ESSAYS ON DEMAND ESTIMATION

A Dissertation

Presented to

The Faculty of the Department

of Economics

University of Houston

In Partial Fulfillment

Of the Requirements for the Degree of

Doctor of Philosophy

By

Vinh Pham

August, 2018

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Abstract

This dissertation is a collection of two essays in the fields of empirical industrial organization. The overall theme of the dissertation is the estimation of the demand models. The estimated models can be used to study the implications of policy experiments in different industries. The first essay investigates competition in the taxi industry in New York City. With the advance of internet-based mobile technology, ride-hailing services, including Uber, have created new competition in the market that is traditionally dominated by the government-regulated Yellow Cab. Facing with new competition, the government, however, has not changed its pricing of Yellow Cab. What happens to the market if the government decides on different pricing policies is an empirical question. To study it, I adopt a discrete choice model where taxi consumers can choose among products offered by Yellow Cab and Uber, or an outside option. Using a comprehensive Yellow Cab data set, combined with unique Uber data, I estimate the parameters of consumers' utility function. The estimated model is used to assess the changes in the market share of Yellow Cab and Uber in different counter-factual scenarios. I find that a small decrease in Yellow Cab's fare increase its market share significantly. Simulating the effect of recent city regulations, I find that if Uber were banned, Yellow Cab's market share would increase by 9%. I also find that consumers value brand characteristics. If Uber could replicate the characteristics of Yellow Cab, its market share would more than double. In the second chapter, Andrea Szabó and I investigate recent government decisions related to net neutrality rules. Net neutrality rules limit internet providers' ability to change the download speeds of competing online content providers. To understand the impact of such government regulations, we estimate consumer demand for download speed in the video-on-demand market using an original data set. We collect our data using a hypothetical choice experiment in which subjects choose between different platforms for viewing specific video content. Estimating the model using this data, we find that consumers are sensitive to both price and download times. In counterfactual experiments, we find that changes in download times for streaming have large impact on the market share of cable-on-demand. These findings show that a provider of both internet and cable has an incentive to differentiate download speeds in the absence of Net neutrality rules.

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Chapter 1

Government Pricing of Yellow Cab after the Introduction of Uber in New York City

1.1 Introduction

In most cities, the taxi industry is heavily regulated. Governments often authorize a single firm to provide taxi services, and regulate the fares set by this firm. Under these circumstances, price changes tend to be infrequent, and usually do not reflect competitive pressures but rather are driven by factors such as inflation or cabdriver strikes. On the other hand, with the advance of mobile phone-based applications in recent years, ride-hailing services, including Uber, have been on the rise. This creates new competition in the taxi market. What the impact of different government policies would be on the new market? This paper aims to answer this question.

This paper investigates competition and pricing in the Manhattan taxi industry in June 2015. Manhattan offers an ideal setting. First, there is a taxi exclusion zone in Manhattan where only Yellow Cab taxis can pick up street-hailing riders. Other services can only pick up pre-arranged riders in this area. Second, Uber started to grow in New York City in 2014 and brought an unprecedented competition to the market.

According to New York City's Taxi & Limousine Commission - the government agency that directly regulates the taxi industry in the city, Uber has grown dramatically in Manhattan.[1] Third, despite increased competition from Uber, Yellow Cab's fare has remained the same. The last time Yellow Cab adjusted its fare was in 2012, which is before Uber started to gain momentum in New York City. Looking further back, Yellow Cab fare has changed only 16 times over the last 50 years. Taking inflation into account, Yellow Cab's fare has been stable over an extended period of time. Thus, it is interesting to estimate the impact of different government pricing schemes of Yellow Cab.

Studying this question involves two major difficulties. First is the lack of readily available data. To estimate consumer's demand, we need to observe the products that consumers can choose from. In other words, for every Yellow Cab trips, we want to observe the fare of the same trip, but operated by other taxi options. However, the defining aspect of the taxi market is that no matter how comprehensive a dataset is, the trips that could have been chosen, but were not, are never observed.

Fortunately, we can infer the fare of non-existent Uber trips. Uber's application can estimate the fare of any trip if given the starting and ending location. I write a program that obtains from this application the fare of Uber for every Yellow Cab trip in the data set.

The second difficulty is the need to estimate consumers' utility function using data on market shares. To do this, I use the random coefficient discrete choice approach proposed by Berry et al., 1995. In my application, people in neighborhoods of Manhattan choose between differentiated taxi products (trips) offered by Yellow Cab, Uber and an outside option. This model allows for rich heterogeneity in consumer preferences between products. Moreover, it provides an explicit link between the observed market level data and individual preference parameters. Estimating the model allows one to recover these preference parameters.

[1]Uber registered a 275% increase in pickups from June 2014 to June 2015, while taxi pickups declined by 9% over the same period. Uber made 1.4 million more Manhattan pickups in June 2015 than it did in June 2014, while taxis made 1.1 million fewer pickups. However, Uber still accounts for less than 15% of total Manhattan pickups in June 20115.

With the recovered demand parameters, I am able to simulate different counterfactual scenarios. First, Yellow Cab fares are reduced by 10%, the case which would equate average Yellow Cab fares with average Uber fare. If Uber fares are constant, the market share of Yellow Cab increases by about 22% while Uber's market share decreases by 13%. If Uber is allowed to respond to the reduction in Yellow Cab's fare, it would cut its fare by 1.4% and its market share would go down by only 8% instead of 13%. One implication of these results is that a 10% reduction in fare is enough to boost the market share of Yellow Cab significantly.

Second, I simulate a scenario when Uber is banned from the city. This replicates the recent decisions made by various cities' governments to ban hail-riding services, including Austin and London. My results show that, if Uber were banned, the market share of Yellow Cab would increase by 9%. Customers who would have chosen Uber would go back to use either Yellow Cab or public transportation - the fraction depends on the destination of the trip. For the trips going to downtown and midtown, most of Uber's lost customers would switch to public transportation. On the other hand, for the trips to the airports, more of Uber's lost customers would switch to Yellow Cab.

Third, I simulate the scenario when managers of Uber decide to copy the image of Yellow Cab. This corresponds to a scenario where, for example, Uber would adopt driver dress codes or background checks similar to those used by Yellow Cab.[2] To model this, I reduce the gap between the estimated Yellow Cab and Uber brand dummies by a half. My results show that the market share of Uber would more than double.

Results in this paper should not be seen as optimal government policy. The government may have a variety of different goals in this setting other than keeping Yellow Cab profitable. Thus, my analysis provides at most one ingredient to studying

[2]One of the main reasons why Uber runs into trouble with authorities around the world is its failure to commit with criminal background check regulations. Overlooking these strict background check, on one hand, helps Uber attract more drivers, but on the other hand, create images of an unsafe services. Uber, in stead of conforming to current regulations, often clashed with authorities by either withdrawing out of the city and lobbying later to get in again (such as Austin), or merged with local services (such as in China)

optimal policies.[3]

Attempts at estimating demand for taxi services in the past have faced several challenges. First, trip level data was not readily available until recently when New York City's government published all records of Yellow Cab trips on their website.[4] Second, even when Yellow Cab trip records are available, Yellow Cab fares do not change frequently, hence fare variation for demand parameters to be identified is lacking.[5] Third, data sets on Yellow Cab competitors are lacking. To my knowledge, Cohen et al., 2016 is the only that has access to a comprehensive Uber data set with all information of all Uber trip. It exploited the ratio of people who search for Uber to people who actually order one after searching to estimate different local demand elasticities and infer the whole demand curve for Uber. To the best of my knowledge, my paper is the first to estimate demand for both Yellow Cab and Uber in one system and takes into account competition between them.

The rest of the paper is organized as follows: Section 1.2 provides detail on the background of the taxi industry in New York City. Section 1.3 describes the data and summary statistics. Section 1.4 discusses the empirical model. Section 1.5 provides results for parameters estimates, elasticities and marginal cost. Section 1.6 uses recovered parameter estimates to investigate different counterfactual scenarios. Section 1.7 concludes.

1.2 Background of the industry

When it comes to taxi service in New York City, Yellow Cab is the biggest supplier of trips, providing about 400,000 trips daily. Yellow Cab is heavily regulated by New York City government: both its total number of cabs and its fare are set by the government and do not change frequently. Table 1.12 shows the history of Yellow

[3]This paper also does not discuss labor supply or any dynamic question, which government usually takes into account before changing fares

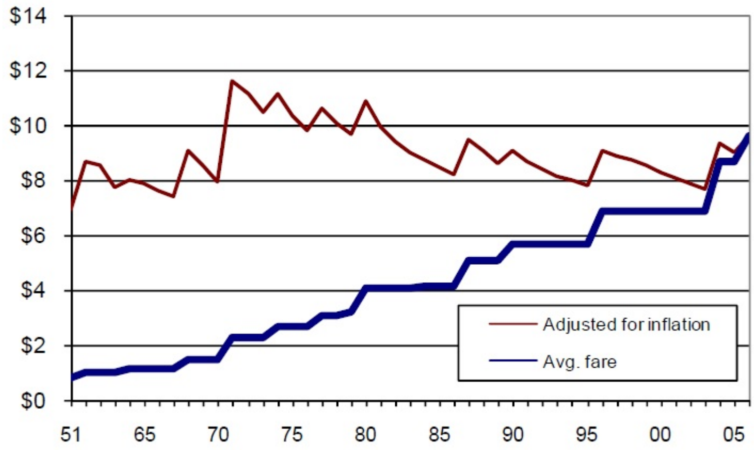
[4]Papers using the same dataset include: Camerer et al., 1997 which studies labor supply of New York City cabdrivers and Farber., 1995 which uses trips data set from 2009 - 2013 to reevaluate labor supply of cab drivers

[5]Recently, Frechette et al., 2016 and Buchholz., 2016 exploited search friction, i.e., waiting time in Yellow Cab data set to estimate demand for Yellow Cab

Cab fares in New York City from 1952 until now. Since 1950, Yellow Cab fare was changed only 16 times and the last time happened in July 2012.

Figure 1.1 extracted from The New York City Taxicab Fact Book pointed out that while nominal Yellow Cab fare increases, adjusted inflation fares remain stable. In 2012, to explain for higher Yellow Cab fares, TLC officials explicitly stated that "there were compelling reasons to grant the industry's wish for higher prices, like allowing fares to keep up with the rate of inflation and recent increases in gasoline prices".[6] This indicates that most of fare changes seemed to account for inflation and had nothing to do with demand for trips.

Figure 1.1: Yellow Cab average fares in nominal and 2006 inflation-adjusted dollars



Note: Derived from the NYC Taxicab Fact Book 2006

In recent years, Yellow Cab has lost ground to smart phone-based ride-hailing apps, of which Uber is the most significant competitor. Uber Technologies Inc is an American worldwide online transportation network company. Uber developed the application that allows smart-phone users to submit a trip request. Since its inception in 2011, Uber quickly gained recognition in many cities including New York City. Even though Yellow Cab is still the largest provider of taxi trips in the city, Uber is catching up while Yellow Cab is dropping its popularity.

Since Uber started to expand its activities in the city in August 2013, there are two

[6] http://www.nytimes.com/2012/05/22/nyregion/new-york-taxi-fares-may-soon-go-up.html

opposing trends happening in the New York City taxi industry, a downward trend in Yellow Cab's number of daily trips and an upward trend in Uber's. In a typical market with small number of players, each player often compete based on pricing. In New York City however, only Uber company has been changing the price of its products to respond to new market circumstances, whereas New York City government kept its Yellow Cab price constant. The last time Yellow Cab fares were changed was in 2012 which was even before Uber started to grow in the city. It is therefore interesting to see what would happen to competition in this market if government of New York City decided that they would change their current pricing schedule.

1.3 Data

1.3.1 Yellow Cab Data

Yellow Cab data is readily available from NYC's Taxi & Limousine Commission (TLC) website. The main data set I used in this paper is Yellow Cab data in June 2015. There are 12 millions Yellow Cab's trips made in this data set. Information includes longitude/latitude of starting and ending points, starting time, number of passenger and total fare of every trip. I dropped trips with unreasonable starting and ending points, and fares. I also dropped trips that is not originated from Manhattan. I wrote a ArcGIS based-Python script to spatially joint each of the starting geographical coordinates with one of the neighborhoods in Manhattan. Without loss of generality and to make it more manageable, I randomly chose 250 hours out of 720 potential hours in June 2015 as my sample. The resulting sample consists of roughly 4 million observations.

1.3.2 Uber Data

Real Uber trip data

Under the Free of Information Law (or FOIL), TLC is responsible for publishing taxi trip record in New York City upon request. Uber trip record released by TLC only contain information on the starting time and starting neighborhood of the Uber trip, but not the ending location and the total fare. With this data set, I can count the number of Uber trips actually taken in each starting neigborhood-hour market. I only kept the same 250 hours as in the Yellow Cab data set. The resulting sample for Uber consists of roughly 900 thousands observations. Table 1.1 provides trip distributions of Yellow Cab trips and real Uber trips. From the table, it is clear that consumers use Yellow Cab and Uber in a similar way - it is not likely that consumers use Yellow Cab only in weekend or use Uber only in the morning, etc.

Table 1.1: Trip distribution of Yellow Cab trips and real Uber trips

Trip distribution	Yellow Cab	Uber
Weekend	23%	25%
Morning (6am - 11am)	25%	20%
Midday (11am - 6pm)	30%	28%
Night (11pm - 6am)	27%	31%
Evening (6pm - 11pm)	18%	20%
Observations	3,396,487	912,215

Notes: These numbers are the actual number of Yellow Cab and Uber trips happen in the chosen hours

Imputed Uber fare

To model alternative choice for New Yorker taxi riders, I wrote a Python script to impute the "estimated" Uber price for the Yellow Cab trips in the Yellow Cab data sets. These are the Uber prices of the Yellow Cab trips had the consumers use Uber service instead of Yellow Cab service. My program can match the time of the actual Yellow Cab trips with the hypothetical Uber trips to the minute, hour, and day of the week level.[7]

[7]To illustrate, if in Yellow Cab data set, the actual Yellow Cab trip is recorded to happen at 18:32 on Wednesday, the program will hold until 17:32 Wednesday Houston time (due to one hour

Table 1.2 compares the fare of Yellow Cabs with imputed fare of Uber. On average Yellow Cab fare is about 12.5 USD per trip while the imputed Uber fare for the same trip is slightly cheaper at 11.USD. In only about 40% observations of the data set that we observe Yellow Cab being the cheaper option compared to Uber. Yellow Cab fare from the two airports is fixed at 52 USD no matter how long the trip is, whereas Uber does not have this feature. Another point that is worth noting here is that the *imputed* Uber fare is calculated in September 2016, while the Yellow Cab data set is from June 2015.

Table 1.2: Summary statistics individual data

	Mean	Standard Deviation	p10	p90
Yellow Cab fare per trip	12.5	7.9	6.3	20.8
Imputed Uber fare per trip	11.1	6.4	7.5	16.5
Yellow Cab fare per mile	6.7	3.1	3.7	10.2
Imputed Uber fare per mile	6.7	4.4	3.0	11.9
(=1 YC fare is cheaper)	0.4	0.5	0.0	1.0
Percent fare difference*	-0.02	0.33	-0.34	0.40
Observations:	3,396,487			

Notes: Percentage fare difference is calculated as: (Uber price - Yellow Cab price)/Yellow Cab price so negative means Yellow Cab is more expensive

1.3.3 Pattern of the trip characteristics

For each observation in the data set described in Section 1.3, various characteristics of the actual Yellow Cab trips are recorded (fare, the time, the starting points, etc). The corresponding hypothetical Uber trips are almost identical to their Yellow Cab counterpart, i.e they have the same starting and ending geographical point, start at the same time on the same day of the week. However, their fares are different. Only 40% of observations has Yellow Cab fare per trip being the cheaper option compared to Uber. This means 60% of the time, consumers in this data set are ended up choosing the more expensive option (Yellow Cab), suggesting that price is not the only determinants of their decisions. Consumers take into account other non-price

earlier time zone of Houston) to impute price for the hypothetical Uber trip. Thus the hypothetical Uber trip happens at the exact time and on the same day of the week with Yellow Cab trip characteristics of the trip, be it observed characteristics such as where and when the trips start, brand image of the cab services, etc or unobserved characteristics (to the econometrician) but observable to the consumers such as Yellow Cab cars are more smelly.

