Essays in Industrial Organization

by

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LIST OF ABBREVIATIONS

DMA Designated Media Area

GMM Generalized Method of Moments

FCC Federal Communications Commission

DOJ Department of Justice

ABSTRACT

My research analyzes the impact that new technology can have on consumers' welfare and the strategic responses from firms. My dissertation focuses on the television industry, which has experienced dramatic changes within the last decade with improvements in technology and the introduction of streaming video services. The entry of streaming video services is important to study because this new product has had a disruptive effect on the economic environment for the television industry, including direct and indirect effects on consumer welfare.

In chapter one, I explore the implications of the direct effect of streaming video services on consumer product choice and consumer welfare. To quantify the benefits from streaming video services, I build a model for the demand of television services in the United States. The model uses the multiple-discrete choice framework, which allows for consumers to choose a traditional package, a streaming video service, or a combination of these services. To estimate the model, I construct a new market-level dataset with prices, product characteristics, and observed demand for 2014 and 2015. I then conduct three counterfactual simulations to measure the change in consumer welfare when a product is removed from the choice set. The simulation results suggest that removing the streaming service has around 3 times as large of an effect on consumer welfare as compared to removing a satellite provider.

Then, in chapter two I explore the indirect effects that the entry of streaming services had on consumer welfare through cable television package prices. In particular, I examine the strategic response to this new product for the cable package prices. I quantify

this effect by expanding upon the methodology from chapter one to include a supply-side Bertrand-Nash equilibrium with differentiated products. Then, I use GMM to estimate the cost parameters for cable providers. After these parameters are estimated, I run a counterfactual simulation that removes the streaming service from the consumer's choice sets and re-evaluates the equilibrium prices for cable providers. I find that the entry of streaming services may have led to a \$15 increase in cable prices per month, and the median consumer welfare effect is \$6.26 per month, which means that as of 2014 and 2015 the median household would be willing to pay \$6.26 per month to avoid the higher cable prices from the entry of Netflix.

Finally, changes in the economic environment from the entry of a new product will have implications for competition. Therefore, streaming services should be considered when analyzing antitrust cases, new policies, and regulations. In the third chapter, I use the models and data from chapters one and two to examine a proposed horizontal merger between the top two cable providers in the era of streaming services to understand the impact that this merger would have on consumer welfare. When considering a horizontal merger, antitrust authorities weigh the pros and cons. The case for a merger would be synergies in production or increased scale which could lead to lower costs and ultimately lower prices for consumers. The case against a merger could be the concern for increased concentration where the firms can exert more market power and ultimately raise prices. The counterfactual simulation in this chapter quantifies the consumer welfare effect from the proposed merger between Comcast and Time Warner Cable. I find that the median consumer welfare effect is \$4.01 per month, which means that as of 2014 and 2015 the median household would be willing to pay \$4.01 per month to avoid the higher cable prices from the merger of Comcast and Time Warner Cable. Therefore, the antitrust authorities were justifiably concerned about this proposed merger.

INTRODUCTION

My dissertation is comprised of three chapters, tied by motivation and methodology. Each successive chapter deepens my analysis of the impact that new technology can have on the economic environment within an industry. In particular, my dissertation focuses on the television industry, which has experienced dramatic changes within the last decade with the improvements in technology and the entry of streaming video services.

The entry of a new product will have implications for the economic environment within an industry. However, not all new products have the same impact on an industry. When a new product enters the market, it can be categorized as a minor improvement to an existing product, or it can define an entirely new category of a product. For example, the introduction of satellite and streaming services offer an interesting contrast. Satellite services could be classified as a minor improvement to a pre-existing product, cable packages. While streaming video services could be classified as a more disruptive new product, creating an entirely new type of television service. They offered a new and more flexible way for viewers to consume television. Therefore, the entry of streaming video services is important to study because this new product has had a disruptive effect on the economic environment for the television industry, including direct and indirect effects on consumer welfare.

The direct effect of a new product on consumer welfare is captured with the consumer product choice decision. When a new product enters, consumers can choose an entirely new type of television service, which can directly affect their welfare. The indirect effect on consumer welfare includes changes to characteristics of other products in the market, such as price. There are two channels in which a new product can affect the price of television services: (1) the pricing condition for television distributors through increased competition and (2) the bargaining between upstream television content producers and downstream television content distributors. The increased competition should have downward pressure on prices. While the bargaining environment could have upward pressure on prices due to the changes to the market structure in the television industry, which could lead to increased input costs from the negotiations over licensing fees for content.

The three channels that a new product can affect consumer welfare are studied in chapters one and two. I explore the implications of the direct effect on consumer product choice and consumer welfare in chapter one. Then, in chapter two I explore the indirect effects that the entry of streaming services had on consumer welfare through cable television package prices. Finally, changes in the economic environment from the entry of a new product will have implications for competition. Therefore, streaming services should be considered when analyzing antitrust cases, new policies, and regulations. In chapter three, I use the models and data from chapters one and two to examine a proposed horizontal merger between the top two cable providers in the era of streaming services.

CHAPTER 1

Quantifying the Benefits to Consumers of Subscription-based Streaming Video Services

1.1 Introduction

The television industry has changed dramatically within the last decade, with vast improvements in technology and the entry of streaming video services. Streaming video services flourished, and consumers started opting-out of their traditional services with the first ever decline in the total traditional subscriber count in 2013. Traditional providers recognize the competitive pressures they face from this new delivery method:

> "...any analysis of the state of video competition that ignores or minimizes the impact of online video distributors will seriously miss the mark." (Comcast comment for Federal Communications Commission (FCC) 2015 Video Competition Report)

However, the literature and policy analysis continue to isolate traditional services when analyzing the industry. Using new data, in this chapter, I quantify the direct effect that streaming services have had on consumer welfare. As outlined in the introduction to my dissertation, this is the first of three channels for the entry of streaming services to impact consumer welfare.

In order to quantify the benefits from streaming video services, I build a model for the demand of television services in the United States. I use a random coefficient multiple-discrete choice framework which allows for consumers to choose a traditional package, a streaming video service, or a combination of these services. The model is estimated using a new market-level data set that I assembled from a variety of sources. This dataset includes information on product characteristics, subscription prices, and market shares for the top providers for 2014 and 2015. Based on the model's estimates, I find that even after allowing for the multiple-discrete choice, the cross-price elasticities between traditional and streaming services are positive, which suggests that consumers view these services as substitutes.

Then, using my model, I run three counterfactual simulations. In each simulation I remove a provider from the choice set, and then I use compensating variation to quantify the welfare effect. I find that the median household[1] would need to be paid \$69 annually in order to be compensated for the loss of Netflix. [2] This is approximately three times the \$25 compensation required when the simulation is repeated with the DirecTV services removed for the same years. These results highlight that streaming video services are highly valued by consumers, and suggest that it is important to include streaming services in the model for the demand of television services.

This chapter contributes to three branches of the industrial organization literature: new product valuation, multiple-discrete choice framework, and studies of the television industry. When a new product enters the market it can be categorized as a minor improvement to an existing product, or it can define an entirely new category of a product. For example, one could classify the entry of satellite services as a minor improvement to pre-existing cable packages. In contrast, streaming services were a more disruptive innovation—they offered a new and more flexible way for viewers to consume television. Previous studies have investigated the welfare effects from the introduction of satellite services, such as Goolsbee and Petrin (2004), Chu (2010), and Crawford et al. (2019). A key assumption in these papers was that consumers were making a single-discrete choice. This assumption was appropriate given the nature of the products available at the time (cable and satellite subscriptions). However, after streaming services were introduced some consumers subscribed to a combination[3] of traditional and streaming services. Therefore, the single-discrete choice is no longer appropriate.

My chapter extends previous studies of the television industry in three ways. The first extension allows consumers to choose more than one type of television service. My model for demand builds on the methodology developed in the multiple-discrete choice literature, such as Fan (2013), Hendel (1999), Dube (2004). The multiple-discrete choice assumption implies that consumers can choose a variety of services, an important feature of the current landscape. The second extension is the construction of a new dataset[4]. This dataset spans a later time period, and it is the first to include streaming video services in the product market

[1] This is the median of the average-per household compensating variation.

[2] Note, this is a short-run effect. In the long run, there could be changes to products characteristics or market structure which could further impact consumer welfare.

[3] The SNL Kagan Consumer Insights survey from 2016 finds that 43% of households consume a traditional and streaming service. While other consumers "cut the cord", by canceling their cable subscription and only choose to subscribe to streaming services.

[4] Following the historical cable prices data collection method outlined in Crawford et al. (2018).

definition.

The new economic environment created by the entry of streaming video services has implications for competition within the television industry. Modeling the competition is important for policy analysis and regulation. Therefore, the framework established in this chapter can be used as a building block towards understanding the broader impact that streaming services have had on the television industry. Streaming services could be included when analyzing antitrust cases (e.g., the AT&T and Time Warner merger), new policies (e.g., net neutrality), or legacy regulations (e.g., program access and broadcast retransmission fees, regulations which only effect traditional providers).

The remainder of the chapter is organized as follows: the second section highlights the trends within the television industry, the third section describes the dataset, the fourth section formalizes the model for the demand of television services, the fifth section details the estimation procedure and results, the sixth section presents the counterfactual simulation, and the seventh section concludes.

1.2 Evolution of the Television Industry

The innovation of streaming video services fundamentally changed the television industry. Given this change, it will be valuable to discuss a brief history of the television industry. This examination will serve two purposes. First, it will provide context for the analysis done in this chapter by describing trends in the subscription patterns over time. Second, it will provide details for the evolution of television services.[5]

1.2.1 The Fall of Traditional Television

Historically, the television industry has seen the entrance of new types of subscription television services, starting with satellite providers in the late 1990s then followed by telephone providers (telco) in the mid-2000s. However, these new television services were very similar to the pre-existing products offered by cable providers—packages of channels offered as tiers of service (e.g. Basic, Expanded Basic). The television content that was being sold was largely[6] the same, especially after the 1999 Satellite Home Viewers' Improvement Act passed, which allowed satellite providers to air local channels.

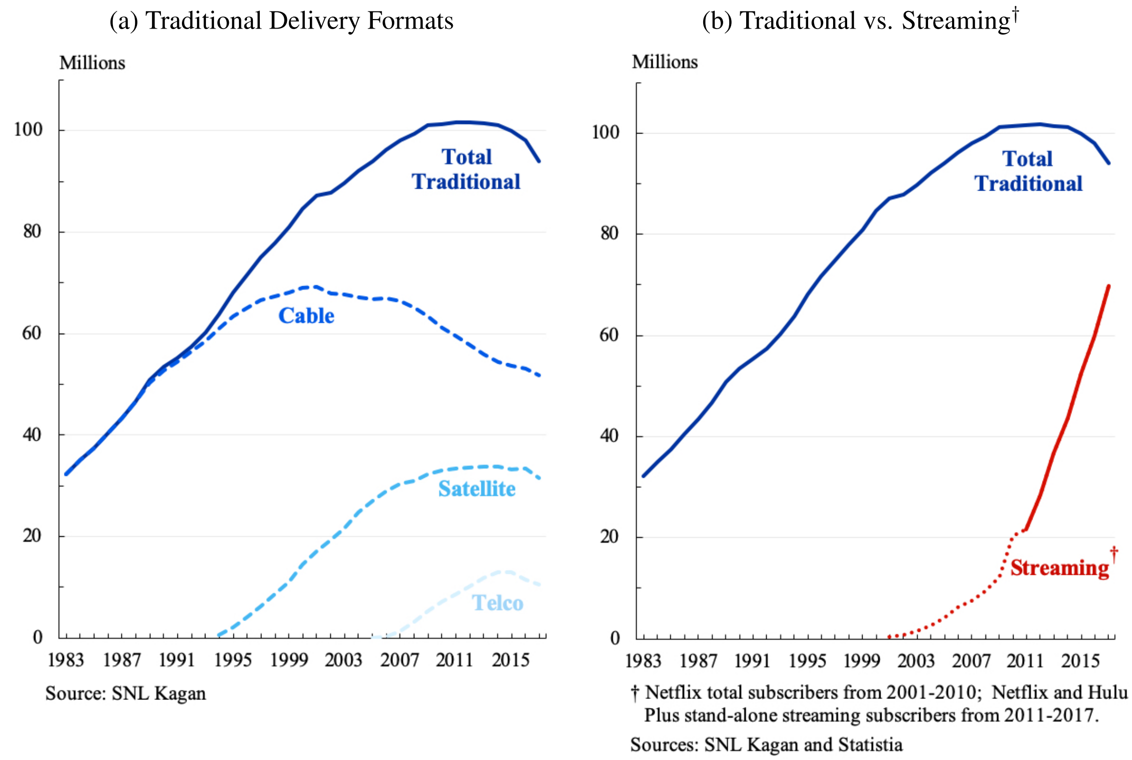
As these new services were introduced, the overall subscriber count for traditional services grew. Figure 1 panel (a) demonstrates the historical trends for the total traditional

[5]Note that the dataset includes the years 2014 and 2015 and focuses on the dominant streaming provider, Netflix.

[6]There was some differentiation across delivery formats with the bundling of television and internet via cable and telco providers, or the availability of out-of-network regional sports networks via satellite.

subscriber counts and the breakdown by delivery format. As shown in this figure, the consumption of television services changed in a noteworthy way over the past decade—the total traditional subscriber count plateaued around 2009[7]

Figure 1.1: Number of Subscribers to Television Services in the U.S.



