

The Welfare Effects of Bundling in Multi-Channel Television Markets *

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January 23, 2009

Abstract

This paper evaluates the welfare effects of bundling in multichannel television markets. We use market and viewership data to estimate preferences for over 50 cable television channels. We conduct short-run counterfactual simulations of *à la carte* policies that require cable and satellite television distributors to offer individual channels for sale to consumers. Assuming programming costs to distributors increase by 75%, mean consumer surplus increases by an estimated 8.3%, or \$4.8 billion/year. Total industry profits decrease by an estimated 7.7%, with most losses to content providers, particularly high-cost channels offering niche programming.

*We would like to thank Dan Akerberg, John Asker, Luis Cabral, Allan Collard-Wexler, Bill Greene, Ariel Pakes, Amil Petrin, Steve Stern, John Thanassoulis, and seminar participants at the NBER Summer Institute, University of Wisconsin-Madison, Duke University, NYU Stern, Oxford University, the University of Warwick, and the University of Virginia. Yurukoglu acknowledges the funding provided by the NYU Stern Entertainment, Media, and Technology department. Correspondence may be sent to Gregory S. Crawford, Department of Economics, University of Warwick, Coventry CV4 7AL, UK, phone +44 (0)2476 523470, email crawford@warwick.ac.uk or Ali Yurukoglu, 44 West 4th St, 7th Floor, Economics Department, New York, NY 10012, phone 212-998-0217, email ayurukog@stern.nyu.edu.

1 Introduction

The proposal of an à la carte pricing regulation in the U.S. multi-channel television industry has polarized policy makers, consumers, and industry participants.^{1,2} The arguments for or against usually rest upon a prediction of how prices, quantities, qualities, or costs will change if firms are subject to à la carte pricing regulations. Despite the widespread debate, there is no consensus on what the regulation's effects would be. Empirical evidence would be useful because the multi-channel television industry reaches 95 million households in the United States, and the average American household spends around seven hours per day watching television. This impressive fraction of leisure time is increasingly allocated to watching programming from a channel available predominantly through multi-channel television. À la carte pricing proposes to radically alter the choice sets facing the roughly 110 million U.S. television households. It is therefore important to predict the regulation's impact on the distributions of consumer and producer welfare.

This paper estimates a model of demand and pricing of multi-channel television services. We use the model to simulate counterfactual outcomes of à la carte pricing policies. We estimate the distribution of household preferences for over 50 individual cable television channels by exploiting the two-sided nature of multi-channel television markets: cable and satellite systems sell access to bundles of program channels to households, and the channels sell audiences to advertisers. We employ aggregate data on outcomes from both markets. Aggregate weekly cable ratings data for 65 cable channels, 50 DMAs, and 7 years trace out the marginal utility of individual channels. Market shares and prices for a sample of over 20,000 cable and satellite bundles over 11 years translate that utility into dollars.

We assume households allocate their viewing of channels optimally given their preferences for channels and the channels they have access to in a bundle. For each household, this yields two outcomes: the time they devote to watching each channel in the bundle they choose to purchase and the total utility enjoyed from access to this bundle. This model of household

¹By multi-channel television, we mean television services provided by cable and satellite television systems. These are also called multi-channel video program distributors (MVPDs).

²In addition to numerous articles in the popular press (e.g. Reuters (2003), Squeo and Flint (2004), Shatz (2006)), the Federal Communications Commission (FCC) has published two reports analyzing à la carte pricing (FCC (2004), FCC (2006)). The National Cable and Telecommunications Association (NCTA) has a useful webpage summarizing industry perspectives at <http://www.ncta.com/IssueBrief.aspx?contentId=15>.

viewing matches naturally to a model of bundle purchases: the utility to a household from a given bundle depends on the utility the household enjoys for the channels in the bundle and other attributes like the price of the bundle. From these household models of viewing choice and bundle purchase, we aggregate across the distribution of households within markets and relate the model's implied viewership and purchases to their observed counterparts in the data.

Following existing evidence on the structure of preferences for media products (e.g. Anderson (2006), Shiller and Waldfogel (2008), Byzalov (2008)), we assume household tastes for each channel follows a mixture distribution: some fraction of households are assumed to have no demand for the channel, and the remaining households are assumed to be distributed over the positive line according to an exponential distribution. We estimate the share of households with positive tastes for each channel using cumulative ratings data which measure what percentage of unduplicated households watches a channel. As correlation in tastes is an important determinant of the welfare effects of bundling, we exploit the variance and covariance of aggregate ratings across markets and time to estimate these correlations.

We use the bundle purchase and pricing model along with observed prices, market shares, and characteristics to estimate the distribution of preferences for income, as well as estimates of the marginal costs of providing each observed bundle. With the estimated distribution of preferences for channels, the former permits us to measure the distribution of households' willingness-to-pay (WTP) for individual cable channels that form the foundation of our counterfactual à la carte policy simulations.

The estimated distribution of channel demand replicates many features of the ratings data. For example, WTP for Black Entertainment Television (BET) is estimated to be higher on average for black households. Similarly, WTP for Nickelodeon and Disney Channel are estimated to be higher on average for family households than for non-family households. We find moderate correlations in WTP for most pairs of channels. Estimated own-price elasticities for basic cable, expanded basic cable, and satellite services are on average -1.93, -4.81, and -2.98, respectively.

We use these estimates to simulate the welfare effects of an à la carte pricing regulation. In the baseline counterfactual simulation, three downstream operators must move from each

selling a single bundle of 52 channels to setting a fixed fee and pricing each component channel individually. We assume channels increase their affiliate fees in an à la carte world by 75%. We also estimate the effect on each channel's ratings and advertising profits.

Bundling in multi-channel television markets appears to facilitate surplus extraction by firms: mean consumer surplus increases by an estimated 8.3% under à la carte and cable industry profits decrease by an estimated 7.7%. We estimate à la carte regulations decrease total welfare even though households not served channels they value under bundling are partially served under à la carte. This is because households served all channels under bundling no longer receive some channels of moderate value.

There are important differences in welfare effects across channels. The change in consumer welfare is higher the fewer channels a household purchases and the less they value high-cost channels like ESPN or The Disney Channel. On the firm side, we estimate distributor profits to increase and aggregate channel advertising revenue to change negligibly. Despite their fee increases, all estimated losses come from reduced revenue to content providers. While our results are sensitive to our assumptions about the percentage increase in programming costs in an à la carte environment (75% in our baseline results), we find that average consumer welfare gains persist even if these input costs increase by 150%.

2 The Multi-Channel Television Industry

The multi-channel television market is a two-sided market. Cable and satellite systems provide a platform connecting households and program producers and advertisers. Figure 1 provides a graphical representation of the supply chain by which programming is produced and sold to households and audiences are created and sold to advertisers. Downward arrows represent the flow of programming from content providers to households.³ Upward arrows

³The distribution rights to content (e.g. a television program like "Crocodile Hunter") is purchased by a television channel (e.g. CBS or The Discovery Channel) and placed in its programming lineup. These channels are then distributed to consumers in one of two ways. Broadcast networks, like ABC, CBS, and NBC, distribute their programming over the air via local broadcast television stations at no cost to households. Cable channels like The Discovery Channel, MTV, and ESPN distribute their programming via cable or satellite television systems that charge fees to consumers. The dashed arrow between content providers and consumers represents the small but growing trend to distribute some content directly to households via the Internet.

represent the creation and sale of audiences to advertisers. In this paper, we focus on the for-pay distribution and advertising markets.

Insert Figure 1 Here

2.1 The MVPD Market

Multi-Channel Television Services: Bundles of Program Channels Cable television systems choose a portfolio of television channels, bundle them into services, and offer these services to consumers in local, geographically separate, markets. Satellite television systems similarly choose and bundle channels into services, but offer them to consumers on a national basis.

All cable and satellite systems offer several types of channels. The focus in this paper will be on the broadcast and cable programming channels that are typically included in bundles. *Broadcast channels* are advertising-supported television signals broadcast over the air in the local cable market by television stations and then collected and retransmitted by cable systems. Examples include the major, national broadcast channels – ABC, CBS, NBC, and FOX – as well as public and independent television stations. *Cable programming channels* are advertising- and fee-supported general and special-interest channels distributed nationally to systems via satellite. Examples include MTV, CNN, and ESPN.⁴

Broadcast channels and cable channels are typically bundled and offered as *Basic Service* while premium programming channels are typically unbundled and sold as *Premium Services*.⁵ Distributors now offer cable channels on multiple services, called *Expanded Basic* and *Digital Services*.

Regulation in Multi-Channel Television Markets The 1992 Cable Act introduced two significant regulations. First, the Act required the creation of a Basic tier of service containing at least all offered broadcast and public-interest programming carried by the

⁴The other types of channels are Premium programming channels, advertising-free entertainment channels like HBO and Showtime, and Pay-Per-View channels, specialty channels devoted to on-demand viewing of the most recent theatrical releases and specialty sporting events.

⁵In the last 5 years, premium channels have begun “multiplexing” their programming, i.e. offering multiple channels under a single brand (e.g. HBO, HBO 2, HBO Family, etc.).

system. Second, the Act introduced Must-Carry/Retransmission Consent. These regulations give local broadcast stations the option either to demand carriage on local cable systems (Must-Carry) or negotiate with those systems for payment for carriage (Retransmission Consent).

The 1992 Cable Act also re-introduced price regulation into cable television markets. Regulation only applied if a system was not subject to “effective competition.”⁶ Regulation of higher tiers, however, was phased out by the 1996 Telecommunications Act as of March 31, 1999. Regulation of Basic Service rates in areas of little competition remains the only source of price regulation in the cable industry.

In the programming input market, cable and satellite systems negotiate carriage agreements for channels on a bilateral basis between groups of cable channels owned by the same firm (e.g. Disney), and an individual distributor system or groups of systems, also known as Multiple System Operators (MSOs). These agreements specify transfers between the two parties and terms of carriage such as which tier the channel will be on. See Yurukoglu (2009) for details on regulations concerning this part of the market.

The Satellite Home Viewer Improvement Act (SHVIA) was passed on November 28, 1999. It permitted satellite providers to distribute local broadcast signals within local television markets.⁷ This leveled the playing field between cable and satellite systems and established the latter as an effective competitor in U.S. multi-channel television markets.⁸ Unlike cable systems, satellite providers have never been subject to price regulations.

2.2 The Advertising Market

Most advertising space is sold by channels, but also for a few minutes per hour by the local cable system.⁹ Advertising revenues account for nearly one half of total channel revenues.

⁶See Crawford (2006) for a survey of the history of price regulation in cable television markets.

⁷Within a year, satellite providers were doing so in the top 50-60 television markets. They now do so in almost 150 television markets, allowing them to provide a set of services comparable to those offered by cable systems for the vast majority of U.S. households.

⁸Every net new subscriber to multi-channel television markets since 2000 has been a satellite subscriber. See Crawford (2006) for details.

⁹Local advertising revenue to cable systems for 2006 accounted for approximately 5% of total cable system revenue.

Advertising revenues depend on the total number and demographics of viewers. These figures, called ratings, are measured by Nielsen Media Research (hereafter Nielsen). Ratings are measured at the Designated Metropolitan Area (DMA) level, of which there are 210 in the United States. In urban areas, the DMA corresponds to the greater metropolitan area. DMA's usually include multiple cable systems with different owners. We discuss ratings in more depth in the next section.

2.3 Related Literature

We measure the consequences of “discriminatory” bundling as in Adams and Yellen (1976), Schmalensee (1984), and Bakos and Brynjolfsson (1999). The estimation builds on the models of differentiated product demand and pricing of Berry (1994) and Berry, Levinsohn and Pakes (1995).

This paper is also related to empirical policy analysis in these markets¹⁰ as well as a number of papers addressing the identical topic. Crawford (2008) tests the implications of bundling in cable markets using reduced-form techniques. While suggestive, he does not identify the structure of channel demand required to estimate the welfare effects of bundling. Byzalov (2008) estimates a model of demand for multichannel television using household-level survey data from a cross-section of four large DMA's in 2004. While his household-level data are valuable for describing the distribution of viewing at a more disaggregate level than we can here, our papers differ on several other dimensions.¹¹ In contrast to this paper, he estimates that forcing cable distributors to offer theme tiers would decrease average consumer welfare at fixed wholesale prices. Finally, Yurukoglu (2009) extends this paper's model to estimate a model of bilaterally oligopolistic bargaining between channels and distributors which is used to predict responses in the wholesale market.

¹⁰See, e.g., Crawford (2000), Chipty (2001), Goolsbee and Petrin (2004).

¹¹These include his focusing on channel genres and a policy of theme tiers, exempting satellite service from à la carte regulations, focusing on a single year, and data limitations that prevent him from identifying the specific bundles his households purchase.

3 The Data

This section describes the data underlying this study. We divide the data into two categories: market data, which measure households' purchasing decisions or firms' production decisions, and viewership data, also called ratings, which measure households' utilization of the cable channels available to them. We document many further features of the data and our results in a set of supplementary materials.

3.1 Market Data

Market data in the MVPD industry comes from two sources: Warren Communications and Kagan Research. Warren produces the Television and Cable Factbook Electronic Edition monthly (henceforth Factbook). The Factbook provides data at the cable system level on prices, bundle composition, quantity, system ownership and other system characteristics. Kagan produces the Economics of Basic Cable Networks yearly (henceforth EBCN). EBCN provides data at the national channel level on a variety of revenue, cost, and subscriber quantities.

Factbook and Satellite Data Our Factbook sample spans the time period 1997-2007. The Factbook collects the data by telephone and mail survey of cable systems. The key data in Factbook are the cable system's bundle compositions, the prices of its bundles, the number of monthly subscribers per bundle, and ownership.

