Estimating Willingness to Pay in Subscription Business Models

December 2022

Abstract

We demonstrate the conditions under which it is possible to obtain the distribution of consumer willingness to pay (WTP) for subscription products, where consumers typically pay a constant price each period for potentially unlimited usage, e.g. Spotify. In the absence of price variation, we demonstrate how the variation in usage and subscription choice together can identify the WTP distribution. We also investigate whether it is possible to identify switching costs in the absence of price variation and to obtain conditions on pricing that make such identification possible. Our method is nonparametric and does not rely on specific functional forms or distributions. We apply our method to an empirical application using the data from a music streaming service. Using the estimated WTP distribution, we obtain the revenue-maximizing prices for different consumer segments.

1 Introduction

Our paper studies how to obtain the distribution of consumer willingness to pay (WTP) for subscription products in the absence of price variation. Estimating the distribution of WTP given consumer and product characteristics is an essential and the most challenging step to understand and predict demand responses, to identify how consumers value various features of the product, and to decide how alternative products should be priced. Consider the example of Spotify, which has a monthly Standard plan priced at \$9.99 in the US. When the firm is interested in evaluating how demand might vary with price increases (i.e., price elasticity), we would need to obtain the WTP distribution so that we can infer the percentage of consumers who are still willing to pay more than the new higher price.

Subscriptions are becoming increasingly popular across the world for both physical and digital products and services with growth over 100% in 2013–2018 (Columbus, 2018; Chen et al., 2018). Subscription plans are prevalent across a wide variety of industries, ranging from media to software-as-a-service to eCommerce and transportation, as detailed in Table A1. There are a number of reasons for this popularity, including low marginal costs (relative to fixed costs), reduced consumer risk, no transaction costs from the consumers' perspective, and predictability in revenue stream as well as increased loyalty from the firms' perspective (Xie and Shugan, 2001).

In most subscription markets, prices are typically fairly stable (except for promotions like free trials). Spotify has always set the monthly price for unlimited ad-free streaming at $9.99 from 2011 to the present. Apple (Music and iCloud) and Microsoft (Office 365) are similar in terms of lack of price variation. While we might expect that digital technology reduces menu costs and makes firms more likely to change prices (Stamatopoulos, Bassamboo and Moreno, 2021), subscription firms are often especially wary of experimentation, especially on price (Ariely, 2010). The reasons cited include wanting to avoid consumer confusion, consumer strategic timing, or perceptions of unfairness, among others. On the other hand, we often have access to high-frequency data about the usage of a subscription product (e.g., the amount of time spent listening to Spotify at daily or hourly frequencies).

One of the crucially important decisions is pricing, which depends on the distribution of consumer WTP. Almost all extant research deals with obtaining WTP when prices vary, making it important to understand how WTP can be obtained in subscription markets. We examine the following research questions with subscriptions of digital entertainment services (e.g., streaming TV and music) as the empirical context. First, in an empirical setting without price variation, what can we infer about the distribution of consumer valuation of the product from usage and subscription data? Second, is usage variation equivalent to price variation in obtaining all economic primitives? If not, what further inference is possible when we have price variation in addition to usage variation?

The essential feature of obtaining WTP from data (both observational and conjoint-like approaches) is that prices vary exogenously. This variation informs us of the shape of the demand curve. Demand estimation in economics and marketing has depended on the presence of data with price variation. Thus, the absence of price variation presents a major challenge in identifying the distribution of WTP—how would you predict the demand response to the change of price when price does not change at all in data? This lack of price variation poses a challenge for using the common revealed preference approach to recover the distribution of WTP, which relies on price variation, a feature common to the entire literature (Guadagni and Little, 1983; Train and Weeks, 2005; Danthurebandara, Yu and Vandebroek, 2011; Lewbel, McFadden and Linton, 2011). Firms in such markets set prices based on market research, typically using conjoint analysis or similar survey elicitation responses (Green and Rao, 1971; Green and Srinivasan, 1978). While conjoint analysis is a very useful tool to obtain relative preferences, consumers have sometimes been found to have a different WTP when making actual purchase choices. Moreover, this approach does not get around the requirement for price variation. To the best of our knowledge, no existing research demonstrates the identification of WTP distribution without price variation.

The research contribution lies in our insight that purchase is separate from usage for subscription products—two Spotify subscribers paying the same price can have substantially different amounts of usage. Because the price paid becomes a sunk cost at the beginning of the subscription period, a consumer chooses an optimal usage level according to his or her usage preference and available leisure time. When two subscribers pay the same monthly fee but have different usage levels, these two consumers are paying a different price per unit of usage, which opens up the opportunity of identifying the WTP distribution. We prove that the combination of usage and subscription data can identify the WTP distribution under a broad set of conditions. Overall, we propose a novel method to identify and estimate the conditional distribution of WTP given product features and customer characteristics when price variation is absent. We examine the other question of whether usage variation is a replacement for price variation, and we find that while usage variation is helpful, it does not serve as a replacement for price variation in general.

Our framework to demonstrate how to obtain WTP in the absence of price variation is built upon a microfoundation-based model of product *usage* (which occurs at a high frequency, say daily) and connects that to a model of *purchase*, where consumers decide whether to subscribe to the service or not (at a lower frequency, say monthly). The model separates out expected monthly leisure that is spent on the focal service from a monthly WTP shifter and can accommodate correlation between these factors. The usage model can accommodate utility functions that are homogeneous of degree 1, and it requires exogenous shifters (e.g., holidays) to be able to provide variation required to identify the leisure process. Consumers trade off using the focal service compared to an outside option. Usage in this micro-model is shown to be proportional to leisure, although we can accommodate zero usage to reflect that consumers might choose to opt for alternative leisure activities. The model can also incorporate serial correlation in usage, or equivalently, in the leisure process. Consumers have rational expectations over the exogenous shifters that impact daily leisure for the future subscription month, and they know the distribution of the daily shocks but not the future realization of these shocks. The daily expected utility of using the product over a month is aggregated to obtain WTP for the monthly service.

With regard to identification, we demonstrate our results in two steps. We first show that the leisure process is identified by using only the leisure shifters and usage data. We thus recover daily leisure, and from this, we can recover the expected monthly leisure. The expected monthly leisure is then combined with both observable and unobservable shifters which are potentially correlated with it. We show that the resulting aggregate WTP distribution is identified nonparametrically.

We provide a detailed estimation algorithm comprised of simple steps that uses commonly available data from subscription services to obtain the conditional WTP distribution. Recall that we separate out WTP as depending on monthly expected leisure and (potentially correlated) monthly shifters. We first use the high-frequency usage data and the exogenous leisure shifters to estimate the parameters of the usage model. We then estimate the expected leisure at the consumer-month level, which plays an important role in determining the subscription decision. Having obtained the expected monthly leisure, we model the conditional distribution of the unobservable factors driving subscription based on usage parameters. This helps connect the leisure and monthly purchase shifters, and we show that the estimation is reduced to a discrete choice model for subscription purchase.

Having obtained the parameters of the usage model and subscription model, we can estimate the conditional WTP. The demand curve and other primitives like elasticity are obtained from the conditional WTP, and counterfactuals can then be performed.

Our method is focused on obtaining the aggregate WTP distribution, or overall demand curve, rather than the WTP for a specific consumer. However, we are able to obtain conditional WTP distributions based on demographics, e.g., for students.

Lastly, we take our method to data using an application of music streaming, featuring monthly subscription choices and daily usage (daily hours listening to streaming music) data. We estimate the distribution of WTP and price elasticities of the WTP for its current monthly streaming plan for different age and gender groups. We find that the age elasticity of usage is negative, whereas the elasticity of the WTP with age is positive, indicating that older users use the product less, but value it more than younger users. We find female subscribers are less price sensitive than male subscribers. Finally, using our estimates and model, we obtain the revenue maximizing prices for different consumer segments.

Although we examine the case of parametric identification in the main paper, we show non-parametric identification and estimation in Appendix B. We also examine in the paper how switching costs might be identified and show that we need at least two price levels for identification. Thus, while usage data are useful in identifying WTP, usage data are not a complete replacement for price variation.

We note that the paper has a scope beyond subscription markets in identifying WTP. The crucial aspect is that we need a *separation of purchase and consumption*, and we need *data on both*. We discuss in the conclusion how the method can be applied to typical packaged goods markets, for instance.

Our framework for obtaining WTP has specific limitations. The model relies on specific properties of the microfoundations on utility of usage. Here, price is sunk and does not play a role. We require the usage utility to be homogeneous of degree 1, which includes some common utility functions like Cobb Douglas, or perfect complements or perfect substitutes or CES. However, it does not include other utility functions like some quasilinear functions. The reason for focusing on linear homogeneous utility functions is that it allows the monthly WTP to be expressed as a separable product of monthly expected leisure (which depends on the parameters of the usage utility) and a shifter (which does not depend on usage utility parameters). This separation allows us to separately identify the leisure process and then integrate it as a known quantity into the subscription choice model.

The rest of the paper is organized as follows. Section 2 reviews the literature. In

Section 3, we model a consumer's choices of whether or not to subscribe to a product/service and the amount of usage of the subscription if subscribed. After the model setup, we discuss in Section 4 how to identify and estimate the model and to obtain the distribution of consumer WTP by leveraging the data of usage and subscription choices. We leave the extensions (the value of price variation, the effect of switching cost, and the effect of the entry of new service providers) to Section 5. Section 6 uses our approach in an application of music streaming subscription to demonstrate its empirical value. Section 7 concludes the paper. The appendix contains additional results about the nonparametric identification and estimation of the WTP distribution. The online appendix contains the technical proofs and a simulation study that examines the finite sample properties of the estimator.

2 Literature

There are multiple streams of literature focused on measuring and characterizing WTP or the distribution of consumer valuations. An important distinction should be made between methods that use stated preference to obtain *hypothetical* WTP and those that use revealed preference to obtain *real* WTP. In the real WTP case that involves consumer choice, to the best of our knowledge, there is currently no general method that can obtain the WTP distribution in the absence of price variation. On this point lies the primary contribution of this paper.

Within the *stated preference* stream of literature, customer populations are surveyed to obtain an estimate of hypothetical WTP. Such approaches are typically used to obtain hypothetical WTP since consumers do not have to actually pay a price or face financial consequences. Within this stream there are two broad approaches: direct surveys (Mitchell and Carson, 2013; Hanemann, 1994) and choice-based conjoint analysis (Green and Rao, 1971; Green and Srinivasan, 1978; Rao, 2014; Ding, 2007). Direct surveys ask individuals to place a monetary value on a product or service (contingent valuation). Conjoint on the other hand asks consumers to rank order choices, which can vary based on price and other characteristics. The appeal of this methodology is in its simplicity and in obtaining an economically relevant quantity, although researchers have long pointed out the challenges in obtaining an accurate estimate (Diamond and Hausman, 1994; Hausman, 2012; Kalish and Nelson, 1991; Wertenbroch and Skiera, 2002; Voelckner, 2006).

Next is the well-established literature on demand estimation *using observational data*, either at the individual consumer level like in much of the marketing literature (e.g. Guadagni and Little, 1983) or at the market-level like in (e.g. Berry, 1994; Berry, Levinsohn and Pakes, 1995) and related literature. It is striking that *none of the above methods* provide any help when there is no price variation in the data. There is a small set of papers that include demand estimation when prices are fixed. In a model with multiple products, i.e., print and online newspapers, Gentzkow (2007) uses moments derived from supply-side first order conditions to obtain identification. In contrast, our approach does not assume a supply-side model or even require multiple products. However, we do need access to usage data, consistent with our focus on subscription markets.

The closest paper we could find is Nevo, Turner and Williams (2016), who estimate demand for residential broadband using usage (download/upload in GBs) and plan choice (e.g., unlimited usage plans vs usage-based plans) data when subscribers face a three-part tariff, featuring an *overage price* for each GB of usage in excess of a specified allowance. They model a forward-looking consumer as realizing that the opportunity cost of usage depends on the distance to this allowance or quota, changing their *shadow price*.

Their identification strategy for demand estimation exploits the *variation of shadow price, induced by usage*, as the accumulated usage approaches the included allowance. In contrast, our identification arguments do not rely on the presence of *overage price*. This is important in practice because subscription products typically do not use three-part tariff pricing.

3 Model

We develop an integrated model of (product or service) usage from microfoundations and connect it with the subscription choice of the consumer. Consumers in this usage model trade off between the focal activity (e.g., streaming music or movies) and other leisure activities. We show that any utility model for usage that is homogeneous of degree 1 (e.g., CES) would be compatible with our framework.[1] The consumer's WTP for monthly service is determined by the stream of daily usage utilities that she expects to receive during the course of the month. Thus, our model connects the high-frequency usage choices with low-frequency subscription or purchase choices. At a high level, the WTP of the customer population is identified by a combination of usage variation, subscription choices (or churn), and an exogenous shifter that impacts leisure, which in turn impacts usage. We show that usage variation and the exogenous leisure shifters are both necessary and sufficient to identify WTP for the service among the consumer population.

3.1 Setup and Summary of the Main Results

We focus on the subscription of digital entertainment (e.g., streaming music and TV) as the empirical context. For concreteness, consider a monthly music streaming service. Let $i = 1, \ldots, n$ index a consumer, and let $m = 1, \ldots, M$ index a month. The sample has M months consisting of T days in total indexed by $t = 1, \ldots, T$. Denote $m(t)$ the month containing day t. We observe consumer monthly binary subscription choice $S_{im} = 1$ (subscribing in month m) or 0 (not) and daily usage $Q_{it} \geq 0$ of the service if subscribed. In addition, we may observe consumer characteristics X_{im}.[2] Daily usage Q_{it} can be understood as the amount of time a consumer spends in listening to music using the subscription on day t. The data follow a cohort of consumers who were subscribing to the service in the first sample month. So for all sampled consumers, we observe their usage for at least one month.

Consumer i makes a choice on whether or not to subscribe in month m at the beginning of the month by comparing the expected indirect monthly utility with a subscription W_{im} and the monthly subscription cost P:

$$S_{im} = \mathbf{1}(W_{im} - P > 0). \tag{1}$$

So W_{im} can be interpreted as the WTP or reservation price in month m, and $(W_{im} - P)$ is the consumer's surplus. In subscription settings, it is important to allow flexibility

[1] There are utility functions that do not satisfy this condition (e.g., quasi-linear), and extending our framework to accommodate these utility functions is left for future work.

[2] Let $X_{im} = 1$ if we do not observe any. We can also let X_{im} include observable product characteristics if available.

for WTP to vary month to month, due to the change of product (e.g., the release of new contents) or individual situation (e.g., student users have less leisure near the end of the semester).

The question is how to identify and estimate the distribution function $F_W(w)$ of W_{im} and other distributional features of W_{im}, such as its median or mean. When price P does not change, the subscription choice S_{im} alone cannot identify the entire function $F_W(w)$; we only know the proportion of consumers who have WTP greater than the price, i.e., we know $F_W(P) = 1 - \Pr(S_{im} = 1)$ at the fixed price P by eq. (1).

What determines the distribution of the WTP for the service? Intuitively, the WTP for a service (e.g., music streaming) may vary across consumers because some consumers have more leisure, and hence, they expect to use the service more. In addition, some consumers have a higher valuation of leisure activities; therefore they are willing to pay more. Moreover, even for the same consumer, his or her WTP may vary over time due to product changes (e.g., the release of new content or income shocks) that affect the valuation of leisure activities including using the subscription. We model these parsimoniously by allowing for time-varying WTP. The primitives include a time-varying leisure process and a utility function of leisure activities.

We begin with an overview of the method. Our solution relies on the following expression of consumer WTP for the service in month m, i.e., W_{im}:

$$W_{im} = \alpha_{im} L_{im} \qquad \text{or equivalently} \qquad \ln W_{im} = \ln \alpha_{im} + \ln L_{im}, \tag{2}$$

where L_{im} is the expected amount of leisure in month m and α_{im} is a parameter representing consumer i's valuation of leisure activities when she has a subscription.[3] While the linear form of the WTP might appear restrictive, we show that this form actually holds for a class of utility models that serve as a microfoundation of usage (see Theorem 1 below).

There are two sources of heterogeneity in consumer WTP in eq. (2): leisure amount (L_{im}) and the valuation of leisure activities including using the subscription (α_{im}). The two dimensional heterogeneity can accommodate two types of consumers of the music streaming service: subscribers who have more leisure (who hence expect more usage

[3] More precisely, α_{im} is the maximum money-metric utility consumer i could obtain from 1 unit of leisure time when she subscribes and optimally allocates that leisure between using the subscription product and doing other leisure activities.

of the product, like college students) and subscribers who are willing to pay more for listening to music (even though they may have lower usage due to less leisure time, e.g., professionals like lawyers). Broadly, if we assumed that utility (and WTP) were higher across consumers with higher levels of usage, we would be conflating these two underlying factors, resulting in biased estimates. In our empirical study of streaming music, we in fact find that though the older consumers use less, they are indeed willing to pay more for the subscription.

By decomposing WTP W_{im} into two components (α_{im} and L_{im}), we can separately obtain and then combine the information from both usage (for L_{im}) and subscription choices (for α_{im}). First, we will prove a result for observed usage in terms of unobserved leisure (in part (2) of Theorem 1 below). This formula is crucial in recovering the expected leisure L_{im}. This step involves only usage data. Second, knowing the expected monthly leisure L_{im}, we only need the distribution of α_{im} in order to find the distribution of $W_{im} = \alpha_{im} L_{im}$, provided that α_{im} and L_{im} are independent (denoted by $\alpha_{im} \perp\!\!\!\perp L_{im}$). To be clear, our method *does not* require this independence assumption, but we use it only in this overview to make the logic and intuition transparent.

This second step uses data from subscription choices. To see how, note that eq. (1) can be written as $S_{im} = \mathbf{1}(\alpha_{im} > P/L_{im})$ when $W_{im} = \alpha_{im} L_{im}$. If $\alpha_{im} \perp\!\!\!\perp L_{im}$, we have $\Pr(\alpha_{im} \leq a) = \mathrm{E}(1 - S_{im} \mid L_{im} = P/a)$ for any value a,[4], and the conditional expectation is known because S_{im} is observed and L_{im} can be recovered from usage. Below, we will add the modeling details of how we address the correlation between α_{im} and L_{im} and how to incorporate observed consumer heterogeneity X_{im}. The key condition is that there exist some exogenous variables that will change expected leisure L_{im} but not preference α_{im}.