The top three streaming providers during this period of time were Netflix, Amazon Prime Video, and Hulu Plus. At the end of 2014, Netflix had over thirty-seven million domestic subscribers, and Hulu Plus had approximately seven million domestic subscribers[8,9] Furthermore, according to Nielsen Local Watch estimates, Netflix accounted for over sixty-five percent of subscribers among these three providers in 2014. Given Netflix's dominance at the time, and data constraints for the other providers, the analysis done in this chapter

[7]The Great Recession is an important economic setting to keep in mind for this point in time. The recession caused disposable income to fall, so people were cutting back on their expenses. Having said that, the recession cannot be the sole explanation for this pattern given that subscriber counts continued to fall, and the decline accelerated even after the economy recovered.

[8]Hulu is not a publicly traded company, so the total domestic subscriber counts are estimates based on values that are reported by the company or calculated by SNL Kagan.

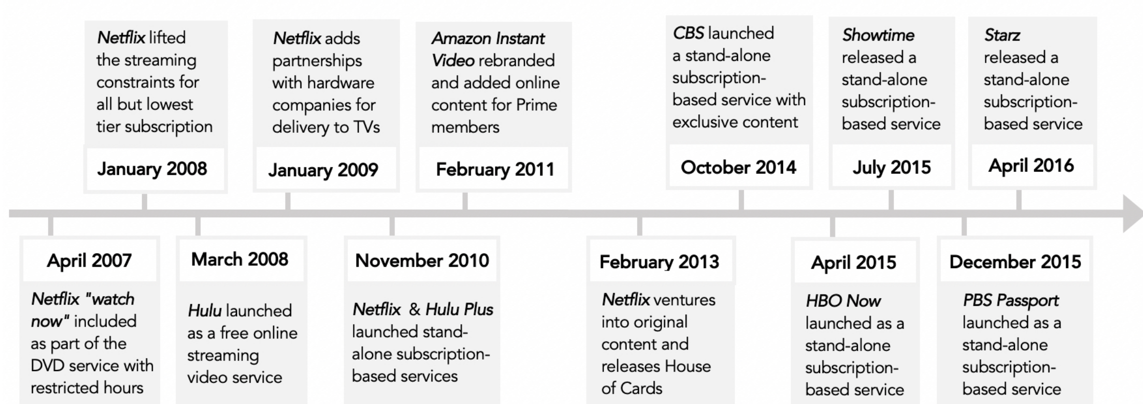
[9]Amazon's streaming video service is offered as a bundled product and is included in the Prime membership, which includes, among other benefits, the 2-day shipping speed for their e-commerce sales. The bundling of these services means that I am not able to isolate the historical series of Amazon's "video services" users from their annual reports, which only list Prime subscribers. This data restriction is why panel 1(b) only includes national subscriber counts for Netflix and Hulu Plus.

will focus on Netflix. The next section summarizes the entry of streaming video services, thus establishing a timeline of events and their role in the industry.

1.2.2 The Entry of Streaming Video Services

With a view to understand the role of streaming video services within the industry, I establish a timeline for their entry into the market. This timeline will include an examination of the popular streaming services that were released from 2007 to 2016. For perspective, the analysis done in this chapter will focus on Netflix for the periods 2014 and 2015. However, the roll-out of streaming services as a whole will contextualize the analysis done in this chapter, and describe trends within the industry. The remainder of this section details key events for streaming services, which are highlighted in figure 1.2 below.

Figure 1.2: Timeline for the Entry of Streaming Video Services



In February 2007, Netflix started offering a "watch now" feature which allowed their subscribers to view content directly on Netflix's website. This feature was included with their standard DVD subscription service, but it had some restrictions on the amount of streaming allotted per month. These restrictions ranged from around 6 to 18 hours, which was determined by their subscription plan. Then, in 2008, Netflix lifted this constraint and allowed unlimited streaming for their subscribers. The streaming feature grew in popularity as internet quality improved, and Netflix continued to partner with hardware companies for content delivery. Around the same time, additional streaming services started entering the market, beginning with Hulu in March 2008. Hulu started out as a free streaming service supported by advertising. Then, in November 2010, Netflix and Hulu started offering their stand-alone subscription-based services. These services gave subscribers access to a library of television shows and movies which they could watch at anytime.

From 2007–2012, the streaming providers were acting as content aggregators, then starting in 2013 there was a shift towards producing exclusive original content. Netflix was the first streaming service to venture into original content by releasing *House of Cards* in February 2013. This venture proved fruitful for them, and they have expanded their production of exclusive content. Then, from 2014 to 2016, premium television networks also started to enter the market with stand-alone streaming services (e.g., HBO Now, Showtime, and Starz). In April 2014, HBO released its first stand-alone subscription-based service, HBO Now. Prior to this date, consumers were required to have a cable or satellite subscription to purchase HBO. With the launch of HBO Now, consumers were able to bypass the cable and satellite providers and get content directly from HBO—followed by Showtime Anytime in July 2015 and Starz in April 2016.

The timeline in figure 1.2 ends mid-2016 because the analysis done in this chapter is limited to 2014 and 2015. However, it is important to point out that streaming services continue to thrive, and there were even more streaming video services released after 2016. In particular, some high-profile services were recently released, including Disney+ and Apple TV. Given these events, it is clear that the streaming delivery method has fundamentally changed the marketplace, and the industry will continue to move towards exclusive/original programming and the streaming service delivery method.

1.2.3 Policy Implications

The streaming delivery method had a disruptive effective on the television industry, both in the consumer's purchasing behavior and in the addition of new stand-alone products.[10] Traditional providers recognize the competitive pressures they face from this new delivery method; however, the literature and regulators[11] continue to isolate traditional services when analyzing the industry. Excluding streaming services from the analysis ignores the importance of this new distribution method, and this exclusion could impact conclusions drawn about the competition within the industry. Therefore, this decision could also have important implications for the understanding of current policy issues and regulations (e.g,

[10] Traditional distributors have also started offering virtual services (e.g., DirecTV Now, Sling TV) which are sold as skinny bundles, and expanding their TV Everywhere channel lineups. The skinny bundles won't be included as a product in this analysis because the subscriber counts are only available at the national-level. Note, these services comprise a very small share of the market—around one percent.

[11] On page 63 of U.S. District Court Judge Richard Leon's opinion for the AT&T and Time Warner merger he defined the relevant product market definition to include traditional linear television services. Though, in footnote 21 he points out that the government (who proposed the product market definition) also stated that a broader definition which includes streaming video services and virtual traditional services would also constitute a relevant product market definition. United States v. AT&T INC. (2018)

antitrust cases[12], net neutrality, or legacy regulations[13]).

1.3 Data

There are two market definitions that are necessary when estimating demand: the relevant product market and the relevant geographic market. These definitions affect the scope of the dataset that needs to be assembled for the estimation. The prior literature restricted the product market to the television packages that are offered by the traditional distributors. This chapter expands on this definition by including the dominant streaming service, Netflix. The geographic market definition will be the combination of year, Designated Media Area (DMA), and county. The remainder of this section will describe details of the dataset including the sources, the sample selection, and the summary statistics.

The new dataset assembled in this chapter includes characteristics and market penetration rates for the top traditional distributors' packages and the top streaming service for 2014 and 2015. The dataset was constructed by collecting and combining information from a variety of sources. Table 1.1 displays a summary of the sources used for the specific variables within the dataset. This table also lists the geographic availability of the data and indicates when the data from that source is from a year other than 2014 or 2015.

Table 1.1: Data Sources (2014 - 2015)

	Variables	**Source(s)**	**Geography**
Traditional Distributors	Package price	SNL Kagan, Web Archive, Warren	Select DMAs, County, National
	Package subscribers	SNL Kagan	County
	Channel lineup	SNL Kagan	DMA
	24 hr listings by channel	Channel Guide	National
Netflix	Subscribers	Nielsen	Select DMAs
	Price	Web Archive	National
	Aggregate title count	SNL Kagan	National
Joint: Traditional & Streaming	Market penetration	SNL Kagan, 2016 Survey	National
Demographics	Median HH income	Census, ACS	County
	Population density	Census, ACS	County
	Share of HH by age	Census, ACS	County
	Share of HH with access to 3mbs internet	Census, ACS	County

[12] Such as the recent AT&T and Time Warner merger.
[13] Such as program access and broadcast retransmission fees.

The SNL Kagan Media and Communications dataset includes information on the traditional distributors' subscriber counts, channel lineups, and aggregate title counts for Netflix. Information on prices were found using the web archive, local cable commission websites, provider's forums, or the Warren Communications TV Factbook. The subscriber penetration rates for Netflix at the DMA-level come from Nielsen Local Watch Reports for 2014 and 2015, and they are publicly available for Netflix's top 10 DMAs.[14]

Nielsen started tracking the subscription to streaming video services in 2014. For the years 2014 and 2015, Nielsen publicly reported Netflix's penetration rates[15] for the top 10 DMAs in their Local Watch Report.[16] As seen in table 1.2, there is variation in the penetration rates across these DMAs and across time. The market penetration rates for traditional television services come from the SNL Kagan Media Census which includes estimates of the package-specific provider counts at the county-level. The nine traditional distributors shown in table 1.3 capture the majority of subscribers within these DMAs.

Table 1.2: Top 10 DMAs by Netflix Penetration

	2014	**2015**
San Francisco	48%	49%
Washington, DC	47	49
Denver	44	48
Los Angeles	43	49
New York	43	49
Seattle	42	50
Portland, OR	42	52
Boston	42	50
Phoenix	42	43
Sacramento	40	44
National	***36***	***44***

[14] Nielsen (2014) and Nielsen (2015)

[15] As I previously described, Netflix was the dominant streaming service in the market, therefore I include Netflix as the only streaming option in the consumer's choice set. Note however, that this methodology is flexible to including more streaming services if the data permits.

[16] They track the subscription penetration rates for 25 DMAs which use "Local people meters (LPM)." LPM "are used in the Top 25 markets to electronically capture both tuning and viewing at the household and persons level." Nielsen (2019) The data for the additional DMAs is available to purchase. Note that the 2015 Nielsen Local Watch Report excludes broadband only (BBO) homes from the penetration rates. When I spoke with a Nielsen representative he explained that share of BBO homes was very small at this time therefore the rankings should be unchanged.

Table 1.3: Share of Total Traditional Subscribers (2015)

	AT&T	Cablevision	Charter	Comcast	Cox	Directv	Dish	TWC	Verizon	Sum
San Francisco	10.7%			59.3%		17.5%	10.0%			97.6%
DC				35.1	5.6	10.8	6.2		38.3	95.9
Denver				50.5		27.0	17.0			94.5
Los Angeles	7.7		6.2			24.5	15.4	30.5	10.7	95.0
New York		34.8		8.5		9.2	5.6	15.3	24.4	97.8
Seattle				61.9		18.5	11.7			92.1
Portland				51.6		23.5	15.4			90.5
Boston			5.6	64.3		6.4	3.9		15.2	95.4
Phoenix					39.0	30.0	20.0			89.1
Sacramento	10.6			39.0		25.3	16.2			91.2

Historical package prices for traditional distributors can be difficult to find at a local-level. I followed the method described in the Crawford et al. (2018), which involved using the web archive to obtain historical rate cards for the television services. Whenever possible, I used local rate cards or found rates listed in the web archive to populate the data. I supplemented this with data from SNL Kagan and the Warren Communications TV Factbook. SNL Kagan collects an annual snapshot of package prices for the top traditional distributors in select DMAs, however, this source is incomplete. There are DMAs that a distributor serves that SNL Kagan did not record. Therefore, I also sought additional sources, such as the Warren Communications TV Factbook. Warren includes datasets for cable package prices at a principal community level.[17,18] However, I only used Warren as a source for basic prices if this information was not available elsewhere. Prices for the satellite and streaming providers were easier to track down because the price is national. This information was found by visiting the distributor's website stored in the web archive.

The TV show variables are constructed to create a common characteristic between traditional and streaming services. The unique TV show title count for traditional distributors is found by using the 24 hour TV listings from the Channel Guide and the channel lineups for each package from SNL Kagan. The unique TV show title count for Netflix is found by scraping the content library on the web archive. After these variables are constructed, I can calculate the percentage overlap of TV show titles across traditional and streaming services. This measure will represent content differentiation across traditional and streaming

[17] The principal community includes a list of counties that are served by this provider in the area.

[18] There are well-documented downsides with this source (e.g. sample attrition, they only track cable distributors, which means telco packages aren't included).

services.

The market demographic variables come from the Census American Community Survey. These variables are at the county/year level and include information on the median household income, the population density, the share of heads of households in a county that fall within an age bin, and the share of households with access to 3 mbs internet. The age bins roughly align with generational breakdowns. At the time the youngest group, ages 15 to 34, maps to the millennial generation. The second age bin, 35 to 54, maps to the number of households in Gen X. The final age bin, 55+, maps to generations of Boomers and older. Additional details about the dataset can be found in Appendix A.

The summary statistics for the dataset are presented in table 1.4, and table 1.5 shows the summary statistics broken down by type. The price is defined as the monthly advertised price for a provider's television package[19], adjusted for inflation. For some firms, these are national prices (e.g. Dish and DirecTV), while for other firms the prices may vary at the county or DMA-level. The channel lineups and TV show title counts varies at the DMA-level, and the demographic information vary by county. The total number of provider/package observations across markets is 9,163. The dataset includes 458 distinct markets, which are the county/DMA/year combinations.

Table 1.4: Summary Statistics (2014 - 2015)

	N	**Mean**	**SD**	**Min**	**Max**
Monthly Advertised Price	9163	71.72	30.56	8.99	157.99
Unique TV show title count	9163	992.25	400.91	199	1441
Overlap of TV show titles with Netflix (%)	9163	7.23	1.88	0	11.29
Median HH income ($10k)	458	5.94	1.91	2.68	12.4
Population density (per sq. mile)	458	1627.55	6238.47	.2	71596.9
Share of HH aged 15 to 34	458	.166	.057	.049	.466
Share of HH aged 35 to 54	458	.368	.0623	.169	.554
Share of HH aged 55+	458	.464	.088	.269	.718
Share of HH with access to 3mbs internet	458	.628	.215	.1	.9

[19]For traditional providers this will not include bundle discounts from combining services. For streaming services this will represent the monthly subscription rate.

