alternative(s). Each set defines:

   - Segment: index into the segmentDefinitions list (should probably just convert this to use the name)
   - Vector: possible values: durable/transient: which coefficient vector in the alternative(s) this set of coefficients applies to
   - Offset: offset into the relevant Coefficient Vector
   - Coefficients: a list of lists; first index is which alternative (i.e. alternatives are rows).

For each alternative row there are as many values as elements in the corresponding segmentDefinitions' DataRange value. For example, for 'DataRange' : [5,10,15,20], each row below will have 4 elements. For a data value of 5, the coefficients would come from the first column of data. These coefficients will be substituted into the coefficients array for each alternative at the offset specified below. The segmentCoeffMap contains by default only the coefficients that apply to the Total Cost and Constant variables; however at this point, the code is revised by adding the coefficients that apply to the RT distance variable.

```
segmentCoeffMap = [
{'Segment': 0, 'Vector': 'transient', 'Offset': 1,  # Total Cost
'Coefficients':
 # INC0              # INC1        # INC2         # INC3      # INC4
[-0.00316198,-0.00182647,-0.00135147,-0.00100,-0.00069220],# DA
[-0.00316198,-0.00182647,-0.00135147,-0.00100,-0.00069220],# S2
[-0.00316198,-0.00182647,-0.00135147,-0.00100,-0.00069220],# S3
[-0.00316198,-0.00182647,-0.00135147,-0.00100,-0.00069220],# TW
[-0.00316198,-0.00182647,-0.00135147,-0.00100,-0.00069220],# TD
[-0.00316198,-0.00182647,-0.00135147,-0.00100,-0.00069220],# BK
[-0.00316198,-0.00182647,-0.00135147,-0.00100,-0.00069220],# WK
]
},
{'Segment': 1, 'Vector': 'transient', 'Offset': 5, 'Coefficients':
  # FI0       # FI1       #FI2     ....     #FI54
[0.00000000,-0.00110118,-0.00092201, ... ,-0.00006044],DA
[0.00000000,-0.00055059,-0.00046100, ... ,-0.00003022],S2
[0.00000000,-0.00031462,-0.00026343, ... ,-0.00001727],S3
[0.00000000, 0.00000000, 0.00000000, ... , 0.00000000],TW
[0.00000000, 0.00000000, 0.00000000, ... , 0.00000000],TD
[0.00000000, 0.00000000, 0.00000000, ... , 0.00000000],BK
```

```
[0.00000000, 0.00000000, 0.00000000, ... , 0.00000000],WK
]
},
]
```

Since the OperatingCostCentsPerMile is set equal to 0 (Step 1), the RT Distant transient coefficients by FUELINCOME class are defined as follows:

$$Coeff_{FI\ CLASS,TM}^{RT\ Dist} = Coeff_{FI\ CLASS,TM}^{Total\ Cost} * \frac{\frac{VehOpCost}{MFE_{FI\ CLASS}}}{VehOccup_{TM}}$$

where $Coeff_{FI\ CLASS,TM}^{RT\ Dist}$ is the transient coefficient by FUELINCOME class and tour mode from the RT Dist matrix, $Coeff_{FI\ CLASS,TM}^{Total\ Cost}$is the transient coefficient by income class and tour mode from the Total Cost matrix, $VehOpCost$ is the vehicle operating cost per gallon for the specific scenario and is fixed for all users, $MFE_{FI\ CLASS}$ is the mean fuel efficiency for the particular FUELINCOME class in mpg from Table 11, and $VehOccup_{TM}$ is the vehicle occupancy factor by tour mode which are defined in the Globals.py script file.

It is noted that the correspondence between FUELINCOME classes and income classes can be found in Table 12. It is also noted that only the DA, S2, S3 tour modes are affected by the vehicle operating cost; TW, TD, BK and WK are not, therefore the corresponding RT Dist transient coefficients are set equal to 0.

