ETM

ENGINEERING & TECHNOLOGY MANAGEMENT

Measure change in the overall benefit index of Portland's residents if Uber Transport Network Company is permitted to operate.

Expressing Decision Parameters in NonLinear Programming

Course Title: Management of Engineering and Technology
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Instructor: Dr. Timothy Anderson
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Team Uber: Mitsutaka Shirasaki
Shihab Hanayneh
Michael Smith
Sridharkumar Paneerselvam
Swati Kar

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Abstract

This paper aims at using an operation research model methodology to emulate the existing ride-to-hire business in the Portland area. Operation research tools were used to assess how Uber's request to offer service in the Portland area will affect the ride-to-hire stakeholders and the overall market structure. The Model is a Multiple-Objective Nonlinear Program (MONLP) which uses inputs which could be impacted by City of Portland policy changes. The model is optimized for "Attributes" that would benefit some of the stakeholders.

Background

In mid-2014, the total number of licensed taxis serving Portland, a city of more than a half – million residents reached 460. Two years earlier the city come to the decision to add 200 more taxis, but had only added 100 since then. In spite of that modest increase, there is still a believe to be a shortage in taxis, given that the city has just recently agreed to add 240 more licenses[4]. Uber's proposal to the city is to provide customers with a Transportation Network Company (TNC) based service by using smartphones application. Nonetheless, Uber's ability to operate in Portland run against the existing city code and regulations (Private For-Hire Transportation Regulations).

Literature Review

The team surveyed several sources of information either primary or secondary articles on the subject of benefit index of Portland's residents and on Uber's business proposition. The team used Google search engine and Google Scholar search engine; however, our relentless effort came empty handed. It is recognized that the subject of benefit index is more of a hypothetical analytical platform used to assess and measure the outcome when several conflicting policy decisions need to take place.

Several meeting were conducted with Dr. Timothy Anderson to discuss the underlying challenges. The team became aware that the selected subject matter was uncharted territory. Furthermore, the team's technical tool box was limited relative to the challenges at hand.

The team became aware of the project complexities as our learning curve got steeper. By week eight going into the course we started to recognize that policy decision assessments by definition are nonlinear.

Through the guidance and continues consultation with Dr. Anderson the concept of creating a general model to reflect the benefit index became clearer. Furthermore, that general model required submodels to address a specific number of attributes that might be interrelated.

To gain understanding of the issues at hand, a team member attended City of Portland hearings on the subject. In addition the team reviewed papers which directly relate to the taxi industry in Portland [10] [11] [12].

Due to lack of scholarly literature on Uber, the team used a number of newspaper articles [1] [6,7]; in addition to having a meeting with Uber's general manager for the Seattle [1], and the Portland areas; Portland City commissioners[4], Uber drivers in Portland, and in San Francisco[2], as well as Lift (another TNC) and taxi drivers in those locations[3], attended Task force meetings [5] and referred to interviews available online [15].

Business Model

Conceptually, Uber is a company that gives a consumer the ability to submit a trip request, which is routed to Uber divers by using an online computer based platform. Uber is described as a TNC. Each driver / car owner registered with Uber may offer their own labor and a car to people who request a ride in Uber’s virtual marketplace. Other TNCs are creating a services of matching offered vehicles and drivers to riders; however, none is operating in the Portland area yet. Theoretically, Uber drivers tend to be part-time operators and would not necessarily charge regulated taxi fares.

Ride fare computation is based on estimated ride distance; in addition to factors like time it takes to reach the destination, delays caused by traffic congestion and other factors also comes to play into Uber’s online fare estimate system. The clearing price for each drive is facilitated and cleared online through the use of mobile technology.

Taxis as an Urban Transportation Modality

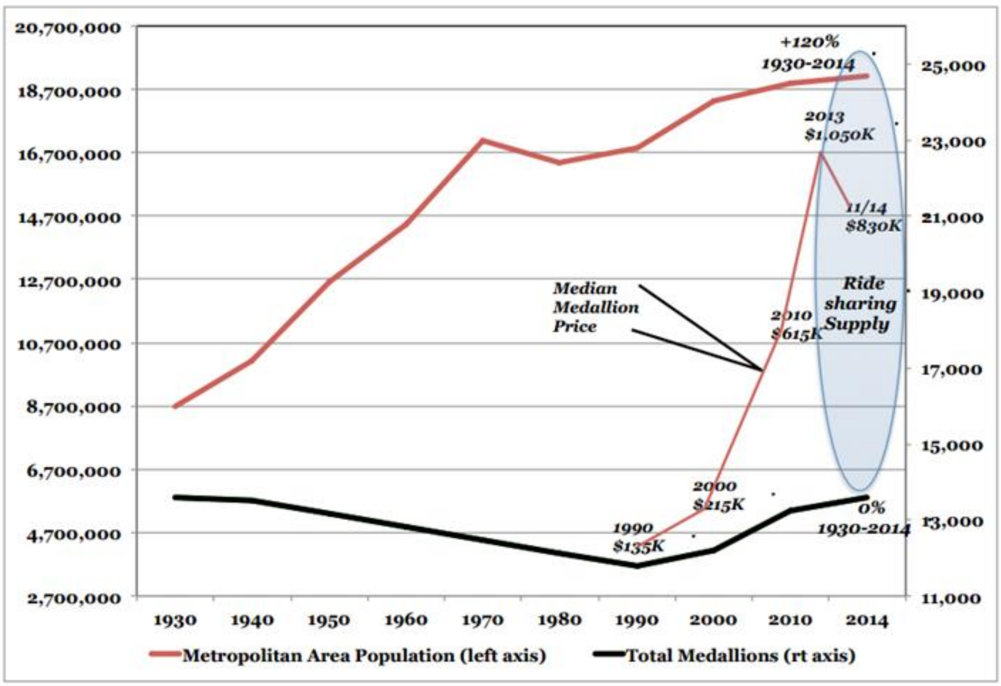
The Taxi industry is a highly regulated business by each city government. Generally speaking, different rules can be applied in different countries. However, the industry is best described as an oligopoly market structure, where there are few sellers (taxi service suppliers) and large demand created by urban population. City government issues limited licenses of taxis and requires “the few operators” to strictly operate within the framework of enforced rules. Thus, market and industry inefficiencies are created as a result of the oligopolistic market structure. The following are key examples of such an inefficiencies:

1. strong hold over the market creates the ability to make huge profits as there are few players in the market.
2. low incentive for product innovation or product development.
3. high barriers to entry and uneconomical shadow price due mainly to regulations, creates unreasonable agency costs.

Furthermore, another example of such market inefficiencies is that restrictions on the number of issued licenses creates value increase of operating a taxi license over time. This value increase has no new created economic value.

