Demand Estimation for Subscription Models

Identifying Willingness to Pay without Price Variation

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Yale Quant Marketing Seminar

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Subscription business

- Subscription market is fast growing and potentially huge
  - Growth rate $> 100\%$ each year in the past 5 years
  - Multibillion revenue per year
  - Across a wide range of product categories (digital $+$ physical)
  - **Pay upfront and consume over time**

Frontier Airlines Now Has an Unlimited Pass for Summer — Here's How to Score One

"For people with flexible schedules, this is a terrific opportunity to have a truly epic summer and then some, soaking up rays on the beach, exploring national parks and visiting new cities."

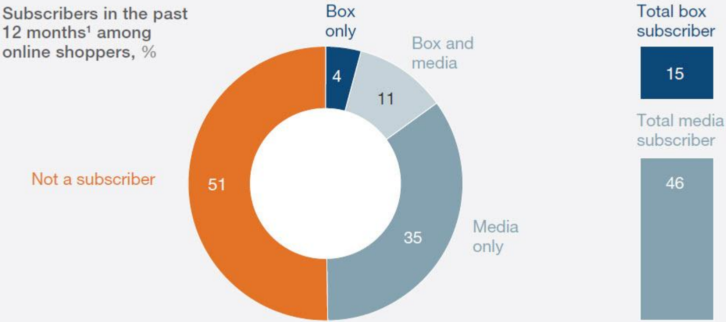
By **Alison Fox** | Updated on February 1, 2023

Pay in advance with (un)limited usage

Industry	Product or Service	Price ($)	Period	Total subscribers
Media & Entertainment	Netflix	9.99	Monthly	23 million (US)
	Spotify	9.99	Monthly	70 million (World)
	New York Times	3.75	Weekly	4 million (US)
	MoviePass	19.95	Monthly	2 million
	Kindle Unlimited	9.99	Monthly	–
	Apple News	9.99	Monthly	36 million
Software-as-a-Service	Microsoft Office 365	9.99	Monthly	120 million
	Adobe Creative Cloud (One App)	20.99	Monthly	15 million
	Dropbox Premium	9.99	Monthly	>11 million
Membership Clubs	Costco (Basic)*	60	Annual	94 million
	Amazon Prime	119	Annual	90 million
	24 hour fitness (Gym)	40	Monthly	4 million
eCommerce	Harry's	35	Monthly	–
	Birchbox	15	Monthly	2 million
	Rent the Runway	159	Monthly	6 million
Transportation	Public Transit Pass (MTA)	121	30-days	–
	Uber Ride Pass*	14.99	Monthly	–
	Jetblue "All You can Jet" Pass	699	Monthly	–

Subscription Services

Subscriptions are an increasingly common way to buy products and services online.



Note: Figures may not sum to 100%, because of rounding.

[1]Which of the following have you purchased or subscribed to in the past 12 months? % of those selecting online subscription-box service that delivers products regularly (eg, Blue Apron, Dollar Shave Club, Ipsy, Stitch Fix), subscription-based media (eg, ClassPass, Hulu, Netflix, Spotify), both, or neither.

McKinsey&Company | **Source:** McKinsey analysis

Subscription Services

E-commerce subscriptions generally fall into one of three categories.

E-commerce subscriptions, %		Key consumer value	Description	Example companies
Subscribe for replenishment	32	Save time and money	Replenish the same or similar items Primary categories are commodity items such as razors, vitamins	Amazon Subscribe & Save, Dollar Shave Club, and Ritual
Subscribe for curation	55	Be surprised by product variety	Receive a curated selection of different items, with varying levels of consumer decision making required Primary categories are apparel, food, beauty products	Birchbox, Blue Apron, and Stitch Fix
Subscribe for access	13	Gain exclusive access	Membership provides access and can convey additional "VIP" perks Primary categories are apparel, food	JustFab, NatureBox, and Thrive Market
	100%			

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  - Demand curve
  - **Elasticities of the WTP to product changes**

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Idea: Leverage high frequency usage data for identification.

Usage is captured at higher frequency than purchase.

