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CONGESTION PRICING IMPACT ANALYSIS USING INPUT-OUTPUT MODEL

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ABSTRACT

In this article, we modeled the economic impactsofcongestion pricing policies on micro and macro levels of the economy. On the consumer side of the market, we ran a discrete choice model and examined how travelers behave differently in response to higher driving costs caused by road congestion. While on the macro level, we defined the congestion pricing policyas an exogenous shock on economy and simulated the impacts of this stimulator on several sectors of economy.

Results for the case study ofthe Greater New York Metropolitan area shows thata congestion pricing policy on three designated freeways, with a daily flow over 3.5 million vehicles will induce around $0.55 blnincrease in GDP. This growth is caused not only by the expansion of value added items, but also by the direct impact on GDP due to less fuel consumption and consequently less oil imports.

***Keywords**: Congestion pricing, input-output model, bi-level modeling, hybrid algorithm.*

I. INTRODUCTION

Congestion pricing or road pricing is a system of surcharging users of public goods because of the congestion they impose, not only to reduce the traffic flow, but also to improve the network infrastructure performance. In other words, congestion pricing is 'a way of harnessing the power of the market to reduce the waste associated with traffic congestion'.This pricing strategy, in general, regulates demand, making it possible to manage congestion without increasing supply and eventually panelize commuters in response to their usage. Market theory postulates that with a congestion pricing scheme, users are forced to pay for the negative externalities they create, making them conscious of their travel social costs and potentially more aware of their travel impacts on others. Congestion pricing could encourage the redistribution of the demand in space or in time, or shift the demand to the consumption of a substitute public good; for example, switching from private cars to the public transport or switching from rush hours to non-peak hours.

The rationale for implementing congestion pricing on roads was summarized in a testimony to the United States Congress Joint Economic Committee in 2003: "congestion is considered to arise from the mispricing of a good; namely, highway capacity at a specific place and time. The quantity supplied (measured in lane-miles) is less than the quantity demanded at what is essentially a price of zero. If a good or service is provided free of charge, people tend to demand more of it – and use it more wastefully – than they would if they had to pay a price that reflected its cost. Hence, congestion pricing is premised on a basic economic concept: charge a price in order to allocate a scarce resource to its most valuable use, as evidenced by users' willingness to pay for the resource".[1]

However, there are intense debates over congestion pricing applications; such as how, where, by who, and by what intensity this policy should be implemented. Moreover, congestion pricing requires strong political supports (Richards, 2008). This support may not be happened unless policy makers end up on a meaningful, reasonable and accurate model to show what parts of the society burden the congestion weight and by what degree of strength, what part of society host the pressure and by what degree and how to optimize the tolling policy.

[1]https://www.cbo.gov/sites/default/files/cbofiles/ftpdocs/41xx/doc4197/05-06-congestionpricing.pdf

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Numerous studies have analyzed real-life congestion pricing schemes. These studies usually offer narrow modeling frameworks due to the complex nature of practical studies. As a prominent example, Prud'homme and Bocarejo (2005) estimated demand and supply functions for the London congestion pricing scheme and determined the optimal road usage and the optimal congestion toll for the congestion zone. They showed that the London congestion pricing is an economic failure despite its political success.

Hamilton (2011) also indicated that the congestion pricing in the case of Stockholm, Sweden results in unpredicted and excessive costs. Nevertheless, Hamilton (2011) showed that it would be possible to establish a system such as the Stockholm congestion charging system, for a considerably lower cost by: (1) reducing the insurance-like costs (unneeded technical staffs, unnecessary cameras, and redundant network connections), (2) forecasting and preparing for the election's role in ensuring the future of the system, and (3) informing the public from the start and provide the support to design a less-costly system that does not need acceptability ex-post. Olszewski and Xie (2005) modeled the effects of the pricing on traffic flows in Singapore.

The study found that time-variable road pricing or 'shoulder pricing' method, increasing the charges before the peak and lowering them after, tends to transfer congestion to other periods and other routes and is an effective method of controlling congestion. Xie and Olszewski (2011) proposed a methodology for using the traffic data from the Singapore's Electronic Road Pricing (ERP) system to forecast the short-term impacts of peak period traffic volume (trip rate) adjustments.

However, tolling systems should be supported by extremely complicated mathematical modeling considering policy and economics components which make it even more complicated. As touched upon before, the primary questions are: how much should the toll must be on specific road (in case of fully toll roads)?; who must pay the toll?; and where should the money collected from tolls go? To calculate the costs of congestion, and investigate the optimal approach to manage and invest the driven capital by such policy, this study introduces a new and innovative 'dynamic-hybrid' model to determine i) the economic impact that should be expected due to tolling policies; ii) the approach to control the impact on GDP; and iii) the optimum approach to invest the money collected from tolling.

The rest of the paper is organized as following: first, we cite the literature review that have been done on this area, and then make a brief review over the sorts of impact the congestion will impose to society. Following to article review we appraisal impact of such policy on economy, in both micro and macro levels and then explain our methodology. The case study will then be examined and assumption methods for modeling will be defined. Result and discussion and analysis on driven calculation are being provided in section eight and eventually we summarize the article by conclusion and also a number of recommendations that might be a potential subject for further investigations.

II. COST OF DRIVING

Driving costs can be divided into two main elements: direct and indirect. The former element covers the cost which paid directly by drivers while the latter includes costs that are byproducts of travel and not paid directly by users. Direct cost includes:

- Fixed Costs – Insurance, licensing, registration, motor vehicle taxes;
- Finance Charges – Interest charges on money borrowed to purchase vehicle;
- Depreciation – The difference between what paid for the vehicle and what sold;
- Fuel – Out of pocket expenses for gas. The price includes not only the fuel cost itself, but also fuel taxes and fees;
- Maintenance and Tires – Out of pocket expenses for car maintenance (regular service and oil) estimated at $566 per year, and tires, estimated at $96 per year;
- Residential Parking – The value of a single off-street parking space on residential property is estimated at no less than $950 per space per year; and
- Parking and Tolls – User fees paid at parking facilities and toll booths.

Indirect costs include but are not limited to

- Travel Time – Includes costs to drivers of unpaid time, costs to employers for work time spent in travel, and costs associated with opportunities lost in travel time;
- Accidents ;
- State and Local Construction Improvements, Maintenance and Operations of Roadways – Approximately 59% of the $41.5 billion cost in 2005 came from fuel taxes and user fees that are paid directly by drivers, with the remaining $17 billion financed through state and local taxpayers, property owners, and others;[2]
- Commercial and Employer Parking;
- Waste Disposal – Disposal of tires, batteries, junked cars, oil (long-term), and other semi-hazardous materials resulting from motor vehicle production and maintenance. However, the cost to dispose of these materials still amounts to approximately $1.2 billion per year;[3]
- Air Pollution Damage – Fuels are getting cleaner, and more people are driving cars with higher gas mileage. However, motor vehicles are still a major source of carbon monoxide and smog because vehicles are being driven more miles than in the past. Air pollution damages human health, crops, materials, vegetation and lowers visibility;
- External Resource Consumption Costs – Vehicle production and use is one of the largest consumers of natural resources – primarily petroleum, various metals, and rubber. Passenger vehicles account for about 40% of the petroleum products consumed in the U.S. each year[4];
- Road Noise – Noise negatively affects human health and causes declines in property values;
- Carbon Dioxide (CO2) Emissions – Carbon Dioxide is the predominant greenhouse gas that causes global warming. More than one-fourth of the carbon dioxide emissions in the United States (US) are transportation related. According to the latest annual EPA report on emissions, cars alone account for more than 625 million tons of carbon dioxide emitted into the nation's atmosphere each year[5];
- Transportation Diversity and Equity – Transportation diversity and equity means providing adequate transportation for non-drivers, particularly for those who are economically, socially, or physically disadvantaged. Non-drivers face a relative lack of mobility options when it comes to jobs, housing, education, social services and activities. This impact is accelerated by auto-oriented land use patterns.
- Land Use Change Costs;
- Congestion Costs– Congestion usually occurs during rush hour when traffic volumes reach or surpass a roadway's capacity. As discussed above, traffic congestion increases travel time, air pollution, vehicle operating costs, driver's stress, and insurance rate due to higher accident risks, etc.