Therefore, the taxi companies have strong incentive to lobby city governments to keep the number of licenses low. New York City is a good example of how the taxi permits have been limited to far less of an increase than the change in population, as shown in the graph below:

Exhibit 2 History of New York City Medallions versus Metropolitan Population



Source: Taxi and Limousine Commission, http://www.city-data.com/forum/city-vs-city/1786915-historical-population-metropolitan-areas-decade.html and industry sources.

Notice that the number of taxis in 2014 in New York City is the same as those in 1940, despite of the fact that the population increased from 8.7 million to 19 million. Consequently, this left a large gap between the number of passengers and the number of taxes available.

Uber’s Business Proposition

Uber’s business proposition is to transform the taxi industry from oligopoly market structure to more of a free market competition. Such a proposal should reduce the existing inefficiencies within the taxi business. Uber strives to create a model that fills the gap between the number of potential passengers and the number of available drivers. Uber increases the number of drivers (supply) by allowing for a raise in fares as there is predicted increase in passengers. However, raised fares will also slightly decrease the number of potential passengers (demand). Uber's goal is to make sure that there is always a ride available to anyone who needs a ride [9]. Understanding this complexity of creating a free market, open and less regulated urban transportation modality alongside the traditional existing oligolectic market structure poses challenges. Therefore, to measure change in the overall benefit index of Portland's residents if Uber Transport Network Company is permitted to operate involves more than building and interpreting a simple supply and demand relationship between riders and providers of services.

City of Portland Regulations

The city of Portland's regulations[12] stipulate that because the TNC sector is viewed as an integral part of the private for hire transportation services and that constitutes an essential part of the City's transportation system. The city views are that some regulations are necessary to insure that the public safety is protected, the public need is met, and the public convenience is promoted. Therefore, city rules require each provider has the mechanism to ensure safe, fair and efficient operation of services. On the other hand the city requires that the operators are able to provide services without the unnecessary restraint.

The following are some of the regulations which Portland has for Ride-For-Hire businesses which will not work for a TNC such as Uber.

- Customers to arrange a trip with an executive sedan or limousine at least 60 minutes prior to pick-up time [12].
- Executive sedans and limousines to charge a 35% fixed premium above current taxi rates established by the city of Portland.
- Skills test and continued training for each driver is required.
- Need for a private, for-hire driver permit should be obtained prior to offering service by each service provider (driver).

Furthermore, taxi owners pointed out that Uber terms and conditions include no responsibility to [riders] related to any transportation or logistics provided [by the driver] by third party providers, potentially unsafe, offensive, harmful to minors, or otherwise. Taxi owners are quick to say that Uber does not guarantee the suitability, safety or ability of third party providers. Also, Uber require that [riders] agree to indemnify and hold Uber and its officers, directors, employees and agents, harmless from any and all claims, demands, losses, liabilities and expenses.

Consequently, due to Uber's lack of compliance with existing laws and other regulations that apply to the taxi drives and other ridesharing vendors operating within the greater Portland area, the city has filed suit against Uber Technologies Inc. on Dec 8th, 2014. The lawsuit seeks declaratory relief that Uber is subject to and in violation of the City of Portland's Private for Hire Transportation Regulations and Administrative Rules. The City's lawsuit is asking for a declaration by the court that Uber is subject to the City's regulations. Furthermore, the lawsuit asks the Court to order Uber to stop operating in Portland until it is in compliance with the City's safety, health and consumer protection rules.

Using Operation Research Tools

Due to the complexity of the subject matter, the team designed a matrix that reflects the interest of all stakeholders; including the local government, drivers, taxi and transport network companies as one group clustered on one row of the matrix against number of selected attributes that reflect the makeup of the market place. A number of decision attributes were selected, where each attribute is made up of several decision variables. A system of heuristic solutions was developed to "Test" how a change in attribute system(s) affect the change in the overall benefit index.

Cross Section Comparative Review

This era of new technology where every task is managed through apps on mobile phones, it did not take time for the ride sharing companies to implement this technology and encash on the opportunity. Unlike traditional taxi companies, advent of such apps drove up the revenue by registering more business for the company. One of our proposals talks about making some technological changes that could help customers locate taxis/Uber and help them find a ride in the shortest possible time.

While this was a major breakthrough for Uber to enter the ridesharing market, there were other cons that resisted the entry of Uber.

Across many cities, Uber gained momentum in no time. But it also ran into a number of hurdles. Lets take a look at the cities where Uber has been operating successfully compared to cities where Uber had to withdraw its service.

New York treats Uber similar to the other black car services. Drivers pay an annual fee of $625 to register and inspect their cars; another $84 towards obtaining a special license [13]. Even with these restrictions in place, the Uber has more than 7000 registered vehicles and pay about $5 million in fees.

Uber hails Colorado and Washington, D.C as models of regulation. Drivers are required to carry a commercial insurance, but the service requirements and fare regulations are not as restrictive as for taxis. Background checks are required on Uber drivers going back seven years, annual safety inspections, and $1 million liability insurance [14]. However, Cities on the west coast have been less friendly to Uber. Los Angeles and San Francisco have recently sued the company, An out of court settlement was reached with TNCs, saying they misled consumers about background checks conducted on the drivers.

After facing resistance from the city of Portland[8], Uber decided to suspend its operation until Portland reach verdict on changing its regulations on ridesharing business. Some of the major concerns (see Appendix B)which Uber has been currently dealing with and which has caused Uber to withdraw services at cities like Seattle and Portland are as follows:

1. Disability act compliance
2. Local regulations
3. Insurance
4. Airport policies

These are the existing concerns that Uber needs to address in order to be able to operate in any city. Portland city council has been working on policy measures which revolve around these parameters. We have looked at the problems at a more granular level and come up with attributes which could play an important role in making policy decisions in the city of Portland. The team has optimized these attributes which are Working condition of the driver, Safety, Passenger experience and Impact to local business using multiple objective nonlinear programming (MONLP) to redirect attention towards a new approach of looking at the problem how ridesharing companies can smoothly work in the city of Portland.