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- No existing research that demonstrates how to obtain the WTP distribution in the **absence of price variation**.
  - **Nevo, Turner and Williams (ECTA, 2016) leverages an "overage charge"**

Focus: Obtain WTP estimates for a subscription service with high frequency usage data

More specifically:

1. **In absence of price variation, under what conditions on usage is it possible to identify distribution of WTP?**

Research questions

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2. **What demand responses and profits to counterfactual product and pricing choices by the firm can be determined?**

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More specifically:

1. In absence of price variation, under what conditions on usage is it possible to identify distribution of WTP?
2. What demand responses and profits to counterfactual product and pricing choices by the firm can be determined?
3. **Is price variation the same as usage variation or is there additional value?**

Cross section data with price variation.

Notation

- i indicates a consumer
- Subscription decision: $S_i = 1$ (sub) and $= 0$ (not).
- WTP: W_i
- Price: P_i

- Decision rule:

$$\underbrace{W_i - P_i}_{\substack{\text{money-metric}\\ \text{utility of service}}} \quad \text{vs} \quad \underbrace{\mu = 0}_{\substack{\text{money-metric utility}\\ \text{of outside option}}} \quad \Rightarrow$$

$$S_i = \begin{cases} 1, & W_i > P_i \\ 0, & W_i \leq P_i. \end{cases}$$

or $S_i = \mathbb{I}(W_i > P_i)$.

- When $W_i \perp\!\!\!\perp P_i$, for any w in the support of P_i

$$\underbrace{\Pr(W_i > w)}_{\text{Parameter: prob WTP}} = \underbrace{\Pr(S_i = 1 \mid P_i = w)}_{\text{Data: Mkt shr in the}}.$$

Model Overview and Elements

Model is based on microfoundations of usage based on leisure, and aggregated over time

- **(High frequency): Consumer has a daily leisure budget, allocated between focal good and everything else**

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  - Rational expectations (or perfect foresight)
- **(Low frequency): Consumer makes purchase (subscription) decisions every T periods at constant price P**

Consider the consumer allocating leisure time:

- **consumer leisure time spent in focal activity, e.g. listening to streaming music q_{it},**

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- consumer leisure time spent in focal activity, e.g. listening to streaming music q_{it},
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- **Specify a money-metric utility function:**

$$\max u_{it}(q_{it}, q_{0it}) \textbf{ subject to } q_{it} + q_{0it} = \ell_{it}$$

$$u_{it}(q_{it}, q_{0it}) = D_{it} u^{(1)}(q_{it}, q_{0it}; \theta_{im(t)}) + (1 - D_{it}) u^{(0)}(q_{0it}; \theta_{im(t)})$$

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- **$D_{it} \in \{0, 1\}$ is an indicator for whether the focal activity is present or absent $\implies$ rationalizes zero usage in many periods**

We need to characterize usage at the daily level and relate to the monthly level WTP

- **Daily leisure is modeled as depending on exogenous factors Z_{it}:**

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- **Monthly expected leisure** $\boxed{L_{im} \equiv \sum_{t:m(t)=m} (\mu_i + \gamma' Z_{it})}$

Connecting daily usage of focal service to monthly indirect utility:

Theorem (Usage to Indirect Utility)

For any utility function homogeneous of degree 1, the difference between the expected monthly indirect utilities with and without a subscription, W_{im}, satisfies

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- What class of utility functions are included?
  - **Cobb-Douglas, CES, perfect substitutes, perfect complements, Leontief**

Subscription Decisions

We know that WTP is: $W_{im} = \alpha_{im} L_{im}$

- **account of consumer heterogeneity, both observed X_{im} and unobserved U_{im}. Consider a linear projection of $\ln \alpha_{im}$ onto X_{im} as:**

$$\ln \alpha_{im} = \beta_0 + \beta_1' X_{1im} + U_{im},$$

where $\beta' = (\beta_0, \beta_1')$ and $X_{im}' = (1, X_{1im}')$.