Tables 1-2 provide summary statistics for the Factbook data. An observation is a system-bundle-year (e.g. NY0108's Expanded Basic in 2000). We observe data on over 20,000 system-year-bundles, based on almost 16,000 system-years from over 6,800 systems. Most systems in our data offer a single bundle, while the majority of the rest offer just two bundles. Much of our data comes from early in the sample period when fewer offerings were the norm. For each of these bundles and by market type, Table 1 reports the average price of the bundle in 2008 dollars, its market share, and the number of cable channels offered. The average Basic service in our data costs \$24.14 and offers 17.4 cable channels, the average Digital

Basic bundle costs \$48.33 and offers 81.2 channels.¹²

There is the variation in composition of bundles, across markets and over time. Table 2 presents the share of systems in our sample that offer each of the thirty most widely available channels as of 2006. The first column indicates whether the channel is carried on any tier of service while the second-fourth columns indicate on which tier the channel is offered. For example, ESPN is carried by almost all systems (97%) in our data. Of these, most (77%) carry it on Basic Service. Smaller channels are frequently offered on a Digital Service.¹³

Unlike for cable service, satellite offerings do not vary by geography. We collected satellite menus and prices by hand. We then matched this to aggregate satellite penetration data, $\frac{\text{totalsatellitesubscribers}}{\text{totaltvhouseholds}}$, at the DMA level from Nielsen Media Research. Table 4 in the supplementary materials provides price and total channels information by year for the DirecTV Total Choice package.

Kagan (ECBN) Data We use the 2006 and 2008 editions of the EBCN (Kagan World Media (2008)). The 2006 sample covers 120 cable channels with yearly observations dating back to 1994 when applicable. Information collected includes total subscribers, license fee revenue, advertising revenue, and ownership. The data are collected by survey, private communication, consulting information, and some estimation. The exact methods used are not disclosed. Summary statistics for those data are provided in Table 5 in the supplementary materials. While we don't use ECBN data in our estimation, we do use two variables in our counterfactuals: the national average affiliation fee paid by cable and satellite systems to each of the channels Kagan covers and the 2008 advertising revenue by channel.

¹²Digital basic packages were made possible by cable systems investments in digital infrastructure in the late 1990's and 2000's. This dramatically increased the bandwidth available for delivering television channels. Prior to digital upgrades, most systems offered simply a basic bundle or a basic bundle and an expanded basic bundle. Following the digital upgrades, many systems also offered a higher tier, called digital basic, and, sometimes, a digital expanded basic bundle.

¹³Tables 1-3 in the supplementary materials duplicate this table for all the channels included in our analysis.

3.2 Viewership Data

Our viewership data comes from Nielsen Media Research. We use tuning data from the 56 largest DMA's for about 65 of the biggest cable channels over the period 2000-2006 in each of the "sweeps" months of February, May, July, and November. The main variables are the DMA, the program, the channel, the program's rating, and the channel's cumulative rating. The rating is the percentage of television households in the DMA viewing the program. The channel's cumulative ratings ("cume") indicates what percentage of unduplicated television households with access to the channel tuned to the channel for at least ten minutes in a given week.

We aggregate the information across programs on each channel within each month of our data. Thus an observation is a channel-DMA-year-month. We have 1,482 such combinations. Table 6 in the supplementary materials presents some summary statistics for a subset of channels considered in our analysis. It demonstrates that there is considerable variance in the monthly DMA average ratings both within and across channels. The fifth column in Tables 2 presents the average rating for each of the top 30 cable channels in our analysis; the sixth column presents the national average cumulative rating for the third quarter of 2006.¹⁴

We observe that channels' ratings vary from DMA to DMA and within DMA across months and years. Two important types of variation we use are (1) how ratings vary with the demographic composition of a DMA and (2) how ratings co-vary conditional on demographic differences. We focus on eight demographic factors: Urban/Rural status, Family status, Income, Race, Education, and Age.¹⁵ Table 7 in the supplementary materials reports the DMA average values for these variables for the DMAs for which we have ratings data. Figure 1 in the supplementary materials provides an illustrative example of the impact demographic characteristics can have on ratings by comparing average ratings for Black Entertainment Television (BET) across markets. Unsurprisingly given the target audience of BET, the channel has its highest ratings in heavily black populated DMA's such as Memphis and its lowest ratings in sparsely black populated DMA's such as Salt Lake City.

Similar examples demonstrate the importance of ratings co-variation in our data. Table 8

¹⁴We would prefer to have the cumulative ratings at the DMA-month, but were not able to obtain it.

¹⁵We follow U.S. Census definitions for each of these variables.

in the supplementary materials reports correlations in the DMA-month-year ratings across a subset of cable channel pairs. Most of these are consistent with prior beliefs about likely patterns of correlation in viewer tastes. In particular, ratings for children’s programming are negatively correlated with ratings for arts programming and old movies (A&E and Turner Classic Movies, TCM). Similarly, ratings for all of ESPN’s various sports programming channels are positively correlated.

Data Quality We call attention to the nonstandard features of these data sets in the supplementary materials. We focus on missing market share and price data. About two thirds of the possible observations on market share and price for cable bundles are either missing, not updated from the previous year, or both. We assume this data is missing at random conditional on the observable characteristics of the system. We justify this assumption in the supplementary materials.

4 The Econometric Model

Our model of multi-channel television markets consists of three parts: household viewership of television channels, household subscriptions to cable and satellite bundles, and firms’ pricing of bundles. Demand is a discrete-continuous model as in Hanemann (1984). The continuous choice is the viewership decision of how much time to watch each channel in a bundle. The discrete choice is to which bundle to subscribe. Modeling both household viewing behavior and bundle purchases allows us to incorporate the information contained in our two sources of data, ratings and bundle purchases, into our estimation.¹⁶

These three decisions have a sequential order. Firms first set prices. Households next decide to which bundle to subscribe, if any, conditional on prices. Finally, conditional on the bundle chosen, households allocate time to watching the various channels available. As pricing depends on demand for bundles and that, in turn, depends on households viewing choices, we present the model in reverse order.¹⁷

¹⁶Several recent papers incorporate multiple sources of data in the estimation of supply and demand, including Petrin (2003) who uses utilization data as we do, and Berry, Levinsohn and Pakes (2004) who use second-choice survey data.

¹⁷In this paper, we take firms’ product choice and bundling decisions as given. Yurukoglu (2009) uses

4.1 Household Viewing

Let j index a bundle of programming being offered by cable system n in DMA d in month-year m (e.g. Comcast Digital Basic in Arlington, VA in the Washington, DC DMA in November 2003).^{18,19} We will suppress the market subscripts n , d , and m for the moment. Let C_j be the set of channels offered on bundle j . Suppose household i has T_i hours per month of leisure time.²⁰ We assume the utility to household i from spending their leisure time watching television and doing non-television activities has the Cobb-Douglas in logs form:

$$v_{ij}(t_{ij}) = \sum_{c \in C_j} \gamma_{ic} \log(t_{ijc}) \quad (1)$$

where t_{ij} is a vector with component t_{ijc} , t_{ijc} is the number of hours household i watches channel c when the channels in bundle j are available, and γ_{ic} is a parameter representing i 's tastes for channel c .²¹ Households may opt to not watch any channel, and we call this state channel 0, $0 \in C_j \forall j$, with t_{ij0} the amount of time household i spends on non-television leisure activities and γ_{i0} their preferences for such activities.

Each household i is assumed to allocate its leisure time between watching the channels available and non-television leisure by solving:

$$\begin{aligned} \max_{t_{ij}} \quad & \sum_{c \in C_j} \gamma_{ic} \log(t_{ijc}) \\ \text{subject to} \quad & \sum_{c \in C_j} t_{ijc} \leq T_i \end{aligned} \quad (2)$$

The solution exhibits proportional shares:

$$t_{ijc}^*(\gamma_{ij}, T_i, C_j) = \frac{\gamma_{ic}}{\sum_{c \in C_j} \gamma_{ic}} T_i \quad (3)$$

observed bundling decisions to infer unobserved costs.

¹⁸For convenience, we index month-year combinations (e.g. November, 2003; May, 2004; November, 2004) by the single index, m .

¹⁹Note we have two geographic identifiers: cable markets n and Nielsen DMAs d . This is necessary due to the different levels of geographic aggregation in our two sources of data.

²⁰This is without loss of generality. A model where the time a household spends watching television each month depends on bundle j (i.e. $T_{ij} = T_i(C_j)$) yields an identical econometric model. We maintain the chosen specification for analytical convenience.

²¹Strictly speaking, this utility function isn't defined when a household chooses not to watch a given channel, i.e. $t_{ijc} = 0$. We could accommodate this defect by simply defining utility only over those channels, $c \in C_j$, for which $t_{ijc} > 0$. This introduces significantly more notation, however. In its place, we note that by l'Hôpital's rule, such a restricted utility function is the limit of our chosen specification as $\gamma_{ic} \rightarrow 0$.

where $\gamma_{ij} = \{\gamma_{ic} | c \in C_j\}$. Plugging this back into Equation (2) yields household i 's indirect utility from viewing:

$$\begin{aligned} v_{ij}^*(\gamma_{ij}, T_i, C_j) &= \sum_{c \in C_j} \gamma_{ic} \log\left(\frac{\gamma_{ic}}{\sum_{c \in C_j} \gamma_{ic}} T_i\right) \\ &= \sum_{c \in C_j} \gamma_{ic} \log(t_{ijc}^*) \end{aligned} \quad (4)$$

Equation (4) states that the indirect utility household i enjoys from viewing the channels on bundle j depends on three factors: preferences for the channels offered on bundle j , $\gamma_{ic}, c \in C_j$, the channels on the bundle, C_j , and the amount of leisure time it has allocated to itself, T_i .

4.2 Bundle Purchases

Consider next a household's choice of cable bundle. This will depend on v_{ij}^* as well as other characteristics of the bundle and cable system and the price they have to pay for it. We assume the utility household i derives from subscribing to bundle j in market n in DMA d in month m as:

$$u_{ijnm} = v_{ijnm}^* + z'_{jndm} \psi + \alpha_i p_{jndm} + \xi_{jndm} + \sigma_\epsilon \epsilon_{ijnm} \quad (5)$$

where, $v_{ijnm}^* = v_{ijnm}^*(\gamma_{ij}, t_i, C_j)$, from (4), represents the indirect utility to household i from viewing the channels available on bundle j , p_j is the monthly subscription fee of bundle j , and z_j are other observed system and bundle characteristics of bundle j in market n . $\alpha_i = \alpha + \pi_{ip} y_i$, with y_i household i 's income, is a taste parameter measuring the marginal utility of income and ψ is a taste parameter measuring tastes for system and other bundle characteristics. ξ_j and ϵ_{ij} are unobserved portions of household i 's utility. We assume that the unobserved term has a component which is common to all households in the market, ξ_j , and an idiosyncratic term, ϵ_{ij} . We further assume that the idiosyncratic term is an i.i.d. draw from a type I Extreme Value distribution whose variance we estimate, denoted σ_ϵ .²²

²²Typically this variance term is not identified separately, see Berry and Pakes (2007) for detail. Since units of utility are chosen with the ratings data, in our setting this variance term is identified.

The components of z_j include by which MSO, if any, the bundle is being offered, the year the bundle is being offered, and bundle dummies (e.g. “Tier 1”, “Tier 2”, etc.). ξ_{jn} is an aggregate term which represents the deviation of unobserved demand shocks or bundle attributes from the MSO-year-bundle mean. These unobserved attributes include Internet, high definition (HD) service, promotional activity, technical service, and quality of equipment. Theory predicts these unobservable attributes will be correlated with price as they affect both valuations and marginal cost. We use the instrumental variables assumption to disentangle the effect of price on utility from the effect of unobservable attributes. Identification is discussed in section 5.2.

4.3 Bundle Pricing

We assume that observed prices are part of a Nash equilibrium. Each local cable system’s profit before fixed costs is

$$\max_{\{p\}_{j=1}^{J_{ndm}}} \sum_{j=1}^{J_{ndm}} (p_{jndm} - mc_{jndm}) s_{jndm}(p_{ndm}) + r_j(s_{jndm}(p_{ndm}))$$

where mc_{jndm} are the marginal costs of providing bundle j in market n in DMA d and month m , s_{jndm} is bundle j ’s market share and r_j is the local advertising revenue that is generated by subscribers of bundle j . Our Nash assumption implies that the first order condition of this profit function holds at observed prices for all systems.

5 Estimation

We estimate the model in two steps. We first parameterize and estimate the distribution of marginal utility derived from each channel using ratings data. We then estimate the marginal utility of income using market share, price, and bundle characteristics data. While it would be efficient to estimate all the parameters jointly, we significantly reduce computational time by separating the estimation.

5.1 The First Stage: Using Ratings Data

Overview The indirect utility to household i from viewing the programming on bundle j is given by

$$v_{ij}^*(\gamma_{ij}, T_i, C_j) = \sum_{c \in C_j} \gamma_{ic} \log(t_{ijc}^*)$$

where $t_{ijc}^*(\gamma_{ij}, T_i, C_j) = \frac{\gamma_{ic}}{\sum_{c \in C_j} \gamma_{ic}} T_i$. For each channel, c , we define β_{ijc} to be the contribution of channel c to bundle j 's indirect utility

$$\beta_{ijc} = \gamma_{ic} \log(t_{ijc}^*) \tag{6}$$

where t_{ijc}^* is the number of hours of channel c watched by household i subscribing to bundle j in the suppressed market n , DMA d , month m , γ_{ic} is the share of monthly leisure time household i would watch channel c if it had the ability to watch all channels as desired. Given our definition of β_{ijc} , the indirect utility from viewing can be written as

$$v_{ij}^* = \beta_{ij}' x_j \tag{7}$$

where β_{ij} is a vector with components β_{ijc} and x_j is a vector of dummy variables whose components x_{jc} indicate whether channel c is on bundle j .

Parameterizing the indirect utility from purchasing a product as a function of its characteristics as in Equation (7) is standard in the literature on empirical demand estimation. The link between β_{ijc} and the underlying γ_{ijc} is critical as it provides the mechanism by which both ratings data and bundle purchase data can help identify the distribution of β_{ijc} .²³

A complication arises because of the dependence of a household's tastes for a channel on the bundle on which it is offered (i.e., β_{ij} depends on j). While a natural consequence of competition among channels for a viewer's time, allowing tastes for each channel to depend on the other channels offered in the bundle would require estimating 2^{N_j} distributions,²⁴ a practical impossibility. Instead, we approximate a household's preferences for each channel

²³In the counterfactual exercise we use this link to infer the values of γ_{ic} for households that choose to purchase each channel, c . Plugging these γ_{ic} 's for each household back into Equation (4) allows us to calculate the effect on ratings and advertising revenue of an à la carte policy environment.