Social costs

Congestion imposes large social costs in addition to lost time and fuel. Babies developing near congested traffic have worst health outcomes while longer commuting time are associated with more obesity and higher divorce rates[6]. Traffic congestion also has negative effects on labor productivity. Lee et al show that lower level of congestion allows for a larger effective labor market size, which means that businesses can better locate the workers they need. Congestion is also worsening over time, as annual hours of delay per peak time traveler increase 136 percent between 1982 and 2009 in the nation's fourteen largest urban areas.

Cost on Transportation Network Infrastructure and the Road Damage Cost

Besides the required cost on infrastructure development, network expansion and modernization of current facilities, many segments of existing transportation system are mature relative to original design standards and suffer from years, if not decades, of deferred maintenance. Thirty-two percent of America's roads are now in poor or mediocre

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[2] http://commutesolutions.org/external/tcod.html
[3] http://commutesolutions.org/external/tcod.html
[4] http://www.hubbertpeak.com/pimentel/bioscience/conservation/conservation.pdf
[5] http://www.biologicaldiversity.org/programs/population_and_sustainability/climate/pdfs/USPopulationEnergyandClimateChange.pdf
[6] Currie, Janet and Reed Walker, 2011. "Traffic Congestion and Infant Health: Evidence from E-ZPass," American Economic Journal: Applied Economics, American Economic Association, vol. 3(1), pages 65-90, January.

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condition, and deicing on such roads costs motorists $67 billion in additional operating costs and annual repairs. Although, all vehicles are responsible on the cost of road usage such as pavement repair and road maintenance fees, the type of vehicle could affect the fees. The performance, number of axels, type and size of the engine, and vehicle specifications (weight, etc.) can affect road usage implications.

III. DISCRETE CHOICE MODEL AND MICROECONOMETRICS OF TRAVEL BEHAVIOR

By implementing a tolling system, there would be an inevitable impact on discrete choice model of travel behavior, specifically, on modal share. If the travelers commute base on four main modes of car, walk, cab, and subway (seems rational assumption, since carpool and bus are having a very slight modal share in the City of New York), Toll policy will induce a huge shift on travel behaviors, namely on commuting mode. Hence, to study and examine such an impact on micro level activities of commuters, we will consider the discrete choice model (DCM) and the impact caused by road pricing policy.

MMNL; the Mixed Multinomial Logit Model

Mixed Logit models assume a utility function U_{in} conformed by a deterministic component V_{in}, a random component ε_{in} which is *iid*, independent and identically distributed, and one or more additional random terms. These additional error terms can be grouped together in an additive term h_{in}, that can be function of the data (attributes of alternatives), and that potentially models the presence of correlation and heteroscedasticity. So, the utility function is defined as

$$U_{in} = V_{in} + \eta_{in} + \varepsilon_{in}$$

Where ε_{in}~ Gumbel(0, l) and h_{in}~ f(h/q*), with *f* a general density function and *q** are fixed parameters that describe it (e.g. mean and variance). As ε is *iid* Gumbel, then the probability conditional in *h* of individual n choosing alternative *i* corresponds exactly to the Multinomial Logit model:

$$P_n\left(\frac{i}{n}\right) = L_{in}(\eta) = \frac{e^{V_{in}+\eta_{in}}}{\sum_j V_{jn}+\eta_{jn}} \qquad (1)$$

So, the probability of choosing the alternative corresponds to the integral of the conditionalprobability over all the possible values of *h*, which depends on the parameters characterizing the distribution, this is:

$$P_{in} = \int L_{in}(\eta) f\left(\frac{\eta}{\theta}*\right) d_\eta \qquad (2)$$

As a particular case, it can be assumed a utility function with the following specification

$$U_{in} = \beta' X_{in} + U'_{in} Z_{in} + \varepsilon_{in} \qquad (3)$$

In this expression the assumption is that the deterministic component of the utility is linear in the β parameters that multiply the attributesX_{in}. Furthermore, it is assumed that *h* depends of certain parameters and data observed related to alternative *i* (Z_{in}), relation which is also supposed linear in the parameters. An additional assumption is that the *n* term is a property of the individual, with no variation over alternatives. The latter means:

$$\eta_{in} = \varrho'_n z_{in} \qquad (4)$$

The interesting point to highlight is that the Mixed Logit model, allowing the presence of correlation between alternatives, is capable to release the assumption of independence of irrelevant alternatives, characteristic of the Multinomial Logit model. In other words, the substitution patterns between alternatives are flexible.

In effect, given a Mixed Logit probability, it can be shown that the ratio between probabilities of two alternatives depends on all the set of available alternatives.

$$P_{in} = \int_{-\infty}^{+\infty} \dots \int_{-\infty}^{+\infty} \left\{ \frac{e^{(\beta' x_{in} + \Pi'_n z_{in})}}{\sum_{l=1}^{j} e^{(\beta' x_{ln} + \Pi'_n z_{ln})}} \right\} f(x_{kn}) dx_{ln} \qquad (5)$$

Estimation

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The choice probability of a Mixed Logit model, like the presented above, does not have a mathematical closed expression as in the Multinomial or Nested Logit. Even more, the integral cannot be solved analytically and simulation must be used. Nevertheless, the fact that the conditional probability has a Multinomial Logit form can be exploited.Then, if R values of h are obtained from its density function f (h/q*), then for each of this repetitions it is possible to calculate.

$$P_n\left(\frac{i}{n^r}\right)= L_{in}\,(n^r) = \frac{e^{V_{in}+n_{in}}}{\sum_j e^{V_{jn}+n^r{}_{jn}}} \tag{6}$$

with r =1, ..., R. Accordingly to this, it is possible to obtain an average probability

$$P_{(i)} = \frac{\sum_{r=1}^{R} L_{in}\,(n^r)}{R} \tag{7}$$

Building a Crossed Nesting Structure by MMNL

A nested logit model is appropriate when the set of alternatives faced by a decision-maker can be partitioned into subsets, called “nests,” in such a way that the following properties hold. (1) For any two alternatives that are in the same nest, the ratio of probabilities is independent of the attributes or existence of all other alternatives. That is, IIA holds within each nest. (2) For any two alternatives in different nests, the ratio of probabilities can depend on the attributes of other alternatives in the two nests. IIA does not hold in general for alternatives in different nests.

However, a particular Mixed Logit specification could be equivalent to a Nested Logit model. This last model was conceived to deal with correlation between alternatives, grouping similar alternatives into nests within which the iid assumption does hold (Williams, 1977). The aggregation into nests implies a particular structure of the covariance matrix, because if two or more alternatives are grouped in a nest, the corresponding off diagonal elements will be different from zero. Train (1999) argues that a Mixed Logit model could be “analogue” to a Nested Logit. This particular model is built grouping the alternatives into nests; then, in the utility function a dummy variable is added for each nest indicating if the alternative belongs to it or doesn’t belong. A common random parameter is associated to each one of these variables. In this way the model has a correlation structure such that in the alternatives belonging to the same nest an off diagonal term appears. This model will be discussed in further details in methodology.

IV. ECONOMY IN A MACRO LEVEL

Besides the influence of such a policy in micro level, Economy in Macro level also will host many impacts. If we translate the new policy to a trigger for financial shock and the hosting basin to economy, the financial circulation of influences could be simulated, and then the policy impact on economy be examined. More precisely, by understanding a relationship between economy’s sectors and knowing how output from one industrial sector may become an input to another industrial sector, any financial shock could be tracked down and any policy can be examined prior to implementation.

Accepting of the economy as consisting of linked sectors will lead us to the inter-sectoral correlation of a given economy, which is almost always summarized in an input–output model. I-O model is a quantitative economic pattern consisting of a system of linear equations that represents the interdependencies between different branches of a national economy or different regional economies and provides the simulation basin to not only studying the economy’s portions, but also affords the mathematical modeling tool for predicting hypothetical events. The fundamental information used in input-output analysis concerns the flow of the products from each industrial sectors, consider as a producer, to each of the sector, itself and others, considered as consumers.