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- **Subscription choice $S_{im} = \mathbb{I}(\ln W_{im} > \ln P)$ becomes**

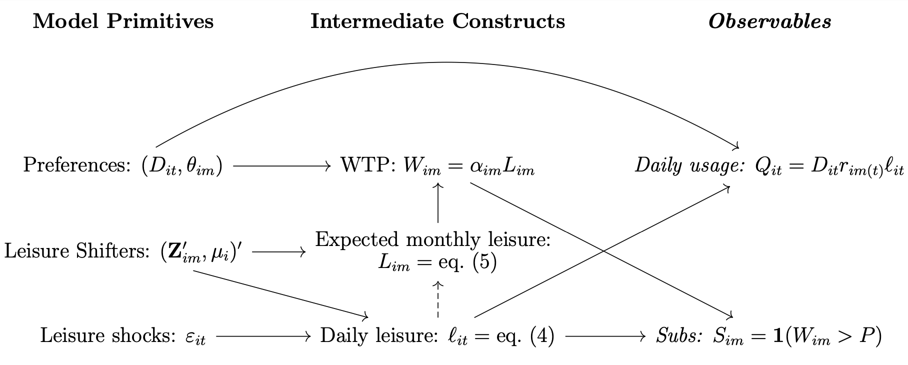
$$S_{im} = \mathbb{I}(\ln L_{im} + \beta' X_{im} - \ln P + U_{im} > 0).$$

What exogenous variations are required for identification?

Assumption (Exogenous Variation in Leisure)

$\mathbf{Z}_{im} \perp\!\!\!\perp U_{im} \mid (X_{im}, \mu_i)$,

- Above implies $L_{im} \perp\!\!\!\perp U_{im} \mid (X_{im}, \mu_i)$ because the randomness of L_{im} only comes from $\mathbf{Z}_{im}$ and μ_i.


Model Primitives
Intermediate Constructs
Observables
Preferences: (D_{it}, θ_{im})
WTP: $W_{im} = \alpha_{im} L_{im}$
Daily usage: $Q_{it} = D_{it} r_{im(t)} \ell_{it}$
Leisure Shifters: $(\mathbf{Z}'_{im}, \mu_i)'$
Expected monthly leisure:
L_{im} = eq. (5)
Leisure shocks: ε_{it}
Daily leisure: ℓ_{it} = eq. (4)
Subs: $S_{im} = \mathbf{1}(W_{im} > P)$

Theorem (Parametric Identification of WTP)

We have the following results when $U_{im} \,|\, (X_{im}, \mu_i) \sim \mathcal{N}(\sigma_{u,\mu}\mu^*_{im}, \sigma^2_u)$

1. *The unknown parameters* $(\beta, \sigma_u, \sigma_{u,\mu})$ *are identified.*
2. *The distribution of WTP is identified, and*

$$F_W(w \,|\, X_{im}, \mu_i, L_{im}) = \Phi\left[\frac{1}{\sigma_u}\left(\ln w - \ln L_{im} - \beta' X_{im} - \sigma_{u,\mu}\mu^*_{im}\right)\right].$$

We do not need any parametric assumption like above.

- **What happens without usage data? Subscription equation**

$$
\begin{aligned}
S_{im} &= \mathbb{I}(\ln L_{im} - \ln P + \beta' X_{im} + U_{im} > 0) \\
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Cannot distinguish between L_{im} **and** U_{im}

What are the boundary conditions of this approach?

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- **Need both usage data and exogenous shifters**

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- Average daily listening hours range from 45 mins to >6 hours
- **Average monthly listening hours range from less than 1 hour to more than 150 hours.**

Estimation – Usage

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- **Step 2: Estimate monthly expected leisure L_{im} by substituting the unknown parameters (μ_i, γ') with the estimates $(\hat{\mu}_i, \hat{\gamma}')$. Denote this estimator by $\hat{L}_{im}$.**

Estimation – Subcription

WTP for the service: $W_{im} = \alpha_{im} L_{im}$

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- **Step 4: Run the probit regression of S_{im} on $\ln(\hat{L}_{im}/P)$, X_{im}, and $\hat{\mu}^*_{im}$. The probit regression provides estimates of σ_u^{-1}, β/σ_u, $\sigma_{u,\mu}/\sigma_u$. Then the estimates of β and $\sigma_{u,\mu}$ are obtained easily.**

