● 論　文 ●

Bundling Products with Decreasing Value: Evidence from the US Cable Television Industry

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Abstract

Using an empirical framework based on the bundling theory for a multi-product monopolist, we estimate consumers' preference distributions for bundles of cable television channels in the US cable television industry. The estimated distributions are then used to measure the extent of surplus extraction by a monopolist. In contrast to the theoretical predictions of studies such as Bakos and Brynjolfsson (1999), the surplus extraction does not increase with bundle size. This is because of the decreasing value of a television channel in a larger bundle, as suggested by Geng et al. (2005).

1. Introduction

In many markets, firms sell bundles of their differentiated products at fixed prices that do not depend on how many goods are actually used by buyers. Recent papers by Bakos and Brynjolfsson (1999) and Armstrong (1999) analyze the implication of bundling multiple goods, and find that bundling very large numbers of unrelated goods rather than selling them separately can be surprisingly profitable for a seller. They show that, under a very general set of conditions, a probability distribution of consumer valuation for a collection of goods has proportionately more mass near the mean, and hence, the seller is able to extract more of a consumer's surplus than would be possible without bundling. A more recent study by Geng et al. (2005), however, shows that bundling is not always superior for the seller even in the cases shown in previous studies, because the consumer's valuation for a good in a bundle may decrease as the bundle size increases.

Using this bundling theory, this study estimates consumers' valuations for bundles of cable television channels in the US cable television industry. Cable television companies are mostly local monopolists. They bundle television channels and offer them to households in local cable television markets. Despite this practice and the theoretical potential of bundling for surplus extraction, the measure of its extent has rarely been examined. In this paper, we introduce an empirical framework that explicitly takes into account the power of bundling and estimate the parameters of the probability distributions of consumer valuation (preference distribution) for cable channel bundles in order to measure the extent of surplus extraction in each local cable market.

The preference distribution for a bundle varies across markets: firstly because consumers' characteristics differ across markets; and secondly, because different portfolios of channels are offered in different markets. To separate these two sources of variation, we introduce two estimation steps. In the first step, we pool our market-level data so that each pool has markets that offer the same portfolio of channels. Notably, the only source now making the preference distribution vary across markets *in each pool* is consumer characteristics. We estimate the parameters of the preference distribution for a bundle in each pool controlling for consumer characteristics. Having obtained the parameter values in each market for each pool, in the second stage, we examine to what extent variations in channel offerings *across pools* explain variations in consumer preferences.

Using the estimated preference distributions, we measure the extent of surplus extraction by a cable company in each local market. We found that the percentage of surplus extraction ranged from 13.7% to 46.7% in most of the markets. As opposed to the prediction of bundling theories such as that of Bakos and Brynjolfsson (1999), the extent of extraction does not increase with the bundle size. This is because of decreasing valuation of a channel, as suggested by Geng et al. (2005)—that is, the mean valuation decreases with the bundle size.

The rest of the paper is organized as follows. In Section 2, we review the bundling theory of a multiproduct monopolist, which forms the foundation of our empirical model. In Section 3, we describe the cable television industry and its bundling practice. This is followed in Section 4 by a description of our data and empirical method. Section 5 presents the findings, and Section 6 concludes the paper.

2. Bundling theory for price discrimination

Bundling has many potential benefits, including savings in production and transaction costs, complementarities between the bundle components, and reducing consumer heterogeneity on their valuation (see Varian (2003)). This study investigates the last incentive for bundling, heterogeneity reduction, in the US cable television industry.

The power of bundling exists on its ability to reduce consumer heterogeneity. For example, consider the case in which there are two classes of consumers and two different goods: good 1 and good 2.[1] Type A consumers are willing to pay \$120 for good 1 and \$100 for good 2. Type B consumers have the opposite preference: they are willing to pay \$120 for good 2 and \$100 for good 1. The marginal cost is negligible. Suppose that a monopolist sells each item separately. Then the profit maximizing policy is to set a price of \$100 for each item and to receive a total profit of \$400. Now suppose a monopolist bundles the items together. In this case, it could sell each bundle for \$220, and receive a net profit of \$440. By this way, bundling allows the monopolist to reduce preference heterogeneity and to extract all available consumers' surplus. In general, when bundle sales are preferred to component sales is dependent upon the extent of heterogeneity reduction and the level of marginal costs for components.

