The Welfare Effects of Bundling in Multichannel Television Markets

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Web Appendix

1 Data Quality, Counterfactual Robustness, and Appendix Tables

1.1 Data Quality

1.1.1 Warren Factbook Data

The Factbook data suffers from two weaknesses: persistent non-updating of entries and incomplete observations. When comparing yearly entries on an individual cable system in the Factbook, it is common to see that data does not change between two (and sometimes several) years. Given industry subscriber churn rates, channel introduction during the relevant time periods, and pricing behavior, we are certain that a lack of updating is the cause. Another common occurrence when analyzing the Factbook is that a cable system will have a bundle on offer, but no price and/or quantity is listed. Similarly, some observations are missing the number of homes the cable system passes. We try to estimate this figure when possible using census data on number of households. Sometimes this estimation is obviously unsuccessful, producing market shares well over one, for example. A third dimension of incomplete data in the Factbook deals with geographical market definition. In a few geographical markets, particularly dense metropolitan areas, there is more than one cable system. However, the Factbook does not specify on what portions of the market the cable systems overlap. We drop any observation for which there is a common community served with a distinct cable system, or if Factbook designates the system an overbuild. We present statistics on the extent of these two data quality issues below in Table 6. As can be seen there, the share of observations in a given year that are full and complete varies from 2% (in 2005) to 41% (in 1997).

While we worry in general about the quality of the Factbook data and its suitability for extrapolation to cable systems as a whole, we don't think it poses a serious econometric issue. In particular, we don't think unobservable characteristics of cable systems that impact whether an entry in the Factbook is up-to-date are likely to be correlated with the demand they face and/or their pricing behavior.

1.1.2 Satellite Data

As noted in the text, we only observe market shares for the aggregate of bundles offered by both satellite providers at the DMA level. To accommodate this data limitation, we make the following two assumptions in our modeling approach. First, we assume the only satellite bundle in the DMA is the DirecTV total choice bundle (the most popular satellite bundle offered by either provider). Second, within a DMA, we assume the unobservable quality measure of this bundle does not vary across systems.

1.1.3 Ratings Data

Nielsen is the dominant provider of television ratings. It has a large staff dedicated to data quality, statistical integrity, and metering technology. Our data comes from Set Meters which measure electronically to what channel the television is tuned throughout the day. This data is then linked with which programs aired on the relevant channels. We therefore have considerable confidence in the quality of the ratings data.[1]

1.2 Counterfactual Robustness

Our goal is to accurately measure the welfare effects of à la carte pricing in multichannel television markets. As such, it is important to have confidence that our qualitative results are robust and not sensitive to particular assumptions underlying the counterfactual exercises. In this sub-section we consider the robustness of our results to alternative assumptions on downstream markups, demand, and bargaining in our counterfactual exercises.

Due to the computational cost of estimating the full model, all of these robustness exercises are undertaken for the counterfactual analysis only.[2] The method used to appropriately conduct the counterfactual under each alternative assumption varied; the specifics for each are described below.

We evaluated the robustness of our results in the following dimensions:

- Downstream Markups
  As described in footnote 40 in the text, for computational reasons we assume that downstream channel markups are zero in our counterfactual analysis and that distributors instead earn profit on the fixed fees that they charge. In this robustness exercise, we allow downstream margins to be 10% instead of zero. This is at the upper end of the range we were finding when we tried to flexibly solve for them in the counterfactual equilibrium.

- Demand: Marginal Distributions
  One of the critical assumptions underlying our demand model is the shape of households' distribution of preferences (WTP) for the individual channels that constitute existing service bundles. As discussed in Section IV and motivated by our individual-level data as shown in Figure 3, we assume that the marginal distribution of unobserved tastes for each channel is a mixture of a mass point at zero and an exponential distribution whose (single) mean and variance parameter we estimate for each channel. To evaluate the robustness of this assumption, we conducted our counterfactual analysis under two alternative families of marginal distributions: the Rayleigh Distribution and the Log-Normal Distribution. The Rayleigh

[1] That being said, it is not without its critics. Nielsen data has been criticized both for not accurately capturing the whole television universe, for example out-of-home viewing, and for sample sizes too small to accurately measure the viewing of niche programming.