Table 1.5: Summary of Characteristics by Type (2014 - 2015)

	N	**Mean**	**SD**	**Min**	**Max**
Traditional					
Unique TV Show Titles	9143	991.99	401.31	199	1441
Monthly Advertised Price	9143	71.85	30.46	9.8	157.99
Streaming					
Unique TV Show Titles	20	1107	35.90	1072	1142
Monthly Advertised Price	20	9.57	.6052	8.99	10.16

This new dataset can be used to analyze the television industry with several advantages relative to past studies, including the following: the data spans a new and more recent time period, the inclusion of the new delivery format (streaming services), and the new source for television shows airing on traditional networks.

1.4 Demand

This section details the model for the demand of subscription television services which includes both traditional packages and a streaming service in the consumer's choice set. The household decision for the subscription to television services will be modeled at the county-level. The choice set for the household will include the packages from local cable or telco providers, packages offered by the satellite providers (DirecTV and Dish), and the top streaming service (Netflix). The households can choose to subscribe to one television service, two television services, or none.

For ease of notation, let m denote the market combination of county c, and DMA d. The conditional indirect utility function of subscribing to the television service j, for household i, in market m, in year t, will take the following form:

$$U_{ijmt} = \alpha p_{jmt} + \beta X_{jdt} + \phi Y_{mt} + \eta_{i,format(j)} + \gamma_d + \zeta_t + \xi_{jmt} + \epsilon_{ijmt}$$

where X_{jdt} includes non-price product characteristics, such as the unique count of television shows, and p_{jmt} is the advertised monthly subscription price for the television service.[20] Y_{mt} includes county characteristics such as the fraction of householders by age within a county. Finally, the ξ_{jmt} term is the unobserved product characteristics.

The $\eta_{i,format(j)}$ allows for persistent horizontal differentiation across format types (wired, satellite). These heterogeneous tastes could account for format-specific characteristics, such as the transmission technology itself or alternative features that are included with

[20]Some of the products have prices that are national (e.g. satellite, streaming)

each format type. This term will also capture unobserved, within-market heterogeneity in access to each format type. Finally, the consumers also have an idiosyncratic preference shock for the product j, ϵ_{ijmt}. These are assumed to be i.i.d. draws from a mean zero Type I Extreme Value distribution with the scale parameter, σ, normalized to 1.

The market penetration will follow the method used in Fan (2013), and the probability that household i chooses product j as their first or second choice in market m at time t is:

$$\mathbb{P}(Y_{imt} = j|X, ..) = \underbrace{\mathbb{P}(U_{ijmt} > \max_{s} U_{is}, \forall s)}_{(j \text{ is } first)} + \underbrace{\sum_{j'} \mathbb{P}(U_{ij'mt} > U_{ijmt} > \max_{h \neq j'} U_{ihmt}, U_{ijmt} - \kappa > U_{i0})}_{(j \text{ is } second)}$$

where U_{ijmt} is the conditional utility from consuming the television subscription service j, and κ is the diminishing utility from consuming more than one type of television service.

The market penetration can be found by integrating the probability of choosing product j across households. Then, for streaming services take the weighted average to aggregate the market penetration rates to the observed DMA-level. Further details of the market penetration equation and aggregation can be found in Appendix B.

1.5 Estimation

Following the methodology developed in Berry, Levinsohn, and Pakes (1995), I estimate the demand for television services using a contraction mapping nested within a Generalized Method of Moments (GMM) estimation routine[21]. The contraction mapping routine will search over the mean utility vector until the difference between the predicted market penetration and the observed market penetration is less than a specified convergence threshold. The solution[22] to the contraction mapping will be a vector $\delta_{jmt}(S_{jmt}, \sigma_\eta, \kappa)$ which is a function of the observed market penetration and the non-linear parameters, which is then substituted into the definition of the mean utility:

$$\delta_{jct}(S_{jmt}, \sigma_\eta, \kappa) = \alpha p_{jmt} + \beta X_{jmt} + \phi Y_{mt} + \eta_{format(j)} + \gamma_d + \zeta_t + \xi_{jmt}$$

where the mean utility is the component within the utility of product j which is common to all consumers. Therefore, a linear estimating equation drops out of the contraction

[21] The market penetration function defined for this problem is highly non-linear which complicates the estimation routine.

[22] Fan (2013) includes a proof which shows that a multiple-discrete choice model will have a unique solution to the contraction mapping under two assumptions on the market penetration: (1) $0 < s_{jt} < 1 \forall j = 1, .., J_{ct}$ and (2) $\sum_{j=1}^{J_{ct}} s_{jt} < 2$.

mapping over the non-linear market penetration equation. Because this is a linear equation, it allows for the error term, ξ_{jmt} to be inverted and used in the moment condition. Furthermore, instrumental variable estimating techniques can be used to correct for the endogeniety of prices. Note that the contraction mapping will be nested within the GMM optimization routine, so a new fixed point solution is required for every iteration of the search over the non-linear parameters. Next, I will describe the identification requirements for the parameters in the model for demand.

1.5.1 Identification

The set of parameters in the model for demand include $\alpha, \beta, \phi, \sigma_\eta$, and κ. These can be broken down into two categories, linear and non-linear. The non-linear parameters are terms that affect the household-specific utility whereas the linear parameters affect the mean utility of the product within the market.

The linear parameters β and ϕ follow a standard exogenous variation identification argument, but α will require more care due to the endogeneity of prices. The identification strategy for α is an instrumental variable approach. One of the instruments for price includes a cost shifter, the lagged national subscriber count for the provider, as used in Byrne (2015) and Crawford and Yurukoglu (2012). This will be a valid instrument if it is relevant, correlated with the price and exogenous, not correlated with the error term. The argument for relevance is that licensing fees are the primary marginal costs, and these are the outcome of a negotiation with the channel conglomerates. These fees are not released publicly[23], but it is understood that if a traditional distributor is larger, then they will be able to negotiate a smaller fee. So the size of the distributor effects the marginal cost, which effects the price. The negotiations do not happen every year, so the licensing fees from a lagged year will correspond with the licensing fees from the current year. The argument for exogeneity is that the number of subscribers in a lagged year will not affect the demand for the product in the current year. The first stage results are shown in Appendix C.

The non-linear parameters, σ_η and κ will also require further explanation for their identification. The σ_η is the parameter for persistent heterogeneous preferences for delivery format within the model. Therefore, σ_η^2 is the variance for the household's tastes for format type (wired, satellite), and it will have implications for the substitution patterns across formats. This parameter will be identified based on the changes in the market shares as the choice set varies across markets, and the substitution patterns are driven by exogenous variation in the overall level of prices. If there is a larger variance in these tastes, then there

[23] SNL Kagan includes estimations of the national average for basic cable licensing fees for each channel, as was used in Crawford and Yurukoglu (2012) and Crawford et. al 2018.

will be less substitution across formats in general, relative to substitution within formats. If there is a smaller variance in these tastes, then there is more substitution across formats in general.

The final parameter is κ, which is the diminishing utility from consuming more than one television service. If κ is ∞, then the households would either subscribe to zero or one television service. If κ is $-\infty$, then all of the households would subscribe to zero or two television services. In reality, there is a mixture of households subscribing to the services. This parameter will be pinned down by the joint-decision moment condition. This condition matches the observed fraction of households that subscribe to both types of services (traditional and streaming) to the weighted average[24] of the second choice probability from the model.

1.5.2 Results

The estimated price coefficient of $\hat{\alpha}$ = -0.123 (0.053), which has the expected sign. The exogenous characteristics include the log of the number of TV show titles and the overlap of tv shows between each package and Netflix. The TV show count (β_1) has a positive effect on the mean utility for households, and the overlap (β_2) has a slightly negative effect. The estimates for the remaining parameters are shown in table 1.6.

The estimation accounts for market demographics by including the median income, age bins, and urbanization measures for each county. The population density and income both have negative effects on the households' mean utility for television services. This result aligns with a story that people in more urban and affluent areas rely less on television as a form of leisure. The age bins are the share of households aged from 15 to 34, 35 to 54, and 55 and over. The oldest age group is the reference group for the estimation. The coefficient is negative for the youngest, and positive for the middle. This result suggests that, on average, middle-aged households prefer television the most, then the oldest households, followed by the youngest. The DMA fixed effects (not reported) range from -1.09 to 0.95.

The non-linear parameters are κ and $\sigma_{format(j)}$. The parameter κ measures the diminished utility of subscribing to a second television service.[25] I find that the estimate of κ in this model is 0.295. The $\sigma_{format(j)}$ terms capture the heterogenous tastes for a format type. The estimates for these parameters imply that there is a high degree of horizontal differentiation, with the highest value being assigned to wired services.

[24]This second choice probability is aggregated across households, products, and DMAs.

[25]Note that setting the kappa parameter to infinity will recover the standard single discrete choice model, with the implication that consumers will buy at most one product.

Table 1.6: Multiple-Discrete Choice Estimation Results

		Estimates	Std. Error
Mean utility			
Price	α	-0.123*	(0.053)
log(TV show count)	β_1	6.240**	(2.30)
TV show overlap with Netflix (%)	β_2	-0.648**	(0.215)
Median HH income ($10k)	ϕ_1	-0.142**	(0.052)
Population density (/1000)	ϕ_2	-0.019***	(0.005)
Share of HH aged 15 to 34	ϕ_3	-4.162***	(1.154)
Share of HH aged 35 to 54	ϕ_4	-1.264	(1.389)
Share of HH with 3mbs internet	ϕ_5	-0.232	(0.776)
Horizontal heterogeneity			
Wired format	σ_{wired}	3.187	(2.586)
Satellite format	$\sigma_{satellite}$	2.796	(4.455)
Diminishing utility	κ	0.295	(2.366)
Observations	9163		
GMM Objective	1.333e-04		

Note: The age bin for share of households aged 55 and over is excluded because the shares sum to 1. The unit for population is 1000 individuals. The estimation includes fixed effects for format, year, and DMA. $^{*}\ p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Next, I calculate the price elasticities for the demand of television services. The price elasticity calculation in this chapter will be more complicated than a standard single-discrete choice model because the market penetration equation has additional terms for the second choice. Further details of this price elasticity calculation can be found in Appendix D.

I find that the median own-price elasticity for all television services implied by the model is -7.15. I also find an intuitive pattern in the median own-price elasticities across the tiers of services; consumers are more elastic as the tier increases, as shown in table 1.7.

Table 1.7: Median Own-Price Elasticity Across Tiers

Basic	-2.07
Expanded	-7.06
Premium	-14.73

The magnitude of the median own-price elasticity falls within the range of reported own-price elasticities from other studies. Crawford and Yurukoglu (2012) find median own-price elasticities of -4.12 for the basic packages, -6.34 for expanded basic packages, and -13.11 for digital basic packages. Goolsbee and Petrin (2004) report an elasticity of -1.5 for expanded basic cable packages. Both studies display the same pattern across tiers as my estimates: demand is more elastic as the package quality increases.[26] I also find that the cross-price elasticities between Netflix and traditional services are positive, and thus consumers treat these products as substitutes.[27]

1.6 Counterfactual Simulation

The counterfactual simulation in this chapter follows the method developed in Petrin (2002). The consumer welfare effect is defined as compensating variation, which is the dollar amount required for a consumer to be indifferent between the observed and counterfactual scenarios. Note that this is interpreted as a short-run consumer welfare effect given the time frame and the model used in this chapter. In the long run, there could be changes to products characteristics or changes to the market structure which could further impact consumer welfare. The formula for the compensating variation will be based on the closed form solution derived in Small and Rosen (1981).

$$CV_{imt} = \frac{V_i^0 - V_i^1}{\alpha}$$

where α is the structural parameter for price[28], V_i^0 is the observed inclusive value for consumer i and the V_i^1 is the inclusive value from the counterfactual. As in Fan (2013) the closed form solution from Small and Rosen (1981) needed to be extended to allow for the consumer to choose up to two products. Note that in chapter one, all of the counterfactuals will assume that there is no supply side response, which can be interpreted as a short-run calculation where the prices and characteristics of the traditional distributors have not responded. Further details of the derivation for the closed form compensating variation expression can be found in appendix E.

I consider three counterfactual simulations. The first simulation removes Netflix from the consumer's choice set—this scenario will simulate a world in which the streaming ser-

[26] Additional results include the average cable provider's elasticity of -1.69 and satellite own-elasticities of -2.9 and -4.15 in Crawford et al. (2018), the basic own-price elasticity estimates of -1.5 in Rubinovitz (1993),-5.9 in Chipty (2001), and -2.19 in FCC (2002).

[27] Even after I allow consumers to choose a combination of services with the multiple-discrete choice. The price elasticity matrix for a sample market is included in Appendix D.

[28] Due to the linear specification of the utility function.

vice disappeared in 2014 and 2015.[29] The second and third simulations remove Comcast and DirecTV from the consumer's choice set, respectively. This is a useful exercise to see how consumer welfare responds across delivery formats. Moreover, it provides a benchmark for the streaming result.[30]

Table 1.8: Counterfactual Simulations (Monthly)

	Median $\overline{\Delta\text{Welfare}_{ct}}^1$	ΔWelfare (millions)
Remove Netflix	-\$5.71	-\$315.9
Remove Comcast	-\$5.47[2]	-\$194.7
Remove DirecTV	-\$2.11	-\$80.7

[1]The monthly average per-household CV

[2]Excludes markets that Comcast does not serve.

