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MEDIA BUREAU STAFF RESEARCH PAPER

A Survival Analysis of Cable Networks

by Keith S. Brown

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A Survival Analysis of Cable Networks

KEITH S. BROWN*

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Abstract

This paper employs survival/duration analysis to determine how subscriber levels affect cable networks' survival probabilities. According to these survival/duration estimates, a cable network that grows at our calculated mean rate requires approximately 42 million subscribers by its tenth year to obtain a 70% chance of survival over its first ten years.

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*Senior Economist, Media Bureau. The views expressed are those of the author and do not necessarily reflect the views of the Media Bureau, the Commission, or other members of the Commission's staff.

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I. Introduction

The majority of Americans today receive their television programming from a multi-channel video programming distributor (MVPD). The most widely available MVPDs are cable television and direct broadcast satellite (DBS) systems.[1] Over 88% of the 106,641,910 U.S. television households subscribe to an MVPD service, with 74.87% of the MVPD subscribers choosing cable service and 21.63% choosing DBS service. In addition to delivering local broadcast stations, MVPDs carry *"cable" networks*.[2] Cable and satellite providers generally package these cable networks in bundles and/or tiers, and offer some additional programming services on a per-channel or pay-per-view basis.[3] Because so many U.S. households choose MVPD service, such services play an important role in the quality of people's lives.

The number of national cable networks and the variety of programming they offer have increased dramatically in recent years. In 2003, 339 satellite-delivered national cable networks were in operation, an increase of 233 networks since 1994.[4] Similarly, competition among cable networks and their diversity of source and content has increased. In 1992, there was only one non-broadcast national news network, CNN. Today, CNN competes with MSNBC, Fox News Channel, and CNBC for subscribers. In children's programming, consumers can now choose from Nickelodeon, several Disney networks, Cartoon Network, and Noggin. With respect to basic service movie channels, before 1992, there was only AMC; now there are TCM, Fox Movie Channel, Sundance, Independent Film Channel and the Lifetime Movie Network. Today, there is also a tremendous variety of more specialized niche programming, such as Food Network, Sci-Fi, Golf, HGTV, Outdoor Life, and the Speed Channel. Even in niches where an existing network enjoys a strong brand name, new networks are entering, as National Geographic has entered to challenge Discovery.

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[1] Other technologies for distributing multi-channel video programming may be available in some areas and/or in planning stages in some areas. Cable and satellite currently make up the vast majority of MVPD subscriptions.

[2] These non-broadcast networks are often referred to as cable networks, because they were initially developed for cable carriage. Today, MVPDs (e.g., cable, DBS, private cable, or Satellite Master Antenna TV operators) distribute these networks.

[3] Under the provisions of the Communications Act, a cable operator can require a subscriber to buy no more than the *basic tier* (i.e., the programming tier with broadcast and PEG channels) in order to subscribe to premium channels (e.g., HBO, Showtime) or other services, such as pay-per-view.

[4] *See 10th Annual Report on Video Competition*, 19 FCC Rcd at 1690-91.

Over the years, a significant number of cable networks have been announced and planned.[5] Some networks launched and succeeded, other networks have yet to initiate service, other networks have begun operation and failed, and still others have begun operation and then merged with other services. For a variety of reasons, researchers, policymakers, and investors want to know the primary determinants of cable network survival. We therefore benefit the public if we reasonably answer the following questions:

1. How many subscribers have cable networks needed in the past to continue operations?

2. What does this tell us about the revenue structure, cost structure, and exit decisions of cable networks?

When a cable network begins operations, it often attracts very few households and suffers heavy losses during its start-up period, seeking future present-valued quasi-rents[6] that will equal or outweigh the initial losses. Given the high losses that a cable network suffers during its start-up phase, that network must expect many future households as subscribers in order to begin operations.

A cable network's decision to exit depends on its expected present value of future quasi-rents; if the expected present value of future quasi-rents drops below zero, then the network exits. Because a cable network incurs sunk entry costs, the quasi-rents a cable network needs to stay in business are clearly far less than the expected profits that induce entry by a cable network.[7] Once a cable network incurs sunk entry costs, these sunk entry costs are not relevant to the cable network's later exit decision. For example, suppose that a cable network incurs sunk entry costs of $10, expecting $11 in present-valued future quasi-rents. Subsequently, the cable network discovers that its present-valued future quasi-rents are only $5. Notwithstanding the negative difference between its sunk costs and quasi-rents, the cable network would still continue operations, since the sunk entry costs are not affected by continuing operations or shutting down and exiting the market. Some positive level of quasi-rents, although insufficient to recover total sunk costs, helps minimize losses.