Table 1.3 below shows the correlation between difference of Yellow Cab and Uber fare per trip in different starting time. One noticeable pattern in the data set can be observed: the probability of Yellow Cab fare that is cheaper than Uber counterpart is lower during evening and night time. It suggests that there maybe events during evening and night time that makes the Yellow Cab to be more expensive or Uber to be cheaper than other time of the day. It could be the case that during evening and night time, vehicles move more slowly than normal and Yellow Cab algorithm punishes slow movement more badly than Uber. All of these cases imply that unobserved trip characteristics are important in determining consumer choices. Next, I introduce my discrete choice model that would take into account these unobserved characteristics.

Table 1.3: Correlation between price difference and some observed trip characteristics

	=1 if YC is cheaper	Percentage fare difference*
Weekend	-0.01***	0.00***
	(-13.37)	(-7.92)
Night (11pm - 6am)	-0.21***	-0.15***
	(-256.94)	(-289.52)
Midday (11am - 6pm)	-0.10***	-0.07***
	(-140.98)	(-141.54)
Evening (6pm - 11pm)	-0.19***	-0.15***
	(-261.00)	(-306.22)
Observations	3,396,487	3,396,487

Notes: t-statistics in parentheses. Morning is from 6am - 11am. Percentage fare difference is calculated as: (Uber price - Yellow Cab price)/Yellow Cab so the two columns coefficients should have the same sign

1.4 Model

Estimating demand for different taxi services in this setting faces two challenges. First, it is unclear what a product is in this market. Unlike in other consumer good markets where consumers observe two competing brands of cereal on the store's shelf before making decision, in the market of taxi service, consumers do not observe two identical trips offered by two competing brands beforehand, the trip is only created *after* the decision is made. Because no trip is offered by both Yellow Cab and Uber (same starting point, ending point at the same time), competing products would never be observed.[8] I resolve this concern by computing Uber price using information of Yellow Cab trip as discussed in previous sections.

Furthermore, simultaneity bias is another concern in any demand estimation exercise due to the correlation between unobserved product characteristics and fares. This necessitates a set of instrumental variables that satisfy the conditional mean assumption. The product setup described earlier allows for reasonable instruments identifying my model. First, each product's fare is instrumented by average fare of same firm's other products from the same market. This is because firms likely to have a common cost component that is shared among products within the same firm. Second, each product's fare is instrumented by the average fare of the competing firm's products. The reason for this is that in each market, firms may choose fare based solely on fare of competing firms and not based on any other unobserved characteristics.

Specifically, in each starting market two competing "firms" Yellow Cab and Uber offer three products, indexed by j: going to Financial District, going to Upper East Side and going to Airports. From a starting neighborhood-hour market, each consumer has 7 options to choose from: the six products offered by Yellow Cab and Uber, and an outside option of choosing public transportation such as subway, buses or going somewhere else other than above destinations. The reason for this is that many consumers in New York City tend to take cabs as part of a longer trips. Since the Financial District, Upper East Side and Airports have many other complement transportation methods, assumption that people choose one of these destinations at the same time as choosing type of cab services is not too strong.

[8] Even if my data consists of ending points of every Uber trips, this is still true

1.4.1 Demand specification

I follow the division by New York City government definition to divide Manhattan into different neighborhoods. The month June 2015 is also divided into 720 hours (30 days x 24 hours). I consider a combination of neighborhood-hour a market $t \in$ {1,2,...,T} , each with I_t consumers. In each of neighborhood-hour market, each firm (Yellow Cab or Uber) offers three 3 products: going to Financial District, going to Upper East Side and going to Airports. I observe the aggregate number of trips taken for each Yellow Cab and Uber products, the average fare for each of Yellow Cab products and the average *imputed* fare for each of Uber products. Table 1.4 and Table 1.5 below gives a summary statistics of the data set that would be used in this section. On average, Yellow Cab "products" offered by Yellow Cab are more expensive than Uber those offered by Uber. However, number of Yellow Cab trips is higher than that of Uber. 22% of the starting neighborhood-hour markets are night markets (from 11pm to - 6am), 30% are midday (from 11am - 6pm) and 20% are evening (from 6pm - 11pm). The size of starting market is the imputed sum of *all* Yellow Cab trips, Uber trips, and MTA and buses rides from that neighborhood in that hour. The average size of 3,992 markets in the data set is 958.

Table 1.4: Summary statistics of Six products

	To Financial District		To Upper East Side		To Airport	
	Yellow Cab	Uber	Yellow Cab	Uber	Yellow Cab	Uber
Fare per trip	15.98	13.28	14.29	12.32	52.39	44.53
Distance	3.89	3.89	3.20	3.20	17.06	17.06
# of trips	62.93	15.11	89.26	14.40	7.41	1.40
Market share	6.97%	1.87%	9.02%	1.54%	1.17%	0.28%

Notes: I assume the imputed distance given by Uber API is exactly the same as the distance recorded by the same Yellow Cab trips.

The demand model adopts the standard random coefficient discrete choice model of Berry at al., 1995. Each product is characterized by a $(K \times 1)$ vector $\mathbf{x}_{jt}$ of observed product characteristics (fare, distance and time of the products), brand dummy representing average popularity of the brand Yellow Cab and Uber $\bar{\xi}_j$, product characteristics unobserved to the econometrician ξ_{jt}, such as the waiting time, driver's

Table 1.5: Summary statistics of origin neighborhood-hour markets

Origin markets	Percent
Night market (11pm - 6am)	22%
Morning market (6am - 11am)	28%
Midday market (11am - 6pm)	30%
Evening market (6pm - 11pm)	20%
Weekend market	23%
Mean size of origin markets	958
Number of origin markets	3,992

Notes: Origin markets are neighborhood AND hour of when the trip is started

attitude, etc., and a Type I Extreme Value stochastic term ε_{ijt}. Choice-level utility consumer i receives from choosing product j in market t is specified in Equation 1.1:

$$U_{ijt} = \boldsymbol{\beta_i}\mathbf{x}_{jt} + \bar{\xi}_j + \xi_{jt} + \varepsilon_{ijt} \tag{1.1}$$

Consumers' preference towards product fare and other observed characteristics are captured by coefficients β_i. Following Berry et al., 1995 and Nevo., 2001, I let heterogenous taste in fare vary across individuals based on 'observed' demographic characteristics D_i and 'unobserved' consumer characteristics ν_i:

$$\boldsymbol{\beta_i} = \boldsymbol{\beta} + \mathbf{\Pi}\mathbf{D_i} + \mathbf{\Sigma}\boldsymbol{\nu}_\mathbf{i} \tag{1.2}$$

In typical logit models, parameters are (β) (without subscript i), and consumer heterogeneity enters the utility function only through the idiosyncratic taste ε_{ijt} whose distribution is i.i.d Type I Extreme Value. Random coefficient model allows interaction between consumer demographic characteristics and product characteristics, thus allows for more realistic substitution pattern. Note that the $(D \times 1)$ vector of 'observed' demographic characteristics $\mathbf{D_i} = (D_i^1, ..., D_i^D)$ is actually not observed for each individual, however its empirical distribution is generally known (for example from Census). 'Unobserved' individual characteristics $\boldsymbol{\nu_i}$ represents consumer i's deviation in taste for the fare of the trip. I assume ν_i to be a random draw from a mean zero Normal distribution $\nu_i \sim N(0,1)$. Parameters to be estimated are $\boldsymbol{\theta} = (\boldsymbol{\theta_1}, \boldsymbol{\theta_2})$ where $\boldsymbol{\theta_1} = \boldsymbol{\beta}$ and $\boldsymbol{\theta_2} = (\boldsymbol{\Pi}, \Sigma)$. $\boldsymbol{\theta_1}$ is a $(K \times 1)$ vector and is calculated linearly. $\boldsymbol{\theta_2}$ is calculated in a non-linear fashion, in which $\boldsymbol{\Pi}$ is a $(K \times D)$ matrix and $\boldsymbol{\Sigma}$ is a scaling $(K \times K)$ matrix. The demand system is completed by defining the utility from consumption of outside option:

$$U_{i0t} = \boldsymbol{\beta_i}\mathbf{x}_{0t} + \xi_{0t} + \varepsilon_{i0t} \tag{1.3}$$

which is identified by normalizing the utility from the outside good to zero: $u_{i0t} = \varepsilon_{i0t}$.

Substituting Equation 1.2 into Equation 1.1, the consumers' utility function can be decomposed into three components: mean utility component that is common to all consumers $\delta_{jt} \equiv \boldsymbol{\beta}\mathbf{x}_{jt} + \bar{\xi}_j + \xi_{jt}$, the heterogeneous utility component unique to each consumer $\mu_{ijt} \equiv (\boldsymbol{\Pi}\mathbf{D_i} + \boldsymbol{\Sigma}\boldsymbol{\nu_i})\mathbf{x}_{jt}$ and the idiosyncratic taste ε_{ijt}:

$$U_{ijt} = \delta_{jt} + \mu_{ijt} + \varepsilon_{ijt}$$

Given the products in the market, consumer i will choose transportation j that maximizes his utility U_{ijt}.

$$\{(\mathbf{d}_i, \mathbf{v}_i, \boldsymbol{\varepsilon}_{it}) | U_{ijt} \geq U_{ilt} \ for \ l = 0, 1, ..., J\}$$

. By specifying the consumer taste, ε_{ijt}, as having extreme value distribution, the probability that consumer i choose product j in market t is given by:

$$s_{ijt}(\mathbf{x}_{jt}, \bar{\xi}_j, i, \delta(\boldsymbol{\theta}_1), \boldsymbol{\theta}_2) = \frac{exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{j=1}^{J}(\delta_{jt} + \mu_{ijt})} \tag{1.4}$$

Integrating individual choice over the distribution of consumer types $\mathbf{D_i}$ and $\boldsymbol{\nu_i}$ will give the probability of any consumer choosing product j, which is interpreted as the market share of that product:

$$s_{jt}(\mathbf{x}_{jt}, \bar{\xi}_j, \delta(\boldsymbol{\theta}_1), \boldsymbol{\theta}_2) = \int_i^{I_t} \frac{exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{j=1}^{J}(\delta_{jt} + \mu_{ijt})} d\hat{P}_D^*(D) d\hat{P}_v^*(v) \tag{1.5}$$

With random coefficients, the predicted market share s_{jt} does not have a closed form solution and therefore is computed using simulations. Parameters $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_2$ are estimated by matching the market share predicted by the model, s_{jt}, with the observed market share S_{jt}.

1.4.2 Supply

I assume that firms (Yellow Cab and Uber) compete on price following a Nash-Bertrand fashion. In each market, firms try to maximize their static profit function, Π_t, over the set of products $\Psi(j)$ that they have:

$$\Pi_t = M_t \sum_{j \in \Psi(j)} (p_{jt} - mc_{jt}) s_{jt}(\mathbf{x}_{jt}, \bar{\xi}_j, \delta(\boldsymbol{\theta}_1), \boldsymbol{\theta}_2) \tag{1.6}$$

where M_t is the market size and t, p_{jt}, mc_{jt}, s_{jt} are price, marginal cost and market share of product j in market t, and $\Psi(j)$ is the set of products that firm produces. I assume that each of the firms will choose the price to maximize its profits given the characteristics of its own products and of its competitor's products. For each product $j \in \Psi(j)$, firms choose price for its product p_{jt} that satisfies the first order condition:

$$\frac{\partial \Pi_t}{\partial p_{jt}} = s_{jt} + \sum_{k \in \Psi(j)} (p_{kt} - mc_{jk}) \frac{\partial s_{kt}}{\partial p_{kt}} = 0 \tag{1.7}$$

1.4.3 Identification

Demand estimation has to deal with the endogeneity problem of price. Even with the assumption that observed characteristics of the trips are exogenous, and therefore not related to price, firms choose price based on their knowledge of variables that are known to them but unobserved by the econometricians, in other words $E[p_{jt}\xi_{jt}] \neq 0$.

Another reason that instrumenting is essential in this practice is that the building block of the GMM procedure proposed by Berry at al., 1995 requires at least as many moments as the number of parameters of the model $\boldsymbol{\theta}$. Different instruments are needed to create these moments for the model to be identified. I constructed 8 instrumental variables. First instrument, denoted iv_1, is the average price of products from the same brand in the same market. For example, the fare of Yellow Cab going to Financial District from market 1 will be instrumented by the average fare of Yellow Cab going to Upper East Side and Airports from that market 1. Second instrumental variable, denoted iv_2, is average price of products offered by the competitors from same market. To illustrate, fare of Yellow Cab going to Financial District from market 1 is instrumented by average fare of all products (going to Financial District, Upper East Side and Airports) by Uber from same market 1. The rest of instrumental variables are created by combination, up to quadratic, of these two instruments.

1.4.4 Estimation

This section presents the estimation procedure for the demand side. I follow closely the standard Generalized Method of Moments (GMM) procedure described in Berry., 1994, Berry et al., 1995, Nevo., 2000 and Nevo., 2001 . Consumers' indirect utility is estimated using a two-step GMM method with the use of an optimal weighting matrix. Specifically, let $\mathbf{Z}$ be set of variables such that:

$$E[\mathbf{Z}w(\boldsymbol{\theta_0})] = 0 \tag{1.8}$$

in which w is some function of model parameter $\boldsymbol{\theta}$, and $\boldsymbol{\theta_0}$ is the true estimate of $\boldsymbol{\theta}$. Then it follows that the GMM estimate of $\boldsymbol{\theta}$ is:

$$\boldsymbol{\theta_{GMM}} = \underset{\boldsymbol{\theta}}{\operatorname{argmin}}\, w'(\boldsymbol{\theta})\mathbf{Z}\mathbf{W}\mathbf{Z}'w(\boldsymbol{\theta}) \tag{1.9}$$

where $\mathbf{W}$ is the weight matrix that gives more weight to the moments whose variance is smaller. The optimal weight matrix is proportional to covariance-variance matrix

$E[\mathbf{Z}'w(\theta)w(\theta)'\mathbf{Z}]$ which is a function of consistent estimate of true parameter θ. In the first step of the two-steps GMM procedure, I used $(\mathbf{Z}'\mathbf{Z})^{-1}$ as the weight matrix to derive consistent parameters $\boldsymbol{\theta_{GMM}}$. In the second step, I used parameters $\boldsymbol{\theta_{GMM}}$ derived in the first step to calculate the optimal weight matrix $\mathbf{W}_{optimal} = (E[\mathbf{Z}'w(\theta_{GMM})w(\theta_{GMM})'\mathbf{Z}])^{-1}$. I then repeated the whole procedure using $\mathbf{W}_{optimal}$.

The central idea of this procedure is to express unobserved characteristics ξ_{jt} as an explicit function of the model's parameters $\boldsymbol{\theta}$. That way, $\xi_{jt}(\boldsymbol{\theta})$ replaces $w(\boldsymbol{\theta})$ in Equation 1.9 as long as I can find $\mathbf{Z}$ that satisfies Equation 1.8.