[2] For example, estimating the full demand model under alternative assumptions for marginal distributions would take several weeks for each assumption considered.

distribution is also a single-parameter family, but, relative to the exponential, it has a slightly smaller coefficient of variation (COV), a non-zero mode, and smaller skewness and kurtosis. It looks a bit like a log-normal, but with a thinner right tail than both it and the exponential. The Log-Normal distribution is a two-parameter family which, for mean and variance comparable to those we find for individual channels using our exponential distribution, also has a non-zero mode and larger skewness and kurtosis. With these choices, we are effectively allowing tastes to (1) have more mass nearer the center of the distribution and (2) relatively thinner or thicker tails than an exponential.

To evaluate the robustness of our distributional assumption on the marginals, we maintain the assumption of the zero mass point,[3] but calibrate the parameters of the Rayleigh or Log-Normal for each channel to match as closely as possible the implied mean and variance of the estimated WTP for that channel. We then re-estimated our Full ALC counterfactual using these implied marginal distributions and the input costs implied by renegotiation under the exponential distribution.[4]

- Demand: Correlations

  One of the primary motivations for bundling identified in the theoretical literature is the degree of correlation in tastes for bundle components. We allow for correlation from both demographic differences in tastes as well as correlation in unobserved tastes. We evaluate the robustness of our findings to these correlations by conducting our Full ALC counterfactual eliminating unobserved correlations.[5] To do so, we set all off-diagonal elements of the covariance structure of our estimated $G()$ distribution to zero. For the same reasons as for the marginal distribution calculations above, we do so at the renegotiated input costs implied by the full (with correlation) model.

- Bargaining: Halve/Double Input Costs

  A key element of this paper is our ability to estimate bargaining parameters and predict renegotiated input costs in an ALC environment. It is possible, however, that true bargaining outcomes would differ from our predictions. To get a sense of how important this might be, we evaluate our Full ALC counterfactual under two different assumptions: that estimated input costs are either half or double our estimated renegotiated values.

- When a Channel is Watched Less but Valued More (Monte Carlo)

  In our model, we assume that channels that are viewed more are valued more by households. It is possible, however, that minutes of different types of programming provide different utility profiles. For example, some programming (e.g. sports programming) may provide more value to households even if

[3] It is an important factor allowing us to accurately predict the number of channels watched by households when offered a bundle of channels.

[4] Using the renegotiation input costs under our exponential assumption was also necessary due to the high computational costs of calculating renegotiation equilibria. Overall mean WTP for the bundle under the alternative distributions differed slightly from that coming out of the exponential. To ensure comparability across the counterfactuals, we allocated this mean WTP difference to CS and/or Profit at the same proportion as that implied by the counterfactual for that distributional family.

[5] It is more complicated to eliminate correlations due to demographics as they influence both the mean and variance-covariance matrix of tastes for channels. Because demographics explained only 5% of the variation in mean tastes, we decided to simply eliminate correlation due to the unobserved component.

it is watched for fewer minutes than other programming. We explore the consequences of this possibility using monte carlo simulation.

1.2.1 Markup, Demand, and Bargaining Robustness

Table 7 at the end of this Appendix reports the results of each of our robustness exercises except the monte carlo. For each different assumption considered, we report the percent change in consumer surplus, industry profit, and total surplus. The first row replicates these values for our baseline, Full À La Carte counterfactual.

Assuming the larger 10% markup downstream reduces all of consumer, firm, and total welfare relative to the Full ALC baseline. This is due to the standard consequences of double marginalization: prices are higher (reducing consumer welfare), but total industry profits and total surplus decline. Each of the predicted changes is small relative to the Full ALC baseline and therefore yield qualitatively similar conclusions.

Changes in demand assumptions have slightly larger effects. Assuming preferences are distributed according to a Rayleigh (Log-normal) distribution yields lower (unchanged) consumer surplus and lower (higher) industry profits. These suggest firms are profiting from high-valued consumers in the tails of the taste distributions under ALC. Eliminating correlations reduces consumer surplus and increases profit, suggesting the overall pattern of correlations in the estimated preferences is positive. Similar to the effect of correlation on demand for bundles, eliminating this positive correlation reduces the heterogeneity in household WTP for their preferred channels under ALC, increasing firm profits and reducing consumer surplus. None of these effects, however, materially change the conclusions about the welfare effects of ALC.

By contrast, alternative bargaining assumptions have substantial effects on our estimated welfare changes. Recall the total increase in input costs under our baseline counterfactual was an estimated 103.0%. If we halve those, we find a substantially different picture: consumer welfare increases considerably (+18.5%), industry profits fall (-10.1%), and total surplus increases. These effects are qualitatively similar to that which we found when evaluating the welfare effects while keeping input costs at their level in a bundling equilibrium: it is the sharp rise in input costs (and prices) that prevents a significant increase in consumer welfare under ALC. Doubling our estimated renegotiation input costs would, not surprisingly, be even worse for consumers, reducing consumer surplus by an estimated 27.6%. Industry profits rise significantly in this setting and total welfare falls.