Our team did not jump to MONLP directly. We researched various models that had previously looked into the same or similar problems, and came up with this unique multiple MONLP model using weights. Our team came up with this model after going through a lot of trial and error with model creations. We initially aimed at creating a linear model using Simplex LP but realized not all of our our attributes and decision variables were quantitative. We moved on to a nonlinear model and tried to identify some key decision variables for the same. We first identified the stakeholders who were getting impacted from this whole dilemma and wanted to use them as decision variables. So we decided to optimize the benefit index for these stakeholders. We interviewed all of our stakeholders and prepared a list of survey questions and asked them for their input. The survey questions helped us narrow down to 15 decision variables (see Appendix A) which we could use in our nonlinear model. Our survey questions asked the stakeholders to rate the variables on a scale of 1-10 based on importance to them. Consequently, different stakeholders rated variables differently. We wanted to use this rating as part of our model. So we decided on using weights as a standard multiplier for each variable and sum the end values to come up with a number which we could then compare with the created model “ideal scenario” (i.e all attributes rated as 10) and suggest ways to improve the magnitude of that number to maximize our benefit index.

With this model we could not justify how those variables could contribute in suggesting a potential solution to the problem statement which was how to reduce the animosity between taxicab drivers and Uber drivers and strike a cohesive balance. We could not list variables which were more sensitive or less sensitive as we had weights for each variable and every variable was taken into account with the same importance. We decided on picking the most important attributes which would use relevant decision variables from our previous list and optimize the attributes to understand which variable was affected the most. In order to be able to pick the most important attribute from the list of decision variables we referred to Multiple criteria decision making (MCDM) concept. This concept helped us in planning and solving our problem involving multiple criteria. In this paper we took a conservative approach using MCDM to reason out the most important attributes from the list of available alternative variables (see Appendix A).

The Model : Multiple Objective Nonlinear Programming (MONLP):

To facilitate decision making, there are number of ways to determine what aspects of decision parameters are important for a given option. In traditional decision making model, decision parameters are weighted and scored so that more important decision parameter can have more influence in the final decision making process. However, some decision parameters can interact with one another in such way that although such decision making parameters were not considered important on their own. This created a situation of having more impact on certain decision parameters and have deeper impact on the overall decision making process. The following will describe a methodology that will capture such intertwined decision parameters in a real world example such as the one we are working on.

Defining Policy Knobs

Number of rides and price are considered as policy knobs in the model. We have considered that the number of rides and fees since the entry of Uber will have an impact on these two parameters. Uber would increase the number of rides as it adds more drivers into the system, and also fee since it has dynamic pricing system. Our model finds out how much the impact of changes in policy knobs will have on the attributes of working condition of driver, impact to local business, passenger experience and safety.

Defining Decision Making Attribute

Attributes are defined as the parameters that we are optimizing. There were several factors considered that we saw as possibly benefiting the people of Portland (refer to Appendix A). There are number of items that need to be considered when an option needs to be selected. For example, one may consider cost, net present value, resource needed, schedule, or the likelihood of success when deciding on a project to work on. In the case of Uber policy in Portland, we have decided that the following attributes are the ones which we feel we can have an impact on by policy changes and that are important to many of the stakeholders.

Attribute 1: Working Condition of the Driver
Attribute 2: Passenger Safety
Attribute 3: Passenger Experience
Attribute 4: Impact to the local business

Weighted Scale for Stakeholder(s)

There are multiple stakeholders to any decisions making process, and each stakeholder(s) has their own set of priorities. At times several stakeholders have conflicting priorities; however, the same attribute can commonly be important to multiple stakeholders. These shared attributes will be weighted heavier as the accumulative weight from multiple stakeholders on such attribute will be heavier.

Let W be a weight for each attribute i, then the accumulative weight for each attribute can be described as;

$$\sum_{h} W_{i,h} \forall h,$$
$$where\ h \equiv stakeholder \in \{City\ Government, Taxi\ Driver, Taxi\ Company, \dots\}$$

The total weight then will be multiplied by the score for each attribute of the option to be compared or measured. Let this scoring be Si for each attribute index i. Then the total weighted score for each attribute can be calculated as product of Si and Sum of Wi for each stakeholder. The sum of all weighted and scored for each attribute is the final score for the option.

$$Final\ Score \equiv \sum_{i} \sum_{h} S_i \cdot W_{i,h}\ \forall i, h$$

Attributes

Attributes are the factors that we consider to benefit (positively or negatively) the people of Portland. [*Refer to Appendix A for a complete list*]. In attempting to maximally benefit the people of Portland, we are optimizing the following attributes:

- Working Conditions of the Driver
- Passenger Experience
- Impact to Local Business
- Safety

Decision Variables

Decision parameters are such values that were deemed impactful to the given attribute. For example, workload, taxi fare, effective payment system, and health care are decision parameters for Working Conditions of the Driver. Furthermore, some of these parameters are static parameters that are used to describe the attribute. Some of these parameters are variables that are impacted and changed through non-linear relationships with decision variables. We used 6 different ways for the decision parameters and decision variables to impact each other and impact the attribute.