To explicitly write ξ_{jt} as a function of the model parameters, I first start with the constraint:

$$||s_{jt}(p_{jt}, \mathbf{x}_{jt}, \delta(\boldsymbol{\theta}_1), \boldsymbol{\theta}_2) - S_{jt}|| = 0 \tag{1.10}$$

which matches the predicted market share with the observed market share. The first part of Equation 1.10 is calculated by simulation from Equation 1.4. Specifically:

$$s_{jt}(\mathbf{x}_{jt}, \delta(\boldsymbol{\theta}_1), \boldsymbol{\theta}_2, \hat{P}^*_D(D), \hat{P}^*_v(v)) = \frac{1}{ns}\sum_{1}^{ns} s_{ijt}$$

The second part of Equation 1.10 is obtained directly from the data set

$$S_{jt} = \frac{count_{jt}}{M_t}$$

where M_t is the market size and $count_{jt}$ and the number of products j sold in market t. Berry., 1994 and Berry et al., 1995 show that for a given $\boldsymbol{\theta}_2$, mean utility $\delta(\boldsymbol{\theta}_1)$ can be calculated by inverting Equation 1.10 using the following contraction mapping:

$$\delta_t^{h+1}(\boldsymbol{\theta}_1) = \delta_t^h(\boldsymbol{\theta}_1) + ln(s_{jt}(\boldsymbol{\theta}_1)) - ln(S_{jt}) \qquad h = 1, .., H \tag{1.11}$$

where H is the smallest integer such that $||\delta_t^{h+1} - \delta_t^h||$ is smaller than some arbitrary tolerance level, and δ_t^H is the approximation for δ_t. Assume the set of instrument variables $\mathbf{Z}$ satisfies Equation 1.8, it follows that $\boldsymbol{\theta}_1$ can be estimated linearly:

$$\boldsymbol{\theta}_1 = [\mathbf{x}'_{jt}\mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{x}_{jt}]^{-1}\mathbf{x}'_{jt}\mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'\delta_{jt} \tag{1.12}$$

For each given value of $\boldsymbol{\theta}_2$, there will be a value of $\boldsymbol{\theta}_1$ that approximately satisfies equation Equation 1.10. Using this $\boldsymbol{\theta}_1$, I can derive unobserved characteristics ξ_{jt} for each value of $\boldsymbol{\theta}_2$ by substituting $\boldsymbol{\theta}_1$ into the following:

$$\xi_{jt}(\boldsymbol{\theta}_2) = \delta_{jt} - \boldsymbol{\theta}_1\mathbf{x}_{jt} - \bar{\xi}_j \tag{1.13}$$

Next, I need to find the value of $\boldsymbol{\theta}_2$ that minimizes the objective function created by the mean condition requirement Equation 1.8. I use Matlab to search numerically over the value of $\boldsymbol{\theta}_2$ that minimize the objective function.

1.4.5 Elasticities, Marginal cost

Once demand parameters are recovered from estimation procedure explained above, one can calculate elasticities, imply substitution patterns, compute marginal cost and conduct various counterfactual scenarios.

Elasticities:Price elasticities of market shares from logit model are given by Equation 1.14:

$$\eta_{jkt} = \frac{\partial s_{jt} p_{kt}}{\partial p_{kt} s_{jt}} = \begin{cases} -\alpha p_{jt}(1 - s_{jt}) & \text{if} \quad j = k \\ \alpha p_{kt} s_{kt} & \text{otherwise} \end{cases} \tag{1.14}$$

Price elasticities of market shares from the full model are:

$$\eta_{jkt} = \frac{\partial s_{jt} p_{kt}}{\partial p_{kt} s_{jt}} = \begin{cases} -\frac{p_{jt}}{s_{jt}} \int \beta_i s_{ijt}(1 - s_{ijt}) d\hat{P}^*_D(D) d\hat{P}^*_v(v) & \text{if} \quad j = k \\ \frac{p_{kt}}{s_{jt}} \int \beta_i s_{ijt} s_{ikt} d\hat{P}^*_D(D) d\hat{P}^*_v(v) & \text{otherwise} \end{cases} \tag{1.15}$$

where s_{ijt} calculated using Equation 1.4 is the probability that person i choosing product j in market$t$. Equation 1.15 is not analytical and is calculated using simulation:

$$\eta_{jkt} = \frac{\partial s_{jt} p_{kt}}{\partial p_{kt} s_{jt}} = \begin{cases} -\frac{p_{jt}}{s_{jt}} \sum_1^{ns} \beta_i s_{ijt}(1 - s_{ijt}) & \text{if} \quad j = k \\ \frac{p_{kt}}{s_{jt}} \sum_1^{ns} \beta_i s_{ijt} s_{ikt} & \text{otherwise} \end{cases} \tag{1.16}$$

Marginal cost: Computing counterfactual prices and market shares necessitates calculation of each firm's marginal cost for each of their products. In each market, firms maximizes their static profit function, Π_t, over the set of products $\Psi(j)$ they produce:

$$\Pi_t = M_t \sum_{j \in \Psi(j)} (p_{jt} - mc_{jt}) s_{jt}(p_{jt}, \mathbf{x}_{jt}, \bar{\xi_j}, \underline{\xi_t}, \delta(\boldsymbol{\theta}_1), \boldsymbol{\theta}_2) \tag{1.17}$$

where M_t is the size of market t. Assuming pure strategic pricing, for each product j $\in \Psi_j$, firms choose price p_{jt} that satisfies the first order condition:

$$\frac{\partial \Pi_t}{\partial p_{jt}} = s_{jt} + \sum_{k \in \Psi_j} (p_{kt} - mc_{jk}) \frac{\partial s_{kt}}{\partial p_{kt}} = 0 \tag{1.18}$$

Define the ownership matrix Ω where:

$$\Omega_{jk} = \begin{cases} 1 & \text{if product j and k are owned by the same firm} \\ 0 & \text{otherwise} \end{cases} \tag{1.19}$$

Equation 1.18 then can be written in vector notation by stacking all the F.O.C conditions together:

$$\mathbf{s} + \boldsymbol{\Omega}.* \frac{\partial \mathbf{s}}{\partial \mathbf{p}}(\mathbf{p} - \mathbf{mc}) = 0 \tag{1.20}$$

where .* denotes element-by-element matrix product. Marginal cost is then derived by rearranging Equation 1.20:

$$\mathbf{mc} = \mathbf{p} + (\boldsymbol{\Omega}.* \frac{\partial \mathbf{s}}{\partial \mathbf{p}})^{-1}\mathbf{s} \tag{1.21}$$

1.5 Results

1.5.1 Parameter estimates

OLS logit demand models: First column of Table 1.6 presents one specification of standard logit models.[9] Trips characteristics in this specification include fare, brand dummy (Yellow Cab or Uber), distance of the trips, whether the trips started on weekend, at night, midday or evening and use price-per-miles variables created in following subsection 1.4.3 as 8 instruments for the price of Uber and Yellow Cab. In all specifications, fare coefficients are negative which is expected, implying that higher price bring dis-utility to consumers. The OLS analysis, however, is useful as they serve as benchmark to compare the random coefficient models to.

Random coefficient logit demand models: The rest of Table 1.6 presents the estimates of random coefficient model along side with the logit specification. Random coefficient model allow the integration of consumer heterogeneity to come into the equation. The model requires searching for $\boldsymbol{\theta}_2$ numerically. The mean utility derived from the standard logit model is used as the initial guess for δ_{jt}, while starting values of $\boldsymbol{\theta}_2$ are chosen arbitrarily. I employed several methods to search for the true value of $\boldsymbol{\theta}_2$. First, I followed Nevo., 2000 to use a Quasi-Newton method with the supply of a gradient matrix. While this method is faster to converge, convergence depends on the choice of initial values for θ_2. To overcome non-convergence issues, I use Nelder-Mead simplex direct search which was employed by Berry et al., 1995 and Pattern Search method proposed by Hooke et al., 1961. Both of these methods only find local minimum therefore estimated parameters are subject to different initial values. To overcome, I try different starting values of $\boldsymbol{\theta}_2$ to find the global minimum. Overall, Nelder-Mead simplex direct search converges faster and is more consistent for me. I only report results using Nelder-Mead search method.

Random coefficient demand results reported in Table 1.6 allows for interaction between the fare of the products and demographics which include age and income.

[9]For the full table of all standard OLS logit models, see Table 1.13 in the Appendix. This table is column 10

$\boldsymbol{\theta}_2$ parameters are the coefficients of these interaction terms. Coefficient on income is positive implying that higher income makes mean fare coefficient less negative. This is realistic as one would expect that richer people to be less price sensitive. As demographics for simulated individual consumers are available, I can compute the marginal dis-utility of fare for each individual following Equation 1.2: $\boldsymbol{\beta_i} = \boldsymbol{\beta} + \boldsymbol{\Pi}\mathbf{D}_i + \boldsymbol{\Sigma}\boldsymbol{\nu}_\mathbf{i}$. Figure 1.2 graphs the histogram of fare coefficients throughout simulated consumers in all the markets together. About 94% of the population have negative price coefficients.

Table 1.6: Demand parameter estimates

	Logit with IV	Random coefficient model			
		Mean	Sigma	Age	Income
Fare per trip	-0.11***	-0.55***		0.01***	0.06***
	(0.01)	(0.03)		(0.00)	(0.03)
Yellow Cab	-1.27***	2.69***	0.01		
	(0.10)	(0.27)	(1.53)		
Uber	-3.41***	0.34	-0.06		
	(0.05)	(0.48)	(8.29)		
Distance	0.12***	0.24***			
	(0.03)	(0.07)			
Weekend	-0.13***	-0.34*			
	(0.02)	(0.26)			
Night	-0.42***	-0.21**			
	(0.03)	(0.10)			
Midday	0.12***	0.34***			
	(0.02)	(0.14)			
Evening	-0.34***	-0.52**			
	(0.02)	(0.25)			

Notes: This employs Nelder-Mead simplex direct search method. The OLS specification chosen is column 10 in Table A2 in the Appendix. This version uses 8 instruments for fare. After the first time run, I calculated the new weighting matrix, which is considered optimal weighting matrix, and ran the whole procedure again. I repeated this process 4 times, the objective function does not go down too much after the second iteration.

1.5.2 Elasticties

Elasticity Pattern: With the estimated demand parameters, I calculate own-price and cross-price elasticities by market based on Equation 1.14 and equation Equation 1.16. Results are reported in Table 1.8 and Table 1.9 respectively. The numbers

Figure 1.2: Distribution of price sensitivity

Notes: Price coefficient from the random coefficient model that is equivalent to the OLS specification in column (10) of Table 1.13

are interpreted as the percentage increase/decrease of market share of row products if the price of column products increase by 1%. For example, first element in Table 1.8 implies that market share of Yellow Cab to Financial District will decrease by 1.28% if its price goes up by 1%. While in both models, own-price and cross-price elasticities have expected signs, those of logit models are unrealistic. First, in logit model, own-price elasticities depend mostly only on the price of the products. This implies that the magnitude of own-price are driven mostly by how expensive the products are. Since the products "to the airports" are the most expensive, this explains why own-price of them are biggest in magnitude. Second problem with logit model lies with strange pattern of cross-price. One would expect that if price of one product goes up high enough, consumers who previously consume that product would choose the second option that has characteristics that is most similar, driving the market share of the closest substitute to go up the most. Since the logit model ignores consumer heterogeneity, cross-price elasticities depend only on the market share and price of the good that is substituted. As a result, cross-price elasticities are the same for every substitute, which is highly unrealistic. Random coefficient models fix this problem.

As can be seen in Table 1.9, if price of "Yellow Cab going to Financial District" increases, people would substitute the most to using "Uber going to Financial District" or "Yellow Cab to Upper East Side".

1.5.3 Marginal cost

Marginal cost: In this section, I compute the underlying marginal cost of the products, which is a necessary ingredient for my policy experiments. Table 7 Table 1.7 reports the marginal costs and price-cost margins for the six products. The price-cost margin is highest for trips to Financial District and lowest for trips to Airports.

Table 1.7: Median marginal cost and price-cost margin from random coefficient models

	Marginal cost	Price-cost margin
Yellow Cab to Financial District	12.98	2.06
Yellow Cab to Upper East Side	11.56	1.98
Yellow Cab to Airports	52.79	1.82
Uber to Financial District	10.82	1.75
Uber to Upper East Side	9.83	1.64
Uber to Airports	42.37	1.50

Notes: Price cost margin is calculated by subtracting marginal cost from average product fare in each market

Table 1.8: Matrix of median elasticities from Logit model

	YC to Financial District	YC to Upper East Side	YC to Airports	Uber to Financial District	Uber to Upper East Side	Uber to Airports
YC to Financial District	-1.28	0.08	0.03	0.01	0.01	0.00
YC to Upper East Side	0.08	-1.13	0.03	0.01	0.01	0.00
YC to Airports	0.08	0.08	-4.91	0.01	0.01	0.00
Uber to Financial District	0.08	0.08	0.03	-1.12	0.01	0.00
Uber to Upper East Side	0.08	0.08	0.03	0.01	-1.02	0.00
Uber to Airports	0.08	0.08	0.03	0.01	0.01	-3.94

Notes: Elasticities are calculated from the parameters derived from the OLS specification in column (10) of Table 1.13

Table 1.9: Matrix of median elasticities from BLP model

	YC to Financial District	YC to Upper East Side	YC to Airports	Uber to Financial District	Uber to Upper East Side	Uber to Airports
YC to Financial District	-2.73	0.14	0.03	0.10	0.32	0.09
YC to Upper East Side	0.04	-2.66	0.04	0.10	0.30	0.10
YC to Airports	0.00	0.03	-2.22	0.01	0.06	0.00
Uber to Financial District	0.04	0.14	0.04	-3.30	0.32	0.10
Uber to Upper East Side	0.04	0.13	0.04	0.10	-3.27	0.10
Uber to Airports	0.01	0.04	0.00	0.02	0.10	-3.00

Notes: Elasticities are calculated from the parameters derived from the random coefficient model that is equivalent to the OLS specication in column (10) of Table 1.13

1.6 Policy experiments

Demand parameters derived from the previous part allow me to assess the market in different counterfactual scenarios.

Scenario 1: Changes in government pricing of Yellow Cab

Table 1.10 shows how market share of Yellow Cab and Uber would change in different Yellow Cab pricing scenarios, given that Uber does not change its fare. Results show that, a small change in Yellow Cab fare can change the market shares of both Yellow Cab and Uber greatly. For example, the market share of Yellow Cab gains 11% while the market share of Uber decreases by about 6% if Yellow Cab fare goes down by only 5%. In New York City, the fare of Yellow Cab is currently about 10% higher than that of Uber. If the government decides to decrease Yellow Cab fare to Uber level, the impact on the market is even larger, increasing by 24% for Yellow Cab while decreasing by 13% for Uber. While it is unlikely that Uber would keep its fare constant facing change in fares of Yellow Cab, this result shows negative own-price elasticity of Yellow Cab - the lower its fare, the higher its market share.

Table 1.10: Market shares change with different Yellow Cab fare change

Market share	Yellow Cab fare change					
change	-15%	-10%	-5%	+5%	+10%	+15%
Yellow Cab	+37%	+24%	+11%	-9%	-17%	-25%
Uber	-14%	-13%	-6%	+6%	+13%	+19%

Notes: Market share change is in percentage

Next, I will let Uber change its fare to adapt to 10% decrease in the fare of Yellow Cab. I assume the goal of Uber is to maximize its profit. New fare of Uber has to satisfy the First Order Condition of Equation 1.17

$$\mathbf{s} + \mathbf{\Omega}.*\frac{\partial \mathbf{s}}{\partial \mathbf{p}}(\mathbf{p} - \mathbf{mc}) = 0 \tag{1.22}$$

In each market, I know the fare of Yellow Cab, the ownership matrix $\mathbf{\Omega}.*\frac{\partial \mathbf{s}}{\partial \mathbf{p}}$ and the marginal cost. The only unknown from this equation is the fare of Uber which enters in this equation through both vector of price $\mathbf{p}$ and vector of market share $\mathbf{s}$.

My results show that the new Uber fare would be 1.4% lower than before. With the new fare, I was able to calculate new market shares for both Yellow Cab and Uber. Compared to a no-Uber-response scenario, the market share of Yellow Cab increases by 22% instead of 24%, while the market share of Uber decreases by only 8% instead of 13%.