Table 1.8 shows the median change in average-per household welfare[31] across the three simulations. In the first simulation, I find that the median household would need to be compensated \$5.71 per month, or \$68.52 annually to achieve the same level of utility as when they can consume Netflix.[32] In the second and third simulations, I find that consumers need to be compensated \$5.47 per month to account for Comcast being removed, and \$2.11 per month to account for DirecTV being removed. Overall, consumer welfare declines by \$315.9 million when Netflix is removed from the choice set.

Figure 3 shows the average per-household welfare change across markets.[33] The markets in the three panels are sorted according to the welfare loss from removing Netflix. The data within the panel is labeled for the population density of each market—the markets that are above the median population density are marked in light blue and the markets below the median are marked in black. Note that because products are being removed from the choice set, the welfare change is expected to be negative. The median welfare loss from the removal of Netflix is the largest, and there is variation across markets. The markets with the most extreme welfare loss are more densely populated. Panel (a) shows the distribution of welfare loss from the removal of Netflix. Panels (b) and (c) show how the welfare

[29]Ideally, this simulation would go back to the "pre-period" to capture the effect of the introduction of streaming services. However, the data restrictions prevent this time period from being estimated.

[30]In many ways, the simulation for the satellite provider will be a cleaner comparison for streaming (e.g., both providers are available nationally, and without bundles for internet).

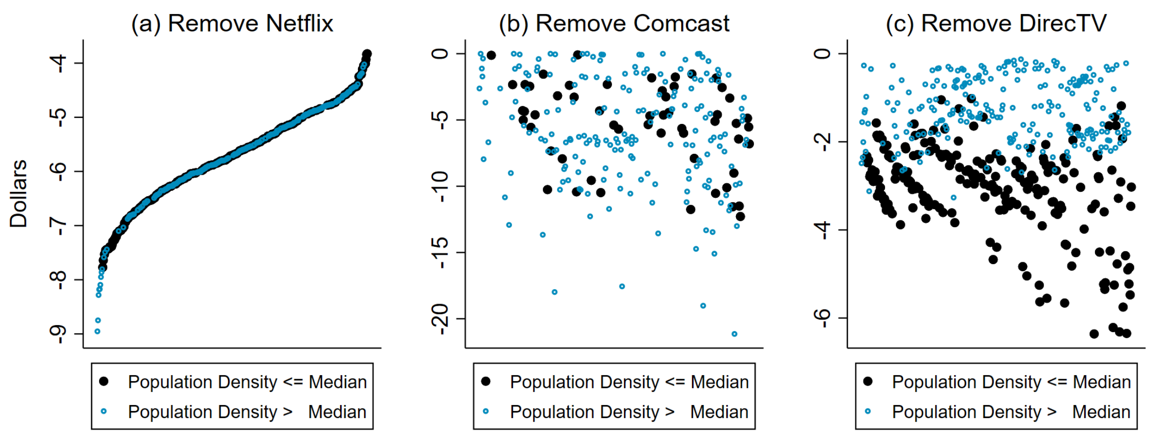
[31]Calculated using the average-per household compensating variation expression.

[32]An interesting benchmark is the value that was calculated in Goolsbee and Petrin (2004), they find that consumers have a compensating variation of \$127–190 per year from the introduction of satellite services. Note that this isn't a directly comparable result but a useful reference point.

[33]Each dot represents a different market's welfare effect.

changes for the other two providers with the markets sorted by the welfare loss from Netflix.Interesting patterns emerge across both the panels.

Figure 1.3: Average Per-Household Welfare Effect Across Markets



Notes: Each dot represents a different market. All three figures show the markets sorted by the welfare change from removing Netflix.The median population density for the sample is 103.13 people per square mile. Panel (b) excludes markets that Comcast does not serve.

In panel (b) there is a negative relationship between the welfare loss for Comcast and Netflix. In particular, a market that experienced a higher welfare loss when Netflix was removed will tend to exhibit lower welfare loss when Comcast is removed. In panel (c) a separate, yet interesting pattern emerges. When considering less densely populated markets, the negative relationship between the welfare change for Netflix and DirecTV is very stark. Markets with high welfare loss for Netflix tend to exhibit lower welfare loss for DirecTV. The markets that are more densely populated appear to be invariant to the removal of Netflix. A potential explanation for these markets could be that households in these areas have access to satellite, but have more impediments for using the satellite services (e.g., tall buildings); therefore when satellite services are removed, there will be less of an effect on their welfare.

Further analysis for the relationship between the welfare measure and the market characteristics are shown in table 1.9. I run a regression of the compensating variation measure on market characteristics to further understand how the welfare effect varies across markets. Note, that the impact of a provider's removal from the choice set depends on how viewers value watching television services. Therefore, if the households in a market do not like watching television, then their welfare will not be largely affected by a product being removed.

Table 1.9: Average Per-Household Welfare Effect Across Markets

	(1) Remove Netflix	(2) Remove Comcast	(3) Remove DirecTV
Median HH Income ($10k)	-0.049	-0.118	0.110**
	(0.028)	(0.133)	(4.01)
Population Density	0.008	-0.036	-0.006
	(0.006)	(0.026)	(-0.91)
Share of HH aged 15 to 34	-2.452***	-4.538	5.402***
	(0.608)	(2.909)	(7.68)
Share of HH aged 35 to 54	2.108**	-18.37***	1.797
	(0.733)	(3.506)	(2.02)
Share of HH with access to 3mbs internet	1.370***	-6.203***	0.336
	(0.231)	(1.102)	(0.303)
Count of wired providers (ex. Comcast)	0.179**	2.663***	0.234**
	(0.593)	(0.284)	(3.39)
Observations	458	458	458

Note: The age bin for share of households aged 55 and over is excluded because the shares sum to 1. The unit for population density is 100 individuals per sq. mile. The estimation includes fixed effects for year and DMA. Standard errors are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The first regression uses the welfare measure when Netflix is removed. Markets with younger households are hurt more when Netflix is removed, relative to the oldest age bin. This aligns with the intuition that younger households tend to prefer the streaming services format. The second regression uses the welfare measure when Comcast is removed.[34] Markets that are younger tend to have a larger welfare loss after the removal of Comcast. Additionally, markets with more wired competitors tend to experience less of a welfare effect from the removal of Comcast. Which aligns with the story that these households could replace their wired services with another provider. Finally, the third regression uses the welfare measure when DirecTV is removed. Markets with more households in the oldest age bin tend to have the largest welfare loss when DirecTV is removed.[35] Taken together, these results highlight the importance of the new product, streaming video services.

[34]Note, the Comcast simulation does not provide a clean comparison to Netflix because wired video providers also offer internet services. The demand estimation includes the format-specific fixed effect, which should absorb the internet services. However, the simulation which removes Comcast from the choice set will not be able to separate out the welfare effect from the removal of Comcast video and internet services.

[35]This aligns with the story that older households value traditional delivery methods more, which is consistent with their viewership behavior. Nielsen has data on live television viewership across age groups, and the oldest groups have not changed their viewership behavior, while younger groups have decreased. With the largest drops in viewerships being attributed to the youngest groups.

1.7 Conclusion

The television industry saw the entry of new types of subscription television services, starting with satellite providers in the late 1990s, then followed by telephone providers (telco) in the mid–2000s. However, these were similar to the pre-existing products offered by cable providers—packages of channels offered as tiers of service.[36] In contrast, the entry of streaming services brought a product into the market with a lower price and more flexible viewing options. Streaming services flourished, and consumers started opting-out of their traditional services. This "cord-cutting" behavior led to the first ever decline in the total traditional subscriber count in 2013, and it has continued to decline ever since. Traditional providers recognize the competitive pressures they face from this new delivery method. However, the literature and policy analysis continue to isolate traditional services when analyzing the industry, and therefore they ignore important innovations that have occurred within the industry.

This is the first paper to study the effect that streaming services have had on the demand for television services. The empirical model exploits new market-level data on prices, product characteristics, market shares, and market characteristics. Based on the demand estimation, I find that even after allowing consumers to choose a combination of services, the cross-price elasticities between traditional and streaming services are positive, which suggests that consumers view these services as substitutes. I also find that the median own-price elasticity across all television services is -7.15, with households being more elastic for higher quality traditional packages.[37] Moreover, I quantify the benefit of streaming services using several simulations. I find that the median household must be compensated \$69 per year if streaming services are removed from their choice set in 2014 and 2015. The simulation results show that Netflix had over three times as much of an effect on consumer welfare when compared to DirecTV. My results suggest that streaming video services are highly valued by consumers, highlighting the importance of including them in the model for the demand of subscription television services.

The framework established in this chapter is a building block towards understanding the broader impact that streaming services have had on the television industry. Future work

[36] There was some differentiation across delivery formats with the bundling of television and internet via cable and telco providers, or the availability of out-of-network RSNs via satellite. However, even with the differentiation across delivery format, the television content being sold was largely the same, especially after the 1999 Satellite Home Viewers' Improvement Act passed, which allowed satellite providers to air local channels.

[37] As discussed in section 5.2, this value lies within the range of elasticities estimated within the previous literature. However, it is closer to previous estimates of expanded basic or premium services, which suggests that consumers are overall becoming more price-sensitive. The finding that households are more elastic for higher-tiered products matches previous results as well.

can use this method to incorporate a model for the supply of television services which endogenizes prices and characteristics of cable packages. Further analysis could include an investigation of the effects from: the unbundling of the traditional packages[38], the indirect network effects through advertising, the increased consolidation within the industry[39], the revenue model of streaming services (subscription vs. subscription + advertising), or the release schedule of streaming television shows (linear vs. non-linear). Furthermore, there could be extensions to the model for demand to allow for preference externalities of content. Finally, the new economic environment created by the entry of streaming video services has implications for competition within the television industry. Therefore, streaming services should be included when analyzing antitrust cases, new policies, or legacy regulations.[40]

[38]Due to the entry of streaming platforms offered by cable channels (e.g., HBO Now, Starz, CBS All Access)

[39]This includes both vertical and horizontal mergers across content producers and distributors (e.g., vertical: AT&T and Time Warner; horizontal: Sinclair Broadcasting, AT&T and Dish Network).

[40]Such as program access and broadcast retrans. fees, regulations which only effect traditional providers.

CHAPTER 2

The Effects of Streaming Video Services Entry on Cable Television Prices

2.1 Introduction

The entry of a new product can have implications for competition within the industry. As I described in the introduction to my dissertation, the impact that this new product has will depend on the degree of innovation that it introduces. Streaming video services created an entirely new type of television service, which resulted in a disruptive impact on the industry. The direct effect on consumer welfare was explored in chapter one. I explore the impact from the two indirect effects in this chapter.

There are two channels for streaming video services to indirectly effect[1] consumer welfare through their impact on prices: increased competition and a change to the bargaining environment. The traditional distributors within the television industry recognize the competitive pressure they face from the entry of streaming services with the loss of subscribers to cord cutting and cord shaving. At the same time, traditional distributors are also facing increased content costs. These two changes will indirectly effect consumer welfare through their impact on prices. For example, when a new product enters the market incumbents could respond by lowering their prices which could lead to an increase in consumer welfare. On the other hand, if the entrant competes for inputs in the same upstream market then it could drive up the input costs leading to higher downstream prices and a decrease in consumer welfare. In this chapter, I quantify the consumer welfare effect from these two channels.

In order to answer this question, I expand the methodology from chapter one to include a model for the supply side which has firms competing in a Bertrand-Nash equilibrium with differentiated products. I use GMM to estimate the cost parameters for cable providers. After these parameters are estimated, I run a counterfactual simulation which removes the

[1] Further details of the three channels that the entry of a new product can have on consumer welfare are included in the introduction to my dissertation.

streaming service from the consumer's choice sets and then re-evaluates the equilibrium prices for cable providers. Finally, I use compensating variation to quantify the change in consumer welfare.

I find that the entry of streaming services may have led to a $15 increase in cable prices per month, and the median consumer welfare effect is $6.26 per month, which means that as of 2014 and 2015 the median household would be willing to pay $6.26 per month to avoid the higher cable prices from the entry of Netflix. The counterfactual simulation in this chapter accounts for both indirect channels when calculating the consumer welfare effect. However, further counterfactual simulations can be done to decompose the indirect effects into the two channels from increased competition and changes to the bargaining environment.

This chapter builds off of the methodology established in chapter one. This extension fits within the strand of literature which examines entry within the television industry such as Chu (2010) and Goolsbee and Petrin (2004). However, these papers focus on the entry of satellite providers. I contribute to the literature by examining and quantifying the impact that streaming services have had on cable prices. Streaming services are lower cost, offer differentiated content, and more flexibility for viewing. The streaming platform also changed the structure of the television industry–many channels started offering direct-to-consumer television services (e.g., HBO Now, CBS All Access, Showtime Anytime). Therefore, streaming video services are an important new product to study because they were a very disruptive entrant.

The remainder of the chapter is organized as follows: the second section focuses on important details of the television industry, the third section describes the dataset, the fourth section formalizes the supply of cable packages, the fifth section lays out the estimation and the results, the sixth section presents the counterfactual simulation, and the seventh section concludes.