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[5] *See, e.g.*, 19 FCC Rcd at 1735-37, Table C-4; 17 FCC Rcd at 26901, 26992-94, Table C-4; 17 FCC Rcd at 1244, 1357-58, Table D-4.

[6] These revenue streams are quasi-rents and not profits, because they may not equal the sunk costs of entry, but still may be greater than the minimum revenue required to keep the cable network operating.

[7] Dixit (1989) explores this gap between the prices that induce exit and the prices that induce entry and finds that even a small gap induces significant hysterisis.

Cable programming has a high fixed cost of production and a very low marginal cost of distribution. That is, producing programming can be very expensive, but distributing that programming to an additional household is virtually costless. It costs a cable network as much to produce programming that could reach one subscriber as it does to produce the same programming that could reach one million subscribers.[8] Programming costs therefore do not rise when the programming network reaches more subscribers, but revenues do increase when the network reaches more subscribers. Hence, profits definitely increase with the number of subscribers, so that cable networks seek to maximize program distribution, conditional on price.

Analyzing cable networks' profit and revenue streams may seem ideal, but because revenue and cost data for many networks (particularly "deceased" networks) are unavailable, such analysis is not possible. In addition, Fisher and McGowan (1983) and others demonstrate the virtual impossibility and high likelihood of error when researchers try to infer economic profits from observed accounting profits, so that using profit and revenue data may not be desirable.

Survival/Duration analysis enables us to estimate the number of subscribers that cable networks need to stay in business. Engineers and biologists first applied Survival/duration methods to estimate how different ball bearings affect a machine's longevity or how a new drug affects a patient's longevity. Economists then discovered survival/duration analysis and applied it to a variety of economic settings. For example, Lancaster (1979) uses survival analysis to analyze unemployment duration, as does Meyer (1990). Chung, Schmidt and Witte (1991) employ survival analysis to determine causes of criminal recidivism. Ham and Lalonde (1996) use survival analysis to study the effect of a job training program on unemployment duration. Lancaster (1990) provides a notable monograph on survival analysis.

The economics/business/finance literatures are rich with survival/duration analyses of media products like movies (DeVany and Walls (1996), DeVany and Walls (1997), Walls (1998)), Broadway shows (Simonoff and Ma (2003)), and newspapers (Kranenburg, Palm, and Pfann (2002)). However, no published research has applied survival analysis to cable networks. Moreover, there does not appear to be any data source that specifically deals with cable networks that have failed in the past. This is not surprising; non-existent cable networks do not attract interest from most consumers of cable industry data, and MVPD data producers therefore do not collect and keep such data.

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[8] Of course, programmers may charge distributors on a per-subscriber basis, but that does not change the fact that the cost of making a program is fixed, and that the actual cost of making the program need not rise when the program reaches more subscribers.

II. Data

We collected data on cable networks from a variety of sources.[9] The *Television and Cable Factbooks*[10] from the years 1984-2001 report the number of subscribers for a cable network in a given year from 1984-2001. This study focuses on national non-premium networks, and therefore includes neither regional cable networks nor premium networks like HBO and Showtime. If we do not observe a cable network in a given year's *Factbook* after it appeared in previous *Factbooks*, then we assume that the cable network exited (unless we see it again in following *Factbooks*).

The number of subscribers and network genre may determine a cable network's survival. Network genre may determine survival probabilities because important underlying determinants of survival vary across network genres. Production costs may vary across genre, because different types of programming have different costs of production. This variation would generate a different relationship between subscribership and survival probability.

Different genres may also face different demands from subscribers. One genre might attract intense interest from a handful of households and only the slightest interest from all other households. In this case, as Spence and Owen (1977) demonstrate, the cable operator would capture only a fraction of subscribers' total willingness to pay for the channel.[11] A different genre, however, might attract middling interest from all households. In this case, the cable operator can capture (almost) the entire sum of subscribers' willingness to pay for a channel.[12] Therefore, different programming genres may require different numbers of subscribers for survival, even if these genres have identical programming costs.

Other factors, however, may also be important. A cable operator's ownership interest in a programming network may lead that operator to favor the

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[9] Ms. Jane Frenette provided valuable assistance with this important task.

[10] Warren Communications, *Television and Cable Factbook*, Warren Publishing, 1984-2001.

[11] The intuition of this proposition is illustrated in the following example: Ten households are willing to pay $10 for an old classic movie channel, while 90 households are only willing to pay $1 for the same channel. The sum of households' willingness-to-pay is $190. The most the single-price cable operator can obtain, however, is $100, by charging $10 and attracting only ten households. This case represents a more convex demand schedule.