Is Usage Variation the Same as Price Variation

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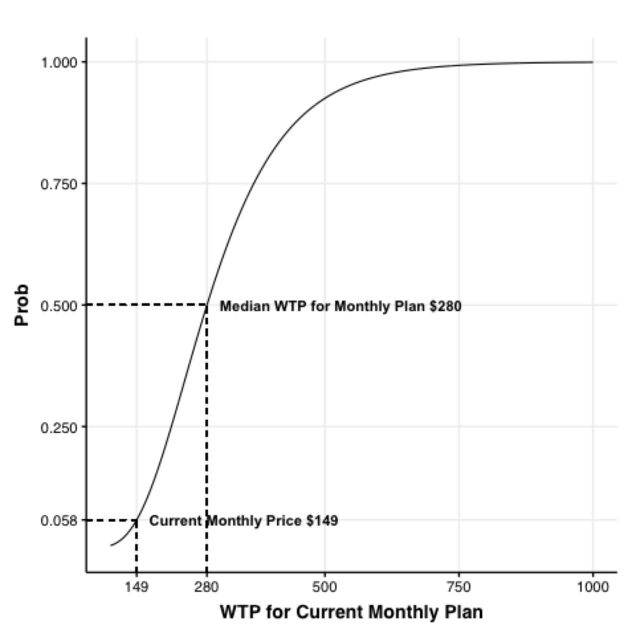
-
  - **Need at least 2 price levels**

Empirical Application with Music Streaming

	All Users	Never Cancelled	Ever Cancelled
Monthly Usage (Hours)	41.73	44.25	18.48
	(50.65)	(52.07)	(24.76)
Daily Usage (Hours): Weekend	1.31	1.39	0.57
	(2.21)	(2.27)	(1.41)
Daily Usage (Hours): Weekdays	1.39	1.47	0.62
	(2.28)	(2.35)	(1.30)
Age	30.91	31.12	29.69
	(9.09)	(9.32)	(7.56)
Female (%)	42.00	42.35	40.00
Number of Users	300	255	45

Empirical Application with Music Streaming



	Parameters	Estimates	Std Err
Usage eq.	$\mu_{Type\,1}$	0.8279	(0.0471)
	$r_{Type\,1}$	2.1130	(0.1566)
	$\gamma_{Holiday,Type\,1}$	0.0297	(0.0157)
	$\gamma_{Weekend,Type\,1}$	0.0257	(0.0142)
	$\mu_{Type\,2}$	0.8339	(0.0539)
	$r_{Type\,2}$	5.3138	(0.9502)
	$\gamma_{Holiday,Type\,2}$	−0.0365	(0.0223)
	$\gamma_{Weekend,Type\,2}$	−0.0369	(0.0251)
	$\gamma_{Humidity}$	−0.0010	(0.0005)
	$\gamma_{Precipitation}$	0.0004	(0.0002)
Subscription eq.	β_0/σ_u	5.9226	(1.4853)
	$1/\sigma_u$	2.5261	(0.7895)
	β_{Age}/σ_u	0.0115	(0.0039)
	β_{Female}/σ_u	0.1095	(0.0698)
	$\sigma_{u,\mu}/\sigma_u$	−6.2721	(14.0592)

Empirical Application with Music Streaming

Segment	Price Elasticity		Revenue Max Price	Mean Usage	Median WTP ($)
All Users	−0.31	(0.10)	206	1.37	280.00
Male	−0.33	(0.11)	202	1.43	275.00
Female	−0.27	(0.08)	212	1.29	288.00
Age $\leq$ 22	−0.37	(0.13)	197	1.45	268.00
Age 23–30	−0.34	(0.11)	201	1.55	273.00
Age $>$ 30	−0.26	(0.08)	214	1.22	290.00

Empirical Application with Music Streaming

User Groups	Humidity Only	Precipitation Only	Both
All Users	−0.307	−0.367	−0.366
	(0.098)	(0.106)	(0.105)
Male	−0.332	−0.397	−0.396
	(0.111)	(0.122)	(0.121)
Female	−0.273	−0.326	−0.325
	(0.083)	(0.090)	(0.089)
Age $\leq$ 22	−0.368	−0.439	−0.437
	(0.129)	(0.142)	(0.141)
Age 23–30	−0.339	−0.405	−0.403
	(0.114)	(0.125)	(0.124)
Age $>$ 30	−0.261	−0.313	−0.312
	(0.078)	(0.083)	(0.083)