Appendix D. Additional Graphs

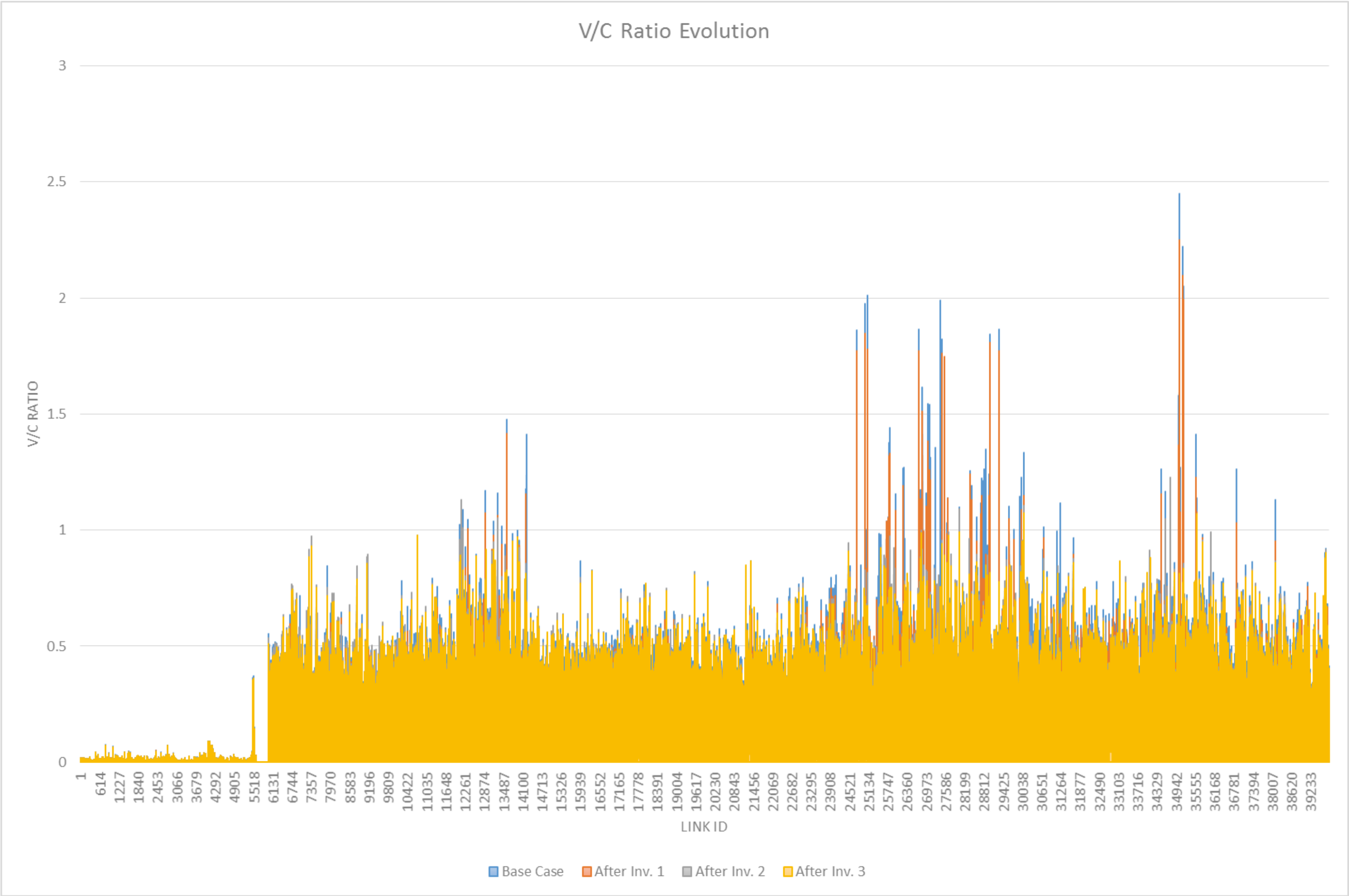


Figure 108 Link-Level V/C Evolution per Iteration – Outlook A