[12] Consider this example: All 100 households in a system may be willing to pay $1.90 for a channel featuring game show reruns. The cable operator charging a single price can obtain all $190 by charging $1.90 and attracting all 100 households. This case represents a more concave demand schedule.

programming network in its carriage decisions[13] (possibly because the operator receives some of the programming network's advertising revenue). We therefore include the vertical ownership measure obtained from past *FCC Video Competition Reports* (which rely heavily on the National Cable Television Association's *Cable Developments*) and Kagan's *Economics of Basic Television Networks*. So-called "spinoff" networks (cable networks spawned by other programming networks) may also face a higher survival probability, possibly because they can forgo the costs of producing original programming by airing previously-aired programming from their parent cable network. We collected data on these spinoffs from past *FCC Video Competition Reports* and Kagan's *Economics of Basic Television Networks*. Finally, a cable network's start year may influence its probability of survival. Our sample begins in 1984. Therefore, among the cable networks starting before 1984, we observe only those that survive at least until 1984.

We do not observe every explanatory variable for every cable network. In addition, our ability or inability to observe a variable may reveal important information concerning a network's survival probability. Table 1 lists the explanatory variables, their data source, the number of networks with missing observations for each variable, the number of failures observed, and the probability of failure. As we can observe more about a cable network (including the network's subscriber count, vertical integration, and spinoff status) the cable network's survival probability rises. More specifically, if we observe a cable network's subscriber count, vertical integration, and spinoff status, that cable network has an estimated failure probability of 19.0%. All other networks have a 43% chance of failure.[14]

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[13] To clarify, the operator would favor the programming network by carrying it under circumstances in which it would normally not carry a comparable network in which it lacks any ownership.

[14] The derivation of this estimated failure probability is as follows: (96 total failures - 28 "observe everything" failures) = 68 failures. (305 total networks - 147 "observe everything" networks) = 158. Dividing 68 by 158 yields 43%.

TABLE 1
EXPLANATORY VARIABLES AND DATA SOURCES

Explanatory Variable	Number of Observed Networks	Source	Number of Failures	Percentage Failures
Network Name, Genre, Start Year	305	*Factbooks*	96	31.5
Number of Subscribers	194	*Factbooks*	47	24.2
Vertical Integration	210	*FCC Video Reports, Kagan*	53	25.2
Spinoff	210	*FCC Video Reports, Kagan*	54	25.7
Subscribers, Vertical, and Spinoff Observed	147	*Factbooks, FCC Video Reports, Kagan*	28	19.0

We adjust for the bias induced by missing observations by creating two dummy variables that take on a value of one when the number of subscribers (*Missing Subs*) and vertical integration (*MissingVerticalorSpinoff*) cannot be observed.[15] We create two more new variables by multiplying the measures of subscribers and vertical integration status by one minus the value of *Missing Subs* and *Missing Vertical*. This creates two new variables; namely, *SubsMiss* and *VerticalMiss*, which equal zero when observations are missing.

The population sample begins in 1984. Many cable networks, however, began (and possibly ended) before 1984. The data therefore suffer from *stock sampling*, which occurs where the researcher samples from the population at a given point in time. The sampling period ends in 2001, notwithstanding that cable networks continued in business after 2001. We therefore face *right censoring*, which occurs where the researcher ends the sampling period at a given point in time. We do not observe network exits or entrances before 1984. Consequently, there are truncation problems stemming from the stock sampling.[16] In addition, we cannot observe cable network exits that occur after 2001 (right censoring). We therefore employ analysis that takes this censoring

[15] Because we obtain data on vertical integration and spinoff status from the same sources, any observation that is missing for vertical integration is also missing for spinoff status (though one more observation is missing for spinoff status), so that it is unnecessary to create a missing dummy variable for both vertical integration and spinoff status.

[16] However, because all networks' start dates are observed, left censoring problems are avoided.

into account. Finally, there remains the issue of grouped duration data. Ideally, we could observe the exact date and time of each programming network's exit. Instead, we only observe the year of exit. Consequently, cable networks can exit during only 17 intervals, one for each possible year of exit. Therefore, we employ a methodology that addresses grouped duration data. Discrete time survival/duration models provide this analysis.

Survival models first estimate an underlying *baseline hazard function*, which simply means estimating the cable network's underlying probability of exit in each period, given that the network did not exit in the past. The researcher then multiplies that baseline hazard by measures of different covariates. [17] Once the hazard is estimated, it can be used to calculate a network's chance of survival for any given amount of time and to estimate a programming network's chance of survival for any given future time period, given that the network has survived so far.