²⁴With N_j given by the number of channels offered on any bundle in our sample.

as its preferences for that channel when offered on the *average* bundle and include covariates to measure the differences in tastes for channels when offered on the average versus observed bundle. These covariates include the number of channels in the bundle, the sum of average ratings for these channels, and an interaction term.²⁵ We denote these approximation covariates a_j . Table 7 in the supplemental materials provides sample statistics for these approximation covariates.

A second problem arises due to the selection of households into bundles across markets within a DMA. While Nielsen samples households at random, those households have already chosen what bundle of channels they subscribe to. Our procedure would work perfectly if Nielsen also randomly assigned what channels each household receives. To accommodate this feature of the data, we condition our estimates on functions of covariates measuring prices and market shares of channels across markets within that DMA. With enough computing power, we could do this conditioning exactly according to the demand model. That is, the demand model provides the correct function to condition on. However, to maintain the computational simplicity of the two stage estimation, we condition on a flexible function of the ingredients that would go in the demand model.²⁶

Formally, we parameterize each component β_{ijc} , of the vector β_{ij} as

$$\beta_{ijc} = \begin{cases} 0 & \text{with prob } 1 - \rho_c \\ \beta_c + \pi_c D_i + v_{ic} + \theta_c a_j & \rho_c \end{cases} \quad (8)$$

where β_c measures the marginal utility to channel c when offered on the average bundle, D_i measure the demographic characteristics of household i , v_{ic} measures household i 's unobserved tastes for channel c , ρ_c is the fraction of households that earn positive utility from subscribing to channel c , and a_j are our approximation covariates described above.

Our parameterization for marginal utility for channels is intended to reflect existing research on preferences for media products. This research generally finds that preferences exhibit “long tails”: many people have low to zero tastes for a given product while a smaller number

²⁵These capture the logic that the marginal utility of a channel is likely to be lower the more or more popular channels it must compete against.

²⁶This is not guaranteed to work. We tested it, however, using data simulated from the model's estimated parameters and found it worked well.

have strong tastes.²⁷ We capture this by assuming some fraction of households do not value channel c at all, while the remainder value them according to a distribution that is convex to the origin. In our current specification, $v_i \sim G(v|\lambda, \Sigma)$, with each $v_{ic} \sim \text{Exponential}(\lambda_c)$ and the rank correlation matrix of v_i given by Σ .

Using an indicator function χ_{ic} for whether household i has positive utility for channel c implies that the vector β_{ij} has the form:

$$\beta_{ij} = \vec{\chi}_i'(\beta + \Pi D_i + v_i + \Theta a_j) \quad (9)$$

Of those households who have positive utility for the channel, we assume that bundle characteristics enter additively separably from household characteristics. We further assume that the additively separate terms are linear in parameters. The utility, and ultimately the willingness to pay, for channels depends on the other channels in the bundle in an additively separable manner that does not vary across individuals. Implicitly, this assumption restricts the set of possible population distributions of γ_i .

The goal of our first-stage estimation is to exploit the link between individual utility from viewing (Equation (6)) and the implied tastes for bundles (Equation (8)). We use the variation in ratings across DMAs and months to trace out the marginal utility of channels (i.e. the distribution of β_{ic}). Getting there requires aggregating across both households and markets within a DMA-month and describing the implications of this aggregation for the econometric model. This is done in Appendix A.

From Appendix A we obtain our first-stage estimating equation for each channel, c :

$$r_{cdm} \log(r_{cdm}T) = \beta_c + \Pi_c D_d + \Theta \bar{a}_{dm} + \eta_{cdm} \quad (10)$$

where r_{cdm} is the vector of ratings for each channel in a given DMA d in month m , T is the average number of minutes of television viewing measured by Nielsen, \bar{a}_{dm} are the aggregated approximation covariates, and $\eta_{cdm} \equiv \Upsilon^{dm} v_{ic}$, i.e. the average (across households in DMA d

²⁷Shiller and Waldfogel (2008) find such patterns in tastes for individual recorded music tracks and Byzalov (2008) finds them in the number of channels watched by households. Anderson (2006) describes a number of information and media products whose demand has this shape.

and month m) unobserved tastes for channel c .²⁸ Let Π be the $C \times 8$ matrix of parameters from each of these regressions and let η_{dm} be the $C \times 1$ vector of residuals with component η_{cdm} .

The left hand side of this equation, $r_{cdm} \log(r_{cdm}T)$ is data. D_d is demographic data from the Census. We compute DMA-year aggregated bundle characteristics (i.e. \bar{a}_{dm}) from the market share data. We can then estimate Π and Θ by ordinary least squares. A byproduct of this estimation are estimated residuals $\hat{\eta}_{dm}$. We then estimate $G(v_i|\lambda, \Sigma)$ as a distribution whose distribution of Nielsen sample averages shares a set of moments with $\hat{\eta}_{dm}$. This says that any variance in ratings net of demographic differences is a result of the distribution of unattributable preferences for channels from which Nielsen is not able to sample perfectly.²⁹

First-stage estimation proceeds in four steps. First, for each channel c , we estimate the share of household with positive tastes for that channel, ρ_c . We start with the Nielsen “cume” for each channel, from Table 2, defined as the average share of unduplicated households tuned into that channel in each week of the third quarter of 2006. ρ_c , on the other hand, measures the share of households with positive tastes for a channel in a given *month*. This is likely to be greater than the Nielsen “cume” both because households must watch weakly more channels in a given month than in a given week within that month and because there may be an option value to having access to a channel even if a household doesn’t watch it in a given week. We therefore scale the Nielsen cume by a common factor to match the average number of channels watched by U.S. households under the assumption that tastes for channels are independent across channels within a household, a number we take to be 21.^{30,31} Doing so yields a scale factor of 3.0. The resulting values for ρ_c are given in the “Share Positive”

²⁸ Υ^{dm} is a function that takes the simple average over the Nielsen households in DMA d and month m . It is defined in Appendix A.

²⁹We adjust the estimated variance of unattributable preferences both for the aggregating effects of the Nielsen averaging as well as the effects of a fraction $1 - \rho_c$ of households with zero tastes for the channel.

³⁰There is significant discretion in selecting this value. Nielsen Media Research (2008) finds that the average U.S. household watches 16 channels in a given week in 2007. This must be adjusted (upwards) for monthly viewing, (downwards) for broadcast channel viewing, and (upwards) for option value. On balance, we thought a value slightly larger than 16 appropriate. Because the more channels a household prefers, the more likely it is to like the bundle, if this assumption is in error, any bias in our results would likely favor bundling. As such, we treat this as a conservative assumption.

³¹The assumption of independent viewing across channels within a household is strong, but introducing within-household correlation necessarily breaks the construction of the multivariate distribution of tastes as further described below.

column of Table 3.

Second, we estimate the regression in (10), yielding estimates $\hat{\Pi}$, $\hat{\Theta}$, and $\hat{\eta}_{dm}$. $\hat{\eta}_{dm}$ is the average of unobserved tastes for channel c , $G(v|\lambda, \Sigma)$. We can therefore infer features of the distribution of those unobserved tastes by analyzing estimates of the variance and covariance of $\hat{\eta}_{dm}$. The set of moments of $\hat{\eta}_{dm}$ we choose G to match are Kendall's τ ³² and the variance of the marginal distributions. Still, G is not identified by these moments. We further assume that the marginal distributions for each channel, among those households with positive tastes, follow an Exponential distribution with parameter λ_c .³³

Third, given $\hat{\eta}_{dm}$, we compute Kendall's τ of $\hat{\eta}_{dm}$ and create a t-copula based on $\hat{\tau}$. We then choose the Exponential distribution parameter, λ_c , whose sample averages distribution has the variance of the observed marginal distributions (accounting for the $1 - \rho_c$ fraction of households that value that channel at zero). We can sample from this distribution by drawing multivariate uniformly distributed random variables from the estimated t-copula (preserving the rank correlation of the $\hat{\eta}_{dm}$), applying the inverse cdf of the exponential distribution, and setting $1 - \rho_c$ of those to zero. The multivariate distribution of sample averages of these draws will preserve $\hat{\tau}$ and the chosen mixture of zeros and an Exponential distribution will have sample average variances equal to those of $\hat{\eta}_{dm}$.

Fourth, we select β_c for each channel so that no household has negative willingness to pay.³⁴

5.2 First-Stage Identification

The basic identifying assumption in our first-stage estimation is that the time spent by households watching channels is informative for what they are willing to pay for access to those channels. We assume the more a household watches a channel, the more it values that

³²Kendall's τ is a measure of ordinal correlation. It can be calculated for two data series as $\frac{4P}{n(n-1)} - 1$ where P sum, over all the items, of items ranked after the given item by both rankings. Explicitly, $P = \sum_{i=1}^N \sum_{j=1}^N \chi_{\{x_j > x_i \wedge y_j > y_i\}}$. τ is equal to 1 if the orderings of the two data series are perfectly harmonious and -1 if the orderings are completely discordant. τ is invariant under CDF and inverse CDF operations.

³³We discuss this important decision in greater detail in the next sub-section.

³⁴These estimates are very highly correlated ($\rho \approx 0.80$) with the values of $\hat{\beta}_c$ estimated, but not used, in the second step. We are using the assumption of free disposal for the consumption of television channels.

channel. If a household never watches a channel, it values that channel at zero.³⁵

For our estimates of the impact of demographics on tastes, Π , identification is clear: we will estimate greater mean marginal utility for a channel c among a demographic group the higher are mean ratings for that channel in a given DMA and month that have more of that group. Thus, mean marginal utility for BET is estimated higher for black households because ratings for BET are higher in markets with greater numbers of black households.

Identification of G is more subtle. It is the distribution of unobservable marginal utility of channels, assumed to be common across DMAs and months once we control for the channels available and demographic differences across markets. This is identified by variation in the ratings across DMAs and markets due to random variation in the sampling process undertaken by Nielsen across markets and time. The error in our estimation regression, η_{cdm} , is the average across the Nielsen households in DMA d in month m of the underlying household-specific taste shock, v_{ic} , i.e. $\eta_{cdm} = \Upsilon^{dm} v_{ic}$ where $\Upsilon^{dm} = \frac{1}{N_{dm}} \sum_{i \in \text{Nielsen sample of DMA } d \text{ and month } m}$. If Nielsen were able to sample from a continuum of households within each DMA d in month m , this error would be zero. As they cannot, there is variation between our first-stage dependent variable ($r_{cdm} \log(r_{cdm} T)$) and that predicted in the population ($\beta_{cdm} + \Pi D_d + \Upsilon^{dm} v_{ic}$).

The Shape of the Marginals While we can identify the variance and covariances of the underlying preferences, $G(v)$, our data do not identify their shape. Within each DMA and month, the Nielsen aggregates the viewing choices of a sample of a few hundred households. If preferences are independent across households, and the variance is finite, then Central Limit Theorems tell us that the distribution of average viewing choices will be normally distributed no matter the shape of the distribution underlying that average. If we observe an average rating of 3.0 for a channel in a given DMA-month, we cannot tell if this meant 3% of households were watching that channel 100% of the time or if 30% of households were watching it 10% of the time, or any other equivalent combination. We address this identification problem both by incorporating cumulative ratings data and additional assumptions. Nielsen reports indicate that the typical household does not watch many of the channels

³⁵We are therefore assuming away the “option value” associated with having access to a channel. While we would like to measure such an effect, there is no way to do so with observational data. As a channel must eventually be watched in order to provide utility, we think it unlikely this effect is strong for any but a few channels (e.g. news, weather).

included in cable bundles (Nielsen Media Research (2008)). Our model says that their WTP for these channels is around zero. Therefore, we assume that the distribution of tastes for channels has a mass point at zero, representing the share of the population that does not value the channel enough to view it, and a distribution with support over the positive line. We assume that the positive portion of the mixture distribution is exponential motivated by the view that tastes for media products have “long tails.”

5.3 The Second Stage: Estimation on Market Share Data

Given $\hat{\beta}$, $\hat{\Pi}$, \hat{G} , and $\hat{\Theta}$, in the second stage we estimate the remaining parameters of the model using our market share data in the spirit of Berry (1994) and Berry et al. (2004). As this is now standard in the empirical demand literature, we develop the formal econometric model in Appendix B and present an informal discussion here.

Our demand-side instruments follow standard practice in demand estimation on aggregate data. First, we allow observed product characteristics (largely dummy variables for non-channel bundle characteristics such as firm, year, and tier name), z_{jndm} , to instrument for themselves. Second, we accommodate the endogeneity of price by instrumenting for it with w_{ndm} , where w_{ndm} is the average price of other cable systems bundles within the same DMA as cable system n and with the channel dummy variables. These will be valid instrumental variables if, for bundle j in market n , (a) the unobservable demand shock, ξ_{jndm} , is uncorrelated and (b) “net” marginal costs are correlated with prices within n ’s DMA outside market n . The former is likely to be true in multichannel television industry because cable systems are physically distinct entities for which local managers have wide authority. The latter will be true, for the average price variable, as labor costs and advertising rates are often correlated within DMAs. Following Hausman (1996), these are often called “Hausman” instruments. Additionally, the channel dummy variables are uncorrelated with the unobservable term as the utility generated by the channels was by construction taken out of δ . They are correlated with price through input costs.

Our supply-side instruments include cost shifters, w_{jndm} , instrumenting for themselves, the predicted markup, \hat{markup}_{jndm} , instrumenting for the $markup_{jndm}$, and the predicted mar-

ket share instrumenting for the market share. As the predicted markup and predicted market share are functions of exogenous variables and instruments from the demand side, this means we are instrumenting for the markup with demand shifters as in Berry et al. (2004).

