

# Analyzing Business Dynamics of Ride-Hailing Services A DPM Approach Applied to Uber Inc.

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## Keywords

Ride-Hailing Business, System Dynamics Modelling, Simulation, Dynamic Performance Management

## Abstract

*Purpose* – The purpose of this paper is to explore business dynamics of a rising ride-hailing service industry through case study and foster understanding of hypothetical feedback effects within the broader system.

*Design/methodology/approach* – The research adopts the dynamic performance management framework with simulation-based methodology for developing a dynamic case interpretation of specific type of business complexity.

*Findings* – Scenario analysis shows that changes in the commission percentage for drivers, and cutting prices for customers (car hailing) by competitors have significant impacts on the car hailing industry.

## ACKNOWLEDGEMENTS

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## **Introduction**

Uber Inc. (hereafter called Uber), since its foundation in March 2009, has experienced significant growth during recent years both internally and externally. Internally speaking, the company has been successful in expanding its service capacity in all the cities where it operates. Externally speaking, Uber has been strategic in developing not only its company name-value, but also in acquiring additional funds. Recent Uber's strategic partnership with Toyota (U.S.) (Bloomberg.com, 2016), a top global automobile company, shows the on-going business dynamics of the company and prospective business future. At the same time, market valuation of the company shows an outstanding growth, which could be interpreted as one of clear indicators of such excitement and business expectation.

Uber's core business is providing a market for the ride-hailing service supported by point-to-point software technology and mobile phone application, connecting drivers and passengers. In this paper, based on the "qualitative" case study "Uber: Changing the Way the World Moves" (Moon, 2015), we attempted to interpret this business-specific case study from management decisions perspective, through System Dynamics "quantitative" modeling approach.

Particularly we focused on the company's business area in New York City. The concept used in Dynamic Performance Management (hereafter called DPM) is also utilized to foster the understanding of complex, multilayer factors affecting its core business area. To the best of our knowledge, such a research attempt has not been performed or made available so far, which became one of our challenges to overcome in this research together with limited available data due to the company's private status.

## **Critical factors impacting on Performance Management design and implementation**

In recent years, simulation as a research method has gained attraction, allowing for the analysis of complex strategic phenomena that incorporate a multitude of interrelated issues which may lead to inflexible analytical models and are particularly difficult to manage in empirical research.

Conventional Performance Management (PM) systems represent useful tools to drive decision-makers in both designing competitive strategies and measuring resulting outcomes. However, they often lack to capture the dynamic complexity of managerial decision-making. In fact, they may fail to consider a number of relevant factors influencing organizational performance. Such factors can be associated to delays, non-linearity, intangibles, to the unintended consequences

on human perceptions, and to a behavior caused by a superficial or mechanistic approach in setting performance targets, especially if such targets are used as a basis for organizational incentive and career systems. In addition, these PM systems tend to frame business performance from a too static point of view that does not allow one to properly assess policy impacts with reference to the trade-offs existing between both short- vs. long-term effects (time), and results related to different strategic business and functional areas within an organization (space). This implies a weak understanding of both the impact of current decisions on future growth and the strategy to undertake to cope with major changes. As De Geus (1997) found, misperceiving dynamic complexity is a main cause of poor organizational performance and crisis. For instance, despite its widely recognized advantages, even the Balanced Scorecard (BSC) by Kaplan and Norton (1996) presents some conceptual and structural shortcomings. Linard et al. (2002) assert that the BSC fails to translate company strategy into a coherent set of measures and objectives, because it lacks a rigorous methodology for selecting metrics and for establishing the relationship between metrics and firm strategy. Sloper et al. (1999) remark that the BSC is a static approach. Although Kaplan and Norton stress the importance of feedback relationships between BSC variables for describing the trajectory of a given strategy, the cause-and-effect chain is always conceived as a bottom-up causality, which totally ignores feedbacks, thereby confining attention only to the effect of variables in the lower perspectives (Linard and Dvorsky, 2001). Misperceiving the dynamic relationships between the system's feedback structure and behavior (Davidsen, 1996; Sterman, 2000) often leads managers to make their decisions according to a linear, static and bounded point of view, in terms of time horizon and relationships between variables. Therefore, conventional approaches to PM may limit decision-makers' strategic learning processes (Sloper et al., 1999; Linard and Dvorsky, 2001) and, as a result, impoverish management decision effectiveness.

As a result, a "dynamic" perspective in designing and implementing PM systems is particularly valuable in complex and unpredictable contexts, as it implies the identification and analysis of end-results, value drivers and related strategic resources accumulation/depletion processes, according to a "cause-and-effect" perspective. A feedback analysis may allow decision-makers to better frame the relevant structure underlying performance and, consequently, to design and assess a set of alternative strategies to adopt, so to affect the system structure according to the desired performance behavior.

In recent years, System Dynamics (SD) modelling combined with strategic PM systems hold promise to be effective in fostering strategic learning processes and, as a result, supporting

decision-making and performance improvement according to a systemic perspective (Bianchi, 2002, 2012; Bianchi et al., 2015; Cosenz and Noto, 2016). This approach, known as Dynamic Performance Management (DPM), aims at supporting decision-making through a better coordination between performance measurement reporting and strategy design (Bianchi, 2016; Bianchi et al., 2015). In fact, the application of SD to PM helps business analysts to trace both causes and drivers that have led to a given performance level over time and, in doing so, contributes in enhancing the diagnosis process that enables business managers to put in place corrective actions and strategies oriented to fill the gap between the actual and the target performance value.

In the next sections, this paper analyzes how SD modelling may add value to PM in Ride-Hailing Services operating in dynamic and complex contexts. To this end, the Uber Inc. case-study will be illustrated and discussed to provide empirical evidence on the effectiveness of this approach to management decision and control.

### **Research Methodology: A DPM approach to analyze Ride-Hailing Service Business Dynamics**

To identify and analyze causal relationships underlying ride-hailing business performance dynamics with the intent to understand how the company reacts to alternative strategies, we take advantage of the combination between conventional PM tools (Neely, 1999; Neely et al., 1997; Otley, 1999; Kaplan and Norton, 1996) and SD methodology (Forrester, 1961; Sterman, 2000).

In particular, conventional PM systems aim at managing organizational performance through a perspective that focuses on end-results in order to design a selected, though significant, set of performance drivers. These drivers represent not only useful measures of performance, but also strategic levers on which to intervene in order to fill the gap between actual and expected results. To affect such drivers, managers must build up, preserve, and deploy a proper endowment of strategic resources. The feedback loops underlying the dynamics of the different strategic resources imply that the flows affecting such resources depend on end-results and are measured over a time lag. End-results are modelled as in- or out-flows, which over a given time span, change the corresponding stocks of strategic resources, as the result of actions implemented by decision-makers (Bianchi, 2016). For instance, liquidity (a strategic resource) may change as an effect of cash flow (an end-result); the change in the image of a firm (an end-result) may change as an effect of its customer satisfaction (a strategic resource).

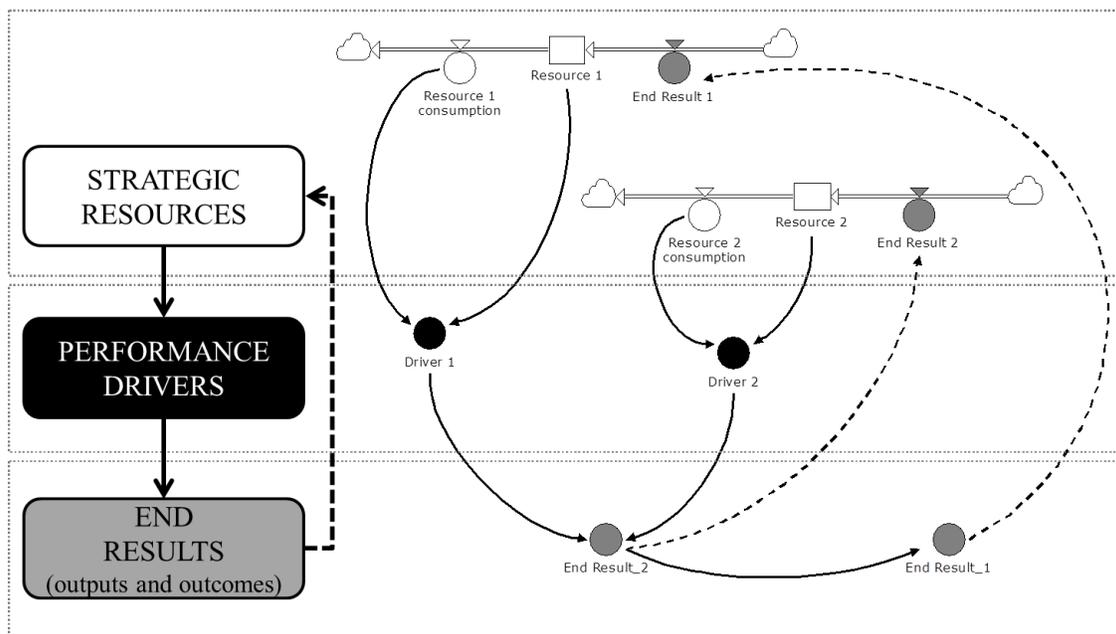
On the other hand, SD is an approach for modelling and simulating complex physical

and social systems, and experimenting with the models to design policies for management and change (Forrester, 1961). As such, SD modelling is adopted to map system structure to capture and communicate an understanding of behavior driving processes and the quantification of the relationships to produce a set of equations that form the basis for simulating possible system behaviors over time. SD models are powerful tools to help understand and leverage the feedback interrelationships of complex management systems. They are based on a feedback view of business systems, seen as a closed boundary, i.e. embodying all the main variables related to the phenomenon being investigated. These models offer an operational methodology to support decision-making and management. Decision-makers can use the models to test alternative scenarios and explore what might have happened – or what could happen – under a variety of different past and future assumptions and across alternative decision choices (Sterman, 2000). Model structures are realized by linking those relevant variables, which determine certain behavior of the observed system over time. In these connections, feedback loops are the main building blocks for articulating the dynamics of these models and their interactions can explain the system behavior (Morecroft, 2007).

In comparison to other methodologies, the use of SD modelling may lead to remarkable results in terms of identifying and analyzing both determinants and implications of a given business phenomenon. As such, SD methodology frames the complex interactions among feedback loops, rejects notions of linear cause-and-effect, and requires the analyst to view a complete system of relationships whereby the “cause” might also be affected by the “effect”. This means that a variable – other conditions being equal – influences another variable (1) positively (i.e., an increase of the one corresponds to an increase of the other and vice-versa), (2) negatively (i.e., an increase of the one corresponds to a decrease of the other and vice-versa), and (3) according to a non-linear relation between them. In addition, if such relations originate closed circuits, these are defined as feedback loops and determine the system behavior. Shortly, reinforcing loops (R) produce exponential trends of the system over time; while, balancing loops (B) limit such an effect by tending to a steady state. The underlying principle is that if the process structure determines the system behavior, and the system behavior determines the business performance (Davidsen, 1991; Richardson and Pugh, 1981; Sterman, 2000), then the key to developing sustainable strategies to optimize performance is understanding the relationship between processes and behaviors and managing the leverage points (Ghaffarzadegan et al., 2011). By framing the dynamics of a complex business system, including interactions among key-actors, actions, organizational structures and

processes, analysts can better decide how to reinforce positive factors or diminishing the negative pressures exerted upon them. Therefore, SD allows managers and entrepreneurs to link strategy to action, to better perceive interdependencies between business units and functions, as well as between the firm and its environment, and to understand the crucial role of strategic resources on firm performance and survival. Therefore, combining SD and PM enables one not only to capture causal relationships underlying the functioning of a business system, but also to simulate performance behavior over time and, as a result, contributes in evaluating the trade-offs between short- and long-term outcomes related to the adoption of a given strategy.

Figure 1 illustrates the mechanism through which performance indicators are built and, according to a causality-based perspective, connected to both end-results and strategic resources.