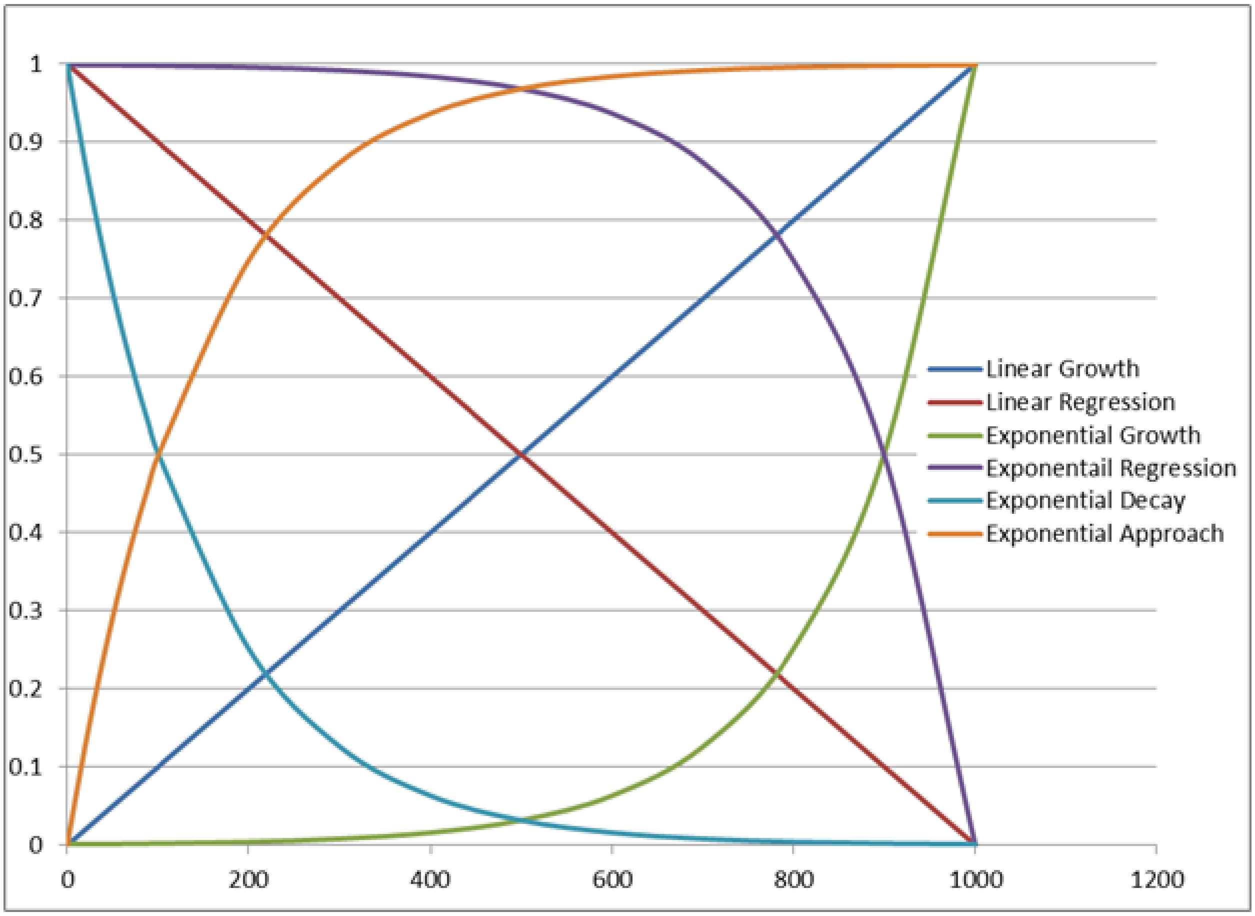


Figure 1: Impact Model to Attribute

Each Impact Model is defined as follows:

Linear Growth Model:

$$LNRG = a \cdot x + b \, where \, a = \frac{1}{Max - Min} \; and \; b = \frac{Min}{Max - Min}$$

Linear Regression Model:

$$LNRR = -a \cdot x + b \, where \, a = \frac{1}{Max - Min} \; and \; b = \frac{Max}{Max - Min}$$

Exponential Growth Model:

$$EXPG = a \cdot e^{b \cdot x} \; where \; a = 1000^{\left(\frac{-Max}{Max - Min}\right)} \; and \; b = \frac{\ln(1000)}{Max - Min}$$

Exponential Regression Model:

$$EXPR = 1 - a \cdot e^{b \cdot x} \; where \; a = 1000^{\left(\frac{-Max}{Max - Min}\right)} \; and \; b = \frac{\ln(1000)}{Max - Min}$$

Exponential Decay Model:

$$EXPD = a \cdot e^{-b \cdot x} \; where \; a = 1000^{\left(\frac{Min}{Max - Min}\right)} \; and \; b = \frac{\ln(1000)}{Max - Min}$$

Exponential Approach Model:

$$EXPA = 1 - a \cdot e^{-b \cdot x} \; where \; a = 1000^{\left(\frac{Min}{Max - Min}\right)} \; and \; b = \frac{\ln(1000)}{Max - Min}$$

To decide the score for each attribute, we took the following approach. First, for each attribute, we decided on decision parameters that impact the given attribute. Then we decided on the impact of each decision parameter to the attribute such as linear increase/decrease or exponential growth or decay. Each impact was assessed for weight and positive/negative impact.

By creating the model using the Maximum and Minimum values for each decision parameters and decision variables, equation depicted in Figure 1 transposes the input value to weighted value between 0 and 1 following the impact model decided for that particular input. See below for an example:

Working condition of driver

Working Condition of Driver					Data Range Start	C
	Taxi Driver Income	Workload	Effective Payment System	Health Benefits	Data Range End	F
Input Variables	$32,901	30.0003	1	100		
Input Maximum	$75,000	80	1	100		
Input Minimum	$10,000	0	0	0		
Optimal	$47,000	40	1	100		
Type Curve	EXPA	EXPR	LNRG	LNRG		
a	2.894266125	0.001	1	0.01		
b	0.000106273	0.086346941	0	0		
Weighed Input	0.912289938	0.986664463	1	1		
Weight	10	5	2	5	22	
Weighted Score	0.454545455	0.227272727	0.090909091	0.227272727	1	
Output Maximum	10					
Output Optimum	10					Optimum Gap
Output Function	1	1	1	1	9.5710	0.0429

Figure 2: Working Condition of Driver Excel Model

In this Attribute, we have decided that taxi driver income has an impact to the working condition of the driver[12] has an exponential positive trend and is reflected with a curve depicting such a trend .

Inputs then are weighted between 0 and 10, 10 being the most impactful to the Attribute. Total weight is used to distribute the weight. The final score of the attribute can be described as follows:

$$S_i \equiv \sum_j \frac{w_{i,j}}{\sum_j w_{i,j}} \cdot f_l\left(Max_{i,j}, Min_{i,j}, x_{i,j}\right) \cdot Output_{Max_i}$$

$$where\ w_{i,j} \equiv Weight\ of\ input\ j\ for\ Attribute\ i$$

$$f_l\left(Max_{i,j}, Min_{i,j}, x_{i,j}\right)$$
$$\equiv Input\ Impact\ function\ based\ on\ Max, Min, and\ Input\ value\ x\ of\ function\ type\ l$$
$$l \in \{LNRG, LNRR, EXPG, EXPR, EXPD, EXPA\}$$

The same approach is taken for the relationship between the decision parameters and the decision variables. For example, within the above model, decision parameter workload is related to other decision parameters and decision variables as follows:

Workload				Data Range Start	C
	Number of Ride	Number of Passenger	Price	Data Range End	E
Input Variables	350	2229	3.994887688		
Input Maximum	350	10000	4		
Input Minimum	0	0	2		
Optimal	5000	5000	2		
Type Curve	EXPD	EXPA	EXPR		
a	1	1	0.000001		
b	0.019736444	0.000690776	3.453877639		
Weighed Input	0.001	0.785502603	0.017502322		
Weight	10	10	2	22	
Weighted Score	0.454545455	0.454545455	1	1.909090909	
Output Maximum	80				
Output Optimum	30				Optimum Gap
Output Function	1	1	1	30.0003	0.0000

Figure 3: Workload Excel Sub Model

$$Parameter_{i,j} \equiv \sum_k \frac{w_{i,j,k}}{\sum_k w_{i,j,k}} \cdot f_l\left(Max_{i,j,k}, Min_{i,j,k}, x_{i,j,k}\right) \cdot Output_{Max_k}$$

$$where\ w_{i,j,k} \equiv Weight\ of\ input\ k\ for\ Parameter\ i,j$$

Optimum gaps are defined for each sub-model output and the main model output. The objective function is defined as below:

$$\min\left\{\sum_{k}\frac{(Output_{optimum\ k} - Output_{k})}{Output_{Max_k}} - \frac{|S_i - Output_{Optimum\ i}|}{Output_{Maximum\ i}}\right\}$$

Impact to local business

Other models follow the similar approach as described above, but parameters are changed depending on attributes. In this case, number of rides, price and wait time are considered to have an effect on attribute “Impact to local business”. Number of rides will have an exponential positive approach effect as increase in cars available to ride would have positive impact to local business and the impact flattens after reaching a point. Similarly, price and wait time are considered to have an exponential regression and exponential growth effect on impact to local business.