Figure 1, taken from Bakos and Brynjolfsson, presents the striking implication of the consequences of bundling for more than two goods when marginal costs are negligible. It presents the demand per good (for price per good) for a bundle of sizes 1, 2, and 20 for i.i.d. valuations (or willingness to pay (WTP)) that is uniformly distributed in [0,1] (i.e., linear demand for each component). When bundles are large, the law of large numbers operates—that is, the WTP distribution for the bundle becomes more concentrated around the mean as the bundle size increases. As a consequence, the seller can better extract the consumer surplus. Bakos and Brynjolfsson show that as the size goes to infinity, by setting the price equal to the mean value, the seller can extract the whole consumer surplus.

The example in Figure 1 assumes i.i.d. valuation and therefore, the mean valuation for each component is always identical. Geng et al. (2005), however, argue that consumers' mean value for consuming a stream of goods declines with the number consumed, and argue that we should look at the coefficient of variation (the standard deviation over the mean) rather than variance to see the power of bundling. When the coefficient of variation is very small, consumers' valuations are tightly concentrated around the mean, and the power of bundling is strong. However, if consumers' values for subsequent goods decrease quickly, bundling a large number of goods becomes suboptimal because the coefficient of variation may still be large despite the variance reduction.

3. Bundling in the US cable television industry

3.1. Bundling in the industry

The cable television industry is divided into a number of independent local markets, where one or two cable television companies operate to distribute cable television channels.[2] Cable companies offer bundles of cable television channels as services; most offer tiers of services. The largest service (tier) is called basic service, and contains broadcast channels and basic cable programming channels. Most cable companies also offer larger basic services, called expanded basic services, which contain some extra basic programming channels in addition to the basic service. There are also premium services, made up of premium programming channels, which are offered on a stand-alone basis although consumers must purchase a basic service in order to purchase any premium services. In addition, consumers can purchase on demand a particular program as part of a pay-per-view service. Cable companies thus have two instruments at their disposal with respect to bundle marketing: decisions related to tiering, i.e., how many, if any, expanded basic services are offered; and carriage, i.e., what channels to offer. Their marketing decisions vary across cable companies though all companies offer a basic service, and the majority also offers at least one expanded service. The summary statistics for the bundle types are shown in Table 1. It shows the bundle types, the average number of channels in each service, and the number of local markets that offer each service.

Such a specific feature of the industry's observed bundling practice is explained by a few existing studies. For example, the existence of multiple bundles of basic channels (i.e., basic service and expanded basic services) can be explained as being a result of a sorting of consumers as is discussed in the monopoly nonlinear pricing literature (Crawford and Shum (forthcoming)). The reason premium channels are sold separately from basic and expanded basic services may be the high cost of premium channels. As discussed, the benefit of bundling depends on the level of marginal costs for components. Because bundling requires consumers to purchase all goods in a bundle, some below-cost sales of components can result, reducing the gains from bundling. This is more likely when the marginal costs for the components are high. It is thus more beneficial to unbundle high-cost premium programming channels and sell them separately with independent prices. The reason for the existence of pay-per-view services is explained in Bakos and Brynjolfsson (1999). They argue that such a program such as a prizefight should be sold separately with an independent high price because a small fraction of consumers have a very high willingness to pay for it.