**Figure 1: Dynamic Performance Management framework**

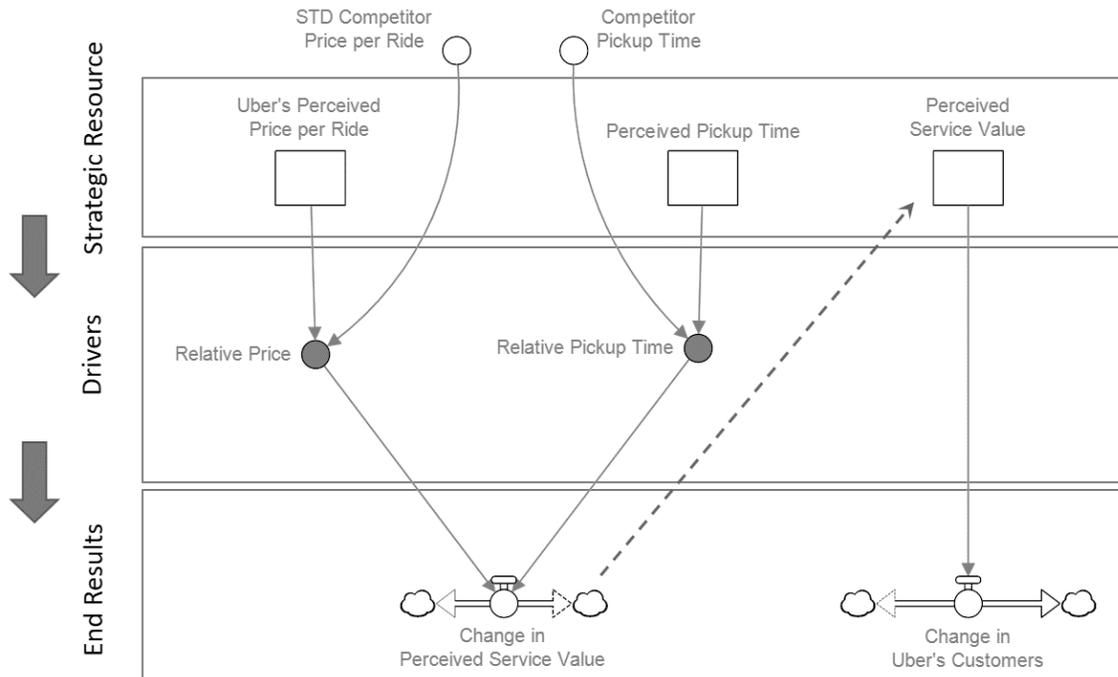
*(source: Bianchi 2016, p. 73)*

**Case Illustration:**

***Uber Specific DPM Chart in Action***

In this section, we present the dynamic performance management (DPM) chart applied for this case study. It is rather a schematic diagram, and it is meant for fostering insights about the business system structure and provides a basis for our next step where we introduce a system dynamics quantitative model.

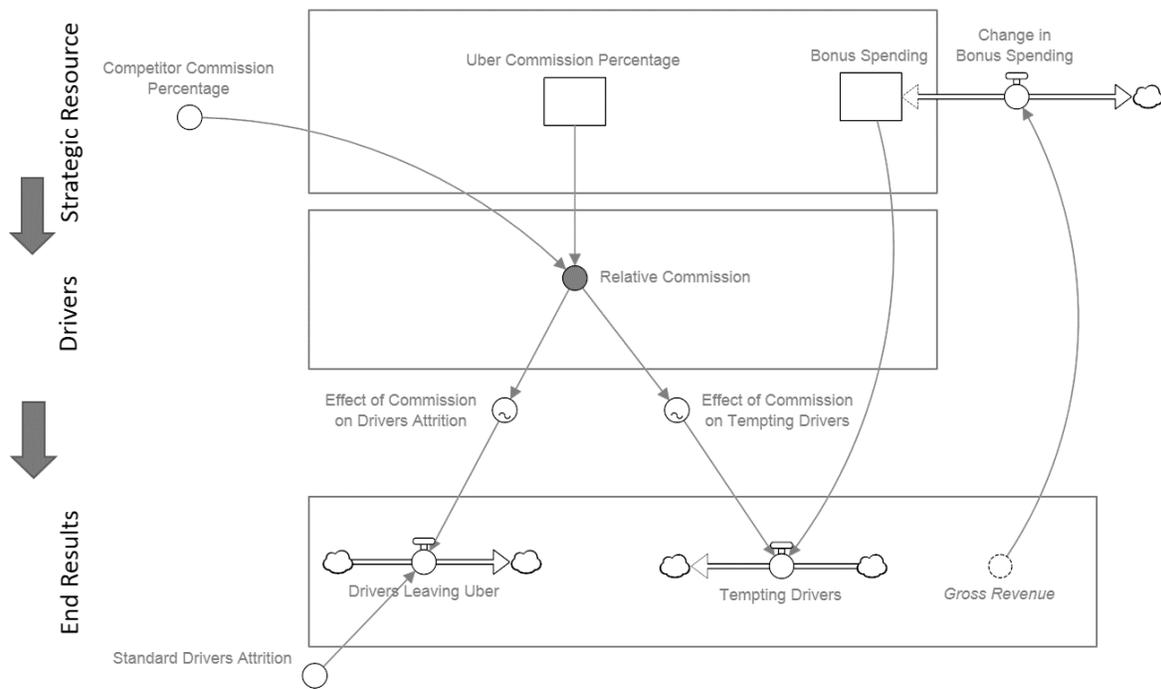
Figure 2 and Figure 3 depicts some of the selected variables that are important in this specific case illustration, depicting *Performance drives* (hereafter, called PD) named *Relative Price*, *Relative Pickup time*, and *Commission Ratio* are situated in the middle. In Figure 2, we assume that the first two drivers affect *perceived service value* which ultimately leads to change in *Uber's customers*. These connections between PDs and *Uber's customers* are based on our assumption that people who are using the application consider two factors when they decide to choose Uber's ride-hailing service among others.



**Figure 2: DPM chart around service price and pickup time**

Figure 3 partly illustrates the dynamics of driver-partners with Uber. *Relative Commission* is defined by the ratio between Uber's current commission percentage and that of competitor(s). If there's a huge gap between the two, either one of them attracts more driver-partners than the other.

Bonus spending is classified as a strategic resource. We have done so based on two reasons. One is that in our model we could not find any financial data. However, it was necessary to incorporate bonus spending as one of the factors affecting the number of new drivers into Uber (Moon, 2015). Bonus spending is a broad term, related to available financial resources to attract additional drivers, and includes car leasing loans, performance-based bonuses provided, etc.



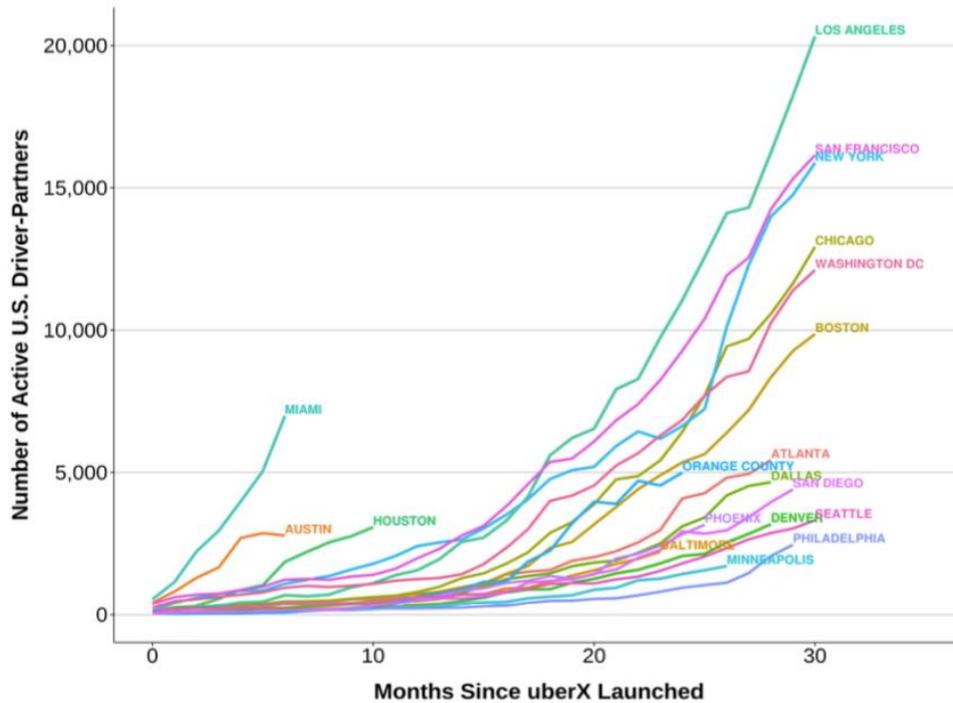
**Figure 3: DPM chart related to commission percentage**

Figure 4 is our reference mode and shows the behavior of the number of active drivers in the US by cities. What remarkable about this reference behavior is that the number of active drivers increased exponentially in almost all cities. This implies that there is a strong reinforcing feedback in the development in the number of driver-partnerships. Based on this observation, we considered word of mouth effect is consistent with what is happening in reality, and is a realistic structure in supply side of our model. The system, however, has its limits to growth. In the same figure, the number of drivers in Austin seems to have stopped increasing and reached its peak. What has happened in that area? This could be explained by a balancing feedback loop, which imposes limits in resource (driver-partnerships).

### ***Model Description***

In this section, we describe the structure of the model part by part. The model structure contains logical assumptions. Therefore, such assumptions are also explained in this section.

Let us begin this section with a description of selected variables in demand-side part. Please note that each part of the model is connected in many ways and such connections are cut for the sake of simplicity of presentation.



Note: Figure reports the number of U.S. UberBLACK and uberX driver-partners making at least one trip in the specified month, indexed to the number of months since Uber began in the city or June 2012, whichever came later.

**Figure 4: Uber Active U.S Drive-Partners by City**

*Source: Hall and Krueger (2015)*

## Demand-side of the model

The demand side of the model is built upon the basis of word of mouth effect. Assumptions made in each variable are explained below. Figure 5 illustrates this part of model view. First, the Potential Customers<sup>2</sup> in NYC become interested in using ride-hailing service in general when they hear about the service from current users and become *Ride-hailing Customers* (They may choose Uber or other competitors such as Gett, Lyft). This variable considers those who have used the ride-hailing business at least once and may request such ride in any time. There is an implicit assumption that some of mentioned customers may use the service more often than the others in the same population. Some continue to use the services of this business while portion of them stop using it (here, called Regreters).

Figure 6 illustrates the point of the model structure where service demand for Uber-car

<sup>2</sup> This variable considers those who have never used the service and those who have used it but previously regretted and stopped using it. Normal number of people who stop being a ride-hailing user and go back to become potential customers varies according to surging price.

hailing is finally determined. It is important to note that customer's *Perception of Service Value* determines number of Uber's customers; the mentioned "Perceive" itself is dependent on two performance drivers in our analysis: Relative pickup time, and Relative Service Price, both defined by a ratio.

### Supply-side of the model

This part of the model also assumes the word of mouth effect. Therefore, it has same structure as the demand side. Figure 7 illustrates the supply side part of the larger model.

While the demand-side part of the model describes the ride-hailing market size in terms of number of customers, the model structure for supply side of the model is confined to dynamics of drivers who are interested particularly in Uber. Consequently, *Potential Drivers* will eventually become *Uber-drivers in NYC*.<sup>3</sup> *Uber drivers* spread the word and attract more *Potential Drivers in NYC* to become a driver-partnership (a reinforcing loop).