	A	B	C	D	E	F	G
1		Impact to Local Business				Data Range Start	C
2			Number of Ride	Price	Wait Time	Data Range End	E
3		Input Variables	1700	2	9		
4							
5		Input Maximum	1700	$4	60		
6		Input Minimum	0	$2.00	2		
7		Optimal	5000	$2.00	5		
8							
9		Type Curve	EXPA	EXPR	EXPG		
10		a	1	0.000001	0.000788046		
11		b	0.004063385	3.453877639	0.119099229		
12							
13		Weighed Input	0.999	0.999	0.002310521		
14		Weight	10	10	-5	20	
15		Weighted Score	0.5	0.5	-0.25	0.75	
16							
17		Output Maximum	10				
18		Output Optimum	10				Optimum Gap
19		Output Function	1	1	1	9.9842	0.0016
20							

Figure 4: Impact to local business model

Passenger Experience

For attribute "passenger experience", wait time, price and attitude were considered to have an impact. Wait time will have an exponential decay effect because increase in wait time will have a negative impact on passenger experience. Price is considered to have exponential growth, if passenger pays a higher price, they would get good service as well as passenger experience. Attitude of passenger will have a linear relations with passenger experience. The model is also connected with submodels of wait time as shown below.

	A	B	C	D	E	F	G
1		Passenger Experience				Data Range Start	C
2			Wait Time	Price	Attitude of driver	Data Range End	E
3		Input Variables	16	5.949669396	100		
4							
5		Input Maximum	60	15	100		
6		Input Minimum	2	2	0		
7		Optimal	0	2	50		
8							
9		Type Curve	EXPD	EXPG	LNRG		
10		a	1.268961003	0.000345511	0.01		
11		b	0.119099229	0.531365791	0		
12							
13		Weighed Input	0.196432222	0.008155717	1		
14		Weight	10	-2	10	20	
15		Weighted Score	0.5	-0.1	0.5	0.9	
16							
17		Output Maximum	10				
18		Output Optimum	10				
19		Output Function	1	1	1	5.9740	
20							

Figure 5: Passenger Experience

	A	B	C	D	E	F
85		Wait Time			Data Range Start	C
86			Number of Ride	Number of Passenger	Data Range End	D
87		Input Variables	365	1482		
88						
89		Input Maximum	10000	10000		
90		Input Minimum	1	0		
91		Optimal	500	500		
92						
93		Type Curve	EXPD	EXPG		
94		a	1.000691083	0.001		
95		b	0.000690845	0.000690776		
96						
97		Weighed Input	0.777658779	0.002784459		
98		Weight	5	10	15	
99		Weighted Score	0.333333333	0.666666667	1	
100						
101		Output Maximum	60			Gap
102		Output Optimum	2			
103		Output Function	1	1	16	0.26108

Figure 6: Wait time sub-model

Results and Discussions

Working condition of driver

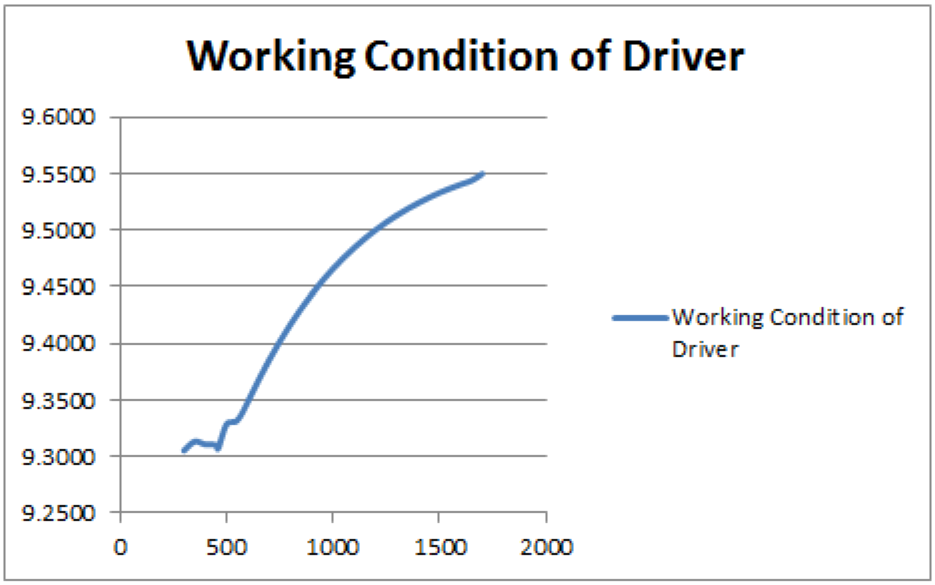


Figure 7: The overall Working Conditions of Driver vs Number of Ride

The working conditions of the driver are impacted by: workload, driver income, number of passengers, wait time, effective payment system, and health benefits. We have placed effective payment system and health benefits in our model as part of the characteristics of Working Conditions of the Driver. However, the effective payment system and the health benefits are deemed as static parameters. We are having the following impacts affected as follows.

Workload - driven by number of rides (aka number of drivers) and number of passengers

Driver Income - driven by workload

Number of Passengers - driven by wait time and price (aka fare)

Wait Time - driven by number of rides and number of passengers

Detailed graphs of the above can be found in Appendix D.

We found that the working condition of the driver can be improved as the price increases, but that eventually the price gets too high and the number of passengers decreases. The decrease in the number of passengers decrease the working conditions of the driver.
(Refer to Appendix D for other detailed graphs.)

Safety

Safety is impacted by the condition of the ride (car & road), driver skill, driver workload, driver background check, right to refuse passenger a ride. Although we have added these factors into the model, only affecting the driver workload is within the scope of this project. We have safety impacted by workload using the Exponential Regression function (EXPR). Since we found that the workload is positively impacted an increase in fare up to a point, then we have also concluded that increasing the fare will also increase the safety of the ride up to a point.