3.2. The existing empirical literature

Crawford (2005) empirically examines the incentive to bundle in the cable television industry. As explained above, there exist multiple incentives for a seller to bundle their products. He tests which incentive can best describe the bundling practice in this industry. Specifically, he tests the unique implication of the heterogeneity reduction incentives—wherein the preferences for bundles become more concentrated with increases in bundle size. The natural measure of preference variation is the coefficient of variation (CV), the standard deviation over the mean. Because decreasing the CV increases the demand elasticity at the profit-maximizing point for all but very small values of the CV, he tests whether the bundle demand curve becomes more elastic as the bundle size increases. He finds strong support for the heterogeneity reduction theory. His result suggests that adding nine of the top 15 cable television channels to bundles significantly increase the elasticity of cable demand. The present study differs from Crawford (2005); whereas he tests the heterogeneity reduction theory, we use the theory as an assumption in the model. Inasmuch as Crawford finds strong support for the theory, it may be considered that using this assumption in our study is supported by his result.

4. Data and estimation strategy

4.1 Data

We use two data sources: for the data for cable companies, the *Television and Cable Factbook* (1996) produced by Warren Publishing Inc.; and for consumers' income data, the census in the *County and City Data Book* (1994). The *Television and Cable Factbook* consists of information on all the cable companies that existed in 1995. This amounts to over 11,000 companies in the sample. Our data set is company-level as well as local market-level because only one company operates in most of the local markets. After excluding observations missing necessary information, 7,910 companies remain in our data set for the estimation. We merge county-level income information with this market-level data. We obtain the data for the median family money income and the percentages of households with income of less than $15,000, between $15,000 and $25,000, between $25,000 and $35,000, between $35,000 and $75,000, and $75,000 or more. From these, we calculate the mean and the variance of the income distribution. The summary statistics are shown in

Table 2. The first set of variables consists of the characteristics of the largest bundle in each cable market (i.e., each cable company). *Fee* refers to the monthly fee for the largest bundle. *Market share* is calculated as the number of subscribers for the largest bundle divided by the number of homes that have access to cable services. *Bundle size* is the number of cable channels in the largest bundle. CSPAN, CNN, Discovery, ESPN, Family, Lifetime, Nashville, TNT, USA and WTBS are all indicator variables of the top 10 channels, which take the value 1 if the channel is in the largest bundle. See the description of the top 10 channels in Table 3.

As explained in the next section, our estimation methods consist of two steps. In the first step, we pool the observations according to the portfolio of the channels in the largest bundle. After pooling, in order to obtain better estimates, we exclude those pools that have less than 20 observations. Seventy-four pools then remain with a total of 3,428 observations. The bundle size varies from 1 to 30. In Table 4, we show the summary statistics of the largest pool. The largest pool is Pool 29 with 206 observations, implying that this portfolio of cable television channels is the most common. In the markets in this pool, a bundle that consists of 12 channels is offered with, on average, a price of $27.70. The average market share in these markets is rather small, at 0.42.

4.2 Estimation strategy

This study estimates consumers' valuation for a bundle of cable channels using bundling theory. We estimate the parameters of the preference distribution for a bundle in each local cable market. The preference distribution for a bundle varies across markets, firstly because consumers' characteristics differ across markets, and secondly because different portfolios of channels are offered in a bundle in different markets. To separate these two sources of variation, in the first step of estimation, we pool our market-level data so that in each pool, we have markets that offer the same portfolio of channels. This means that the only source of variation in the preference distributions across markets in a pool is the variation in consumers' characteristics. In each pool, we estimate the parameters of the preference distribution for a bundle controlling for consumers' characteristics across markets. Specifically, we consider the income distribution in a market to constitute consumers' characteristics, as heterogeneity in income is usually considered as the main source of heterogeneity in consumers' WTP. Having estimated the preference distribution for a bundle in each market in each pool, in the second stage, we examine to what extent variation in channel offerings across pools explain variation in consumer preferences.