6 Estimation Results

Table 3 presents estimates of the key parameters in the model, including channel-specific estimates for a selection of channels.³⁶ Among the non-channel estimates, the table reports the price sensitivity parameter, (α), the impact of income on price sensitivity (π_p), and the approximation covariates. The estimated price sensitivity parameter is -0.13 .³⁷ In markets that offer Basic, Expanded Basic, and Digital Basic cable services, this yields an average own price elasticity for Basic of -1.93 , for Expanded Basic of -4.81 , and for Satellite of -2.98 .³⁸ These are comparable to previous results in the literature.³⁹

Estimated median marginal costs for bundles range from \$9.95 for Basic to \$28.13 for Digital Basic and estimated median margins vary from 47% to 54%. While the estimated bundle marginal costs are robust, the projection of estimated marginal costs onto the individual channels that form the bundle are often imprecisely estimated. In the counterfactuals, we therefore rely on national average marginal costs for channels from Kagan World Media (2008).

Preferences for Channels Previous demand system estimates for multichannel television either did not define preferences over channels in bundles (Goolsbee and Petrin (2004), Chu (2006)) or restricted the preferences for individual channels to be the same for all households (Crawford (2000), Rennhoff and Serfes (2007)). Our demand system allows for flexible

³⁶Results for the full set of channels are available in Tables 11-13 in the supplementary materials.

³⁷Moving from OLS ($\hat{\alpha} = -0.04$) to IV using just the demand-side moments ($\hat{\alpha} = -0.08$) to IV using both demand and pricing equations ($\hat{\alpha} = -0.13$) suggests that our instrumental variables strategy is working as theory would predict and that the optimal pricing assumption has a moderate effect on the price sensitivity estimate.

³⁸Table 14 in the supplementary materials reports a full set of own- and cross-price elasticities for these markets.

³⁹The FCC (2002) (-2.19), the GAO (2003) (-3.22), Beard, Ford and Hill (2005) (-2.5), Chipty (2001) (-5.9), and Goolsbee and Petrin (2004) (-1.5 for EB, -3.2 for DB, -2.4 for Satellite), have all separately estimated the average own price elasticity of cable services, using market share regressions, diverse data sets, and instrumental variables techniques.

multivariate distributions of preferences for channels.

Table 3 reports features of the distribution of preferences for a subset of channels. We report the distribution shift parameter, β_c , in column 2, and the exponential parameter λ_c , in column 4. For convenience, we also report for each channel information about the distributions of WTP implied by our estimates. The last three columns of the table report, for a simulated set of 20,000 households, the share of households with positive tastes for each channel,⁴⁰ the overall mean WTP for the channel, and the mean WTP among those households that value the channel positively. Figure 2 presents the estimated distribution of willingness-to-pay for a subset of the channels in our analysis in a sample of 20,000 households.

We can use the connection between β_{ijc} and γ_{ijc} to back out the implied $\hat{\gamma}_{ijc}$ from $\hat{\beta}_{ijc}$. Using this connection, we would like to draw attention to two issues in the estimation. First, part of identifying preferences for channels is based on the assumption of free disposal; All households have non-negative willingness to pay for a channel. We force this assumption to hold by shifting the distributions of preferences so that the minimum value is zero. Since the shifting is done to all households, it preserves the estimated variance structure. However, it results in the implied sum of $\hat{\gamma}_{ijc}$ being greater than one for some households which violates the viewership models assumptions. We could use more restrictions imposed by the viewership model to fix this problem in estimation, but we choose not to because the extent of the violations is minor relative to the required additional computational burden.

Demographic Impacts We estimate a non-degenerate distribution of taste parameters for a channel if its ratings vary across markets or time periods. The variance of this distribution could be driven by demographic differences, through Π , or if not by demographic differences, through the variance of $G(v)$. Two channels will have positively correlated tastes if their ratings co-vary in the same direction with the same demographic features or if their portions of ratings unexplainable by demographics co-vary positively. Tables 15 and 16 in the supplemental materials display estimated correlations in willingness to pay for a subset of pairs of channels in our specification. Tables 17-19 in the supplementary materials report

⁴⁰This is an estimate of ρ_c , the share of households with positive tastes for channel c , itself equal to 3 times the average weekly “cume” in the last column of Table 2.

all the elements of Π that are estimated to be statistically significant at conventional levels. Demographic results are consistent with intuition. Preferences for BET are higher for Black than Non-Black households; preferences for Disney and Nickelodeon are higher for families, preferences for the American Movie Classics and the Weather Channel are higher for older households; and preferences for Country Music Television are higher for rural households. In most cases, the estimated highest value households match the desired audience of the targeted channel.⁴¹ These patterns are direct consequences of the conditional correlations of a channels ratings in a DMA with that DMA's demographics.

7 The Welfare Effects of À La Carte

7.1 Theoretical Predictions

Holding fixed the current set of offered channels, the social marginal cost of an extra household receiving a channel is effectively zero. The socially optimal allocation would therefore deliver every channel in existence to each household that has a positive willingness to pay for that channel. Bundling excludes households that have positive willingness to pay for some channels, but do not derive a value from the full bundle that justifies its price. À la carte pricing of channels allows for those excluded under bundling to enter the market. However, à la carte partially excludes households who have positive valuations for channels that do not exceed the prices at which the channels are being sold. Which of these two effects dominates is one output of the counterfactual exercise.

How the surplus generated by the service of multichannel television is split between and within consumers and firms is also of importance to policy makers. Bundling theory under monopoly suggests that consumers with highly variant preferences, as we estimate television households to be, are better off under à la carte pricing in the short run (Adams and Yellen (1976)). The theory under oligopoly is less established and offers ambiguous predictions about the effects of à la carte on consumer welfare.

⁴¹Distributions of WTP for particular demographic groups are reported in Table 20 in the supplementary materials.

In the long run, the conclusions of economic theory on the welfare effects of à la carte depend on even more decisions. Many opponents of à la carte claim smaller channels appealing to niche tastes will become unprofitable and exit in an à la carte environment. Others claim they may invest less in program quality. We do not model the impact of à la carte on these long-run outcomes. Further research of their evolution in an equilibrium setting is necessary to assess these effects of à la carte regulations.

7.2 Counterfactual Simulations

Supporters have suggested various implementations of a la carte policies. These range from requiring firms which bundle to allow consumers to opt out of programming and receive a rebate (Family and Consumer Choice Act of 2007) to separately priced themed tiers to offering separately priced individual channels. While we could implement any of these, for simplicity our simulation requires the channels to be separately priced and offered individually by all operators. Operators also charge a fixed fee that households must pay in order to purchase any individual channel.

Baseline Counterfactual Simulation The main building block of our baseline counterfactual is the estimated demand system. We combine the demand system with an upstream cost structure, detailed in the next paragraph, and a pricing game. We compare the pricing game’s equilibrium under bundling with its equilibrium under à la carte pricing regulations. The pricing game is characterized by the two satellite firms playing a simultaneous-move price setting game against a “representative” nationwide cable firm with consumers simulated from the nationwide demographics distribution. We compute a Nash equilibrium solution.

For input costs of channels, our primary input is the nationwide average cost per subscriber as reported in Kagan World Media (2008).⁴² Our baseline counterfactual assumes that input costs are higher by 3% for the cable system and by 5% and 8% for the satellite firms. Following research on the impact of à la carte on bargaining in the wholesale market

⁴²While our estimated marginal costs of bundles are in line with outside estimates, when we project these bundle costs onto their components, the resulting estimates are either not credible or not precise enough to use.

(Rennhoff and Serfes (2008), Yurukoglu (2009)), we assume these input costs rise by 75% in the à la carte counterfactual. We evaluate the robustness of our results to this assumption below.

We assume all three firms offer identical products. We allow these products to include all channels for which we were able to estimate non-degenerate distributions of preferences and for whom the 90% percentile of the WTP distribution is greater than the Kagan estimate of their marginal cost. As we are constructing a “nationally representative” cable system, we cannot apply all our estimates directly into the counterfactual. We therefore interpret the logit error as an idiosyncratic disturbance term on the set of channels that deliver the most net utility from each provider. We estimate the variance of this error and the level of the constant term for each provider to make predicted market shares and prices match their actual 2007 levels.⁴³ To incorporate installation costs we require consumers who would not purchase under bundling to pay an extra \$5 monthly fee if they choose to purchase channels à la carte.

Profits for distributors are their revenue from selling to consumers net of the input costs they pay to channels. Profits for the content providers are the affiliate fees plus their advertising revenue. We compute ad revenue as the channel’s bundling ad revenue adjusted for the change in viewing in an à la carte world. This is determined in the model by solving for each household the value of γ_{ic} corresponding to their WTP for channel c , WTP_{ic} (itself a function of their marginal utility for that channel, β_{ic}). Given the channels household i purchases, viewing follows from equation (3). Aggregating across households gives the aggregate ratings effect for channel c . We assume advertising prices per ratings point (p_c) are constant for each channel, so that $\Delta AdRev_c = p_c \Delta Ratings_c$.

Finally, we make a number of assumptions consistent with a short-run analysis. We assume that preferences are invariant to the policy change. We assume that channels do not alter their programming following the policy change, nor do new channels enter or existing channels exit. We assume the accounting and marketing costs of firms are the same when firms are allowed to bundle as when firms are forced to sell channels à la carte.⁴⁴ Each of these

⁴³Formally we estimate these four parameters based on the 6 national average cable and satellite market shares and prices.

⁴⁴The magnitudes of these costs are a matter of disagreement in the ongoing policy debate.

issues could be addressed in a long-run analysis.

Counterfactual Results Table 4 presents the results of our baseline counterfactual. We focus first on the left-most columns describing the bundling equilibrium. Equilibrium prices for a bundle of all 52 modeled cable channels vary from \$35.28 to \$51.79 in year 2008 dollars. The total market share across distributors is 88.0%. Industry profits per household per month are an estimated \$53.23, with distributors earning slightly less than channels on average. Mean consumer surplus is \$44.13 per household per month, although it varies significantly across households, with some households garnering surplus of over \$100/month. Total estimated welfare is \$97.36 per household per month (roughly \$128 billion/year on a national basis).⁴⁵

We turn next to predicted outcomes in an à la carte equilibrium. We report channel prices and market shares for a subset of our channels, as well as the average across all our analyzed channels. We predict fixed fees of \$31.94 for cable and \$15.58-\$17.16 for satellite. Marginal prices for channels are fairly low: most are under \$1, with the most expensive being ESPN at \$6.35 per subscriber per month. Predicted channel market shares are moderate, with an average share of 39.3%. As a consequence, subscribing households are predicted to purchase an average of 17.9 of the 52 channels. Distributor profits are estimated to increase slightly, channel affiliate fee profits to drop considerably (by 31.1%), and there to be effectively no change in advertising revenue. We predict a total decrease of 7.7% in industry profits. Estimated average consumer expenditure for subscribers is \$39.93 per month, a reduction of 13.6%. Mean consumer surplus increases by 8.3%, or approximately \$4.8 billion/year. Predicted total welfare decreases by 0.4% to \$96.94 per household per month.

Tables 5 and 6 break down these welfare gains by channel for both firms and consumers. On the firm side, the first three columns reports total revenue to each channel in the bundling and à la carte equilibria and the change between them. The next two columns break down this total percentage change into the percentage changes in revenue from affiliate fees versus advertising. The final line in Table 6 aggregates these effects across the 52 channels in the counterfactual.⁴⁶

⁴⁵We convert these to aggregate annual figures by multiplying by 110 million U.S. households x 12 months.

⁴⁶2008 advertising revenue was not available for three of our channels: The Disney Channel, Turner Classic

Some striking effects are evident in the table. First, there is considerable heterogeneity in who wins and loses from à la carte. While the average channel loses 17.5% of its revenue, some channels do substantially worse (ESPN, E!, and most channels outside the top 30) while some are predicted to benefit from an à la carte environment (TBS, TNT, USA). Overall it appears that small and/or high-cost channels suffer most. Changes in affiliate fee revenues and advertising revenues are also heterogeneous, with those channels catering to general-interest tastes doing best.

The dominant predictor of household benefits from à la carte is the number of channels it chooses to purchase: households that purchase fewer channels do much better from à la carte as they aren't forced to pay the full bundle price to obtain access to the few channels they prefer. That being said, there are important differences in consumer welfare benefits across channels. The last column of Tables 5 and 6 reports, for each channel, the average percentage change in consumer welfare from bundling to à la carte for consumers that purchase that channel in an à la carte environment as a share of the average change in welfare of all consumers. This tries to capture the benefits to those households that like particular channels as compared to the average benefit across all households. To control for the number-of-channels-purchased effect, this calculation is made for only those households among 5,000 simulated households that purchase the median (+/- 1) number of channels. Households that choose not to purchase relatively expensive networks like ESPN or The Disney Channel do substantially better on average than those that do, indicating that high-cost channels impose a substantial aggregate welfare cost on consumers when they must purchase them in a bundle.

Robustness of Results to Alternative Assumptions A key factor in these calculations is our assumption that affiliate fees increase by 75% in an à la carte equilibrium. Table 7 assess the consequences of relaxing this assumption. The first three columns of Table 7 summarize the previously presented results in Table 4. The next group of columns reports similar results under the assumption that affiliate fees to cable systems do not change under à la carte. The last two columns report results should they double our baseline assumption

Movies, and Regional Sports. We predict ratings changes for these networks of +4.0%, +2.8%, and -7.0%, respectively.

and increase by 150%.⁴⁷ When input costs are unchanged, consumer welfare benefits are substantial. Consumer surplus increases by over 30% and total industry profits fall by 15.8% (with a greater than 50% decrease in channel’s affiliate fee profits). Interestingly, this environment yields a 5.5% *increase* in total surplus. By contrast, if input costs increase by 150%, consumer benefits are moderated. Industry profits fall only 6.6% and consumers surplus is estimated to only increase 1.7% despite a 8.9% decrease in expenditure.