Scenario 2: Government bans Uber from the market

This scenario is not too far-fetched from reality as Uber has faced legal and regulatory battles around the world. One of the latest and more controversial cases was the Uber ban in Texas' capital city of Austin. In December 2015, Austin City council issued an ordinance that would require Uber or any other transportation network companies to do fingerprint-based background checks of their drivers, among other things such as clearly labeling their cars with company logo, or refraining from picking up and dropping off passengers in certain city lanes, or publishing their trip data.[10] Uber felt that conforming to such a rule, especially fingerprint-based background check, were too costly and slow, and would hurt their operation in the city. It, together with the other big ride-sharing company Lyft, proposed Proposition 1 to advocate for removing the fingerprint-based check requirement. In May 2016, despite the two corporate companies' 9-million dollar-lobby effort to advocate for Proposition 1, Austin voters voted against it. Consequently, Uber and Lyft, instead of conforming to the ordinance, decided to suspend their operation and left the city entirely. Not until very recently in June 2017 did Uber and Lyft come back to the city thanks to the State of Texas's House Bill 100 (HB100) that overrode the city of Austin' regulation and permitted the Transportation network companies (TNCs) such as Uber to operate without fingerprint background checking their drivers. Ride-hailing in Austin has suddenly become much more competitive due to the emergence of many local startup companies that, both provide almost identical service as Uber and has conformed to the city's ordinance. Deeper analysis of the current Austin taxi market, however, would require more data, and thus be beyond the scope of this paper.

[10]ORDINANCE NO. 20151217-075: An ordinance amending City Code Chapter 13-2 relating to transportation network companies (TNCs) and terminating TNC operating agreements

Compared to Austin City, such chaos has not happened in New York City yet. First, unlike Austin, the taxi market here is mostly competed between Yellow Cab and Uber while other local companies share is negligible. It is therefore unclear if local companies in New York can come up with new competition. Second, the government here regulation is more lenient towards transportation network companies like Uber. However, there is no guarantee that some regulation like Austin's city ordinance would not happen in the future. For example, there has been a conflict between Uber and NYC government about publishing trip record data. While Yellow Cab data is publicly available, Uber refused to submit their data to the government. If conflict cannot be resolved between them, Uber being ridden out of the city is not impossible.

I replicate the scenario in which Uber left the city and the only option left is Yellow Cab and public transportation. I removed every Uber product in my choice set, and kept only Yellow Cab products and its derived demand parameters. Riders in New York City would choose between taking Yellow Cab or an outside option. My results show that, if Uber were banned, the market share of Yellow Cab products will increase. Table 1.11 summarizes the change in market share of Yellow Cab products in the no-Uber scenario. Yellow Cab to Airports will benefit the most from not having competition from Uber, increasing its market share by almost 13%. Notice that when Uber options are not available, not every Uber rider switch to using Yellow Cab. To illustrate, the market share of Yellow Cab's "To Finanical District" product would have been 8.84% instead of 7.59%. This implies that a big portion of Uber riders would use outside options had Uber not been available to them. I calculated the fraction of Uber lost customers who would go back to use Yellow Cab versus to use public transportation for the 3 destinations. I found that, most of Uber lost customers would substitute Uber with public transportation if the purpose of the trip is to Financial distric (72%) and to Upper East Side (61%). If the destination of the trip is to the airports, more of Uber lost customer will switch back to Yellow Cab (51%).

Scenario 3: Uber mimics Yellow Cab's brand characteristics Policy counterfactual scenarios presented in previous section indicates that Uber market share

Table 1.11: Market shares in no-Uber scenario

	To Financial District	To Upper East Side	To Airports
Before banning Uber			
Market share of Uber	1.87%	1.54%	0.28%
Market share of Yellow Cab	6.97%	9.02%	1.17%
After banning Uber			
Market share of Uber	0%	0%	0%
Market share of Yellow Cab	7.59%	9.72%	1.32%
Fraction of Uber riders go back to Yellow Cab vs to public transportation	28/72	39/61	51/49

Notes: Financial District are neighborhoods MN24, MN25, MN27, MN28; Upper East Side are neigbhorhoods MN31, MN32, MN40; Airports is neighborhood QN98 according to New York NTA code

is impacted by large margin if New York City government decreased its pricing of Yellow Cab by 10%. If Uber were to change its fare only, its market share would still go down by 8%. This suggests that competition in this industry is not just about fare.

There are reasons that Uber can be a risky choice for consumers, despite its relatively cheaper fare. First, the drivers lack of professional driving qualifications. Yellow Cab drivers are often held to a certain standard: they must show proof of residency, good health and hygiene, has clean criminal record, and complete taxi driving training. On the other hand, Uber drivers can be just about anyone who has a relatively new car. Second, Uber is notorious for its faulty background check system. Cases were disclosed in which the Uber drivers were convicted felon with violent past. This is one of the most heated clashing points between Uber and the authority: in Austin, Uber failed to conform to fingerprint background check rules; in London, the authorities revealed Uber had failed to report serious criminal offenses allegedly committed by its drivers, and accused Uber of not conducting rigorous background and medical checks on its drivers, to name a few. The consequence of not conforming to the city rules is its ruined image as a safe choice for consumers. What if Uber, instead of competing on price, improves its image in consumers' eyes. One way to increase the sense of security by making their cabs to be more uniform (such as dictating cars to have the same color). This is what Uber in reality has been trying to do with its Uber Black service.

I examine a scenario in which Uber managers find a way to close the gap between its brand images and Yellow Cab, i.e consumers attach more similar quality with brand between Uber and Yellow Cab. I do that by keeping all parameters in the demand system the same, except for Uber brand dummies which will be chosen so that its gap to Yellow Cab dummies parameters is cut by half. I find a large impact on the market. Yellow Cab share would decrease by 14% while Uber market share would more than double its current level, increasing by 151%. Consumers are drawn towards Uber because it is pretty much the same as Yellow Cab, but its fare is lower.

1.7 Conclusion

This paper analyzes the taxi industry in New York City and evaluates the impact of several policy experiments on market shares. It estimated a random coefficient discrete choice model in which taxi riders in New York City where a more traditional service Yellow can choose one option between different products offered by Yellow Cab, Uber and an outside option, that give them the highest utility. The model allows consumer heterogeneity by interacting cab fares with simulated consumers demographic characteristics such as income and age. Recovered demand system is used later to conduct different counterfactuals. Results show that Yellow Cab fare reduction have large positive impact on the market share of Yellow Cab and negative impact on that of Uber. However, if Uber is allowed to change their fare to respond to Yellow Cab fare reduction, its market share does decrease less. A ban on Uber does not bring many consumers back to Yellow Cab, suggesting that those riding Uber switched from outside options. Furthermore, my result suggests that Uber can take even more consumers from Yellow Cab if it can build a brand image that is closer to that of Yellow Cab.

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1.8 Appendix

Figure 1.3: Yellow Cab exclusionary zone

Notes: Taken from the website of New York City's Taxi and Limousine Commission

[11]First 15 fare changes was derived from The New York City Taxicab Fact Book made by Schaller Consulting in 2006. The last fare change in 2012 was reported in TLC website

Table 1.12: History of Yellow Cab fares[11]

	Initial charge	Mileage charge	Wait time	Charge per Mile	Charge per Minute	Average fare
– 1952	$0.2 first 1/4 mi.	$0.05 per 1/4 mi	$0.05/2 mins	$0.20	$0.03	$0.83
Jul-52	$0.25 first 1/5 mi	$0.05 per 1/5 mi.	$0.05/90 secs	$0.20	$0.03	$1.06
Dec-64	$0.35 first 1/5 mi	$0.05 per 1/5 mi.	$0.05/90 secs	$0.20	$0.03	$1.16
Jan-68	$0.45 first 1/6 mi	$0.1 per 1/3 mi.	$0.1/2 mins	$0.30	$0.05	$1.48
Mar-71	$0.6 first 1/5 mi	$0.1 per 1/5 mi.	$0.1/72 secs	$0.50	$0.08	$2.30
Nov-74	$0.65 first 1/6 mi	$0.1 per 1/6 mi.	$0.1/60 secs	$0.60	$0.10	$2.71
Mar-77	$0.75 first 1/7 mi	$0.1 per 1/7 mi.	$0.1/60 secs	$0.70	$0.10	$3.09
Jul-79	$0.9 first 1/7 mi	$0.1 per 1/7 mi.	$0.1/60 secs	$0.70	$0.10	$3.24
Apr-80	$1 first 1/9 mi	$0.1 per 1/9 mi.	$0.1 /45 secs	$0.90	$0.13	$4.06
Jul-84	$1.1 first 1/9 mi	$0.1 per 1/9 mi.	$0.1/45 secs	$0.90	$0.13	$4.16
May-87	$1.15 first 1/8 mi	$0.15 per 1/8 mi.	$0.15/60 secs	$1.20	$0.15	$5.08
Jan-90	$1.5 first 1/5 mi	$0.25 per 1/5 mi.	$0.25/75 secs	$1.25	$0.20	$5.70
Mar-96	$2 first 1/5 mi	$0.3 per 1/5 mi.	$0.3 /90 secs	$1.50	$0.20	$6.85
May-04	$2.5 first 1/5 mi	$0.4 per 1/5 mi.	$0.4/120 secs	$2.00	$0.20	$8.65
Nov-06	$2.5 first 1/5 mi	$0.4 per 1/5 mi.	$0.4/60 secs	$2.00	$0.40	$9.61
Jul-12	$2.5 first 1/5 mi	$0.5 per 1/5 mi.	$0.5/60 secs	$2.50	$0.50	$11.59

Note: Average fare based on 2.8-mile trip with 4.77 minutes of wait time

Table 1.13: OLS logit specifications

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Fare	-0.11***	-0.11***	-0.15***	-0.16***	-0.40***	-0.31***	-0.05***	-0.03***	-0.11***	-0.11***	-0.20***	-0.21***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
YC	-1.46***	-1.43***	-1.12***	-1.04***	2.45***	1.04***	-2.67***	-2.95***	-1.27***	-1.27***	-0.55***	-0.50***
	(0.11)	(0.08)	(0.05)	(0.05)	(0.43)	(0.25)	(0.10)	(0.10)	(0.10)	(0.08)	(0.08)	(0.07)
Uber	-3.59***	-3.58***	-3.44***	-3.41***	-0.92**	-1.93***	-4.57***	-4.76***	-3.41***	-3.41***	-3.06***	-3.04***
	(0.05)	(0.04)	(0.03)	(0.03)	(0.31)	(0.19)	(0.09)	(0.09)	(0.05)	(0.04)	(0.04)	(0.04)
Distance	0.12***	0.13***	0.23***	0.26***	0.77***	0.56***	0.02	-0.02**	0.12***	0.12***	0.34***	0.36***
	(0.04)	(0.03)	(0.02)	(0.02)	(0.07)	(0.04)	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)
Des 1					-1.55***	-0.96***	0.58***	0.69***				
					(0.19)	(0.13)	(0.07)	(0.07)				
Des 2					-1.33***	-0.76***	0.74***	0.85***				
					(0.19)	(0.13)	(0.07)	(0.07)				
W'kend									-0.13***	-0.13***	-0.22***	-0.22***
									(0.02)	(0.02)	(0.02)	(0.02)
Night									-0.42***	-0.42***	-0.51***	-0.52***
									(0.03)	(0.03)	(0.03)	(0.03)
Midday									0.12***	0.12***	0.16***	0.17***
									(0.02)	(0.02)	(0.02)	(0.02)
Evening									-0.34***	-0.34***	-0.40***	-0.40***
									(0.02)	(0.02)	(0.03)	(0.03)

(1) use 5 instruments: $ivppm_1, ivppm_2, ivppm_1 * ivppm_2, ivppm_1^2, ivppm_2^2$

(2) use 8 instruments: $ivppm_1, ivppm_2, ivppm_1 * ivppm_2, ivppm_1^2, ivppm_2^2, ivppm_1 * ivppm_2^2, ivppm_1^2 * ivppm_2, ivppm_1^2 * ivppm_2^2$

(3) use 5 instruments: $iv_1, iv_2, iv_1 * iv_2, iv_1^2, ivp_2^2$

(4) use 8 instruments: $iv_1, iv_2, iv_1 * iv_2, iv_1^2, iv_2^2, iv_1 * iv_2^2, iv_1^2 * iv, iv_1^2 * iv_2^2$

Des 1: To Financial District, Des 2: To Upper East Side, Des 3: To Airports is omitted

Number of observations is 23952, which is equal to 6 products for each of 3992 starting neighborhood-hour markets

Table 1.14: Demand parameter estimates with different demographic interactions

	OLS Logit with IV	Random coefficient model			
		Mean	Sigma	Age	Income
Fare per trip	-0.11***	-0.11	0.20		
	(0.01)	(0.07)	(0.01)		
Yellow Cab	-1.27***	-1.27	-0.02		
	(0.10)	(0.58)	(7.76)		
Uber	-3.41***	-3.41	-0.05		
	(0.05)	(0.44)	(3.77)		
Distance	0.12***	0.12			
	(0.03)	(0.11)			
Weekend	-0.13***	-0.13			
	(0.02)	(0.08)			
Night	-0.42***	-0.42			
	(0.03)	(0.08)			
Midday	0.12***	0.12			
	(0.02)	(0.11)			
Evening	-0.34***	-0.34			
	(0.02)	(0.08)			
GMM objective 1:		359.07	Computer time 1:		88.58
GMM objective 2:		110.51	Computer time 2:		25.48
# of instruments:		8	Degrees of freedome:		5
Critical values:		14.07			

Notes: This employs Nelder-Mead simplex direct search method. The OLS specification chosen is column 10 in Table A2 in the Appendix. This version uses 8 instruments for fare. After the first time run, I calculated the new weighting matrix, which is considered optimal weighting matrix, and ran the whole procedure again. I repeated this process 2 times.

Table 1.15: Demand parameter estimates with different demographic interactions

	OLS Logit with IV	Random coefficient model			
		Mean	Sigma	Age	Income
Fare per trip	-0.11***	-0.65	0.02	0.01	0.04
	(0.01)	0.04	0.01	0.00	0.01
Yellow Cab	-1.27***	3.27			
	(0.10)	0.31			
Uber	-3.41***	0.84			
	(0.05)	0.16			
Distance	0.12***	0.29			
	(0.03)	0.09			
Weekend	-0.13***	-0.39			
	(0.02)	0.07			
Night	-0.42***	-0.11			
	(0.03)	0.08			
Midday	0.12***	0.35			
	(0.02)	0.10			
Evening	-0.34***	-0.56			
	(0.02)	0.11			
GMM objective 1:		481.15	Computer time 1:		122.08
GMM objective 2:		41.18	Computer time 2:		84.25
# of instruments:		8	Degrees of freedome:		5
Critical values :		14.07			

Notes: This employs Nelder-Mead simplex direct search method. The OLS specification chosen is column 10 in Table A2 in the Appendix. This version uses 8 instruments for fare. After the first time run, I calculated the new weighting matrix, which is considered optimal weighting matrix, and ran the whole procedure again. I repeated this process 2 times.

Table 1.16: Demand parameter estimates with different demographic interactions

	OLS Logit with IV	Random coefficient model			
		Mean	Sigma	Age	Income
Fare per trip	-0.11***	-0.55		0.01	0.06
	(0.01)	0.03		0.00	0.03
Yellow Cab	-1.27***	2.69	0.01		
	(0.10)	0.27	1.53		
Uber	-3.41***	0.34	-0.06		
	(0.05)	0.48	8.29		
Distance	0.12***	0.24			
	(0.03)	0.07			
Weekend	-0.13***	-0.34			
	(0.02)	0.26			
Night	-0.42***	-0.21			
	(0.03)	0.10			
Midday	0.12***	0.34			
	(0.02)	0.14			
Evening	-0.34***	-0.52			
	(0.02)	0.25			
GMM objective 1:		178.49	Computer time 1:		42.46
GMM objective 2:		55.58	Computer time 2:		53.03
# of instruments:		8	Degrees of freedome:		4
Critical values :		9.488			

Notes: This employs Nelder-Mead simplex direct search method. The OLS specification chosen is column 10 in Table A2 in the Appendix. This version uses 8 instruments for fare. After the first time run, I calculated the new weighting matrix, which is considered optimal weighting matrix, and ran the whole procedure again. I repeated this process 2 times.