Across these robustness exercises, only the changes in bargaining outcomes have a meaningful impact on the magnitude of our estimated welfare effects. How then should one interpret them? *If* our assumptions on renegotiated input costs under à la carte are incorrect, we conclude that because a doubling of input costs increases industry profits, that makes it the more likely of the two deviations. If so, prospects are even worse for consumer and total welfare than in our baseline results presented in the body of the text. Like our baseline, these results also do not take into account any additional implementation or marketing costs that might arise in an à la carte environment. We therefore conclude that our qualitative conclusions about à la carte are robust: in the absence of input costs changes, it would likely improve consumer welfare, but in their presence, consumers are likely better off with existing bundles.

1.2.2 When a Channel is Watched Less but Valued More (Monte Carlo)

To allow for the possibility that a channel that is watched less than another is nonetheless valued more, we begin by specifying a richer model for consumer utility than that used in the paper. We consider the case of three goods: two television channels, $c = \{1, 2\}$, and an outside good, denoted $c = 3$. Let c index channels and assume all households face a bundle with both channels. We assume the utility to household i from spending their time watching television and doing non-television activities has the following form:

$$v_i(t_i) = \sum_{c \in \{1,2,3\}} \frac{\gamma_{ic}}{1 - \nu_{ic}} (1 + t_{ic})^{1-\nu_{ic}} \tag{1}$$

where t_i is a vector with components t_{ic} which denote the number of hours household i watches channel c. As in the Cobb-Douglas specification in Equation (1) in the text, γ_{ic} is a parameter representing i's tastes for channel c. The novelty in this specification is ν_{ic}. ν_{ic} governs the shape of marginal utility household i obtains from watching channel i. Marginal utility in this specification is $\frac{\partial v_i}{\partial t_{ic}} = \frac{\gamma_{ic}}{(1+t_{ic})^{\nu_{ic}}}$. As $\nu_{ic} \to 1$, $\forall c$, this functional form converges to the Cobb-Douglas specification, with relatively steep decreases in marginal utility across minutes. As $\nu_{ic} \to 0$, marginal utility converges to a constant across-minute value, γ_{ic}.

Interesting patterns can result from this specification when households have high values of γ_{ic} and ν_{ic} for some channels and low values for others. Figure 1 provides an example. This figure presents graphically the optimal decision-making for a household with preference parameters, $\gamma_c = [2.5 \;\; 6.0 \;\; 2.9]$ and $\nu_c = [0.2 \;\; 0.9 \;\; 0.2]$. For convenience, we omit the i subscript. Let $v_c = \frac{\gamma_c}{1-\nu_c}(1 + t_c)^{(1-\nu_c)}$ be defined as the contribution channel c makes to the household's utility. The left-hand panel presents household i's utility for various values of time spent watching channel 1, given the optimal time spent not watching TV (which, for these parameters, is $t_3 = 14.3$ hours).[6] The increasing, dashed line and the decreasing, dotted line plot the utility channel 1 and 2 contribute to total utility, given by the solid line at the top of the left panel. Utility from channel 1 (channel 2) increases (decreases) with time spent watching channel 1. The optimal time spent watching channel 1 (channel 2) is 6.6 (3.1) hours. The optimal t_1^* is denoted in both panels with a vertical dashed line. In the right-hand panel is shown that this optimum is obtained at the point where the marginal utility of an additional minute watching channel 1 (again given by the dashed line) equals the marginal utility of an additional minute watching channel 2 (again given by the dotted line).

[6] The figure is constructed so that time spent watching channel 2 is given by the distance from the right on the horizontal axis.