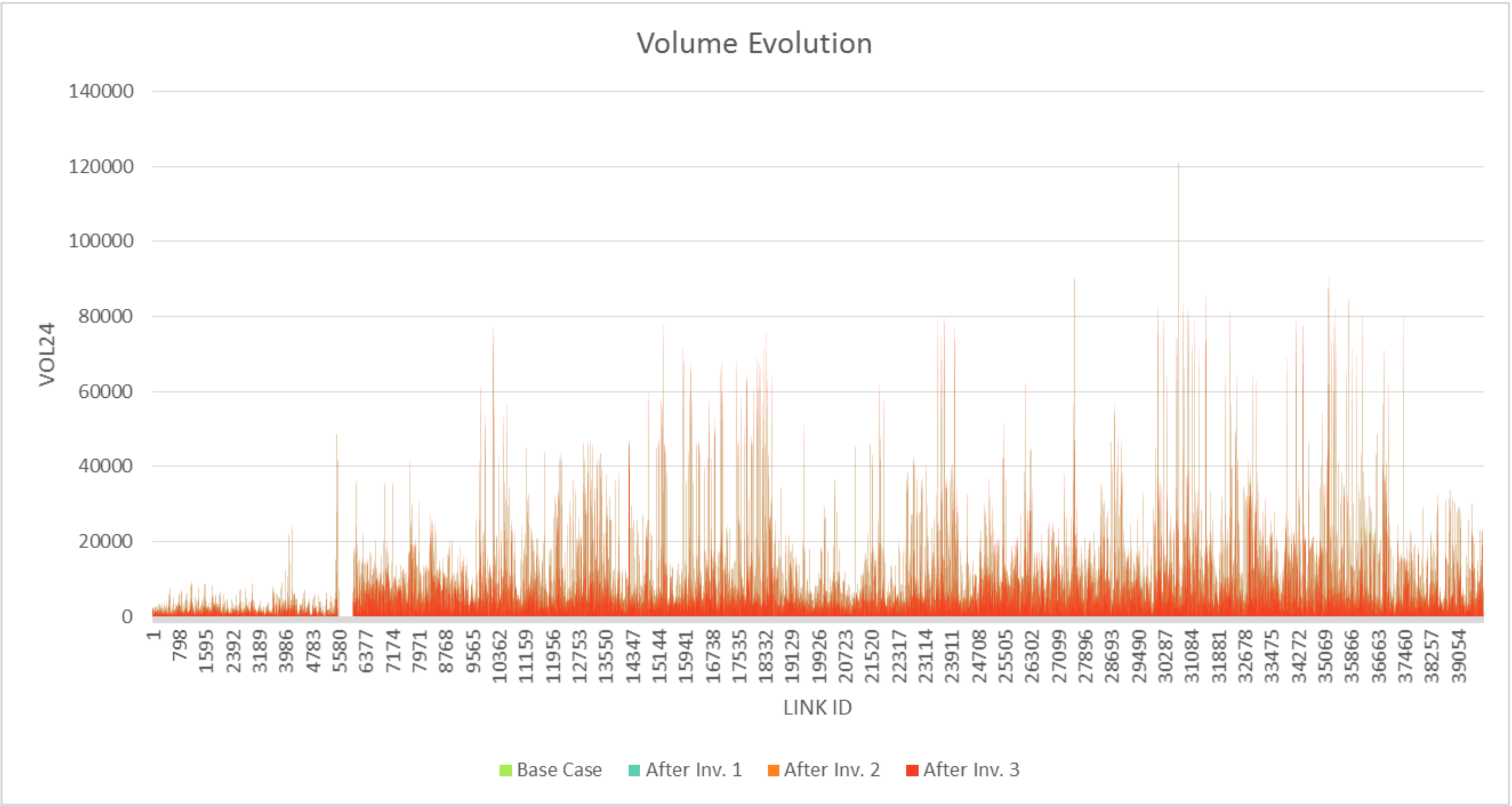


Figure 109 Link-Level Volume Evolution per Iteration – Outlook A