Safety						Data Range Start
	Condition of Ride	Driver Skill	Driver Workload	Driver Background Check	Right to Refuse Passenger	Data Range End
Input Variables	40	100	30	100	1	
Input Maximum	100	100	80	100	1	
Input Minimum	0	0	30	0	0	
Optimal	100	100	30	100	1	
Type Curve	EXPG	EXPG	EXPR	LNRG	LNRG	
a	0.001	0.001	1.58489E-05	0.01	1	
b	0.069077553	0.069077553	0.138155106	0	0	
Weighed Input	0.015848932	1	0.999	1	1	
Weight	5	10	5	4	1	25
Weighted Score	0.2	0.4	0.2	0.16	0.04	1
Output Maximum	10					
Output Function	1	1	1	1	1	8.0297

Figure 8: NLP model of Safety

Impact to local business

Number of rides parameters is changed to find out its effect on impact to local business. As seen from the chart below, impact to local business increases as the number of rides increases in a nonlinear way. Similarly, effect of number of rides on number of passenger and wait time are plotted. Number of passenger has a positive effect, whereas wait time has a negative effect on impact to local business. Policy makers can consider the optimal number of rides based on this model as they can find particular value for impact to local business when they change number of rides.

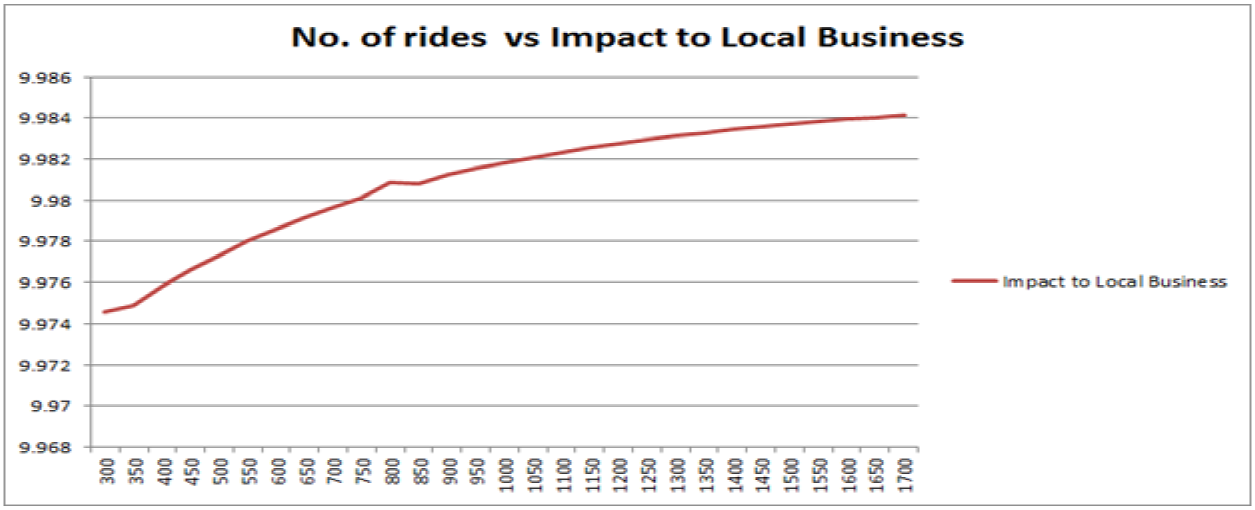


Figure 9: Number of rides versus Impact to local business

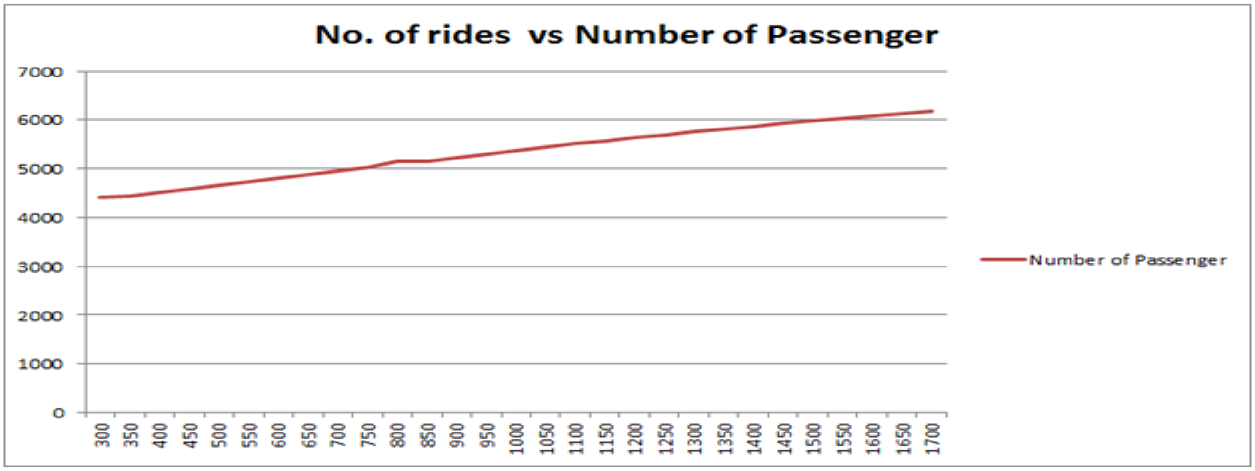


Figure 10: Number of rides versus Number of passenger

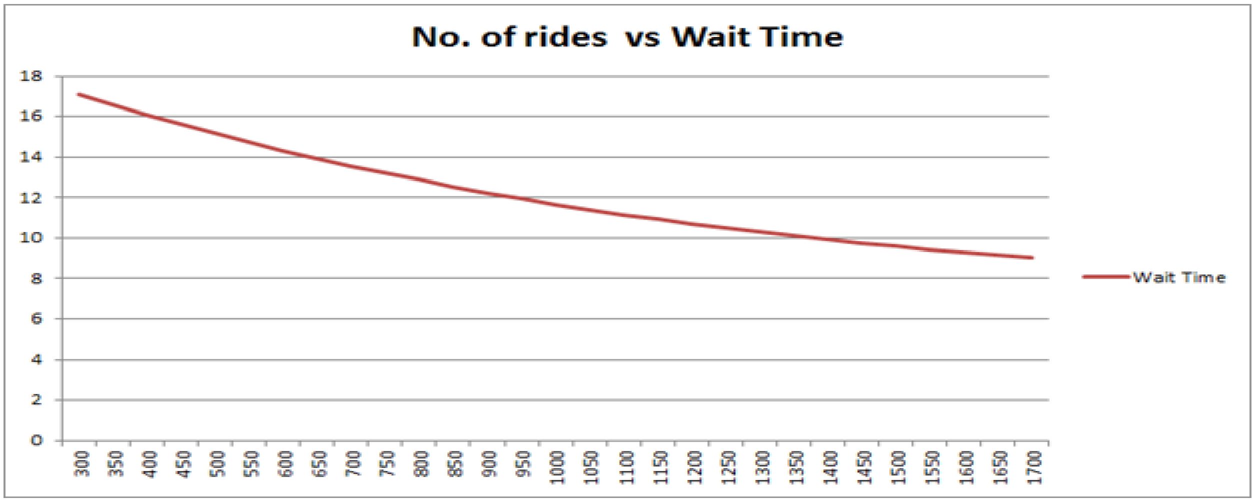


Figure 11: Number of rides versus Wait time

Passenger Experience

The effect of number of rides and price on passenger experience are studied in the model. The number of rides has a relatively linear relation to passenger experience as seen from the chart below.