III. Estimation Methods and Empirical Results

A. Overview

We estimate a model of survival for cable networks using two methods. One method is *parametric*, where we assume that the hazard survival probabilities follow a known statistical distribution. The parametric method has one distinct advantage; unlike some other methods to be discussed later, the researcher need not assume a condition called *strict exogeneity* to obtain statistically sound estimates.[18] In addition, parametric methods enable the researcher to model easily unobserved heterogeneity. This means that the researcher can adjust for many differences between cable networks even where the researcher cannot observe such differences.[19] One drawback to parametric methods is that they estimate a smooth curve on the survival probability, which may impose unnecessary structure on the hazard and survival probabilities and can at times lead to some odd predictions based on the smooth curve itself.[20] These odd

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[17] Technically, this discussion applies to proportional hazards models only, and not to accelerated failure time models. Since this study employs a proportional hazards approach, we focus the discussion on these models.

[18] *Strict exogeneity* (also called *sequential exogeneity*), unlike the usual definition of exogeneity, means that there is no correlation between unobserved characteristics and future values of a time-varying explanatory variable.

[19] However, the researcher must then assume strict exogeneity of the explanatory variables, conditioned on the unobserved heterogeneity. In addition, the unobserved heterogeneity must be distributed independently of the explanatory variables. The expectation of the unobserved heterogeneity cannot be larger or smaller based on the size of any of the independent variables.

[20] This would occur if extrapolating well beyond existing data points based on the smooth curve itself.

predictions may indicate misspecification introduced by imposing the wrong statistical distribution.

A second method employs *semi-parametric* estimation, which uses the data itself to build an underlying baseline hazard function. Because semi-parametric estimation methods use the actual data to build the baseline hazard function, there is no curve-fitting for the baseline hazard, which avoids the imposition of structure on the data. This allows the researcher to avoid errors arising from misspecifying the underlying probability distribution. Unfortunately, because of data limitations, the researcher cannot easily employ this method to model unobserved heterogeneity. In addition, according to Wooldridge (2002), ". . . with time-varying covariates, Cox's method evidently requires the covariates to be strictly exogenous".[21] Meanwhile, another semi-parametric method, piecewise-constant proportional hazard estimation,[22] does not easily allow for stratification.

The assumption of strict exogeneity is problematic. Kalbfleisch and Prentice (1980), discussing time-varying covariates (i.e., those explanatory variables that vary over time), divide these covariates into *external covariates* and *internal covariates*. In this context, if a time-varying covariate moves independently of whether or not a cable network exits, then that covariate is external. If a time-varying covariate's value depends on whether the programming network exits, then that covariate is internal. The number of subscribers is an internal covariate, because a cable network cannot attract any subscribers after it exits. Internal covariates clearly cannot be strictly exogenous, so that the assumptions underlying the Cox semi-parametric method and the parametric method with unobserved heterogeneity do not hold. However, these methods still impose less structure or model possibly important unobserved heterogeneity. We estimate the parametric model without unobserved heterogeneity, thereby gaining estimates that do not rely on the strict exogeneity assumption. We then check these estimates against the semi-parametric estimates and parametric methods with unobserved heterogeneity that require strict exogeneity. We can therefore discover whether the violation of strict exogeneity generates seriously inaccurate estimates. Table 2 lists the advantages and drawbacks of each estimation method. None of our three estimation methods scores three for three on our list of three virtues, but each method has different virtues. Consequently, each method can be compared to discover which method yields the greatest overall net advantage.

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[21] Wooldridge, *Econometric Analysis of Cross Section and Panel Data*, p. 714.

[22] The piecewise-constant proportional hazard method is called "semi-parametric" only because it does not estimate an underlying hazard function as a smooth curve over time. The piecewise approach is parametric in that it employs an underlying statistical distribution.

TABLE 2

ADVANTAGES AND DRAWBACKS OF EACH ESTIMATION METHOD

	Semi-Parametric (Cox/Piecewise)	Parametric (no unobserved heterogeneity)	Parametric (with unobserved heterogeneity)
Impose structure?	No/No	Yes	Yes
Model unobserved heterogeneity?	No/No	No	Yes
Requires strict exogeneity?	Yes/No	No	Yes

B. Estimation and Results Of Parametric Models

For estimating the parametric model, we employ the Weibull distribution. The Weibull tends to be the more popular parametric distribution for survival estimation, because the Weibull is straightforward to estimate and has enough flexibility to allow the researcher to check for an increasing, constant, or decreasing probability of survival over time.