2.2 Television Industry

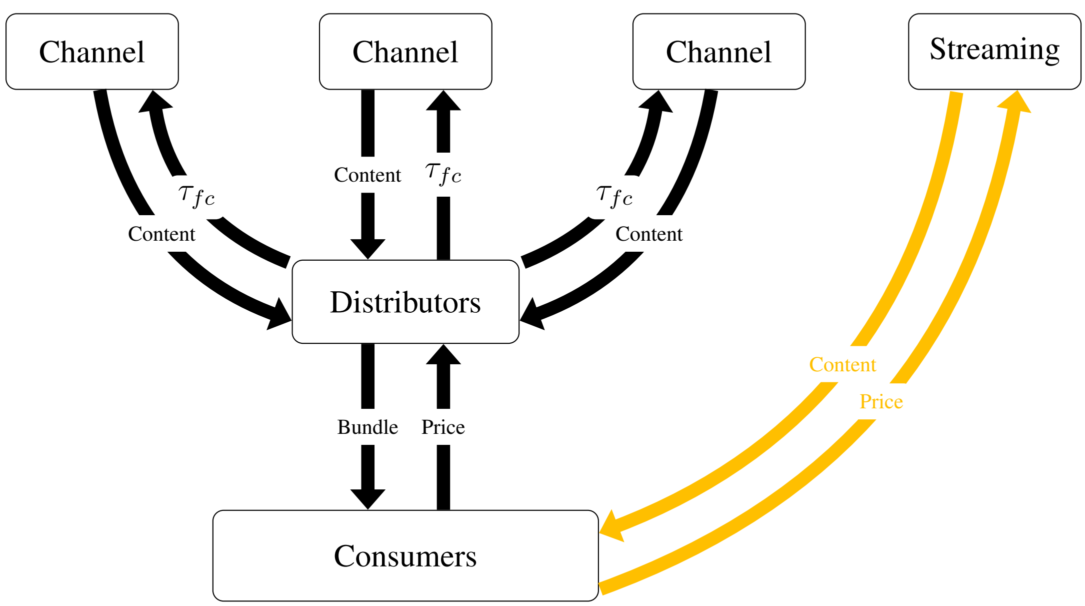
As outlined in chapter one, the television industry has changed dramatically over the past decade. In particular, there is a new distribution method for television services, subscription-based streaming video services. In this section, I highlight key deails for the changes within the industry, including the market structure and cable price trends.

2.2.1 Market Structure

The market structure of the television industry is shown in figure 2.2. There are four relevant players in this market, upstream channels, downstream distributors, streaming providers, and consumers.

The vertical structure of the industry includes upstream channels (e.g., Bravo, HGTV, ESPN) that license their television shows to the downstream distributors (e.g., Comcast, AT&T, Dish). The downstream distributors bundle these channels into a package and sell them as packages to the consumers for a monthly subscription price. The new addition to the structure of the television industry is the streaming service, as shown in figure 2.2 with yellow arrows. In this chapter, the television industry will be modeled in two stages: (1) the downstream cable distributors set prices (2) the consumers choose television services. The consumer's choice for the television services is described in chapter one, and the model for cable prices will be described in section 2.5.

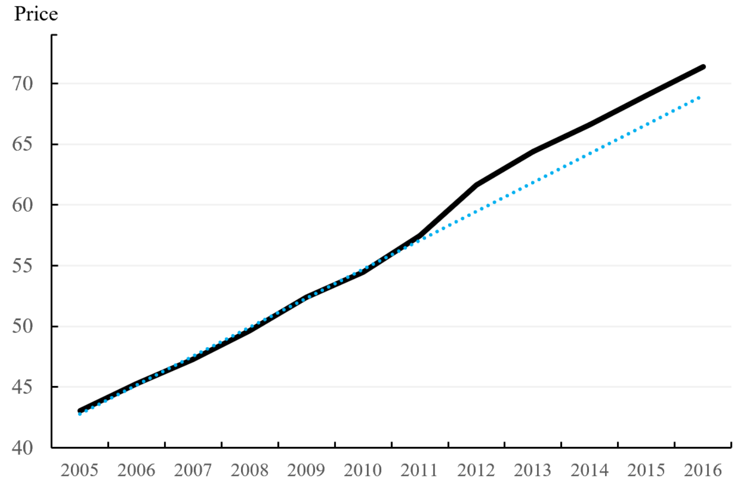
Figure 2.1: Television Industry with Subscription-based Streaming Video Services



2.2.2 Cable Price Trends

Traditional distributors bundle networks into different tiers of services. These bundles typically fall into two types of tiers: basic and expanded basic. The basic cable package tend to include all free-to-air TV channels and a select few cable channels, and the expanded basic cable packages increase in cable channels included in the package. The average cable prices for basic and expanded basic packages have been rising over the last decade, as seen in figures 2.1 and 2.2. The data for these figures comes from the 2018 FCC Report on Cable Industry Prices. The FCC is statutorily required to track cable prices annually through a national survey of randomly sample of cable distributors in various communities nationwide.

Figure 2.2: Average Expanded Basic Cable Prices in the United States

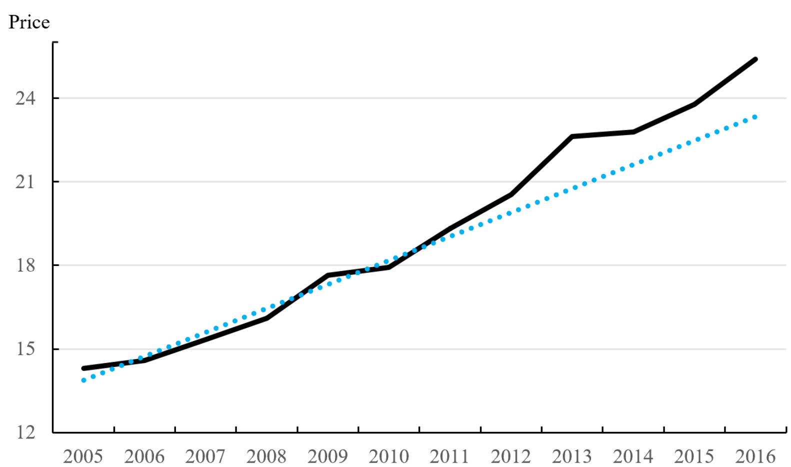


Source: FCC Report on Cable Industry Prices (2018)

Notes: The blue dashed line shows the projected average cable price using data from 2005 to 2011.

Figure 2.1 shows the average expanded basic cable prices in black, and the blue dashed line shows the projection from a linear trend using the data from 2005 to 2011. Around 2011, there was a jump in the average cable price.

Figure 2.3: Average Basic Cable Prices in the United States



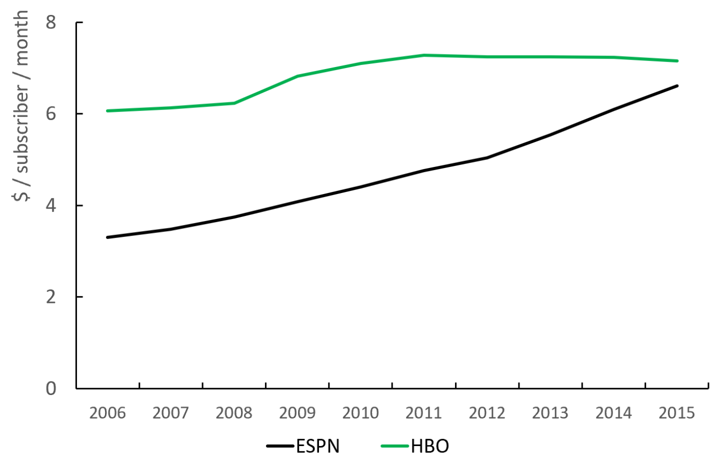
Source: FCC Report on Cable Industry Prices (2018)

Notes: The blue dashed line shows the projected average cable price using data from 2005 to 2011.

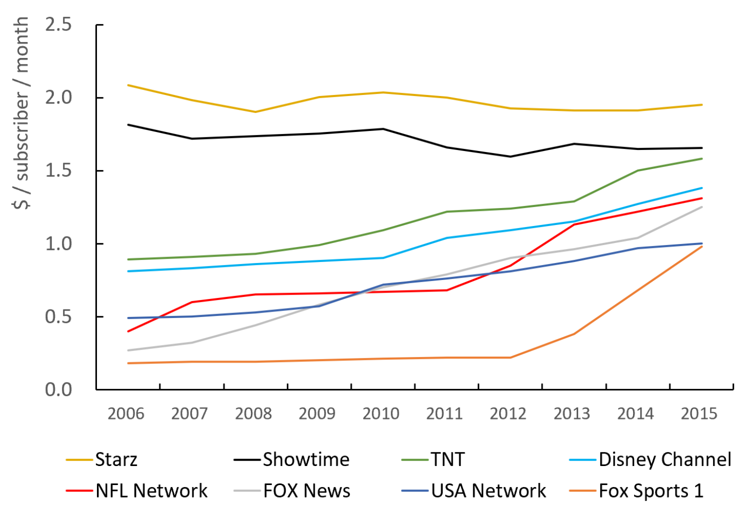
There was also an increase in basic cable prices starting in 2011, as shown in figure 2.2. The timing of this change is interesting, because it is around the same time that Netflix and Hulu launched their stand-alone streaming services. The increased competitive pressure from the entry of a substitute should have downward pressure on prices.[2]. One potential explanation could be that the rise in popularity of the streaming services increased the pressure for inputs, driving up input costs such as the licensing fees.

Figure 2.4: Average License Fees for the Top Networks ($ per subscriber per month)

(a) ESPN and HBO Fees



(b) Other Top Networks



[2]An alternative explanation could be explored which considers a price discrimination story. The new lower cost product causes the incumbent to target a specific segment within the market, the more price insensitive customers. This effect has been found in prescription drugs for generic entry and newspapers with online and print.

The top networks' estimated licensing fees are shown in figure 2.4. The data from the years 2014 and 2015 will be used for the estimation of the cost parameters. Over the last ten years licensing fees have been increasing at a rate which has outpaced inflation. These licensing fees are an important input cost for cable distributors, they are the cost of getting content from the upstream networks. It is interesting to note the change in slopes for the sports networks, in particular, around 2012. One potential explanation is that live sporting events were becoming relatively more important within a cable package and the sports networks were therefore able to charge more for their content due to increased bargaining power.

2.3 Data

The dataset I constructed includes information on cable providers in the United States from 2014 to 2015[3]. I focus on cable providers in this chapter because they make their pricing decision at a local level. I exclude distributors that price nationally, such as satellite and streaming services. The rationale for this decision is that the product characteristics are for a subset of these national provider's markets[4]. In order to understand the satellite and streaming provider's pricing decision it would be necessary to expand the scope of this dataset and to capture more of the national market.

The data required to estimate the model of supply includes product characteristics and information on the cost of providing the service, as well as the demand parameters estimated in chapter one. In the remainder of the section, I describe the sources that I used to obtain each variable, and then I provide summary statistics for the dataset. The sources are shown for each of the relevant variables in table 2.1.

Table 2.1: Data Sources (2014 - 2015)

	Variables	**Source(s)**	**Geography**
Cable Distributors	Package price	SNL Kagan, Web Archive, Warren	Select DMAs, County, National
	Package subscribers	SNL Kagan	County
	Channel lineup	SNL Kagan	DMA
	Avg. Licensing fees by Network	SNL Kagan	National
	Distributor size	SNL Kagan	National
	Vertical integration	SNL Kagan	National

[3]There is one exception to this timeframe, I use licensing fee data that goes back to 2011.
[4]The product characteristics are described in greater detail in chapter 1.

The package price, package subscribers, and channel lineup are the same sources that were used in chapter one. The package prices are difficult to find at a local level, so this information was pulled from a variety of sources including SNL Kagan, the web archive, local cable commission websites, and Warren Communications TV Factbook. The package subscribers and channel lineup data comes from the MediaCensus database within SNL Kagan.

The additional data needed for the supply-side estimation comes from SNL Kagan. This source includes information on average licensing fees by network, total subscribers by distributor, and vertical integration. The average licensing fees by network are estimated by SNL Kagan with units of $/subscriber/month. These fees are a key input cost, and the price that downstream distributors pay to upstream channels to package their television content into a service to be sold to consumers. The distributor size is the national subscriber count for a distributor. This is an important determinant for input costs that traditional distributors are charged. Finally, the vertical integration is the ownership share that a distributor has for the channels in their package lineup.[5] The summary statistics for the new data are shown below in table 2.2.

Table 2.2: Summary Statistics (2014 - 2015)

	N	**Mean**	**SD**	**Min**	**Max**
Monthly Advertised Price ($)	1,700	60.24	32.58	9.80	157.99
Vertical integration	1,700	2.9	3.9	0	10
Total channels	1,700	111.83	72.89	8	245
Licensing fee ($/subscriber/month)	392	0.30	0.72	0.01	7.23
Distributor Size (/10 million)	10	0.864	0.786	0.257	2.151

The number of observations for the monthly advertised price, vertical integration, and total channels is 1700. This count includes data that varies at the provider/package/year/county level. The licensing fee data has 392 observations, which has information at the channel/year level. Finally, the distributor size data has 10 observations which varies at the provider/year level.

2.4 Supply

The model for the competition in the television industry will be Bertrand-Nash with differentiated products. The profit-maximization problem will be defined for the downstream

[5]If the distributor owns the channel in their lineup then the vertical integration for that channel is 1. This is repeated for all channels in the lineup and the total ownership share is used.

competition.

The cable distributors will be setting prices at the county-level to maximize profits. Cable distributors are multiproduct firms, and will set the prices for all products they offer within that market. The profit function is shown in the equation below:

$$\Pi_{fm}(\boldsymbol{p}_m) = M \sum_{j \in J_{fm}} \left(p_{jm} - \sum_{c \in C_{jm}} \tau_{fc} \right) s_{jm}(\boldsymbol{p}_m)$$

Where M is the market size, J_{fm} are the set of packages that the cable firm offers in the market m, p_{jm} is the price for the package, $\sum \tau_{fc}$ is the sum of the licensing fees across channels included in the package, and s_{jm} is the market share for the package.