Consider a local cable market m where a cable company m operates. Suppose that cable company m supplies N_m discrete cable channels in a bundle to a set of consumers Ω_m. For each consumer $\omega \in \Omega_m$, let $\mathcal{U}_{ni}(\omega)$ denote the valuation of a good i where a total of n goods are in a bundle. We allow $\mathcal{U}_{ni}$ to depend on n so that the distributions of valuation for individual goods can change as the number of goods purchased change. In this way, it is able to reflect the argument of Geng et al. (2005) concerning decreasing valuation. Such a collection of random variables $\mathcal{U}_{n1}(\omega)$, $\mathcal{U}_{n2}(\omega),\ldots,\mathcal{U}_{nn}(\omega)$ are denoted by V_n and referred to as a triangular array:

$$V_n(\omega) = \begin{bmatrix} \mathcal{U}_{11}(\omega) & & \\ \mathcal{U}_{21}(\omega) & \mathcal{U}_{22}(\omega) & \\ \vdots & & \ddots \\ \mathcal{U}_{n1}(\omega) & \mathcal{U}_{n2}(\omega)\ldots & \mathcal{U}_{nn}(\omega) \end{bmatrix}.$$

We assume that the joint distribution of these valuations for the components of a bundle of size n is multivariate normal, and that preferences are additively separable. Specifically, we assume that the distribution of consumer valuations $\mathcal{U}_{n1}(\omega)$, $\mathcal{U}_{n2}(\omega)$, ... ,$\mathcal{U}_{nn}(\omega)$ are normally distributed with means $E[\mathcal{U}_{ni}(\omega)]=\mu_{ni}$, variances $V[\mathcal{U}_{ni}(\omega)]=\sigma^2_{ni}$, and correlations $corr(\mathcal{U}_{n1}(\omega), \mathcal{U}_{nk}(\omega))=\rho_{nlk}\ \forall l, k \in 1, \ldots n, 1 \neq k$, and the valuation of a bundle of size n for consumer ω is $\mathcal{U}_{n,bun}(\omega)=\sum_{i=1}^{n}\mathcal{U}_{ni}(\omega)$. Then in a market m with N_m cable channels supplied, consumer ω's valuation for a bundle is also normally distributed with mean and variance as follows:

$$\mu_{Nm,\,bun} = \sum_{i=1}^{Nm} \mu_{Nmi}(\omega),$$

$$\sigma^2_{Nm,\,bun} = \mathrm{Var}\left(\mathcal{U}_{Nm,\,bun}(\omega)\right)$$

$$= \mathrm{Var}\left(\sum_{i=1}^{Nm} \mu_{Nm,i}(\omega)\right),$$

$$= \sum_{i=1}^{Nm} \sigma^2_{Nmi} + 2\sum_{i=1}^{Nm}\sum_{i=1+1}^{Nm} P_{Nmil}\,\sigma_{Nmi}\,\sigma_{Nm1}\ .$$

Now let $\bar{\mathcal{U}}_{Nm}(\omega) = \frac{1}{Nm}\,\mathcal{U}_{Nm,\,bun}$ be the per-good valuation of consumer ω for a bundle. Then it is also normally distributed and the mean and the variance of the per-good valuation are given as:

$$\bar{\mu}_{Nm}(\omega) = \frac{1}{Nm}\,\mu_{Nm,\,bun,}\ (1)$$

$$\bar{\sigma}^2_{Nm}(\omega) = \frac{1}{Nm^2}\,\sigma^2_{Nm,\,bun,}\ (2)$$

The variance of the per-good valuation for the bundle equals $1/N_m$ times the average variance. As the law of large number shows, this drives the more concentrated per-good preferences of the larger size of the bundles, as shown in Figure 1.

Now let $\bar{p}_m$ represent the per-good price of a bundle in market m. Consumers then purchase a bundle of size N_m if and only if $\bar{\mathcal{U}}_{Nm} \geq \bar{p}_m$. Using the assumption of a normal distribution with the mean and the variance in equations (1) and (2), the market share s_m of a bundle of size N_m can be expressed as:

$$s_m = \mathrm{prob}(\bar{\mathcal{U}}_{Nm} \geq \bar{p}_m) = 1 - \Phi(\bar{p}_m \,|\, \bar{\mu}_{Nm}, \bar{\sigma}^2_{Nm}),\ (3)$$

where Φ is the cumulative distribution function of normal distribution. We estimate the mean and variance in equation (3) for each market given the observed market share, price and the number of channels in a bundle.