8 Conclusion

This paper has combined a model of the multichannel television industry with market and viewership data in order to evaluate the welfare effects of proposed à la carte pricing regulations. We begin by extending a standard demand model to a setting of joint purchasing and viewership decisions and estimate the model using demand, pricing, and viewership data from the industry. We use the estimated model to simulate an unrealized regulatory environment: à la carte pricing regulations. We compare the distributions of consumer and producer surplus under a simulated à la carte setting with those under bundling and predict that, in the short run, welfare will increase for many consumers under à la carte regulations, while industry profits will decrease, substantially so for content providers. Finally, we assessed the robustness of our results to changes in our assumptions of outcomes in the wholesale market between content providers and cable and satellite distributors. A more detailed analysis of the long run effects of à la carte regulations remains an area for further research.

⁴⁷Rather than adjusting assumptions about affiliate fees, Yurukoglu (2009) estimates a model of the wholesale bargaining between content providers and distributors to predict these changes on a channel-by-channel basis.

A First-Stage Estimation: Model Aggregation Details

Let Υ^{dm} be the operator that takes a dataset whose units of observation are households within a DMA into the mean of the sample of television household Nielsen takes in DMA d and month m .⁴⁸ Since Nielsen strives to match its sample of television households to the actual demographic distribution, Υ^{dm} has the property that the samples it generates are consistent estimates of the demographic profile of the population of the DMA.⁴⁹ For example, $\Upsilon^{dm}(\{T_i\}_{i \in d})$, in a DMA where Nielsen samples 400 television households, would produce the sample average of 400 observations of leisure time devoted to watching television in DMA d where the demographic distribution of the sample is equal (as close as possible for 400 draws) to the DMA population demographic distribution. Applying Υ^{dm} to the dataset of any demographic variable would produce a sample estimate of the population average of that demographic. For variables involving some choice by the households, applying the Nielsen operator produces a sample estimate of the selected distribution. In our case, applying the Nielsen operator to time spent watching a channel produces the sample mean time spent watching a channel conditional on the bundle selected by each household.

Applying Υ^{dm} to the right-hand side of Equation (9) produces

$$\begin{aligned}\Upsilon^{dm}\beta_{ij} &= \rho'\Upsilon^{dm}(\beta + \Pi D_i + v_i + \Theta a_j) \\ &= \rho'(\beta + \Pi D_d + \eta_{cdm} + \Theta \bar{a}_{dm})\end{aligned}\tag{11}$$

where we assume $D_d = \Upsilon^{dm}D_i$ doesn't vary with m (as the demographic data is taken from the year 2000 Census), $\eta_{cdm} = \Upsilon^{dm}v_i$, and $\bar{a}_{dm} = \Upsilon^{dm}a_j$ are population averages of our approximation covariates for each market and time period.

Before applying Υ^{dm} to the right-hand side of Equation (6), we will manipulate it to overcome difficulties due to its nonlinearity in γ_{ic} . Let t_{cdm} be the average amount of leisure time allocated to watching channel c in DMA d in month m in the bundles chosen by the respective households ($t_{cdm} = \Upsilon^{dm}\{t_{ijc}\}$). Similarly, let γ_{cdm} be the demographic weighted average of

⁴⁸ $\Upsilon^{dm} = \frac{1}{N_{dm}} \sum_{i \in \text{Nielsen sample of DMA } d \text{ and month } m}$ where N_{dm} is the number of households in the Nielsen sample of DMA d and month m . Υ^{dm} satisfies $\Upsilon^{dm}\{kx_{id}\} = k\Upsilon^{dm}\{x_{id}\}$ for k constant and data x . We call Υ^{dm} the Nielsen operator.

⁴⁹Any sampling error here is going to be attributed to unattributable variation in preferences.

the fraction of leisure time households would allocate to channel c if they had all channels available ($\gamma_{cdm} = \Upsilon^{dm}\{\gamma_{ic}\}$).

A first-order Taylor Series expansion of $\gamma^{ic} \log(t_{ijc})$ around (γ_{cdm}, t_{cdm}) yields

$$\gamma_{ic} \log(t_{ijc}) \approx \gamma_{cdm} \log(t_{cdm}) + \log(t_{cdm})(\gamma_{ic} - \gamma_{cdm}) + \frac{\gamma_{cdm}}{t_{cdm}}(t_{ijc} - t_{cdm})$$

Applying Υ^{dm} to this approximation of the right hand side of Equation (6) produces:

$$\Upsilon^{dm} \gamma_{ic} \log(t_{ic}) \approx \gamma_{cdm} \log(t_{cdm}) \quad (12)$$

where the second and third terms in the approximation are 0 by the definition of Υ^{dm} .⁵⁰

Equating Equations (11) and (12) yields our approximation of the population relationship in the data. For channel c ,

$$\gamma_{cdm} \log(t_{cdm}) = \beta_c + \Pi_c D_d + \Theta \bar{a}_{dm} + \eta_{cdm} \quad (14)$$

To estimate this relationship, we replace the population values, t_{cdm} and γ_{cdm} with their sample analogs. For t_{cdm} , this is a direct substitution. Recall the Nielsen rating, r_{cdm} , is measured as:

$$r_{cdm} = \frac{1}{T} \sum_{h=1}^T \Upsilon^{dm} \{ \chi_{\text{household } i \text{ watches } c \text{ in hour } h} \} \quad (15)$$

⁵⁰A second-order approximation would yield, after application of Υ_{dm} :

$$\begin{aligned} \Upsilon^{dm} \gamma_{ic} \log(t_{ijc}) \approx & \gamma_{cdm} \log(t_{cdm}) + \frac{1}{2} [\Upsilon^{dm} (\frac{1}{t_{cdm}} (\gamma_{ic} - \gamma_{cdm}) (t_{ijc} - t_{cdm}))' \\ & - \Upsilon^{dm} (\frac{\gamma_{cdm}}{t_{cdm}^2} (t_{ijc} - t_{cdm})^2)] \end{aligned} \quad (13)$$

The credibility of our first order approximation depends on the variance of the aggregated second order terms. As we do not have information about the variance of t_{ijc} or the covariance between γ_{ic} and t_{ijc} within DMA d and month m , we cannot estimate these additional terms. Our assumption is that the variation in $\Upsilon^{dm} \gamma_{ic} \log(t_{ic})$ is driven by the 0th-order term, $\gamma_{cdm} \log(t_{cdm})$, rather than the second-order terms in the more general approximation.

and t_{cdm} by definition is:

$$\begin{aligned} t_{cdm} &= \Upsilon^{dm}\{t_{ic}\} \\ &= \Upsilon^{dm}\left\{\sum_{h=1}^T \chi_{\text{household } i \text{ watches } c \text{ in hour } h}\right\} \end{aligned}$$

which implies that $r_{cdm}T = t_{cdm}$ because Υ^{dm} is a linear operator.

Determining a sample analog for γ_{cdm} presents more difficulties. Recall that γ_{cdm} is the average fraction of leisure time Nielsen households would allocate to channel c if they had all channels available. The Nielsen rating, on the other hand, is the average fraction of leisure time Nielsen households actually devote to the channel. Because some households do not have access to all channels, γ_{cdm} will generally be less than the Nielsen rating, r_{cdm} .

To account for this difference, we approximate γ_{cdm} with a first-order Taylor Series expansion around r_{cdm} . In particular,

$$\begin{aligned} \gamma_{cdm} \log(r_{cdm}T) &\approx r_{cdm} \log(r_{cdm}T) + \log(r_{cdm}T)(\gamma_{cdm} - r_{cdm}) \\ &\approx r_{cdm} \log(r_{cdm}T) + \zeta_{cdm} \end{aligned} \tag{16}$$

Again, we note that ζ_{cdm} will be smaller the closer the average bundle in DMA d and market m comes to including all potential offered channels and the smaller the total viewing of the bundles (due to the dependence of ζ_{cdm} on $\log(r_{cdm}T)$). These, however, are the same as our approximation-error covariates, \bar{a}_{cdm} . Thus Θ should pick up the effects both of the reduction in utility to a channel due to competition from other channels as well as the difference between measured ratings for a channel and the share of time devoted to it in the presence of all channels.

Inserting our sample estimates of the population values in Equation (14) yields our first-stage estimating equation:

$$r_{cdm} \log(r_{cdm}T) = \beta_c + \Pi_c D_d + \Theta \bar{a}_{dm} + \eta_{cdm} \tag{17}$$

where r_{cdm} is the vector of ratings for each channel in a given DMA d in month m , T is the number of minutes of television viewing measured by Nielsen, \bar{a}_{dm} are the aggregated approximation covariates, and $\eta_{cdm} \equiv \Upsilon^{dm}v_{icm}$.

B Aggregation and Estimation on Market Share Data

This appendix describes our second-stage model and estimation on market share data. As this is standard in the literature, we present an abbreviated version here.

B.1 Aggregating to Market Shares

Recall the utility model (from Equation 5) is given by

$$u_{ijn\text{dm}} = v_{ijn\text{dm}}^* + z'_{jn\text{dm}}\psi - \alpha_i p_{jn\text{dm}} + \xi_{jn\text{dm}} + \sigma_\epsilon \epsilon_{ijn\text{dm}} \quad (18)$$

where $v_{ijn\text{dm}}^* = v_{ijn\text{dm}}^*(\gamma_{ij}, t_i, C_j)$, from (4), represents the indirect utility to household i from viewing the channels available on bundle j in market n , DMA d , and month m .

We normalize the mean utility of not subscribing to any bundle to zero and assume that each household subscribes to the bundle which delivers the highest positive utility, or to no bundle at all. We derive market shares by aggregating households' choices.

Let the portion of utility of bundle j that is common to all households in market n in DMA d in month m be given by

$$\delta_{jn\text{dm}} = z_{jn\text{dm}}\psi - \alpha p_{jn\text{dm}} + \xi_{jn\text{dm}} \quad (19)$$

and let the household specific utility derived from viewing programming in the bundle and price be denoted as

$$\mu_{ijn\text{dm}} = v_{ijn\text{dm}}^* + (\alpha_i - \alpha)p_{jn\text{dm}} \quad (20)$$

Substituting these into Equation (5) yields the following formulation for the indirect utility to household i from bundle j in market n in DMA d :

$$u_{ijn\text{dm}} = \delta_{jn\text{dm}} + \mu_{ijn\text{dm}} + \sigma_\epsilon \epsilon_{ij} \quad (21)$$

Let $A_{jn\text{dm}}$ be the set of households whose individual-specific characteristics induce bundle j having the highest positive utility from the set of bundles available, including the empty

bundle outside good $k = 0$, in market n , DMA d , and month m .⁵¹ Thus

$$A_{jndm} = (i | \delta_{jndm} + \mu_{ijndm} \geq \delta_{kndm} + \mu_{ikndm} \quad \forall k \in J_{ndm}) \quad (22)$$

Under the assumption that $\epsilon_{ij} \sim$ Type I Extreme Value, the model's predicted market share for bundle j in market n in DMA d in month t is given by

$$s_{jndm} = \int_{A_{jndm}} \frac{\exp((\delta_{jndm} + \mu_{ijndm})\sigma_\epsilon^{-1})dF(i)}{\sum_{k=0}^{J_{ndm}} \exp((\delta_{kndm} + \mu_{ikndm})\sigma_\epsilon^{-1})} \quad (23)$$

where $J_{ndm} \equiv \{J_{ndm}^c, J_{ndm}^s, 0\}$ are the set of bundles on offer in market n in DMA d in month m . These consist of all offered cable bundles (J_{ndm}^c), satellite bundles (J_{ndm}^s), and the outside good.

Estimation will partly be based on setting these predicted market shares equal to their empirical counterparts.

B.2 Pricing

In our estimation, we focus on the demand and pricing of cable services and not satellite services. We do this for two reasons: satellite systems price on a national basis and our satellite market share data is limited. The combination of these features limit the information provided by satellite data and increase the costs of using it.⁵²

We assume that each cable system chooses the price of its offered bundles to maximize profits. Due to satellite systems' nationwide-pricing strategy, we assume that individual cable system's take satellite prices as given.

Due to the two-sided nature of television markets, cable system profits consist of both advertising and subscription profits. A sophisticated model of advertising profits would account for the differentiated "audiences" produced by each of its offered bundles, the resulting demand for those audiences by advertisers, and competition between cable systems and other producers of audiences (e.g. satellite and broadcast television providers as well as other

⁵¹In the next section, we describe our parameterization of the individual-specific characteristics of v_{ijndm}^* as a function of household i 's demographic characteristics, D_i , and unobserved tastes for channels, v_i .

⁵²We do, of course, account for the price and characteristics of satellite bundles when measuring cable demand.

media). We unfortunately do not have the data for such a specification. Instead we model the advertising revenue (profits) from bundle j to depend only on the quantity (share) of subscribers that purchase that bundle, denoted $r_j(s_{jndm})$.⁵³

Each system's problem is then

$$\max_{\{p\}_{j=1}^{J_{ndm}}} \sum_{j=1}^{J_{ndm}} (p_{jndm} - mc_{jndm}) s_{jndm}(p_{ndm}) + r_j(s_{jndm}(p_{ndm}))$$

where mc_{jndm} are the marginal costs of providing bundle j in market n in DMA d and month m .⁵⁴

The first-order conditions for this problem are:

$$s_{jndm} + \sum_{j=1}^{J_{ndm}} (p_{jndm} - mc_{jndm}) \frac{\partial s_{jndm}}{\partial p_{jndm}} + r'_j(s_{jndm}) \frac{\partial s_{jndm}}{\partial p_{jndm}} = 0 \quad (24)$$

As marginal cost and marginal advertising revenue are not observed, we assume a functional form for the relationship between the sum of these two terms and other variables in the data:

$$mc_{jndm} - r'_j(s_{jndm}) = w'_{jndm} \theta + \omega_{jndm}$$

where w_{jndm} is a vector of cost shifters (channel, year, and MSO dummies) and market share. ω_{jndm} is an unobservable stochastic term containing factors which affect marginal cost not accounted for in w . These include the deviation from the MSO year means of discounts available to systems of large systems on programming input costs and the quality of the system's local advertising opportunities.

B.3 Estimation on Market Share Data

Recall we estimate $\hat{\beta}$, $\hat{\Pi}$, \hat{G} , and $\hat{\Theta}$ in our first-stage estimation. In the second stage we estimate the remaining parameters of the model using moments from both the bundle demand and pricing equations.