Generally, the I-O table is a linear model of deterministic functions which show non-stochastic and fixed links between an economy of sector in both manners of input and output. In other words, this table shows, how a given economy spends the wealth and gather that, and how these flows moves between origins and destinations. A point to highlight is that this table is designed based on an economics fundamental of an open economy. Where the total value of such economy is equal to the summation of consumption, investment, government investment and net export, where the import as a sub-division of net export will connect the economy to other economies.

$$Y = C + I + G + NX \tag{8}$$

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Again, each sector spends the same amount of monetary value which makes. This equilibrium requests a $(n+1)^2$ table which embedded a n^2 matrix of inter-sectoral links in addition a row of total input and a column of total output, where

$$\sum_{i=1}^{n} Z_{in} = X_n \tag{9}$$

$$\sum_{j=1}^{n} Z_{nj} = X_n \tag{10}$$

By putting these two functions equal, we will have

$$X_{(n+1)j} = X_{j\,(n+1)} \tag{11}$$

		Buying Sector					
		1	…	j	…	n	
Selling Sector	1	Z_{11}	…	Z_{1j}	…	Z_{1n}	$\boldsymbol{X_1}$
	.	.		.		.	
	.	.		.		.	
	.	.		.		.	
	i	Z_{i1}	…	Z_{ij}	…	Z_{in}	$\boldsymbol{X_i}$
	.	.		.		.	
	.	.		.		.	
	.	.		.		.	
	n	Z_{n1}	…	Z_{nj}	…	Z_{nn}	$\boldsymbol{X_n}$
		$\boldsymbol{X_1}$		$\boldsymbol{X_j}$		$\boldsymbol{X_n}$	

Table 3: I-O Table of Inter-Industry Flows, where i=j

However, to make the rows and columns value equal, there are other components than inter-industry interaction flows, known as value-added and final demand. The former one includes government services (paid for in taxes), capital (interest payment), land (rental payments), entrepreneurship (profit) and so on. In contrary, the latter one consists of such factors as labors.

Since the interaction in such table is deterministic, by having a coefficient parameter, we can replicate and mimic the same correlation by a given change on elements (such as defined shock or policy implementation). In other words, the factorial shares of any cell with respect to the $(n+1)^{th}$ row and table as well as other cells show the linkage between different cells. However, by implementing a change in any of sectors, the coefficient system imposes a change on the system as whole, the new injected impact will also do the same based on the same coefficient system. This series of impact of driven impact on new coefficient system continues for infinite times. By knowing the fact that all coefficients are less than a unit, then by increasing the iteration, the impact would be smaller and smaller to reach the value close to zero.

To gain a deeper grasp on the role of labor, household and the social institutions of the economy, the extension of I-O framework is recommended. In particular, by adding detailed characterization of the economies fragments, we would be able to capture in more detail the employment features of economy, consisting of income from employment and its disposition, labor cost and demographics of the work force in a labor market's supply and demand sides. In addition, we also can find the more appropriate analysis over any shock by I-O extension, since the model could be tailored base on scenarios. These goals could be accomplished by hiring the Social Accounting Matrix, so-called SAM. By way of illustration, SAM helps us to employ, simulate and analyze social and economic policies in a more comprehensive way that I-O model does.

By including the input-output table of inter-industry income and output, and the institutional income and expenditure associated with Final Demand and Value Added sectors, SAM could be managed base on the closure of economy's sectors, which is the key decision in employing multipliers in any given analysis. By way of illustration, we can control and determine which sectors would be viewed as exogenous into I-O model and which sectors would be incorporated endogenously (closure the model). Therefore, in developing a simple multiplier model, the first step is to decide which accounts should be exogenous and which are to be endogenous. It's recommended to consider government account, the capital account and the rest of the world account to be exogenous.

This is because government outlays are essentially policy-determined, the external sector is outside domestic control, and as the model has no dynamic features so investment is exogenously-determined. In contrary, the endogenous accounts are therefore usually limited to those of production (activities and commodities), factors and households. By the same logic as I-O model works, the endogenous row accounts can then be written as a series of linear identities and the system can be solved to give the simulated impact.

Y-AY=X

Y(I-A)=X

$$\frac{Y(I-A)}{I-A} = \frac{X}{I-A}$$

$$Y=(I-A)^{-1}X \tag{12}$$

Where $(I-A)^{-1}$ is the SAM multiplier matrix. SAM-based multipliers rely on some strong assumptions; first, the implicit assumption is that there is excess capacity in all sectors and unemployed factors of production. In this case the multipliers work through to the equilibrium solution, but if there are capacity constraints of any kind then the multipliers will overestimate the total effects and the final distributional effects will be uncertain. Secondly, as prices are fixed, there is no allowance for substitution effects anywhere, or at any stage. Again this may also lead to an overestimation of the total response. Thirdly, when prices are not fixed they may be expected to rise (fall) to offset excess demands (supplies) in any of the markets. Therefore, any price changes would tend to mitigate the total effects implied by the fixed price model.

Overall it is obviously difficult to generalize about the validity of the SAM multipliers in all settings. However, in some cases the assumption of a perfectly elastic supply of outputs and factors is reasonable, while in most of the case is not rational. At best, SAM multipliers provide us with a first-cut estimate of the effects of a policy or external shock, relying only on the SAM structure. It is an appealing though somewhat limited analytical technique which should not be applied mechanically without due care.

V. METHODOLOGY

A tolling system could be considered as a financial shock; A shock on transportation industry, and hence on entire economy. However, in literatures the impact of implementing a tolling policy on entire economy is either misunderstood or studied incompletely. As a policy, tolling system will change the traveling behaviors in micro level as well as changing the output on macro levels of economy. Nevertheless, economy in micro and macro levels is strongly tied and any alteration on either side will impose ripple impact on other side. This ripple effect could be tracked inside a hybrid model which connects the micro and macro structures. The two model classes differ mainly with respect to the emphasis placed on structure of economics and the comprehensiveness of endogenous market adjustments.

Bottom-Up Model

Button-Up model is mainly focused on discrete choice modeling which is introduced by McFadden. The model considers a random utility for each modal choice and based on attributes of each mode; estimate the expected probability of choosing such one mode by a given alternative and eventually by the whole commuters. Mode shifting on micro level will cause a shift on total welfare of the transportation system (transit + traffic) as well as direct and indirect impact of policy on regional economy.

By considering the four main travel modes in the City of New York and an assumption of time, cost and comfort as relative attributes, the utility function can be defined as follows.

$$U_{i,Car} = \beta_{Car} + \beta_{Cost} X_{1,Cost} + \beta_{Time} X_{1,Time} + \beta_{Comfort} X_{1,Comfort} + \varepsilon_{i,Car} \tag{13}$$

$$U_{i,Walk} = \beta_{Walk} + \beta_{Cost} X_{1,Cost} + \beta_{Time} X_{1,Time} + \beta_{Comfort} X_{1,Comfort} + \varepsilon_{i,Walk} \tag{14}$$

$$U_{i,Subway} = \beta_{Car} + \beta_{Cost} X_{1,Cost} + \beta_{Time} X_{1,Time} + \beta_{Comfort} X_{1,Comfort} + \varepsilon_{i,Subway} \tag{15}$$

$$U_{i,Cab} = \beta_{Car} + \beta_{Cost} X_{1,Cost} + \beta_{Time} X_{1,Time} + \beta_{Comfort} X_{1,Comfort} + \varepsilon_{i,Cab} \tag{16}$$

Where i is an individual and $\varepsilon_{i,mode}$ is a random term which shows the noise on utility. Since the model is logit, the noise is randomly distributed with logistic distribution. A point to highlight is that the subtraction of two logistically random terms is a random variable with extreme value types I (gumble) distribution with the probability distributing function and cumulative distribution function as follows.