Step 1

We estimate equation (3) using the observed market share, per-channel price, and the number of channels in a bundle in each market. The parameters to be estimated include $\bar{\mu}_{Nm}$, and $\bar{\sigma}_{Nm}$. However, these parameter values differ in each market depending on consumer characteristics and on which cable channels are offered in a bundle in each market. Correspondingly, in the first step, we pool the markets according to the channels offered in a bundle. This is done in order to isolate the latter determinant of the parameters—that is, we pool the data so that the same portfolio of channels is offered in every market in each pool and every market that offers the same portfolio is in the same pool.

In each pool, the only item that makes the mean and the variance of the preference distribution for a bundle vary across markets in a pool is the variation in consumers' characteristics. In this study, we consider the income distribution in a market as indicative of consumers' characteristics because heterogeneity in WTP is often thought to be driven by heterogeneity in income, and thus cannot be ignored. We specifically assume that the mean and the variance of the income distribution linearly affect the mean and the variance of the preference distribution, respectively. Then we estimate equation (3) using market share data, per-channel price, the number of channels in a bundle, and the mean and the variance of the income distribution in each market for each pool. Having estimated the mean and the variance in each market for each pool, we also calculate the coefficient of variation, $\frac{\bar{\sigma}_{mp}}{\bar{\mu}_{mp}}$ and consumer surplus. Firm surplus is also calculated using the cable channel license fee for each channel in a bundle as a constant marginal cost for the channel.[3]

During this step, we make two simplifications. First, we only use the largest bundle in each market for the estimation. This is usually the largest expanded basic service bundle. Although this simplification wastes additional information, finding markets that offer exactly the same tiers of the same services decreases the number of observations in a pool significantly. Therefore, we use this simplification. The second simplification is that, for a pooling, we only identify the top 10 channels—that is, we put markets in the same pool if they offer the same portfolio of top 10 channels and the same number of additional channels. This is the same as assuming that nontop 10 channels have an identical preference distribution. This simplification was needed, again, to maintain a certain number of observations in a pool. Furthermore, we do not count the number of broadcast channels in a bundle size, as its access is free of charge.

Step 2

The second step is to explain variation in preference distributions across pools. We examine to what extent variations in channel offerings across pools explain variations in the mean and variance estimated in the first step. Specifically, we regress the estimated mean and the variance by indicator variables of top 10 channels and the bundle size. The detailed specifications on the regressions are available in Suzuki (2006).

5. Findings

Step 1

The results of the first step of our empirical procedure yield the parameters in the mean and the variance equations for each pool. As space is limited, we only show the implied mean and variance values for Pool 1 and Pool 74, the pools with bundle size 1 and 30, in Table 5. Standard errors are obtained by 1,000 bootstrap subsamples. The estimates are statistically significant at the 1% level in almost all the pools. The detailed results are available upon request. We can see that, as in bundling theory, the variance of the WTP for the larger bundle is much smaller than that for the small bundle. The variance is 223.51 for a bundle of size 1 in Pool 1 and decreases to 10.22 for a bundle of size 30 in Pool 74. The mean of WTP shows an interesting tendency. Consumers value one cable channel in a bundle of size 1 at $17.91 in Pool 1, while they value one channel in a bundle of size 30 at $2.22 in Pool 74.

Figure 2 plots the implied mean and variance for each market against bundle sizes. It can be seen that the variance of consumers' preference distribution declines with bundle size, as suggested by bundling theories. Variance reduction seems to occur as the bundle size decreases. Variance is 223.5 for a bundle of size 1 in Pool 1 and decreases to 19.57 for a bundle of size 4 in Pool 5. After that, variance stays around 10, even when the bundle size increases from 5 to 30. The average (per-good) means of the preference distributions show the same tendency: as the bundle size increases, the average mean decreases, and the speed is fast when the bundle size is small.