3.2 Microfoundations of Usage

The monthly utility of a subscription is built up from the indirect utility that is obtained from the daily usage of the product. We adopt a money-metric representation of the daily direct utility a consumer receives from her leisure time spent in listening to streaming music, denoted by q_{it}, and in doing other leisure activities (e.g. watching

[4]By $S_{im} = \mathbf{1}(\alpha_{im} > P/L_{im})$, we have $\Pr(1 - S_{im} = 1 \mid L_{im} = P/a) = \Pr(\alpha_{im} \leq P/(P/a) \mid L_{im} = P/a) = \Pr(\alpha_{im} \leq a)$. The last identity used the condition $\alpha_{im} \perp\!\!\!\perp L_{im}$.

TV), denoted by q_{0it}.[5]

If consumer i has a subscription on day t, she chooses $(q_{it}, q_{0it})'$ to maximize her utility from leisure activities:

$$\max u_{it}(q_{it}, q_{0it}) \qquad \text{subject to} \qquad q_{it} + q_{0it} = \ell_{it}, \tag{3}$$

where $\ell_{it} > 0$ denotes the unobservable (to researchers) leisure time on day t. The daily utility function takes the following form,

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

Here $u^{(1)}$ and $u^{(0)}$ are two parametric utility functions (e.g., Cobb-Douglas utility in Example 1 below): $u^{(1)}$ is used to describe a consumer's utility from listening to the streaming music and doing other leisure activities; $u^{(0)}$ determines the utility a consumer will receive when she does other leisure activities only but not use the streaming subscription, even though she has purchased the service. The parameter vector $\theta_{im(t)}$ denotes consumer i's preference in month m and captures one's valuation of leisure time as a whole and relative preference over different leisure activities (using our focal subscription service and doing other leisure activities). The binary variable D_{it} indicates the occurrence of certain events that cause a consumer not to use the focal subscription even though she has leisure. This might be because there may be other leisure activities that take away all the time allocation for the day, e.g., going to a theme park. Taking Netflix as another example, we can let $D_{it} = 1$ if a subscriber found interesting shows to watch on day t, which may not happen every day. If consumer i does not have a subscription, her daily utility is simply $u^{(0)}(q_{0it}; \theta_{im(t)})$. We do not need to normalize $u^{(0)}(q_{0it}; \theta_{im(t)})$ to zero or any other value in order to specify WTP (see Example 1 for details).

We let the daily leisure be

$$\ell_{it} = \mu_i + \gamma' Z_{it} + \varepsilon_{it}, \tag{4}$$

[5] Money-metric utility functions are commonly used in the study of the WTP for non-market goods or services, such as the amenities of school and neighborhood (Altonji and Mansfield, 2018); money-metric utility functions also have a long history in the literature of hedonic models (starting from the seminal paper by Rosen, 1974), which serve as the workhorse model in estimating the WTP for amenities (e.g., neighborhood racial composition, violent crime, and air pollution) in housing markets (Bayer et al., 2016) and the WTP for product features (Bajari and Benkard, 2005).

where Z_{it} denotes a vector of exogenous covariates that affect leisure (e.g., weekend or holiday dummy variables or weather). These variables ultimately affect the usage of subscription. Note that μ_i is the unobserved consumer heterogeneity in the amount of leisure (e.g., age, gender, household size). Suppose ε_{it} is a standard normal random variable truncated below at zero and then centered so that finally $\mathrm{E}(\varepsilon_{it}) = 0$, and suppose $\varepsilon_{it} \perp\!\!\!\perp (\mu_i, Z_{it})$. This implies that conditional on (μ_i, Z_{it}), the daily leisure ℓ_{it} also follows a truncated normal distribution. In the online appendix, we provide empirical evidence supporting this distributional assumption. Here we have normalized the variance of daily leisure shocks ε_{it} to be a known constant (i.e., $1 - (2\phi(0))^2$). In Remark 1, we will argue that this normalization and the heteroscedasticity of daily leisure shocks are innocuous for the identification of the distribution of WTP.

Consumers do not have perfect foresight; particularly, they do not know exactly their amount of leisure in future days and which days they will use the subscription. When making a subscription decision for a month, the consumer must form expectations of leisure and whether she would use the subscription for all days in the month. The following assumption specifies the information available to consumers at the beginning of each month m, conditional on which they make these inferences.

Assumption 1 (Consumer's Belief)**.** *Let I_{im} denote the information consumer i has at the beginning of month m.*

(1) Let $\mathbf{Z}_{im} \equiv \{Z_{it} : m(t) = m\}$. Assume that $(\theta_{im}, \mu_i, \mathbf{Z}_{im}) \in I_{im}$. In other words, at the beginning of month m, consumer i knows $\mathbf{Z}_{im}$, her leisure heterogeneous effect μ_i, and her preference parameters θ_{im}.

(2) A consumer cannot foresee which days she will use the subscription, i.e., $\mathbf{D}_{im} = \{D_{it} : m(t) = m\}$, but she knows the probability $\pi_{im} \equiv \Pr(D_{it} = 1 \mid I_{im})$ that is assumed to be constant across different days in month m. Note such a probability π_{im} can vary across consumers and months.

(3) Let $\boldsymbol{\varepsilon}_{im} \equiv \{\varepsilon_{it} : m(t) = m\}$ be the vector of all daily leisure shocks in month m. For any month m, $\boldsymbol{\varepsilon}_{im} \perp\!\!\!\perp (I_{im}, \mathbf{D}_{im})$.

(4) Let $F(\boldsymbol{\varepsilon}_{im}; \rho)$ be the parametric joint distribution function of $\boldsymbol{\varepsilon}_{im}$. The distribution function $F(\boldsymbol{\varepsilon}_{im}; \rho)$ is known up to a finitely dimensional vector of parameters ρ, which specifies the serial correlation among daily leisure shocks.

This assumption characterizes consumer knowledge at the time the consumer makes a subscription purchase. Consumers form forecasts of exogenous variable evolution over the period of the subscription. The leisure shocks serve to rationalize usage patterns, and the above assumption indicates that consumers cannot predict future leisure shocks. The above assumption allows us to characterize the optimal usage at the daily level and the corresponding indirect utility at the monthly level for a wide class of daily usage utility functions. Though our framework can accommodate both perfect foresight and rational expectations, we focus on the latter for the rest of the paper including the application.[6]

The parametric joint distribution $F(\boldsymbol{\varepsilon}_{im}; \rho)$ is to accommodate the possibility that the daily leisure shocks are serially correlated.[7] We have assumed that ε_{it} is a centered standard normal random variable truncated below at zero. One convenient way of specifying the joint distribution of $\boldsymbol{\varepsilon}_{im}$ is to use a copula function (such as Gaussian copula).[8]

Theorem 1. *Suppose the observed daily usage Q_{it} is derived from microfoundations in eq.* (3) *trading off between using the subscription and doing other leisure activities;*

[6]Consumers in the model can incorporate information on consumption preference and leisure time, so the information set I_{im} includes Z_{it} for all t such that $m(t) = m$ (i.e., all days in month m). The framework can accommodate both rational expectations and perfect foresight. For rational expectations, consider that consumer i does not know the errors ε_{it}, but she does know its distribution, in particular $\mathrm{E}(\varepsilon_{it} \mid I_{im}) = 0$ according to her belief. The model is also consistent with the perfect foresight setting, in which consumers observe these errors in advance, and we do not take expectations over the errors. In this case, the definition of L_{im} becomes $L_{im} = \sum_{t:m(t)=m} (\mu_i + \gamma' Z_{it} + \varepsilon_{it})$. Since the usage model can be estimated, and the parameters μ_i and γ are estimated, we can obtain the residuals to be the "errors" that are known in advance by the consumer with the perfect foresight assumption. We focus on the rational expectations approach.

[7]If $\boldsymbol{\varepsilon}_{im}$ are serially independent, $F(\boldsymbol{\varepsilon}_{im}; \rho)$ is simply the product of the known marginal distribution function of ε_{it}.

[8]One might be tempted to use multivariate truncated normal distribution with serial correlation, but one caveat is that the marginals of truncated multinormal variates are not truncated normal in general. We illustrate the form of $F(\boldsymbol{\varepsilon}_{im}; \rho)$ by taking Gaussian copula as one example. Suppose $t = 1, \ldots, T_1$ are the days from month m. Then

$$F_\varepsilon(\boldsymbol{\varepsilon}_{i,m}; \rho) = \boldsymbol{\Phi}(\Phi^{-1}(F_\varepsilon(\varepsilon_{i1})), \ldots, \Phi^{-1}(F_\varepsilon(\varepsilon_{iT_1})); \rho),$$

where $\Phi^{-1}(\cdot)$ is the inverse cumulative distribution function (CDF) of a standard normal, and $\boldsymbol{\Phi}(\cdot; \rho)$ is the joint CDF of a multivariate normal distribution with mean zero and covariance matrix ρ.

the monthly utility is additively separable in daily utility, and Assumption 1 holds. If the daily utility functions $u^{(1)}$ *and* $u^{(0)}$ *are homogeneous of degree* 1 *(including Cobb-Douglas, CES, perfect substitutes, perfect complements, Leontief, etc.), we have the following results:*

(1) The difference between the expected monthly indirect utilities with and without a subscription, W_{im}*, satisfies*

$$W_{im} = \alpha_{im} L_{im} \qquad \textit{or equivalently} \qquad \ln W_{im} = \ln \alpha_{im} + \ln L_{im},$$

where L_{im} *is the expected monthly leisure.* L_{im} *is a function of the conditioning variables* $\mathbf{Z}_{im}$ *and unobserved heterogeneity in leisure amount* μ_i*, and it equals the following,*

$$L_{im} \equiv \sum_{t:m(t)=m} \left(\mu_i + \gamma' Z_{it}\right). \tag{5}$$

(2) The daily usage of the subscription satisfies

$$Q_{it} = D_{it} r_{im(t)} \ell_{it},$$

for a parameter $r_{im(t)}$ *that is a function of the preference parameters* $\theta_{im(t)}$*. The interpretation of* $r_{im(t)}$ *is the share of leisure budget spent in listening to streaming music. Neither* $\alpha_{im(t)}$ *nor* $r_{im(t)}$ *involve the leisure budget* ℓ_{it}*.*

We note that the critical assumption required for our method, the linear relationship between WTP W_{im} and the monthly expected leisure L_{im}, holds for a class of common utility functions. In Section D of the online appendix, we use the American Time Use Survey (ATUS) 2019–2020 data about how Americans spend their leisure time to show that the assumption that one's utility from leisure activities is homogeneous of degree 1 is reasonable for leisure market.

The interpretation of α_{im} is the difference between the expected maximum utility one could obtain from 1 unit of leisure time with and without a subscription.[9] We also allow for flexibly modeling usage utility to be time varying at a monthly level (through

[9] In the proof of this theorem, we show that $\alpha_{im} = \pi_{im}\left[u^{(1)}(r_{im}, 1 - r_{im}; \theta_{im}) - u^{(0)}(1; \theta_{im})\right]$. Note that π_{im} is the probability that one will use her subscription on a particular day, and r_{im} and $1 - r_{im}$ are the optimal time allocated to using the subscription product and doing other leisure activities when she has 1 unit of leisure time.

the $r_{im(t)}$ parameter) to rationalize that consumers might have seasonal variations in usage. When usage data are available at a higher frequency than purchase data, this becomes especially useful in capturing such temporal variations.

We use the familiar Cobb-Douglas utility function to illustrate the general conclusion in the above theorem and point out why the preference parameter α_{im} could be correlated with the expected monthly leisure L_{im}.

Example 1 (Cobb-Douglas Utility)**.** *Consider Cobb-Douglas utility functions for $u^{(1)}$ and $u^{(0)}$, and let*

$$\begin{aligned} u_{it}(q_{it}, q_{0it}) &= D_{it} \times u^{(1)}(q_{it}, q_{0it}; \theta_{im(t)}) + (1 - D_{it}) \times u^{(0)}(q_{0it}; \theta_{im(t)}) \\ &= D_{it} \times \left[\eta_i \cdot \left(q_{it}^{r_{im(t)}} q_{0it}^{1-r_{im(t)}}\right)\right] + (1 - D_{it}) \times (\eta_i \cdot q_{0it}). \end{aligned}$$

In this example, the preference parameters $\theta_{im(t)} = (\eta_i, r_{im(t)})'$. The coefficient $r_{im(t)}$ is the marginal rate of substitution (MRS) between the two leisure activities (listening to streaming music and doing other leisure activities like watching TV), which depends on individual preference and product characteristics. Because the product characteristics (e.g., the number of shows) could change over time, we let the MRS be time varying. When we adopt a money-metric representation of the utility from leisure activities, it is natural to incorporate the possibility that people would assign different dollar values to their utilities of leisure due to heterogeneity such as wage rates. The parameter η_i, which can be viewed as a function of wage rate according to the neo-classical economics theory (e.g., chapter 4 of Deaton and Muellbauer, 1980), is to capture such heterogeneous valuation of leisure—the η_i of professional lawyers is higher than the η_i associated with students. Finally, D_{it} denotes the occurrence of the events on day t that make a consumer listen to music or not.

We have that the optimal amount time of listening to streaming music is

$$Q_{it} = D_{it} r_{im(t)} \ell_{it}$$

which is the second conclusion of Theorem 1. The optimal amount time of watching TV is then $Q_{0it} = (1 - D_{it} r_{im(t)})\ell_{it}$. Particularly, for one unit of leisure, $D_{it} r_{im(t)}$ and $1 - D_{it} r_{im(t)}$ are the optimal amount of time spent in music and TV, respectively.

The difference between the indirect utility on day t with and without a subscription can be shown as follows,

$$V_{it} = \ell_{it} \times D_{it} \times \left[\eta_i {r_{im(t)}}^{r_{im(t)}} (1 - r_{im(t)})^{1-r_{im(t)}} - \eta_i\right]$$

At the beginning of month m, consumer i cannot foresee ℓ_{it} and D_{it}. Instead, she forms her expected V_{it} conditional on the information I_{im} as specified in Assumption 1,

$$\mathrm{E}(V_{it} \mid I_{im}) = \underbrace{(\mu_i + \gamma' Z_{it})}_{=\mathrm{E}(\ell_{it}|I_{im})} \times \underbrace{\pi_{im}\left[\eta_i r_{im(t)}{}^{r_{im(t)}}(1 - r_{im(t)})^{1-r_{im(t)}} - \eta_i\right]}_{=\alpha_{im(t)}}.$$

Let the term in the bracket be $\alpha_{im(t)}$ in Theorem 1. So the interpretation of $\alpha_{im(t)}$ is the difference between the expected money-metric value of one unit of leisure when the consumer has a subscription and is optimally trading off between using the subscription and doing other activities, compared with the situation when she does not have a subscription; it depends on a consumer's valuation of leisure, preference regarding alternative leisure activities, and the likelihood of using the subscription at all. Because the monthly utility is additively separable in the daily utility, the expected monthly difference is the sum $\alpha_{im} \sum_{t:m(t)=m} \mu_i + \gamma' Z_{it}$ that is $\alpha_{im} L_{im}$ in Theorem 1.

In this Cobb-Douglas utility function, α_{im} depends on the MRS $r_{im(t)}$ between the two activities (listening to streaming music and watching TV) and the dollar value assigned to the utility from leisure (η_i). The latter (η_i) is presumably correlated with one's wage rate, which is further related to one's expected leisure L_{im}. The MRS $r_{im(t)}$ can also be correlated with L_{im}. For example, the MRS is affected by whether or not the consumer has a Netflix subscription. The consumer decision about subscribing to Netflix intuitively will also depend on her expected leisure L_{im}. So in general we expect that α_{im} and L_{im} are correlated.

It is also worth noting that we do not normalize $u^{(0)}(q_{0it}; \theta_{im(t)})$ to be zero or an arbitrary constant—it is $u^{(0)}(q_{0it}; \theta_{im(t)}) = \eta_i q_{0it}$ here. Though without normalizing $u^{(0)}$, we will not be able to separately identify $u^{(1)}$ and $u^{(0)}$ in general; such a normalization is not necessary for our identification of the WTP, which only requires recovering the expected difference between the monthly indirect utilities with and without subscription.

Up to now, we have shown the decomposition $W_{im} = \alpha_{im} L_{im}$ or equivalently $\ln W_{im} = \ln \alpha_{im} + \ln L_{im}$.

Consumer Heterogeneity and Correlation: We now focus on two other aspects of the model that allow it to be more realistic. First, we show how to incorporate the observed consumer heterogeneity X_{im} into the indirect utility and consequently the purchase decision. This is important since the value of leisure α_{im} may depend on consumer characteristics, in addition to time-varying unobservables. Second, we show how the model can incorporate correlation between value of leisure and expected monthly leisure, L_{im}. This correlation is important, for instance, if we expect that in months that consumers have more leisure, they might have income shocks that also impact their value of leisure, and in turn, their WTP.

We first detail how we take account of observed consumer heterogeneity X_{im}. Consider a linear projection of $\ln \alpha_{im}$ onto X_{im} as:

$$\ln \alpha_{im} = \beta' X_{im} + U_{im} = \beta_0 + \beta_1' X_{1im} + U_{im}, \tag{6}$$

where $\beta' = (\beta_0, \beta_1')$ and $X_{im}' = (1, X_{1im}')$.[10]

The residual U_{im} can be interpreted as the unobserved consumer heterogeneity in the valuation of leisure activities with an active subscription after controlling for the observed factors X_{im} that could be both time-varying and heterogeneous. Because $\ln W_{im} = \ln L_{im} + \ln \alpha_{im}$, we have

$$\ln W_{im} = \ln L_{im} + \beta' X_{im} + U_{im}. \tag{7}$$

This equation says that β can be interpreted as the semi-elasticity of WTP with respect to the change of X_{im}, other things being equal. Moreover, the binary subscription $S_{im} = \mathbf{1}(\ln W_{im} > \ln P)$ becomes

$$S_{im} = \mathbf{1}(\ln L_{im} + \beta' X_{im} - \ln P + U_{im} > 0). \tag{8}$$

This equation resembles the familiar threshold crossing binary choice model, though the log of expected monthly leisure is unobserved.