Chapter 2

Net Neutrality Rules and Consumer Substitution Between Cable and Streaming Services

2.1 Introduction

Internet service providers who also provide media content have an incentive to limit access of their consumers to services that provide similar content online. For example, an internet service provider (ISP) who also provides cable on-demand could lower the download speed of streaming services that offer similar movies or TV shows. Regulators in the US have recently begun addressing this possibility: in February 2015 the Federal Communications Commission (FCC) adopted rules known as "Net Neutrality" to limit ISPs ability to discriminate across content providers. In a sharp policy reversal that received much attention, in June 2018 the FCC voted to repeal this regulation.

What is the impact of Net Neutrality (and its repeal) on the market for media content? As a first step, answering this complicated question requires understanding how consumers substitute between the affected products as a function of download speed - the main product attribute regulated by the policy.[1] In order to measure this substitution and simulate the effect of Net Neutrality, we conduct a hypothetical choice experiment. In the experiment, consumers are presented with different ways of consuming a specific media content (in one version of the experiment, a TV show, in another version, a movie). Consumers can view the content on cable on-demand, a streaming service, or they can go to a store to buy a physical DVD. Each option is described by different combinations of price and "buffer time" (in the case of downloaded content, this is the waiting time before the content begins to play; in the case of DVD, it is the time it takes to buy the physical product). Consumers in the experiment are presented with different combinations of these attributes, and their choices allow us to estimate a random utility discrete choice demand model that describes their preferences.

We use the estimated demand model to simulate the impact of Net Neutrality rules on the market for media content by eliminating the buffer time for streaming. This corresponds to a situation where the ISP cannot create extra buffer time for the streaming service compared to cable on-demand. We study a scenario where all prices are held constant, as well a scenario where the cable provider adjusts its price to match the (lower) streaming price in order to limit the adverse impact of the regulation on its market share.

Our estimates imply that the median consumer's willingness to pay for 1 minute less buffer time is 3.5 cents for the TV show and 3.1 cents for the movie. With a typical internet connection, we estimate that the average consumer would be willing to pay 10 percent more for completely eliminating streaming buffer time for the 140 minute long high-definition movie used in our experiment. In our setting, consumers appear to attach high value to download time when choosing how to view a specific type of content. We also find that demand for the various viewing methods is price elastic, particularly for streaming and cable.

[1]See Becker et al. (2010) for a discussion of other considerations related to Net Neutrality. As the authors note, "We are unaware of any evidence on the magnitude of various spillover effects." (517).

In the counterfactual experiment on Net Neutrality rules, we find that eliminating the buffer time for streaming increases this platform's market share by 1.4 (4.6) percentage points for the TV show (movie). Cable on-demand loses the most from this change, with a decline in its market share of 0.7 (2.2) percentage points for the TV show (movie). This finding highlights the incentive that an ISP who also offers cable on-demand has to limit the speed of competing streaming providers in the absence of Net Neutrality.

When the introduction of Net Neutrality is followed by the cable provider matching the price of the streaming service, this wipes out the gain of streaming from the reduction in buffer time in the case of the TV show. For the movie, the gains from the buffer time reduction for streaming are large enough that its market share increases even after the cable price reduction. Here both streaming and cable gain a market share of around 2.7 percentage points, while the DVD market share declines. These findings show that if Net Neutrality eliminates competition in download speed, the nature of competition in the remaining attribute, price, is likely to be a crucial determinant of the impact of the regulation on the market shares of different content providers.

Our paper complements previous studies analyzing consumer's tradeoffs between price and speed in the context of internet subscription plans (e.g., Nevo et al., 2016; Liu et al., 2018). Whereas a monthly internet service can be used to access a variety of services and content, here we study consumers' platform choices while experimentally holding the content constant. This allows us to model the impact of Net Neutrality on the market for on-demand media content, which is one of the markets most likely to be affected by this regulation.

In the remainder of the paper, section 2.2 presents our experiment and the data, section 2.3 describes the demand model and the estimation method, section 2.4 contains the estimation results, section 2.5 presents the policy experiments, and section 2.6 concludes.

2.2 Data

2.2.1 Survey design and data collection

In studies investigating how consumers trade off price and speed for online content, it is common to study choices between broadband internet plans with different characteristics. Here we follow a different route. We pick a product that is homogenous across platforms except in terms of price and download (buffer) time,[2] and study how consumers choose between viewing platforms *for this product* as a function of these two characteristics. We do this using a conjoint survey experiment, where subjects face hypothetical choices described by different characteristics. Studying these choices as a function of price and buffer time allows us to identify the tradeoffs between these two characteristics.

In picking the product, we aimed to make the hypothetical choice scenarios for the consumers as close to real choices as possible. Before the experiment, we identified two products, a TV show and a movie, which cannot be rented either through on-demand cable TV or streaming services, nor can be streamed with a subscription service such as Hulu, Netfix, or Amazon Prime. Thus, a consumer who wants to consume these products has to purchase them.

In the analysis below, consumers face hypothetical choice scenarios about either season 1 of the TV series "Modern Family" in standard definition (SD), or about the movie "Star Wars Episode III – Revenge of the Sith" in high definition (HD). Both of these products satisfy the above criteria: Table 2.11 in the Online Appendix shows the actual availability and prices of these products in March 2016.

For both of these products, there is substantial price variation across viewing platforms: the same product is about 20 percent cheaper on any streaming service compared to cable on-demand, and buying the physical disc provides the cheapest option in both cases (see Table 2.11). There is also substantial variation in buffer

[2]When viewing movies or TV shows online, some of the content needs to be downloaded in advance in order for the video to run uninterrupted. The amount of time elapsing while this is taking place, i.e., the waiting time before the video starts, is referred to as buffer time.

time. To compute this, we used the speed of specific internet providers in the area where our experiments were conducted. See Table 2.12 and 2.13 in the Appendix for more details. Naturally, the buffer time is substantially different for a short TV show compared to a long HD movie.[3]

The setup of our choice experiment closely follows the design of Leung (2013), who also studies tradeoffs between price and download time (in the context of software piracy). We refer the reader to that paper for a discussion of the literature on conjoint surveys and comparisons of hypothetical choices and real market data. In our context, the main advantage of using a conjoint survey is that (i) real market data is not available, (ii) even if such data was available, studying the impact of characteristics such as price on consumer choices would require an instrument akin to the exogenous variation created in our survey experiment.

The choice experiment presented hypothetical scenarios in which subjects chose between different viewing platforms to watch the same product (either the movie or the TV show). About half of the subjects received the movie and half the TV show version of the experiment. For example, in the movie experiment, we started with the statement:

"Imagine you would like to watch the popular movie "Star Wars Episode III – Revenge of the Sith" (2005) in High Definition. You currently don't own this movie. This movie is not available on Netflix, Amazon Prime or Hulu, and it is also not available for rent anywhere. This movie is only available for purchase. Imagine the four options below are your only choices. Which one would you choose?"

Respondents could choose to purchase a physical DVD, use a cable provider's on-demand service, or use an on-demand streaming service (Amazon, VUDU, or Google Play). In addition, they could choose the option "I do not buy or watch this movie." Each viewing option was described by two characteristics: (1) price and (2) buffer time. We varied these two characteristics and asked the respondents the same hypo-

[3]For the TV show, even if the consumer watches several episodes of the season back-to-back, buffering occurs before each episode. The viewer only has to wait until the specific episode can play uninterruptedly.

thetical choice question. The values of the characteristics used in the experiment are shown in Table 2.1 and Figure 2.7.3 shows how the survey was presented.

Table 2.1: Values of the choice attributes used in the experiment

	Option 1 Buying a DVD	Option 2 Cable on-demand	Option 3 Streaming	Option 4 Do not buy
TV show				
Price	5, 8, 12, 20, 30	21, 25, 30, 35, 40	10, 20, 24, 28, 36	-
Buffer time (minutes)	5, 10, 20, 30, 60	0	0, 3, 15, 30, 120	-
Movie				
Price	6, 12, 20, 24, 29	21, 25, 29, 35, 38	8, 14, 20, 25, 30	-
Buffer time (minutes)	5, 10, 20, 30, 60	0	0, 15, 45, 120, 540	-

Notes: Check Appendix 7.2 for more details on prices and download time of the products in the baseline

Each subject was asked to make choices in 10 scenarios. We varied a total of 50 scenarios among the subjects for both the TV and the movie version, creating 10 distinct survey designs for both versions. The Online Appendix shows all possible versions of the survey. Before beginning the choice experiment, subjects were also asked some basic demographic characteristics, and questions on how they typically viewed TV shows / movies.

2.2.2 Data description

The experiment was administered in person at the University of Houston among students and some staff and faculty. We randomly selected 12 classes from the Summer 2016 catalog and surveyed all students in these classes. The data was collected through self-administered surveys. In total, we received survey questionnaires from 416 respondents. Of these, 93 always marked the "Do not buy" option, while 11 always marked one of the other options (e.g., always option 1). In the analysis below, we use surveys of the 312 subjects whose responses exhibit variation in choices. Our dataset contains choices in a total of 3054 scenarios (1563 for the TV show and 1491 for the movie).

Table 2.2 presents the characteristics of the respondents, as well as the average product characteristics (price and buffer time) across all choice options. The respondent samples do not differ significantly between the TV show and the movie version of the experiment.

Table 2.2: Summary statistics of respondent demographics and product characteristics

	TV sample	Movie sample	Difference	p-value	N
Demographics					
Age	21.917	21.855	0.062	0.905	302
	(4.162)	(4.871)			
Low income	0.278	0.207	0.071	0.145	312
	(0.449)	(0.406)			
Medium income	0.253	0.240	0.013	0.790	312
	(0.436)	(0.429)			
High income	0.463	0.540	-0.077	0.175	312
	(0.500)	(0.500)			
Owns a dvd player	0.619	0.698	-0.079	0.144	309
	(0.487)	(0.461)			
Owns a bluray player	0.563	0.557	0.005	0.923	309
	(0.498)	(0.498)			
Owns high speed internet	0.809	0.820	-0.011	0.797	312
	(0.395)	(0.385)			
Product characteristics					
TV Price	17.205				6252
	(13.361)				
TV buffer time	19.689				6252
	(34.698)				
Movie price		16.779			5964
		(12.468)			
Movie buffer time		48.690			5964
		(122.928)			

Notes: Average respondent characteristics (with standard deviations in parentheses) for the 312 respondents used in the analysis. Product characteristics are for all choice options in all all scenarios. The third and fourth columns show the difference in means and the p-value for the equality of means t-test. Variable definitions are in the Appendix.

About 28% of the respondents had household incomes less than $40,000 per year, and 47% had more than $70,000. The mean age of the respondents is 22 with a range of 18 to 50. Ten percent of the students were aged 27 or older, and 5 percent were 30 or older. More than 80 percent of the respondents have high speed internet connection at home, but less than 60% have a Blu-ray player, likely showing the changing trends in the industry.

There could be a concern that this younger population may have different preferences and hence make different choices than the US population. This could lead to non-representative counterfactuals and potentially misleading interpretations of the overall results. In on-going work, we will address this in two ways. First, since we estimate individual-specific parameters and include demographic variables in the estimation, we can estimate some of our results for older populations. Second, we will also reestimate the model using weights based on age, family income, access to high-speed internet and ownership of Blu-ray player for the US population.

2.3 Demand model

We describe decision makers using a mixed logit model (Train, 2009). Facing a choice scenario t, the utility that decision maker n obtains from choosing alternative j is given by

$$U_{njt} = \alpha_n p_{njt} + \beta_n b_{njt} + z_n' \gamma + \varepsilon_{njt}, \tag{2.1}$$

where p_{njt} is price, b_{njt} is buffer time, z_n is a vector decision maker characteristics, and ε_{njt} is a random term drawn from a Type I extreme value distribution. The individual-specific coefficients (α_n, β_n) are drawn i.i.d. from a distribution $f(.|\theta)$, where θ are parameters of the distribution. In addition to the different viewing platforms, the decision maker can also choose not to view the given product, and we normalize the utility of this to 0. The probability that the decision maker chooses alternative i is

$$P_{ni} = \int \frac{\exp(\alpha_n p_{njt} + \beta_n b_{njt} + z_n' \gamma)}{\sum_{j=1}^{J} \exp(\alpha_n p_{njt} + \beta_n b_{njt} + z_n' \gamma)} f(\alpha, \beta|\theta) d(\alpha, \beta).$$

Since we observe an individual making several choices, this can be taken into account in the analysis. The probability of a particular sequence of choices is given by

$$P_{ni} = \int \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp(\alpha_n p_{njt} + \beta_n b_{njt} + z_n' \gamma)}{\sum_{j=1}^{J} \exp(\alpha_n p_{njt} + \beta_n b_{njt} + z_n' \gamma)} \right]^{I_{njt}} f(\alpha, \beta|\theta) d(\alpha, \beta) \tag{2.2}$$

where $I_{njt} = 1$ if the individual chose alternative j in choice scenario t and 0 otherwise.

The parameters θ and γ can be estimated by maximizing the simulated log-likelihood corresponding to (2.2). We implement this estimator using the "mixlogit" command in STATA (Hole, 2007), simulating the integral in (2.2) using 1000 Halton draws.

Parameter estimates are in Tables 2.14 and 2.15 in the Appendix. Each specification contains a set of demographic characteristics interacted with choice-specific constants to allow for the utility of each option to vary for different groups of consumers. These demographic characteristics include age, income, whether the individual owns a DVD or Blu-ray player, and whether he has high-speed internet access at home.

In both tables, column (1) allows for individual heterogeneity in the price coefficients by assuming a normal distribution on this parameter. Column (2) adds heterogeneity in the buffer time parameter as well, using a normal distribution independent from the price parameter. Column (3) and (4) repeat these specifications replacing the normal distributions with log-normal. As shown in the table, the model produces the lowest log likelihood value in column (4) specifications, where both parameters have a log-normal distribution. In column (5) we allow for correlation between the buffer time and price coefficients and estimate the covariance matrix of these two variables. We find that the covariance parameters are not statistically significant either for the TV show or for the movie. In addition, the model's fit is virtually unchanged compared to the specification in column (4), indicating that the specification using independent random coefficients is adequate.

Demographic characteristics are not significant once choice specific constants are included, but in all cases their inclusion improves the model's fit. The estimated distribution of the buffer time and price coefficients across individuals is shown in Figures 2.7.4 and 2.7.4 in the Appendix, and corresponding summary statistics are reported in Table 2.3. In both cases we find important variation in the coefficients across individuals. The rest of the paper uses parameter estimates from our preferred specification, column (4) of Table 2.14 and 2.15 in the Appendix. In this specification, the lognormal distribution ensures that the price coefficients are always negative, and that the willingness-to-pay values calculated below have finite moments (Daly, Hess, and Train, 2012).

Table 2.3: Summary statistics of individual coefficients and WTP for price and buffer time

	Mean	Median	St.dev.	10%	90%	N
TV show						
Price	-0.210	-0.156	0.154	-0.426	-0.078	157
Buffer time	-0.039	-0.006	0.128	-0.083	-0.002	157
WTP for buffer time	0.244	0.035	1.038	0.014	0.417	157
Movie						
Price	-0.224	-0.170	0.127	-0.391	-0.104	144
Buffer time	-0.017	-0.005	0.032	-0.046	-0.002	144
WTP for buffer time	0.092	0.031	0.206	0.007	0.262	144

Notes: Summary statistics for price and buffer time coefficient estimates from column (4) of Tables 2.14 and 2.15 in the Appendix, and implied willingness to pay for buffer time.

2.4 Results

2.4.1 Willingness to pay estimates

To describe the heterogeneity across individuals, we compute the marginal utility of substitution between price and buffer time (i.e., the willingness to pay for buffer time) for each individual based on the parameter estimates. Since the utility is linear in the choice attributes, willingness to pay (WTP) for the non-price attribute (buffer time) is the negative of the ratio of the estimated individual coefficients for this attribute and for price.