The first-order condition to maximize firm f's profits with respect to the price of package k in market m is

$$\frac{\partial \Pi_{fm}(\boldsymbol{p_m})}{\partial p_{km}} = \sum_{j \in J_{fm}} \left(p_{jm} - \sum_{c \in C_{jm}} \tau_{fc} \right) \frac{\partial s_{jm}(\boldsymbol{p_m})}{\partial p_{km}} + s_{km}(\boldsymbol{p}_m)$$

This first order condition will be used in the GMM estimation.

2.5 Estimation

The parameters are estimated using a GMM routine. Following Crawford and Yurukoglu (2012), the GMM estimation will consist of two types of moments, one that matches the national average for the licensing fees[6] and one that matches the pricing first order condition.

2.5.1 National Average Licensing Fees

The licensing fee, τ_{fc}, that distributor f pays for channel c is parameterized using the specification in Crawford and Yurukoglu (2012). These input costs are a function of channel characteristics and are scaled by a function of firm and channel.

$$\hat{\tau}_{fc}(\eta, \phi) = (\eta_1 + \eta_2 \tau_c) exp(\phi_1 SIZE_f + \phi_2 VI_{fc})$$

[6]The licensing fees for each network, the most important variable cost for distributors, are observed as a national average.

Where τ_c is the (observed) Kagan average input cost for channel c, $SIZE_f$ is the firms total number of subscribers, and VI_{fc} is the ownership share firm f has in the channel c. This functional form allows for different channels to have different base rates for each distributor, but the distributor size and vertical integration effect will be the same for all channels. For example, based on it's size, Charter Communications could have a 10 percent discount on the rate for the Disney channel, a channel that it does not own[7]. With this input cost specification, it will also have a 10 percent discount on any other channel that it does not own. This is a restrictive assumption; however, this specification captures the distributor size effect, which is known to be the most important determinant for differences in the licensing fees for a given channel across firms.

The weighted average of τ_{fc} over firms predicts the national-average input cost for each channel c. These will be matched to the observed data in the Kagan Economics of Basic Cable Network dataset's channel input costs, τ_c.

$$E_f[\hat{\tau}_{fc}(\eta, \phi)] - \tau_c = 0$$

This is the first set of moment conditions—the national average licensing fee predicted by the model should equal the observed licensing fee.

2.5.2 Profit Maximization

The second set of moment conditions will result from the profit maximization for cable distributors. The cable distributors will be setting prices at the county-level to maximize profits. Cable distributors are multiproduct firms, and will set the prices for all products they offer within that market. The profit function for firm f in market m is shown in the equation below.

$$\Pi_{fm}(\boldsymbol{p}_m) = M \sum_{j \in J_{fm}} \left(p_{jm} - \sum_{c \in C_{jm}} \tau_{fc} \right) s_{jm}(\boldsymbol{p}_m)$$

where M is the market size, J_{fm} are the set of packages that the cable firm offers in the market, p_{jm} is the price for the package, $\sum \tau_{fc}$ is the sum of the licensing fees across channels included in the package, and s_{jm} is the market share for the package.

The first-order condition to maximize firm f's profits with respect to the price of package k in market m is shown in the equation below.

[7] Representing the vertical integration between that distributor and that channel, VI_{fc}.

$$\frac{\partial \Pi_{fndm}(\boldsymbol{p}_m)}{\partial p_{km}} = \sum_{j \in J_{fm}} \left(p_{jm} - \sum_{c \in C_{jm}} \tau_{fc} \right) \frac{\partial s_{jm}(p)}{\partial p_{km}} + s_{km}(\boldsymbol{p}_m)$$

The first-order conditions can be used to form the following set of moment conditions for the Nash pricing:

$$\begin{bmatrix} \frac{1}{J}\sum_j SZ_{jm}(\hat{mc}_{jm} - \sum_{c \in C_{jm}} \hat{\tau}(\eta, \phi)) \\ \frac{1}{J}\sum_j VI_{jm}(\hat{mc}_{jm} - \sum_{c \in C_{jm}} \hat{\tau}(\eta, \phi)) \end{bmatrix} = 0$$

2.5.3 Results

I find that the estimated median marginal costs for packages ranges from \$7.94 for basic, \$29.87 for expanded basic, and \$67.52 for premium.

The demand estimates from chapter one are combined with the two sets of moment conditions: (1) the average licensing fee per channel from SNL Kagan, and (2) the Nash pricing assumption to estimate the input cost parameters η and ϕ. The results from the estimation are shown in table 2.3.

Table 2.3: Input Cost Parameters

	Parameter	Estimate	Standard Error
Constant	η_1	0.044	0.379
SNL Kagan scale	η_2	0.959	3.916
Distributor size	ϕ_1	-0.284	3.721
Vertical integration	ϕ_2	-0.207	0.891

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The input cost parameters are $\boldsymbol{\eta}$ and $\boldsymbol{\phi}$. The η_1 and η_2 account for the different base rates for different channels, and the ϕ_1 and ϕ_2 will differentiate the effect for distributor size and vertical integration for a distributor for all channels.[8] The first set of moment conditions help the model match the aggregate level of input costs and the second set of moment conditions help to pin down the variation of input costs across firms. I find that the

[8]This follows the parametrization from Crawford and Yurukoglu (2012), which they admit is restrictive because a distributor will have the same discount for all channels that it is not vertically integrated. However, it will capture the impact from the distributor size which is known to be the most important factor for differences in fees for a particular channel across distributors.

estimated effect of the distributor size and vertical integration is negative. The identification of these parameters can be motivated by the two regressions shown in Table 2.4. The regression results show that the size of a distributor is negatively related to the price after conditioning on the product characteristics. These results indicate that a larger distributor will have a lower per-channel input costs. Larger distributors also have lower estimated marginal costs. A more vertically integrated[9] distributor has lower prices when more of the channels they own are included in the package, although estimated marginal costs are not.

Table 2.4: Regression Analysis of Distributor Size on Price and Estimated Marginal Cost

	(1)		(2)	
	Price	Std. Error	Estimated marginal cost	Std. Error
Distributor size (/10M subcribers)	-5.703***	0.536	-19.806***	5.365
Vertical integration	-6.384***	7.772	28.239	77.737
Channel Fixed Effects	Y		Y	
Tier Fixed Effects	Y		Y	
Year Fixed Effects	Y		Y	
Observations	1700		1700	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.6 Counterfactual

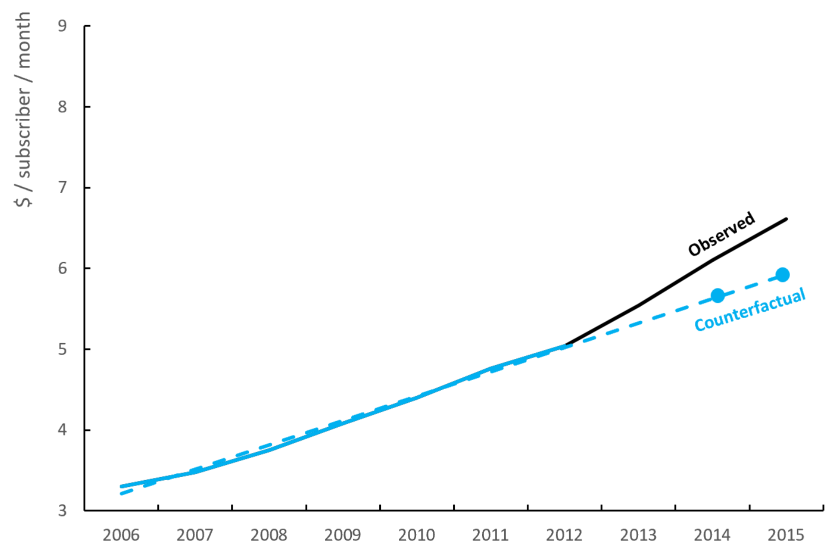
The counterfactual simulation removes the streaming service from the consumer's choice sets, and re-evaluates the equilibrium prices for firms that set local prices. This simulation will capture the indirect effect that streaming services had on cable prices.

An important data limitation that impacts this simulation is that the time period for the estimation is restricted to the "post" introduction period, which means that the marginal costs for the distributors will already incorporate the effect of streaming services. To address this limitation, I use historical SNL Kagan licensing fee data from 2006 to 2011, a period of time prior to the rise of streaming services, and project fees for 2014 and 2015. This methodology allows me to proxy for a counterfactual situation without streaming services. Note, that this is an assumption on the licensing fees that would have prevailed in the absence of streaming services. Figure 2.5 shows the counterfactual fees for ESPN and HBO.

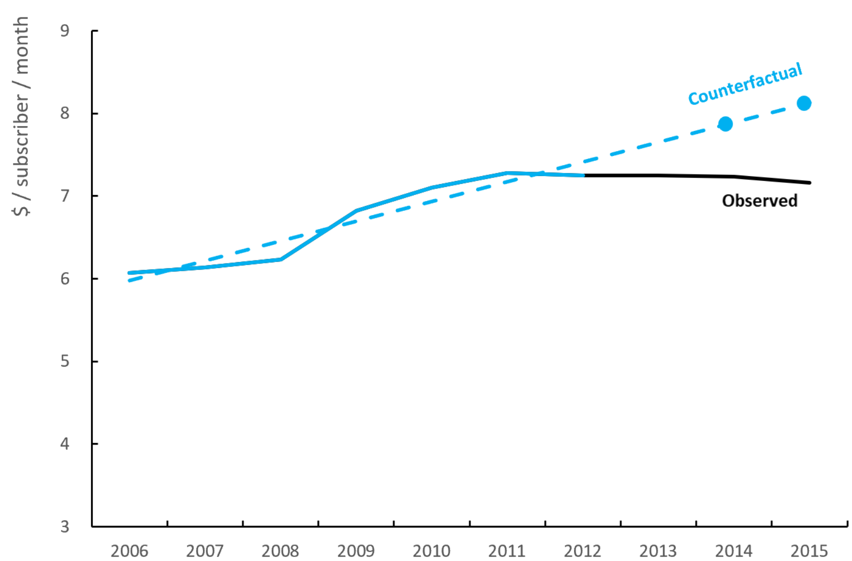
[9]The amount of channels in their package that they own. This value ranges from zero to one and represents the fractional ownership of the company.

Figure 2.5: Counterfactual Average License Fees ($ per subscriber per month)

(a) Average ESPN Licensing Fee



(b) Average HBO Licensing Fee



Source: SNL Kagan.

Notes: The blue dashed line shows the projected fee using the data from 2006 to 2012.

The solid line in figure 2.5 (a) and (b) show the licensing fee (dollar per subscriber per month) that the average television distributor had to pay to the networks to air their content. The solid line shows the observed fees and the blue dashed line shows the projected fees based on the data from 2006 to 2011. The two blue dots show the counterfactual fees for the average distributor that are used for each network for 2014 and 2015. This projection is done for all available networks. It is interesting to note that HBO had a decrease in the licensing fee relative to the projected amount, whereas ESPN's licensing fee increased relative to the projected amount. One potential explanation for this outcome is that HBO could be viewed as a substitute to the streaming services and ESPN (live sports) could be viewed as a complement. Moreover, ESPN remained exclusively on cable packages, while HBO started offering HBONow as a stand-alone service in 2015.

The counterfactual licensing fees are then used in the marginal cost specification

$$\hat{\tau}_{fc}^{cf}(\eta,\phi) = (\eta_1 + \eta_2\tau_c^{cf})exp(\phi_1 SIZE_f + \phi_2 VI_{fc})$$

where τ_c^{cf} is the counterfactual Kagan average input cost for channel c, $SIZE_f$ is the firms total number of subscribers, and VI_{fc} is the ownership share firm f has in the channel c. This new marginal cost is used to find the counterfactual price vector. Finally, I use the new price vector to calculate the consumer welfare effects using compensating variation. Note, given the time horizon in the data set this can be interpreted as a short run effect.

After adjusting the licensing fees for the counterfactual simulation, I find that on average prices for cable packages would have been around \$15 less[10]. Table 2.5 shows the median change in average-per household welfare[11] for the simulation. I find that the median consumer welfare effect is \$6.26 per month, which means that the median household would be willing to pay \$6.26 per month to avoid the higher cable prices from the entry of Netflix.

Table 2.5: Counterfactual Simulation (Monthly)

Median $\overline{\Delta\text{Welfare}_{ct}}^1$	ΔWelfare (millions)
\$6.26	\$2122.87

[1]The monthly average per-household CV

2.7 Conclusion

The entry of a new product can have implications for competition within the industry. The success of the streaming platform changed the structure of the television industry–many channels started offering direct-to-consumer television services (e.g., HBO Now, CBS All

[10]The average price of a cable package in the observed data is \$59.59 and the average price of the counterfactual cable package is \$44.23.

[11]Calculated using the average-per household compensating variation expression.

Access, Showtime Anytime). I contribute to the literature by examining and quantifying the indirect impact that streaming services have had on cable prices and the consumer welfare.

In order to answer this question, I expand the methodology used in chapter one to include a supply side which has firms competing in a Bertrand-Nash equilibrium with differentiated products. I use GMM to estimate the cost parameters for cable providers. After these parameters are estimated, I run a counterfactual simulation which removes the streaming service from the consumer's choice sets and then re-evaluates the equilibrium prices for cable providers. This means that there are two channels for streaming services to affect the industry, first through the direct decision of what products consumers subscribe to, and second through the indirect effect of prices. I find that the entry of streaming services may have led to a $15 increase in cable prices per month, and the median consumer welfare effect is $6.26 per month, which means that the median household would be willing to pay $6.26 per month to avoid the higher cable prices from the entry of Netflix.

Further work can be done to understand the impact that streaming services had on the television industry. Currently, I am only accounting for the change in price, however, there are other characteristics of television services that have changed after the introduction of streaming services. Therefore, future work could endogenize other product characteristics and quantify their impact on consumers. There could also be work done that incorporates the vertical structure of the industry to understand how the bargaining environment has evolved during the streaming era. There could also be work done on antitrust or policy issues such as the horizontal and vertical mergers that are occurring within the television industry.