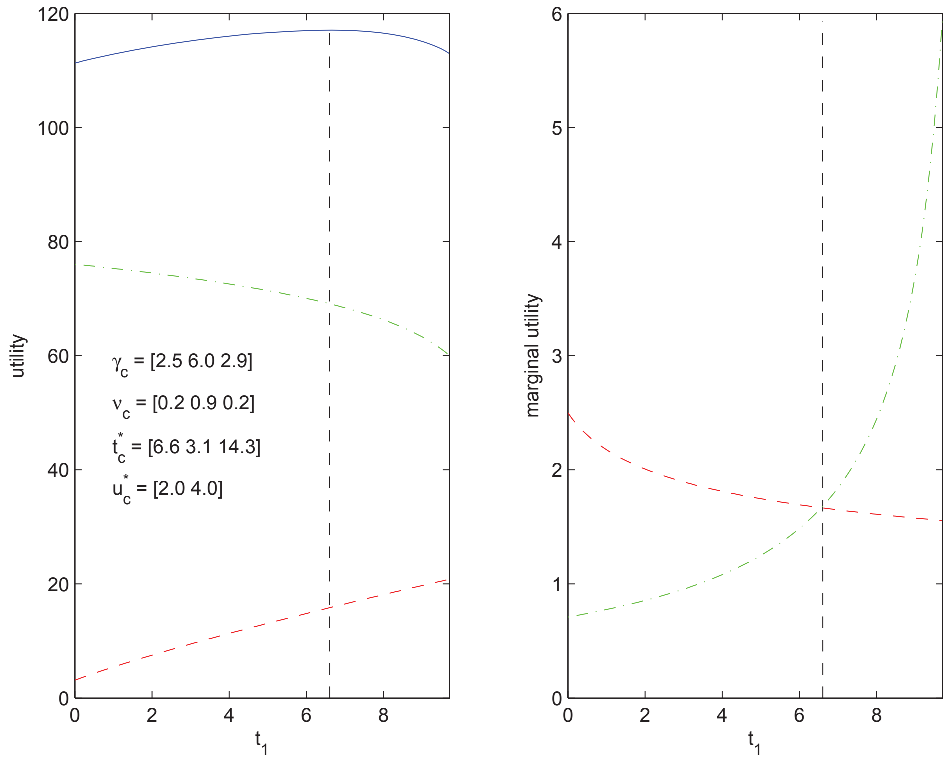

Figure 1: When a Channel is Watched Less but Valued More

What is different about channels 1 and 2 is the shape of marginal utility for minutes provided by each. Channel 1 has relatively low values of γ and ν and consequently has a relatively flat marginal utility profile in the right-hand panel. Channel 2 has relatively high values of γ and ν and a relatively steep marginal utility profile (when read from the right axis). The consequence of these shapes is that channel 2 contributes relatively more to the household's utility, *despite being watched for fewer minutes*. This is captured in the figure by u^*_c.[7] For these parameter values, channel 2 is watched less than half as much as channel 1 (3.1 hours versus 6.6 hours), but the household would be willing to pay twice as much for it (4.0 utils versus 2.0 utils).

We explore the consequences of preferences like those in Figure 1 using monte carlo simulation. We first generate data from a true distribution modeled on that described above. We then estimate parameters based on a Cobb-Douglas utility model like that estimated in our paper. Finally, we compare the difference in aggregate market outcomes (market shares, prices, welfare measures) in the true data compared to what we estimate. We describe each of these stages in turn.

Data Generated from True Preferences We generate data from a single market with a distribution of households with preferences, $\theta_i \equiv (\gamma_i' \;\; \nu_i')'$, whose means are similar to those in Figure 1. Based on their preference draws for channels, individual households decide how much they would watch each channel if they purchased

[7] u^*_c measures the maximum utility from watching all the channels less the maximum utility when not watching channel c, e.g. $u^*_1 = v(t^*_1, t^*_2, t^*_3) - v(0, t^{**}_2, t^{**}_3)$ where t^{**}_{-c} are the optimal times spent watching channels other than channel c.

the bundle, t_i^*, and compare their utility from that viewing, $v_i^*(t_i^*)$, to the bundle price plus a random error distributed as a type 1 extreme value.

$$u_i \quad = \quad v_i^*(t_i^*(\theta_i)) - p + \epsilon_i \tag{2}$$

The predicted market shares for the bundle is then just

$$s_b(p,\theta) \quad = \quad \int \frac{exp((v_i^*(t_i^*(\theta_i))) - p)dF(i)}{1 + exp((v_i^*(t_i^*(\theta_i))) - p)} \tag{3}$$

where θ is a vector with typical element, θ_i and $dF(i)$ is the true distribution of θ_i in our population. We approximate this integral using simulation with 150 households. We assume a vertically integrated monopoly programmer/distributor sells a bundle of two television channels at its short-run profit-maximizing price facing zero marginal costs, implying an optimal bundle price, p_b. This implies an equilibrium market share, $s_b(p_b,\theta)$, as well as mean consumer surplus, $CS_b(\theta)$, profit, $\Pi_b(\theta)$, and total surplus, $TS_b(\theta)$.