The decreasing mean valuation may have an important implication. Geng et al. (2005) concludes that the optimality of bundling depends on the speed at which valuation decreases. If consumers' valuations decrease quickly, one should expect bundling to be suboptimal. This is because the speed of decrease in the mean and the variance determines the coefficient of variation. When the coefficient of variation is very small, consumers' valuations are tightly concentrated around the mean, and there is strong power of bundling through heterogeneity reduction. Adding an additional good to a bundle is not always beneficial to the seller if the mean decreases more quickly than the variance.

Using the estimated parameters, we can recover the demand function, or equation (3). Using this demand function, we can calculate consumer surplus (per channel per consumer) using the observed price in each market. Furthermore, using the published cable channel license fee for each cable channel as the marginal cost of offering the channel, we calculate firm surplus in each market.[4] We find that the percentage of surplus extraction by a cable company (firm surplus/total surplus) ranges from 13.7% to 46.7% in most of the markets. Figure 3 shows the box plots of the coefficient of variation and the percentage of surplus extraction by a cable company with the bundle size. The coefficient of variation, in fact, does not exhibit a decreasing tendency with bundle size. Therefore, unlike what is predicted by Bakos and Brynjolfsson, in the case of the cable television industry, adding an additional television channel does not always reduce heterogeneity, and surplus extraction by a monopolist cannot be easily achieved.

Step 2

In the second step, we regress the estimated mean and variance on indicator variables of the top 10 channels and the bundle size. All the variables in the two equations are statistically significant at the 5 % level, except Family and Lifetime channels in the mean equation. The detailed results from these regressions are available in Suzuki (2006).

Using the estimated coefficients of the top 10 channels and the bundle size, we calculate the pseudo mean and variance values of various bundles with different portfolio and bundles sizes to calculate the coefficients of variation of these bundles. In Figure 3, we saw that the coefficients of variation do not decrease with the bundle size, implying that adding an extra channel does not necessarily decrease heterogeneity. This time, we look at the effect of each channel on such a tendency.

We found that if the bundle size increases from 1 to 30 and all the channels in the bundles are nontop 10 channels, the coefficient of variation increases until bundle size 11 and decreases thereafter. This is because the speed of the decreasing mean valuation is initially fast, and becomes moderate later. The coefficient of variation is smallest when the bundle size is 1, implying that there is little heterogeneity reduction caused by bundling of nontop 10 channels. As for the top 10 channels, we found that adding WTBS, ESPN, TNT, the Family, and Nashville channels (to the bundle of nontop 10 channels) reduces the coefficient of variation for most sizes of bundles. The reduction effects of WTBS and ESPN are especially outstanding. Adding these two channels reduces the coefficient of variation even when the bundle size is relatively small, while the reduction effect is negligible for the cases of the other three channels when the bundle size is small. The effect of WTBS seems to come from its high mean valuation, while that of ESPN is derived from its low variance. It is interesting to note that WTBS and ESPN are in practice the most likely to be included in the basic bundle when the bundle size is small. Our data set shows that 86.15%, 86.99%, and 91.00% of markets that offer bundles of sizes 2, 4, and 5, respectively, include WTBS, while 20.00%, 82.19%, and 86.16% of markets include ESPN. These numbers are much lower for the other top 10 channels.

This could be interpreted as suggesting that cable companies recognize the heterogeneity reduction effect by WTBS and ESPAN, and therefore are encouraged to carry these two channels.

6. Conclusion

Using an empirical framework based on bundling theory for a multiproduct monopolist, we estimated consumers' preference distributions in the US cable television industry. We introduced an empirical framework that explicitly takes into account the power of bundling with respect to heterogeneity reduction, and estimate the parameters of consumers' preference distributions for bundles in order to measure the extent of surplus extraction in each local cable television market.