⁵³For convenience in estimation, we further assume the marginal advertising revenue of a subscriber is the same across all bundles offered by the cable system, i.e. $r_j(s_{jndm}) = r(s_{jndm}) \forall j \in J_{ndm}$.

⁵⁴The assumption of constant marginal costs within a cable market is appropriate given that contracts between cable systems and content providers uniformly specify affiliate fees that are linear in subscribers.

The Demand Side The demand-side moments are:

$$\begin{aligned}
 E[\xi_{jndm} z_{jndm}^d] &= 0 \\
 \xi_{jndm} &= \delta_{jndm}(s_{ndm}, x_{ndm}, p_{ndm}; \hat{\beta}, \hat{\Pi}, \hat{G}, \hat{\Theta}, \sigma_\epsilon, \pi_{ip}, \cdot) - z'_{jndm} \psi + \alpha p_{jndm} \\
 Z_{jndm}^d &= [z_{jndm} w_{ndm}]
 \end{aligned}$$

where $\delta_{jndm}(s_{ndm}, x_{ndm}, p_{ndm}; \hat{\beta}, \hat{\Pi}, \hat{G}, \hat{\Theta}, \sigma_\epsilon, \pi_{ip}, \cdot)$ equates predicted and observed market shares for bundle j in market n and month m , given the set of model parameters listed after the semi-colon. It can be computed quickly using the contraction mapping in Berry et al. (1995). In practice, computing these values requires computing a multidimensional integral with no known analytic solution. We use simulation techniques to approximate the true integral, accounting for this approximation in the standard errors.

There are two important issues that arise with this specification. First, while there are two large satellite providers, we observe only the aggregate satellite market share within each DMA. We therefore assume that there is just a single satellite product with characteristics given by the DirecTV Total Choice package.⁵⁵ Second, we are assuming product characteristics, x_{jndm} , are uncorrelated with the unobservable term, ξ_{jndm} . We don't believe the likely bias induced by violations of this assumption will be quantitatively important, in related work, we have worked on relaxing that assumption (Ackerberg and Crawford (2007)). While we are certain that the components of the bundle are chosen purposefully and strategically by the firms,⁵⁶ we do not believe that the factors influencing this decision are correlated with the unobservable term.⁵⁷ Preliminary results in Yurukoglu (2009) generally confirm this belief.

⁵⁵Less restrictive assumptions are possible. We could predict all satellite shares and aggregate the predicted shares to the level of the data.

⁵⁶Other work of ours, Crawford and Shum (2006) and Yurukoglu (2009), incorporates this information into the estimation of demand or cost parameters.

⁵⁷We note that ξ_{jndm} measures the deviation from the MSO-year-bundle mean of extra options such as Internet or high definition (HD) service, promotional activity, technical service, and quality of equipment.

The Supply Side The supply-side moments are of the form

$$\begin{aligned}
E[\omega_{jndm} z_{jndm}^p] &= 0 \\
\omega_{jndm} &= p_{jndm} - (mc_j + r'(s_{jndm}) - \Omega^{-1} s_{ndm}(p_n dm)) \\
&= p_{jndm} - \Omega^{-1} s_{ndm}(p_n dm) - w'_{jndm} \theta \\
&= p_{jndm} - markup_{jn} - w'_{jndm} \theta \\
z_{jndm}^p &= [w_{jndm} \hat{markup}_{jndm}]
\end{aligned}$$

where $S_{jr,n} = -\partial s_{rn} / \partial p_{jn}$, $j, r = 1, \dots, J_n$,

$$\Theta_{jr,n} = \begin{cases} 1, & \text{if in market } n \text{ there exists } f : \{r, j\} \subset F_f; \\ 0, & \text{otherwise} \end{cases} \quad (25)$$

and $\Omega_{jr,n} = \Theta_{jr,n} * S_{jr,n}$.

Estimation proceeds by GMM using a consistent estimate of the optimal weighting matrix. We discuss our choice of instruments in the body of the text.

B.4 Standard Errors

In the first-stage estimation, we calculate block-bootstrap standard errors allowing for correlation within DMA. In the second-stage estimation, there are three sources of error: Sampling Error, Simulation Error, and 1st-Stage Estimation Error. We calculate standard errors using the usual GMM formulas modified to account for the additional sources of error as in Berry et al. (2004). We first compute the expectation of the derivative of the moment conditions at the estimated values. We then compute the variance in the moments generated by sampling error at the estimated values of the parameters. Simulation error arises from simulating the values of the model's predicted market shares in order to compute the set of δ . We fix β , Π , G , and Θ at their estimated values and re-calculating the variance in moment conditions repeatedly using different sets of simulation draws. 1st-Stage estimation error arises from using our estimates, $\hat{\beta}$, $\hat{\Pi}$, \hat{G} , and $\hat{\Theta}$ when calculating market shares. We fix the simulation draws and re-calculate the variance in the moment conditions by repeatedly using draws from the estimated asymptotic distributions of β , Π , G , and Θ . As these three sources of error

are independent, we can simply add the three variance-covariance matrices of the sample moments from each type of error to calculate total standard errors using these aggregates.

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Figure 1: Television Programming Industry

THE CONTENT MARKET

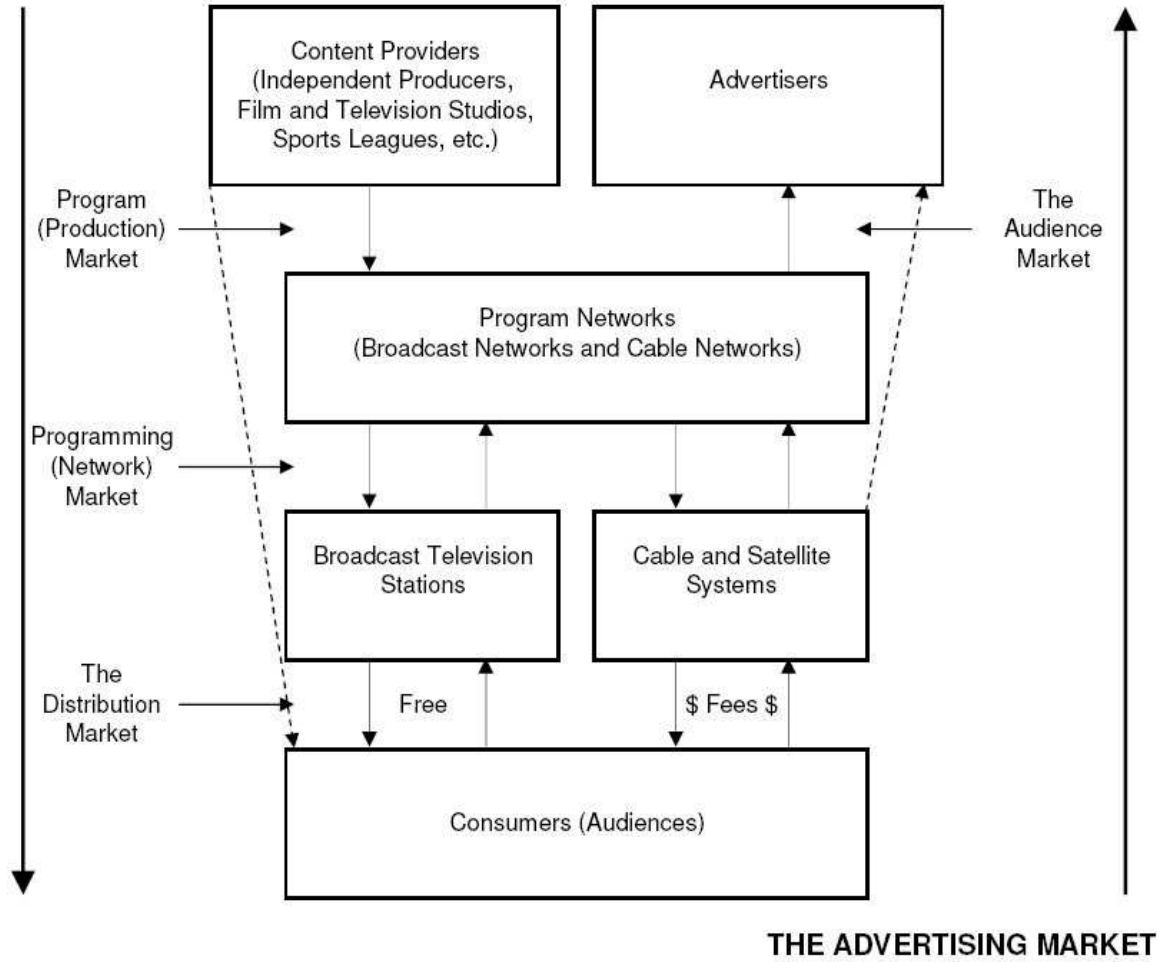
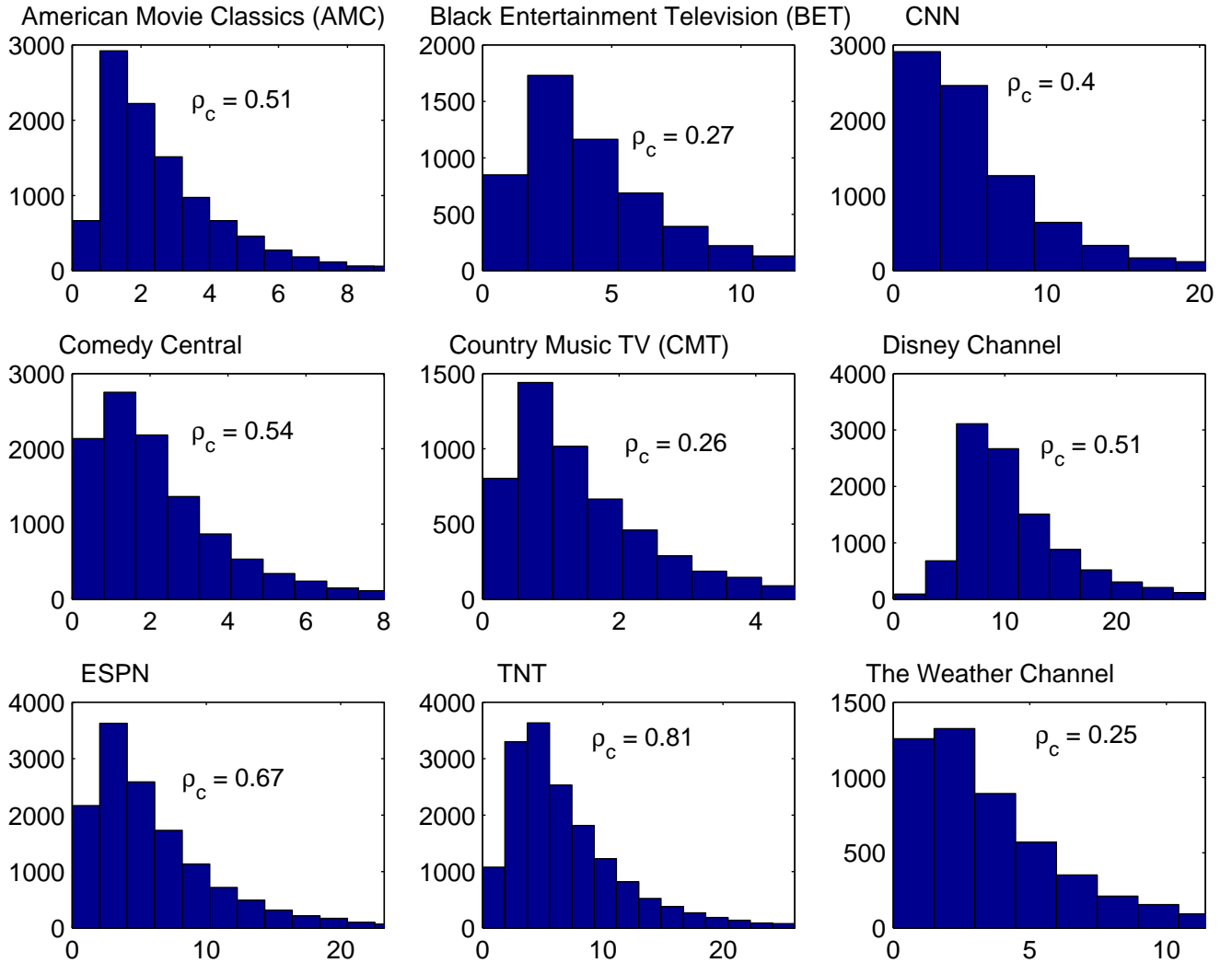


Figure 2: Estimated WTP for a Subset of Channels

Among households with Positive WTP for each Channel, Page 1



Notes: This figure documents the estimated willingness-to-pay for a subset of cable channels among 20,000 simulated households. Reported is the share of those households that value a network positively (ρ_c) and the distribution of WTP among that subset. In each figure, the y-axis reports households and the x-axis reports WTP in 2008 dollars.