CHAPTER 3

Horizontal Merger Analysis in the Streaming Era

3.1 Introduction

A key concern within the field of Industrial Organization is the impact that a merger will have on consumer welfare. On one hand, a merger could lead to synergies in production or increased scale which could lower costs and lead to lower prices for consumers. While on the other hand, a merger could lead to anticompetitive behavior–a more concentrated market with firms able to exert more market power leading to higher prices for consumers. Over the last ten years, the television industry has been undergoing technologial innovations in delivery of content, and there has been an increase in concentration. In this chapter, I consider a horizontal merger within the television industry allowing for the inclusion of streaming services within the product market defintion.

To quantify this effect, I rely on the models, data, and estimation established in chapters one and two. The dataset includes information for the top traditional distributors in ten DMAs within the United States for 2014 and 2015. The demand parameters were estimated in chapter one using a nested fixed point algorithm, and the supply parameters are estimated in chapter two using GMM. Using these parameters, I run a horizontal merger simulation for the proposed merger between Comcast and Time Warner Cable to determine the welfare effect on consumers. The change in consumer welfare is defined as the compensating variation. I find that the median consumer welfare effect is \$4.01 per month, which means that as of 2014 and 2015 the median household would be willing to pay \$4.01 per month to avoid the higher cable prices from the merger of Comcast and Time Warner Cable.

This chapter contributes to two strands of the literature—merger analyses and studies of the television industry. Some relevant papers within the literature include Nevo (2000), Crawford and Yurukoglu (2012), Chu (2010), Goolsbee and Petrin (2004), Goolsbee (2007), and Fan (2013). I contribute to the literature by using a new dataset which includes data from the streaming era.

The remainder of the chapter is organized as follows: the second section provides historical context for mergers in the television industry, the third section describes the dataset, the fourth section formalizes the model, the fifth section details the estimation procedure and results, the sixth section presents the counterfactual simulation, and the seventh section concludes.

3.2 Mergers in the Television Industry

There are two classifications for mergers that can occur within an industry: horizontal and vertical. Horizontal mergers are between two firms that operate in the same space in the supply chain, and often are competitors offering the same product. Vertical mergers occur when two firms merge that operate in different parts of the supply chain. In this chapter, I focus on horizontal mergers between traditional distributors.

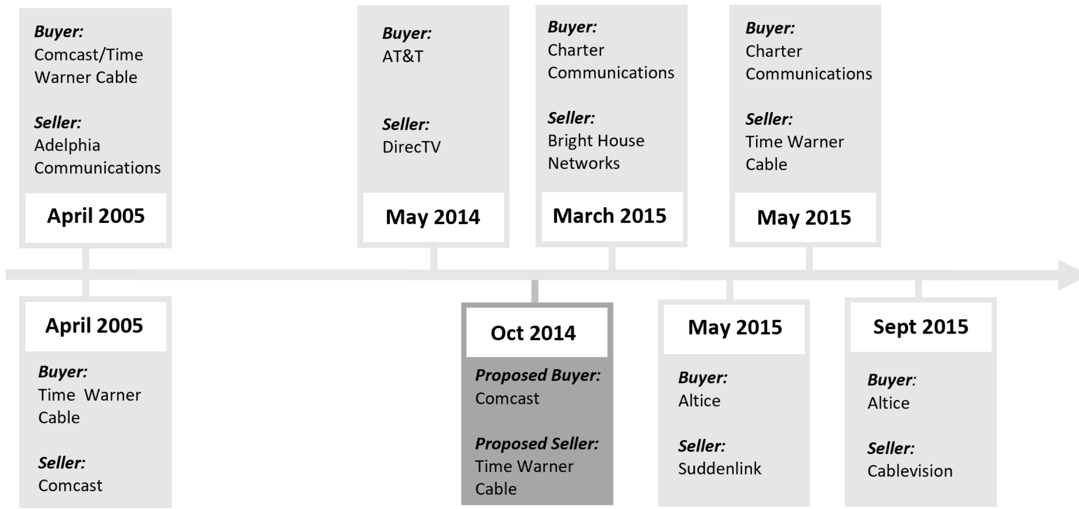
Over the last decade, traditional distributors have been consolidating ownership and increasing the concentration within the industry. According to a 2015 study from Leichtman Research Group, the top 13 traditional television distributors controlled 95% of the total number of traditional subscribers. Leichtman (2015) The number of subscribers for the top television providers for 2014 are shown in table 3.1. Next, I highlight some of the larger horizontal mergers in figure 3.1 to provide historical context for this chapter.

Table 3.1: Top Traditional Television Subscribers in the U.S. (2015 end of Q3)

	Subscribers	**Share**
Cable		
Comcast	22,258,000	23.7%
Time Warner Cable	10,977,000	11.7%
Charter	4,274,000	4.5%
Cablevision	2,604,000	2.8%
Suddenlink	1,094,100	1.2%
Mediacom	862,000	0.9%
Cable ONE	380,807	0.4%
Other Major Cable	6,360,000	6.8%
Total Top Cable	*48,809,907*	*51.9%*
Satellite (DBS)		
DIRECTV	19,570,000	20.8%
DISH	13,909,000	14.8%
Total DBS	*33,479,000*	*35.6%*
Telco		
AT&T U-verse	5,880,000	6.3%
Verizon FiOS	5,807,000	6.2%
Total Top Telco	*11,687,000*	*12.4%*
Total Top Providers	*93,975,907*	*100%*

Source: Leichtman Research Group (2015).

Figure 3.1: Top Mergers in the Television Industry



In 2005, Comcast and Time Warner Cable agreed to seperately acquire Adelphia Communications[1]. Time Warner Cable and Comcast also had to exchange cable systems in certain markets[2]. The next wave of consolidation occurred between 2014 and 2015. In May 2014, AT&T announced that it would purchase DirecTV a deal that combined the second largest traditional distributor with the sixth largest distributor. AT&T and DirecTV are also the top telco and satellite distributors. Then, in October 2014, Comcast announced their intention to merge with Time Warner Cable. This proposed merger which would have combined two of the largest traditional distributors[3]. The Department of Justice (DOJ) and the FCC were concerned with the consolidation of market power. Comcast would have become "an unavoidable gatekeeper for Internet based-services that rely on a broadband connection to reach consumers" DOJ (2015). Comcast abandoned the merger in 2015 after 14 months of trying to get through the approval process. This failed merger is the focus of the counterfactual simulation. Finally, in 2015 there was a series of acquisitions announced by Charter and Altice. Charter Communications announced mergers with Bright House Networks and Time Waner Cable. Then Altice announced mergers with Suddenlink and

[1] Adelphia was the fifth largest cable distributor and the seventh largest traditional distributor.

[2] "In the exchange transactions, Time Warner Cable will receive current Comcast systems located in or around Los Angeles, California; Cleveland, Ohio; and Dallas, Texas, and systems currently owned by Century-TCI California Communications, L.P., in the Los Angeles area, and by Parnassos Communications, L.P. and Western Cablevision, L.P., in Ohio and western New York. Comcast will receive Time Warner's current cable systems serving portions of Philadelphia, Pennsylvania and certain systems currently owned by Adelphia located in California, Colorado, Connecticut, Florida, Georgia, Kentucky, Massachusetts, Maryland, North Carolina, New Hampshire, New York, Pennsylvania, Tennessee, Virginia, Vermont, Washington and West Virginia." Cannon (2005)

[3] Comcast was the largest distributor and Time Warner Cable was the fourth largest distributor.

Cablevision.

Future work on mergers within the television industry can focus on the impact of vertical mergers. With the rise in streaming services and the prevalence of exclusive content on streaming platforms, there has been an increase in the vertical integration between content producers and content distributors.

3.3 Data

To run a merger simulation you need data for the product characteristics, market shares, market characteristics, and input costs. The data spans 2014-2015 for the top traditional distributors in ten DMAs in the United States, and is the combination of the datasets constructed in chapter one and two. The sources for each variable are shown in table 3.2.

Table 3.2: Data Sources (2014 - 2015)

	Variables	**Source(s)**	**Geography**
Traditional Distributors	Package price	SNL Kagan, Web Archive, Warren	Select DMAs, County, National
	Package subscribers	SNL Kagan	County
	Channel lineup	SNL Kagan	DMA
	24 hr listings by channel	Channel Guide	National
	Avg. Licensing fees by Network	SNL Kagan	National
	Total subscribers	SNL Kagan	National
	Vertical integration	SNL Kagan	National
Netflix	Subscribers	Nielsen	Select DMAs
	Price	Web Archive	National
	Aggregate title count	SNL Kagan	National
Joint: Traditional & Streaming	Market penetration	SNL Kagan, 2016 Survey	National
Demographics	Median HH income	Census, ACS	County
	Population density	Census, ACS	County
	Share of HH by age	Census, ACS	County
	Share of HH with access to 3mbs internet	Census, ACS	County

3.4 Model

3.4.1 Demand

As in chapter one, the conditional indirect utility function of subscribing to the television service j, for household i, in market m, in year t, will take the following form:

$$U_{ijmt} = \alpha p_{jmt} + \beta X_{jdt} + \phi Y_{mt} + \eta_{i,format(j)} + \gamma_d + \zeta_t + \xi_{jmt} + \epsilon_{ijmt}$$

where X_{jdt} includes non-price product characteristics, such as the unique count of television shows, and p_{jmt} is the advertised monthly subscription price for the television service.[4] Y_{mt} includes county characteristics such as the fraction of householders by age within a county. Finally, the ξ_{jmt} term is the unobserved product characteristics.

The $\eta_{i,format(j)}$ allows for persistent horizontal differentiation across format types (wired, satellite). These heterogeneous tastes could account for format-specific characteristics, such as the transmission technology itself or alternative features that are included with each format type. This term will also capture unobserved, within-market heterogeneity in access to each format type. Finally, the consumers also have an idiosyncratic preference shock for the product j, ϵ_{ijmt}. These are assumed to be i.i.d. draws from a mean zero Type I Extreme Value distribution with the scale parameter, σ, normalized to 1.

3.4.2 Supply

As in chapter two, the model for the competition in the television industry will be Bertrand-Nash with differentiated products. This estimation technique relies on the profit-maximization condition to back out the marginal costs. The profit-maximization problem will be defined for the downstream competition among distributors following Crawford and Yurukoglu (2012). The profit function for the multiproduct firm f in market m takes the following form

$$\Pi_{fm}(\boldsymbol{p}_m) = M \sum_{j \in J_{fm}} \left(p_{jm} - \sum_{c \in C_{jm}} \tau_{fc} \right) s_{jm}(\boldsymbol{p}_m)$$

where M is the market size, J_{fm} are the set of products that the firm offers in the market, p_{jm} is the price of the product, τ_{fc} is the licensing fee for each channel within the package, and s_{jm} is the market share for the product. The first-order condition to maximize firm f's profits with respect to the price of package k in market m is shown in the equation below.

[4] Some of the products have prices that are national (e.g. satellite, streaming)

$$\frac{\partial \Pi_{fm}(\boldsymbol{p}_m)}{\partial p_{km}} = \sum_{j \in J_{fm}} \left(p_{jm} - \sum_{c \in C_{jm}} \tau_{fc} \right) \frac{\partial s_{jm}(p)}{\partial p_{km}} + s_{km}(\boldsymbol{p}_m)$$

The first order condition for the multiproduct firm in a market can be rearranged and written in matrix form

$$\boldsymbol{\tau_f} = \boldsymbol{p_m} - \Delta(\boldsymbol{p}_m, \boldsymbol{X})^{-1} s(\boldsymbol{p})$$

where $\Delta(\boldsymbol{p_m}, \boldsymbol{X})$ is the matrix of own and cross-price share derivatives that accounts for ownership[5] of the products within the market, τ_f is the sum of the licensing fees for the channels included in the product, p_m is the price of the product, and $s(\boldsymbol{p_m})$ is the market share for the product.

3.5 Estimation

The demand parameters are found in chapter one using a nested fixed point algorithm, and the supply parameters are found in chapter two using a GMM estimation routine. The parameter values are shown in tables 3.3 an 3.4 below.

Table 3.3: Demand Parameters

		Estimates	Std. Error
Mean utility			
Price	α	-0.123*	(0.053)
log(TV show count)	β_1	6.240**	(2.30)
TV show overlap with Netflix (%)	β_2	-0.648**	(0.215)
Median HH income ($10k)	ϕ_1	-0.142**	(0.052)
Population density (/1000)	ϕ_2	-0.019***	(0.005)
Share of HH aged 15 to 34	ϕ_3	-4.162***	(1.154)
Share of HH aged 35 to 54	ϕ_4	-1.264	(1.389)
Share of HH with 3mbs internet	ϕ_5	-0.232	(0.776)
Horizontal heterogeneity			
Wired format	σ_{wired}	3.187	(2.586)
Satellite format	$\sigma_{satellite}$	2.796	(4.455)
Diminishing utility	κ	0.295	(2.366)

Note: The age bin for share of households aged 55 and over is excluded because the shares sum to 1. The unit for population is 1000 individuals. The estimation includes fixed effects for format, year, and DMA. * $p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

[5]If the two products have the same owner, then the entry within the matrix will be the deriviate of the market share with respect to price. If the two products have different owners then the entry will be 0.

Table 3.4: Input Cost Parameters

	Parameter	Estimate	Standard Error
Constant	η_1	0.044	(0.379)
SNL Kagan scale	η_2	0.959	(3.916)
Distributor size	ϕ_1	-0.284	(3.721)
Vertical integration	ϕ_2	-0.207	(0.891)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.6 Counterfactual

The counterfactual conducted in this chapter will calculate the consumer welfare impact from the proposed merger between Comcast and Time Warner Cable. This merger would have consolidated power among the first and second largest cable distributors, which caused concern among the antitrust authorities.