Based on these true preferences, we also simulate outcomes when the monopolist sells products à la carte (ALC). In this case, a household's choice set now has four options: channel 1 alone, channel 2 alone, a bundle of both channels, or no television. The logic of preferences, market shares, optimal prices, and welfare measures follows analogously to the bundle case, implying true ALC prices, $p_{alc} = \{p_{alc,1}, p_{alc,2}\}$[8], market shares, $s_{alc,c}, c \in \{1,2,b,3\}$, consumer surplus, CS_{alc}, profit, Π_{alc}, and total surplus, TS_{alc}.

Estimation Model To assess the biases from having less-watched channels be more valuable, we outline our model used for estimation. It is similar to the true model, except that we assume a straight Cobb-Douglas utility specification analogous to that used in our paper rather than the richer utility function used to generate the data.

$$v_i(t_i) = \sum_{c\in\{1,2,3\}} \gamma_{ic} \log(1 + t_{ic}) \tag{4}$$

As in the paper, we assume γ_{ic} is drawn from a distribution with known parameters, ϕ. In practice, we will assume $\phi \equiv [E\gamma_{ic} \quad \sigma_{\gamma_{ic}}]$, i.e. the mean and standard deviation of γ_{ic} for $c = \{1,2,3\}$, with $\gamma_{i3} = 10, \forall i$ normalized to set the scale of utility. Based on these assumed preferences, households decide how much they would watch each channel if they purchased the bundle, t_i^*, and compare their utility from that viewing, $v_i^*(t_i^*)$, to the bundle price plus a random error distributed as a type 1 extreme value.

$$u_i \quad = \quad v_i^*(t_i^*(\phi_i)) - \alpha p + \epsilon_i \tag{5}$$

where α is an (estimated) parameter measuring marginal utility of income ($\alpha = 1$ in the true data generating process). Let $\delta = (\phi' \quad \alpha)'$ define the vector of (six) parameters to be estimated.

The predicted market shares for an estimated bundle is then just

$$s_b(p,\delta) \quad = \quad \int \frac{exp((v_i^*(t_i^*(\phi_i))) - \alpha p)dF_\phi(i)}{1 + exp((v_i^*(t_i^*(\phi_i))) - \alpha p)} \tag{6}$$

[8]With $p_{alc,b} = p_{alc,1} + p_{alc,2}$.

where $dF_\phi(i)$ is the distribution of γ_i in our estimation model. As above, we approximate this integral using simulation with 150 households. We continue to assume a vertically integrated monopoly programmer/distributor that sells a bundle of two television channels at its short-run profit-maximizing price facing zero marginal costs, implying an optimal estimation model bundle price, p_b^{cd}, where cd stands for Cobb-Douglas, our estimation model. This implies an equilibrium market share, $s_b^{cd}(p_b^{cd}, \delta)$, as well as mean consumer surplus, $CS_b^{cd}(\delta)$, profit, $\Pi_b^{cd}(\delta)$, and total surplus, $TS_b^{cd}(\delta)$.

Once we have estimated parameters for this model, we also simulate outcomes from the estimation model when the monopolist sells products à la carte (ALC). As earlier, a household's choice set now has four options: channel 1 alone, channel 2 alone, a bundle of both channels, or no television. The logic of preferences, market shares, optimal prices, and welfare measures follows analogously for the bundle case, implying estimation model ALC prices, $p_{alc}^{cd} = \{p_{alc,1}^{cd}, p_{alc,2}^{cd}\}$, market shares, $s_{alc,c}^{cd}, c \in \{1, 2, b, 3\}$, consumer surplus, CS_{alc}^{cd}, profit, Π_{alc}^{cd}, and total surplus, TS_{alc}^{cd}.

Estimation For estimation, we must generate the true data, calculate moments for that true data, and compare those moments to moments generated by our estimation model in order to estimate the parameters of that estimation model.

The true data were generated with six free utility parameters.[9] The eight moments we use in estimation are the mean and standard deviation of average viewing time for the three channels and the mean and variance of the bundle market share.[10]

The estimation model also predicts outcomes with six free utility parameters.[11] We calculate the same eight moments from the estimation model to compare with the moments from the true data. In estimation, we weight the difference between each of the "true" and predicted moments equally.