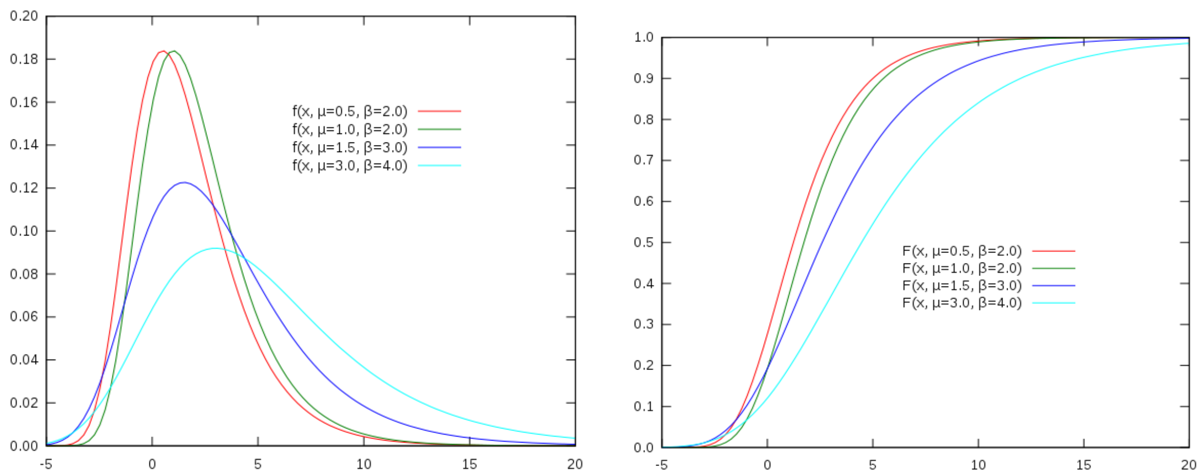

Fig 4: pdf., Fig 5: cdf of extreme value type I (gumble) distribution

However, as mentioned before this model is a crossed nested multinomial logit (CNL-MMNL) which on one side the coefficient of each attributes for each individual and each alternative is vary and also the subway and cab will have nesting correlation which impose a Homoscedasticity inside the random variable of two modes. The nesting structure of this modal share system can be summarized in following figure.

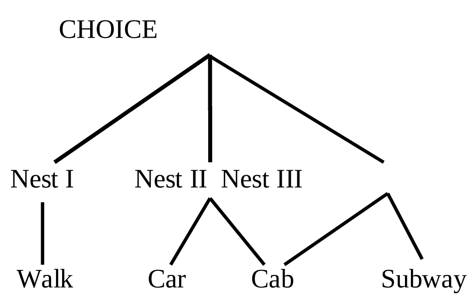

Fig 6: Nesting Diagram

As shown in above figure, the three out of four modes are somehow correlated. The cab and subway are nested together as non-private modes and car and cabs are also nested as modes which are both be reflected by implementation of tolling strategies. However, there is a cross correlation between nest II and nest III. Meaning, the mode 'cab' is sharing the covariance with nests II and III. Such a modal shift from tolled-based model to toll-free modes is subjected to be an economic shock trigger. Without a doubt, drop on private vehicle modal share will impose negative shocks on industries which are providing service to individual commuters.

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For example, sectors such as 'petroleum production', 'insurance' or 'gasoline station' will be affected negatively, since the gas consumption and hence the gas demand will be decreased by such reduction on number of trips. In other side, the modal shift from carpool and private vehicle to walk and subway will boost a positive injection on a number of sectors such as 'rail transportation', health-based sectors and 'transit and ground passenger'. Detail of such assumption and the magnitude of such impacts are being provided in attached appendix.
In addition to obvious impacts (mostly positive) in Bottom-Up model, which are caused by fewer trips, the gas consumption is also drops by the same percentage that private vehicle and cab do. However, such drop in gas consumption which is an imported good in the state of New York, will improve the level of GDP, since the dollar value of importing goods has a negative value in GDP calculation. By way of illustration, the higher drop in vehicle mode share, the larger fall on gas consumption and imported gas. Such decrease on imported good will affect the GDP positively and hence increase on GDP with exact amount of non-burned gas.

Top-Down Model
Considering the transport services, the toll does indeed increase the cost of production and delivering for various industries and may subsequently affect consumer prices. Thus, the magnitude of the sectoral price effects should be inspected. Increasing in goods' cost, can be translated into negative impact on sectoral industries, since the burden driven by cost escalating will be imposed on industries. To have a better estimation on industries and the magnitude of such negative impact, there must be research to be on micro level and consumer levels. Nevertheless, in this report we designated twenty-two sectors which will be hosting such negative impacts by 0.2-3 percent of their current total output. (Shown in Appendix). Besides such negative impact (Shock) on industries, the expenditure of toll gathered by government will impose positive shock. However, this expenditure is not designed to compensate the negative shocks, driven by collecting tolls.

There are many debates and argues about the spending the toll prices, and policy makers who fight against such policy argue that the dollar value of collected tolls are amassed easily, but the expenditure will be like dragging money from 'lock box'. In this study we assume whatever collected by tolling policy must be invested on industries that are effected mostly; 'construction', 'transportation equipment' and 'hospital' by 70, 10 and twenty percent, respectively. So far in Top-Down model we defined two series of economic shocks including negative shock due to increasing on goods cost and the positive shock driven by the injection of tolling money into three sectors.

Dynamic-Hybrid Model
Assuming that 'Road transport' passes the price effects on to the demanding industries, the cost increase for consumer goods mainly depends on the output coefficients of road transport and the importance of transport services for the respective sector. The results give a first idea of the direct price effects of road transportation but do not account for indirect price effects that might affect the whole economy. In fact, services provided by the industry 'Road transport' have a strong intermediate character, which in turn causes indirect price effects for all industries. Aside this direct impact, the tolling policy (as an external financial shock) will have indirect impact on economy. As shown in following diagram, any change on driving cost will decrease the car and cab modes' utility, due to negative random coefficients of cost and time attributes. Such change will cause a modal shift from toll based modes to non-tolled modes such as walk and subway. This modal swing will inject a sort of impact series on economic model as explained in last section. For instance, drop in private vehicle mode will cause a number of impacts such as decrease in:

- Gas consumption
- Emission and Green House Gases
- Congestion Social Costs
- Vehicle Sells
- Parking industry

Each of these parameters could also be translated into new financial shock and then extra impacts on economy. However financial shocks on economy (where the economy is closed with respect to Value Added value such as

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employee compensation) will change the GDP. As we know one of the methods of calculating GDP is the Value Added technique where the GDP=VA-Import

Well, by imposing such shocks in economy, we can find the change on VA and Import which can clearly depict the direct change on GDP. But, the question is what happens on discrete choice model afterward. When the GDP goes down, commuters are poorer in average, and then they do care more about the travel cost and take subway more, since it is cheaper. This will be shown on discrete choice model as well by higher value for cost coefficient (β_{Cost}). Since the cost has a negative impact, the larger value of coefficient, will impose the larger dislike on private vehicle and also the more interest on walk and train modes. A point to highlight is that we assume the increase in coefficient will be implemented on mean and standard deviation by the same level. The new coefficient will bring the new modal share and an updated modal share will cause the same ripple effect that the initial modal share did. In conclusion, this circular impact continues for infinite time and mathematically calculating such an impact is not possible.

To make it doable, we can define convergence criteria, either by putting bound on the objective function value change, percent change on GDP or any other restriction. In this model, we can use a convergence pattern as $GDP_1+GDP_2+GDP_3= 15GDP_n$. (Technically, it stops the iterations when the change on GDP drops to less than twenty percent of the average of the first three values). When the model does converge, the GDP will be fixed on a value which can be interpreted as a new GDP.