In survival models, negative duration dependence indicates increasing exit probability over time, because the probability of survival falls as the subject gets older. Adult humans exhibit negative duration dependence, because our likelihood of dying increases as we age. Positive duration dependence indicates that the probability of survival increases as the subject gets older.

Examination of the Weibull distribution illuminates its advantages. The conditional Weibull probability density function tells us the probability of exiting at time t conditional on the explanatory variables x_i. The Weibull probability density function is $f(t \mid x_i;\theta) = \exp(x_i\beta)\alpha t^{\alpha-1}\exp[-\exp(x_i\beta)t\alpha]$. The parameters to be estimated are α and β. In this model, the value of α determines whether the process exhibits positive or negative duration dependence, and the values in the vector β determine the impact of the explanatory variables on the probability of survival. Several other functions can be derived from the Weibull probability density function. The *survivor function,*

$$S(t;x_i) = \exp[-\exp(x_i\beta)t^{\alpha}] \tag{1}$$

is the probability of a cable network surviving until at least time t. Dividing the Weibull probability density function by the survivor function generates the *hazard function*

$$\lambda(t;x) = \exp(x\beta)\alpha t^{\alpha-1} \quad . \tag{2}$$

This hazard function provides the probability of the network exiting at time t, conditional on not having exited prior to time t. It is this function that we estimate to recover α and β.

As noted previously, the data for this study begin in 1984, after some programming networks had already launched; cable networks that both launched and died before 1984 are not observed. Also noted previously, this creates a stock sampling issue, where the data suffer left-truncation, meaning cable networks that both entered and exited the market before 1984 are not seen. In addition, the data set ends at 2001, so cable networks that exit after 2001 are not observed. This means that the data are right-censored. Given these data restrictions, estimation requires maximization of the log-likelihood function

$$\sum_{i=1}^{N}\{d_i \log[f(t_i \mid x_i;\theta)] + (1-d_i)\log[1-F(t_i \mid x_i;\theta)] + \log[k(a_i \mid x_i;\eta)] - \log\int_0^b 1-[F(b-\mu \mid x_i;\theta)]k(\mu \mid x_i;\eta)d\mu \ , \tag{3}$$

where F is the cumulative Weibull distribution; t is time; b is the point where the sampling period begins; d_i is a binary variable that equals zero if the network was still surviving in 2001 and one otherwise; and a_i measures when each observation enters the sample.[23] In addition, $k(\bullet \mid x_i;\eta)$ is the density of starting times given x_i. The statistical estimation package *Stata* performs this estimation procedure when the researcher has identified the relevant values b and a_i.

We now consider unobserved heterogeneity, which represents unobserved determinants of cable network duration. In order to model unobserved heterogeneity, we must make the following three assumptions:

(1) The heterogeneity is independent of the observed covariates.
(2) The heterogeneity has a distribution known up to some finite number of parameters.
(3) The heterogeneity enters the hazard function multiplicatively.

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[23] η and θ are both vectors of parameters to be estimated.

We illustrate these assumptions by adding heterogeneity to the Weibull distribution. The Weibull marginal hazard is

$$\lambda(t;\ x_i,\ v_i) = v_i \exp(x_i \beta) \alpha t^{\alpha-1} \tag{4}$$

where v_i is the unobserved heterogeneity, which enters the distribution multiplicatively. Because this heterogeneity cannot vary across covariates, the primary value of including this unobserved heterogeneity is that it allows more flexible estimation of duration dependence. Lancaster (1990) notes that ignoring multiplicative heterogeneity in the Weibull model results in underestimating the value of α.

Applying independence of x_i and v_i, the new cumulative distribution function t_i^* given x_i is

$$G(t \mid x_i;\ \theta,\ \gamma) = \int_0^\infty F(t \mid x_i, v; \theta)\, h(v; \gamma)\, dv \ , \tag{5}$$

where F is the Weibull distribution function, and h is the probability density function of v with mean one and variance γ. Of course, stock sampling and right censoring remain problems. We therefore substitute the new distribution and density functions, G(.) in equation (5) and its derivative g(.), that incorporate unobserved heterogeneity into the earlier likelihood function that is adjusted for right censoring and stock sampling. This yields

$$\sum_{i=1}^{N} \{ d_i \log[g(t_i \mid x_i)] + (1-d_i) \log[1 - G(t_i \mid x_i)] + \log[k(a_i \mid x_i;\ \eta)] - \log \int_0^b 1 - [G(b-\mu \mid x_i)] k(\mu \mid x_i;\ \eta)\, d\mu \tag{6}$$