The distribution of the individual WTP values implied by the parameter estimates is shown in Table 2.3 and Figure 2.4.1. The median willingness to pay for 1 minute less buffer time is 3.5 cents for the TV show and 3.1 cents for the movie. WTP values tend to larger for the TV show: the $10 - 90$ percentile range is $1.4 - 41.7$ cents for the TV show compared to $0.7 - 26.2$ cents for the movie. This is plausible: since the TV show is shorter than the movie, an extra minute of buffer time is a larger fraction of the total viewing period for the former. Perhaps for the same reason, the standard deviation of WTP for buffer time is also larger in the case of the TV show: five times the mean, compared to twice the mean for the movie.

In our counterfactual experiment below we investigate the impact of eliminating a typical buffer time of 23 minutes for the movie or 3 minutes for the TV show.[4] To put those results in context, note that the WTP estimates shown in Table 2.3 imply that the median (average) consumer is willing to pay 71.3 cents ($2.12) more for eliminating a 23 minute buffer time for the movie. This corresponds to 3.6% (10.6%) of the movie's price of $19.99. Interestingly, the average WTP corresponds almost exactly to the price difference between streaming the movie or watching it on cable on demand with no buffer time (for $21.99). For the TV show, the median (average) consumer's WTP for eliminating the 3 minutes buffer time is 10.5 cents (73.2 cents).

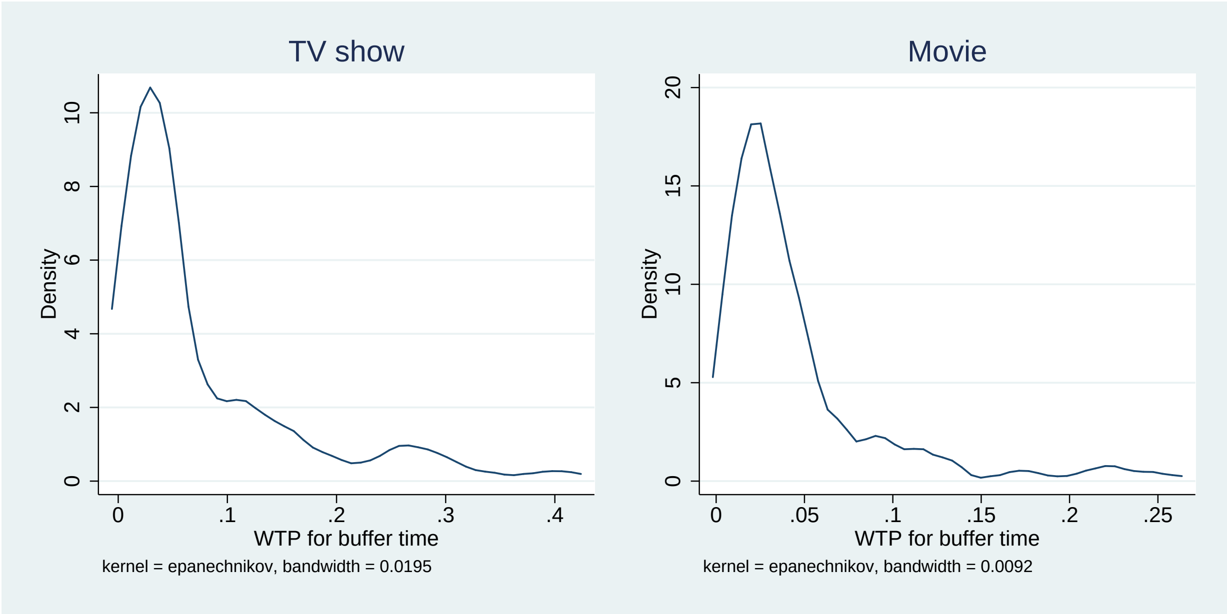
As noted by Train and Week (2005), in some cases WTP values computed using the parameter estimates of mixed logit models produce implausibly large values for large shares of consumers. In such cases, they suggest estimating the model "in WTP space," assuming a normal or log-normal distribution for the individual WTP values rather than the coefficients themselves. In our case, the WTP estimates obtained using the parameters do not seem implausibly large. Still, to assess the robustness of the patterns above, in the Appendix we re-estimate the model in WTP space. The results are qualitatively similar to those reported above.

We are not aware of directly comparable willingness to pay estimates for download speeds in the existing literature. Nevo et al. (2016) estimate that consumers are willing to pay between 0 and 5 dollars per month for increasing their internet speed by 1 megabyte per second (Mbps), with an average of 2 dollars. This is based on a dataset of internet subscribers and the internet plans they purchased. Liu et al. (2018) study a choice experiment where subjects choose between different hypothetical internet plans, and estimate that consumers are willing to pay around 2 dollars a month for one extra Mbps at low Mbps levels, but only 2 cents per extra Mbps at high Mbps levels (above 100 Mbps).

Our setting differs from both of these studies since we are studying willingness to

[4]See the Appendix for the computation of these values.

Figure 2.1: Distribution of individual WTP for time



Notes: Individual WTP for buffer time computed using the parameter estimates in column (4) of Table 2.14 and 2.15 in the Appendix. Values are for the 10-90 percentile range.

pay for internet speed when consuming a specific product, rather than when choosing monthly internet subscriptions. Still, to translate our findings into WTP for internet speed we can do the following. Based on Table 2.3, the median WTP for 1 minute less buffer time is 3.5 cents in the TV sample and 3.1 cents in the movie sample. If a consumer's connection speed is 3 Mbps, the buffer time for a 20-minute episode of the TV show is around 3 minutes. Based on the median WTP, this consumer would be willing to pay 10.5 cents to eliminate the 3 minute buffer time. Alternatively, he could also achieve the same experience by upgrading his internet speed to a bandwidth that is large enough to stream the TV show without buffer time. If the streaming service for the TV show has a bit rate of 3.5, the internet speed would have to be upgraded to 3.5 Mbps to achieve this. In this sense, the consumer would be willing to pay 10.5 cents for the 0.5 Mbps faster connection, or 21 cents for an extra 1 Mbps. For the movie, the median WTP for 1 minute less buffer time is 3.1 cents, and the buffer time for the 140 minute long movie at 3 Mbps connection speed is 23 minutes. Assuming that WTP increases linearly, the customer would be willing to pay 71.3

cents to download the movie immediately. This translates to a WTP of \$1.43 for 1 Mbps increase in speed. In this experiment consumers appear to attach high value to internet speed when choosing how to view a specific type of content.[5]

2.4.2 Substitution patterns

In order to study the substitution patterns implied by our model estimates, we first use the estimates to compute price elasticities. To do this, for each viewing platform, we first predict demand (choice probabilities) at the actual prices of using that platform. We then raise this price by 1 percent, and predict demand for all viewing platforms at this new price. (Throughout, prices of the other platforms are held fixed at the values given in the choice experiment.) We compute individual price elasticities as the percentage change in demand following this price change. In each case, demand predictions are based on 1000 simulations for each consumer from the estimated distribution of individual coefficients. Note that, because the mixed logit model relaxes the Independence of Irrelevant Alternatives (IIA) assumption of the simple logit model, the cross-price elasticities of the different alternatives are not restricted to be equal. Indeed, this is an important advantage of using mixed logit, which therefore allows for more realistic substitution patterns.

Summary statistics of the individual price elasticities for each platform and each program (TV show or movie) are given in Table 2.4. For example, in the case of the TV show and a 1 percent change in the price of the DVD, the median price elasticity of the DVD is -1.102 percent, while the (cross-)price elasticities of cable and streaming are, respectively, 0.505 and 0.627. In general, Table 2.4 indicates that consumer demand is price-elastic for each platform, with mean and median own-price elasticities around 1-1.5 percent for the DVD and around 2.1-2.2 for cable and streaming. The own-price elasticity appears to be lower for DVD than for the other two platforms.

[5] This is consistent with Krishnan and Sitaraman (2013), who find that consumers start abandoning online videos after as little as 1 second extra buffer time.

Table 2.4: Price elasticities

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
Price change for DVD					
DVD	-1.114	-1.102	0.263	-1.513	-0.780
Cable	0.499	0.505	0.164	0.281	0.705
Streaming	0.652	0.627	0.176	0.429	0.907
Outside	0.804	0.828	0.287	0.350	1.171
Price change for cable					
DVD	0.418	0.278	0.301	0.144	0.875
Cable	-2.129	-2.131	0.195	-2.372	-1.881
Streaming	0.480	0.422	0.267	0.177	0.841
Outside	0.246	0.227	0.122	0.102	0.402
Price change for streaming					
DVD	0.478	0.372	0.321	0.142	0.960
Cable	0.493	0.413	0.282	0.166	0.892
Streaming	-2.101	-2.092	0.197	-2.360	-1.834
Outside	0.243	0.189	0.185	0.042	0.507
Panel B: Movie					
Price change for DVD					
DVD	-1.663	-1.636	0.376	-2.191	-1.173
Cable	0.848	0.896	0.340	0.311	1.265
Streaming	0.986	1.025	0.393	0.428	1.484
Outside	0.841	0.907	0.364	0.256	1.271
Price change for cable					
DVD	0.762	0.670	0.510	0.183	1.544
Cable	-2.150	-2.165	0.284	-2.504	-1.747
Streaming	0.706	0.541	0.482	0.207	1.478
Outside	0.511	0.444	0.317	0.154	1.005
Price change for streaming					
DVD	0.703	0.615	0.484	0.112	1.455
Cable	0.609	0.570	0.404	0.112	1.186
Streaming	-2.160	-2.224	0.327	-2.556	-1.681
Outside	0.467	0.396	0.344	0.038	0.997

Notes: Percentage change in demand (choice probabilities) following a 1 percent change in the price of the indicated platform. Changes are computed relative to the actual price of using the platform (TV show: 12.99 for DVD, 29.99 for cable, and 24.99 for streaming; movie: 16.96 for DVD, 21.99 for cable, 19.99 for streaming.

Table 2.5 presents the impact of varying buffer time. To make buffer time changes meaningful, we consider the impact of increasing buffer time from 0 to, respectively, 3, 5, and 10 minutes. We present the resulting changes in demand (i.e., choice probabilities) in percentage points. These can be interpreted as the changes in market shares resulting from the increase in buffer time. We find that, naturally, the impact is largest on streaming service, resulting in a decline in market shares between 0.8 and 3.2 percentage points. The decline is always larger for the TV show, presumably because the buffer time is a larger fraction of the viewing experience in that case. Table 2.5 also shows that cable is the closest substitute of streaming for these changes in buffer time, followed by the outside good (not watching the program), and finally DVD. Based on these results, cable benefits most from slower streaming speeds. In the Appendix, we show that the findings are qualitatively similar if we consider relative changes in demand (percent instead of percentage points, Table 2.17).

Table 2.5: Demand impacts of changes in buffer time

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
Buffer time changes: 0 to 3 min					
DVD	0.207	0.156	0.162	0.044	0.431
Cable	0.626	0.584	0.227	0.358	0.945
Stream	-1.334	-1.340	0.461	-1.918	-0.667
Outside	0.501	0.416	0.318	0.114	0.939
Buffer time changes: 0 to 5 min					
DVD	0.340	0.257	0.267	0.073	0.694
Cable	0.905	0.832	0.344	0.503	1.369
Stream	-1.971	-1.934	0.741	-2.971	-0.948
Outside	0.727	0.573	0.489	0.152	1.394
Buffer time changes: 0 to 10 min					
DVD	0.650	0.503	0.514	0.142	1.282
Cable	1.415	1.286	0.588	0.725	2.219
Stream	-3.207	-3.058	1.358	-5.186	-1.469
Outside	1.143	0.856	0.834	0.212	2.282
Panel B: Movie					
Buffer time changes: 0 to 3 min					
DVD	0.196	0.159	0.144	0.049	0.406
Cable	0.287	0.254	0.153	0.120	0.518
Stream	-0.783	-0.812	0.224	-1.050	-0.469
Outside	0.300	0.286	0.157	0.080	0.521
Buffer time changes: 0 to 5 min					
DVD	0.325	0.261	0.240	0.080	0.664
Cable	0.456	0.396	0.240	0.196	0.809
Stream	-1.260	-1.321	0.379	-1.699	-0.714
Outside	0.479	0.471	0.259	0.117	0.836
Buffer time changes: 0 to 10 min					
DVD	0.640	0.514	0.475	0.160	1.269
Cable	0.817	0.702	0.439	0.331	1.468
Stream	-2.324	-2.484	0.772	-3.227	-1.191
Outside	0.867	0.871	0.505	0.183	1.566

Notes: Changes in demand (choice probabilities) in percentage point following an indicated change in buffer time.

2.5 Policy experiment

Net Neutrality rules would prohibit internet service providers (ISP) from discriminating between different content providers by slowing down some providers and speeding up others. Presumably, these rules would have a major impact on content providers that directly compete with services offered by the ISP, such as the streaming services who compete with the ISP's cable on-demand service. Without Net Neutrality, the ISP has an incentive to slow down the competing streaming service; with Net Neutrality, it cannot do so. In order to gain some insight into the possible effect of Net Neutrality rules through this channel, we consider the effect of making streaming faster. Specifically, we model the impact of lowering streaming buffer time to 0 (i.e., equal to the buffer time for cable on-demand). We study two versions of this experiment, one where prices are held constant, and one where the cable provider adjusts its price to match the price of the streaming service (so that *both* buffer time and price is equalized between these two platforms).

2.5.1 Baseline

As our baseline, we compute demand using prices and buffer times that approximate the actual product attributes currently available on the market. Based on the prices listed in the Appendix (Table 2.11), we set the price of the TV show for DVD, cable, and streaming to 12.99, 29.99, and 24.99, respectively. We set the price of the movie to 16.99, 21.99, and 19.99 for these three platforms. Since cable on-demand involves no buffering, its buffer time is set to 0. For streaming, we set the buffer time to 3 minutes for the TV show and 23 minutes for the movie based on the computations described in the Appendix. For the DVD option, time depends on many unobserved factors (like transportation options, traffic, etc.). Here we set the times equal to the actual times given in the choice experiment scenarios (between 5 and 60 minutes): predicted demand will reflect each consumer's average choices across these values. These baseline attribute values are summarized in Table 2.6, and Table 2.7 shows predicted demand in the baseline.

Table 2.6: Baseline attribute values for the counterfactual experiments

	DVD / Blu-Ray	Cable	Streaming
TV show			
Actual prices	12.99	29.99	24.99
Actual buffer time (minutes)	Between 5 and 60	0	3
Movie			
Actual prices	16.99	21.99	19.99
Actual buffer time (minutes)	Between 5 and 60	0	23

Notes: Check Appendix 7.2 for more details on prices and download time of the products in the baseline

In the baseline, DVD has the largest market share, which can be explained by the lowest price of this option. The market share of DVD is relatively larger in the case of the TV show, where the price difference relative to cable or streaming is particularly large. For the movie, the price advantage of DVD is smaller, and consequently the market shares are more equalized.

Table 2.7: Predicted market shares at baseline

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
DVD	0.428	0.425	0.070	0.341	0.522
Cable	0.112	0.111	0.015	0.094	0.133
Streaming	0.169	0.169	0.023	0.139	0.197
Outside	0.291	0.299	0.059	0.218	0.349
Panel B: Movie					
DVD	0.311	0.300	0.068	0.233	0.401
Cable	0.209	0.198	0.069	0.124	0.308
Streaming	0.208	0.198	0.051	0.150	0.273
Outside	0.272	0.260	0.036	0.234	0.323

Notes: Predicted market shares (choice probabilities) under the baseline attribute values (see Table 2.6).