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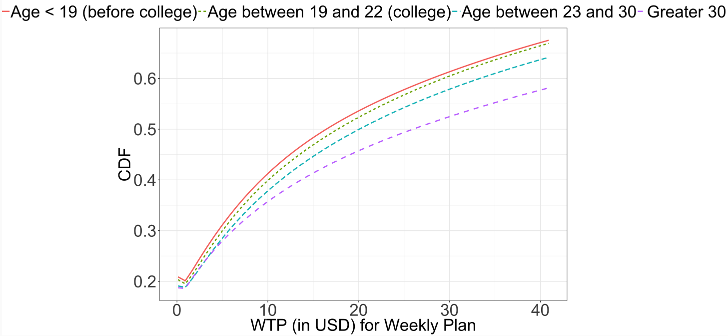
WTP variation with age / college status



Without Price variation, can we obtain WTP?

- **A: Qualified Yes.**
- What big data on usage tracking **can tell** us?
  - The distribution of WTP under some restrictions
- Can design counterfactual products and pricing strategies
- Cannot replace the role price variation, even limited, in identifying switching costs

Duration as a segmentation device

- Firms offer plans of different durations, e.g. Amazon offers Prime monthly and annual plans
- What's the distribution of the WTP for the shorter plan?
- One idea is to examine whether we can use duration effectively as a segmentation device
- When does it work well and when does it not?

Can we design shorter plans? Segmentation by duration

- **Identify interesting new mechanism based on plan duration**

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  - **Shorter plans allow flexibility and could increase consumer WTP**

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    - **WTP for Prime might be higher during holiday season, maybe I just buy then?**

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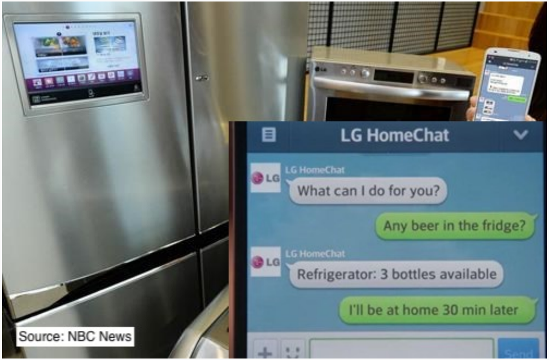
    - Makes it easier to extract surplus
  - **Duration can be a strategic design decision so the firm**

A bigger picture (of a fridge)



- Essentially, we need the separation of purchase (subscription) and consumption (usage).

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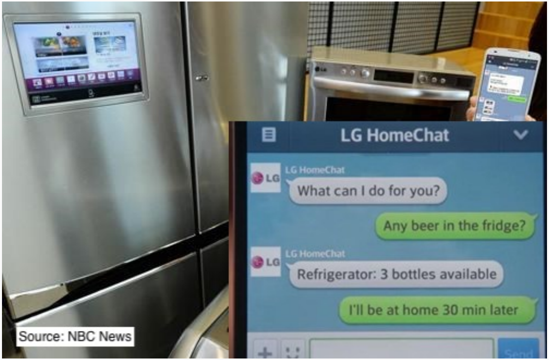

- Essentially, we need the separation of purchase (subscription) and consumption (usage).
- Such separation also holds in packaged goods (beer)—but we did not track the usage.
- 5G and Internet of Things could enable such tracking.

My Research Overview

- Substantive: Digital Business Models
- Methodological: Structural Models $\Longleftrightarrow$ Machine Learning
  - Different approaches to ML

Some projects:

- Nonparametric Bandits Leveraging Informational Externalities to Learn the Demand Curve, with Ian Weaver (Major Revision at Marketing Science)
- Automatically Discovering Visual Product Characteristics, with Ankit Sisodia and Alex Burnap (Revision at Journal of Marketing Research)

ADDITIONAL SLIDES