which we maximize in order to estimate survival following a Weibull distribution with unobserved heterogeneity. We use the Gamma distribution to model the distribution of unobserved heterogeneity, as this is the only applicable distribution available in *Stata 8* to estimate discrete-time duration models with heterogeneity. Under the Gamma distribution of unobserved heterogeneity, $h(v) = \delta^{\frac{1}{\gamma}} v^{\frac{1-\gamma}{\gamma}} \exp(-\frac{v}{\gamma}) / \Gamma(\frac{1}{\gamma})$, where $\Gamma(\bullet)$ is the Gamma function.

We estimate a discrete-time Weibull mode with and without unobserved heterogeneity, and we stratify by the sports and shopping genres. Table 3 displays the estimation results. Estimating the Weibull marginal hazard, i.e.,

$$\lambda = \exp(x_i \beta) \alpha t^{\alpha-1} \ , \tag{7}$$

generates an estimate of α, which yields the baseline marginal hazard probability together with the vector β, which yields the covariates' effects on a network's marginal hazard, i.e., its probability of exit in a given period, given that it did not exit before that period.[24]

[24] Using discrete-time models, the estimated marginal hazard is actually $1-e^{-e^{(X\beta+\alpha \ln t)}}$.

TABLE 3

PARAMETRIC WEIBULL SURVIVAL ESTIMATES

(Z-statistics in parentheses)

	Weibull (No Unobserved Heterogeneity)	**Weibull (Gamma-distributed Unobserved Heterogeneity)**
Millions of Subs	-0.07*** (3.92)	-0.13*** (3.95)
Missing Subs	-0.65*** (2.61)	-1.07** (2.31)
Vertical Integration	0.00 (0.07)	0.00 (0.02)
Spinoff	-1.39*** (2.64)	-2.69*** (2.67)
Missing Vertical or Spinoff	0.56** (2.51)	1.74*** (3.22)
Born before 1984	-0.89* (1.94)	-3.48*** (3.25)
Constant	-2.87*** (9.23)	-4.46*** (6.58)
α	0.28* (1.83)	2.39*** (3.95)
α_{sports}	0.79 (1.63)	3.36 (1.27)
α_{shop}	0.68** (2.52)	4.26*** (2.57)
γ variance		6.30*** (3.24)
Observations	305	305
Failures	96	96
Log Likelihood	-363.10***	-348.97***

*- significant at 10% level, ** - significant at 5% level, *** - significant at 1% level

In the estimation without unobserved heterogeneity, an additional one million subscribers reduce the marginal probability of exit by 7%. Ten million subscribers generate a hazard ratio of $e^{(10*(-.07))} = e^{(-.7)} = .50$, so that 10 million subscribers would reduce the probability of exit by 50%. If the observation on the number of subscribers is missing, then the hazard ratio is 0.52, so the probability of exit is 48% lower than the probability of exit if we observe zero subscribers. Thus, observing over nine million subscribers confers the same probability of exit as not being able to observe the number of subscribers, because $e^{(9*(-.07))} = e^{(-.63)} \approx 0.52$. Spinoff networks have a hazard ratio of 0.25, so a network's probability of exit declines by 75% if that network is a spinoff network. If cable network's vertical ownership or spinoff status cannot be observed, then that cable network has a 75% greater chance of exit. If the network began before 1984, then we do not observe other networks in its birth cohort that died before 1984. That network's marginal probability of exit therefore declines by 59%. In addition, both sports channels and shopping channels have a greater probability of exit than non-sports and non-shopping channels. A sports channel is 67% more likely to exit and a shopping channel is 49% more likely to exit in any given year than are other types of programming networks.

The addition of gamma-distributed heterogeneity significantly changes the coefficient estimates. The likelihood ratio test for these models rejects the null hypothesis that they yield the same coefficient estimates. An additional one million subscribers multiplies the hazard ratio by 0.87, so that one million subscribers reduce the marginal probability of exit by 13%. Ten million subscribers would create a hazard ratio of $e^{(10*-(.13))} = e^{(-1.3)} = .27$, so that ten million subscribers would reduce the probability of exit by 73%. If the observation on the number of subscribers is missing, then the hazard ratio is 0.34, so the probability of exit is 66% lower than the probability of exit if we observe zero subscribers. Thus, observing over 8 million subscribers confers the same marginal probability of exit as not being able to observe the number of subscribers, because $e^{(8*(-.13))} = e^{-1.04} \approx .34$. Spinoff networks have a hazard ratio of 0.07, so a network's probability of exit declines by 93% if that network is a spinoff network. If cable network's vertical ownership or spinoff status is not observed, then that programming network has a 470% greater chance of exit. If the network began before 1984, so that other networks in its birth cohort that died before 1984 are not observed, then that network's marginal probability of exit declines by 97%. In addition, shopping channels have a greater probability of exit than non-sports and non-shopping channels. A shopping channel is 649% more likely to exit in any given year.