We find that the percentage of surplus extraction ranges from 13% to 46%. In contrast to the prediction of such bundling theories as that of Bakos and Brynjolfsson (1999), the surplus extraction does not increase with bundle size. This is because of decreasing valuation, as suggested by Geng et al. (2005). The valuation for a channel decreases by about 87% when the bundle size increases from 1 to 30.

We also examined the effect of the top 10 television channels on heterogeneity reduction. WTBS and ESPN are found to be especially successful at heterogeneity reduction, and such findings are strengthened by the observed high likelihood of these channels being included in services.

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1 This example is taken from Varian (2003).

2 Cable television channels consist of four types: *Broadcast channels* are signals broadcast over the air by television stations and collected and retransmitted by cable companies. Examples of this are ABC, CBS, NBC, and FOX. *Basic cable programming channels* are advertising-supported channels distributed to companies via satellite. Examples include CNN and TBS. *Premium programming channels* are advertising-free channels, such as HBO and Showtime. Finally, there are *Pay-Per-View channels* that are specialty channels devoted to on-demand viewing of programs.

3 The detailed estimation functions for the mean and the variance of preference distribution and their results are available in Suzuki (2006).

4 License fees are collected from Kagan Associates Inc., 2000, "Kagan's Economics of Ba-

sic Cable Channels."

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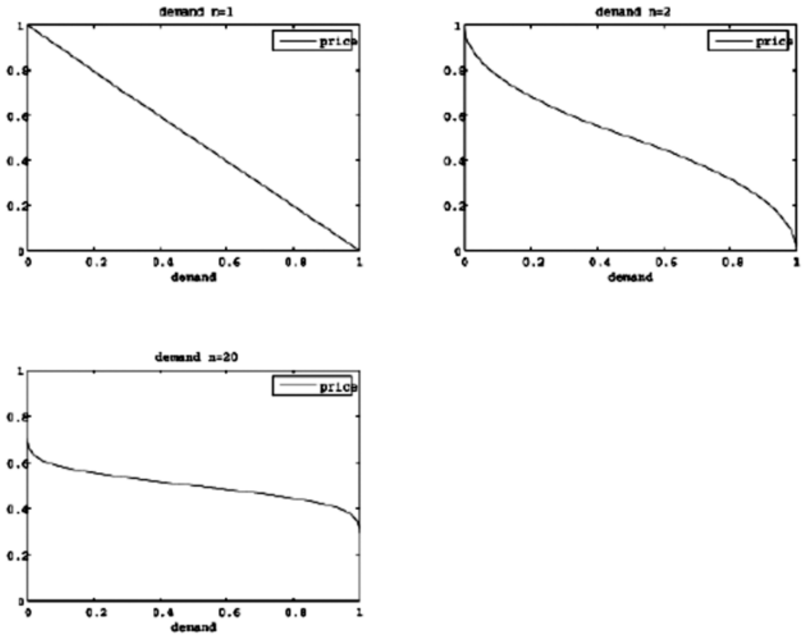

Figure 1: Demand for bundles 1, 2, and 20 goods with i.i.d. valuations uniformly distributed in [0,1]. Bakos and Brynjolfsson (1999).

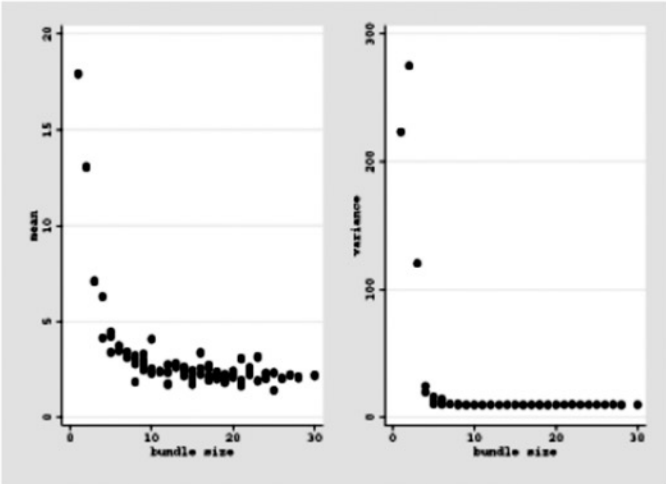

Figure 2: Implied mean (left) and variance (right) of per-good preference distributions