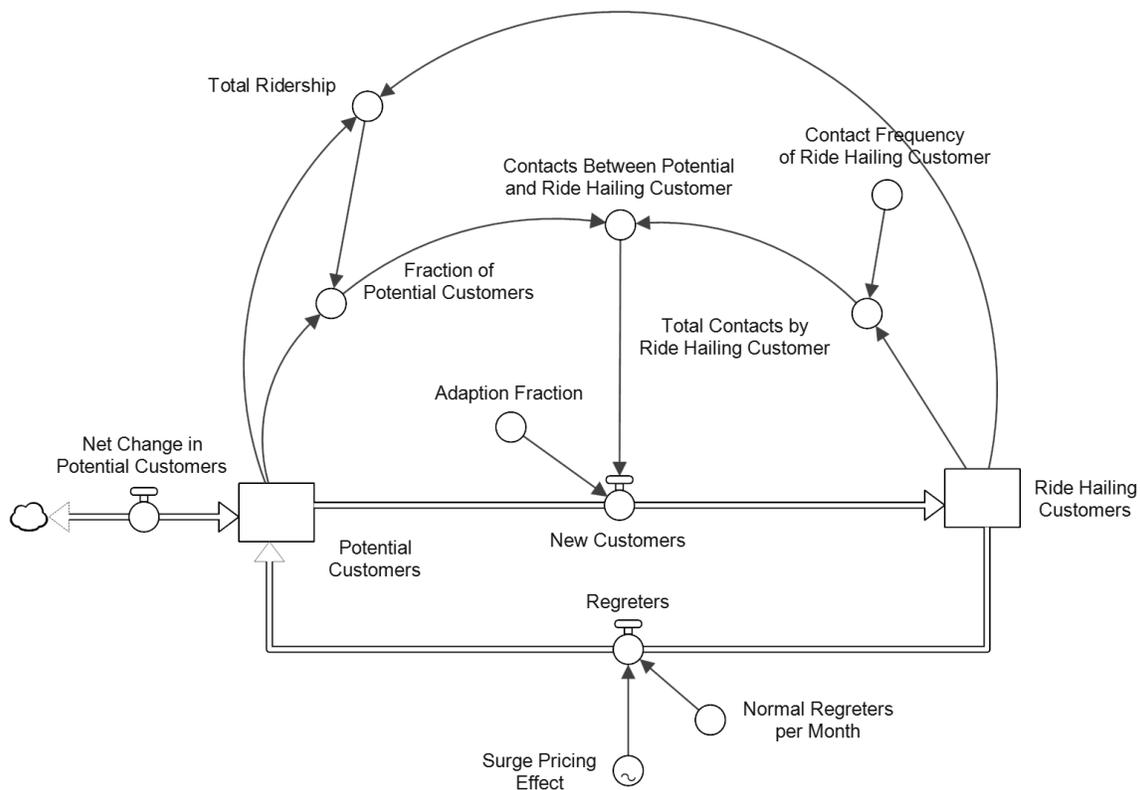
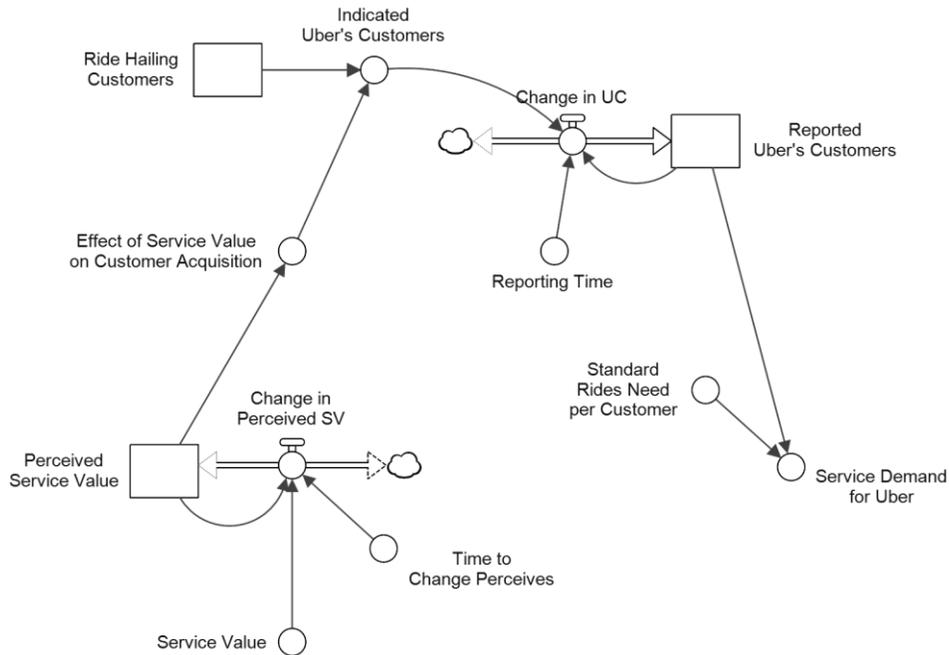


Figure 5: Structure of "Customer Base Dynamics" or "Demand-side"

<sup>3</sup> This variable captures all of those who are registered as driver-partnership with Uber Inc.



**Figure 6: Uber-Customers and their demand for service**

- Potential Drivers in NYC

This variable considers those who have never worked as a driver-partner before or used to work as a driver in ride-hailing industry but have stopped working.

- Awaiting Drivers

This state variable is made to capture those who applied to become a partnership, but have not yet granted an official license for Uber in NYC.

We assumed the presence of the effect of “commission ratio” both on “leaving Uber” and “Tempting Drivers”. Furthermore, behind this structure, we assumed that potential drivers (including those who are already working in competitors’ company) will see opportunity in Uber when they perceive the difference in commission rate and vice versa.

- Active Uber Drivers in NYC

A distinction between “Uber Drivers” and “Active Drivers” are one of the key assumptions. This is based on our observation that not all of people who are currently registered as driver-partnerships are active drivers<sup>4</sup> (Figure 8 illustrates the corresponding part in the model.)

This part of structure is to capture the change in service capacity of Uber platform. Hall,

<sup>4</sup> Definition of “active” is not specifically defined in our model at this point of research. However, we assume that they deliver rides somewhere around 4 times per month according to Hall (2015).

Kendrich and Nosko (2015) observed that the number of Uber drivers, thus service capacity rises when there is a surge pricing policy in effect.<sup>5</sup>

## Service Requests Processing

Figure 9 illustrates Uber’s service requests process. This part of the model is built to describe the dynamics of service requests by Uber customers.

Once Uber’s customers, who are seeking for a ride, open the Uber’s application, they see current price policy and can choose whether they want to request a ride. Number of App openings is determined by the number of Uber’s customers and the standard (or average) number of rides needed per customer in a month.

- Standard Rides need per Uber customer

This variable assumes the average number of rides that Uber-users think they need in a given period of time. It essentially describes how many times Uber-customer opens Uber application to hail a ride.

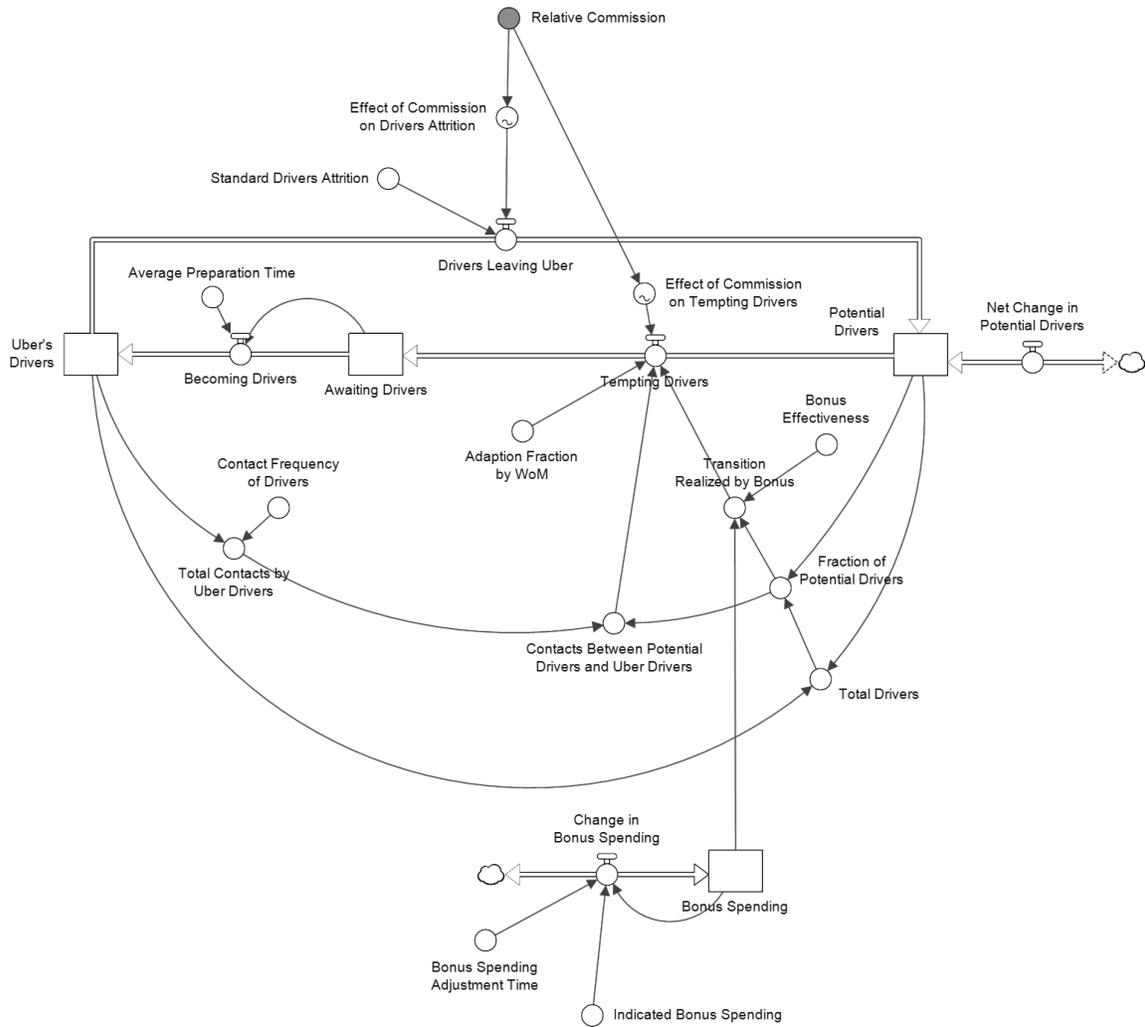
We assumed that such decision is being influenced by how much the current service price per ride (effective service price per ride) is surged relative to the normal price per ride. The ratio between two prices is called *Price Threshold ratio*. If they decided not to request a ride, they just close mobile application. The number of those who will close the app is affected by “Effect of Price Threshold ratio on closing app”. (The assumption for the mentioned graphical function is explained later in this report.)

$$\text{Price Threshold ratio} = \text{Effective Price per Ride} / \text{Uber’s Normal Price per Ride}$$

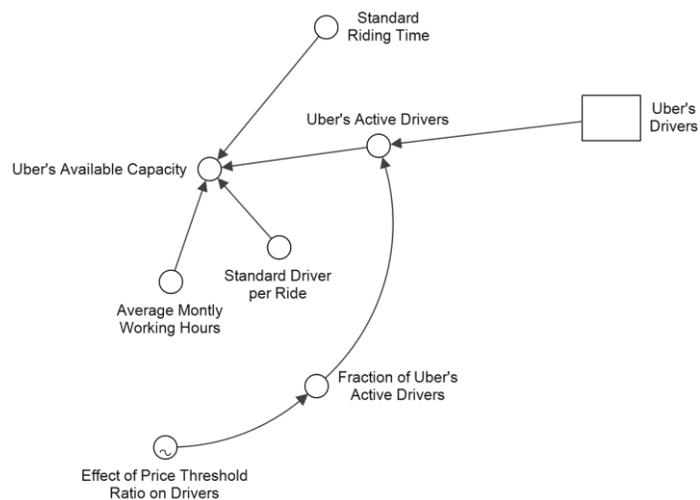
Then, requested rides will be matched or discarded. According to the “Matched Rides” and “Rides Arriving”, one of Uber’s performance indicators, called “Effective Pickup Time”, is defined. This performance indicator affects the customer’s perception of “Pickup time” which will then affect the *Service Value*. Certainly, this will influence service demand from Uber (*Waiting on the street loop*). Those “Matched Rides” are then be delivered by Uber’s drivers. The number of ride services which are delivered generates income for each drivers and gross revenues for Uber.

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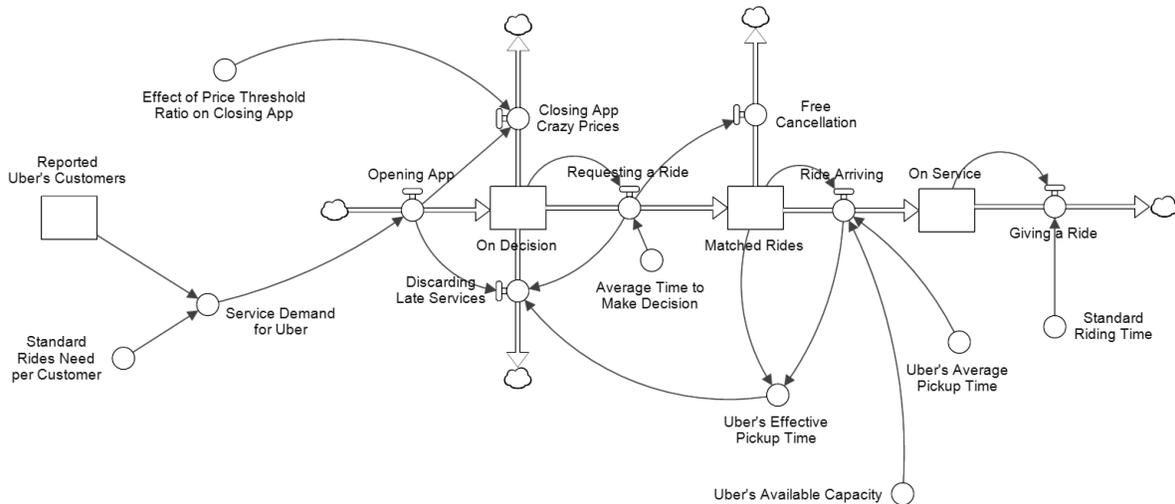
<sup>5</sup> A supporting material, taken from the original research (Hall, Kendrick and Nosko, 2015), is included in Appendix, exhibiting this behavior.