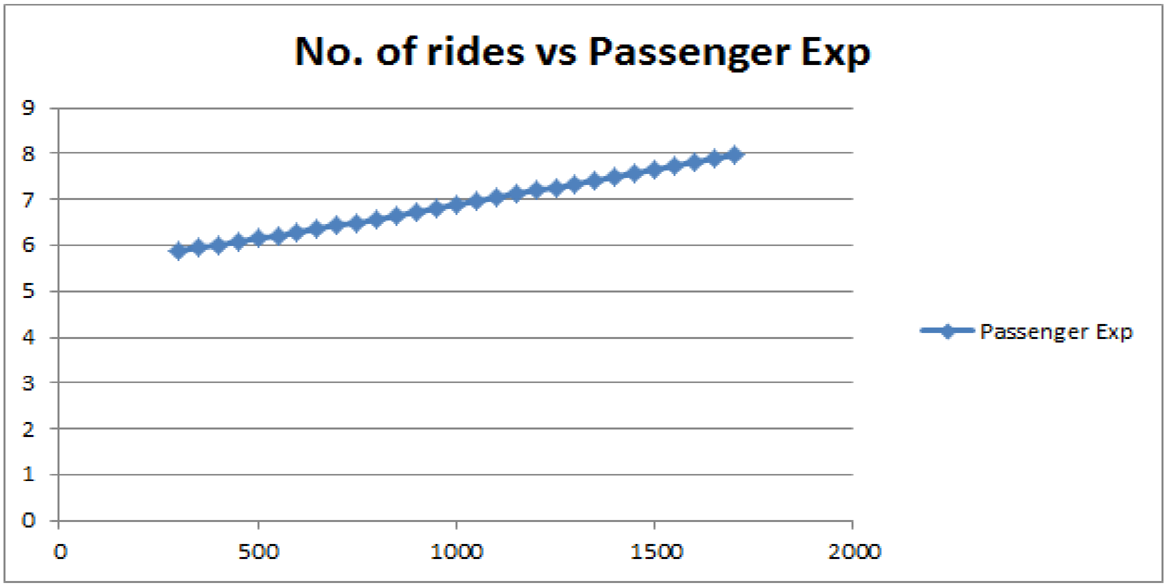


Figure 12: Number of rides versus Passenger Experience

However, passenger experience increased up to some 5 dollars of price and flattens, then started to decrease. Since higher price increase would have lower passenger experience, Uber should be careful about dynamic pricing and limit their price up increase to 6 dollars per ride.

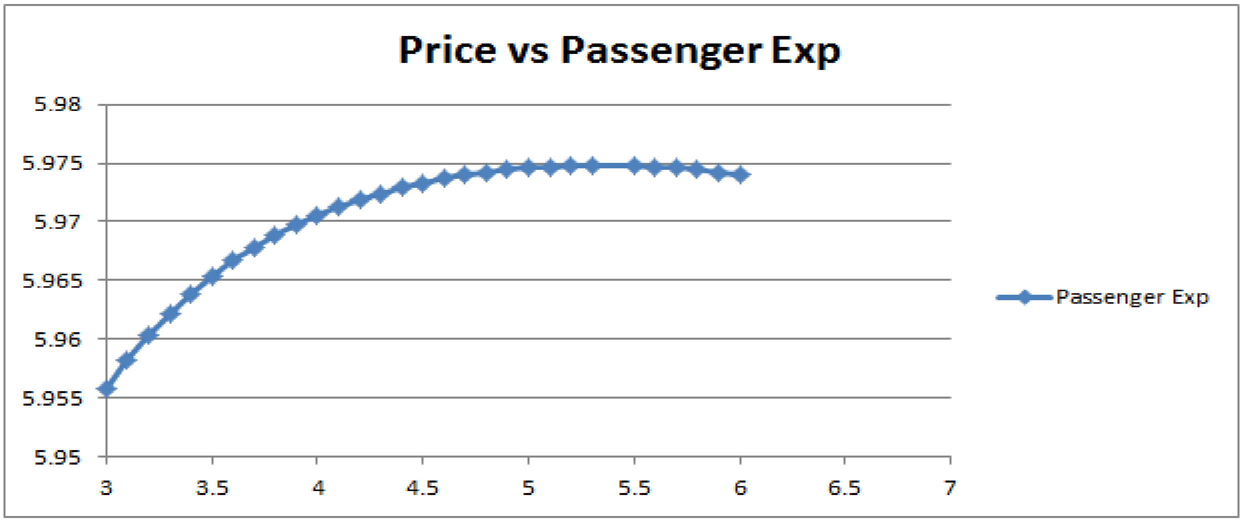


Figure 13: Price versus Passenger Experience

Conclusion

Increasing the number of rides increases the benefits of all attributes up to some limit at which point no significant increase in benefit occurs as the curve flattens out.

Increasing the fee (fare) increases the benefits up to a point, beyond a certain fee, the number of passengers decreases which has a negative impact on certain attributes.It is reasonable to conclude that operation research as a discipline has the tools and the means to address the challenge of measuring changes in the overall benefit index of Portland's residents if Uber, a Transport Network Company is permitted to operate. However, it is also reasonable to conclude that this paper has only touched the surface of such a task.

It is deemed by the team that further work is warranted to address the bigger issue of how two economic models can coexist in the marketplace to bring benefits to residents of an urban community.

The team finds it appropriate to recommend that future research is needed in this area to further enhance the quality of life in urban communities.