Table 1: Sample Statistics, Bundle Purchase Data

| Variable | Nobs | Mean | SDev | Min | Max |
|--|--------|---------|---------|---------|----------|
| Market Types | | | | | |
| Basic Only | 20,117 | 0.601 | 0.49 | 0.00 | 1.00 |
| Basic + Exp. Basic | 20,117 | 0.319 | 0.47 | 0.00 | 1.00 |
| Basic + Dig. Basic | 20,117 | 0.034 | 0.18 | 0.00 | 1.00 |
| Basic + Exp. Basic + Dig. Basic | 20,117 | 0.045 | 0.21 | 0.00 | 1.00 |
| All Markets | | | | | |
| Price | 20,117 | \$29.70 | \$11.59 | \$2.28 | \$146.47 |
| Market Share | 20,117 | 0.461 | 0.259 | 0.010 | 0.990 |
| Total Cable Channels | 20,117 | 20.0 | 15.6 | 0.0 | 176.0 |
| Basic Only Markets | | | | | |
| Basic Service | | | | | |
| Price | 12,105 | \$30.19 | \$7.59 | \$2.43 | \$100.62 |
| Market Share | 12,105 | 0.551 | 0.209 | 0.010 | 0.990 |
| Total Cable Channels | 12,105 | 17.4 | 9.3 | 0.0 | 95.0 |
| Basic + Exp. Basic Markets | | | | | |
| Basic Service | | | | | |
| Price | 3,188 | \$16.53 | \$6.68 | \$2.28 | \$59.82 |
| Market Share | 3,188 | 0.123 | 0.158 | 0.010 | 0.889 |
| Total Cable Channels | 3,188 | 8.1 | 6.9 | 0.0 | 49.0 |
| Exp. Basic Service | | | | | |
| Price | 3,188 | \$34.05 | \$9.05 | \$6.22 | \$89.70 |
| Market Share | 3,188 | 0.559 | 0.193 | 0.010 | 0.969 |
| Total Cable Channels | 3,188 | 26.9 | 9.8 | 3.0 | 84.0 |
| Basic + Dig. Basic Markets | | | | | |
| Basic Service | | | | | |
| Price | 334 | \$45.85 | \$13.42 | \$4.99 | \$78.72 |
| Market Share | 334 | 0.517 | 0.183 | 0.029 | 0.924 |
| Total Cable Channels | 334 | 41.4 | 13.2 | 2.0 | 66.0 |
| Dig. Basic Service | | | | | |
| Price | 334 | \$57.49 | \$18.29 | \$10.36 | \$141.43 |
| Market Share | 334 | 0.120 | 0.081 | 0.010 | 0.705 |
| Total Cable Channels | 334 | 70.0 | 16.5 | 33.0 | 124.0 |
| Basic + Exp. Basic + Dig. Basic Markets | | | | | |
| Basic Service | | | | | |
| Price | 300 | \$16.71 | \$6.92 | \$6.47 | \$48.46 |
| Market Share | 300 | 0.220 | 0.119 | 0.011 | 0.625 |
| Total Cable Channels | 300 | 7.6 | 5.5 | 1.0 | 35.0 |
| Exp. Basic Service | | | | | |
| Price | 300 | \$45.32 | \$10.93 | \$16.69 | \$89.70 |
| Market Share | 300 | 0.367 | 0.145 | 0.013 | 0.799 |
| Total Cable Channels | 300 | 47.0 | 10.8 | 19.0 | 89.0 |
| Dig. Basic Service | | | | | |
| Price | 300 | \$60.43 | \$17.18 | \$23.30 | \$146.47 |
| Market Share | 300 | 0.124 | 0.077 | 0.010 | 0.474 |
| Total Cable Channels | 300 | 81.2 | 20.5 | 39.0 | 176.0 |

Notes: Reported are sample statistics from our bundle purchase data for all markets and by type of bundles they offer. Prices are in 2008 dollars. Market shares are defined as subscribers divided by homes passed, with homes passed defined as the set of households able to purchase cable service from each system. Both are in the data. Total cable channels defined in Table 2.

Table 2: Sample Statistics, Cable Networks 1-30

| Network | Any Tier | Basic | Expanded Basic | Digital Basic | Average Rating | Average Cume |
|-------------------------------|----------|-------|----------------|---------------|----------------|--------------|
| ESPN | 0.97 | 0.77 | 0.19 | 0.00 | 0.91 | 22.2 |
| Discovery Channel | 0.86 | 0.72 | 0.14 | 0.00 | 0.62 | 18.6 |
| TBS | 0.97 | 0.92 | 0.05 | 0.00 | 1.09 | 24.0 |
| TNT | 0.82 | 0.64 | 0.18 | 0.00 | 1.33 | 27.2 |
| USA | 0.87 | 0.67 | 0.19 | 0.00 | 1.17 | 27.2 |
| Nickelodeon | 0.68 | 0.53 | 0.15 | 0.00 | 1.83 | 0.0 |
| CNN | 0.94 | 0.78 | 0.16 | 0.00 | 0.75 | 13.6 |
| Lifetime | 0.56 | 0.42 | 0.14 | 0.00 | 0.90 | 16.7 |
| Spike | 0.86 | 0.70 | 0.16 | 0.00 | 0.52 | 17.7 |
| The Weather Channel | 0.52 | 0.41 | 0.11 | 0.00 | 0.30 | 8.4 |
| HGTV | 0.21 | 0.13 | 0.07 | 0.01 | 0.55 | 14.0 |
| VH1 | 0.33 | 0.23 | 0.10 | 0.00 | 0.36 | 14.0 |
| TLC (The Learning Channel) | 0.40 | 0.30 | 0.10 | 0.00 | 0.54 | 15.1 |
| ESPN 2 | 0.30 | 0.20 | 0.09 | 0.01 | 0.29 | 12.3 |
| Cartoon Network | 0.24 | 0.16 | 0.08 | 0.00 | 1.57 | 10.0 |
| History Channel | 0.26 | 0.18 | 0.08 | 0.01 | 0.55 | 16.7 |
| ABC Family Channel | 0.91 | 0.76 | 0.14 | 0.00 | 0.42 | 15.8 |
| CNBC | 0.29 | 0.20 | 0.10 | 0.00 | 0.20 | 3.9 |
| Animal Planet | 0.18 | 0.12 | 0.06 | 0.00 | 0.34 | 11.8 |
| Food Network | 0.08 | 0.05 | 0.04 | 0.00 | 0.41 | 12.9 |
| Fox News Channel | 0.15 | 0.10 | 0.05 | 0.00 | 0.76 | 12.8 |
| American Movie Classics (AMC) | 0.48 | 0.32 | 0.17 | 0.00 | 0.52 | 17.0 |
| Arts & Entertainment (A&E) | 0.64 | 0.49 | 0.15 | 0.00 | 0.70 | 18.7 |
| Comedy Central | 0.18 | 0.11 | 0.07 | 0.00 | 0.49 | 18.3 |
| Disney Channel | 0.38 | 0.30 | 0.08 | 0.00 | 1.19 | 16.9 |
| TV Land | 0.19 | 0.15 | 0.04 | 0.00 | 0.47 | 10.8 |
| FX | 0.15 | 0.10 | 0.06 | 0.00 | 0.53 | 19.7 |
| MTV | 0.43 | 0.29 | 0.13 | 0.00 | 0.70 | 17.3 |
| E! Entertainment Television | 0.17 | 0.11 | 0.06 | 0.00 | 0.29 | 13.0 |
| Sci-Fi Channel | 0.24 | 0.16 | 0.08 | 0.01 | 0.53 | 14.7 |
| Top30 | 14.27 | 11.00 | 3.23 | 0.04 | | |
| TopNets | 16.89 | 12.32 | 3.78 | 0.78 | | |
| Regional Sports | 0.39 | 0.24 | 0.12 | 0.02 | | |
| Other Channels | 2.71 | 2.15 | 0.63 | 0.32 | | |
| All Nets | 20.55 | 15.12 | 4.65 | 1.20 | | |

Notes: Reported are summary statistics from both our bundle purchase and viewership data. The first column reports carriage of each cable channel on *any* offered service (Any Tier). The remaining columns disaggregate carriage by tier. The channels reported are the 30 most widely available cable networks as of 2008 (Kagan World Media (2008)). Regional sports aggregates across regional sports networks (which differ across the country). Also reported are the total number of top-30, top-90, and all networks. Only cable channels are included in this table - broadcast, premium, and pay-per-view channels are not. The last two columns report summary statistics from our Nielsen viewership data. The second-to-last column reports the average rating for all programs on that channel for the four Nielsen sweeps months between 2000 and 2006. The last column reports the national average cumulative rating, or “cume”, for that channel during the fourth quarter of 2006. The national cumulative rating of a channel in a given week is the Nielsen estimate of the total number of unique television households that tuned into that channel for at least 15 minutes during that week. The average is across the 13 weeks in the quarter.

Table 3: Parameter Estimates, Selected Channels

| | Demand Estimate (StdErr) | Cost Estimate (StdErr) | Exponential Estimate (StdErr) | Share Positive | Mean | Mean Among Positive |
|---|-----------------------------|---------------------------|----------------------------------|----------------|--------|---------------------|
| Non-Channel Estimates | | | | | | |
| Price | -0.13 (0.00) | — | — | | | |
| Price Income Effect | 0.04 (0.00) | — | — | | | |
| log(# of channels) | -0.36 (0.02) | — | — | | | |
| log(# of channels) x log(1+sum ratings) | -0.65 (0.06) | — | — | | | |
| Channel Estimates | | | | | | |
| ABC Family Channel | 0.01 (0.03) | 0.16 (0.59) | 0.105 (0.004) | 0.465 | \$0.80 | \$1.73 |
| American Movie Classics (AMC) | 0.04 (0.05) | 2.26 (0.44) | 0.128 (0.005) | 0.513 | \$1.12 | \$2.19 |
| Black Entertainment Television (BET) | 0.17 (0.08) | 4.59 (0.56) | 0.206 (0.027) | 0.268 | \$0.97 | \$3.62 |
| Bravo | 0.01 (0.04) | 2.48 (0.90) | 0.093 (0.004) | 0.377 | \$0.49 | \$1.30 |
| CNN | 0.10 (0.11) | 4.47 (0.85) | 0.310 (0.016) | 0.403 | \$1.86 | \$4.62 |
| Comedy Central | 0.10 (0.07) | -5.08 (0.57) | 0.115 (0.004) | 0.543 | \$1.01 | \$1.86 |
| Country Music TV (CMT) | 0.05 (0.03) | 1.95 (0.40) | 0.084 (0.005) | 0.265 | \$0.34 | \$1.27 |
| Disney Channel | 0.46 (0.17) | 3.51 (0.43) | 0.353 (0.020) | 0.515 | \$4.59 | \$8.92 |
| ESPN | 0.23 (0.17) | 3.53 (1.05) | 0.315 (0.019) | 0.674 | \$3.39 | \$5.03 |
| Food Network | 0.07 (0.07) | 2.29 (1.02) | 0.122 (0.005) | 0.388 | \$0.72 | \$1.86 |
| Lifetime | 0.21 (0.12) | 2.74 (0.45) | 0.245 (0.011) | 0.494 | \$2.83 | \$5.73 |
| MTV | 0.02 (0.07) | -0.04 (0.43) | 0.178 (0.006) | 0.513 | \$1.30 | \$2.53 |
| National Geographic Channel | 0.03 (0.02) | 7.51 (1.85) | 0.044 (0.004) | 0.296 | \$0.21 | \$0.72 |
| Nickelodeon | 0.19 (0.15) | -1.66 (0.47) | 0.424 (0.020) | 0.606 | \$6.32 | \$10.43 |
| SPEED Channel | 0.00 (0.02) | 3.85 (1.08) | 0.068 (0.006) | 0.175 | \$0.16 | \$0.92 |
| USA | 0.27 (0.16) | 5.87 (0.55) | 0.243 (0.010) | 0.816 | \$4.05 | \$4.96 |
| VH1 | 0.08 (0.05) | 0.25 (0.48) | 0.099 (0.004) | 0.420 | \$0.67 | \$1.60 |
| The Weather Channel | -0.01 (0.03) | -3.14 (0.45) | 0.219 (0.024) | 0.252 | \$0.79 | \$3.13 |
| Regional Sports | 0.01 (0.08) | 3.44 (0.42) | 0.312 (0.024) | 0.400 | \$1.75 | \$4.38 |

Notes: Reported are combined results from both stages of our estimation procedure. Channel demand (first column, bottom panel) and exponential estimates (third column, bottom panel) are results from our first-stage estimation on aggregate ratings data (cf. Equation 10). For each channel, c , the exponential estimate is the value that equates the variance of the residual in the first-stage regression for channel c , $V(\eta_{cdm})$, across DMAs and months with the variance of the average of 400 Nielsen households drawn from a mixture distribution with $1 - \rho_c$ valuing channel c at zero and ρ_c valuing it according to an exponential distribution. ρ_c is, for channel c , equal to 3 times the average cume as reported in Table 2. The demand estimate is the value of β_c that ensures no households have negative tastes for networks. Non-channel estimates (top panel) and channel cost estimates (in the 2nd column of the bottom panel) are results from the GMM estimation of aggregate demand and pricing for up to 3 cable services and satellite service. Standard errors allowing arbitrary correlation within system-years and accounting for sampling, first-stage estimation, and simulation error are reported in parentheses. To facilitate interpretation of the channel estimates, also reported are the share positive, average WTP, and average WTP among households with positive WTP among 5,000 simulated households.