**Figure 7: Structure of “Driver-Partnerships Dynamics” or “Supply-side”**



**Figure 8: The number of Active Drivers ultimately rises or falls due to Surge Pricing Effect**



**Figure 9: Structure of “Service Requests Process”**

## Customer’s Perception of Service Price

Figure 10 shows the structure where customers perception of service price become updated. Together with competitors Service price, we define another performance driver called *Relative Price (Service Charge loop)*

- Uber’s Normal Price per Ride in NYC

According to Ridesharingdriver.com (2016), Uber’s Fare Price is determined by the following equation;

$$\text{Uber's Fare Price} = \text{Base Fare} + (\text{Cost per minute} * \text{time in ride}) \\ + (\text{Cost per mile} * \text{ride distance}) + \text{Booking Fee}$$

- Uber’s Perceived Pickup Time in NYC Area

This is the perception of time by a customer between a moment a customer hails a ride and a moment the driver arrives.

- Perceived Service Value

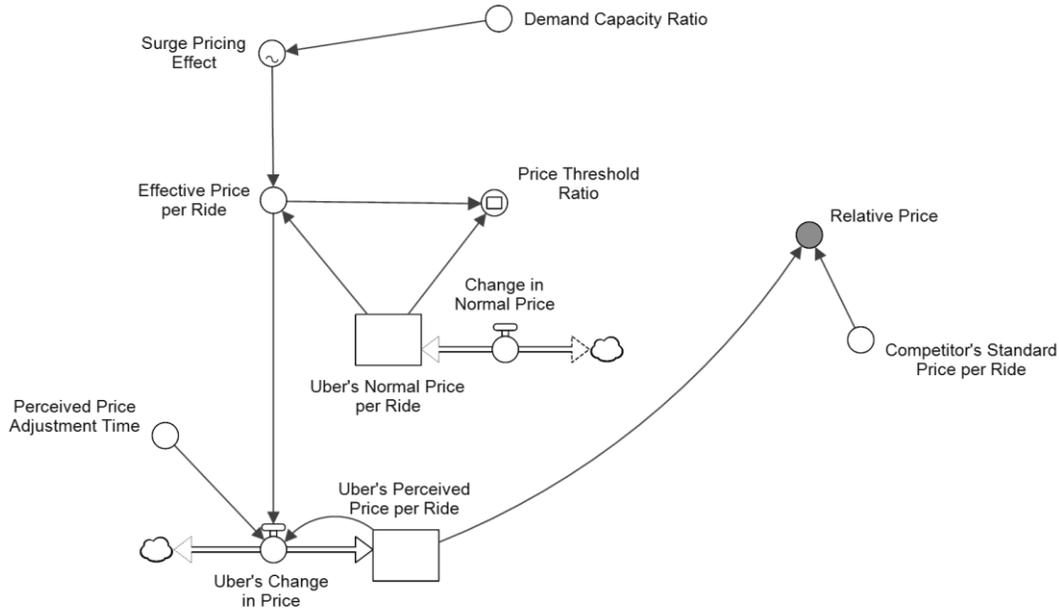
This is the perception of service value by customers themselves. It is based on two factors; Service Price per Ride and Pickup Time. In forming the perception, weights are assigned. Weights between “Service Price” and “Waiting time” are assumed as Service Price: Waiting Time → 75% : 25%.

The logic behind this is that customer’s perception on Uber’s service value weighs more on price than pickup time. Specific value that we choose is not based on reference data, nor

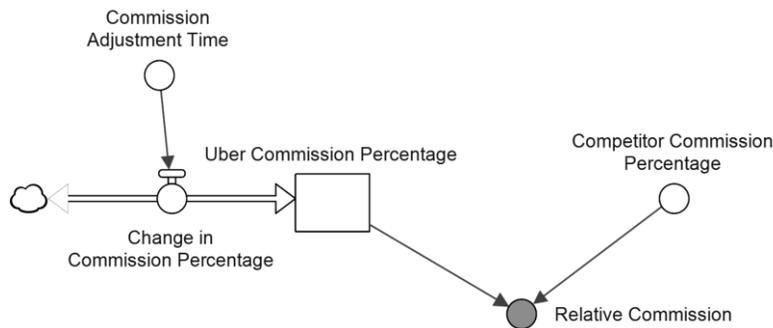
something concrete. It is just to show that our logic about values here has significant effect on the behavior of our model.

- Uber’s Commission percentage

As far as we could find the data, commission percentage for Uber’s Drivers has been 20%; recently Uber raised it to 25% in NYC.



**Figure 10: Price Threshold Ratio and Relative Price**



**Figure 11: Relative commission as a performance driver**

## Revenue & Cost Structure of Uber in NYC

In this section, we illustrate the company’s financial structure assumed in the model. In our analysis, as previously mentioned, financial section is kept simple due to limited information on revenue and cost structure. The company’s gross revenue is defined by how much Uber-drivers deliver services, service price per ride and commission percentage that Uber charges drivers.

Though, this measurement is rather an aggregated measurement of what's done in reality, we tried to capture the company's revenue structure briefly. Cost structure is intentionally limited to bonus spending due to unavailability of financial data and to avoid unnecessary effect on system behavior at this point of research.

## **System Boundary**

In this case study, the boundary of the system or scope of our analysis is set to an area of New York City in terms of geographical boundary and data we have referenced. We consider that deciding system boundary of the analysis is crucial in model development in the sense that it can either improve or limit the capability of an explanatory model. One of the reasons why we set the system in NYC is that the area is highly competitive and reference data were relatively easy to find. Therefore, it serves as a good representation for our group project.

## **Limitations in the model**

Qualitative researches have numerous advantages and strength when they are properly conducted. Before we move into the behavior analysis of the model, we briefly mention a major limitation that our model structure brings into effect.

One of the major constraints is a lack of feedback loop from financial part of the model. As seen above, this is due to a lack of sufficient information about the company's financial results. Consequently, we have decided to focus more on the dynamics of customer and driver acquisition of the business. To be more specific, gross monthly revenue is calculated, yet there is not a single causal relationship with other parts of the model except bonus spending, leaving out possible constraints of financial resources. In reality, however, strategic decisions and policies in organizations are primarily affected by its financial capability. It should be noted that the behavior which the current model produces has this kind of limitations behind it.

## ***Insights from Model Analysis and Discussion***

### **Behavior of the model: Default Case**

We are now in the position to analyze behavior of the model in default case scenario. As we stated in the introduction, Uber has been growing its business operation rapidly both internally and externally. Specifically, our reference mode for active Uber-drivers is at exponential growth as

shown in Figure 4 (by cities). Time = 0 corresponds to the time when Uber began its first ride-hailing service in NYC.

Figure 12 shows our comparative simulation result of Uber's Drivers and active drivers. Empowered by the reinforcing loops of word of mouth both in supply and demand side, the number of drivers increases exponentially.

As a result of such business expansion, the model shows that monthly gross revenue continues to grow at increasing rate. Behaviors of gross revenue and bonus spending are shown in Figure 13. Uber's cost structure in NYC, which consists only of bonus spending in the current model is correspondingly increasing.

Figure 14 shows behavior of Uber's market share in response to the entrance of its main competitor, Gett, to NYC at time = 10 months.<sup>6</sup> Initially, there was no ride-hailing service competitor in NYC. Over time the competitor gradually gain market share until it reaches its steady point. Then at time = 45 months, Uber cuts its service price by 15%.<sup>7</sup> As a result, Uber regain its market share. Moreover, at time = 60 months, one of the competitors, Lyft reduces its pickup time from 6 to 3 minutes.<sup>8</sup> The loss in market share of Uber is a consequence of its competitor's service price change.

### **Limits to growth**

So far, as the model is simulated in default scenario, the number of Uber's customers could continue to grow since the industry itself is expanding, supported by two reinforcing loops of word of mouth. However, when the model is run until 200 months, it reaches a peak and the market seems to saturate. This is certainly a result of limited capacity in the number of drivers and service users in NYC. A specific value does not have significance itself. Rather, system structure which produces certain behavior should be focused.

## **Scenario Analysis**

### **1. Change in Commission Percentage**

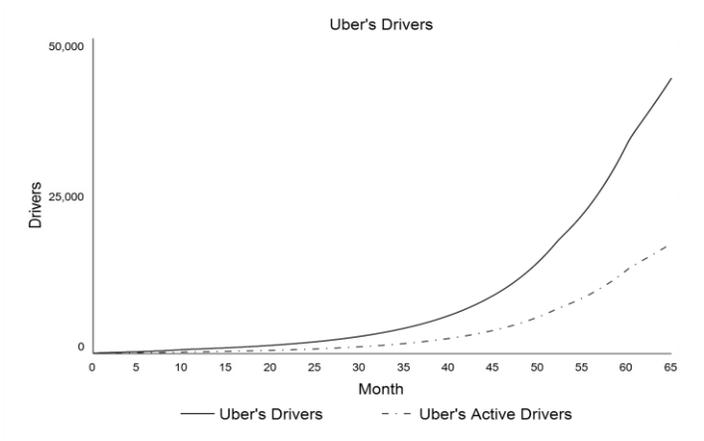
In the scenario 1, competitor cuts its commission from 20% to 10% at time = 60 months. This happened in reality; Gett, one of Uber's main competitor in NYC, reduced its commission

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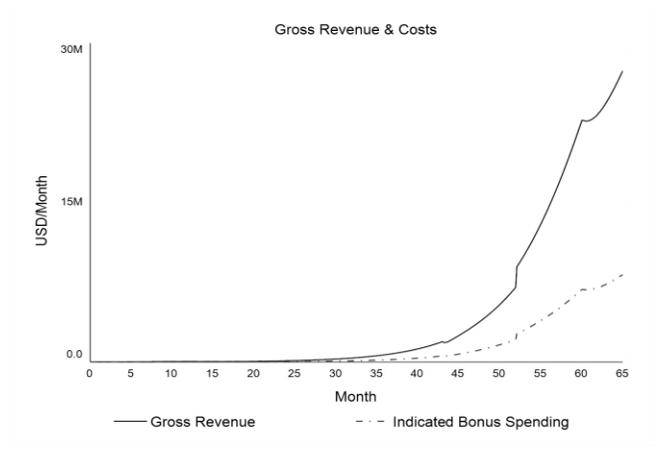
<sup>6</sup> Uber's competitor, Gett, launched operation in NYC in June 2012. (Mashable, 2012)

<sup>7</sup> This change in Uber's price is based on real case in Golson (2016)

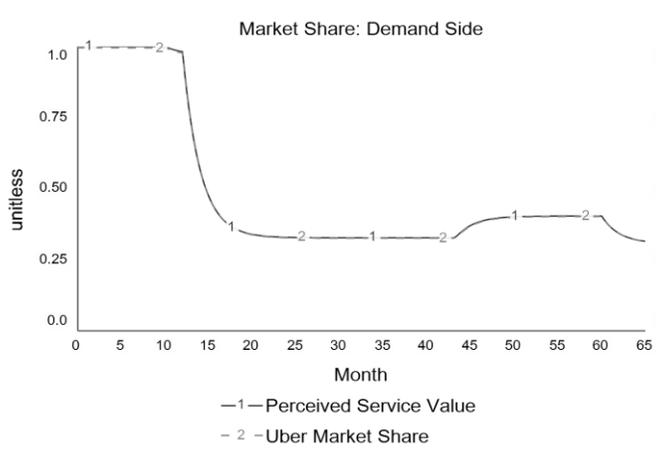
<sup>8</sup> "Since May 2016, Lyft has halved its average waiting time for a ride in NYC" (Wieczner, 2016).