Consider the interpretation of β and U_{im} using the Cobb-Douglas utility function as an example.

Example 1 (continued)**.** *In the Cobb-Douglas utility function, we have seen that* $\alpha_{im} = \pi_{im}[\eta_i r_{im}^{r_{im}}(1 - r_{im})^{1-r_{im}} - \eta_i]$, *and* η_i *depends on one's wage rate. For simplicity, suppose the MRS* r_{im} *between listening to music and watching TV is a constant* r *across consumers and over time. We then have*

$$\ln \alpha_{im} = \ln[r^r(1 - r)^{1-r} - 1] + \ln \eta_i + \ln \pi_{im}.$$

[10]By the *definition* (not an assumption) of linear projection (Wooldridge, 2010, pg. 25), $\beta_1 = [\mathrm{Var}(X_{1im})]^{-1} \mathrm{Cov}(X_{1im}, \ln \alpha_{im})$, and $\beta_0 = \mathrm{E}(\ln \alpha_{im}) - \mathrm{E}(X_{1im})'\beta_1$. The residual U_{im} has mean zero and is uncorrelated with X_{im}.

If the data do not have any observed consumer heterogeneity, $X_{im} = 1$, we have the following after the linear projection

$$\ln \alpha_{im} = \underbrace{\mathrm{E}\big[\ln(\pi_{im}\eta_i[r^r(1-r)^{1-r}-1])\big]}_{\beta_0} + \underbrace{[\ln \eta_i - \mathrm{E}(\ln \eta_i)] + [\ln \pi_{im} - \mathrm{E}(\ln \pi_{im})]}_{U_{im}}.$$

It is clear that β_0 in this example is the population mean of the log of the difference between the money-metric value of one unit of leisure when one does and does not subscribe. The term U_{im} consists of two parts: (a) $\ln \eta_i - \mathrm{E}(\ln \eta_i)$ is the individual valuation of leisure (relative to its population mean), and (b) $\ln \pi_{im} - \mathrm{E}(\ln \pi_{im})$ is the variation of the (log) probability of using the focal service in month m.

In the above example, we have seen that it is possible that α_{im} and L_{im} are correlated. It would be easier to assume that they are uncorrelated, but that would lead to inaccurate inference. The observed consumer heterogeneity X_{im} explains part of the correlation between α_{im} and L_{im}. When the correlation between α_{im} and L_{im} is due to the unobserved heterogeneity (such as unobserved wage rate), we have to rely on an exogenous shifter of leisure, Z_{it}.

Endogeneity: We detail the necessary exogenous variations required for identification in Assumption 2 below. This assumption allows for the correlation between leisure fixed effect μ_i and unobserved preference heterogeneity U_{im} across consumers for any given month m.

Assumption 2 (Exogenous Variation in Leisure)**.** *Assume that $\mathbf{Z}_{im} \perp\!\!\!\perp U_{im} \,|\, (X_{im}, \mu_i)$, which implies $L_{im} \perp\!\!\!\perp U_{im} \,|\, (X_{im}, \mu_i)$ because the randomness of L_{im} only comes from $\mathbf{Z}_{im}$ and μ_i.*

To understand why Assumption 2 is necessary, consider the case where L_{im} is known to us. According to the linear expression of $\ln W_{im}$ in eq. (7), we need to know β and some distributional features about U_{im} in order to obtain the distribution of WTP W_{im}.

We typically have to use the binary subscription choice S_{im} in eq. (8) to obtain β and the distribution of U_{im}. However, when the regressor L_{im}, a function of $\mathbf{Z}_{im}$ and μ_i, is correlated with U_{im} due to the correlation between leisure fixed effect μ_i and U_{im}, we have the familiar endogenous regressor problem in discrete choice models. To address

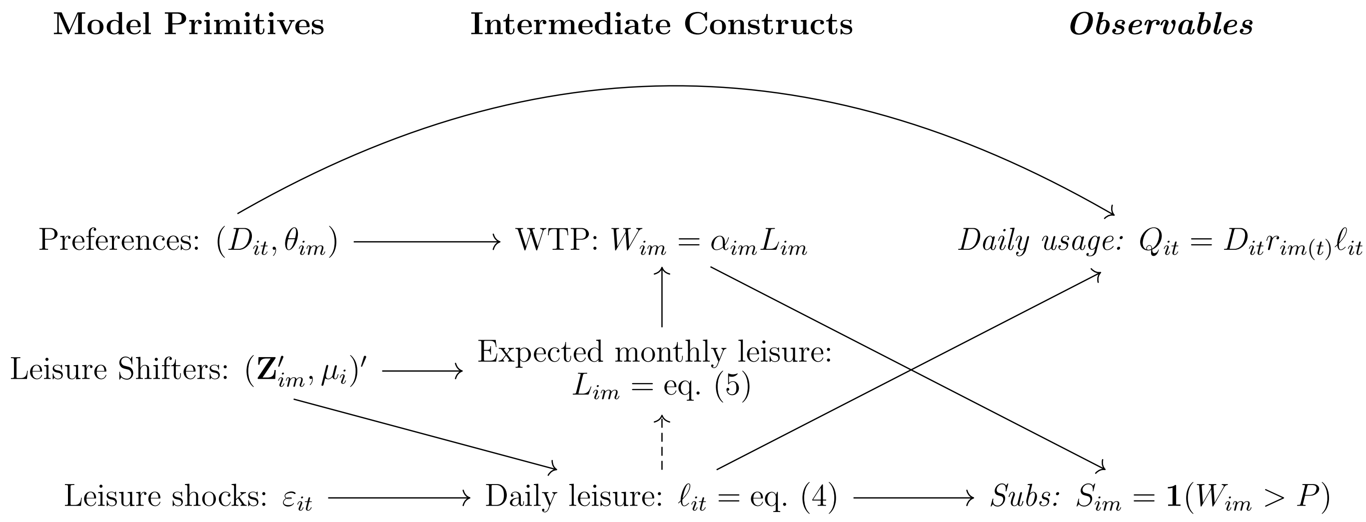

Figure 1: Conceptual Model Schematic

this endogeneity issue, we typically obtain instrumental variables (IV) that affect leisure L_{im}, the endogenous regressor, but not the error term U_{im}, the unobserved preference heterogeneity. The instruments $\mathbf{Z}_{im}$ we suggest later in the application in Section 6 involve precisely this type of variable. In addition, μ_i, the source of endogeneity, will be recovered from the high-frequency usage data as we will show later. The endogeneity of L_{im} can be controlled by adding μ_i as a control variable in the binary choice equation eq. (8); $\mathbf{Z}_{im}$ generates the exogenous variation of expected leisure L_{im} that identifies the binary subscription model.

Conceptual Model: We summarize the mechanism of our model with a schematic in Figure 1. The model primitives impact Intermediate Constructs, and both of these generate the observed data. From left to right of Figure 1, the model primitives consist of preference parameters (D_{it}, θ_{im}), observed and unobserved leisure shifters $(\mathbf{Z}'_{im}, \mu_i)'$, and daily leisure shocks ε_{it}. The leisure shifters and daily leisure shocks determine the daily amount of leisure ℓ_{it}. Summing up the daily leisures for all days in one month and taking the expectation, we have the expected monthly leisure L_{im}, which is a function of the leisure shifters. The expected monthly leisure together with the preference parameters determines the WTP W_{im}. We observe daily usage of the subscription Q_{it} and binary monthly subscription choices S_{im}. The daily usage Q_{it} equals the daily leisure ℓ_{it} multiplied by the share of leisure budget spent on the subscription $D_{it} r_{im(t)}$.

The subscription choice S_{im} is a result of comparing the WTP W_{im} and the subscription cost P.

Identification Logic: The intuition requires both usage and subscription models and the connection between then. The usage model allows the consumer to trade off her leisure budget between the focal activity (e.g., music streaming) and other leisure options. The subscription model requires the consumers to form expected WTP for the service for a month, and consumers subscribe each month only when their WTP is greater than the price.

Consumers first form expectations over the daily leisure process over each day of the month and corresponding usage utility they obtain from each day's usage. They aggregate these daily usage utilities into a monthly expected utility. We show that the WTP for monthly service can be expressed as a product of monthly aggregate leisure (derived from daily leisure), and a WTP shifter, which may be correlated with leisure.

We first prove that for a class of usage utility models (homogeneous of degree 1), the monthly WTP can be expressed as a product of monthly expected leisure and a WTP shifter. For simplicity, we consider the high frequency daily usage data to be available along with low frequency monthly subscription purchase data. Next, we demonstrate that the monthly expected leisure can be obtained using only the daily usage data. Intuitively, we show that the daily usage is proportional to daily realized leisure, which allows us to obtain the parameters governing the daily leisure process. The monthly expected leisure is then identified since it represents the expectation of daily leisure, aggregated over the days of the month. We then have exogenous shifters of the leisure process that impact WTP only through the expected leisure (or equivalently, expected usage), allowing us to separate the effect of the WTP shifter and monthly expected leisure, thus implying the WTP distribution for the customer base is identified. We prove in Appendix A that the WTP is non-parametrically identified, and therefore it does not rely on strong functional form or distributional assumptions. In Appendix E, we show that the model allow for serial correlation in usage. We also show the importance of both usage data and the exogenous leisure shifters – without either of these, we find that WTP is not identified.

Our model can flexibly accommodate two-dimensional heterogeneity, i.e., in the leisure process and in valuation shifters. It is important to note that our approach does not impose independence of usage and the shifter across users. Imposing an independence assumption would imply that a user with higher (expected) usage will have higher WTP for the service. Consider the usage of streaming music by a low-income student, who listens to a lot of music but has low WTP, whereas a professional lawyer may show little usage but have a high WTP. Our modeling approach of allowing dependence between the monthly WTP shifters and monthly expected leisure allows flexibility. We obtain the conditional expectation of this shifter, given the leisure process to help with WTP estimation. We show that by explicitly modeling this dependency (with conditional expectation), we can identify all the WTP parameters, including the dependence as well as conditional WTP (for example, for demographic groups).

Estimation: The estimation process follows the same logic. We show that WTP at the monthly level is comprised of the following: a) monthly expected leisure, b) observable monthly WTP shifters, and c) unobservable monthly WTP shifters. We first obtain the parameters of the daily leisure process using only the usage data and exogenous leisure shifters. This ensures that aggregate expected leisure at the monthly level becomes a known quantity. We then model the unobservable WTP shifter as correlated with the leisure process, and we obtain its conditional distribution. In the parametric specification with a normal conditional expectation used for simplicity, the subscription equation can be transformed into a probit model, and the estimated parameters have a one-to-one mapping with the WTP model parameters. Once we have obtained the conditional WTP, then we can use it as a primitive in counterfactual analysis of product or pricing changes. We next detail the model setup.

4 Identification and Estimation of WTP Distribution

The objective is to identify and estimate the distribution function of W_{im} or equivalently its monotone transformation $\ln W_{im}$. We have seen that $\ln W_{im}$ has a linear additive form,

$$\ln W_{im} = \ln L_{im} + \beta' X_{im} + U_{im}.$$

We first discuss the identification strategy, which proceeds in two steps. In the first step, we use the observed daily usage $Q_{it} = D_{it} r_{im(t)} \ell_{it}$ to recover the parameters γ and μ_i inside the daily leisure ℓ_{it}. Knowing γ and μ_i, we know the expected monthly leisure L_{im} by its formula in eq. (5). In the second step, we identify β and the conditional distribution of U_{im} given (X_{im}, L_{im}) from the monthly subscription choices $S_{im} = \mathbf{1}(\ln W_{im} > \ln P)$. Then the distribution of $\ln W_{im}$ is recovered by the above linear additive form.

4.1 Identification

Step 1: Usage By the formula that $Q_{it} = D_{it} r_{im(t)} \ell_{it}$, the observed daily usage Q_{it} can also be written as follows,

$$Q_{it} = \begin{cases} (r_{im(t)}\gamma)' Z_{it} + r_{im(t)}\mu_i + r_{im(t)}\varepsilon_{it}, & D_{it} = 1 \\ 0, & D_{it} = 0. \end{cases} \tag{9}$$

By the assumption $\boldsymbol{\varepsilon}_{im} \perp\!\!\!\perp (\mathbf{D}_{im}, \mu_i, r_{im(t)})$ in Assumption 1 and the assumption that we know the parametric joint distribution function of $\boldsymbol{\varepsilon}_{im}$, we can identify (r_{im}, μ_i, γ') for each month m and consumer i using only the observations of positive usage Q_{it}. So $(r_{im(t)}, \mu_i, \gamma')$ is identified using *only* usage data, including the exogenous leisure shifter Z_{it}, but without requiring any subscription data. Consequently, the expected monthly leisure L_{im} is identified with only usage data.

Step 2: Subscription We next consider the identification of preference parameters β and the distribution of U_{im} from the subscription choice:

$$S_{im} = \mathbf{1}((\ln L_{im} - \ln P) + \beta' X_{im} + U_{im} > 0).$$

Note that after the first step, L_{im} is identified and can be viewed as known. Since the constant price P is known as well, it remains to identify β and the distribution of the unobservable U_{im}.

We focus on the parametric identification by assuming that the conditional distribution of U_{im} given (X_{im}, μ_i) is a normal distribution. With the normal distribution assumption, the binary choice of S_{im} is the standard probit model from which we can identify the unknown parameters (see Theorem 2 below). We demonstrate that the distribution of the WTP and β are *nonparametrically identified*, i.e., the joint distribution of (X_{im}, μ_i, U_{im}) can be left unrestricted for each month m (see Theorem B.1 in the appendix).[11] Given Theorem B.1, we can demonstrate that our source of identification comes from the exogenous variation of $\mathbf{Z}_{im}$ rather than imposing particular parametric assumptions. However, we focus on the parametric form below because it is more likely to be used in applications and also conveys the essential intuition that is more generally applicable.

If there were no correlation between expected monthly leisure L_{im} and the unobservable shock U_{it} corresponding to the subscription decision, then the model would be simple to estimate. However, it would not capture the situation where usage might be positively or negatively correlated with U_{it}. Recall the discussion earlier, where a professional lawyer (profession is unobserved in data) has high WTP and low usage, whereas a student (again, student status unobserved) has lower WTP but higher usage.

One approach to model this correlation is to directly specify the correlation of L_{im} and U_{im}. However, recall that leisure includes exogenous shifters Z_{it}, which are conditionally independent of U_{im} (by Assumption 2). Thus, the part of L_{im} that can be correlated with U_{im} is effectively μ_i.This motivates the specification of U_{im} in Assumption 3 below.

Assumption 3 (Normal Distribution). *(1) For each month m, assume that*

$$U_{im} \mid (X_{im}, \mu_i) \sim \mathcal{N}(\sigma_{u,\mu}\mu^*_{im}, \sigma_u^2),$$

where μ^*_{im} is the residual of the linear projection of μ_i onto X_{1im}.[12] *Note that we do not assume U_{im} is serially uncorrelated across months.*

(2) Let $R_{im} \equiv (X'_{im}, \ln L_{im}, \mu_i)'$. Assume that $\mathrm{E}(R_{im}R'_{im})$ *is of full rank.*

This conditional normal assumption is widely used in the correlated random effect model (see Chamberlain, 1980). We assume that the conditional mean of U_{im} given (X_{im}, μ_i) depends on the *residual* of the linear projection of μ_i onto X_{1im}; in particular,

[11] We also provide a simple formula for $\mathrm{E}(W_{im} \mid X_{im}, \mu_i)$ and $\mathrm{E}(\ln W_{im} \mid X_{im}, \mu_i)$, and elasticities β can be estimated by an OLS estimator.

[12] That is $\mu^*_{im} = \mu_i - \mathrm{E}(\mu_i) + \sigma_{\mu,x}\Omega_{x1}^{-1}(X_{1im} - \mathrm{E}(X_{1im}))$, where $\sigma_{\mu,x1} = \mathrm{Cov}(\mu_i, X_{1im})$, and Ω_{x1} is the covariance matrix of X_{im}.

$\mathrm{E}(U_{im} \mid X_{im}, \mu_i) = \sigma_{u,\mu}\mu^*_{im}$.[13] This is because X_{1im} is uncorrelated with U_{im} by the construction of the linear projection of $\ln \alpha_{im}$ onto X_{im}, given X_{1im}, U_{im} will only be correlated with the part of μ_i that is uncorrelated with X_{1im} (i.e. μ^*_{im}). The estimate of μ^*_{im} is the residual after running the linear regression of μ_i on X_{im} for each month m using all consumers $i = 1, \ldots, n$.

Part (2) of Assumption 3 makes the role of $\mathbf{Z}_{im}$ in the parametric identification clear. When we do not have access to the instrumental variable $\mathbf{Z}_{im}$ and μ_i is large so that the latent leisure variable ℓ^*_{it} is greater than 0, $L_{im} \approx \mu_i T_m$ (T_m is the number of days in month m) and R_{im} becomes $(X'_{im}, \ln L_{im} = \ln \mu_i + \ln T_m, \mu_i)'$. Because $\ln \mu_i$ and μ_i are highly collinear, the rank condition is unlikely to be satisfied.