References

Citations from In-person interviews:

[1]Brooke Steger – Manager of Oregon & Washington Uber

[2]10 Uber Drivers in San Francisco & 1 in Portland

[3]Cab Drivers in San Francisco & Portland

[4]Frank Dufay – City of Portland Transportation Manager

Citations from In-person government meeting:

[5]Transportation Task Force

Citations from Print Media:

[6]*Portland Business Journal*

[7]*Washington Post*

[8]Oregonian Editorial Board, "Uber's Portland invasion reminds city, taxi industry of public need: Editorial Agenda 2015", *The Oregonian*, February 28, 2015

Citations from papers and journals:

[9] Author- Allan Kruger, Jonathan Hall (2014) "An Analysis of the Labor Market for Uber's Driver-Partners in the United States"

[10] Author- Kathleen Butler(2012)City of Portland Revenue Bureau Office of Management and Finance "Preliminary Findings Taxi Driver Labor Market Study: Long Hours, Low Wages"

[11] Author- Sorin Garber(August 2009) Chapter 16.40 "Private For-Hire Transportation Regulations"

[12] Author- John W. Boroski And Gerard C.S. Mildner(April 1998)Portland State University "Economic Analysis of Taxicab Regulation in Portland, Oregon".

Citations from Electronic resources:

[13] http://www.bostonglobe.com/business/2014/12/25/uber-lyft-save-big-avoiding-regulations/pQAMk1KMOavlyZhWi4XIaJ/story.html

[14] http://www.buzzfeed.com/jacobfischler/dc-just-passed-a-law-that-uber-says-could-serve-as-a-model-f#.mrAJqayL9

[15] https://www.youtube.com/watch?v=sa0I6sBU0E8

YouTube Interviews

Travis Kalanick – CEO, Founder

Thuan Pham – CTO

Appendix A: Attributes considered to impact the benefits to Portland

***Working Conditions of Driver**

***Passenger Experience**

Driver Workload

Health Benefits

***Safety**

City Revenue

Taxi Business Profitability

Driver Profitability

Price Fare

Price of Tips

Idle time of Drivers

Waiting Time for Passengers

***Impact to Local Business**

Fuel Costs

Attitude of Driver

Competence of Driver

Cleanliness of Vehicle

* = Attributes upon which this report focuses

Appendix B: Additional Considerations

Disability act compliance:

Currently, the company cars are not wheelchair friendly and this appears as a discrimination against the disabled. Uber provides no guidance or training to its drivers to meet the needs of disabled customers which has led to a federal complaint against such ridesharing companies and is a major concern for any city government to address.

Local Regulations:

While Uber and similar ridesharing companies are trying to crush each other, taxi companies are picking up fights with the industry by protesting against the fact that they are being treated differently. In Seattle, the taxi operators association filed a lawsuit against unfair business practices as the city council were speculating on the local regulations.

For local taxi drivers the frustration stems from the fact that only they have to abide with the rules and regulations- license fees, commercial insurance laws, uniform rates etc. Unlike Uber, taxi companies are subjected to stricter pricing models where as Uber prices changes with the demand in the number of drivers.

Insurance:

Uber claims to offers a $1 million liability insurance which is way higher than what any of the taxi companies offer today. But it only kicks in when a driver is en route to a rider and when the rider is actually being transported. When the driver has the app on but is not actively picking up or transporting a passenger, they are not covered under Uber insurance instead their personal insurances come into play and Uber in not liable for the driver's negligence during this course of time.

Airports:

Airports in all cities are major revenue generating sources for any city government. Ride sharing companies also make good revenue by using the airport premises to pick and drop passengers. The airports take a share/cut to provide permits to taxi companies to continue their services. SFO uber passengers end up paying an additional $4 if picked or dropped at the airport and this extra charge goes to the airport as permit fee.

Appendix C: Riders Top Reasons for Using Uber

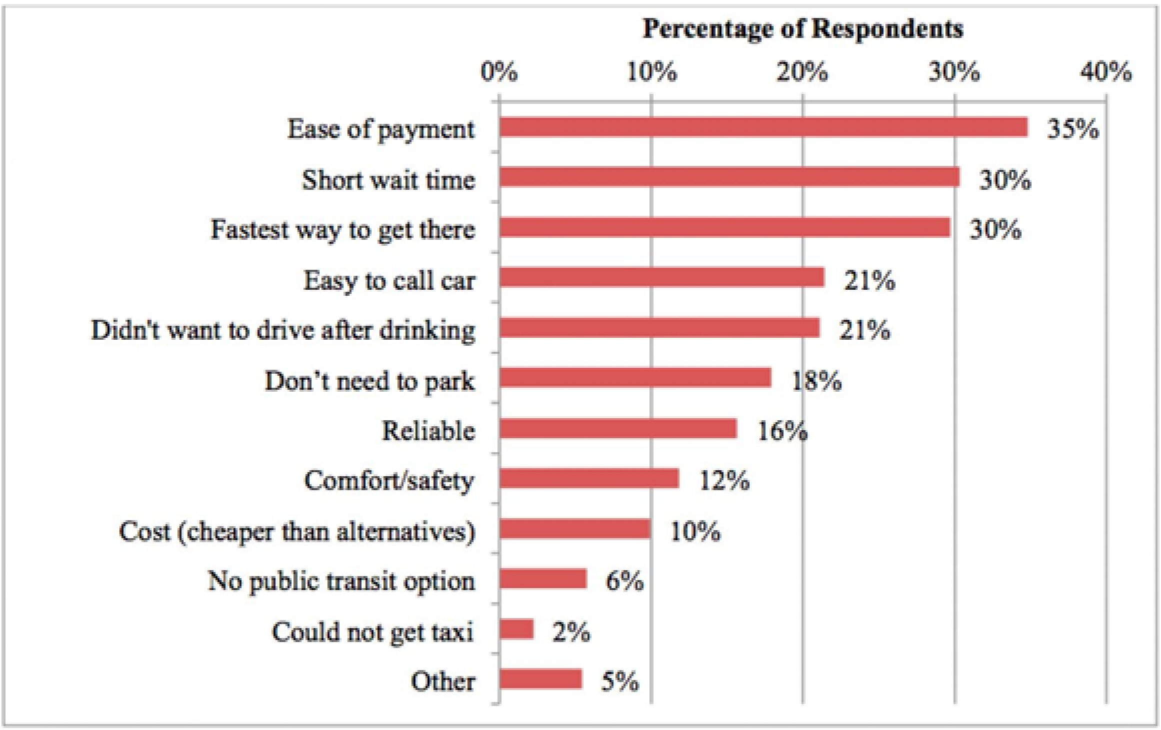


FIGURE 2 Responses to "What are the top two reasons you used [X service] for this trip? (n = 313).

http://www.washingtonpost.com/blogs/wonkblog/wp/2015/01/19/how-uber-and-lyft-have-exploited-long-waits-slow-travel-and-poor-service-to-crack-open-transportation/

Appendix D: Factors Affecting the Working Conditions of the Driver