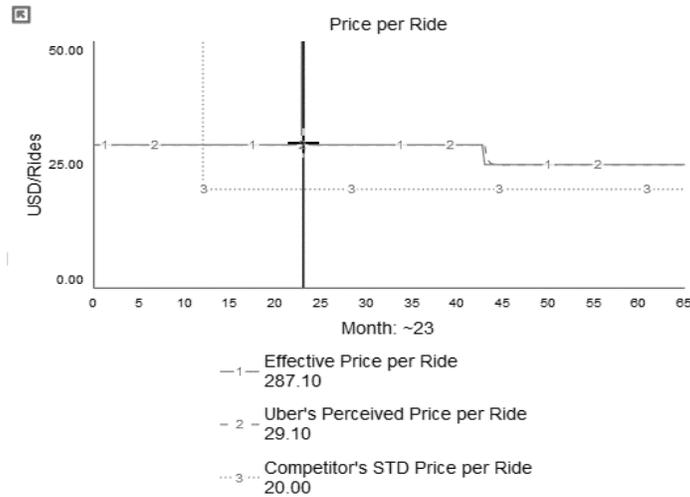
**Figure 12: Behavior of Uber Drivers and Active Drivers**



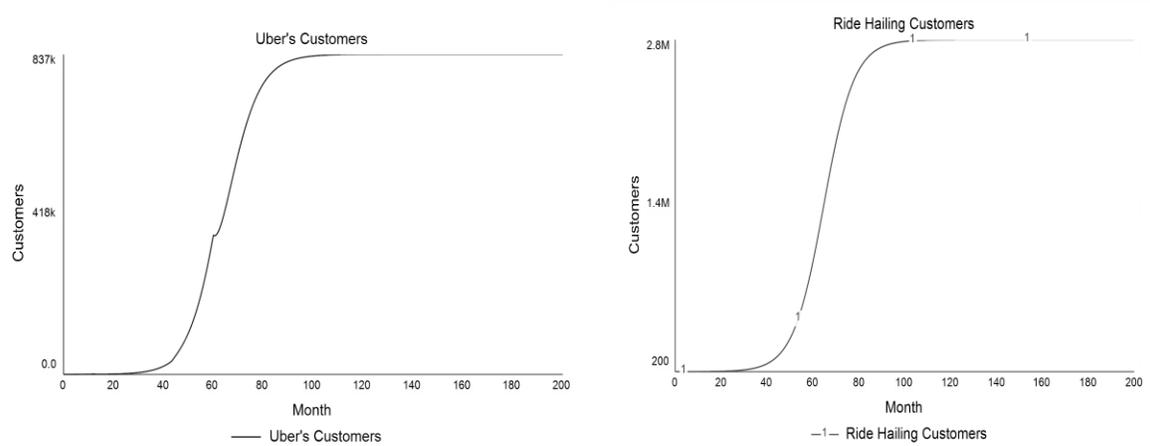
**Figure 13: Behavior of Financial Performance Indicators**



**Figure 14: Response in Uber’s Market Share**



**Figure 15: Uber’s Service Price per Ride**

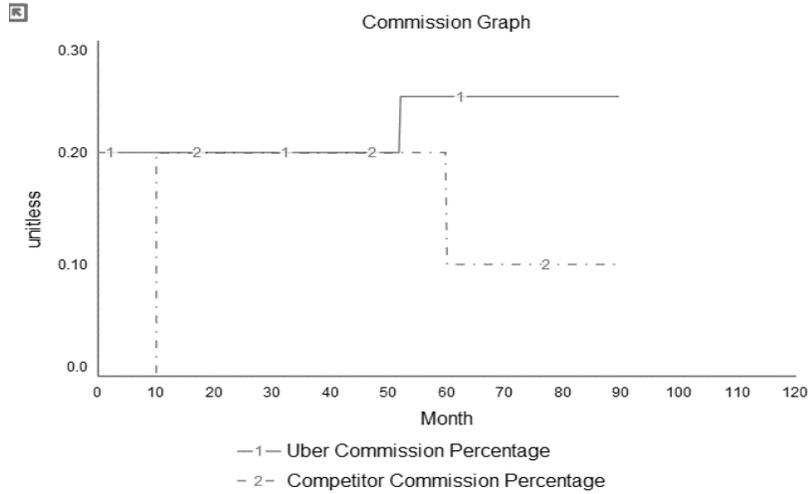


**Figure 16: Market Saturation**

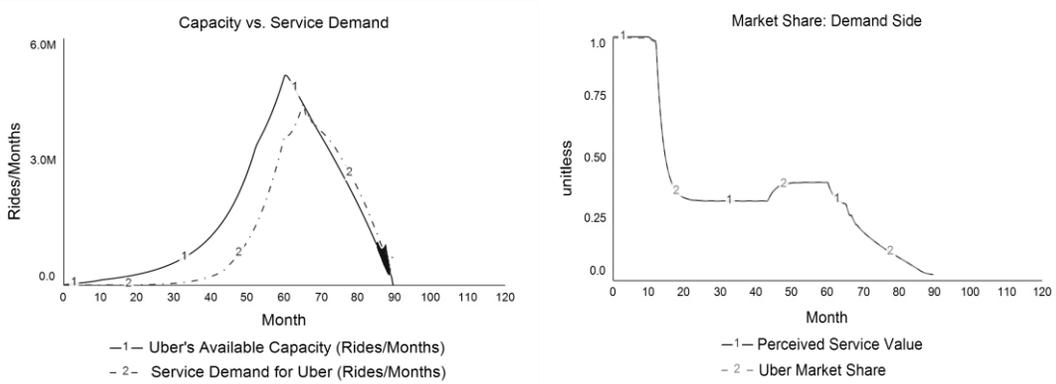
to %10 in May 2016. If Uber will not react to it and just let its commission percentage as it is, this company loses its drivers and, therefore, also loses service capacity, and ultimately will go out of the business due to further decrease in service demand. Figure 18 shows dramatic change of Uber’s service capacity and demand. Therefore, Uber loses its entire market share and will go out of the business in NYC. This simulation results can be used to argue that the model produces realistic system behavior in such a case.

**2. When Competitor Cuts Service Price.**

Competitor cuts its Service Price per Ride at time = 80 months for \$10 (Figure 19). In this scenario, If Uber does not react to competitor’s cut in service price, it loses large portion of customers reflected in Uber’s loss in market share (Figure 20).



**Figure 17: Change in Commission Percentage**



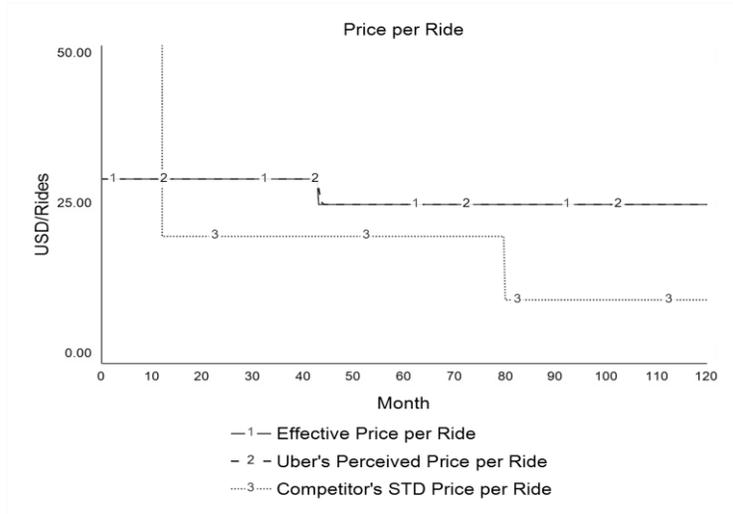
**Figure 18: Uber's loss of service capacity and market share**

## Policy Analysis

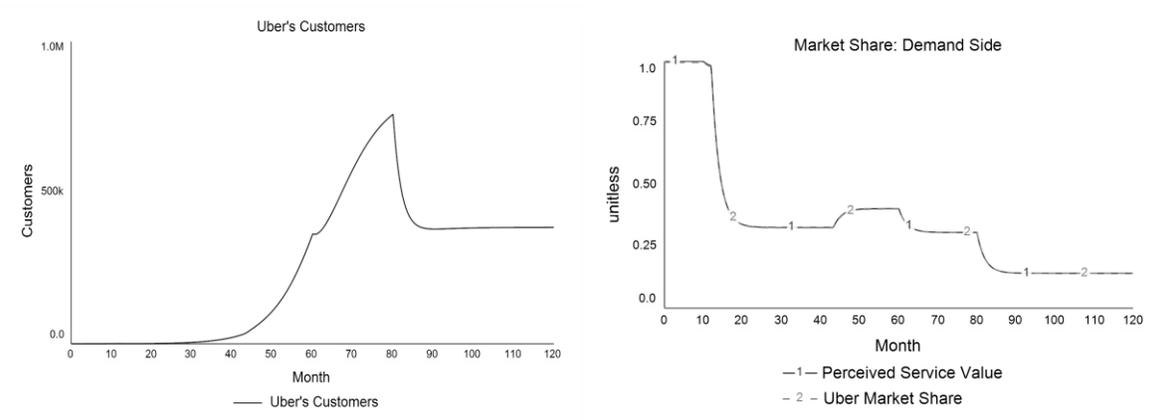
In this section, policies for each scenario case is presented and explained:

### 1. Policy for Scenario of War on Commission

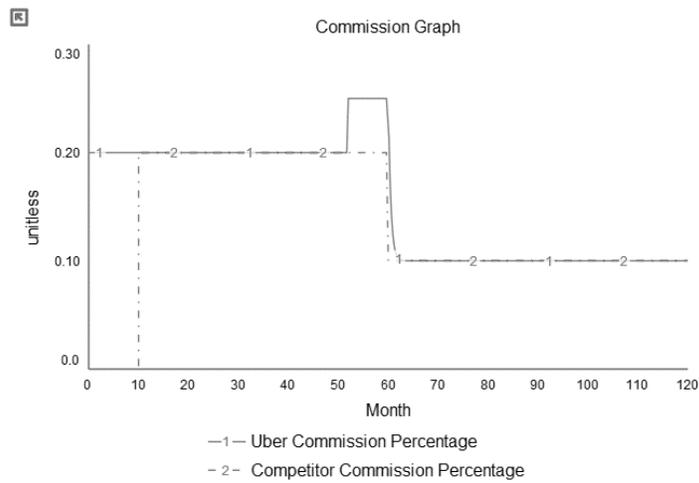
Suppose that we introduce a policy where Uber adjusts “commission percentage” in response to a change in competitor’s commission. In scenario 1, at time = 60 months, as competitor cuts its commission from 20% to 10%, Uber perceives such move in competitor and adjusts its commission with a small delay.



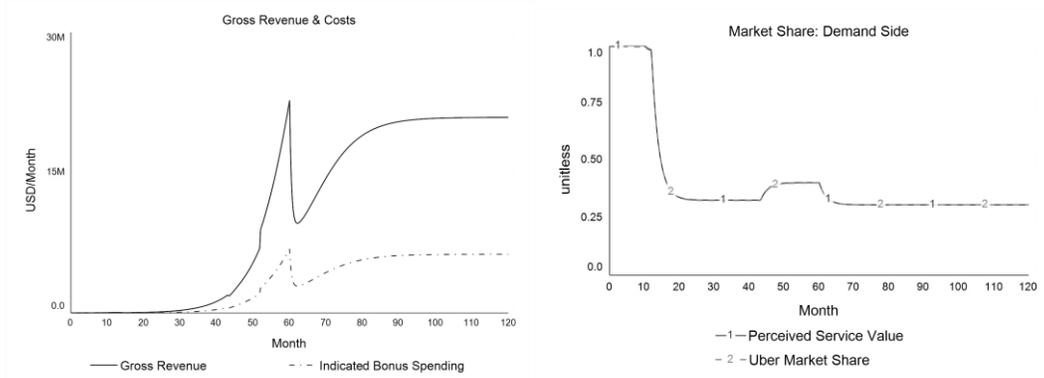
**Figure 19: War on Service Price per Ride**



**Figure 20: Competitor's cut in Service Price takes customer from Uber**



**Figure 21: War on Commission Percentage**

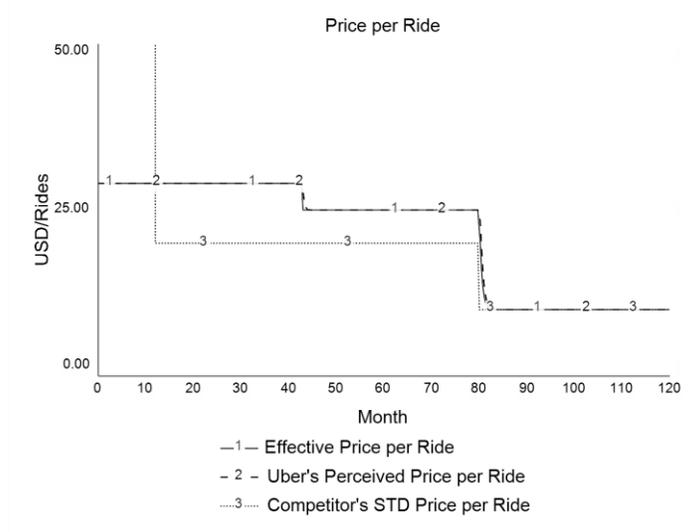


**Figure 22: Behavior of gross revenue and market share during War on Commission**

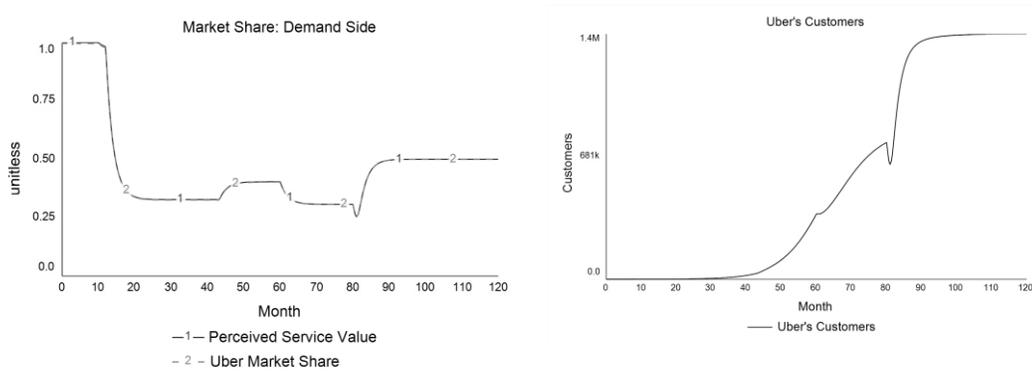
## 2. Policy for Scenario of War on Service Price

We note that for this policy, commission ratio of Uber and its main competitor set to be equal; otherwise, one of them will go out of business very soon.