Under Assumption 1 to 3, we have

$$\Pr(S_{im} = 1 \mid X_{im}, \mu_i, L_{im}) = \Phi\left(\frac{1}{\sigma_u}\ln(L_{im}/P) + \frac{\beta'}{\sigma_u}X_{im} + \frac{\sigma_{u,\mu}}{\sigma_u}\mu^*_{im}\right). \qquad (10)$$

We can view the binary subscription choice S_{im} as the binary outcome and view $\ln(L_{im}/P)$, X_{im}, and μ^*_{im} as the explanatory variables. The usual panel data probit regression identifies the parameters σ_u^{-1}, β/σ_u, $\sigma_{u,\mu}/\sigma_u$. We use the partial likelihood estimation (e.g., section 13.8 in Wooldridge, 2010) to estimate these parameters, so we do not need to specify the serial correlation of U_{im}. Then β and $\sigma_{u,\mu}$ are obtained easily by transformation. This is our conclusion in part (1) of Theorem 2 below. Knowing the parameters $(\beta, \sigma_u, \sigma_{u,\mu})$, we know the conditional distribution of U_{im} given (X_{im}, μ_i) by Assumption 3. We then can derive the distribution of the WTP W_{im} easily by using $F_W(w \mid X_{im}, \mu_i, L_{im}) = \Pr(\ln W_{im} \leq \ln w \mid X_{im}, \mu_i, L_{im})$ and that $\ln W_{im} \leq \ln w$ is equivalent to $U_{im} \leq \ln w - \ln L_{im} - \beta' X_{im}$ because $\ln W_{im} = \ln L_{im} + \beta' X_{im} + U_{im}$.

Theorem 2 (Parametric Identification of WTP)**.** *Suppose Assumption 1 to 3 hold. We have*

1. *The unknown parameters $(\beta, \sigma_u, \sigma_{u,\mu})$ are identified.*

2. *The distribution of WTP is identified, and*

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

[13]Though in general $\sigma_{u,\mu}$ is a coefficient that determines how μ^*_{im} shifts the conditional mean of U_{im}, it can be shown that $\sigma_{u,\mu} = \mathrm{Cov}(\mu_i, U_{im})$ when the vector (U_{im}, μ_i, X'_{im}) follows a joint normal distribution (for each month m), which is why we denote it as $\sigma_{u,\mu}$.

As one particular application of the above theorem, we detail the estimation of the price elasticity e_{price} without price variation:

$$e_{price} = -\frac{\partial F_W(P)}{\partial P} \frac{P}{1 - F_W(P)}.$$

Using the expression of $F_W(w \mid X_{im}, \mu_i, L_{im})$ in Theorem 2, we have that

$$\begin{aligned} e_{price} &= -\frac{1}{\sigma_u \Pr(S_{im})} \int \phi \left[\frac{1}{\sigma_u} (\ln P - \ln L_{im} - \beta' X_{im} - \sigma_{u,\mu} \mu^*_{im}) \right] \mathrm{d}\, F(X_{im}, \mu_i, L_{im}) \\ &\approx -\frac{1}{\sigma_u \Pr(S_{im})} \frac{1}{nM} \sum_{i=1}^{n} \sum_{m=1}^{M} \phi \left[\frac{1}{\sigma_u} (\ln P - \ln L_{im} - \beta' X_{im} - \sigma_{u,\mu} \mu^*_{im}) \right]. \end{aligned} \tag{11}$$

The approximation follows from using the sample analog to estimate the integral. Note that the above elasticity e_{price} is the "overall" price elasticity across all consumers and all months. One of the advantages of our approach is that we can obtain WTP for different segments. Because we have identified the *conditional expectation of WTP* $F_W(w \mid X_{im}, \mu_i, L_{im})$, it is straightforward to compute the price elasticity for different consumer segments (such as student subscribers) and different months (e.g., holidays). In the empirical analysis, we will demonstrate the managerial value of these elasticities by considering the pricing of the subscription for different consumer segments.

Importance of Usage Data: We have now shown the identification when we have both usage and subscription data. To better understand the results, it is helpful to consider the consequence when we do not observe usage. In the absence of usage data, we will be unable to obtain the parameters (μ_i, γ) in daily leisure and consequently the expected monthly leisure L_{im}. The binary subscription equation

$$\begin{aligned} S_{im} &= \mathbf{1}(\ln L_{im} - \ln P + \beta' X_{im} + U_{im} > 0) \\ &= \mathbf{1}[(\beta_0 - \ln P) + \beta_1' X_{1im} + (\ln L_{im} + U_{im}) > 0] \end{aligned}$$

now involves two unknown error terms $\ln L_{im}$ and U_{im}. In such a situation with only subscription data, even if we made the stronger distributional assumption that the sum $(\ln L_{im} + U_{im})$ follows a normal distribution with unknown variance, we could at most identify β up to scale and could not identify the variance of $(\ln L_{im} + U_{im})$, which is actually essential even for a simple task like inferring the mean of the WTP W_{im}, which follows a log-normal distribution. So it is not possible to obtain WTP without observing usage, highlighting the unique role played by usage data.

Remark 1 (Heteroskedastic Leisure Schocks with Unknown Variance)**.** *By writing* $\ell_{it} = \mu_i + \gamma' Z_{it} + \varepsilon_{it}$ *and assuming* ε_{it} *is a centered standard normal random variable truncated below at zero, we have assumed that the variance of the daily leisure shocks is known and identical across individuals. This remark explains that this assumption is innocuous for our analysis.*

We consider the following specification of daily leisure:

$$\ell_{it} = \mu_i + \gamma' Z_{it} + \sigma_{\varepsilon,i}\varepsilon_{it},$$

where ε_{it} *is still a centered standard normal random variable truncated below at zero. Here the individual specific standard deviation* $\sigma_{\varepsilon,i}$ *corresponds to the variation of daily leisure shocks for each consumer* i*. Applying the conclusion* $Q_{it} = D_{it} r_{im(t)} \ell_{it}$*, we have*

$$Q_{it} = \begin{cases} (r_{im(t)}\gamma)' Z_{it} + r_{im(t)}\mu_i + r_{im(t)}\sigma_{\varepsilon,i}\varepsilon_{it}, & D_{it} = 1, \\ 0, & D_{it} = 0. \end{cases}$$

Because both $r_{im(t)}$ *and* $\sigma_{\varepsilon,i}$ *are unknown, for each individual* i*, we can only identify* $\gamma/\sigma_{\varepsilon,i}$ *and* $\mu_i/\sigma_{\varepsilon,i}$ *from the positive usage data. Because the coefficient* γ *is constant across different individuals, for any two individuals* i *and* j*, we can identify the ratio* $\sigma_{\varepsilon,i}/\sigma_{\varepsilon,j}$*. Take individual 1 as the reference person, and define the identified term* $\tau_i \equiv \sigma_{\varepsilon,i}/\sigma_{\varepsilon,1}$*. In the special case of homoskedasticity, one just let* $\tau_i = 1$ *for all individuals. So we can write* $\sigma_{\varepsilon,i} = \sigma_{\varepsilon,1}\tau_i$*, where* $\sigma_{\varepsilon,1}$ *is unknown. Define the identified term*

$$\tilde{L}_{im} = \tau_i \sum_{t:m(t)=m} \frac{\mu_i}{\sigma_{\varepsilon,i}} + \frac{\gamma'}{\sigma_{\varepsilon,i}} Z_{it}.$$

It is easy to check that

$$L_{im} = \sigma_{\varepsilon,1}\tilde{L}_{im}.$$

The subscription equation now reads

$$\begin{aligned} S_{im} &= \mathbf{1}(\ln L_{im} + \beta_0 + \beta_1' X_{1im} - \ln P + U_{im} > 0) \\ &= \mathbf{1}(\ln \tilde{L}_{im} + (\ln \sigma_{\varepsilon,1} + \beta_0) + \beta_1' X_{1im} - \ln P + U_{im} > 0). \end{aligned}$$

Under Assumption 1 to 3, we have

$$\Pr(S_{im} = 1 \mid X_{im}, \mu_i, L_{im}) = \Phi\left(\frac{1}{\sigma_u}\ln(\tilde{L}_{im}/P) + \frac{\ln\sigma_{\varepsilon,1} + \beta_0}{\sigma_u} + \frac{\beta_1'}{\sigma_u}X_{1im} + \frac{\sigma_{u,\mu}}{\sigma_u}\mu^*_{im}\right).$$

Because $\tilde{L}_{im}$ *is known, the above is again a probit model, which is similar to eq.* (A.3) *in the main setup. The difference is that we can only identify and estimate the sum* $\ln\sigma_{\varepsilon,1} + \beta_0$ *but not* $\sigma_{\varepsilon,1}$ *and* β_0 *separately. The results in Theorem 2 hold with slight notational modification. In particular, the distribution of WTP is identified, and*

$$F_W(w \mid X_{im}, \mu_i, L_{im}) = \Phi\left[\frac{1}{\sigma_u}\left(\ln w - \ln\tilde{L}_{im} - (\ln\sigma_{\varepsilon,1} + \beta_0) - \beta_1'X_{1im} - \sigma_{u,\mu}\mu^*_{im}\right)\right].$$

4.2 Estimation

The estimation procedure is developed from the two step identification arguments with one noteworthy difference. In estimating the linear model of usage, we use a finite mixture model by assuming that there are a finite number of latent types of $(r_{im(t)}, \mu_i)'$. The reason why we have to take the approach of finite latent types is the following. If we did not group consumers by their latent types, the estimation of individual $(r_{im}, \mu_i)'$ using usage data would have to rely only on the number of observed days with active subscription for consumer i. For a consumer who cancelled her subscription after the first month, we only have about 30 (days) observations. This limited number of observations leads to an estimation error in the estimate of μ_i that enters into the estimate of L_{im}. The challenge is that the estimated L_{im} (containing the nonignorable estimation error) acts as a regressor in the second step probit regression of S_{im} on $\ln(L_{im}/P)$, X_{im} and μ^*_{im}. Consequently, the nonignorable estimation error inside the regressor L_{im} works like the measurement error in the regressors of a regression. It is well known that a measurement error, even classic ones, will bias the estimates of regression coefficients.

We could potentially retain only the consumers who remain subscribers for a longer period, but that would introduce selection issues. To avoid these issues, we use latent classes (or types). By using the latent types, we can pool the information from a large number of consumers that will make the estimation error ignorable. In marketing, the use of latent class models for the purpose of segmentation in choice models has a long history beginning with Kamakura and Russell (1989). It is also worth pointing out that because we observe high frequency usage data (daily in our empirical application), we find in both simulation and empirical studies that we can always identify an individual's latent type with almost certainty. The posterior probability that an individual belongs to one type is always close to either 1 or 0. This is because 30 more (days) observations about one individual might not be sufficient to pin down her individual heterogeneity, but they seem enough to classify their types.

In practice, we use the expectation-maximization (EM) algorithm to estimate the finite mixture model of usage. From the EM algorithm, we obtain the estimates of (γ, μ_i). We then compute L_{im}. The last step is to run a probit model to obtain the rest of the parameters.

We conclude this section with the following estimation algorithm.

1. Estimate the finite mixture model eq. (9) by the EM algorithm. Let $(\hat{\mu}_i, \hat{r}_{im}, \hat{\gamma}')$ be the estimates of (μ_i, r_{im}, γ') after running the EM algorithm. Particularly, $\hat{\mu}_i$ and $\hat{r}_{im}$ are the posterior means of μ_i and r_{im} from the EM algorithm, respectively.

2. Estimate L_{im} for each consumer and month by substituting the unknown parameters (μ_i, γ') with the estimates $(\hat{\mu}_i, \hat{\gamma}')$. Denote this estimator by $\hat{L}_{im}$.

3. For each month m, implement a linear regression of $\hat{\mu}_i$ on X_{im} and save the residuals $\hat{\mu}^*_{im}$. These residuals are the estimates of μ^*_{im}.

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.

Given the sequential nature of the routine, we recommend using a bootstrap to obtain the standard error. In the Online Appendix, we conduct a numerical study and demonstrate the finite sample performance of the estimation algorithm.

Lastly, $D_{it} = \mathbf{1}(Q_{it} > 0)$ is directly observable from usage data. The distribution of D_{it} changes by month, and π_{im} is the probability that $D_{it} = 1$ for a day t in month m according to consumer i's belief right before month m. In our model, π_{im} is embedded in product valuation parameter α_{im}—if one does not expect to use the subscription service often, one has lower valuation. This is also clear in our Cobb-Douglas Example 1, in which α_{im} is an explicit function of π_{im} and other consumer preference parameters. For our purpose of identifying and estimating the distribution of WTP, we only need the distribution of α_{im}, not π_{im} itself.

5 Where is Price Variation Useful?

Our previous analysis has focused on the case where there was no price variation, which is the primary setting of interest. While our prior results have shown how the combination of subscription choice and usage data can identify the WTP distribution, here we demonstrate that having such data is not equivalent to the settings that feature price variation. To see the value of price variation, consider a more general setting with possible price variation:

$$S_{im} = \mathbf{1}(W_{im} > P_{im} + \delta' X_{2im}),$$

where X_{2im} is a vector of observable covariates and P_{im} denotes the price faced by consumer i in month m. We can interpret $P_{im} + \delta' X_{2im}$ as the total cost of a monthly subscription (e.g., price and switching cost). We write price P_{im} to analyze the general case in which price may or may not vary. For simplicity of discussion, assume X_{1im} and X_{2im} are not overlapping, and let $X_{im} = (1, X_{1im}', X_{2im}')'$ in this extension.[14] We have seen the special case $P_{im} = P$ and $\delta = 0$. We maintain our assumption (Assumption 1) about a consumer's utility of using the subscribed service and leisure so that the conclusion $W_{im} = \alpha_{im} L_{im}$ in Theorem 1 holds. Using $\ln W_{im} = \ln L_{im} + \beta_0 + \beta_1' X_{1im} + U_{im}$, we can write the subscription decision in this more general setting as:

$$S_{im} = \mathbf{1}(\ln L_{im} - \ln(P_{im} + \delta' X_{2im}) + \beta_0 + \beta_1' X_{1im} + U_{im} > 0).$$

To see the motivation of this general case, we provide two examples. These two examples are not only interesting by themselves but also showcase different scenarios of identification with and without price variation.

[14] When X_{1im} and X_{2im} overlap, one can easily modify the proof of Theorem 3 below by (a) defining a new notation, say $\tilde{X}_{2im}$, for the vector of variables that appear in X_{2im} but not in X_{1im}, and (b) substituting the occurrence of X_{2im} in the proof with $\tilde{X}_{2im}$. We did not pursue this cumbersome exposition since our current arguments sufficiently achieve the main objective of clarifying the information of price variation.

Case 1 (Entry of New Platform)**.** *Suppose our data are about the subscribers of Spotify. Apple launched Apple Music, its streaming music subscription, on June 30, 2015. It is helpful to understand how our model accounts for the entry of Apple Music and how this entry decision impacts the demand for Spotify. If we have data that include the months before and after the launch of Apple Music, we can create a dummy variable* $Apple_{im}$ *that equals* 1 *for the months after June, 2015 and* 0 *before. The entry of Apple Music changes the value of the outside option. So the subscription rule becomes*

$$\begin{aligned} S_{im} &= \mathbf{1}(W_{im} > P + \delta Apple_{im}) \\ &= \mathbf{1}(\ln L_{im} - \ln(P + \delta Apple_{im}) + \beta' X_{im} + U_{im} > 0), \end{aligned}$$

where δ *captures the effect of Apple Music on consumer* i*'s valuation of the outside option. It is worth noting that in this example it is reasonable to claim that* $\mathrm{Cov}(Apple_{im}, U_{im}) = 0$ *because the launch date of Apple Music is unlikely to be correlated with individual heterogeneity.*

Case 2 (Switching Cost)**.** *The second example addresses the switching cost. Consider*

$$\begin{aligned} S_{im} &= \mathbf{1}[W_{im} > P - \delta \ln(1 + Tenure_{im})] \\ &= \mathbf{1}(\ln L_{im} - \ln(P - \delta \ln(1 + Tenure_{im})) + \beta' X_{im} + U_{im} > 0), \end{aligned}$$

where $Tenure_{im}$ *is consumer tenure up to the beginning of month* m *and* $\delta > 0$*. For a new customer* i*,* $Tenure_{im} = 0$*, and hence* $\ln(1 + Tenure_{im}) = 0$*; the monetary cost of subscription is just the listed price* P*. For a current customer* i*, whose* $Tenure_{im} > 0$*, there is switching cost* $\delta \ln(1 + Tenure_{im})$ *involved in turning off the service. We use log transformation so that the switching cost is concave in tenure. Note that in this example, it would be unreasonable to assume that* $\mathrm{Cov}(\ln(1 + Tenure_{im}), U_{im}) = 0$*.*

It is tempting to conclude that by using our previous results and the variation of X_{2im} (to identify δ in $P_{im} + \delta' X_{2im}$), we *can* identify parameters in both examples without price variation. Though this conjecture is correct under certain conditions (which could be strong in certain applications), it is incorrect in general. In general, we have Theorem 3, and the conclusion depends on whether or not X_{2im} and U_{im} are correlated. Because this extended model involves two new variables, P_{im} and X_{2im}, we need to rephrase the exogenous variation assumption and the normal distribution assumption.

Assumption 2′ (Exogenous Variation of Leisure and Price)**.** *Assume that* $(\mathbf{Z}_{im}, P_{im}) \perp\!\!\!\perp U_{im} \mid (X_{im}, \mu_i)$.

When there is no price variation $P_{im} = P$, the above assumption is the same as $\mathbf{Z}_{im} \perp\!\!\!\perp U_{im} \mid (X_{im}, \mu_i)$ in Assumption 2. It is worthwhile to understand how exogenous price variation provides additional information compared to the case with only usage variation. Note that we only seek to point out the additional information provided the exogenous price variation in addition to the usage variation. Our approach does not correct for the issues that arise due to endogeneity of prices. The latter has been extensively studied in the literature.[15]

Assumption 3′ (Normal Distribution—Extension)**.** *(1) For each month m, assume that*

$$U_{im} \mid (X_{im}, \mu_i) \sim \mathcal{N}(\sigma'_{u,x_2} X^*_{2im} + \sigma_{u,\mu}\mu^*_{im}, \sigma^2_{u2}),$$

where X^*_{2im} and μ^*_{im} are the residuals after applying the linear projection of X_{2im} and μ_i onto X_{1im}, respectively.

(2) Let $R_{im} \equiv (X'_{im}, \ln L_{im}, \mu_i)'$. Assume that $\mathrm{E}(R_{im}R'_{im})$ is of full rank.

Note that the rank condition in part (2) implies that X_{2im} cannot be a constant (recall that X_{im} already includes unit one), otherwise it can be shown that δ will not be identified.