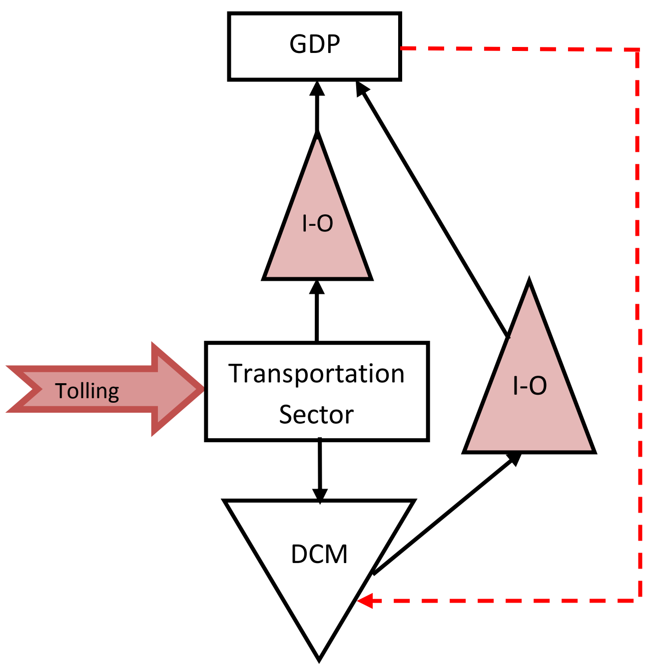

Fig 7: Hybrid Diagram

VI. CASE STUDY

To examine such model, there are a number of parameters to be taken care for picking the case study. In the US the tolling system is mostly implemented in off metropolitan areas; mostly in the North East of the country. However, the State of California has a tolling policy in Southern California on the interstate highway between the City of

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Irvine and San Diego. The Southern California tolling system is not a fully-tolled passage, since just one of the lane is usually designated for tolling, named as HOT Lane (High occupancy/toll lanes).

However, the City of New York has a number of tolled roads and bridges which provide an appropriate basin to examine this model. Besides the tolling system on roads, an available IMPLAN data for The Greater New York makes the five boroughs as a case study candidate. Since the case study includes five counties of Richmond, Queens, Kings, New York and Bronx, we do aggregate the IMPLAN data together and assume the whole boroughs as an isolated single economy with fixed attributes and behavioral sectors.

As well, we assume within The Greater New York metropolitan area, the four main travel modes are private vehicle, cab, train and walk. Walking is a key mode in New York, while in most of the cities in the US has a minor share that even doesn't count in travel mode lists. The main reason of this phenomenon could be the size, density and the direction and the pattern of inner-city roads. The large share of Cab in this city could be justified by the same reasoning in addition to this fact that parking spot is extremely costly.

Subway also has a major role in transporting people; where for the metropolitan in the size of the New York is not surprising. However, in our case study the Bus Rapid Transit and Bus System are not in the center of attention. In addition to these indices, there are a meaningful and accessible data for the New York socio-economic parameters; the income pattern, age, social class, as well as a good estimation for travel time of almost all of inner-city highways. By knowing these parameters, a discrete choice model could be simulated and then any shock on this model can be easily examined.

Modeling the CN-MMNL

In this step we need to model the data set. This will happen in four steps of building heterogeneity, simulating attributes, expecting taste parameters and model aggregation.

Taste Heterogeneity

There are two main strategies to create the nested logit heterogeneity. The first one is McFadden approach which is called Generalization of the Covariance Structure. In this method the flexible models derived directly from the covariance matrix (McFadden Derivation. where

$$G = \sum_1^M \left(\sum_{n \in m} (y_n)^{1/\lambda_m}\right)^{\lambda_m} \tag{17}$$

Where

$$y_n = e^{(\beta_0 + \sum_1^N \beta_n X_n)} \tag{18}$$

Then,

$$P_{in} = \frac{{y_i}^{1/\lambda_m} \left(\sum_{j \in m} (y_j)^{1/\lambda_m}\right)^{\lambda_m - 1}}{\sum_1^M \left(\sum_{n \in m'} (y_n)^{1/\lambda_{m'}}\right)^{\lambda_{m'}}} \tag{19}$$

Simulating models by this method for Mixed Logit is impossible since we do have crossed nested correlation. However, we can use the other methods to deal with random heterogeneity known as Inclusion of Additional Additive Error Terms.

In this strategy the utility models receive an additional noise, instead of randomness in a kernel noise (Williams's derivation).

$$U_{in} = V_{in} + \mu_N + \varepsilon_{in} \tag{20}$$

Where an additional noise can summarize in an additive term μ_N

$$\mu_N \sim N(0, 6_N^2) \tag{21}$$

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ε_{in} ~EV-1(0,1) (22)

Where ε_{in} shows the *iid* core (Kernel) which is distributed by gumbel pattern and μ_N generates normal correlation across alternatives which are nested together. In case of cross nested logit skeleton, the utility of crossed alternative(s) has one additive error term for each nesting tie that it has. In other words, each crossed alternative correlates by other nest-mates via this normal random variable. Consequently, we can develop the utility function of our case study as follows:

$$U_{Walk,n} = V_{Walk,n} + \mu_I + \varepsilon_{Walk,n} \quad (23)$$

$$U_{Car,n} = V_{Car,n} + \mu_{II} + \varepsilon_{Car,n} \quad (24)$$

$$U_{Cab,n} = V_{Cab,n} + \mu_{II} + \mu_{III} + \varepsilon_{Cab,n} \quad (25)$$

$$U_{Subway,n} = V_{Subway,n} + \mu_{III} + \varepsilon_{Subway,n} \quad (26)$$

Where the utility of cab shows the cross nesting structure. It means that cab is not only hosted by Nest II, but also nested under the third category. As mentioned, μ_{Nest} is normally distributed with the expected value of zero and variance of 6^2_{Nset}. This variance shows the covariance between alternatives which are nested together. If this is the case, then

$$6^2_I = \text{Cov}\,(U_{Walk}, U_{Walk}) = 1 \quad (27)$$

$$6^2_{II} = \text{Cov}\,(U_{Car}, U_{Cab}) = \text{Cov}\,(\mu_{II} + \varepsilon_{Car},\ \mu_{II} + \mu_{III} + \varepsilon_{Cab}) \quad (28)$$

$$6^2_{III} = \text{Cov}\,(U_{Cab}, U_{Subway}) = \text{Cov}\,(\mu_{II} + \mu_{III} + \varepsilon_{Cab}, \mu_{III} + \varepsilon_{Subway}) \quad (29)$$

Then, by defining a correlation between alternatives which are nested together, we can have the variance of additive error term corresponding to each nest and hence, complete the utility equation.

$$\rho_{Car,Cab} = \frac{6^2_{II}}{\left(6^2_{II} + \frac{\pi^2}{6}\right)\left(6^2_{II} + 6^2_{III} + \frac{\pi^2}{6}\right)} \quad (30)$$

$$\rho_{Cab,Subway} = \frac{6^2_{III}}{\left(6^2_{III} + \frac{\pi^2}{6}\right)\left(6^2_{II} + 6^2_{III} + \frac{\pi^2}{6}\right)} \quad (31)$$

Then if

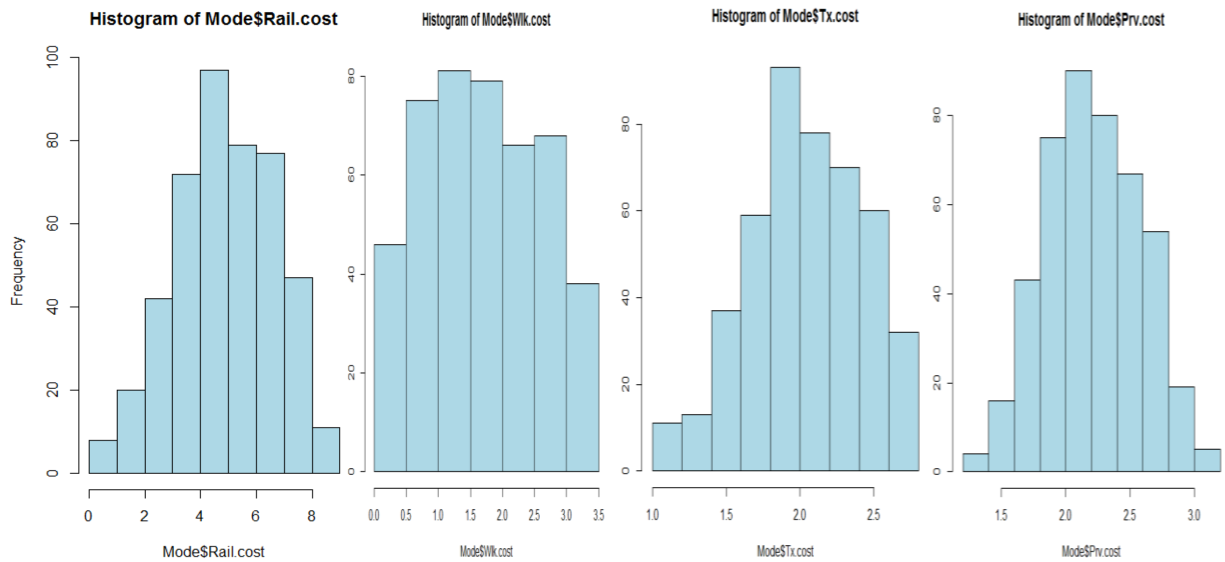
$$\left.\begin{aligned} \rho_{Car,Cab} &= 0.5 \\ \rho_{Cab,Subway} &= 0.2 \end{aligned}\right\} \longrightarrow \left\{\begin{aligned} 6^2_{II} &= 3.86, \\ 6^2_{III} &= 7.98 \end{aligned}\right.$$

Now we have variances of the additive random terms which are going to be shared by nest-mates.