Table 4: Baseline Counterfactual

| Bundling Equilibrium | | | | Full À La Carte Equilibrium | | | | Percent Change | |
|------------------------------|-------------|-------------|-------------|----------------------------------|-------------|-------------|---------------|----------------|-------|
| Bundle Price | | | | Channel Prices and Market Shares | | | | | |
| | Cable | Satellite 1 | Satellite 2 | Channel Prices | | | Shares | | |
| Full Bundle | \$51.79 | \$36.78 | \$35.28 | Cable | Satellite 1 | Satellite 2 | All Platforms | | |
| | | | | Fixed Fee | \$31.94 | \$17.16 | \$15.58 | \$24.10 | |
| | | | | ABC Family | \$0.48 | \$0.51 | \$0.51 | 0.524 | |
| | | | | AMC | \$0.37 | \$0.46 | \$0.46 | 0.563 | |
| | | | | BET | \$0.45 | \$0.41 | \$0.39 | 0.307 | |
| | | | | Bravo | \$0.40 | \$0.40 | \$0.40 | 0.360 | |
| | | | | CNN | \$1.20 | \$1.11 | \$1.11 | 0.408 | |
| | | | | Comedy | \$0.31 | \$0.31 | \$0.31 | 0.565 | |
| | | | | CMT | \$0.02 | \$0.02 | \$0.02 | 0.311 | |
| | | | | Disney | \$4.24 | \$4.24 | \$4.24 | 0.572 | |
| | | | | ESPN | \$6.35 | \$6.35 | \$6.35 | 0.212 | |
| | | | | Food | \$0.21 | \$0.15 | \$0.15 | 0.432 | |
| | | | | Lifetime | \$0.84 | \$0.62 | \$0.55 | 0.576 | |
| | | | | MTV | \$0.64 | \$0.65 | \$0.67 | 0.551 | |
| | | | | Natl. Geog. | \$0.47 | \$0.47 | \$0.48 | 0.189 | |
| | | | | Nickelodeon | \$1.74 | \$1.22 | \$1.10 | 0.695 | |
| | | | | SPEED | \$0.38 | \$0.40 | \$0.41 | 0.137 | |
| | | | | USA | \$0.82 | \$1.02 | \$1.02 | 0.924 | |
| | | | | VH1 | \$0.25 | \$0.26 | \$0.28 | 0.463 | |
| | | | | Weather | \$0.29 | \$0.29 | \$0.29 | 0.282 | |
| | | | | Avg P or Share | \$0.69 | \$0.67 | \$0.67 | 0.393 | |
| Platform Market Shares | | | | Platform Market Shares | | | | | |
| Cable | Satellite 1 | Satellite 2 | Total | Cable | Satellite 1 | Satellite 2 | Total | | |
| 0.564 | 0.201 | 0.115 | 0.880 | 0.580 | 0.213 | 0.123 | 0.916 | 4.1 | |
| Distributor Profits | | | | Distributor Profits | | | | | |
| Cable | Satellite 1 | Satellite 2 | Total | Cable | Satellite 1 | Satellite 2 | Total | | |
| \$19.00 | \$3.58 | \$1.83 | \$24.41 | \$19.61 | \$3.80 | \$1.96 | \$25.37 | 4.0 | |
| Channel Affiliate Fee Profit | | | | Channel Affiliate Fee Profit | | | | | |
| Cable | Satellite 1 | Satellite 2 | Total | Cable | Satellite 1 | Satellite 2 | Total | | |
| \$10.22 | \$3.82 | \$2.22 | \$16.27 | \$6.96 | \$2.67 | \$1.57 | \$11.20 | -31.1 | |
| Channel Advertising Profit | | | | Channel Advertising Profit | | | | | |
| | | | \$12.56 | | | | \$12.58 | 0.1 | |
| Total Industry Profits | | | | Total Industry Profits | | | | | |
| | | | Total | | | | Total | | |
| | | | \$53.23 | | Cable | Satellite 1 | Satellite 2 | Total | |
| Channels Purchased | | | | Channels Purchased | | | | \$49.15 | -7.7 |
| | | | 52.0 | | | | | 17.9 | -65.7 |
| Average Consumer Expenditure | | | | Average Consumer Expenditure | | | | \$39.93 | -13.6 |
| | | | \$46.22 | | | | | | |
| Consumers Surplus | | | | Consumers Surplus | | | | | |
| 25th Perc | Median | 75th perc | Mean | 25th Perc | Median | 75th perc | Mean | | |
| \$23.68 | \$36.39 | \$55.50 | \$44.13 | \$28.06 | \$39.79 | \$58.44 | \$47.79 | 8.3 | |
| Total Welfare | | | | Total Welfare | | | | \$96.94 | -0.4 |
| | | | \$97.36 | | | | | | |

Notes: Reported are results from our baseline counterfactual. In it, we simulate economic outcomes under two scenarios. Both scenarios feature competition between a “nationally-representative” cable system and two national satellite systems, each offering access to their platform and 52 cable channels. In the bundling equilibrium, each firm competes by pricing a single bundle of channels. In the full à la carte equilibrium, each firm competes by setting a fixed fee and individual prices for each channel. Marginal costs to each firm for each channel are assumed to be equal to the national average for that channel for 2008 (from Kagan World Media (2008)) times (1.03/1.08/1.11) for the (cable/satellite1/satellite2) distributor. Reflecting likely changes in the wholesale programming market under the à la carte counterfactual, marginal costs in the à la carte equilibrium are 75% higher than in the bundling equilibrium. Table 7 assess the robustness of our conclusions to variation in that assumption. Individual table elements are described in greater detail in Section XXX. The last column reports estimated changes in various outcomes between the bundling and à la carte equilibria.

Table 5: Welfare Effects by Channel, Channels 1-30

| Network | Firm Effects | | | | | Consumer Effects |
|-------------------------------|---------------|------------|----------------|--------------------------------|------------------------------|--------------------------------------|
| | Total Revenue | | | Component Revenues | | Welfare Discount if Purchase Channel |
| | Bundle | À La Carte | Percent Change | % Change Affiliate Fee Revenue | % Change Advertising Revenue | |
| ESPN | \$3.98 | \$1.53 | -61.7% | -66.3% | -47.5% | -207.1% |
| Discovery Channel | \$0.61 | \$0.59 | -3.2% | -9.2% | 3.2% | -5.5% |
| TBS | \$0.91 | \$1.02 | 12.1% | 25.0% | 4.6% | -3.1% |
| TNT | \$1.63 | \$1.92 | 17.8% | 28.6% | 1.0% | -14.5% |
| USA | \$1.18 | \$1.46 | 24.0% | 46.9% | 6.0% | -4.2% |
| Nickelodeon | \$1.41 | \$1.51 | 7.1% | 10.5% | 5.4% | -16.4% |
| CNN | \$0.89 | \$0.72 | -19.1% | -35.1% | 2.4% | -4.4% |
| Lifetime | \$0.76 | \$0.77 | 1.5% | -7.9% | 6.2% | -15.0% |
| Spike | \$0.51 | \$0.49 | -2.1% | -11.4% | 4.4% | 10.8% |
| The Weather Channel | \$0.26 | \$0.20 | -21.7% | -55.4% | 5.8% | 36.1% |
| HGTV | \$0.54 | \$0.53 | -3.2% | -27.5% | 6.1% | 20.7% |
| VH1 | \$0.51 | \$0.50 | -3.0% | -26.1% | 5.6% | 15.9% |
| TLC (The Learning Channel) | \$0.37 | \$0.34 | -9.3% | -23.6% | 5.0% | 13.6% |
| ESPN 2 | \$0.44 | \$0.31 | -28.7% | -47.4% | 0.0% | -4.8% |
| Cartoon Network | \$0.49 | \$0.48 | -2.1% | -15.8% | 5.5% | 1.3% |
| History Channel | \$0.48 | \$0.46 | -4.1% | -15.7% | 4.7% | 10.7% |
| ABC Family Channel | \$0.44 | \$0.41 | -7.7% | -16.7% | 4.4% | -4.9% |
| Animal Planet | \$0.17 | \$0.14 | -16.8% | -36.5% | 6.1% | -2.0% |
| Food Network | \$0.38 | \$0.38 | 0.2% | -30.4% | 5.6% | 18.4% |
| Fox News Channel | \$0.66 | \$0.58 | -12.2% | -34.2% | 5.1% | -11.6% |
| American Movie Classics (AMC) | \$0.38 | \$0.36 | -5.0% | -10.3% | 5.8% | 8.1% |
| Arts & Entertainment (A&E) | \$0.55 | \$0.56 | 2.4% | -0.5% | 4.6% | -10.4% |
| Comedy Central | \$0.54 | \$0.54 | 0.5% | -10.8% | 4.0% | 3.3% |
| Disney Channel | \$1.97 | \$1.79 | -9.0% | -9.0% | — | -109.0% |
| TV Land | \$0.26 | \$0.23 | -13.3% | -42.2% | 5.4% | 3.7% |
| FX | \$0.62 | \$0.61 | -1.7% | -5.8% | 2.8% | -8.7% |
| MTV | \$1.13 | \$1.12 | -0.8% | -12.4% | 3.8% | -1.4% |
| E! Entertainment Television | \$0.37 | \$0.24 | -33.9% | -51.7% | -6.8% | 3.9% |
| Sci-Fi Channel | \$0.50 | \$0.48 | -4.6% | -21.6% | 5.3% | 10.5% |

Notes: This table reports welfare effects by channel for both firms (content providers) and consumers. The first three columns report the predicted change in total revenue (equal to affiliate fee + advertising revenue) to content providers for each of the 52 channels in our counterfactual simulation. Units are 2008 dollars per subscriber per month. Affiliate fee revenue equals affiliate fee times 110 million US households times market share by distributor aggregated across distributor. Advertising revenue under bundling is from Kagan World Media (2008); advertising revenue under à la carte is the same times the percent change in ratings predicted by the model. The next two columns document the relative importance of changes in affiliate fee and advertising revenue to a channel's total revenue change. The last column reports, for each channel, the average change in consumer welfare (from bundling to à la carte) for consumers that purchase that channel as a share of the average change in welfare of all consumers. This calculation is made for only those households among 5,000 simulated households that purchase the median (+/- 1) number of channels.

Table 6: Welfare Effects by Channel, Channels 31+

| Network | Firm Effects | | | | | Consumer Effects |
|--------------------------------|---------------|------------|----------------|--------------------------------|------------------------------|--------------------------------------|
| | Total Revenue | | | Component Revenues | | Welfare Discount if Purchase Channel |
| | Bundle | À La Carte | Percent Change | % Change Affiliate Fee Revenue | % Change Advertising Revenue | |
| Court TV | \$0.27 | \$0.24 | -10.1% | -31.5% | 5.8% | 8.3% |
| MSNBC | \$0.27 | \$0.19 | -30.5% | -55.0% | 5.3% | 18.3% |
| Bravo | \$0.33 | \$0.26 | -21.0% | -42.6% | 0.0% | 9.9% |
| Black Entertainment Television | \$0.49 | \$0.43 | -12.4% | -51.2% | 6.7% | 0.6% |
| Travel Channel | \$0.18 | \$0.14 | -22.1% | -47.3% | 5.3% | 21.3% |
| Country Music TV (CMT) | \$0.16 | \$0.14 | -11.6% | -50.0% | 9.3% | 40.2% |
| TV Guide Channel | \$0.16 | \$0.14 | -12.1% | -47.8% | 8.8% | 21.8% |
| Turner Classic Movies | \$0.32 | \$0.14 | -56.0% | -56.0% | — | 16.9% |
| SPEED Channel | \$0.26 | \$0.11 | -58.9% | -78.4% | -10.6% | 5.1% |
| Hallmark Channel | \$0.23 | \$0.23 | -2.7% | -32.7% | 9.8% | 4.2% |
| Versus | \$0.18 | \$0.07 | -61.2% | -81.1% | 0.0% | 25.4% |
| Game Show network | \$0.12 | \$0.09 | -26.6% | -67.4% | 9.4% | 13.7% |
| MTV2 | \$0.08 | \$0.06 | -31.2% | -71.4% | 0.0% | 41.8% |
| Oxygen | \$0.31 | \$0.16 | -48.0% | -65.9% | -3.4% | 1.0% |
| WE: Womens Entertainment | \$0.17 | \$0.10 | -42.9% | -68.7% | -1.3% | 21.2% |
| National Geographic Channel | \$0.30 | \$0.14 | -55.5% | -69.9% | -18.1% | 14.2% |
| SoapNet | \$0.16 | \$0.07 | -52.8% | -73.9% | 4.8% | 32.2% |
| Toon Disney | \$0.14 | \$0.08 | -42.2% | -75.4% | 5.1% | 15.1% |
| Noggin / The N | \$0.16 | \$0.04 | -72.8% | -84.7% | 0.0% | -21.8% |
| Lifetime Movie Network | \$0.16 | \$0.10 | -35.9% | -56.6% | 5.9% | 10.0% |
| The Science Channel | \$0.08 | \$0.03 | -65.3% | -82.6% | -16.7% | 18.8% |
| NickToons TV | \$0.07 | \$0.02 | -66.4% | -84.8% | -0.2% | 26.6% |
| Regional Sports | \$1.27 | \$0.52 | -59.2% | -59.2% | — | -97.9% |
| Total (Among These Channels) | \$28.82 | \$23.77 | -17.5% | -31.1% | 0.1% | — |

Notes: See notes for Table 5 above.

Table 7: Counterfactual Robustness

| | Baseline | 75% Higher Costs À La Carte | | Constant Costs À La Carte | | 150% Higher Costs À La Carte | |
|------------------------------|----------|--------------------------------|-------|------------------------------|-------|---------------------------------|-------|
| | | Bundle | Level | Change | Level | Change | Level |
| Results | | | | | | | |
| Fixed Fee | | \$24.10 | | \$22.79 | | \$21.48 | |
| Weighted Average Price | \$46.21 | \$0.68 | | \$0.43 | | \$1.19 | |
| Average Channel Share | | 0.314 | | 0.440 | | 0.338 | |
| Platform Share | 0.880 | 0.916 | 4.1 | 0.954 | 8.4 | 0.898 | 2.1 |
| Distributor Profits | \$24.41 | \$25.37 | 4.0 | \$23.91 | -2.0 | \$22.39 | -8.3 |
| Channel Aff. Fee Profits | \$16.27 | \$11.20 | -31.1 | \$7.90 | -51.4 | \$15.19 | -6.6 |
| Channel Advertising Profits | \$12.56 | \$12.58 | 0.1 | \$12.99 | 3.4 | \$12.16 | -3.2 |
| Industry Profits | \$53.23 | \$49.15 | -7.7 | \$44.80 | -15.8 | \$49.73 | -6.6 |
| Channels Purchased | 52.0 | 17.9 | -65.7 | 23.1 | -55.6 | 18.6 | -64.3 |
| Average Consumer Expenditure | \$46.22 | \$39.93 | -13.6 | \$33.52 | -27.5 | \$42.12 | -8.9 |
| Mean Consumers Surplus | \$44.13 | \$47.79 | 8.3 | \$57.92 | 31.2 | \$44.87 | 1.7 |
| Mean Total Surplus | \$97.36 | \$96.94 | -0.4 | \$102.71 | 5.5 | \$94.60 | -2.8 |
| Assumptions | | | | | | | |
| Marginal Costs | Kagan | Kagan x 1.75 | | Kagan | | Kagan x 2.5 | |
| Channels | All | All | | All | | All | |
| Fixed Fee | None | Comp. | | Comp. | | Comp. | |

Notes: This table reports the sensitivity of our welfare conclusions to our assumptions about the increase in affiliate fees under à la carte. Our baseline assumption in Tables 4-7 are that they increase by 75%. In the second and third groups of columns we report the same economic outcomes as in Table 4 under the assumption that costs do not increase (constant costs) or go up twice as much as in the baseline (150% higher costs).