To obtain marginal effects, we need the specific time period and all of the covariates' values. Because the covariates and the time period affect the marginal hazard through a nonlinear function, the marginal effects at specific values for time and all other covariates must be evaluated. For example, we calculate the marginal effect of increasing the number of subscribers from four million to five million for a cable network in year number five. That network began after 1984; is not vertically integrated; is not a spinoff; and has no missing values for the number of subscribers, the degree of vertical integration, or spinoff status. In addition, the network genre is neither sports nor shopping. Using the Weibull values with unobserved heterogeneity,[25] a network with zero subscribers would face a marginal exit hazard of 40.5%; a network with four million subscribers would face a marginal exit hazard of 26.6%; and a network with five million subscribers would face a marginal exit hazard of 23.7%. Therefore, the marginal effect of going from four million to five million subscribers in year five would reduce the marginal probability of exit by 2.9%.

The discrete-time survivor function at time t is

$$(1-\lambda_1)*(1-\lambda_2)*\ldots*(1-\lambda_t), \tag{8}$$

which is equivalent to

$$e^{\sum_{x=1}^{t} \ln(1-\lambda_x)} . \tag{9}$$

Using this survivor function, which is the discrete-time counterpart of the aforementioned continuous-time survivor function, $S(t;x_i) = \exp[-\exp(x_i\beta)t^{\alpha}]$, we calculate subscriber profiles over a cable network's first X years that generate a given probability of survival, which is one of many ways to examine the influence of subscribers on the success of a network.

Any number of years and any probability of survival may be chosen. For this discussion, we select the first five years and the first 10 years of a cable network's life, and select a 70% survival probability.[26] We assume that the network began after 1984; is not vertically integrated; is not a spinoff; and has no missing values for the number of subscribers, the degree of vertical integration, or spinoff status. In addition, the network genre is neither sports nor shopping. Finally, a realistic

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[25] Recall that the heterogeneity term is independent of the covariates and has a mean equal to one, so that unobserved heterogeneity can be ignored when calculating expected values of the probabilities.

[26] These values simply illustrate how to generate survival profiles and are not intended to suggest appropriate values for the calculation.

growth path of subscribers over the time period must be chosen, because a variety of subscriber profiles over five or ten years could generate a 70% chance of survival. For example, using the Weibull model with unobserved heterogeneity, a cable network could achieve a 70% survival probability over its first five years by obtaining zero subscribers over its first three years and obtaining almost 15 million subscribers in its fourth and fifth years. A cable network could also achieve a 70% survival probability over five years by obtaining 8.6 million subscribers in all five years. Our chosen subscriber growth path reflects the typical subscriber growth rate of cable networks. A good approximation of this growth path is the percentage change in the average number of subscribers for a cable network, conditional on that cable network's age. For example, the average number of subscribers at the end of cable networks' first year is 2.51 million, and the average number of subscribers at the end of cable networks' second year is 3.51 million, which yields a growth rate of 48.26% between the two years.[27]

This simple approach for estimating subscriber growth rates may have problems. If a cable network fails because it grows more slowly, then the estimated growth rate using conditional means may overstate a cable network's rate of subscriber growth as it ages, because we fail to observe those cable networks that grew more slowly, since those networks exit and leave the sample. Thus, we check to determine whether a lower rate of growth increases the chance of failure over time. It may seem obvious that a lower rate of subscriber growth increases the probability of failure, but this is not necessarily so. A cable network may grow rapidly from a small base and still fail for a lack of subscribers. In short, having a low number of subscribers does not necessarily imply a lower past subscriber growth rate.

We test the fitness of the conditional means by considering the procedure used to adjust for a sample selection problem.[28] For the first stage, we employ a probit regression with failure as the dependent variable and the rate of subscriber growth as the independent variable; this probit is calculated for each given cable network age. The next stage employs the inverse Mills Ratios obtained from these regressions in a pooled OLS regression with the growth rate as the dependent variable. The results are not statistically significant, indicating that our conditional means method does not create a biased growth rate. In addition, to the extent there is sample selection bias, this bias does not significantly change the final results of the analysis. Given the small baseline

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[27] Appendix 2 lists the average subscriber growth rates by network age.