Attribute Simulation

To simulate data, I used 'Northern America consumers' choice of modes' data set as data skeleton (Northern America data contains observations of 1877 individuals facing virtual choice situation among four types of mode, provided in 'mlogit' package of R. Another data available is K. Train's SF model available on UC Berkeley

Website). At first, I analyzed Northern America data, finding distribution patterns and then tailored data based on the NYC socioeconomics characteristics. Analyzed pattern for attributes are graphed as following figures.



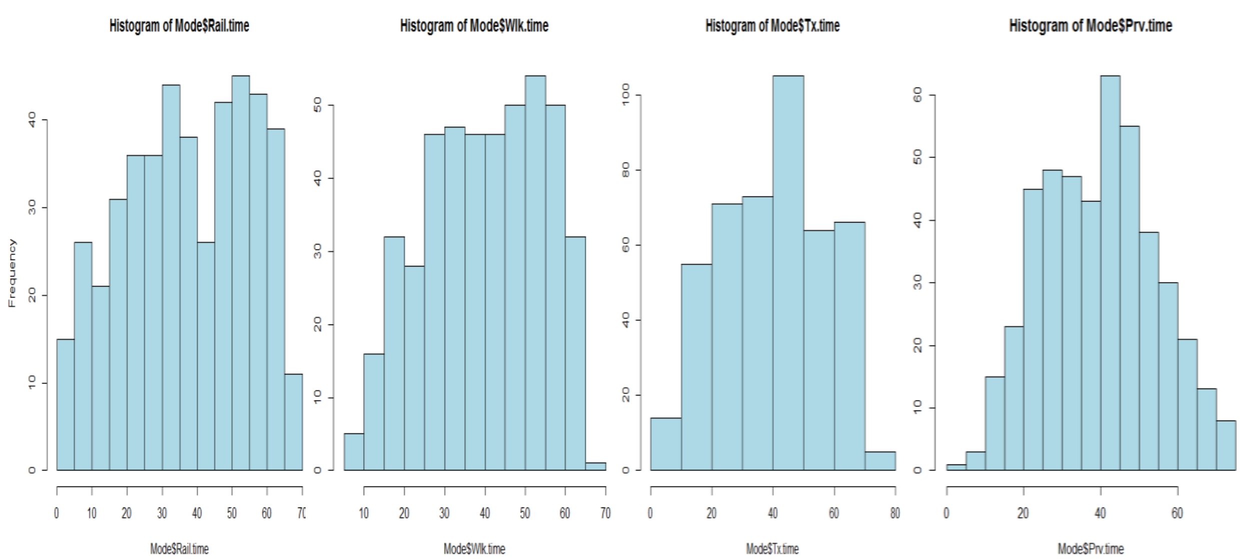


Fig 8; (a) Subway Cost (b) Walk Cost (c) Cab Cost (d) Private Vehicle Cost

Fig 9; (a) Subway Time (b) Walk Time (c) Cab Time (d) Private Vehicle Time

As seen in histogram graphs, the distribution of travel cost correspond to Rail (subway) is close to Beta, with the fat left tailed skew. The cost of mode walk technically could be considered as either non-continuous discrete variable with a fix value or a normal distribution with bounds over the min and max of both tails. The Cab travel cost seems close to left skewed log normal. However, @Risk software recommends Weibull distribution. For the private vehicle travel cost, the distribution of histogram shows the normal pattern with a relatively low standard deviation.

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For the travel time related to four modes, the cost of subway, the bimodal distribution with two peaks seems appropriate. The first peak has a very odd left skewed exponential distribution with non-zero left border and the right pattern fits the lognormal distribution, again with non-zero right border.

The time that travelers spend on walking between an origin and a destination seems a normal distribution with small standard deviation and the corresponding travel time for Cab mode is normal. The histogram of private vehicle mode is a bimodal distribution with two peaks of lognormal random variables.

As examined and interpreted, there are no correlation between patterns and every histogram shows a unique outline and asks for unique distribution. To deal with such issue, instead of using fixed patterns, I will use a simulation modeler which mimic exact the same pattern of above distributions, but with different distribution parameters. This makes the simulation process slower, yet the driven patterns will be close to real ones. The distribution parameters used to tailor the new simulated models are extracted from Population Division - New York City Department of City Planning.

Fixed Taste Parameters

As a reminder, to implement the heterogeneity, we decided to implement the additive error terms. This inclusion makes the taste parameter non-stochastic. Hence, we can implement the deterministic parameter to show the Market Segmentation instead of any randomness on individuals' tastes. Technically, taste of attributes (stochastic or deterministic) is not fixed. Means that these parameters must show the percentage change in quantity demanded in response to a one percent change in price (Price elasticity of demand, PED). By definition the PED is a measure of responsiveness of the quantity of a raw good or service demanded to changes in its price. Where

PED = $e_{\{R\}}$ = (dQ/Q)/(dP/P)

The above formula usually yields a negative value, due to the inverse nature of the relationship between price and quantity demanded, as described by the "law of demand".

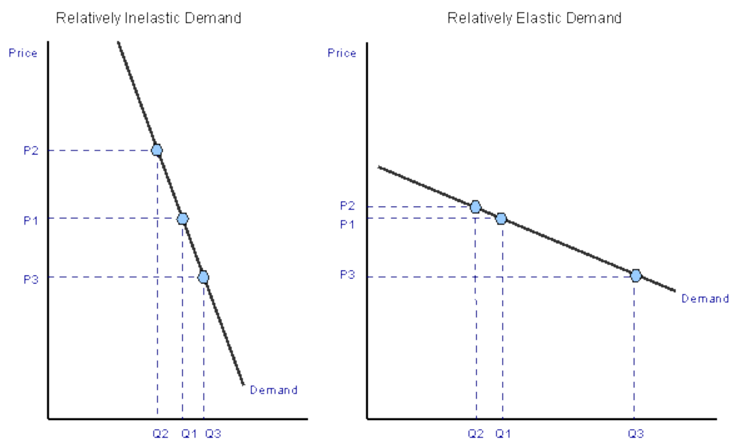

Fig 10; Elasticity in Demand

The taste parameters in this case study are also negative to make the dis-likeness on higher usage of time and cost. For example, the higher cost of driving due to tolling system, will help commuters to dislike the private vehicle mode and cab, hence the probability of choosing such modes by any travelers' decrease, and following to this decrementing on individual probability, the modal share will be decrease too.