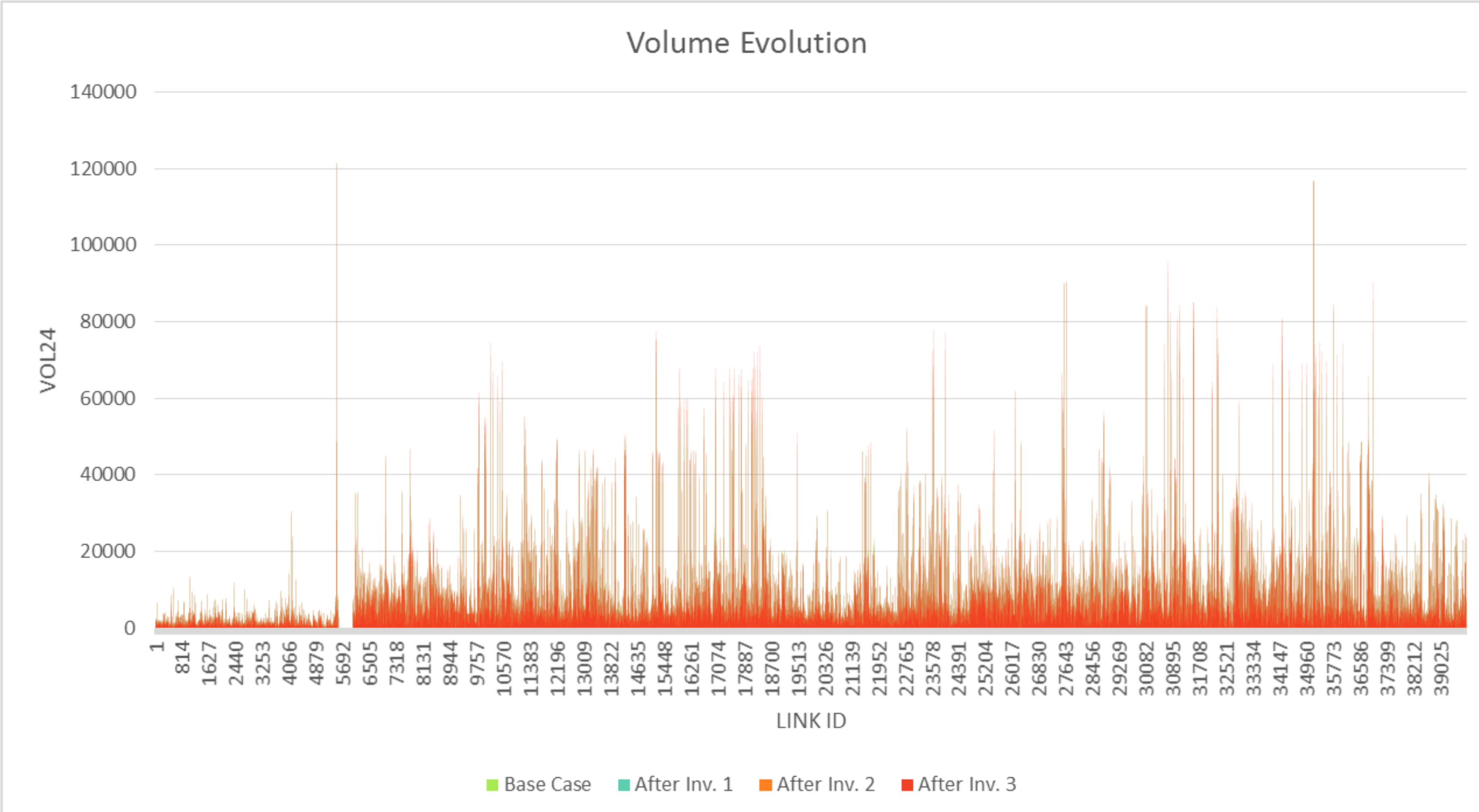


Figure 110 Link-Level Volume Evolution per Iteration – Outlook B

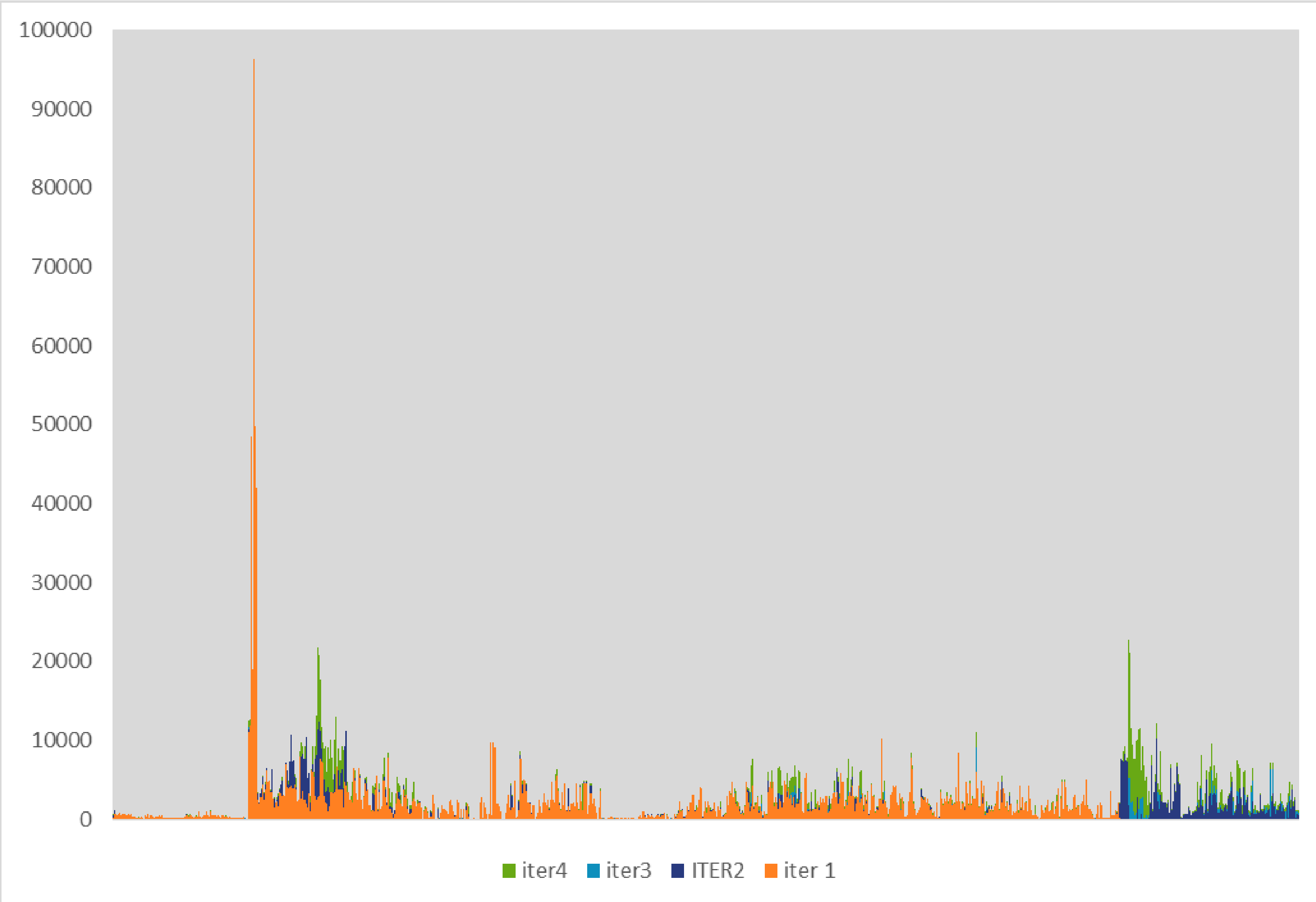