Results: Channels Table 1 presents a summary of the results of the monte carlo exercise. In the first group of columns it presents various outcomes for bundled and à la carte market structures for both the true data and the estimates based on the Cobb Douglas utility function like that used in the analysis in the paper. Reported there are the mean (across 40 replications) ratios of outcomes for channel 1 relative to the same outcomes for channel 2. For example, the first cell in the table reports that, based on the true parameters, the expected viewing of channel 1 is 1.98 times the expected viewing of channel 2 when both are offered in a bundle. The cell adjacent to that reports that, based on the *estimated* parameters, the same ratio of expected viewing of channel 1 to channel 2 in a bundle is 2.12. Below these values are the standard deviation of these values across the 40 replications in our monte carlo study. This first cell suggests the estimated model predicts ratios of viewing times similar to those generated by the true parameters.

The balance of the ratios in the rest of the cells in the first set of columns yield dramatically different conclusions. The richer viewership model induces extreme biases in expected WTP for bundles and prices and

[9] $\gamma_{i1} \sim N(2.5, 0.1^2)$, $\gamma_{i2} \sim N(6, 0.5^2)$, $\gamma_{i3} \equiv 3, \forall i$, $\nu_{i1} \sim U[.15, .25]$, $\nu_{i2} \sim U[.85, .95]$, $\nu_{i3} \sim U[.15, .25]$.

[10] The mean and standard deviation of viewing times depends on whether or not households choose to purchase the bundle. Thus our estimate of the expected true viewing time for channel 1 is $Et_1 = \sum_i [t_{1i} * s_{ib} + 0 * (1 - s_{ib})]$, where $s_{ib} = \frac{exp((v_i^*(t_i^*(\theta_i))) - p)}{1 + exp((v_i^*(t_i^*(\theta_i))) - p)}$.

[11] $\gamma_{i1} \sim N(\gamma_1, \sigma_1^2)$, $\gamma_{i2} \sim N(\gamma_2, \sigma_2^2)$, $\gamma_{i3} \sim N(10, \sigma_3^2)$, and α.

Table 1: When a Channel is Watched Less but Valued More: Monte Carlo Results

	True Preferences	Estimated Preferences		True Preferences	Estimated Preferences	Difference
	Mean (StdDev)	Mean (StdDev)		Mean (StdDev)	Mean (StdDev)	Mean (StdDev)
Ratio: $\text{Outcome}_1/\text{Outcome}_2$			% Difference, ALC - Bun			
Expected viewing	1.98	2.12	Consumer surplus	15.7%	11.6%	4.1%
Bundling	(0.05)	(0.12)		(0.7%)	(3.4%)	(3.5%)
Expected WTP	0.46	3.42	Profit	-11.4%	-5.9%	-5.5%
Bundling	(0.02)	(0.27)		(0.4%)	(3.8%)	(3.7%)
Prices	0.65	1.94	Total surplus	-2.8%	-0.9%	-1.9%
A La Carte	(0.01)	(0.11)		(0.2%)	(1.4%)	(1.3%)
Prices	0.45	1.95				
A La Carte	(0.01)	(0.37)				

Notes: This table reports the results of a monte carlo simulation exercise to demonstrate the consequences when a channel is watched less by a household but is nonetheless valued more. As in Figure 1 above, channel 2 is watched less but valued more than channel 1. The first group of columns reports the mean (across 40 monte carlo replications) ratio of outcomes for channel 1 relative to the same outcomes for channel 2 for both true preferences given by equation (1) in Appendix 1.2 as well as for estimates based on Cobb-Douglas utility like that estimated in the body of the paper. The second group of columns reports the mean percentage difference in aggregate welfare from a bundling to an à la carte environment for both true and estimated preferences as well as their difference. For all cells, the standard deviation across monte carlo replications is reported below the mean.

shares of each channel in an ALC environment. For example, because channel 2 has high utility at low minutes (and channel 1 the opposite), the expected WTP for channel 1 in the true data is less than half (0.46) that for channel 2. By contrast, estimating a Cobb-Douglas model implies, like estimates of expected viewing time, that expected WTP for channel 1 is much greater (3.42 times) than that for channel 2. We similarly mis-estimate prices and market shares for the channels in an ALC world: in each case the true model implies higher values for channel 2 than channel 1, but the estimates imply the opposite.

Results: Welfare The key question for the conclusions in this paper is whether these striking biases at the channel level translate into mis-estimates of the welfare effects of ALC when aggregating *across* channels. The results in the second set of columns demonstrate that this *isn't* the case. Reported there is the mean (across replications) percentage difference in aggregate consumer surplus, profit, and total surplus moving from a bundling to an ALC environment.[12] In the absence of input cost changes, we anticipate that consumers benefit from ALC and the table shows that to be the case: aggregate consumer surplus increases an expected 15.7% for true preferences and by 11.6% in our estimated data. While these are different (by 4.1%), this difference isn't statistically significant. *Thus, while we badly mis-estimate outcomes for individual channel outcomes, aggregating across channels causes these errors to cancel out and yields no significant difference in estimated consumer surplus changes.* Similarly insignificant differences arise for profits and total surplus.