Theorem 3 (Parametric Identification of WTP—Extension)**.** *Suppose Assumption 1, 2′, and 3′ hold. We have*

1. *(Case 1: X_{2im} and U_{im} are uncorrelated, i.e., $\sigma_{u,x_2} = 0$). All parameters β, δ, $\sigma_{u,\mu}$, and σ_{u2} are identified with or without price variation.*

2. *(Case 2: X_{2im} and U_{im} are correlated, i.e., $\sigma_{u,x_2} \neq 0$). All parameters β, δ, $\sigma_{u,\mu}$, σ_{u,x_2}, and σ_{u2} are identified as long as we have at least* ***two*** *distinct prices. Without price variation, these parameters are poorly identified (see more discussion below).*

[15] For example, we can use the control function approach to address endogeneity of price by letting X_{im} include the control variables for price (Petrin and Train, 2010).

Following this theorem, we know that the model of Case 1, in which $X_{2im} = Apple_{im}$, is identified without price variation because $\text{Cov}(Apple_{im}, U_{im}) = 0$. In the second example, in which $X_{2im} = \ln(1 + Tenure_{im})$, it is unreasonable to claim $\text{Cov}(\ln(1 + Tenure_{im}), U_{im}) = 0$. Theorem 3 claims that this model will be poorly identified without price variation. It is shown in the proof of the above theorem that when there is no price variation, the identification depends on whether or not we can identify the parameters in the following nonlinear least square (NLS) regression:

$$Y_{im} = \ln(P + \delta' X_{2im}) - \psi_1 - \psi_2' X_{2im},$$

where Y_{im} is some *known* "dependent variable" defined in the proof. Note that the identification is possible only because $\ln(\cdot)$ is a nonlinear function. This kind of purely parametric identification can lead to poor estimation in practice because the log function is quite close to linear locally.[16] This raises serious concern about the collinearity between $\ln(1 + \delta' X_{2im}/P)$ and X_{2im}. This issue of poor identification is similar to Heckman's two-step method for the sample selection model, in which the identification is possible only because the inverse Mills ratio is nonlinear (though it is close to linear). Having exogenous price variation resolves this difficulty (similar to the case in which Heckman's two-step method requires excluded variables that only affect selection but not the outcome). *Even with only two distinct prices, the theorem shows that we can identify the model.* Once the identification is clear, we estimate the model by the maximum likelihood estimator. Our simulation studies in the Online Appendix show that our estimator works well even with only two prices, and additional price variation (three distinct prices) does not bring noticeable efficiency gain.

6 Empirical Application: Music Streaming Service

We focus on the market of online music streaming service in Southeast Asia during the period January 2016–December 2016. We represent the price in scaled \$ terms for exposition and to avoid attribution to the firm that provided the data. The usage (time of listening to music via this service) data are not scaled.

[16] For example, note that $\ln(1 + c) \approx c$ when c is small. Define $\tilde{P} = P + \delta' \text{E}(X_{2im})$. We can write $\ln(P + \delta' X_{2im}) = \ln\left(1 + \frac{\delta'(X_{2im} - \text{E}(X_{2im}))}{P + \delta' \text{E}(X_{2im})}\right) + \ln(\tilde{P})$. Using $\ln(1 + c) \approx c$, we can see that $\ln(P + \delta' X_{2im})$ is also close to linear in $\delta'(X_{2im} - \text{E}(X_{2im}))$.

We examine an empirical setting in which we study the subscription decision of a customer. We use our method to obtain the estimates of the price elasticities of different segments of consumers (see results in Table 4), the revenue-maximizing prices for each segment (in Table 4), and the distribution of the WTP for the monthly streaming service (Figure 2).

6.1 Data

The data were provided by a music streaming service company targeting the Southeast Asian market. Its service had 80% market share during the sample year. We will focus on the subscription choice of the monthly plan, and the price was always $149 for all consumers in our sample. Though the company sells subscription plans of varying lengths (e.g., monthly, 180 days, 365 days), most users (93.7 percent in our sample) choose the monthly plan. Registered users can also listen to music free for up to 1 hour each day with various restrictions; however, less than 4 percent of the users in our sample have ever used this free service.

We observe the daily usage (the number of seconds each user listened to music with the service) of subscribers from January 1, 2016 to December 31, 2016. We also observe each user's payment transaction history during that period, so we observe consumer monthly subscription choices. In terms of demographics, we only observe age and gender. We sampled 300 users from one city and found the daily weather information (precipitation and relative humidity) of that city during the sample period. These weather variables will be used as the exogenous variables that shift the daily leisure budget. All sampled users were subscribed to the streaming service in the first sample month (January 2016). At the end of our sample (December, 2016), 90% of the users were still subscribing to the service.

We have a few observations from the summary statistics detailed in Table 1. First, it is evident that the users who had cancelled their subscriptions at some point of time in our data used significantly less than (less than one half compared to) those who never cancelled the service. Second, younger and male users seem to be more likely to cancel their subscriptions. Third, consumers use the streaming music service less during weekends. This might be because weekends might involve other leisure activities, especially social activities. Fourth, there is substantial variation in monthly

Table 1: Means of Key Variables in the Streaming Music Data (Jan 1, 2016–Dec 31, 2016)

	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

Note: There is a single price ($149) for all consumers in the sample. The data are panel data at the daily frequency. The standard deviation is in parentheses.

usage in terms of streaming hours as shown by the big standard deviation of monthly usage.

6.2 Model

We need to specify the leisure equation, eq. (4), and the heterogeneous preference equation, eq. (6), for this particular application. First, let the daily leisure ℓ_{it} be

$$\begin{aligned}\ell_{it} = \mu_i + \gamma_{i,Holiday} Holiday_t + \gamma_{i,Weekend} Weekend_t \\ + \gamma_{Precipitation} Precipitation_t + \gamma_{Humidity} Humidity_t + \varepsilon_{it},\end{aligned}$$

where ε_{it} is a centered standard normal random variable truncated below at zero. The exogenous variables Z_{it} in this application are $Precipitation_t$ and $Humidity_t$.[17] $Holiday_t$ and $Weekend_t$ are dummy variables for holidays and weekends. Note that

[17] We also tried the specification that includes age and gender as additional explanatory variables (see Table C.1 in the online appendix), but we found they are insignificant and did not include them in the analysis. Our method does not require Z_{it} to be user-time varying. Time varying, but constant

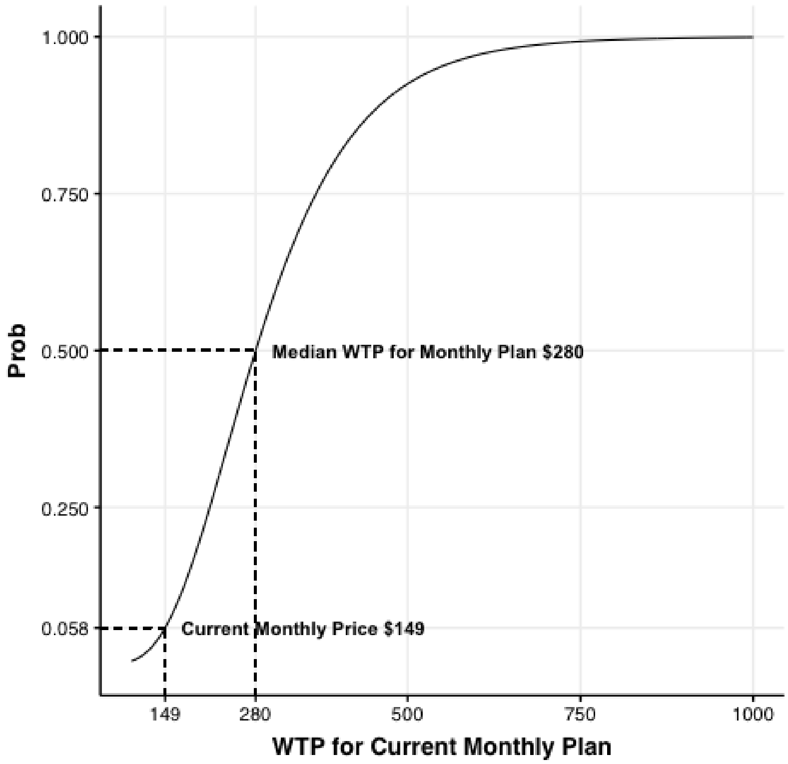

Figure 2: Estimates of the Distribution of WTP for the Monthly Plan

we also allow for heterogeneous effect of holidays and weekends. The usage Q_{it} is generated from $Q_{it} = D_{it} r_{im(t)} \ell_{it}$. In this application, we let $r_{im(t)} = r_i$ be constant across time for simplicity, though it varies across consumers. Second, we consider the linear projection of $\ln \alpha_{im}$ onto age and the female gender indicator variable,

$$\ln \alpha_{im} = \beta_0 + \beta_{Age} Age_i + \beta_{Female} Female_i + U_{im}.$$

6.3 Empirical Results

Table 2 presents the estimates of the main parameters of our model. From the estimates, we can see that the effect of weather on usage is at least statistically significant.

across consumers, exogenous variables like the weather variables here can also be used. The essential condition is to guarantee that in the probit subscription equation $\Pr(S_{im} = 1 \mid X_{im}, \mu_i, L_{im}) = \Phi\left(\frac{1}{\sigma_u} \ln(L_{im}/P) + \frac{\beta'}{\sigma_u} X_{im} + \frac{\sigma_{u,\mu}}{\sigma_u} \mu^*_{im}\right)$, there is no collinearity among these regressors, $\ln(L_{im}/P)$, X_{im}, and μ^*_{im}, for all consumers $i = 1, \ldots, n$ and all months $m = 1, \ldots, M$.

Table 2: WTP for Music Streaming Service: Estimation Results

	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)

Note: Two types of $(\mu_i, r_i, \gamma_{i,Holiday}, \gamma_{i,Weekend})$ were selected according to BIC.

Age has positive partial effect on WTP. Women are willing to pay more than men for this music streaming service. In the estimation of the usage equation, we found two types in the sampled consumers. The two types mainly differ in the (normalized) share of leisure time spent in using the streaming music: $r_{Type\,1} = 2.1130$ and $r_{Type\,2} = 5.3138$. The share for type 2 is more than 2.5 times than the share for type 1—we can call type 2 "heavy users" and type 1 "light users." Holidays and weekends also have the opposite effect on one's leisure for the two types. For light users, holidays and weekends increase their leisure time, but heavy users have less leisure time during holidays and weekends. Regardless of the type, the magnitude of the holiday effect is similar to the magnitude of the weekend effect. To assess the model fit, we report the confusion matrix below.

Table 3: Model Fit: Confusion Matrix

		Actual Subscription Choices		
		Subscribe (1)	Cancel (0)	Total
Predicted Subscription Choices	Subscribe (1)	3346	207	3553
	Cancel (0)	45	2	47
	Total	3391	209	3600

Table 4: Estimates of Price Elasticities, Median WTP, and Revenue Maximizing Prices

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

Note: "All Users" refers to all sampled subscribers in Jan. 2016. The standard error of price elasticities estimates is in parentheses.

There are 3,600 actual observations of about 300 consumer subscription choices over 12 months. From our model, we can estimate $\Pr(S_{im} = 1 \mid X_{im}, \mu_i, L_{im})$. Because 90% of sampled users were still subscribing at the end of our sample, we predict $S_{im} = 1$ if the estimate of $\Pr(S_{im} = 1 \mid X_{im}, \mu_i, L_{im})$ is greater than 0.9, and we let the predicted $S_{im} = 0$ otherwise. The resulting confusion matrix is in Table 3.

Figure 2 plots the (unconditional) distribution function of the WTP for the subscription among all subscribers at the beginning of our sample period. The estimated median WTP is $280. According to the estimated distribution, only about 6% of current subscribers are willing to pay less than the listed price of $149. This might explain the high market share and retention rate of this streaming service.

The model estimates can be connected to economically meaningful measures including price elasticities of different consumer segments and by computing the revenue-maximizing prices. The price elasticity is defined as

$$e_{price} \equiv \frac{\partial \Pr(S_{im}=1)}{\partial P} \frac{P}{\Pr(S_{im}=1)}.$$

It is calculated using eq. (11), and its standard error was calculated using the delta method. For a monthly plan, consumers can always turn on and off the subscription—we do not consider the switching cost here because we have only one price. If the company wants to maximize the annual revenue (12 months), the revenue maximization problem is the following,

$$\max_P \sum_{m=1}^{12} (1 - F_{W,m}(P))P.$$

Here $F_{W,m}(\cdot)$ is the distribution function of the WTP in month m, and $1 - F_{W,m}(P) = \Pr(W_{im} > P)$ is the percentage of consumers who will subscribe in month m. The distribution $F_{W,m}(\cdot)$ can vary month to month because the monthly leisure could change. The revenue-maximizing monthly price satisfies

$$1 = \frac{P}{\sum_{m=1}^{12}(1 - F_{W,m}(P))} \sum_{m=1}^{12} \frac{\partial F_{W,m}(P)}{\partial P},$$

from which we can calculate the revenue-maximizing price. Similarly, using the conditional distribution of the WTP given consumer demographics (age and gender), we can calculate the revenue-maximizing monthly price if the company chooses to target specific consumer groups, like student accounts in Spotify.

Table 4 reports the elasticities and revenue-maximizing monthly prices. The estimates of price elasticities rephrase our earlier conclusion about WTP: younger people and men have higher price elasticities for this product. Overall, the subscribers are relatively inelastic, suggesting that increasing price might be reasonable if the objective is to maximize the current revenue. According to our calculation, the revenue-maximizing price will be \$206, which is about 38 percent higher than the current price of \$149. We also calculated the prices for other consumer segments. For example, the revenue-maximizing price for younger customers (age ≤ 22), who are usually students, is \$197, which is 4% cheaper than our proposed regular price of \$206.

When we compare usage and WTP across groups (the last two columns of Table 4), we have an interesting observation. Reading the column "Mean Usage," we can see that women use less than men and that older consumers use less than younger users. Based

Table 5: Estimates of Price Elasticities by Excluding One Weather Variable

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)

Note: The standard error is in the parentheses. "All Users" refers to all sampled subscribers in Jan. 2016 (the first month of our data).

on the usage pattern, one might think men and youths are willing to pay more for the subscription. Our estimates (the column "Median WTP (\$)") show the opposite. This is because in our model, the WTP depends on both usage and the valuation of the leisure with the subscription. Even though women and older customers use less, they have higher valuation of the leisure as revealed by their higher subscription rate. It should be remarked that this interpretation relies on the homoskedasticity assumption about the variance of leisure shocks. If we adopted the heteroskedastic specification about the variance of leisure shock as detailed in Remark 1, the pattern of WTP across consumer segments could be different as pointed out by an anonymous referee.

Lastly, one essential assumption is that the two weather variables create exogenous variation of usage/leisure, i.e., $\mathbf{Z}_{im} \perp\!\!\!\perp U_{im}|(X_{im}, \mu_i)$. Here $\mathbf{Z}_{im}$ consists of precipitation and humidity. If any of $\mathbf{Z}_{im}$ is correlated with U_{im}, the resulting estimates of WTP distribution (and other parameters, like price elasticities) will be biased. With two weather variables, we indeed over-identify our model—this belongs to the general over-identification issue of the generalized method of moments (GMM) model. So, one way to check the exogenous assumption is to estimate the model using only one weather variable at a time and then to compare each of these estimates with the one using both weather variables. This practice has been used in Altonji, Elder and Taber (2005). In Table 5, we report the estimates of price elasticities using humidity or precipitation alone as the exogenous variation and then compare each of these estimates with the one using both weather variables. We do not observe substantial variation of the estimates, suggesting that weather is a potentially exogenous factor.

7 Conclusion

Many subscription commerce markets charge the same price to every consumer and over time. Thus, price variation is very limited and often non-existent. In such cases, classic results and arguments from the literature discuss how the identification of demand or WTP is not possible without price variation.

Our research suggests that high-frequency usage tracking data and observed subscription choices can identify the price elasticities and the distribution of the WTP. Crucially, our approach works because purchase (subscription) is separated from usage, and the two are related in the sense that obtaining a subscription opens up for the consumer the possibility of using the service for a potentially unlimited amount. We also demonstrate how price variation, even in limited form (e.g., with two price levels), can help identify more sophisticated models of WTP, including incorporating switching costs.

There are a number of avenues for future research. From a modeling viewpoint, there are potentially psychological costs associated with subscriptions. These may offer other ways to rationalize lack of cancellation, especially when combined with low usage. Consumers may be rational and just have a high WTP for each usage unit, which results in continuing subscription. Alternatively, consumers may pay switching costs or costs of attention (Grubb and Osborne, 2015). We show that switching costs require two price levels to identify, and we might expect that identifying some of the psychological costs would also require more price variation, which could be an interesting direction for future research.

Another direction is to consider additional market settings. Even though our paper focuses on subscription markets, the idea has potential more generally. Consider markets in packaged goods which are well studied in marketing. The crucial aspect required for our method is the separation of purchase (subscription) and consumption (usage). The separation implies that consumers may have different rates of consumption after purchase.

In addition, *even in typical packaged goods*, there is a separation between purchase and consumption, but in most such cases we do not observe the consumption. If consumption (usage) data were observable, our approach would be applicable to these settings too. With the advance of technology like 5G telecommunications and the Internet of Things, the high-frequency measurement of consumption is likely to become more prevalent in the future. In fact, there are some companies that already offer such services; notably LG has a smart fridge that monitors consumption of perishables like milk with the idea that these could be automatically replenished without direct consumer intervention.[18]

A Subscription Plan Examples

Table A1 details some common subscription services in the US. Some of the services are all inclusive with unlimited usage (e.g., Dropbox Premium), whereas others charge a marginal price for usage or only include pre-specified quantities.

B Nonparametric Identification and Estimation

In the basic model, we have the following subscription rule,

$$S_{im} = \mathbf{1}(\ln L_{im} - \ln P + \beta' X_{im} + U_{im} > 0),$$

where the expected monthly leisure L_{im} has been identified using the daily usage data. In this section, we will show that the exogenous usage variation ($\mathbf{Z}_{im}$) can identify the distribution of WTP without price variation even when we do not impose parametric assumptions about the joint distribution of (X_{im}, μ_i, U_{im}).