To have a correct and meaningful estimation over these parameters I will estimate and use the values which are corresponded to Mode case study data in mlogit package which observes 453 individual commuters travel behaviors

Cost		Estimate	Std. Error	t-value	Pr {>abs(t)}
	Rail (Subway)	-1.38844	0.705	-5.1313	$2.87*10^{-7}$
	Walk	-0.32727	0.0756663	-4.3252	$1.52*10^{-5}$
	Cab	-1.1651	0.2169	-5.37	$7.87*10^{-8}$
	Private Vehicle	-1.2935	0.21166	-6.1116	$9.865*10^{-10}$
Time		Estimate	Std. Error	t-value	Pr(>abs(t))
	Rail (Subway)	-0.09412	0.01182	-7.963	$1.77*10^{-16}$
	Walk	-0.9695	0.01065	-9.1035	$2.2*10^{-16}$
	Cab	-0.128	0.0127	10.0174	$2.2*10^{-16}$
	Private Vehicle	-0.07824	0.0098	-7.9736	$1.55*10^{-15}$

Table 4; Taste Coefficients

Model Aggregation

Afterward, we are able to examine the choice probability of CNL-MMNL. Worth to say that the MMNL probability has no close form, hence by simulation, we could approximate the expected value of the probability. Since the Mixed logit is exactly the MNL, but with higher number of noises, we use the MNL kernel and approximate the probability through simulation for any given value of normal random term.

$$P_{Walk,n} = \int \frac{e^{(V_{Walk,n}+\varepsilon_{Walk,n})}}{\sum[e^{(V_{Walk,n}+\varepsilon_{Walk,n})}+e^{(V_{Car,n}+\mu_{II}+\varepsilon_{Car,n})}+e^{(V_{Cab,n}+\mu_{II}+\mu_{III}+\varepsilon_{Cab,n})}+e^{(V_{Subway,n}+\mu_{III}+\varepsilon_{Subway,n})}]} \quad (31)$$

$$P_{Car,n} = \int \frac{e^{(V_{Car,n}+\mu_{II}+\varepsilon_{Car,n})}}{\sum[e^{(V_{Walk,n}+\varepsilon_{Walk,n})}+e^{(V_{Car,n}+\mu_{II}+\varepsilon_{Car,n})}+e^{(V_{Cab,n}+\mu_{II}+\mu_{III}+\varepsilon_{Cab,n})}+e^{(V_{Subway,n}+\mu_{III}+\varepsilon_{Subway,n})}]} \quad (32)$$

$$P_{Cab,n} = \int \frac{e^{(V_{Cab,n}+\mu_{II}+\mu_{III}+\varepsilon_{Cab,n})}}{\sum[e^{(V_{Walk,n}+\varepsilon_{Walk,n})}+e^{(V_{Car,n}+\mu_{II}+\varepsilon_{Car,n})}+e^{(V_{Cab,n}+\mu_{II}+\mu_{III}+\varepsilon_{Cab,n})}+e^{(V_{Subway,n}+\mu_{III}+\varepsilon_{Subway,n})}]} \quad (33)$$

$$P_{Subway,n} = \int \frac{e^{(V_{Subway,n}+\mu_{III}+\varepsilon_{Subway,n})}}{\sum[e^{(V_{Walk,n}+\varepsilon_{Walk,n})}+e^{(V_{Car,n}+\mu_{II}+\varepsilon_{Car,n})}+e^{(V_{Cab,n}+\mu_{II}+\mu_{III}+\varepsilon_{Cab,n})}+e^{(V_{Subway,n}+\mu_{III}+\varepsilon_{Subway,n})}]} \quad (34)$$

In this stage, we can find the maximum value of choice probability for each individual and add it into data set as 'choice' column. Any change on travel cost, will impose a lower utility for cab and car (since the coefficient of travel time is negative), though a part of this negativity will be compensated by a faster commuting (lower travel time, then the lower negativity). By decreasing the utility value of car and cab modes, the flow will shift to other modes (subway and walk) and hence the probability of car and cab reduced by some value. The lower probability of sharing a mode is exactly the new modal share of a given alternative and by reducing and escalating a modal share, the impact of that mode will be changed. For example, if the modal share of car reduced by 4 percent, all economic impacts (either positive or negative) driven by car movement will be changed.

	Modal Share	
Mode	Before Tolling	After Tolling
Private Vehicle	0.45	0.34
Cab	0.07	0.06
Train/Subway	0.37	0.48
Walk	0.11	0.12

Table 5; The Expectation on Modal Share Shift after Tolling Policy

Building SAM

To simulate the shocks discussed in previous sections, we used the available IMPLAN data for the five boroughs and aggregate them with respects to '3Digit' aggregation option provided by IMPLAN. By doing so, we close the model (eighty-six sectors) with respect to employee compensation and nine levels of households. After replacing the SAM's inter-industry sectors' quantity with true values driven by I-O model, rearrangement the rows and columns, fixing the total value, and calculating the coefficient table we can eventually build up the SAM multiplier model. By definition the initial n^2 matrix will be expanded into $(n + 9 + 1)^2$ matrix under the closure of household sectors and employee compensation.

VII. RESULT AND DISCUSSION

As discussed in previous sectors, by implementing tolling policy, we can monitor three flows of shocks in SAM model consisting of 1) positive injection into economy by government due to expenditure of the collected tolls, 2) negative shock driven by the higher prices of goods and services caused by elevated travel cost, and also 3) positive shock following the decrease on GHG and emission.

- The first flow of shocks which is tailored to show how collected tolls will be spent by government is assumed to play a stimulating role on three sectors of 'construction', 'transportation equipment' and 'hospitals' by different percentages. To run this part, we need to have a pilot value to initiate and trigger the model. The starting assumption of toll cost will be $1.5 for each vehicle takes a tolled lane and by assuming the daily trespassing of 3.5 million vehicles in tolled routes (consisting three main inner city highways), the total value of collected tolls in a period of 90 days will be 472.5* 10^6$. This amount of collected toll is going to be separated into three portions of 0.7, 0.1 and 0.2 for three designated sectors of construction, transportation and hospital.
- The second stream of shock comes from the impact of higher prices of goods and services on economy due to increase on transportation price. We assume, there are twenty-sectors which are being negatively impacted by such price increment. However, these sectors are not equally influenced as for instance 'crop farming' and 'messengers' are impacted by three percent, while clothing, furniture and wood products influenced by less than a percent of their current total value. The impact on each sector is assumed to be a portion of current output. For instance, we assume the 'food' and 'beverage' sectors are being host of -1.5% of their current total output. In other words, food's sector which currently has an economy as large as 4.632 billion dollars, will host an impact by the size of $ - 0.015*4.32*10^9.

- The third wave of chock is positive and caused due to modal shifts. Where the travel cost goes up, the utility corresponds to vehicle-based modes (private vehicles and cab) go down. Then the negative side effects of driving (health issues, GHG, emission and etc.) also decrease by the same magnitude. Consequently, by modal shift from toll-based modes to non-toll-based modes, the positive shock will be implemented on medical-based sectors such as 'hospital' (which are now running by Feds supports come from Obama-care), 'nursing' and 'health care'. In addition, by decreasing the private vehicle trips, the gas consumption drops. It has a great negative influence on sectors such as 'petroleum production' and 'gasoline station'. However, the subway (train) which used to host less number of commuters before the tolling policy, now faces more travelers willing to take train to transport. This boost on train modal share could stimulate the positive shocks on sectors such as 'transit and ground passenger' as well as 'rail transportation' sector.

Our assumption on the magnitude of the third wave is exactly same as the changes on modal shares. By way of illustration, private vehicle lost 8 percent of current travelers due to tolling policy, hence the gas consumption decrease by the same percentage and GHG and emission follow the same drop rate. In other side, train experiences 11 percent increase on commuting patter. The same eleven percent increases then will be implemented on related sectors of 'transit and ground passenger' and 'rail transportation' sectors.

These three waves of shocks can be added together as

$$FD_{Total} = FD_{1stWave} + FD_{2ndWave} + FD_{3rdWave} \tag{35}$$

The impact of FD_{Total} on economy then could be define as

$$\Delta_{Output} = (I - A)^{-1} FD_{Total} \tag{36}$$

Note that the SAM multiplier has 96*96 dimension and FD_{Total} has 96*1 dimension. Hence Δ_{Output} which is the change on output will keep the same dimension as FD. According to calculation provide in appendix, the exogenous shock will be imposing on thirty-two sectors. Since the model is totally correlated by non-stochastic coefficient, the change will be on all 96 outputs either in positive or negative quantity. For instance, the 'wholesale trade' experience \$145*10^6 lost on total output, whereas 'rail transportation' sector's economy expands by \$8.9*10^6.
Besides all examination and discussion that we can have on expanding or shrinkage of sectors driven by such tolling policy, the GDP also subjects to change. There are two separate parameters which impact GDP:

- Employee compensation is a factor of value added. By change on VA, the GDP will be changed by exact the same value. In our model and under made assumptions, the employee compensation, hence the VA, then the GDP improves by \$278.4*10^6.
- By modal shift from private vehicle and cab to walk and train, the gas consumption drops. By dropping the consumption in demand side, the supply of gas experience the same drop rate and since the gas in the State of NY is imported good, the GDP escalate by the same value as gas import drops. In our study, the private vehicle and cab model drop by 8 percent. If the VMT (Vehicle Mile Traveled) of the vehicle in the State of NY is 9300 miles per year, it means that New Yorkers are commuting 0.08*9300/4 miles less than previous. Such amount decrease on VMT causes 255.75 miles less driving for each private vehicle in a period of three months. If the average MPG (Mile per Gallon) in five boroughs considered as 25, and the total vehicle as 7*10^6, after three months, New Yorkers will consume 7*10^6*255.7/25= 7.16*10^7 gallon less gas than the time before implementation of tolling policy. If the average of gas price assumed to be \$3.8, such drop in gas consumption concludes to \$2.7*10^8. It means tolling policy can cause \$270*10^6 on GDP.