How is it possible to be so wrong for individual channels and not do so badly on average? The answer lies in the data: bundle purchase data like that in the monte carlo (and our paper) must at the end of the day equate total utility from viewing (based on households' total minutes of viewing) with the price of the bundle in a way to match market shares for bundles. Thus in the monte carlo (and the paper), we estimate something like an

[12] e.g., the first cell in the second group of columns calculates $\frac{CS_alc(\theta)-CS_b(\theta)}{CS_b(\theta)}$ associated with households' true preferences, θ.

average-across-channels utility from minutes of viewing. If households value early minutes more highly for some channels (e.g. sports channels), we will tend to underestimate the utility (and prices and market shares) arising from those channels and overestimate these values for channels that have relatively flat marginal utility from minutes. But we won't be nearly as badly wrong about across-channel averages.

1.3 Appendix Figures and Tables

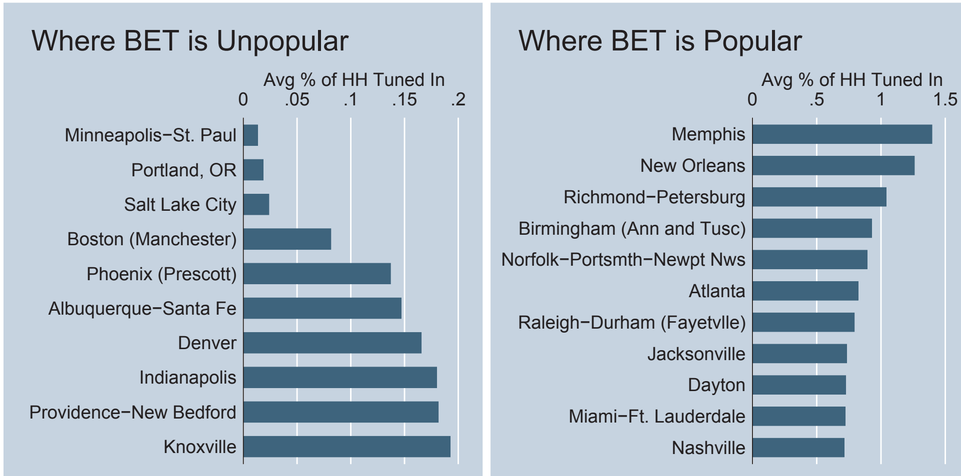

Figure 2: High and Low Rating DMA's for Black Entertainment Television

Table 2: Correlation in the Ratings Data

Network	Cartoon Network	A&E	Turner Classic Movies	Discovery Channel	ESPN	ESPN2	ESPN Classic	ESPN News
Cartoon Network	1							
A&E	-0.14	1						
TCM	-0.29	0.09	1					
Discovery	0.18	0.28	-0.33	1				
ESPN	0.14	0.01	0.07	-0.08	1			
ESPN2	0.11	0.16	0.10	0.08	0.54	1		
ESPN Classic	0.30	-0.10	0.16	-0.17	0.16	0.15	1	
ESPNews	0.35	-0.16	0.06	-0.09	0.26	0.20	0.39	1

Table 3: Sample Statistics, Other Estimation Data

Variable	NObs	Mean	SDev	Min	Max
Channel dummies	See tables in paper				
Demographics					
Urban	56	0.61	0.22	0.14	0.99
Family	56	0.68	0.03	0.59	0.77
Household income	56	$0.48	$0.07	$0.38	$0.75
Black	56	0.10	0.09	0.00	0.34
Hispanic	56	0.12	0.11	0.02	0.54
Asian	56	0.02	0.03	0.00	0.19
College degree or greater	56	0.18	0.06	0.09	0.36
Age	56	0.37	0.02	0.33	0.42

Table 4: Estimated Price Elasticities, B+EB+DB Markets

Price Elasticity of	wrt	Mean	Std. Dev.
Basic	Outside good	0.15	0.27
	Basic	-4.12	2.25
	Expanded basic	2.04	2.53
	Digital basic	0.52	1.10
	Satellite	0.54	0.98
Expanded basic	Outside good	0.50	2.98
	Basic	0.16	0.51
	Expanded basic	-6.34	2.99
	Digital basic	2.12	2.64
	Satellite	1.52	1.47
Digital basic	Outside good	0.09	0.30
	Basic	0.09	0.78
	Expanded basic	5.79	2.96
	Digital basic	-13.11	4.10
	Satellite	2.56	1.89
Satellite	Outside good	0.07	0.20
	Basic	0.05	0.41
	Expanded basic	2.63	2.85
	Digital basic	2.08	2.47
	Satellite	-5.35	3.44

Notes: B+EB+DB Markets are those offering Basic, Expanded Basic, and Digital Basic cable service.