[18] See for example: NBC News (2014)

Table A1: Subscription Plans

Industry	Product or Service	Price ($)	Period	Total subscribers
Media & Entertainment	Netflix	12.99	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)	60.00	Annual	94 million
	Amazon Prime	119.00	Annual	90 million
	24 hour fitness (Gym)	40.00	Monthly	4 million
eCommerce	Harry's	35.00	Monthly	–
	Birchbox	15.00	Monthly	2 million
	Rent the Runway	159.00	Monthly	6 million
Transportation	Public Transit Pass (MTA)	121.00	30-days	–
	Uber Ride Pass	14.99	Monthly	–
	Jetblue "All You can Jet" Pass	699.00	Monthly	–

Note: Data collected Nov. 2019. "–" indicates public data were unavailable.

To state our result (the proof is in the Online Appendix), define the conditional choice probability (CCP) function,

$$\pi(x, \mu, l) \equiv \mathrm{E}(S_{im} \mid X_{im} = x, \mu_i = \mu, L_{im} = l).$$

Note that (a) $\pi(x, \mu, l)$ is nonparametrically estimable; (b) $\pi(x, \mu, l) = \Pr(S_{im} = 1 \mid X_{im} = x, \mu_i = \mu, L_{im} = l)$ by the binary nature of S_{im}.

Theorem B.1 (Nonparametric Identification and Estimation of WTP)**.** *Suppose Assumption 1 to 2 hold. We have that*

$$F_W(w \mid X_{im} = x, \mu_i = \mu, L_{im} = l) = 1 - \pi\left(x, \mu, \frac{P \times l}{w}\right),$$

provided that Pl/w is in the support of L_{im} conditional on (X_{im}, μ_i). In addition, if

(1) L_{im} *is continuous,*

(2) the support of P/L_{im} *covers the support of* α_{im} *given* X_{im} *and* μ_i*,*

(3) $\mathrm{E}(X_{im}X_{im}')$ *is of full rank,*

we have that

(1) the entire distribution $F_W(w \mid X_{im}, \mu_i, L_{im})$ *is nonparametrically identified;*

(2) the conditional mean of WTP equals

$$\mathrm{E}(W_{im} \mid X_{im}, \mu_i) = \mathrm{E}(L_{im} \mid X_{im}, \mu_i)\, \mathrm{E}(Y_{1,im} \mid X_{im}, \mu_i),$$

where

$$Y_{1,im} = \frac{S_{im} - \mathbf{1}(L_{im} \geq \mathrm{E}(L_{im}))}{L_{im} f_L(L_{im} \mid X_{im}, \mu_i)} \frac{P}{L_{im}} - \frac{P}{\mathrm{E}(L_{im})}$$

and $f_L(L_{im} \mid X_{im}, \mu_i)$ *is the conditional PDF of* L_{im} *given* (X_{im}, μ_i)*;*

(3) β *can be consistently estimated by the OLS estimator*

$$\hat{\beta} \equiv \left(\sum_{i=1}^{n} \sum_{m=1}^{M} X_{im} X_{im}' \right)^{-1} \left(\sum_{i=1}^{n} \sum_{m=1}^{M} X_{im} Y_{2,im} \right),$$

where

$$Y_{2,im} \equiv \frac{S_{im} - \mathbf{1}(\ln L_{im} \geq \mathrm{E}(\ln L_{im}))}{f_{\ln L}(\ln L_{im} \mid X_{im}, \mu_i)} + \mathrm{E}(\ln L_{im}) - \ln P,$$

where $f_{\ln L}(\cdot \mid X_{im}, \mu_i)$ *is the conditional PDF of* $\ln L_{im}$ *given* (X_{im}, μ_i)*.*

The above theorem not only shows the identification of the WTP distribution, but also gives estimable formulas of the conditional distribution of W_{im} and the conditional mean of WTP. The conditional mean can be estimated by nonparametric regression easily. The support condition (the support of P/L_{im} covers the support of α_{im} given X_{im} and μ_i) can be restrictive when $\mathbf{Z}_{im}$ is discrete. If the support condition does not hold, we can use Theorem 2, which relies on the normal distribution assumption.

One way to check whether or not the support condition is going to hold is to leverage the parametric identification result. We want the support of P/L_{im} covers the support of α_{im} given X_{im} and μ_i. From data, we observe the range of P/L_{im} given (X_{im}, μ_i) because L_{im} has been estimated. Given the normal distribution assumption, we have

$$U_{im} \mid (X_{im}, \mu_i) \sim \mathcal{N}(\sigma_{u,\mu} \mu_{im}^*, \sigma_u^2).$$

Hence, $\alpha_{im} = \exp(X'_{im}\beta + U_{im})$ follows a log normal distribution given (X_{im}, μ_i). We then can compare the 95% confidence interval of α_{im} given (X_{im}, μ_i) with the observed range of P/L_{im} given (X_{im}, μ_i),

Competing Interests

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript. The authors have no funding to report.

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Online Appendix for

Can Willingness to Pay be Identified without Price Variation? What Usage Tracking Data Can (and Cannot) Tell Us

December 2022

A Proofs of the Theorems in the Paper

Proof of Theorem 1. Let Q_{it} and Q_{0it} denote the optimal solutions of q_{it} and q_{0it} that maximize $u_{it}(q_{it}, q_{0it})$ subject to $q_{it} + q_{0it} = \ell_{it}$. These optimal solutions are also the observed usage by our assumption. When $u^{(1)}$ and $u^{(0)}$ are homogeneous of degree 1, it follows from the properties of homothetic utility functions (e.g. page 147 of Varian, 1992) that

$$Q_{it} = D_{it} r_{im(t)} \ell_{it}, \tag{A.1}$$

for some parameter $r_{im(t)}$ that is a function of the preference parameters $\theta_{im(t)}$ associated with consumer i in month m. This is part (2) of Theorem 1. For the simplicity of notation, assume days t are all from month m. So in the rest of the proof, we simply write month m instead of $m(t)$, e.g. r_{im} instead of $r_{im(t)}$.

In order to show part (1) of this theorem. We first derive the the daily indirect utility with and without a subscription, which are denoted by $V_{it}^{(1)}$ (with a subscription) and $V_{it}^{(0)}$ (without a subscription), as well as their difference $V_{it} \equiv V_{it}^{(1)} - V_{it}^{(0)}$. Then applying the additively separable assumption about consumer preference, we have the difference between the monthly indirect utility with and without a subscription. Conditional on the information I_{im} that consumer i has at the beginning of month m, we finally compute the expected difference of the monthly indirect utilities with and without a subscription. Such expected difference, denoted by W_{im} below, is the WTP.

Without a subscription, consumer spends all her leisure time on the other leisure activities, and her daily indirect utility equals

$$V_{it}^{(0)} = u^{(0)}(\ell_{it}; \theta_{im}) = \ell_{it} u^{(0)}(1; \theta_{im}),$$

because $u^{(0)}$ is homogeneous of degree 1. We next derive the the indirect utility on day *t with a subscription*, denoted by $V_{it}^{(1)}$. By the demand functions in eq. (A.1), we have

$$\begin{aligned} V_{it}^{(1)} &\equiv u_{it}(Q_{it}, Q_{0it}; \theta_{im}) \\ &= D_{it} u^{(1)}(r_{im}\ell_{it}, (1-r_{im})\ell_{it}; \theta_{im}) + (1-D_{it}) u^{(0)}(\ell_{it}; \theta_{im}) \quad \text{by the definition of } u_{it} \\ &= \ell_{it} \left[D_{it} u^{(1)}(r_{im}, 1-r_{im}; \theta_{im}) + (1-D_{it}) u^{(0)}(1; \theta_{im}) \right]. \end{aligned}$$

The last line follows because $u^{(1)}$ and $u^{(0)}$ are homogeneous of degree 1.

The daily difference between the indirect utility with a subscription ($V_{it}^{(1)}$) and without a subscription ($V_{it}^{(0)}$) is

$$V_{it} \equiv V_{it}^{(1)} - V_{it}^{(0)} = \ell_{it} \times D_{it} \times \underbrace{\left[u^{(1)}(r_{im}, 1-r_{im}; \theta_{im}) - u^{(0)}(1; \theta_{im}) \right]}_{\equiv \tilde{\alpha}_{im}}.$$

When the monthly utility is additively separable in daily utilities, the monthly utility difference is

$$\sum_{t:m(t)=m} V_{it} = \sum_{t:m(t)=m} \ell_{it} D_{it} \tilde{\alpha}_{im}.$$

Next, we need to compute the expected monthly difference of the indirect utilities with and without a subscription conditional on the set of information available at the beginning of month m according to Assumption 1. The expected difference of indirect utilities is

$$W_{im} = \mathrm{E}\Big(\sum_{t:m(t)=m} V_{it} \;\Big|\; I_{im} \Big) = \sum_{t:m(t)=m} \mathrm{E}(\ell_{it} D_{it} \tilde{\alpha}_{im} \mid I_{im}).$$

By Assumption 1, we can write

$$\begin{aligned} \mathrm{E}(\ell_{it} D_{it} \tilde{\alpha}_{im} \mid I_{im}) &= \tilde{\alpha}_{im} \, \mathrm{E}(\ell_{it} D_{it} \mid I_{im}) && \text{because } \theta_{im} \in I_{im} \\ &= \tilde{\alpha}_{im} [(\mu_i + \gamma' Z_{it}) \, \mathrm{E}(D_{it} \mid I_{im}) + \mathrm{E}(\varepsilon_{it} D_{it} \mid I_{im})] && \text{because } (\mu_i, \mathbf{Z}_{im}) \in I_{im} \\ &= \tilde{\alpha}_{im} [(\mu_i + \gamma' Z_{it}) + \mathrm{E}(\varepsilon_{it})] \, \mathrm{E}(D_{it} \mid I_{im}) && \text{by } \varepsilon_{it} \perp\!\!\!\perp (D_{it}, I_{im}) \\ &= (\mu_i + \gamma' Z_{it}) \tilde{\alpha}_{im} \, \mathrm{E}(D_{it} \mid I_{im}) && \text{by } \mathrm{E}(\varepsilon_{it}) = 0. \end{aligned}$$

By the assumption that $\pi_{im} \equiv \mathrm{E}(D_{it} \mid I_{im})$ is constant across the days in month m, we finally conclude

$$W_{im} = L_{im} \alpha_{im},$$

where

$$\alpha_{im} = \pi_{im} \tilde{\alpha}_{im} = \pi_{im} \left[u^{(1)}(r_{im}, 1-r_{im}; \theta_{im}) - u^{(0)}(1; \theta_{im}) \right].$$

and

$$L_{im} = \sum_{t:m(t)=m} (\mu_i + \gamma' Z_{it}) .$$

□

For simplicity, in the rest of the proofs, we omit the subscript "$im(t)$", "im", and "it" whenever there is no confusion.

Proof of Theorem 2. We first show that the vector of unknown parameters $(\beta', \sigma_u, \sigma_{u,\mu})'$ is identified. Then we show that the identification of $(\beta', \sigma_u, \sigma_{u,\mu})'$ implies the identification of the distribution of WTP.

We have that

$$\begin{aligned}
\Pr(S = 1 \mid X, \mu, L) &= \Pr(U > \ln P - \beta' X - \ln L \mid X, \mu, L) \\
&= \Pr(U > \ln P - \beta' X - \ln L \mid X, \mu),
\end{aligned}$$

where the second line follows from $\mathbf{Z} \perp\!\!\!\perp U \mid (X, \mu)$ hence $L \perp\!\!\!\perp U \mid (X, \mu)$. Now by assumption 3, we have

$$U \mid (X, \mu) \sim \mathcal{N}(\sigma_{u,\mu}\mu^*,\ \sigma_u^2). \tag{A.2}$$

It then follows from eq. (A.2) that

$$\begin{aligned}
\Pr(S = 1 \mid X, \mu, L) &= 1 - \Phi\left(\sigma_u^{-1}\left[\ln P - \beta' X - \ln L - \sigma_{u,\mu}\mu^*\right]\right) \\
&= \Phi\left(\sigma_u^{-1}\left[\ln L - \ln P + \beta' X + \sigma_{u,\mu}\mu^*\right]\right).
\end{aligned} \tag{A.3}$$

To see the identification, note two things. First, $\Pr(S = 1 \mid X, \mu, L)$ is observable from data—μ and L have been identified before using usage data. Second, the CDF Φ is strictly increasing. We then have that

$$\begin{aligned}
\Phi^{-1}(\Pr(S = 1 \mid X, \mu, L)) &= \sigma_u^{-1}\left[\ln L - \ln P + \beta' X + \sigma_{u,\mu}\mu^*\right] \\
&= \sigma_u^{-1}(\beta_0 - \ln P) + (\sigma_u^{-1}\beta_1)' X_1 + \sigma_u^{-1} \ln L + (\sigma_u^{-1}\sigma_{u,\mu})\mu^*.
\end{aligned}$$

The second line follows from $\beta' X = \beta_0 + \beta_1' X_1$. We want to rewrite the above equation as a "linear regression". Define the vector of "regressors" $\tilde{X} \equiv (1, X_1', \ln L, \mu^*)'$, and define the vector of "regression coefficients" $\tilde{\beta} \equiv (\sigma_u^{-1}(\beta_0 - \ln P), \sigma_u^{-1}\beta_1', \sigma_u^{-1}, \sigma_u^{-1}\sigma_{u,\mu})'$. Note that the identification of $\tilde{\beta}$ implies the identification of β, σ_u, and $\sigma_{u,\mu}$. Using the new notation, the above display reads

$$\Phi^{-1}(\Pr(S = 1 \mid X, \mu, L)) = \tilde{X}'\tilde{\beta}. \tag{A.4}$$

Equation (A.4) resembles a linear regression. Multiplying both sides of eq. (A.4) by the vector $\tilde{X}$ and taking expectation, we have

$$\mathrm{E}\Big[\tilde{X}\Phi^{-1}(\Pr(S=1 \mid \mu_i, \mathbf{Z}, X))\Big] = \mathrm{E}(\tilde{X}\tilde{X}')\tilde{\beta},$$

So $\tilde{\beta}$ is identified, if $\mathrm{E}(\tilde{X}\tilde{X}')$ is invertible. Because μ^* is a linear combination of X_1 and μ, $\mathrm{E}(\tilde{X}\tilde{X}')$ is invertible if and only if $\mathrm{E}(RR')$ is of full rank, where $R \equiv (1, X_1', \ln L, \mu)'$, as assumed in Assumption 3.

Second, we derive the distribution of WTP. We have that

$$\begin{aligned}
F_W(w \mid X, \mu, L) &= \Pr(\ln W \leq \ln w \mid X, \mu, L) \\
&= \Pr(\ln L + \beta' X + U \leq \ln w \mid X, \mu, L) \\
&= \Pr(U \leq \ln w - (\ln L + \beta' X) \mid X, \mu) && \text{by } U \perp\!\!\!\perp L \mid (X, \mu) \\
&= \Phi(\sigma_u^{-1}[\ln w - (\ln L + \beta' X) - \sigma_{u,\mu}\mu^*]) && \text{by eq. (A.2).}
\end{aligned}$$

□

Proof of Theorem 3. In this proof, it is convenient to write $g(P, X_2; \delta) \equiv \ln(P + \delta' X_2)$, or simply g when there is no confusion. We have that

$$\begin{aligned}
\Pr(S=1 \mid \mu, L, X, P) &= \Pr(U > g - \beta_0 - \beta_1' X_1 - \ln L \mid \mu, L, X, P) \\
&= \Pr(U > g - \beta_0 - \beta_1' X_1 - \ln L \mid X, \mu),
\end{aligned}$$

where the second line follows from $(\mathbf{Z}, P) \perp\!\!\!\perp U \mid (X, \mu)$, hence $(L, P) \perp\!\!\!\perp U \mid (X, \mu)$. By assumption $3'$, we have

$$U \mid (X, \mu) \sim \mathcal{N}\left(\sigma_{u,\mu}\mu^* + \sigma_{u,x_2}' X_2^*,\ \sigma_{u2}^2\right). \tag{A.5}$$

It follows from eq. (A.5) that

$$\Pr(S=1 \mid \mu, L, X, P) = \Phi\left(\sigma_{u2}^{-1}\left[(\beta_0 - g) + \beta_1' X_1 + \ln L + \sigma_{u,\mu}\mu^* + \sigma_{u,x_2}' X_2^*\right]\right). \tag{A.6}$$

By the invertibility of the CDF Φ, we have

$$\Phi^{-1}(\Pr(S=1|\mu, L, X, P)) = \sigma_{u2}^{-1}(\beta_0 - g) + (\sigma_{u2}^{-1}\beta_1)' X_1 + \sigma_{u2}^{-1}\ln L + (\sigma_{u2}^{-1}\sigma_{u,\mu})\mu^* + (\sigma_{u2}^{-1}\sigma_{u,x_2})' X_2^*.$$

We know $\Phi^{-1}(\Pr(S=1 \mid \mu, L, X, P))$ from data. This above display resembles a NLS regression model. The nonlinearity comes from g function. The condition whether or not σ_{u,x_2} equals zero matters for the rest of arguments. We first consider the case when $\sigma_{u,x_2} = 0$, which is simpler, then proceed to the case when $\sigma_{u,x_2} \neq 0$.

Case 1: $\sigma_{u,x_2} = 0$. If $\sigma_{u,x_2} = 0$, we have

$$\Phi^{-1}(\Pr(S = 1 \mid \mu, L, X, P)) = \sigma_{u2}^{-1} \underbrace{(\beta_0 - g)}_{\equiv H_1(X_2)} + (\sigma_{u2}^{-1}\beta_1)' X_1 + \sigma_{u2}^{-1} \ln L + (\sigma_{u2}^{-1}\sigma_{u,\mu})\mu^*.$$

For any fixed X_2, the above resembles a linear regression because $H_1(X_2)$ is a constant for a given X_2. When X_2 is fixed, $\sigma_{u2}^{-1}H_1(X_2)$ can be viewed as intercept term. For each value of X_2, define $\tilde{X} \equiv (1, X_1', \ln L, \mu^*)'$. If for any value of X_2, we have that $\mathrm{E}[\tilde{X}(\tilde{X})']$ has full rank, we can identify $\sigma_{u2}^{-1}H_1(X_2)$, σ_{u2}^{-1}, $\sigma_{u2}^{-1}\beta_1$, $\sigma_{u2}^{-1}\sigma_{u,\mu}$, hence $H_1(X_2)$. We then have identified β_1, $\sigma_{u\mu}$ and σ_{u2} by transformation. Note that μ^* is the residual of the linear projection of μ onto X_1, hence it is a linear combination of μ and X_1. So if $\mathrm{E}(RR')$ has full rank with $R = (1, \ln L, X_1', \mu)'$ (as assumed in Assumption 3′), we have $\mathrm{E}[\tilde{X}(\tilde{X})']$ has full rank.