Figure 111 Link-Level Transit Volume Evolution per Iteration – Outlook B

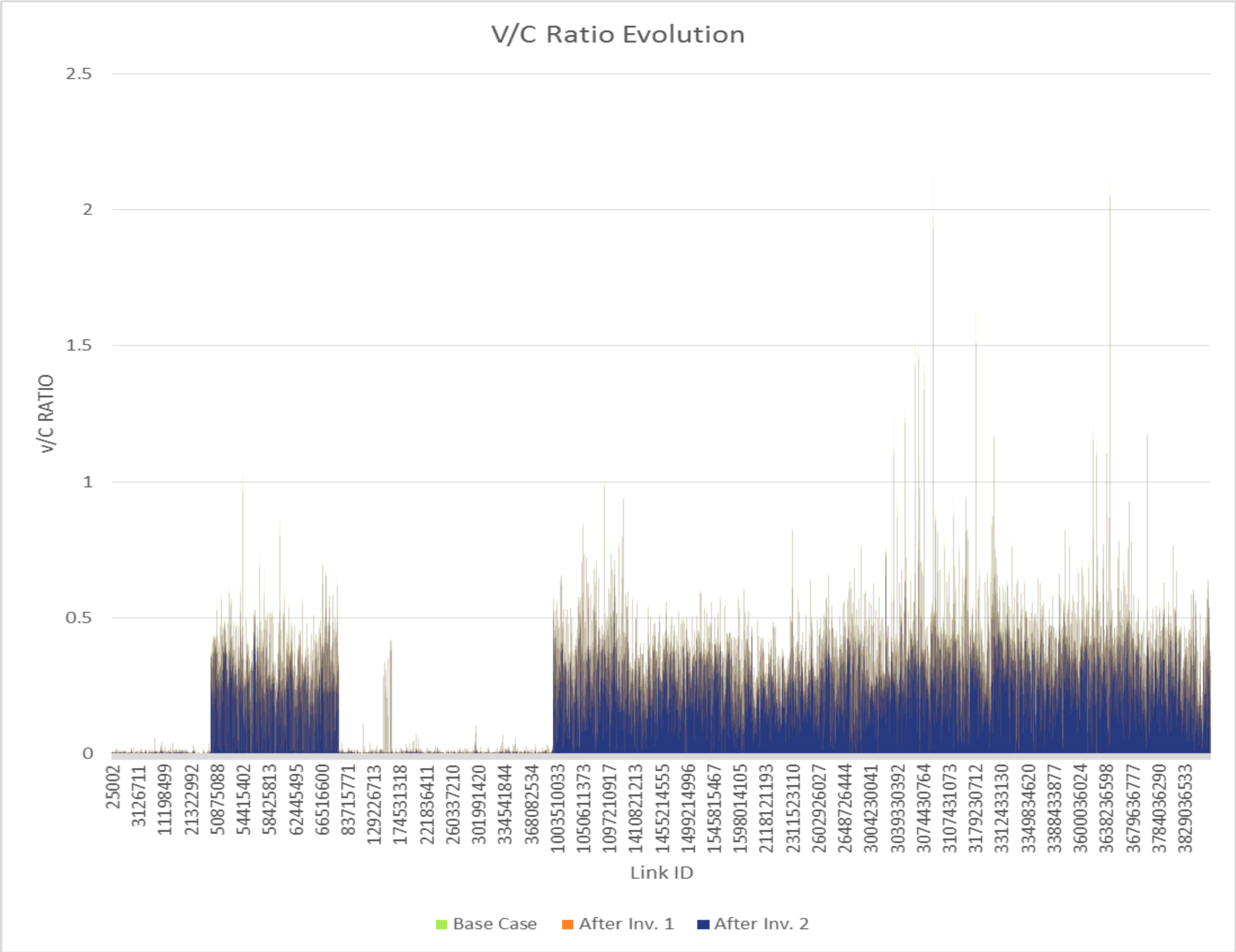


Figure 112 Link-Level V/C Evolution per Iteration – Outlook B

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