Table 5: Carriage of Time Warner Channels by Distributor 2004-2007.

	N	*CNN*	*CNNi*	*Cartoon Network*	*Boomerang*
Charter	1652	0.980	0.078	0.648	0.137
Comcast	2045	0.996	0.007	0.871	0.004
Cox	257	0.988	0.058	0.922	0.144
Time Warner Cable	589	0.988	**0.204**	0.902	**0.447**
Other	6926	0.980	0.008	0.663	0.074

Notes: CNN and Cartoon Network are each over 15 years old. Boomerang and CNN International are digital channels that began distribution in the 2000's. Carriage for the established channels is not systematically different for the vertically integrated operator Time Warner Cable.

Table 6: Data Quality of Factbook

Year	*Variable*	*Number of Bundles*	*Fraction of Bundles*
1997	Total bundles	15,205	100.0%
	Full information	10,740	71.0%
	Updated	9,264	61.0%
	Full information and updated	6,165	41.0%
1998	Total bundles	15,743	100.0%
	Full information	10,872	69.0%
	Updated	4,714	30.0%
	Full information and updated	3,461	22.0%
1999	Total bundles	15,497	100.0%
	Full information	10,444	67.0%
	Updated	5,663	37.0%
	Full information and updated	3,595	23.0%
2000	Total bundles	15,453	100.0%
	Full information	10,312	67.0%
	Updated	3,358	22.0%
	Full information and updated	2,478	16.0%
2001	Total bundles	15,391	100.0%
	Full information	9,793	64.0%
	Updated	4,173	27.0%
	Full information and updated	2,663	17.0%
2002	Total bundles	15,287	100.0%
	Full information	7,776	51.0%
	Updated	5,086	33.0%
	Full information and updated	1,484	10.0%
2003	Total bundles	15,365	100.0%
	Full information	8,370	54.0%
	Updated	9,744	63.0%
	Full information and updated	4,750	31.0%
2004	Total bundles	15,145	100.0%
	Full information	7,137	47.0%
	Updated	8,175	54.0%
	Full information and updated	3,556	23.0%
2005	Total bundles	15,001	100.0%
	Full information	7,009	47.0%
	Updated	846	6.0%
	Full information and updated	327	2.0%
2006	Total bundles	14,653	100.0%
	Full information	4,577	31.0%
	Updated	8,141	56.0%
	Full information and updated	2,303	16.0%
2007	Total bundles	13,879	100.0%
	Full information	4,070	29.0%
	Updated	3,135	23.0%
	Full information and updated	711	5.0%
1997-2007	Total bundles	166,619	100.0%
	Full information	91,100	55.0%
	Updated	62,299	37.0%
	Full information and updated	31,493	19.0%

Notes:

Table 7: Robustness of Counterfactual Results

	% Change Consumer Surplus	% Change Industry Profit	% Change Total Surplus
Baseline Counterfactual			
Full À La Carte	0.2%	4.8%	2.4%
Alternative distributor markup			
10% Distributor markup	-1.6%	2.5%	0.3%
Alternative demand assumptions			
Marginal distributions: Rayleigh	-5.4%	2.4%	-1.7%
Marginal distributions: Log-Normal	0.0%	12.8%	6.0%
Joint distribution: No correlation	-4.2%	8.6%	1.8%
Alternative bargaining assumptions			
Halve input costs	18.5%	-10.1%	5.0%
Double input costs	-27.6%	18.6%	-5.8%

Notes: This table reports the percentage change in consumer surplus, industry profits, and total surplus estimated under our baseline Full À La Carte counterfactual and under alternative assumptions about demand, bargaining conditions, downstream distributor markups, and/or exit in the counterfactual. All counterfactuals rely on parameter estimates from the baseline specification suitably adapted for the specific robustness test - see text for details. Alternative demand assumptions are evaluated at the renegotiated input costs from the baseline demand specification. The baseline counterfactual is as described in Table 10 in the text. See Appendix 1.2 for a description of the specific alternative assumptions considered in the table.