To conduct the counterfactual simulation, I will change the ownership matrix within the first order condition, and adjust the marginal costs for the larger distributor size. Then, using these the counterfactual prices I calculate the change in consumer welfare. The consumer welfare effect will be defined as the compensating variation. The consumer welfare effect is shown in table 3.5.

Table 3.5: Counterfactual Simulation (Monthly)

Median $\overline{\Delta\text{Welfare}_{ct}}^{1}$	ΔWelfare (millions)
\$4.01	\$2945.78

[1]The monthly average per-household CV

I find that the median consumer welfare effect is \$4.01 per month, which means that as of 2014 and 2015 the median household would be willing to pay \$4.01 per month to avoid the higher cable prices from the merger of Comcast and Time Warner Cable. The total consumer welfare effect is \$2945.78 per month.

3.7 Conclusion

The television industry has been experiencing consolidation among distributors for the last decade. An important question within the field of Industrial Organization is whether a merger should be allowed or not. The impact of a merger can either be positive or negative on consumer welfare. In this chapter, I calculate the consumer welfare effect of the proposed merger between Comcast and Time Warner Cable.

Building off the models, data, and estimation established in chapters one and two I quantify the effect of the merger. The dataset includes information for the top traditional distributors in ten DMAs within the United States for 2014 and 2015. The demand parameters were estimated in chapter one using a nested fixed point algorithm, and the supply parameters are estimated in chapter two using GMM. Using these parameters, I run a horizontal merger simulation for the proposed merger between Comcast and Time Warner Cable to determine the welfare effect on consumers. The welfare effect is defined as the compensating variation. I find that the median consumer welfare effect is \$4.01 per month, which means that as of 2014 and 2015 the median household would be willing to pay \$4.01 per month to avoid the higher cable prices from the merger of Comcast and Time Warner Cable. The total consumer welfare effect is \$2945.78 per month.

There is still a lot of work that can be done in this area. Future work could include an examination of the impact of mergers in the television industry. This could include endogenizing the product characteristics to allow for other characteristics to respond to a merger. There could also be studies of the vertical mergers that are occuring within the industry, such as the AT&T and Time Warner merger. These are important issues for antitrust regulators and policy analysts.

APPENDIX A

Dataset Details

A.1 Data Sources

SNL Kagan Media and Communications

The SNL Kagan Media and Communications database includes operating data for companies within the television industry (e.g. cable/satellite providers, streaming distributors, and television networks), content characteristics, and subscriber counts. The content characteristics include channel lineups for the specific packages from SNL Kagan, tv show counts for the streaming providers from SNL Kagan. SNL Kagan also includes an annual survey called Consumer Insights which surveys consumers on their preferences and subscription behavior.

Channel Guide

The Channel Guide is a monthly publication which lists the tv shows airing on over 100 traditional networks. This source includes among other details, the name of the television show and the networks that the television show airs on. I was provided with pdf copies of the archived versions from the publisher.

Nielsen Local Watch Reports

The Nielsen Local Watch Reports are publicly released and include trends across the "Local people meters (LPM)" markets. LPM "are used in the Top 25 markets to electronically capture both tuning and viewing at the household and persons level." Nielsen (2019) Starting in 2014, Nielsen began to track the subscription to streaming video services using LPM. They publicly reported the top 10 DMAs for Netflix for 2014 and 2015. The remaining markets and/or subsequent years are available for purchase.

Warren Communication TV Factbook

The Warren Communications TV Factbook has information on cable packages and prices offered by cable distributors at the "Principal Community" level. This source was discontinued at the end of 2017.

A.2 Constructed Variable Definitions

Monthly Advertised Price ($):

The cost for subscribing to television services from traditional distributors and streaming services. Historical package prices for traditional distributors can be difficult to find at a local-level. I followed the method described in the Crawford et al. (2018), which involved using the web archive to obtain historical rate cards for the television services. Whenever possible, I used local rate cards or found rates listed in the web archive to populate the data. I supplemented this with data from SNL Kagan and the Warren Communications TV Factbook. SNL Kagan collects an annual snapshot of package prices for the top traditional distributors in select DMAs, however, this source is incomplete. There are DMAs that a distributor serves that SNL Kagan did not record. Therefore, I also sought additional sources, such as the Warren Communications TV Factbook. Warren includes datasets for cable package prices at a principal community level.[1,2] However, I only used Warren as a source for basic prices if this information was not available elsewhere. Prices for the satellite and streaming providers were easier to track down because the price is national. This information was found by visiting the distributor's website stored in the web archive.

Unique TV Show Title Count:

For traditional services, this variable is constructed by combining the channel lineups for a package from SNL Kagan with the Channel Guide listings which has the list of television shows aired in a month. For Netflix, this variable is constructed by scraping the content library titles from the web archive.

[1]The principal community includes a list of counties that are served by this provider in the area.

[2]There are well-documented downsides with this source (e.g. sample attrition, they only track cable distributors, which means telco packages aren't included).

Overlap of TV Show Titles with Netflix (%):

This variable is constructed by comparing the unique TV show titles for traditional services with the unique TV show titles for Netflix.

Vertical Integration:

Measures the ownership share that cable distributors have for channels included in their television packages. If the distributor owns 50% stake in the channel then the vertical integration would be 0.5. This value is summed for each provider/package/ county/dma/year observation.

APPENDIX B

Market Penetration

Following Fan (2013)[1], the probability that household i chooses product j as their first or second choice in market m at time t is:

$$\mathbb{P}(Y_{imt} = j|X, type(j), ..) = \underbrace{\mathbb{P}(U_{ijmt} > \max_s U_{is}, \forall s)}_{(j \text{ is } first)} + \underbrace{\sum_{j'} \mathbb{P}(U_{ij'mt} > U_{ijmt} > \max_{h \neq j'} U_{ihmt}, U_{ijmt} - \kappa > U_{i0})}_{(j \text{ is } second)}$$

This probability translates into the following market penetration equation for product j:

$$s_{jmt} = \int \Upsilon_j^{(1)} dF(\nu_i, \eta_i) + \sum_{j'} \int \left(\Upsilon_{j,j'}^{(2_1)} - \Upsilon_j^{(2_2)} \right) dF(\eta_i)$$

$$\begin{aligned} &where \\ \Upsilon_j^{(1)} &= \frac{\exp(\delta_j + \mu_{ij})}{1 + \sum_{s=1,..,J} \exp(\delta_s + \mu_{is})} \\ \Upsilon_{j,j'}^{(2_1)} &= \frac{\exp(\delta_j + \mu_{ij})}{\exp(\kappa) + \sum_{h \neq j'} \exp(\delta_h + \mu_{ih})} \\ \Upsilon_j^{(2_2)} &= \frac{\exp(\delta_j + \mu_{ij})}{\exp(\kappa) + \sum_s \exp(\delta_s + \mu_{ik})} \end{aligned}$$

The market penetration for streaming services is observed at the DMA-level. Therefore, I use the following weighted sum to the aggregate the predicted market penetration from county to DMA-level:

$$s_{jdt} = \sum_{c \in d} (s_{jct} * w_c)$$

[1] Fan (2013) includes a proof which shows that the multiple-discrete choice model will have a unique solution to the contraction mapping under two assumptions: (1) $0 < s_{jt} < 1 \quad \forall j = 1, .., J_{ct}$ and (2) $\sum_{j=1}^{J_{ct}} < 2$.

where w_c is defined as the household weight for county c and s_{jct} is the predicted market penetration of the product j in the county c.

APPENDIX C

Instrumental Variables

The excluded instruments are defined as the following:

IV1	BLP-style	Sum of other providers tv shows in the same county
IV2	BLP-style	Sum of the same providers tv shows in other products in the same county
IV3	BLP-style	Number of competitors in the county by format
IV4	Cost shifter	National subscriber counts from t-1
IV5	Cost shifter	Annual information payroll by county
IV6	Cost shifter	Annual broadcast payroll (ex. internet) by county

Table C.1: First Stage Regression Results

	Price	Std. Error
log(TV show count)	42.355***	(0.687)
Overlap TV show	-3.719***	(0.278)
Share of HH with 3mbs internet	-0.014	(0.491)
Share of HH aged 15 to 34	1.776*	(0.843)
Share of HH aged 35 to 54	3.100**	(0.900)
Median HH Income	-0.0516	(0.043)
Population Density	-0.0523**	(0.016)
Excluded:		
IV1	0.0003	(0.00002)
IV2	0.192*	(0.026)
IV3	-2.35*	(1.138)
IV4	-0.267*	(0.111)
IV5	0 .00006**	(0.00002)
IV6	0.00002	(0.00005)
Observations	9018	
DMA Fixed Effect	Y	
Year Fixed Effect	Y	
Format Fixed Effect	Y	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX D

Price Elasticity of Demand

The price elasticity of demand is defined as $\frac{\partial S_{jmt}}{\partial p_l}\frac{p_l}{S_j}$ which describes how consumers' purchases will change following a price increase of any of the available goods. The price elasticities will be a matrix where the own-price elasticity will be on the diagonal, and the cross-price elasticity will be off-diagonal.

$$\frac{\partial \mathbf{S}}{\partial \mathbf{p}} = \begin{pmatrix} \frac{\partial S_j}{\partial p_j} & \frac{\partial S_j}{\partial p_\ell} \\ \frac{\partial S_\ell}{\partial p_j} & \frac{\partial S_\ell}{\partial p_\ell} \end{pmatrix}$$

Recall the definition for the market penetration equation:

$$S_{jmt} = \int \Upsilon_j^{(1)} dF(\eta_i) + \sum_{j'} \int \Upsilon_{j,j'}^{(2_1)} - \Upsilon_j^{(2_2)} dF(\eta_i)$$

$$\Upsilon_j^{(1)} = \frac{\exp(\delta_j + \mu_{ij})}{1 + \sum\limits_{s=1,..,J} \exp(\delta_s + \mu_{is})}$$

$$\Upsilon_{j,j'}^{(2_1)} = \frac{\exp(\delta_j + \mu_{ij})}{\exp(\kappa) + \sum\limits_{h \neq j'} \exp(\delta_h + \mu_{ih})}$$

$$\Upsilon_j^{(2_2)} = \frac{\exp(\delta_j + \mu_{ij})}{\exp(\kappa) + \sum\limits_{s} \exp(\delta_s + \mu_{ik})}$$

Then, the derivative for the own-price term is the following:

$$\begin{aligned}\frac{\partial S_j}{\partial p_j} &= \frac{\partial}{\partial p_j} \int \Upsilon_j^{(1)} dF(.) + \frac{\partial}{\partial p_j} \sum_{j' \neq j} \int \Upsilon_{j,j'}^{(2_1)} - \Upsilon_j^{(2_2)} dF(.) \\ &= \int \alpha \Upsilon_j^{(1)} \left(1 - \Upsilon_j^{(1)}\right) dF(.) + \sum_{j' \neq j} \int \alpha \Upsilon_{j,j'}^{(2_1)} \left(1 - \Upsilon_{j,j'}^{(2_1)}\right) - \alpha \Upsilon_j^{(2_2)} \left(1 - \Upsilon_j^{(2_2)}\right) dF(.)\end{aligned}$$

The derivative for the cross-price term is the following:

$$
\begin{aligned}
\frac{\partial S_j}{\partial p_\ell} &= \frac{\partial}{\partial p_\ell}\int \Upsilon_j^{(1)} dF(.) + \frac{\partial}{\partial p_\ell}\sum_{j'\neq j}\int \Upsilon_{j,j'}^{(2_1)} - \Upsilon_j^{(2_2)} dF(.) \\
&= \int (-\alpha)\Upsilon_j^{(1)}\Upsilon_\ell^{(1)} dF(.) + \sum_{j'\neq j}\int (-\alpha)\Upsilon_{j,j'}^{(2_1)}\Upsilon_{\ell,j'}^{(2_1)} - (-\alpha)\Upsilon_j^{(2_2)}\Upsilon_\ell^{(2_2)} dF(.)
\end{aligned}
$$

A sample market elasticity matrix is shown on the next page.

APPENDIX E

Compensating Variation

This section will show the expression for the welfare measure used in the analysis. The closed form compensating variation measure from Small and Rosen (1981) will be used to quantify the consumer welfare effect from the introduction of streaming services.

$$CV_{ict} = \frac{V_i^0 - V_i^1}{\alpha}$$

Where α is the structural parameter estimated from the model, and V_i^0 is the inclusive value for consumer i before the introduction of streaming services and the V_i^1 is after the introduction of streaming services.

The inclusive value for consumer i will include the values for the first and second choices. The inclusive value is defined as follows:

$$V_i^0 = \ln\left(\sum_{j=1}^{J_{mt}} \exp(\widetilde{U}^0_{ijmt}) + 1\right) + \sum_{j'} \left(\ln\Big(\sum_{h \neq j'} \exp(\widetilde{U}^0_{ihmt} - \kappa) + 1\Big) - \ln\Big(\sum_{j=1}^{J_{mt}} \exp(\widetilde{U}^0_{ijmt} - \kappa) + 1\Big)\right)$$

where the $\widetilde{U}$ removes the idiosyncratic shock from the consumer's utility function. Note that the $\widetilde{U}$ still depends on unobserved heterogenous terms so I will need to take the expectation of the CV_i over the η_{ijmt} term.

The average-per household change in welfare can be found by averaging across the simulated households:

$$\Delta\overline{Welfare_{ct}} = \mathbb{E}[CV_{ict}]$$

The total welfare loss for these markets can be found by using the following calculation:

$$\Delta Welfare = \sum_{ct} H_{ct} \cdot \overline{\Delta Welfare_{ct}}$$

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