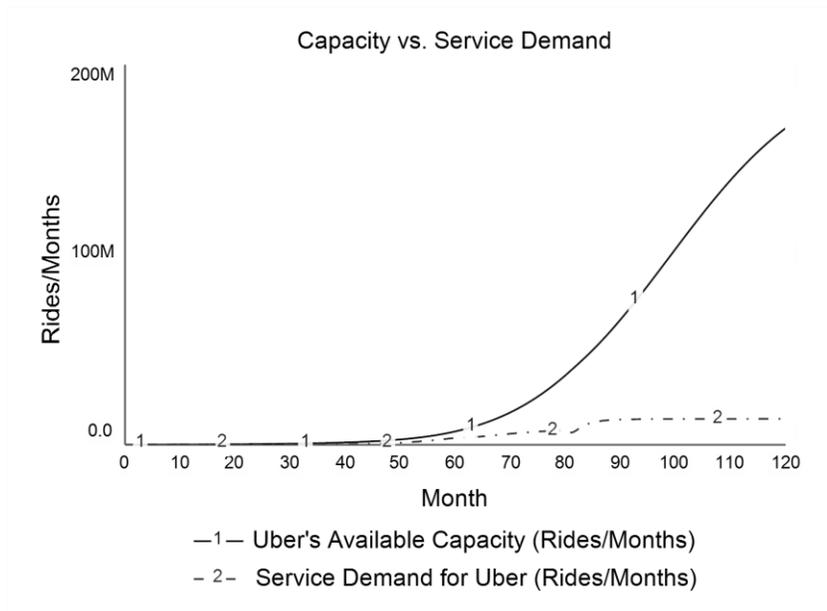
This policy is a reactive policy since Uber adjusts its service price in response to a cut in competitor's price. This policy structure is so-called **War on Service Price**. As a result of this policy, Uber will be able to keep its customers who have remained interested in using Uber (Figure 24). Another interesting consequence is the reaction of Uber's drives to this policy by showing less on the streets and as a result, decreasing the capacity for Uber platform (Figure 25).



**Figure 23: War on Service Price per Ride**



**Figure 24: Uber’s customers’ reaction to policy of cutting service price**



**Figure 25: Uber’s driver’ reaction to policy of cutting service price**

### Concluding Remarks

This paper aims to explore how the dynamic performance management approach could be applied to a case study of Uber Inc. in NYC and to further explore how such a methodology helps to capture holistic view of performance management inherently embedded in complex system. First, the model structure is briefly presented with the help of Dynamic Performance Management Chart to foster understandings of the relationship between performance drives and end results; those end results in turn affect strategic resources of the firm. Then, underlying structure of business system is analyzed and illustrated. The model assumes the word of mouth diffusion mechanism for both customer acquisition and driver-partnership structure of the model. Our default case scenario

showed exponential growth of the ride-hailing service industry and number of Uber driver-partners. The behavior is consistent with what has been observed in the real world. Based on the same explanatory model and assumptions, 2 scenario cases and policies to each scenario examined. Each scenario case produced different behaviors, including the worst case of bankruptcy.

Furthermore, limitations in the model are also highlighted, indicating rooms for further improvements in our current research. Particularly, it is an important question to ask whether any policy is sustainable or not. In this respect, one of our limitations would be that our scenario and policy analysis suffers from lack of financial structure.

Our research particularly contributes to the relatively less explored research domain of ride-hailing service market. It provides a holistic view to such a rising on-demand economy and hypothetical mechanisms which explain the rapid growth behind the business. We acknowledge that our model is simplified due to the lack of credible data, but we believe that the real value of our approach would be realized when business people who are working closely within the system every day, incorporate a similar approach with a more detailed managerial task.

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## Appendix 2: Model Documentation

Adaption Fraction = 0.005

UNITS: unitless

DOCUMENT: Our Assumption

Adaption Fraction by WoM = 0.0041

UNITS: unitless

DOCUMENT: Our Assumption

Average Monthly Working Hours = 15600

UNITS: Minutes/Month

DOCUMENT: {60 minutes = 1 hour, 65 hours/week per driver\* 4 weeks/month, 60\*65\*4 = 15600}

Average Preparation Time = ½

UNITS: Months

DOCUMENT: {4 month /2 weeks} {We assume that it takes 2 weeks to pass the background and vehicle check}

Average Time to Make Decision = 5

UNITS: Minutes

DOCUMENT: Our Assumption

Awaiting Drivers(t) = Awaiting Drivers(t - dt) + (Tempting Drivers - Becoming Drivers) \* dt

INIT Awaiting Drivers = INITIAL Awaiting Drivers

UNITS: Drivers

INFLOWS:

Tempting Drivers = (Contacts Between Potential Drivers and Uber Drivers\*Adaption Fraction by WoM + Transition Realized by

Bonus)\*Effect of Commission on Tempting Drivers

UNITS: Drivers/Months

OUTFLOWS:

Becoming Drivers = Awaiting Drivers/Average Preparation Time

UNITS: Drivers/Month

DOCUMENT: limited capacity for mentioned checks

Bonus Effectiveness = 0.0003

UNITS: Drivers/USD

DOCUMENT: Our Assumption

Bonus Incentives Spending Percentage = 0.3

UNITS: unitless

DOCUMENT: Our Assumption

Bonus Spending(t) = Bonus Spending(t - dt) + (Change in Bonus Spending) \* dt

INIT Bonus Spending = INITIAL Bonus Spending

UNITS: USD/Month

INFLOWS:

Change in Bonus Spending = (Indicated Bonus Spending-Bonus Spending)/Bonus Spending Adjustment Time

UNITS: USD/Month/Month

Bonus Spending Adjustment Time = 1

UNITS: Months

DOCUMENT: Our Assumption

Capacity Demand Ratio = Uber's Available Capacity/Service Demand for Uber

UNITS: unitless

Commission Adjustment Time = 0.5

UNITS: Months

DOCUMENT: Our Assumption

Commission Goal = Effect of Indicated Coverage Ratio on Commission

UNITS: unitless

Competitor Commission Percentage = REAL DATA Competitor Commission + Scenario1 Competitor's Commission Changes\*Scenario1 Switch

UNITS: unitless

DOCUMENT: <http://www.theverge.com/2016/5/12/11664422/gett-commissions-ride-hail-new-york-city>

Competitor Pickup Time = REAL DATA Competitor PT + Scenario2 Competitor's Pickup Time Changes\*Scenario2 Switch

UNITS: Minutes

DOCUMENT: Since May 2016 (month 60 in our model), "Lyft has halved its average wait time for a ride in New York from six minutes to three minutes". <http://fortune.com/2016/03/08/lyft-vs-uber-new-york/>

Competitor's Standard Price per Ride = REAL DATA Competitor Price + Scenario3 War on Price Parameters\*Scenario3 Switch

UNITS: USD/Rides

DOCUMENT: <https://en.wikipedia.org/wiki/Gett> and <http://mashable.com/2012/06/07/gettaxi/>

Contact Frequency of Drivers = 18

UNITS: 1/Month

DOCUMENT: Our Assumption

Contact Frequency of Ride Hailing Customer = 30

UNITS: 1/Month

DOCUMENT: Our Assumption

Contacts Between Potential and Ride Hailing Customer = Fraction of Potential Customers\*Total Contacts by Ride Hailing Customer

UNITS: Customers/Months

Contacts Between Potential Drivers and Uber Drivers = Total Contacts by Uber Drivers\*Fraction of Potential Drivers

UNITS: Drivers/Months

Demand Capacity Ratio = Service Demand for Uber/Uber's Available Capacity

UNITS: unitless

Effect of Commission on Drivers Attrition = GRAPH(Relative Commission)

(0.000, 0.1), (0.250, 0.3), (0.500, 0.4), (0.750, 0.6), (1.000, 1.0), (1.250, 50.0), (1.500, 100.0), (1.750, 150.0), (2.000, 200.0), (2.250, 250.0), (2.500, 300.0), (2.750, 400.0), (3.000, 500.0)

UNITS: unitless

DOCUMENT: The logic here is that as competitor offers less commissions (more gain for Drivers), more and more drivers leave Uber and join its competitor.

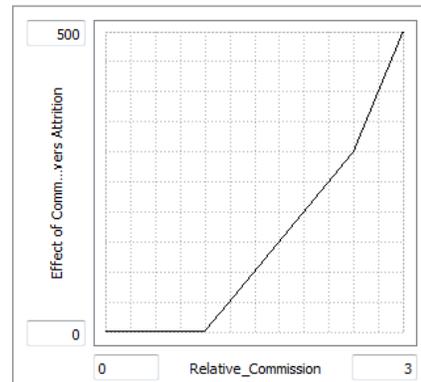


Figure A1: Effect of Commission on Drivers Attrition

Effect of Commission on Tempting Drivers = GRAPH(Relative Commission)

(0.000, 2.000), (0.200, 2.000), (0.400, 1.930), (0.600, 1.825), (0.800, 1.572), (1.000, 1.000), (1.200, 0.611), (1.400, 0.419), (1.600, 0.288), (1.800, 0.148), (2.000, 0.070)

UNITS: unitless

DOCUMENT: The logic here is that as competitor offers less commissions (more gain for Drivers), it becomes more difficult to tempt drivers to join Uber.

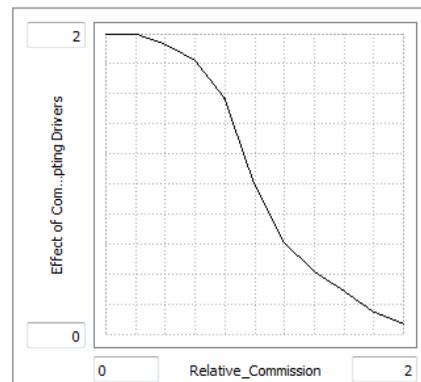


Figure A2: Effect of Commission on Tempting Drivers

Effect of Demand Capacity Ratio on Pickup Time = GRAPH(Demand Capacity Ratio)

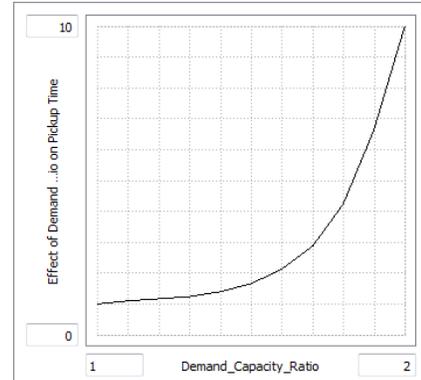
(1.000, 1.00), (1.100, 1.10), (1.200, 1.17), (1.300, 1.24), (1.400, 1.40), (1.500, 1.66), (1.600, 2.14), (1.700, 2.88), (1.800, 4.25), (1.900, 6.65), (2.000, 10.00)

UNITS: unitless

DOCUMENT: An assumption behind this effect is that when service demand becomes (for example, twice as) higher than service delivery capacity of Uber, *Effective Pickup Time* becomes nearly ten times longer than normal time. In other words, having twice as service

demand than service capacity does not simply mean that Uber’s pickup time becomes twice of normal times. In fact, we assumed the effect would be much stronger until it hits certain threshold<sup>9</sup>. Our reasoning is as follows: When the service demand for Uber at a specific period is twice as many as what the company can deliver, each Uber driver in NYC has two people waiting for a ride at the same time. But some of the drivers need to refill the gas or even they may get into traffic jam, etc. Therefore, the effect should be increasingly stronger as *Demand-Capacity* ratio increases.