By adding up two values, the total change on GDP will be over 548 million dollars.

VIII. CONCLUSION

Since the transportation facilities are public assets, the pricing of existing un-priced capacity is inherently a political issue. To make road pricing politically acceptable, a broad investigation on policy implementation impacts is required to expose its benefits to not only citizens in a jurisdiction, but also to policy makers. However, the economic impacts can be used as a justification for any implementation or modification. In this report, we examined the economic impacts driven by such a scheme in both micro and macro levels. On the consumer side (micro level), we ran a discrete choice model and examined how travelers behave differently due to an increase in driving costs caused by road congestion. On other hand (macro level), we translated the policy/scheme into an exogenous shock on economy and simulate the influences due to this stimulator on several sectors of economy. Our results show that in the Greater New York, which consists of five boroughs, a congestion pricing policy on three designated freeways, with a daily flow over 3.5 million vehicles will induce around 0.55 billion dollarincrease on GDP. This growth is caused by not only the expansion of value added items, but also by the direct impact on GDP due to less fuel consumption and oil imports.

The social accounting matrix also helped us to simulate and track down the sectoral behavior of endogenous parameters. The interconnection between endogenous sectors shows what happens for the economy as a whole and what happens for each sector in particular. Results show sectors respond to congestion pricing differently. Some sectors are negatively affected whereas some sectors expand by different magnitudes. This note provided a very brief assessment of congestion pricing policy on economics; the topic that would be of use of policy makers, traffic engineers, as well as urban scientists and politicians. Nonetheless, there are a number of discussions that the authors would like to open for future studies as following.

Public or private sectors who are willing to implement such a policy are interested in finding the congestion pricing in the optimum condition, which maximizes benefits concluded by a tolling system. Such maximization problem needs an optimum toll price which at the same time increases the positive impacts (higher value added on GDP, lower emission rates, GHGs, etc.) and decreases the negative side effects (the negative injection on economy's sectors) together. Although our model could be a very simple simulator for expecting GDP changes due to any value of toll price, it can provide some ideas and bridges between micro and macro levels as well as the idea of dynamic modeling.

Furthermore, we considered households as endogenous sectors. Closure with respect to households provides this chance to track down the economic impacts on different household levels. Such distinction between different levels of consumers also helps us to modify the coefficient used in discrete choice model. For instance, if a congestion pricing policy stimulates a negative impact on GDP, the economy in general will be worse off. As a result ofa weaker economy, all consumers (commuters) will experience some levels of poverty, though for higher income users might not very significant. Such decrease in welfare among travelers, induced by lower GDP, will make travelers more concerned about the price of driving, and then they will have a stronger response to a tolling policy. In other words, the coefficients on the utility function (in the discrete choice model) could be modified based on an increase or decrease on GDP. The new DCM model imposes new modal shares, and the new modal shares imposes new magnitudes of shocks. This ripple effects can be repeated until the model converges.

More, in our case study, the GDP raised by almost half a billion dollar, though that would not be the case for all toll rate scenarios. For instance, if we run the model by ₡50 toll instead of $1.5, the GDP goes down. This also exposes interesting topic to be studied on this area. To find what the toll price must be for a non-negative GDP stimulator or what the toll price must be to induce a special amount of injection on a specific sector.

REFERENCES

1. *Cornes, R. The Theory of Externalities, Public Goods and Club Goods. Cambridge University Press, New York, 1986*
2. *Nash, C., B. Menaz, and B. Matthews. Inter-urban Road Goods Vehicle Pricing in Europe. Richardson, H. and C. Bae (ed.), Road Congestion Pricing in Europe: Implications for the United States. Northampton, MA: Edward Elgar, Cheltenham, UK, 2008, pp. 233–251.*

3. *Pigou, A. C. (ed.). The Economics of Welfare. Macmillan and Co., London, 1920.*
4. *Walters, A. A. The Theory and Measurement of Private and Social Cost of Highway Congestion. Econometrica Vol. 29, 1961, pp. 676–699.*
5. *Vickrey, W. S. Pricing in Urban and Suburban Transport. American Economic Review, Vol. 52, 1963, pp. 452-465.*
6. *Yang, H., and H. J. Huang. Principle of Marginal-Cost Pricing: How Does It Work in a General Road Network? Transportation Research Part A, Vol. 32, 1998, pp. 45-54.*
7. *Rouhani, O. M. and D. Niemeier. Urban Network Privatization: Example of a Small Network. Transportation Research Record, Vol. 2221, 2011, pp. 46–56.*
8. *Olszewski, P., and L. Xie. Modelling the Effects of Road Pricing on Traffic in Singapore. Transportation Research Part A, Vol. 39, No.7, 2005, pp. 755–772.*
9. *Leape, J. The London Congestion Charge. The Journal of Economic Perspectives, Vol. 20, 2006, pp. 157–176.*
10. *Eliasson, J. Lessons from the Stockholm Congestion Charging Trial. Transport Policy, Vol. 15, 2008, pp. 395–404.*
11. *Xie, L., and P. Olszewski. Modelling the Effects of Road Pricing on Traffic Using ERP Traffic Data. Transportation Research Part A, Vol. 45, 2011, pp. 512-522.*
12. *Eliasson, J., and L.G. Mattsson. Equity Effects of Congestion Pricing: Quantitative Methodology and A Case Study for Stockholm. Transportation Research Part A, Vol. 40, 2006, pp. 602–620.*
13. *Eliasson, J. A Cost–Benefit Analysis of the Stockholm Congestion Charging System. Transportation Research Part A, Vol. 43, 2009, pp. 468–480.*
14. *Santos, G., and J. Bhakar. The Impact of the London Congestion Charging Scheme on the Generalised Cost of Car Commuters to the City of London from a Value of Travel Time Savings Perspective. Transport Policy, Vol.13, No. 1, 2006, pp. 22–33.*
15. *Safirova, E, K. Gillingham, I. Parry, P. Nelson, W. Harrington, and D.Mason. Welfare and Distributional Effects of Road Pricing Schemes for Metropolitan Washington, DC. Research in Transportation Economics, Vol. 9, 2004, pp. 179–206.*
16. *Prud'homme, R., and J. P. Bocarejo. The London Congestion Charge: A Tentative Economic Appraisal. Transport Policy Vol. 12, 2005, pp. 279–287.*
17. *Hamilton, C. J. Revisiting the Cost of the Stockholm Congestion Charging System. Transport Policy, Vol. 18, 2011, pp. 836–847.*
18. *de Palma, A., and R. Lindsey. Traffic Congestion Pricing Methodologies and Technologies. Transportation Research Part C, Vol. 19, 2011, pp. 1377–1399.*
19. *Rouhani, O.M., H. O. Gao, and A. Beheshtian. Social and Private Costs of Driving. Presentation at the 2013 Annual Conference of the International Transportation Economics Association, Northwestern University, Evanston, Illinois, 2013.*
20. *Verhoef, E. T., and H. Mohring. Self-Financing Roads. International Journal of Sustainable Transportation, Vol. 3, 2009, pp. 293–311.*
21. *Schweitzer, L., and B. D. Taylor. Just Pricing: The Distributional Effects of Congestion Pricing and Sales Taxes. Transportation, Vol. 35, 2008, pp. 797–812.*