We now knows $H_1(X_2)$ for any value of X_2, and

$$H_1(X_2) = \beta_0 - g.$$

This is just a NLS regression. Now recall $g(P_{im}, X_{2im}; \delta) = \ln(P_{im} + \delta' X_{2im})$, we have

$$H_1(X_{2im}) = \beta_0 - \ln(P_{im} + \delta' X_{2im}) \tag{A.7}$$

for any value of X_{2im}. The objective is to solve (β_0, δ) from eq. (A.7).

Here we only prove the simple case when X_{2im} is a scalar as in our two examples. The general case when X_{2im} can be shown very similarly. Denote X_{2a} and X_{2b} two distinct values that X_{2im} can take (e.g. $X_{2a} = 1$ and $X_{2b} = 0$ in Case 1),[19] and let $H_{1a} = H_1(X_{2a})$ and $H_{1b} = H_1(X_{2b})$. Subtracting eq. (A.7) when $X_{2im} = X_{2a}$ and X_{2b}, we have

$$H_{1b} - H_{1a} = \ln\left(\frac{P + \delta X_{2a}}{P + \delta X_{2b}}\right) = \ln\left[1 + \frac{\delta}{P + \delta X_{2b}}(X_{2a} - X_{2b})\right].$$

For a fixed X_{2b},[20] viewing

$$\tilde{\delta} \equiv \frac{\delta}{P + \delta X_{2b}}$$

as an unknown coefficient, we have a linear equation of $\tilde{\delta}$,

$$(\exp(H_{1b} - H_{1a}) - 1) = \tilde{\delta}(X_{2a} - X_{2b}).$$

[19] X_{2im} at least takes two values, otherwise $\mathrm{E}[(1, X_2')'(1, X_2')]$ does not have full rank as assumed in Assumption 3′.

[20] If 0 is in the support X_{2im}, letting $X_{2b} = 0$ gives rise to $\tilde{\delta} = \delta/P$.

This gives rise to a solution of $\tilde{\delta}$. Knowing $\tilde{\delta}$, δ can be solved if we know δX_{2b}. It is known by noting that

$$\tilde{\delta} X_{2b} = \frac{\delta X_{2b}}{P + \delta X_{2b}}.$$

We then have

$$\delta X_{2b} = \frac{\tilde{\delta} X_{2b} P}{1 - \tilde{\delta} X_{2b}} \qquad \text{and} \qquad \delta = \tilde{\delta}\left(P + \frac{\tilde{\delta} X_{2b} P}{1 - \tilde{\delta} X_{2b}}\right)$$

After obtaining δ, we can solve $\beta_0 = \ln(P + \delta' X_{2im}) + H_1(X_{2im})$. Note that the above arguments do not require price variation.

Case 2: $\sigma_{u,x_2} \neq 0$. When $\sigma_{u,x_2} \neq 0$, the above arguments do not proceed. Particularly, for a fixed X_2, X_2^* and μ^* are linear combination of X_1 and μ. Hence we have collinearity issue in the regression. To clarify the issue, it helps express μ^* and X_2^* explicitly:

$$\begin{aligned} \mu^* &= \mu - \mathrm{E}(\mu) + A_\mu(X_1 - \mathrm{E}(X_1)) \\ X_2^* &= X_2 - \mathrm{E}(X_2) + A_{x2}(X_1 - \mathrm{E}(X_1)), \end{aligned}$$

with

$$A_\mu = \mathrm{Cov}(\mu, X_1)[\mathrm{Var}(X_1)]^{-1}, \qquad \text{and} \qquad A_{x2} = \mathrm{Cov}(X_2, X_1)[\mathrm{Var}(X_1)]^{-1}.$$

Note that both A_μ and A_{x2} are identified from data. Standard but tedious calculation reveals that

$$\begin{aligned} \Phi^{-1}(\Pr(S = 1 \mid \mu, L, X, P)) = \sigma_{u2}^{-1} & \underbrace{(\beta_0 - g + \beta_1' \mathrm{E}(X_1) + \sigma_{u,x_2}'(X_2 + \mathrm{E}(X_2)))}_{\equiv H_2(P, X_2)} \\ + \sigma_{u2}^{-1} \ln L + \sigma_{u2}^{-1} & \underbrace{(\beta_1' + \sigma_{u,\mu} A_\mu + \sigma_{u,x_2}' A_{x2})}_{\equiv \psi_1'}(X_1 - \mathrm{E}(X_1)) + \sigma_{u2}^{-1}\sigma_{u,\mu}(\mu - \mathrm{E}(\mu)). \end{aligned}$$

Now for a fixed X_2, the above resembles a linear regression. If $\mathrm{E}(RR')$ has full rank, we can identify σ_{u2}^{-1}, ψ_1, and $\sigma_{u,\mu}$. If we could further identify σ_{u,x_2}, we can obtain β_1 from ψ_1.

We proceed to leverage to the NLS regression:

$$H_2(P, X_2) = \tilde{\beta}_0 + \sigma_{u,x_2}' X_2 - g, \tag{A.8}$$

where

$$\tilde{\beta}_0 \equiv \beta_0 + \beta_1' \operatorname{E}(X_1) - \sigma_{u,x_2}' \operatorname{E}(X_2).$$

The essence of identification now resides at the identification of δ, β_0 and σ_{u,x_2} from eq. (A.8). Now letting $g(P_{im}, X_2; \delta) = \ln(P_{im} + \delta' X_2)$, we have

$$H_2(P, X_2) = \tilde{\beta}_0 + \sigma_{u,x_2}' X_2 - \ln(P_{im} + \delta' X_2). \tag{A.9}$$

If we observe at least two prices, P_a and P_b, we have

$$\begin{aligned} H_2(P_a, X_2) &= \tilde{\beta}_0 + \sigma_{u,x_2}' X_2 - \ln(P_a + \delta' X_2) \\ H_2(P_b, X_2) &= \tilde{\beta}_0 + \sigma_{u,x_2}' X_2 - \ln(P_b + \delta' X_2). \end{aligned}$$

Subtracting one from the other equation, we have

$$\exp(H_2(P_b, X_2) - H_2(P_a, X_2)) - 1 = \frac{(P_a - P_b) + \delta' X_2}{P_b + \delta' X_2},$$

which can be viewed as an equation of the unknown $\delta' X_2$. We can rewrite this equation as follows,

$$H_3(X_2) = \delta' X_2,$$

where

$$H_3(X_2) = \frac{[\exp(H_2(P_b, X_2) - H_2(P_a, X_2)) - 1]P_b + (P_b - P_a)}{1 - [\exp(H_2(P_b, X_2) - H_2(P_a, X_2)) - 1]}.$$

Hence if $\operatorname{E}(X_2 X_2')$ is of full rank, we can identify δ with only two prices. Once we know δ, we can rearrange eq. (A.9)

$$\ln(P_{im} + \delta' X_2) + H_2(P, X_2) = \tilde{\beta}_0 + \sigma_{u,x_2}' X_2.$$

The left-hand-side variable is now observable, hence $\tilde{\beta}_0$, and σ_{u,x_2} is identified when $\operatorname{E}[(1, X_2')'(1, X_2')]$ has full rank. Without price variation, the regression form eq. (A.9) suffers for serious collinearity because $\ln(P + \delta' X_2)$ and X_2 are highly collinear. $\square$

Proof of Theorem B.1. The starting point is the conclusion of Theorem 1:

$$W = \alpha L.$$

Using the subscription decision rule,

$$S = \mathbf{1}(\alpha L > P) = \mathbf{1}\left(-\frac{P}{L} + \alpha > 0\right)$$

It will be convenient to denote

$$V^* = -\frac{P}{L},$$

and write

$$S = \mathbf{1}(V^* + \alpha > 0).$$

Because L is a function of $\mathbf{Z}$ and μ, V^* is also a function of μ_i and $\mathbf{Z}$ for a fixed price P. Assumption 2 ($\mathbf{Z} \perp\!\!\!\perp U \mid (X, \mu)$) implies $\alpha \perp\!\!\!\perp V^* \mid (X, \mu)$ because α is a function of X and U.

First, we derive $F_W(w \mid X, \mu, L)$. We have that

$$\begin{aligned}
F_W(w \mid X, \mu, L) &= \Pr(W \leq w \mid X, \mu, L) \\
&= \Pr(\alpha L \leq w \mid X, \mu, L) \quad \text{by } L > 0 \\
&= \Pr\Big(\alpha \leq \frac{w}{L} \Bigm| X, \mu, L\Big) \\
&= \Pr\Big(\alpha \leq \frac{w}{L} \Bigm| X, \mu\Big) \qquad \text{by } U \perp\!\!\!\perp \mathbf{Z} \mid (X, \mu), \text{ hence } \alpha \perp\!\!\!\perp L \mid (X, \mu).
\end{aligned}$$

The objective now is to obtain the distribution of $F_\alpha(a \mid X, \mu)$. We have that

$$\begin{aligned}
\pi(x, \mu, l) &= \Pr(S = 1 \mid X = x, \mu_i = \mu, L = l) \\
&= \Pr(\alpha > -v^* \mid X = x, \mu_i = \mu, L = l) \qquad \text{where } v^* = -P/l \\
&= \Pr(\alpha > -v^* \mid X = x, \mu_i = \mu) \\
&= 1 - F_\alpha(-v^* \mid X = x, \mu_i = \mu).
\end{aligned}$$

Alternatively, we can write

$$1 - \pi\left(x, \mu, \frac{P}{a}\right) = F_\alpha(a \mid X = x, \mu_i = \mu),$$

provided that P/a is in the support of L. Now we return to the question: what is $\Pr(\alpha \leq w/L \mid X, \mu)$? We have that

$$\begin{aligned}
\Pr\Big(\alpha \leq \frac{w}{L} \Bigm| X, \mu\Big) &= F_\alpha\left(\frac{w}{L} \mid X, \mu\right) \\
&= 1 - \pi\left(X, \mu_i, \frac{PL}{w}\right).
\end{aligned}$$

We have the conclusion that the conditional CDF of WTP is

$$F_W(w \mid X = x, \mu_i = \mu, L = l) = 1 - \pi\left(x, \mu, \frac{Pl}{w}\right),$$

provided that $(Pl)/w$ is the in support of L conditional of (X, μ).

Second, we derive the formula of $\mathrm{E}(W \mid X, \mu)$. By the conditional independence Assumption 2, we have

$$\mathrm{E}(W \mid X, \mu) = \mathrm{E}(L \mid X, \mu)\, \mathrm{E}(\alpha \mid X, \mu).$$

Because we observe (L, X, μ), we only need to identify $\mathrm{E}(\alpha \mid X, \mu)$. Using the similar arguments in Lewbel (2014), it can be shown that

$$\mathrm{E}(\alpha \mid X, \mu) = \mathrm{E}(Y_1 \mid X, \mu),$$

where

$$Y_1 = \frac{S - \mathbf{1}(V^* \geq \mathrm{E}(V^*))}{f_{V^*}(V^* \mid X, \mu)} + \mathrm{E}(V^*),$$

if V^* is continuous and that the support of V^* covers the support of α given (X, μ). We can rewrite Y_1 equivalently as follows,

$$Y_1 = \frac{S - \mathbf{1}(L \geq \mathrm{E}(L))}{L f_L(L \mid X, \mu)} \frac{P}{L} - \frac{P}{\mathrm{E}(L)},$$

where f_L denotes the observable conditional distribution of L given (X, μ). To see this, first note

$$\mathbf{1}(V^* \geq \mathrm{E}(V^*)) = \mathbf{1}(L \geq \mathrm{E}(L)).$$

Next, viewing L as a transformation of $V^* = -P/L$, we have that

$$f_{V^*}(V^* \mid X, \mu) = f_L(L \mid X, \mu) \frac{L^2}{P}.$$

In summary, we have

$$\mathrm{E}(W \mid X, \mu) = \mathrm{E}(L \mid X, \mu)\, \mathrm{E}(Y_1 \mid X, \mu).$$

Third, we show the OLS estimator of β. We can write the subscription decision rule as follows,

$$S = \mathbf{1}\left(\ln(L/P) + \beta' X + U > 0\right).$$

Note that $\ln(L/P) \perp\!\!\!\perp (\beta' X + U) \mid (X, \mu)$ because L is a function of $(\mu, \mathbf{Z})$, and $\mathbf{Z} \perp\!\!\!\perp U \mid (X, \mu)$ as stated in Assumption 2. Using similar arguments in section 6 of Lewbel (2014), it can be shown that

$$\mathrm{E}(Y_2 \mid X, \mu) = \mathrm{E}(X' \beta + U \mid X, \mu).$$

Multiplying both sides of the above display by X, we have that

$$\begin{aligned} \mathrm{E}(XY \mid X, \mu) &= \mathrm{E}(XX'\beta + XU \mid X, \mu) \\ &= XX'\beta + \mathrm{E}(XU \mid X, \mu). \end{aligned}$$

Taking unconditional expectation of both sides of the above display, we have

$$\mathrm{E}(XY) = \mathrm{E}(XX')\beta + \mathrm{E}(\mathrm{E}(XU \mid X, \mu)) = \mathrm{E}(XX')\beta,$$

because

$$\mathrm{E}(\mathrm{E}(XU \mid X, \mu)) = \mathrm{E}(XU) = 0.$$

Thus, we can express $\beta = \mathrm{E}(XX')^{-1}\,\mathrm{E}(XY_2)$ when $\mathrm{E}(XX')$ is of full rank. □

B Simulation Studies Based on Real Data

We design a simulation study based on two individual level survey data (the Dutch Time Use Survey (DTUS) 2005, and the Living Costs and Food Survey (LCF) 2018–2019 in the United Kingdom) to make our data generation process closer to the reality. To generate data, we need to specify the leisure equation, which gives us the usage, and subscription choice equation. The context in this simulation is household subscription and usage (hours of watching) of TV streaming services like the Netflix. From the DTUS, we can observe how people spent time in many activities including watching TV along with demographic variables. The specification of our usage and leisure equation is based on the DTUS data. To specify the subscription choice equation, we explore the LCF data, which provides microdata about household expenditure on digital or online entertainment subscription(s) such as Netflix and household characteristics (age, household size, income level).

First, we specify the usage and leisure process based on the DTUS data:

$$Q_{it} = D_{it} r_i \ell_{it}, \tag{B.1a}$$

$$\ell_{it} = \mu_i + \gamma_z Z_{it} + \gamma_{Weekday} Weekday_t + \varepsilon_{it}. \tag{B.1b}$$

Here $Weekday_t$ is a dummy variable that equals 1 if day t is a weekday and equals 0 otherwise, and ε_{it} is a centered standard normal random variable truncated below at zero. D_{it} is a binary random variable, and $\Pr(D_{it} = 1) = 0.7$. Note that the usage

$Q_{it} = 0$ when $D_{it} = 0$. We determine consumer fixed effect μ_i by his/her demographic information in the DTUS, and Z_{it} is a variable that affects the observed leisure other than μ_i.[21] Using the observed percentage of leisure time spent in watching TV in the DTUS, we obtain r_i for each individual i. In the simulation, we have two types of (μ_i, r_i). The first type is $(\mu_{Type\,1} = 10, r_{Type\,1} = 0.1)$ accounting for 66% of the population, and the second type is $(\mu_{Type\,2} = 12, r_{Type\,2} = 0.3)$ accounting for 34%. The true values of all parameters are in the table of results that will be discussed later.

Second, we specify the subscription choice equation based on the LCF data. There are two versions below depending on whether or not there is price variation. The first one does not have price variation, and it is

$$\begin{aligned} S_{im} = \mathbf{1}(&\ln L_{im} + \beta_0 + \beta_{Age} Age_i + \beta_{Hsize} Hsize_i \\ &+ \beta_{MiddleIncome} MiddleIncome_i + \beta_{HighIncome} HighIncome_i - \ln P + U_{im}). \end{aligned} \tag{B.2}$$

$Hsize$ is the household size, and $MiddleIncome$ and $HighIncome$ are the dummy variables of income level. The expected monthly leisure L_{im} is computed from the leisure eq. (B.1). The error term $U_{im} \sim \mathcal{N}(0, 1)$, and it is correlated with μ_i. We let price $P = 10$, so that the resulted proportion of subscription in our simulation is about 81.7%. See the table below for the values of other parameters.

In the second version of the subscription choice equation, we consider the case with price variation using the example of switching cost (Case 2)

$$\begin{aligned} S_{im} = \mathbf{1}(&\ln L_{im} + \beta_0 + \beta_{Age} Age_i + \beta_{Hsize} Hsize_i + \beta_{MiddleIncome} MiddleIncome_i \\ &+ \beta_{HighIncome} HighIncome_i - \ln[P + \delta_{Tenure} \ln(1 + Tenure_{im})] + U_{im}). \end{aligned} \tag{B.3}$$

The tenure in our simulation is the number of months with active subscription. The initial tenure was randomly drawn from 0, 1, . . . , 3 with even probabilities. The tenure is correlated with the unobserved heterogeneity U_{im}. There are two prices, 5 and 10, in this second experiment.

[21] In the DTUS, we observe leisure, age, household size, income and the number of children. We first run a linear regression of $\ell_{it} = \mu_i^* + \gamma_{Mon} Mon_t + \gamma_{Tue} Tue_t + \cdots + \gamma_{Sat} Sat_t + \varepsilon_{it}$ with individual specific intercept μ_i^*. Here $Mon_t, \ldots, Sat_t$ are day dummy variables. Then we regress the estimates of μ_i^* on age, household size, income and the number of children. Let μ_i be the fitted value of this regression, and let Z_i^* be the residuals. Finally, we generate $Z_{it} = Z_i^* + \omega_{it}$ with ω_{it} being a centered standard normal random variable truncated below at zero.