Why the maximum is the specific value of 10? Because this is the period between the moment a customer hails a ride and the driver arrives. In NYC, considering the number of available Uber driver, we assume that it will not exceed Uber’s MIN Pickup Time (= 3 minutes) \* Max value of the Effect (= 10) = 30 minutes.<sup>10</sup>



**Figure A3: Effect of Demand Capacity Ratio on Pickup Time**

Effect of Indicated Coverage Ratio on Commission = GRAPH(Indicated Capacity Demand Ratio)

(0.000, 0.2000), (2.000, 0.0100)

UNITS: unitless

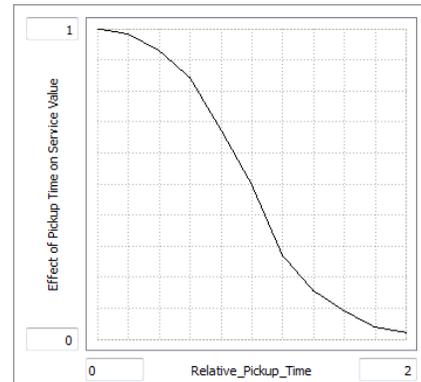
DOCUMENT: Our Assumption

Effect of Pickup Time on Service Value = GRAPH(Relative Pickup Time)

(0.000, 1.000), (0.200, 0.983), (0.400, 0.930), (0.600, 0.843), (0.800, 0.677), (1.000, 0.500), (1.200, 0.271), (1.400, 0.157), (1.600, 0.092), (1.800, 0.039), (2.000, 0.022)

UNITS: unitless

INPUT = Relative Waiting Time



**Figure A4: Effect of Pickup Time on Service Value**

<sup>9</sup> Specifically, the maximum value is set to be 10.

<sup>10</sup> For example, Uber car hailing service can be considered as a super-efficient version of ambulance in a sense that many available cars are ready at a specific moment in NYC.

DOCUMENT: The assumption made behind this structure is that the longer Uber drivers make their customers wait, the more they lose market share (to its competitors such as Gett, Lyft, Yellow cab). The degree of the effect is subjective since, on the shadow of lack of information, we have not conducted regression analysis whatsoever. However, the curve of the graphical function is determined by our logics based on our mental model. The horizontal line in the graph means that there will be no effect if “Relative Pickup time” is 1.

Effect of Price on Service Value = GRAPH(Relative Price)

(0.000, 1.000), (0.200, 0.983), (0.400, 0.930), (0.600, 0.843), (0.800, 0.677), (1.000, 0.500), (1.200, 0.271), (1.400, 0.157), (1.600, 0.092), (1.800, 0.039), (2.000, 0.022)

UNITS: unitless

DOCUMENT: Our Assumption

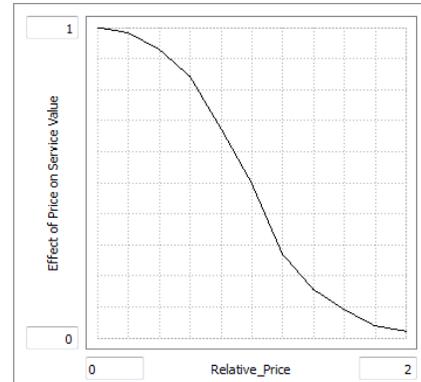


Figure A5: Effect of Price on Service Value

Effect of Price Threshold Ratio on Closing App = (Price Threshold Ratio/10) - 0.1

UNITS: unitless

DOCUMENT:

Threshold	/ 10	- 0.1	=
1	0.1	0.1	0
2	0.2	0.1	0.1
3	0.3	0.1	0.2
4	0.4	0.1	0.3
5	0.5	0.1	0.4
6	0.6	0.1	0.5
7	0.7	0.1	0.6
8	0.8	0.1	0.7
9	0.9	0.1	0.8
9	0.9	0.1	0.8
10	1	0.1	0.9

Figure A6: Effect of Price Threshold Ratio on Closing App

Effect of Price Threshold Ratio on Active Drivers = GRAPH(Price Threshold Ratio {We assume that in normal situation, price ratio of 1 leads to 40% of drivers availability})

(0.00, 0.000), (1.00, 0.400), (2.00, 0.502), (3.00, 0.590), (4.00, 0.664), (5.00, 0.721), (6.00, 0.790), (7.00, 0.834), (8.00, 0.882), (9.00, 0.921), (10.00, 0.978)

UNITS: unitless

DOCUMENT: This effect is used to describe the change in active Uber drivers when service price increase and becomes higher than normal rates. When Uber drivers see service rate is surging, more and more drivers start turning on their car engines and become involved actively. This concept of rise in service capacity is observed in real case study. A case study of Hall, Kendrick and Nosko (2015) shows that the service capacity can get to be 150% higher than normal times during surge period in the event of sold-out musical concert in NYC. {We assume that in normal situation, price ratio of 1 leads to 40% of drivers' availability}

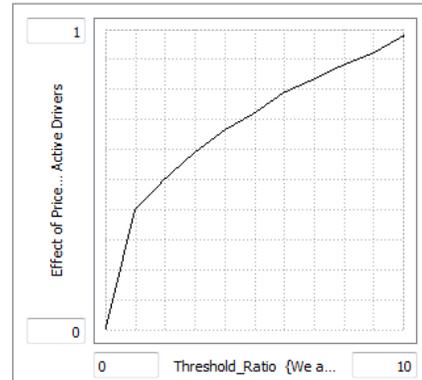


Figure A7: Effect of Threshold Ratio on Active Drivers

Effect of Service Value on Customer Acquisition = Perceived Service Value

UNITS: unitless

DOCUMENT: This variable is an intermediate one and it is equal to Perceived Service Value.

Effective Price per Ride = Uber's Normal Price per Ride\*Surge Pricing Effect

UNITS: USD/Rides

Fraction of Potential Customers = Potential Customers/Total Ridership

UNITS: unitless

Fraction of Potential Drivers = Potential Drivers/Total Drivers

UNITS: unitless

Fraction of Uber's Active Drivers = Effect of Price Threshold Ratio on Drivers

UNITS: unitless

Gross Revenue = Uber Commission Percentage\*Giving a Ride\*Uber's Perceived Price per Ride

UNITS: USD/Month

Indicated Bonus Spending = Gross Revenue\*Bonus Incentives Spending Percentage

UNITS: USD/Month

Indicated Capacity Demand Ratio = Policy4 Desired Capacity Demand Ratio - Capacity Demand Ratio

UNITS: unitless

Indicated Uber's Customers = Ride Hailing Customers\*Effect of Service Value on Customer Acquisition

UNITS: Customers

INITIAL Awaiting Drivers = 0

UNITS: Drivers

INITIAL Bonus Spending = 10\*26850 {10 Bonus \* Average price of new passenger cars sold and leased in 2010}

UNITS: USD/Month

DOCUMENT: Average price of new passenger cars sold and leased, in 2010: 26850 USD

<http://www.statista.com/statistics/183745/average-price-of-us-new-and-used-vehicle-sales-and-leases-since-1990/>

INITIAL On Decision = 1

UNITS: Rides

INITIAL On Service = 0

UNITS: Rides

INITIAL POTENTIAL DRIVERS = 51398 + 1400000

UNITS: Drivers

DOCUMENT:

*As of March 14, 2014, in New York City, there were 51,398 men and women licensed to drive medallion taxicabs.*

*There were 13,605 taxicab medallion licenses in existence, 368 of them having been auctioned by the City of New*

*York between November 2013 and February 2014.*

[https://en.wikipedia.org/wiki/Taxicabs\\_of\\_New\\_York\\_City](https://en.wikipedia.org/wiki/Taxicabs_of_New_York_City)

“According to the data, only 1.4 million households in the City out of the total 3.0 million owned a car”

(<http://www.nycedc.com/blog-entry/new-yorkers-and-cars>) Here, in our model, we ignore the fact that some car owners may have more than one car!

INITIAL POTENTIAL Customers = 8175133/3

UNITS: Customers

DOCUMENT: 8175133 Initial population of NY City in 2010; we assume that just one third of them are potential customers

<http://www1.nyc.gov/site/planning/data-maps/nyc-population/current-future-populations.page>

INITIAL PT = 3

UNITS: Minutes

INITIAL Requested Rides = 1

UNITS: Rides

INITIAL Ride Hailing Customers = 200

UNITS: Customers

INITIAL Uber Commission Percentage = 0.2

UNITS: unitless

INITIAL Uber Drivers = 100

UNITS: Drivers

INITIAL UBER PRICE per RIDE = 29 {We assume it is equal to INITIAL Uber's Normal Price per Ride.}

UNITS: USD/Rides

INITIAL Uber's Normal Price per Ride = 29

UNITS: USD/Rides

DOCUMENT:

After Jan 2016:

\$2.55 Base Fare + \$0.35 per minutes \*30 minutes + \$1.75 per mile \* 6.5 miles from Manhattan to East Brooklyn  
= \$24.425  $\approx$  25

(<http://www.ridesharingdriver.com/how-much-does-uber-cost-uber-fare-estimator/> and <http://uberestimate.com/prices/New-York-City/>)

Before Jan 2016:

\$3.00 Base Fare + \$0.40 per minutes \*30 minutes + \$2.15 per mile \* 6.5 miles from Manhattan to East Brooklyn  
= \$28.975  $\approx$  29

“Uber is slashing prices in New York City The base fare on UberX will go from \$3 to \$2.55, with the per mile rate going from \$2.15 to \$1.75. The per minute rate will go from \$0.40 to \$0.35. UberXL will see drops of similar levels.”

(<http://www.theverge.com/2016/1/28/10864516/uber-cutting-uberx-rates-new-york-city>)

Matched Rides(t) = Matched Rides(t - dt) + (Requesting a Ride - Free Cancellation - Ride Arriving) \* dt

INIT Matched Rides = INITIAL Requested Rides

UNITS: Rides

INFLOWS:

Requesting a Ride = On Decision/(Average Time to Make Decision/Time Converter)

UNITS: Rides/Months

OUTFLOWS:

Free Cancellation = SMTH1(Requesting a Ride\*0.001, 5/Time Converter)\*0 + 0

UNITS: Rides/Months

Ride Arriving = MIN(Matched Rides/(Uber's Average Pickup Time/Time Converter), Uber's Available Capacity)

UNITS: Rides/Months

Normal Regreters per Month = 5

UNITS: Customers/Month

$\text{On Decision}(t) = \text{On Decision}(t - dt) + (\text{Opening App} - \text{Requesting a Ride} - \text{Closing App Crazy Prices} - \text{Discarding Late Services}) * dt$

INIT On Decision = INITIAL On Decision

UNITS: Rides

INFLOWS:

Opening App = Service Demand for Uber

UNITS: Rides/Months

OUTFLOWS:

Requesting a Ride =  $\text{On Decision} / (\text{Average Time to Make Decision} / \text{Time Converter})$

UNITS: Rides/Months

Closing App Crazy Prices =  $\text{Opening App} * \text{Effect of Price Threshold Ratio on Closing App}$

UNITS: Rides/Months

Discarding Late Services = IF (Uber's Effective Pickup Time > 60) THEN SMTH1((Opening App - Requesting a Ride), 1/30)

ELSE 0 {If effective waiting time exceeds 1Hours (= 60 minutes), customers cancel their rides (requests)}

UNITS: Rides/Months

$\text{On Service}(t) = \text{On Service}(t - dt) + (\text{Ride Arriving} - \text{Giving a Ride}) * dt$

INIT On Service = INITIAL On Service

UNITS: Rides

INFLOWS:

Ride Arriving =  $\text{MIN}(\text{Matched Rides} / (\text{Uber's Average Pickup Time} / \text{Time Converter}), \text{Uber's Available Capacity})$

UNITS: Rides/Months

OUTFLOWS:

Giving a Ride =  $\text{On Service} / (\text{Standard Riding Time} / \text{Time Converter})$

UNITS: Rides/Months

Perceived Price Adjustment Time = 1/4 {about a week}

UNITS: Months

$\text{Perceived Service Value}(t) = \text{Perceived Service Value}(t - dt) + (\text{Change in Perceived SV}) * dt$

INIT Perceived Service Value = Service Value

UNITS: unitless

INFLOWS:

Change in Perceived SV = (Service Value - Perceived Service Value)/Time to Change Perceives

UNITS: 1/month

Pickup Time Weight = 0.25

UNITS: unitless

Policy1 Switch = IF TIME > 80 THEN 1\*0 ELSE 0 {0 = off, 1 = on} {Change 1\*0 to 1 to activate this switch} {Tnis scenario is very sensitive to time, if it is activated late, company will fail; here 80 is too much!}

UNITS: unitless

Policy2 Change in MIN Pickup Value = -1

UNITS: Minutes

Policy2 Switch = 0 {0 = off, 1 = on}

UNITS: unitless

Policy2 Time = 80 {month}

UNITS: Months

DOCUMENT: Timing of policy implementation has significant effect on the performance of the business; Test these values: Change in MIN Waiting Time = -3; Policy2 Time = 1 vs 30

Policy3 Adjustment Time = 1/2 {half a month}

UNITS: Months

Policy3 Switch = IF TIME > 80 THEN 1\*0 ELSE 0 {0 = off, 1 = on} {Change 1\*0 to 1 to activate this switch}

UNITS: unitless

Policy4 Desired Capacity Demand Ratio = 3

UNITS: unitless

Policy4 Switch = IF TIME > 70 THEN 1\*0 ELSE 0 {0 = off, 1 = on} {Change 1\*0 to 1 to activate this switch}

UNITS: unitless

Potential Customers(t) = Potential Customers(t - dt) + (Net Change in Potential Customers + Regreters - New Customers) \* dt

INIT Potential Customers = INITIAL POTENTIAL Customers

UNITS: Customers

DOCUMENT: An important assumption: We assume that the population of the NY City is constant during the 5 years period of simulation.