2.5.2 Experiment 1: equal buffer time for streaming and cable

Table 2.8 shows the result of the counterfactual policy experiment where the buffer time for streaming is set to 0. Values are percentage point changes in market shares relative to the baseline values in Table 2.7. The lower buffer time results in an increase of streaming's market share of around 1.37 percentage points for the TV show and 4.6 percentage points for the movie. The change is particularly disadvantageous for cable, which loses 0.7 percentage points in market share for the TV show and 2.2 percentage points for the movie. Because cable on-demand services are typically provided by ISPs, this result highlights the incentive that ISPs have in lowering streaming speeds in the absence of Net Neutrality rules. Alternatively, ISPs may offer paid "fast lanes" to streaming providers, where providers pay a fee for the faster service, thus compensating the ISPs loss in revenue on cable on-demand. The ISPs incentive to slow down speeds or charge fast lane fees in the absence of Net Neutrality rules may be particularly pronounced given that most ISPs command considerable market power on their local markets.

Table 2.8: Experiment 1: equal buffer time for streaming and cable

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
DVD	-0.245	-0.214	0.110	-0.431	-0.118
Cable	-0.686	-0.684	0.141	-0.879	-0.489
Streaming	1.368	1.381	0.110	1.210	1.502
Outside	-0.437	-0.449	0.100	-0.560	-0.301
Panel B: Movie					
DVD	-1.298	-1.221	0.517	-2.025	-0.656
Cable	-2.219	-2.233	0.678	-3.090	-1.293
Streaming	4.560	4.570	0.738	3.583	5.499
Outside	-1.043	-0.956	0.368	-1.561	-0.622

Notes: Changes in market shares when the buffer time for streaming is set to 0. Changes are in percentage points relative to the baseline.

2.5.3 Experiment 2: equal buffer time and price for streaming and cable

In Table 2.9 we consider a second experiment, where in addition to reducing streaming buffer time to 0, we also set the price of cable equal to that of streaming. This may be interpreted as simulating the introduction of Net Neutrality, followed by a price reduction by the cable provider in an attempt to stay competitive with the streaming service. Since for a given content these providers only compete in two dimensions, download time and price, it is interesting to study the impact of competition in price alone if competition in download time is shut down by Net Neutrality rules.[6]

As shown in Table 2.9, eliminating buffer time *and* equalizing the price of cable and streaming lowers the market share of DVD by about 3 percentage points for both the TV show and the movie. For the TV show, the equalization of price wipes out the gains of streaming from the reduction in buffer time, and the market share of cable increases by 5 percentage points relative to the baseline. For the movie, price equalization still benefits cable, but the gains from the buffer time reduction for streaming were large enough that the net effect is an increase in market shares for both cable and streaming by approximately equal amounts (around 2.7 percentage points).

2.6 Conclusion

In this paper, we designed and analyzed a hypothetical choice experiment where consumers decide between various viewing platforms for a specific media content, either a movie or a TV show. Estimating a random utility demand model shows that consumers in this setting are highly sensitive to both price and download time. This sets the stage for our analysis of the impact of Net Neutrality on the market for on-demand media content. When the buffer time of the streaming service is eliminated, cable on-demand loses a significant share of the market. Thus, an ISP who also

[6]Here, since both attributes of cable and streaming are equalized, differences in the demand for the two platforms reflect consumer preferences captured by the choice-specific constants.

Table 2.9: Experiment 2: equal buffer time and price for streaming and cable

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
DVD	-3.209	-3.250	0.598	-3.967	-2.510
Cable	5.038	4.974	0.607	4.298	5.905
Streaming	-0.436	-0.395	0.329	-0.883	-0.049
Outside	-1.392	-1.407	0.341	-1.853	-0.936
Panel B: Movie					
DVD	-3.315	-3.290	0.655	-4.214	-2.437
Cable	2.755	2.671	1.098	1.267	4.231
Streaming	2.711	2.654	0.795	1.725	3.811
Outside	-2.151	-2.179	0.380	-2.588	-1.613

Notes: Changes in market shares when the buffer time for streaming is set to 0, and simultaneously the price of cable is set equal to the price of streaming. Changes are in percentage points relative to the baseline.

provides on demand content has an incentive to restrict the download speed of the streaming provider. By prohibiting this, Net Neutrality hurts the cable provider. If the cable provider reacts to the policy by lowering its price, it can offset these losses, particularly for the product where the price difference is currently larger.

By focusing on consumer choice between platforms for a given content, we have analyzed one important aspect of the impact of Net Neutrality on the market for on demand media content. Future research should study how the nature of price competition mediates the impact of the regulation in this market.

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2.7 Appendix

2.7.1 Definitions of the variables

Table 2.10: Variable definitions

Price	Price of the tv show / movie.
Buffer time	Measured in minutes. This is the wait time until a purchased TV show / movie can be viewed after purchase without interruption. For the physical dvd, the buffer time attribute is travel time to a store.
Age	Age of the respondent
Low income	1 if the respondent's household income is below 40,000 USD, 0 otherwise.
Medium income	1 if the respondent's household income is between 40,001 and 70,000 USD, 0 otherwise
High income	1 if the respondent's household income is above 70,001 USD, 0 otherwise
Owns a DVD player	1 if the respondent owns a dvd-player or a bluray player, 0 otherwise. The TV show scenarios are about an SD version, this can be viewed using either a DVD or a Blu-ray player
Owns a Blu-ray player	1 if the respondent owns a Bluray player, 0 otherwise. The movie scenarios are about an HD version which can only be viewed using a Blu-ray player.
Owns high speed internet	1 if the respondent has a DSL, Cable or Fiber internet connection at home. 0 if the responent has a satellite connection or no internet connection at home.

2.7.2 Product availability, prices, and buffer times

Table 2.11: Availability and price of the products used in the choice experiment

	Movie	TV show
Subscription based services		
Netflix	Not available	Not available
Hulu	Not available	Not available
Amazon Prime	Not available	Not available
Pay per movie		
Google Play - rent	Not available	Not available
Google Play - buy	SD: not available, HD: 19.99	SD: 24.99, HD: not available
Amazon on Demand - rent	Not available	Not available
Amazon on Demand - purchase	SD: 19.99, HD: 19.99	SD: 24.99 or 1.99 per episode, HD: only per episode, 24*2.99=73
Comcast Xfinity on Demand - rent	Not available	Not available
Comcast Xfinity on Demand - purchase	SD: 21.99, HD: 21.99	SD: 29.99, HD:39.99
Dierct TV on Demand - purchase	Not available	Not available
Direct TV on Demand - rent	Not available	Not available
PlayStation - purchase	SD: 19.99, HD: 19.99	SD: 24.99 or 1.99 per episode, HD: not available
PlayStation - rent	Not available	Not available
VUDU - rent	Not available	Not available
VUDU - buy	SD: not available, HD: 19.99	SD: 24.99, HD: 29.99
Redbox	Not available	Not available
YouTube - rent	Not available	Not available
YouTube - purchase	SD: not available, HD: 19.99	SD: 24.99, HD: 29.99
Buy DVD	10.46	12.99
Buy Blu-ray	16.96	15.83
Itunes - rent	Not available	Not available
Itunes - purchase	SD: 19.99, HD: 19.99	SD:24.99, HD: 29.99

Notes: Availability and price of the products for common providers as of 3/16/2016. The movie is "Star Wars Episode III - Revenge of the Sith," the TV show is "Modern Family - Season 1."

This section describes how we selected the buffer time values used in the choice experiment based on actual buffer times available on the market around the time of our study. The two most important factors that determine buffer time are the speed of the internet connection and the bit rates of the streaming service. In order to stream a movie without buffering, one's connection must be able to download its content at least as fast as the bit rate of the streaming service. The lower the internet speed and the higher the video bit rate, the longer is the buffer time.

Denote x the streaming bit rate in megabytes per second (Mbps), y the speed of the internet connection in Mbps and b the length of the content in minutes (140 for the movie, 20 for the TV show). Since the connection can keep downloading while viewers watch, if the connection speed is greater than the video bit rate ($y > x$), streaming can start immediately without interruption. On the other hand if $x > y$, there will be a buffer time. Since viewers can watch while downloading, they do not have to wait for the whole content to be downloaded to be able to watch uninterruptedly. This requires only that the whole content finishes downloading at the same time as the length of the movie plus the buffer time:

$$\text{buffer time} = \text{download time} - \text{video length}$$

In general,

$$\text{Buffer time} = b\frac{x-y}{y},$$

where bx is size of the content, thus $\frac{bx}{y}$ is the time needed to download the full content. Based on the formula, we estimated the buffer time for different types of streaming service with different internet providers These values are shown in Table 2.12 and 2.13 for the movie and the TV show, respectively. Internet connection speed is based on the most popular advertised download tiers for various providers according to the FCC.

Table 2.12: Buffer time in minutes for movie for different combinations of internet and streaming service

Internet provider (download speed, Mbps)	*Streaming service* (video bit rate, Mbps) Comcast on demand HD (15)	Netflix HD (7)	Vudu (4.5)	Amazon HD (3.5)	Amazon SD (0.9)
ATT-DSL (3)	560	187	70	23	0
ATT-Uverse (6)	210	23	0	0	0
CenturyLink (1.5)	1260	513	280	187	0
Frontier DSL (1)	1960	840	490	350	0
Verizon (0.5)	4060	1820	1120	840	112
Windstream (3)	560	187	70	23	0
Cablevision (15)	0	0	0	0	0
Charter (15)	0	0	0	0	0
Comcast (3)	560	187	70	23	0
Cox (5)	280	56	0	0	0
Mediacom (15)	0	0	0	0	0
TWC (15)	0	0	0	0	0
Frontier Fiber (25)	0	0	0	0	0
Verizon Fiber (15)	0	0	0	0	0
Hughes (5)	280	56	0	0	0
Viasat/Exede (12)	35	0	0	0	0

Notes: Download speed values for different internet providers are from Table 1 of "Measuring Broadband America Fixed Broadband Report, A Report on Consumer Fixed Broadband Performance in the United States" by FCC's Office of Engineering and Technology and Consumer and Governmental Affairs Bureau, 2015. (https://www.fcc.gov/reports-research/reports/measuring-broadband-america). If multiple tiers are advertised the lowest tier is used. Video bit rates refer to the amount of data stored for each second of media that is played. Videos that are encoded with higher bit rates usually have higher quality, and therefore need a higher internet speed to download without buffer. Video bit rates are collected from the provider's websites.

Table 2.13: Buffer time in minutes for TV show for different combinations of internet and streaming service

Internet provider (download speed, Mbps)	*Streaming service* (video bit rate, Mbps) Comcast on demand HD (15)	Netflix HD (7)	Vudu (4.5)	Amazon HD (3.5)	Amazon SD (0.9)
ATT-DSL (3)	80	27	10	3	0
ATT-Uverse (6)	30	3	0	0	0
CenturyLink (1.5)	180	73	40	27	0
Frontier DSL (1)	280	120	70	50	0
Verizon (0.5)	580	260	160	120	16
Windstream (3)	80	27	10	3	0
Cablevision (15)	0	0	0	0	0
Charter (15)	0	0	0	0	0
Comcast (3)	80	27	10	3	0
Cox (5)	40	8	0	0	0
Mediacom (15)	0	0	0	0	0
TWC (15)	0	0	0	0	0
Frontier Fiber (25)	0	0	0	0	0
Verizon Fiber (15)	0	0	0	0	0
Hughes (5)	40	8	0	0	0
Viasat/Exede (12)	5	0	0	0	0

Notes: Download speed values for different internet providers are from Table 1 of "Measuring Broadband America Fixed Broadband Report, A Report on Consumer Fixed Broadband Performance in the United States" by FCC's Office of Engineering and Technology and Consumer and Governmental Affairs Bureau, 2015. (https://www.fcc.gov/reports-research/reports/measuring-broadband-america). If multiple tiers are advertised the lowest tier is used. Video bit rates refer to the amount of data stored for each second of media that is played. Videos that are encoded with higher bit rates usually have higher quality, and therefore need a higher internet speed to download without buffer. Video bit rates are collected from the provider's websites.

2.7.3 Survey design

Figure 2.2: Sample scenario from the choice experiment

Imagine you would like to watch the popular movie “Star Wars Episode III – Revenge of the Sith” (2005) in High Definition. You currently don’t own this movie. This movie is not available on Netflix, Amazon Prime or Hulu, and it is also not available for rent anywhere. This movie is only available for purchase.
Imagine the four options below are your only choices. Which one would you choose? (Please indicate your first choice and your second choice)

First choice: ❍1 ❍2 ❍3 ❍4 **Second choice**: ❍1 ❍2 ❍3 ❍4

Option 1: Buy the movie on Blu-Ray.	Option 2: Buy the movie on Cable on Demand (such as Xfinity on Demand)	Option 3: Buy the movie on a streaming service (such as Amazon, VUDU or Google Play)	Option 4: I do not buy or watch this movie.
$12	**$21**	**$30**	
Going to the store and back will take **30 minutes**.	You can start watching the movie **IMMEDIATELY.**	You need to wait **9 hours** before you can start watching the movie.	

2.7.4 Parameter estimates

Table 2.14: Parameter estimates, movie

	(1)	(2)	(3)	(4)	(5)
Mean parameters					
owns dvd player x dvd	0.295	0.236	0.295	0.259	0.235
	(0.529)	(0.543)	(0.566)	(0.585)	(0.595)
owns dvd player x cable	0.313	0.240	0.390	0.327	0.303
	(0.615)	(0.634)	(0.636)	(0.662)	(0.669)
owns dvd player x streaming	-0.096	-0.203	-0.123	-0.188	-0.213
	(0.516)	(0.537)	(0.559)	(0.578)	(0.591)
age x dvd	-0.029	-0.030	-0.019	-0.021	-0.022
	(0.039)	(0.039)	(0.047)	(0.047)	(0.048)
age x cable	-0.052	-0.056	-0.046	-0.050	-0.051
	(0.054)	(0.055)	(0.063)	(0.067)	(0.067)
age x streaming	-0.009	-0.010	0.002	-0.002	-0.002
	(0.034)	(0.035)	(0.043)	(0.042)	(0.043)
owns high-speed x dvd	-0.231	-0.140	-0.086	0.055	0.047
	(0.665)	(0.677)	(0.698)	(0.726)	(0.729)
owns high-speed x cable	0.382	0.494	0.424	0.733	0.724
	(0.717)	(0.731)	(0.762)	(0.730)	(0.728)
owns high-speed x streaming	0.652	0.766	0.789	0.960	0.954
	(0.585)	(0.605)	(0.623)	(0.642)	(0.644)
low income x dvd	0.187	0.084	0.193	0.396	0.355
	(0.688)	(0.717)	(0.747)	(0.805)	(0.802)
low income x cable	-0.699	-0.815	-0.743	-0.631	-0.674
	(0.800)	(0.830)	(0.819)	(0.876)	(0.878)
low income x streaming	-0.230	-0.348	-0.224	-0.056	-0.095
	(0.666)	(0.717)	(0.738)	(0.793)	(0.794)
med income x dvd	-0.460	-0.564	-0.603	-0.331	-0.336
	(0.589)	(0.618)	(0.625)	(0.596)	(0.600)
med income x cable	-1.073	-1.195	-1.227*	-1.126	-1.124
	(0.697)	(0.738)	(0.713)	(0.717)	(0.716)
med income x streaming	-0.855	-0.997	-1.018	-0.717	-0.721
	(0.586)	(0.634)	(0.637)	(0.593)	(0.597)
dvd	4.942***	5.089***	4.778***	5.055***	5.113***
	(1.135)	(1.154)	(1.348)	(1.384)	(1.425)
cable	5.421***	5.602***	5.434***	5.532***	5.611***
	(1.399)	(1.433)	(1.628)	(1.713)	(1.761)
streaming	4.284***	4.441***	4.122***	4.387***	4.439***
	(1.001)	(1.048)	(1.220)	(1.239)	(1.281)
download time	-0.004***	-0.005***	-0.005***	-5.626***	-5.609***
	(0.000)	(0.002)	(0.001)	(0.285)	(0.288)
price	-0.200***	-0.203***	-1.723***	-1.663***	-1.659***
	(0.016)	(0.016)	(0.080)	(0.083)	(0.084)
SD parameters					
download time		0.004*	0.003*	1.814***	1.836***
		(0.002)	(0.002)	(0.204)	(0.268)
price	0.115***	0.115***	0.623***	0.580***	0.574***
	(0.012)	(0.012)	(0.053)	(0.052)	(0.054)
Covariance (price - time)					-0.052
					(0.118)
N	5,728	5,728	5,728	5,728	5,728
Log likelihood at convergence	-1326.77	-1323.59	-1314.97	-1286.49	-1286.34