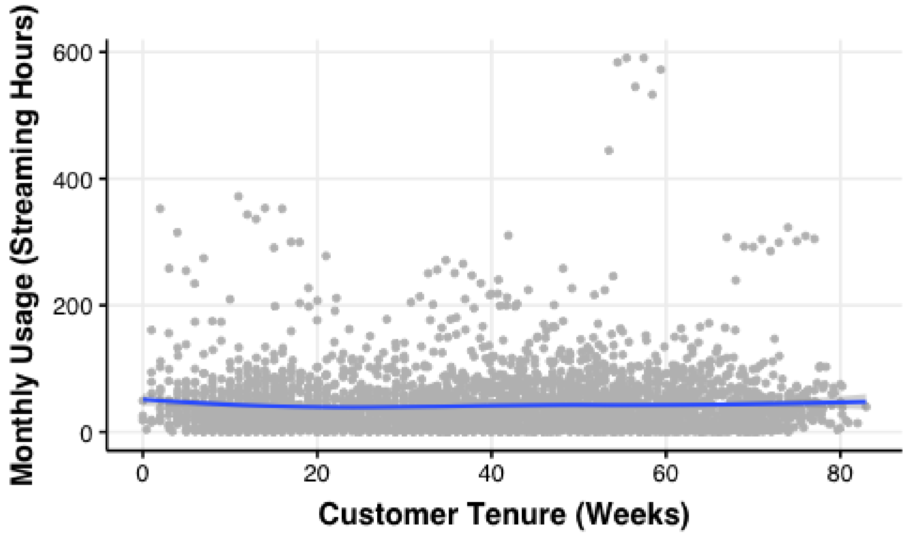


Figure C.1: Monthly Music Streaming Hours and Customer Tenure

Table B.1 reports the simulation results with and without price variation. There are 500 individuals in the panel data, for whom we observe 12 months at the daily frequency. In all experiments, our estimator work well with negligible bias. Comparing the case with and without price variation, we observe the decreasing of standard deviation of the estimates. This highlights the value of price variation. Price variation, even two different prices, allows us to consider more complicated model specification and increases the estimation accuracy.

C Additional Data Pattern and Robustness

Figure C.1 shows how the average usage of the music subscription in terms of streaming hours is related to a customer's tenure. The solid line is from fitting a local polynomial regression. It is interesting that at least on average a consumer's usage does not depend on her tenure for streaming music market. In order to visualize the change of usage with respect to subscription choice, we present Figure C.2. For those consumers who had ever cancelled their subscription, we plot the distribution of their usage during the month right before they cancelled their subscription, and this is the box plot that is labelled as "The Month before Cancellation". For those same consumers, we also plot the distribution of their "normal" usage that is the usage during the months other than

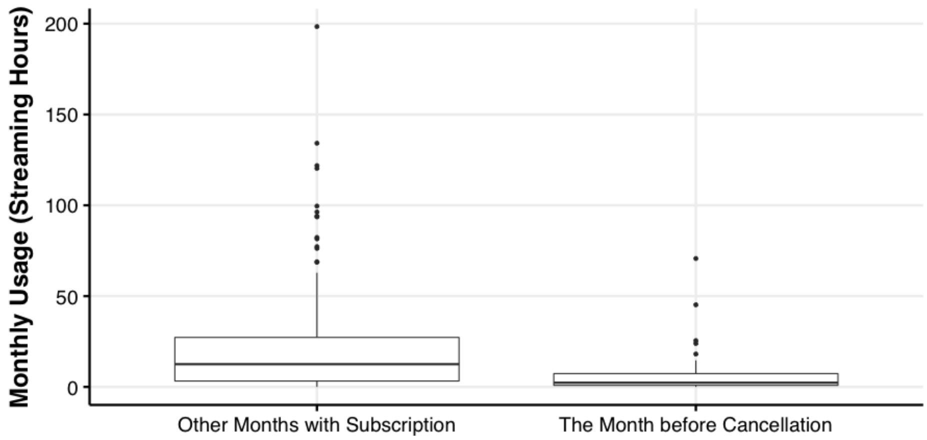


Figure C.2: Monthly Music Streaming Hours before Cancelling Subscription

the month before cancellation. This corresponds to the box plot labelled as "Other Months with Subscription".

We also consider an alternative specification of the leisure equation, in which "Age" and "Female" also enter into the leisure equation. Table C.1 reports the results. There are two observations. First, comparing with Table 2, in which usage equation does not involve "Age" and "Female", there is no significant change in the estimates. This sheds some light on the robustness of the usage equation specification. Second, "Age" and "Female" are insignificant. This is presumably because we have already included individual fixed effect μ_i.

D Evidence for Utility Specification in Leisure Market

One important assumption of this paper is to assume that the daily utility function of leisure activities is homogeneous of degree 1. The assumption implies that if the total leisure time increases by x%, then the optimal time spent on the subscription service as well as that on the outside leisure activities will also increase by x% each". The objective of this appendix is to verify this implication using real data. The difficulty is that we are not aware of any datasets, in which we can observe both total leisure and the time spent in subscription. The closest data we could find is the the American

Time Use Survey (ATUS) in 2019 and 2020 (Hofferth et al., 2020), from which we can observe both total leisure and the time spent in doing various activities. We will focus on the time spent in watching TV, which presumably is streaming TV in 2019 and 2020.

Using the ATUS 2019–2020, Figure D.1 is the scatter plot of the log of daily leisure time (in hours) against the log of daily time spent in watching TV (in hours), together with a regression line from a local polynomial regression. The regression line is quite close to 45-degree line suggesting that as the leisure hours increase by 1%, the hours of watching TV will also increase by 1%. This provides the first empirical evidence supporting our assumption that the daily utility function is homogeneous of degree 1. Next, consider the linear regression of the log of hours watching TV on the log of total leisure hours. Our assumption about the daily utility being homogeneous of degree 1 implies that the regression coefficient associated with the log of total leisure should be close to 1. Table D.1 reports the estimates under various regression specifications, and the coefficients of the log of total leisure range between 0.779 and 0.794. These estimates are the second empirical evidence supporting our assumption of the homogeneous (of degree 1) daily utility function.

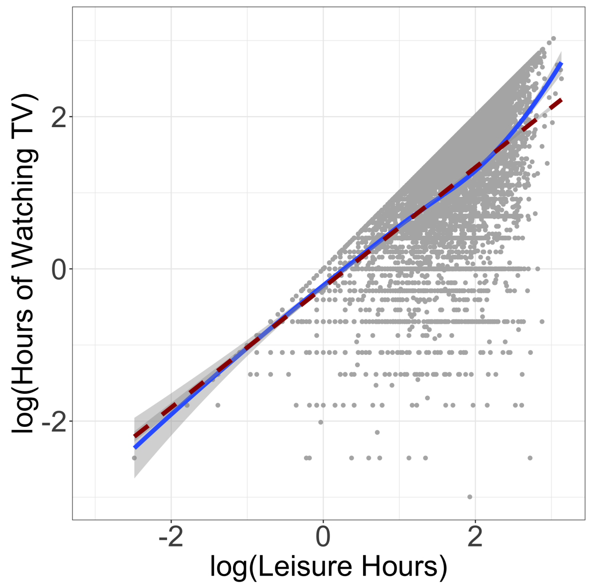
Lastly, using the observed daily leisure in the ATUS, we plot a Q-Q plot in Figure D.2 and find that the truncated normal distribution is a very reasonable specification. This is why we assume that the daily leisure shocks ε_{it} follow a (centered) truncated normal distribution.

E Serial Correlation in Usage Model

Sometimes it is reasonable to believe that the leisure shocks in the past months may affect how consumers predict their leisure, consequently their usage, in the coming subscription month. For our framework, this requires the set of information I_{im}, consumer i accesses at the beginning of month m, to include the leisure shocks in the previous month. This section is to show that we can extend the model to accommodate such a requirement.

Let $\tilde{\varepsilon}_{im}$ denote the leisure shock in the last day of month $m-1$, and assume that $\tilde{\varepsilon}_{im} \in I_{im}$. To be precise, we rewrite Assumption 1 to allow $\tilde{\varepsilon}_{im} \in I_{im}$ below.

Figure D.1: Log of Leisure Hours and the Log of Hours of Watching TV in the ATUS 2019–2020



Note: The ATUS sample used here is pooled across the years 2019 and 2020. The sample includes only respondents aged between 25 and 65 at the time of interview. The solid regression line is from a local polynomial regression.

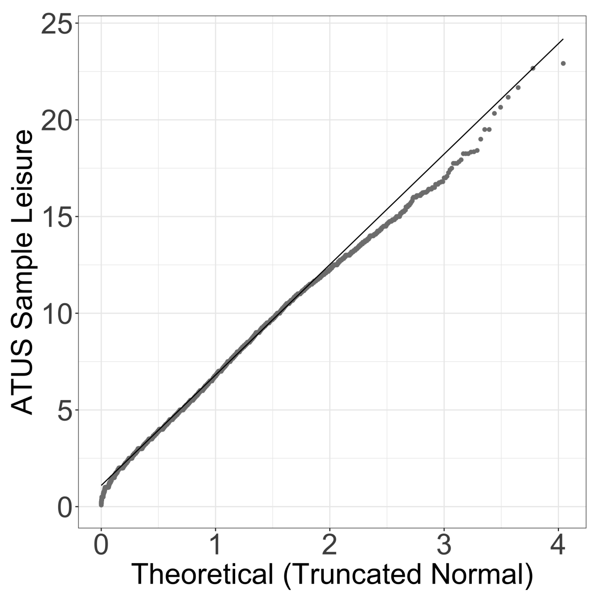


Figure D.2: QQ Plot of Daily Leisure

Assumption E.1. *Let I_{im} denote the information consumer i has at the beginning of month m.*

(1) Let $\mathbf{Z}_{im} \equiv \{Z_{it} : m(t) = m\}$. Assume that $(\theta_{im}, \mu_i, \mathbf{Z}_{im}) \in I_{im}$. In other words, at the beginning of month m, consumer i knows $\mathbf{Z}_{im}$, her leisure heterogeneous effect μ_i, and her preference parameters θ_{im}.

(2) Let $\tilde{\varepsilon}_{im}$ denote the leisure shock from the last day of month $m-1$, and assume $\tilde{\varepsilon}_{im} \in I_{im}$.

(3) A consumer cannot foresee which days she will use the subscription, i.e. $\mathbf{D}_{im} = \{D_{it} : m(t) = m\}$, but she knows the probability $\pi_{im} \equiv \Pr(D_{it} = 1 \mid I_{im})$ that is assumed to be constant across different days in month m. Note such a probability π_{im} can vary across consumers and months.

(4) Let $\boldsymbol{\varepsilon}_{im} \equiv \{\varepsilon_{it} : m(t) = m\}$ be the vector of all daily leisure shocks in month m. For any month m, $(\tilde{\varepsilon}_{im}, \boldsymbol{\varepsilon}'_{im}) \perp\!\!\!\perp (\theta_{im}, \mu_i, \mathbf{Z}_{im}, \mathbf{D}_{im})$.

(5) Let $F(\tilde{\varepsilon}_{im}, \boldsymbol{\varepsilon}_{im}; \rho)$ be the parametric joint distribution function of $(\tilde{\varepsilon}_{im}, \boldsymbol{\varepsilon}'_{im})$. The distribution function $F(\tilde{\varepsilon}_{im}, \boldsymbol{\varepsilon}_{im}; \rho)$ is known up to a finitely dimensional vector of parameters ρ, which specifies the serial correlation among daily leisure shocks.

Under this new assumption, we can modify the proof of Theorem 1. We starts with the following conclusion in the proof of Theorem 1, which still holds under the new assumption:

$$W_{im} = \mathrm{E}\Big(\sum_{t:m(t)=m} V_{it} \,\Big|\, I_{im} \Big) = \sum_{t:m(t)=m} \mathrm{E}(\ell_{it} D_{it} \tilde{\alpha}_{im} \mid I_{im}).$$

By Assumption E.1, we can write

$$\begin{aligned}
\mathrm{E}(\ell_{it} D_{it} \tilde{\alpha}_{im} \mid I_{im}) &= \tilde{\alpha}_{im} \, \mathrm{E}(\ell_{it} D_{it} \mid I_{im}) && \text{because } \theta_{im} \in I_{im} \\
&= \tilde{\alpha}_{im} [(\mu_i + \gamma' Z_{it}) \, \mathrm{E}(D_{it} \mid I_{im}) + \mathrm{E}(\varepsilon_{it} D_{it} \mid I_{im})] && \text{because } (\mu_i, \mathbf{Z}_{im}) \in I_{im} \\
&= \tilde{\alpha}_{im} [(\mu_i + \gamma' Z_{it}) + \mathrm{E}(\varepsilon_{it} \mid \tilde{\varepsilon}_{im})] \, \mathrm{E}(D_{it} \mid I_{im}) && \text{by } (\tilde{\varepsilon}_{im}, \boldsymbol{\varepsilon}'_{im}) \perp\!\!\!\perp (\theta_{im}, \mu_i, \mathbf{Z}_{im}, \mathbf{D}_{im}) \\
&= (\mu_i + \gamma' Z_{it} + \mathrm{E}(\varepsilon_{it} \mid \tilde{\varepsilon}_{im})) \tilde{\alpha}_{im} \, \mathrm{E}(D_{it} \mid I_{im}).
\end{aligned}$$

By the assumption that $\pi_{im} \equiv \mathrm{E}(D_{it} \mid I_{im})$ is constant across the days in month m, we finally conclude

$$W_{im} = L_{im} \alpha_{im},$$

where L_{im} now becomes

$$L_{im} = \sum_{t:m(t)=m} \mu_i + \gamma' Z_{it} + \mathrm{E}(\varepsilon_{it} \mid \tilde{\varepsilon}_{im}).$$

The difference is that we now have a new term $\mathrm{E}(\varepsilon_{it} \mid \tilde{\varepsilon}_{im})$ that captures the long run effect of leisure shocks in the previous month. It should be noted that $\mathrm{E}(\varepsilon_{it} \mid \tilde{\varepsilon}_{im})$ is known from the joint distribution $F(\tilde{\varepsilon}_{im}, \boldsymbol{\varepsilon}_{im}; \rho)$. Such a joint distribution as well as $\tilde{\varepsilon}_{im}$ is also estimable from the usage data. So the new term $\mathrm{E}(\varepsilon_{it} \mid \tilde{\varepsilon}_{im})$ is estimable from the usage data, and our results still hold with small modification.

References

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Table B.1: Simulation Results with and without Price Variation: $n = 500, M = 12$

Parameters	Truth	Price = 10	Price = 5, 10
γ_z	1.000	1.000	1.000
		(0.002)	(0.001)
$\gamma_{Weekday}$	−3.000	−2.999	−3.000
		(0.005)	(0.004)
$\mu_{Type\,1}$	10.000	9.998	10.000
		(0.014)	(0.014)
$\mu_{Type\,2}$	12.000	11.998	12.000
		(0.017)	(0.017)
$r_{Type\,1}$	0.100	0.100	0.100
		(0.000)	(0.000)
$r_{Type\,2}$	0.300	0.300	0.300
		(0.000)	(0.000)
β_0	−2.000	−2.338	−1.986
		(0.254)	(0.145)
β_{Age}	−0.030	−0.030	−0.030
		(0.005)	(0.003)
β_{Hsize}	0.100	0.102	0.101
		(0.026)	(0.020)
$\beta_{MiddleIncome}$	0.300	0.305	0.300
		(0.077)	(0.059)
$\beta_{HighIncome}$	0.620	0.622	0.618
		(0.108)	(0.080)
σ_u	1.000	1.066	1.005
		(0.164)	(0.082)
$\sigma_{u,\mu}$	0.500	0.509	0.504
		(0.103)	(0.058)
$\sigma_{u,Tenure}$	0.500	–	0.501
		–	(0.074)
δ_{Tenure}	−1.000	–	−0.993
		–	(0.170)

Note: The results are from 500 replications. The standard deviation is in the parenthesis. Each month in the simulation has 28 days.

Table C.1: Usage Equation Estimation with Age and Gender

Parameters	Estimates	Std Err
$\mu_{Type\,1}$	0.8545	(0.1052)
$r_{Type\,1}$	2.1166	(0.1770)
$\gamma_{Holiday,Type\,1}$	0.0294	(0.0176)
$\gamma_{Weekend,Type\,1}$	0.0255	(0.0136)
$\mu_{Type\,2}$	0.8978	(0.1164)
$r_{Type\,2}$	5.3031	(1.0305)
$\gamma_{Holiday,Type\,2}$	-0.0368	(0.0232)
$\gamma_{Weekend,Type\,2}$	-0.0374	(0.0266)
γ_{Age}	-0.0012	(0.0026)
γ_{Female}	-0.0014	(0.0513)
$\gamma_{Humidity}$	-0.0010	(0.0005)
$\gamma_{Precipitation}$	0.0004	(0.0002)

Note: Two types of $(\mu_i, r_i, \gamma_{i,Holiday}, \gamma_{i,Weekend})$ were selected according to BIC.

Table D.1: Leisure Elasticty of the Hours of Watching TV according to the American Time Use Survey 2019–2020

	Model			
Independent variable	(i)	(ii)	(iii)	(iv)
log(Leisure Hours)	0.794	0.794	0.780	0.779
	(0.009)	(0.009)	(0.009)	(0.009)
Control for the year 2020	No	Yes	No	Yes
Controls for demographic variables	No	No	Yes	Yes
Adjusted R-squared	0.494	0.494	0.501	0.502

Note: [1] The ATUS sample used here is pooled across the years 2019 and 2020, and the sample size is 8,663. The sample includes only respondents aged between 25 and 65 at the time of interview. [2] The demographic control variables include race (dummy variables for Asian, black, Hispanic), age and sex. [3] Standard errors are in parentheses.