INFLOWS:

Net Change in Potential Customers = 0

UNITS: Customers/Months

Regreters = Surge Pricing Effect\*Normal Regreters per Month

UNITS: Customers/Months

OUTFLOWS:

New Customers = Contacts Between Potential and Ride Hailing Customer\*Adaption Fraction

UNITS: Customers/Months

Potential Drivers(t) = Potential Drivers(t - dt) + (Drivers Leaving Uber + Net Change in Potential Drivers - Tempting Drivers) \* dt

INIT Potential Drivers = INITIAL POTENTIAL DRIVERS

UNITS: Drivers

INFLOWS:

Drivers Leaving Uber = Standard Drivers Attrition\*Effect of Commission on Drivers Attrition

UNITS: Drivers/Month

Net Change in Potential Drivers = 0

UNITS: Drivers/Months

OUTFLOWS:

Tempting Drivers = (Contacts Between Potential Drivers and Uber Drivers\*Adaption Fraction by WoM + Transition Realized by Bonus)\*Effect of Commission on Tempting Drivers

UNITS: Drivers/Months

Price Threshold Ratio = SMTH1(Effective Price per Ride/Uber's Normal Price per Ride, DT, 1) {smoothing time = one DT}

UNITS: unitless

Price Weight = 0.75

UNITS: unitless

REAL DATA Competitor Commission = 10000 + STEP(-10000+0.2, 10) + STEP(-0.1, 60) {To make sure that before arrival of our first competitor in March 2012 (Month 10), all of market share goes to Uber}

UNITS: unitless

REAL DATA Competitor Price = 10000 + STEP(-10000+20, 12) {To make sure that before arrival of our first competitor in March 2012 (Month 10), all of market share goes to Uber} {we assume Gett entered the NYC market with \$20 per ride}

UNITS: USD/Rides

REAL DATA Competitor PT = 10000 + STEP(-10000+6, 10) + STEP(-3, 60) {To make sure that before arrival of our first competitor in March 2012 (Month 10), all of market share goes to Uber}

UNITS: Minutes

DOCUMENT:

*Since May 2016 (month 60 in our model), Lyft has halved its average wait time for a ride in New York from six minutes to three minutes, the spokesperson added by way of explaining the 500% ridership growth. Both Lyft and Uber have also been aggressively slashing their prices in New York and other cities as they compete with each other to win customers. <http://fortune.com/2016/03/08/lyft-vs-uber-new-york/>*

REAL DATA Uber Commission = PULSE(0.05, 52, 0) {in September 2015, increased to 25%; September 2015 = Month 52 in our model}

UNITS: 1/month

REAL DATA Uber Price = PULSE(-4, 43, 0)

UNITS: USD/Rides/Month

DOCUMENT: in Jan. 2016, Uber slashed its prices by 15% in NYC and some other markets. Jan 2016 = Month 43 in our model.

Relative Commission = Uber Commission Percentage/Competitor Commission Percentage

UNITS: unitless

Relative Pickup Time = Uber's Perceived Pickup Time/Competitor Pickup Time

UNITS: unitless

Relative Price = Uber's Perceived Price per Ride/Competitor's Standard Price per Ride

UNITS: unitless

Reported Uber's Customers(t) = Reported Uber's Customers(t - dt) + (Change in UC) \* dt

INIT Reported Uber's Customers = Indicated Uber's Customers

UNITS: Customers

INFLOWS:

Change in UC = (Indicated Uber's Customers-Reported Uber's Customers)/Reporting Time

UNITS: Customers/Months

Reporting Time = 1

UNITS: Months

Ride Hailing Customers(t) = Ride Hailing Customers(t - dt) + (New Customers - Regreters) \* dt

INIT Ride Hailing Customers = INITIAL Ride Hailing Customers

UNITS: Customers

INFLOWS:

New Customers = Contacts Between Potential and Ride Hailing Customer\*Adaption Fraction

UNITS: Customers/Months

OUTFLOWS:

Regreters = Surge Pricing Effect\*Normal Regreters per Month

UNITS: Customers/Months

Scenario1 Competitor's Commission Changes = STEP(-0.09, 80) {Change in Value, Time in Month}

UNITS: unitless

Scenario1 Switch = IF TIME > 70 THEN 1\*0 ELSE 0 {0 = off, 1 = on} {Change 1\*0 to 1 to activate this switch}

UNITS: unitless

Scenario2 Competitor's Pickup Time Changes = STEP(-3, 100) {Change in Value, Time in Month}

UNITS: Minutes

Scenario2 Switch = 0 {0 = off, 1 = on}

UNITS: unitless

Scenario3 Switch = IF TIME > 80 THEN 1\*0 ELSE 0 {0 = off, 1 = on} {Change 1\*0 to 1 to activate this switch}

UNITS: unitless

Scenario3 War on Price Parameters = STEP(-10, 80) {Change in Value, Time in Month}

UNITS: USD/Rides

Service Demand for Uber = Reported Uber's Customers\*Standard Rides Need per Customer

UNITS: Rides/Months

Service Value = Price Weight\*Effect of Price on Service Value + Pickup Time Weight\*Effect of Pickup Time on Service Value

UNITS: unitless

Shock Test Switch = 0 {0 = off, 1 = on}

UNITS: unitless

Shock Time = 23 {month}

UNITS: Months

Shock Value = 0.1 {The Pulse Value is very sensitive to DT. So, a tiny value of 0.1 will be divided by DT = 0.0001 which result in 100}

UNITS: Rides/Customers

Standard Driver per Ride = 1

UNITS: Drivers/Rides

Standard Drivers Attrition = 5

UNITS: Drivers/Month

Standard Rides Need per Customer =  $10 + \text{PULSE}(\text{Shock Value}, \text{Shock Time}, 0) * \text{Shock Test Switch}$

UNITS: Rides/Months/Customers

DOCUMENT: 10 rides per week, 4 weeks in a month {The Pulse Value is very sensitive to DT. So, a tiny value of 0.1 will be divided by  $DT = 0.0001$  which result in 100}

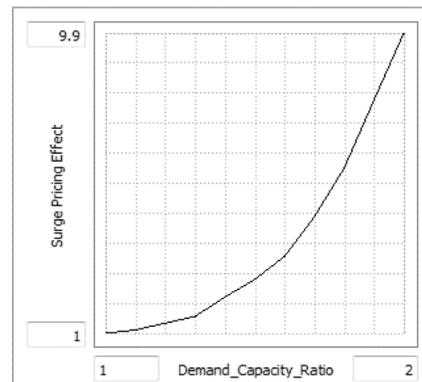
Standard Riding Time = 45 {0.75 hours = 45 minutes}

UNITS: Minutes

Surge Pricing Effect = GRAPH(Demand Capacity Ratio)

(1.000, 1.000), (1.100, 1.100), (1.200, 1.300), (1.300, 1.500), (1.400, 2.074), (1.500, 2.598), (1.600, 3.279), (1.700, 4.459), (1.800, 5.897), (1.900, 7.918), (2.000, 9.900)

UNITS: unitless



**Figure A8: Surge Pricing Effect (Effect of Demand Capacity Ratio on Service Price)**

DOCUMENT:

When the demand for Uber rides peaks, Uber applies a policy called surge pricing. This happens when demand increases largely. However, the algorithm for this policy is not revealed. Information reveals that it can be 2.8x or even 7x of normal rates on New Year's Eve in 2011 (Moon, 2016). At times, it can go even further:

*Surge pricing is one of Uber's most widely hated features. Just look at social media the day after any big holiday and you'll see a flood of screenshots complaining of rates up to 9.9 times the company's normal price. (Kulp, 2016).*

Based on this information, we assumed that company's surging price algorithm features a quite steep slope when demand exceeds service capacity as shown in the Figure A8. This effect lies in the center of interaction of supply and demand side of the model.

Time Converter = 43800

UNITS: Minutes/Month

Time to Adjust Perceived Pickup Time = 1/4 {1 weeks / 4 weeks in a month}

UNITS: Months

Time to Change Perceives = 1

UNITS: Months

Total Contacts by Ride Hailing Customer = Contact Frequency of Ride Hailing Customer \* Ride Hailing Customers

UNITS: Customers/Months

Total Contacts by Uber Drivers = Uber's Drivers \* Contact Frequency of Drivers

UNITS: Drivers/Months

Total Drivers = Potential Drivers + Uber's Drivers

UNITS: Drivers

Total Ridership = Potential Customers + Ride Hailing Customers

UNITS: Customers

Transition Realized by Bonus = Fraction of Potential Drivers \* Bonus Spending \* Bonus Effectiveness

UNITS: Drivers/Months

Uber Commission Percentage(t) = Uber Commission Percentage(t - dt) + (Change in Commission Percentage) \* dt

INIT Uber Commission Percentage = INITIAL Uber Commission Percentage

UNITS: unitless

DOCUMENT: <http://www.forbes.com/sites/ellenhuet/2015/09/11/uber-raises-uberx-commission-to-25-percent-in-five-more-markets/>

INFLOWS:

Change in Commission Percentage = REAL DATA Uber Commission + Policy4 Switch\*(Commission Goal-Uber Commission Percentage)/Commission Adjustment Time + Policy1 Switch\*War on Commission/Commission Adjustment Time

UNITS: 1/Month

Uber Market Share = Indicated Uber's Customers/Ride Hailing Customers

UNITS: unitless

Uber's Active Drivers = Uber's Drivers\*Fraction of Uber's Active Drivers

UNITS: Drivers

Uber's Available Capacity = ((Uber's Active Drivers/Standard Driver per Ride)\*Average Monthly Working Hours)/Standard Riding Time

UNITS: Rides/Months

Uber's Average Pickup Time = Uber's MIN Pickup Time\*Effect of Demand Capacity Ratio on Pickup Time

UNITS: Minutes

Uber's Drivers(t) = Uber's Drivers(t - dt) + (Becoming Drivers - Drivers Leaving Uber) \* dt

INIT Uber's Drivers = INITIAL Uber Drivers

UNITS: Drivers

INFLOWS:

Becoming Drivers = Awaiting Drivers/Average Preparation Time

UNITS: Drivers/Month

DOCUMENT: Later we may add more details: limited capacity for mentioned checks

OUTFLOWS:

Drivers Leaving Uber = Standard Drivers Attrition\*Effect of Commission on Drivers Attrition

UNITS: Drivers/Month

Uber's Effective Pickup Time = (Matched Rides/Ride Arriving)\*Time Converter

UNITS: Minutes

Uber's MIN Pickup Time = 3 + STEP(Policy2 Change in MIN Pickup Value, Policy2 Time)\*Policy2 Switch

UNITS: Minutes

DOCUMENT: "Uber CEO explains why arrival time on the app is never accurate.... Kalanick said that the average wait time in major cities for an ordered Uber is about 3 minutes." (<http://bgr.com/2016/01/04/uber-arrival-time-late/>)

Uber's Normal Price per Ride(t) = Uber's Normal Price per Ride(t - dt) + (Change in Normal Price) \* dt

INIT Uber's Normal Price per Ride = INITIAL Uber's Normal Price per Ride

UNITS: USD/Rides

INFLOWS:

Change in Normal Price = REAL DATA Uber Price + Policy3 Switch\*(War on Price/Policy3 Adjustment Time)

UNITS: USD/Rides/Month

Uber's Perceived Pickup Time(t) = Uber's Perceived Pickup Time(t - dt) + (Change in Pickup Time) \* dt

INIT Uber's Perceived Pickup Time = INITIAL PT

UNITS: Minutes

INFLOWS:

Change in Pickup Time = (Uber's Effective Pickup Time-Uber's Perceived Pickup Time)/Time to Adjust Perceived Pickup Time

UNITS: Minutes/Month

Uber's Perceived Price per Ride(t) = Uber's Perceived Price per Ride(t - dt) + (Uber's Change in Price) \* dt

INIT Uber's Perceived Price per Ride = INITIAL UBER PRICE per RIDE

UNITS: USD/Rides

INFLOWS:

Uber's Change in Price = (Effective Price per Ride - Uber's Perceived Price per Ride)/Perceived Price Adjustment Time

UNITS: USD/Rides/Month

War on Commission = Competitor Commission Percentage - Uber Commission Percentage

UNITS: unitless

War on Price = Competitor's Standard Price per Ride - Uber's Normal Price per Ride

UNITS: USD/Rides

{The model has 139 variables. Stocks: 15; Flows: 21; Converters: 103; Constants: 47; Equations: 77; Graphicals: 8}