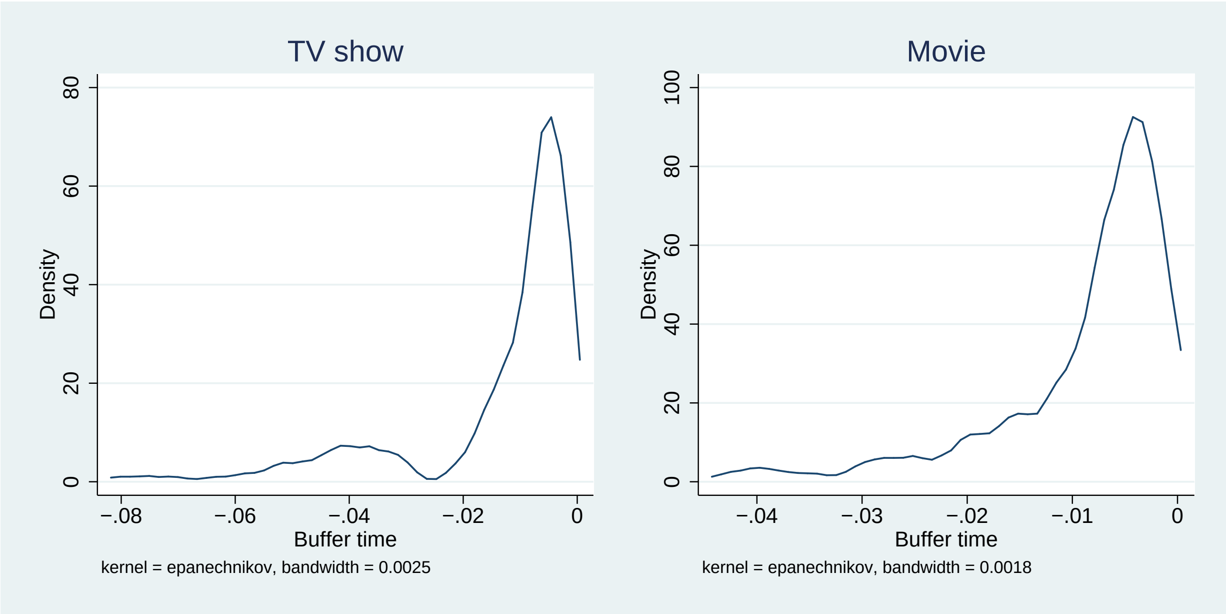
Notes: Parameter estimates from the mixed logit model for the movie scenarios. The specification of the random coefficients is as follows. Column 1: normal distribution for price; column 2: normal distribution for both price and time, independent; column 3: log-normal distribution for price; column 4: log-normal distribution for both price and time, independent; column 5: log-normal distribution for both price and time, correlated. Robust standard errors in parentheses. ***, **, * denote significance at the 1, 5, and 10 percent level, respectively.

Table 2.15: Parameter estimates, TV show

	(1)	(2)	(3)	(4)	(5)
Mean parameters					
owns dvd player x dvd	0.539	0.655	0.878	0.719	0.752
	(0.516)	(0.538)	(0.571)	(0.588)	(0.637)
owns dvd player x cable	0.560	0.622	0.917	0.867	0.881
	(0.566)	(0.573)	(0.619)	(0.587)	(0.665)
owns dvd player x streaming	0.571	0.709	0.979	0.777	0.802
	(0.564)	(0.609)	(0.630)	(0.590)	(0.646)
age x dvd	0.010	0.010	-0.017	-0.024	-0.025
	(0.063)	(0.067)	(0.072)	(0.073)	(0.075)
age x cable	0.029	0.043	0.027	0.011	0.010
	(0.072)	(0.073)	(0.076)	(0.073)	(0.075)
age x streaming	0.049	0.057	0.028	0.020	0.019
	(0.073)	(0.083)	(0.087)	(0.082)	(0.085)
owns high-speed x dvd	-0.735	-1.108*	-0.802	-0.578	-0.541
	(0.588)	(0.595)	(0.640)	(0.675)	(0.681)
owns high-speed x cable	-0.597	-0.989	-0.615	-0.448	-0.400
	(0.714)	(0.687)	(0.706)	(0.724)	(0.725)
owns high-speed x streaming	-0.434	-0.889	-0.539	-0.313	-0.279
	(0.671)	(0.656)	(0.691)	(0.701)	(0.704)
low income x dvd	0.882	0.835	0.823	0.964	0.953
	(0.586)	(0.618)	(0.675)	(0.729)	(0.748)
low income x cable	0.944	0.709	0.661	0.787	0.793
	(0.692)	(0.698)	(0.731)	(0.754)	(0.766)
low income x streaming	0.588	0.493	0.458	0.604	0.603
	(0.651)	(0.693)	(0.734)	(0.749)	(0.769)
med income x dvd	0.618	0.754	0.881	0.813	0.846
	(0.537)	(0.568)	(0.636)	(0.671)	(0.704)
med income x cable	0.942	0.913	1.123	0.917	0.970
	(0.660)	(0.667)	(0.743)	(0.757)	(0.790)
med income x streaming	0.457	0.614	0.751	0.643	0.680
	(0.632)	(0.674)	(0.744)	(0.743)	(0.779)
dvd	2.900*	3.333**	3.582**	3.905**	3.883**
	(1.506)	(1.604)	(1.712)	(1.684)	(1.758)
cable	2.817*	2.962*	2.895	3.365**	3.364*
	(1.665)	(1.731)	(1.778)	(1.670)	(1.736)
streaming	2.381	2.583	2.827	3.253*	3.241*
	(1.749)	(1.960)	(2.036)	(1.882)	(1.969)
download time	-0.005***	-0.012***	-0.011***	-5.637***	-5.498***
	(0.002)	(0.003)	(0.003)	(0.486)	(0.488)
price	-0.179***	-0.179***	-1.850***	-1.811***	-1.816***
	(0.016)	(0.016)	(0.091)	(0.089)	(0.090)
SD parameters					
download time		0.018***	0.016***	2.240***	2.206***
		(0.003)	(0.003)	(0.323)	(0.351)
price	0.116***	0.108***	0.727***	0.699***	0.670***
	(0.015)	(0.013)	(0.067)	(0.066)	(0.076)
Covariance (price - time)					-0.127
					(0.115)
N	6,060	6,060	6,060	6,060	6,060
Log likelihood at convergence	-1493.86	-1463.24	-1445.35	-1433.07	-1432.10

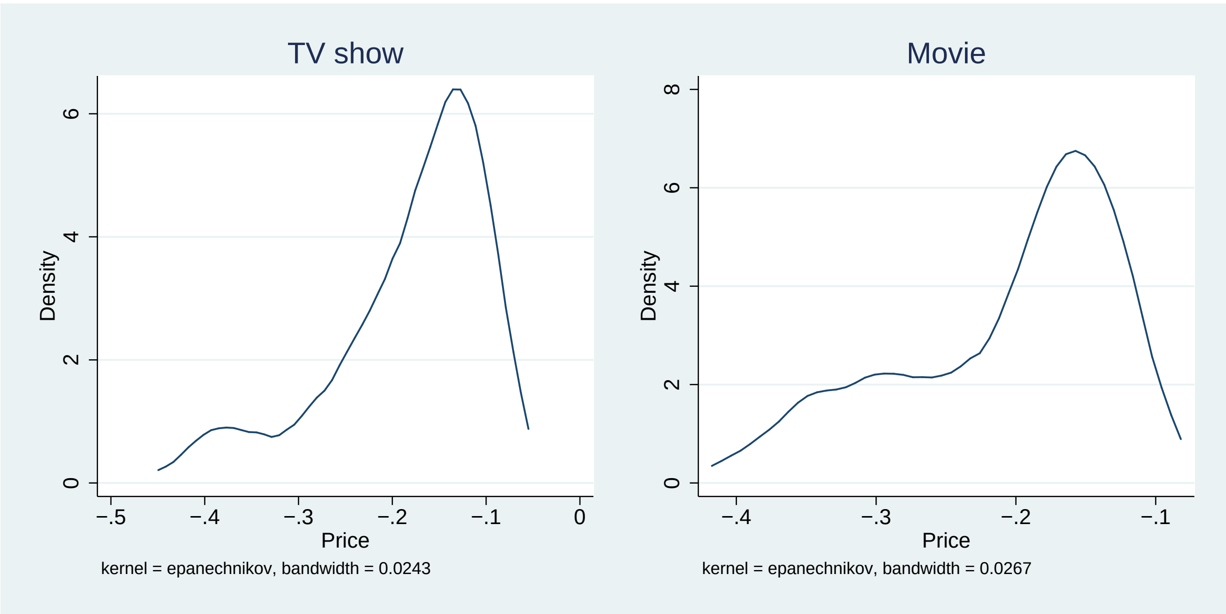
Notes: Parameter estimates from the mixed logit model for the movie scenarios. The specification of the random coefficients is as follows. Column 1: normal distribution for price; column 2: normal distribution for both price and time, independent; column 3: log-normal distribution for price; column 4: log-normal distribution for both price and time, independent; column 5: log-normal distribution for both price and time, correlated. Robust standard errors in parentheses. ***, **, * denote significance at the 1, 5, and 10 percent level, respectively.

Figure 2.3: Distribution of individual buffer time coefficients



Notes: Buffer time coefficients from the specification in column (4) in Table 2.14 and 2.15 for the 157 (144) individuals faced with the TV show (movie) scenario. Graphed values are for the 10-90 percentile range.

Figure 2.4: Distribution of individual price coefficients



Notes: Price coefficients from the specification in column (4) in Table 2.14 and 2.15 for the 157 (144) individuals faced with the TV show (movie) scenario. Graphed values are for the 10-90 percentile range.

2.7.5 Alternative WTP estimates

Following Train and Weeks (2005), we also estimate the model in "WTP space." Here, equation (2.1) is rewritten as

$$U_{njt} = \alpha_n p_{njt} + \alpha_n w_n b_{njt} + z_n' \gamma + \varepsilon_{njt},$$

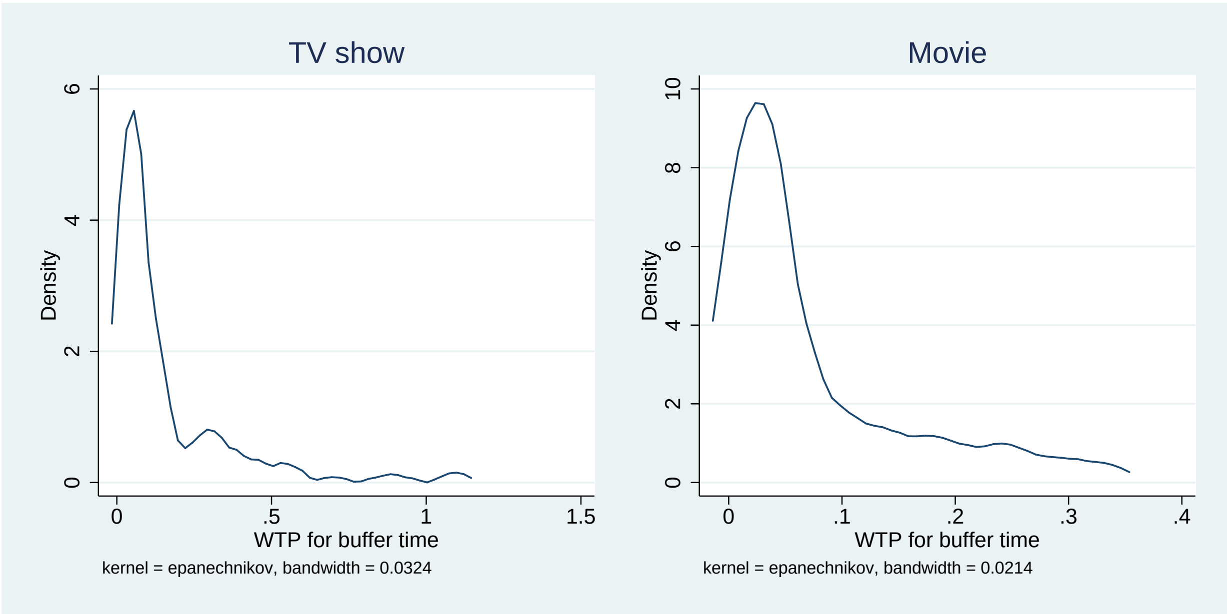
where $w_n = \beta_n / \alpha_n$ is the decision maker's willingness to pay for buffer time. A log-normal distribution is assumed for the price coefficient α_n and the *willingness to pay* coefficient w_n, and estimation proceeds using Simulated Maximum Likelihood as above. Resulting estimates are summarized in Table 2.16 and Figure 2.7.5.

Table 2.16: WTP for buffer time using model estimates in WTP space

	Mean	Median	10%	90%	N
TV show	0.659	0.068	0.017	1.113	157
Movie	0.238	0.037	0.007	0.333	144

Notes: WTP estimates from a model estimated in WTP space, assuming lognormally distributed WTP coefficients for both price and buffer time (see Train and Weeks, 2005). Estimation was performed using the mixlogitwtp command in Stata. The model also controls for demographic variables as described in the text.

Figure 2.5: WTP for buffer time using model estimates in WTP space



Notes: Distribution of WTP estimates from a model estimated in WTP space, assuming lognormally distributed WTP coefficients for both price and buffer time (see Train and Weeks, 2005). Values shown are for the 10-90 percentile range. Estimation was performed using the mixlogitwtp command in Stata. The model also controls for demographic variables as described in the text.

2.7.6 Additional tables

Table 2.17: Relative demand impacts of changes in buffer time

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
Buffer time changes: 0 to 3 min					
DVD	0.786	0.574	0.725	0.165	1.370
Cable	7.399	7.054	4.188	2.584	13.113
Streaming	-6.787	-6.613	2.700	-10.510	-3.360
Outside	3.037	1.837	2.898	0.416	7.012
Buffer time changes: 0 to 5 min					
DVD	1.312	0.919	1.257	0.263	2.282
Cable	10.812	10.236	6.481	3.540	19.979
Streaming	-9.779	-9.586	3.623	-14.694	-5.251
Outside	4.422	2.622	4.441	0.562	10.658
Buffer time changes: 0 to 10 min					
DVD	2.595	1.729	2.624	0.496	4.717
Cable	17.104	15.902	11.167	5.045	33.054
Streaming	-15.314	-15.027	5.030	-21.997	-9.152
Outside	6.977	4.098	7.558	0.798	17.550
Panel B: Movie					
Buffer time changes: 0 to 3 min					
DVD	0.891	0.759	0.654	0.222	1.937
Cable	4.637	4.587	2.376	1.612	7.719
Streaming	-3.459	-3.165	2.088	-6.612	-0.999
Outside	2.305	1.611	1.933	0.381	5.182
Buffer time changes: 0 to 5 min					
DVD	1.496	1.262	1.129	0.358	3.250
Cable	7.587	7.334	4.181	2.402	13.164
Streaming	-5.390	-5.043	3.057	-9.967	-1.713
Outside	3.748	2.470	3.308	0.558	8.773
Buffer time changes: 0 to 10 min					
DVD	3.025	2.504	2.411	0.682	6.628
Cable	14.105	12.957	8.757	3.934	25.985
Streaming	-9.430	-8.999	4.768	-16.545	-3.465
Outside	7.002	4.221	6.756	0.888	17.401

Notes: Percentage changes in demand (choice probabilities) following an indicated change in buffer time.