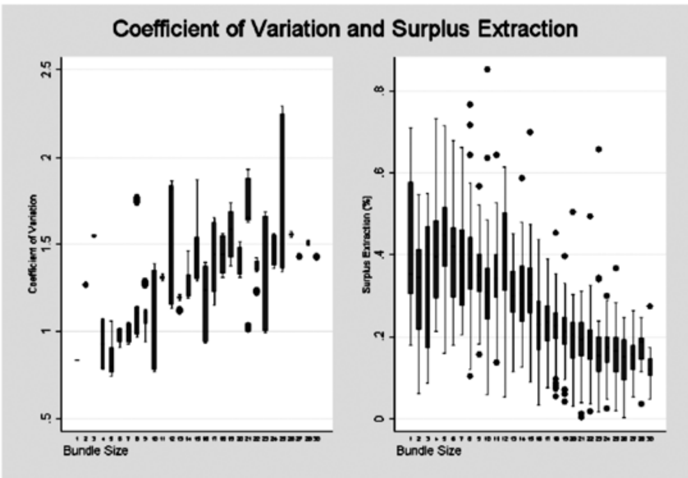

Figure 3: Coefficient of variation (left) and surplus extraction by a cable company (right) with bundle size

Bundle type	Size	Number of markets
Basic bundle	11.98	8110
Expanded basic 1	14.70	2132
Expanded basic 2	12.13	291
Expanded basic 3	11.99	7
Expanded basic 4	11.98	1
The largest bundle	14.74	8110

Table 1: Bundle types, the number of channels in each service, and the number of markets that offer each service

Variable	Mean	S.D.
Characteristics of the largest bundle		
Fee	18.76	5.31
Market share	0.63	0.38
Bundle size	14.92	7.66
CSPAN	0.25	0.43
CNN	0.75	0.44
Discovery	0.62	0.49
ESPN	0.89	0.32
Family	0.72	0.46
Lifetime	0.37	0.48
Nashville	0.71	0.46
TNT	0.61	0.49
USA	0.78	0.42
WTBS	0.71	0.46
Consumer characteristics		
Log (mean income)	9.96	0.24
Log (s.d. income)	9.87	0.09
# of observations	7910	

Table 2: Summary statistics

Rank	Channel	Subscribers (millions)	Programming format
1	TBS superstation	77.0	General interest
2	Discovery Channel	76.4	Nature
3	ESPN	76.2	Sports
4	USA Channel	75.8	General interest
5	C-SPAN	75.7	Public affairs
6	TNT	75.6	General interest
7	FOX Family Channel	74.0	General interest/kids
8	TNT	74.0	General interest/country
9	Lifetime Television	73.4	Women's
10	CNN	73.0	News

Table 3: Top 10 cable channels

Variable	Mean	S.D.
Characteristics of the largest bundle		
Fee	27.70	3.29
Market share	0.42	0.15
Bundle size	12.0	0
Consumer characteristics		
Log (mean income)	9.97	0.20
Log (s.d. income)	9.87	0.07
# of observations	206	

Table 4: Summary statistics of the largest pool

	Implied mean	Implied variance	Bundle size
Pool 1	17.91**	223.51**	1
	(1.28)	(0.40)	
Pool 74	2.22**	10.22**	30
	(0.28)	(0.07)	

Note: Standard errors in parentheses. ** indicates statistical significance at the 1% level. Standard errors are bootstrap standard errors.

Table 5: Implied mean and variance of consumers' WTP distribution in the smallest and the largest pools