[28] Wooldridge (2002) discusses this procedure in detail at pages 581-585.

marginal hazard in each year, then the failure to account for failed networks would not significantly change the year-to-year growth estimates.

TABLE 4

SUBSCRIBER PROFILES FOR 50% SURVIVAL PROBABILITY OVER 5 AND 10 YEARS

Weibull No Unobserved Heterogeneity 5 Years		Weibull No Unobserved Heterogeneity 10 Years		Weibull Unobserved Heterogeneity 5 Years		Weibull Unobserved Heterogeneity 10 Years	
Year	Subscribers (in millions)	Year	Subscribers (in millions)	Year	Subscribers (in millions)	Year	Subscribers (in millions)
1	0	1	0.85	1	1.29	1	4.10
2	0	2	1.27	2	1.91	2	6.08
3	0	3	1.71	3	2.59	3	8.22
4	0	4	2.18	4	3.30	4	10.49
5	0	5	2.75	5	4.16	5	13.22
		6	3.39			6	16.27
		7	4.09			7	19.64
		8	4.73			8	22.74
		9	5.52			9	26.52
		10	5.85			10	28.09

TABLE 5

SUBSCRIBER PROFILES FOR 70% SURVIVAL PROBABILITY OVER 5 AND 10 YEARS

Weibull No Unobserved Heterogeneity 5 Years		Weibull No Unobserved Heterogeneity 10 Years		Weibull Unobserved Heterogeneity 5 Years		Weibull Unobserved Heterogeneity 10 Years	
Year	Subscribers (in millions)	Year	Subscribers (in millions)	Year	Subscribers (in millions)	Year	Subscribers (in millions)
1	0.33	1	3.51	1	3.24	1	5.36
2	0.49	2	5.21	2	4.80	2	7.94
3	0.67	3	7.04	3	6.48	3	10.74
4	0.86	4	8.99	4	8.28	4	13.71
5	1.08	5	11.33	5	10.43	5	17.27
		6	13.95			6	21.27
		7	16.84			7	25.67
		8	19.50			8	29.72
		9	22.74			9	34.66
		10	24.08			10	36.72

TABLE 6

SUBSCRIBER PROFILES FOR 90% SURVIVAL PROBABILITY OVER 5 AND 10 YEARS

Weibull No Unobserved Heterogeneity 5 Years		Weibull No Unobserved Heterogeneity 10 Years		Weibull Unobserved Heterogeneity 5 Years		Weibull Unobserved Heterogeneity 10 Years	
Year	Subscribers (in millions)	Year	Subscribers (in millions)	Year	Subscribers (in millions)	Year	Subscribers (in millions)
1	9.15	1	10.17	1	7.02	1	8.11
2	13.57	2	15.08	2	10.40	2	12.02
3	18.35	3	20.39	3	14.07	3	16.25
4	23.42	4	26.02	4	17.95	4	20.74
5	29.51	5	32.79	5	22.62	5	26.14
		6	40.38			6	32.19
		7	48.73			7	38.85
		8	56.43			8	44.98
		9	65.81			9	52.46
		10	69.70			10	55.56

The gamma-distributed unobserved heterogeneity estimates are all significantly farther away from zero than the estimates without unobserved heterogeneity,[29] and generate very different subscriber profiles for a 70% probability of survival over both five and 10 years. However, these estimates still rest on the assumption of strict exogeneity, a questionable assumption. By using discrete-time data, the statistical estimation actually estimates a panel model, where the dependent variable is whether the programming network exits. By assuming unobserved heterogeneity, we estimate a random-effects panel data complementary log-log model, where the random effect's distribution is the unobserved heterogeneity. By including the log of the cable network's age in the vector of independent variables, we create a Weibull baseline hazard. When we don't assume unobserved heterogeneity, we estimate a complementary log-log population-averaged panel effects model (again including the log of the network's age to create a Weibull baseline hazard), where every programming network is a population, and that population is made up of each yearly observation for that programming network. Thus, ESPN would be one population, and each yearly observation of ESPN would be a member of that population. When we estimate population-averaged effects panel models, we assume that each population has its own within-group correlation structure. In other words, yearly observations of the Lifetime network are correlated with each other but are not necessarily correlated with ESPN's yearly observations. Assuming an independent correlation structure, such that the unobserved heterogeneity is network-specific but random, we obtain the same results as the standard non-panel Weibull regression. If we constrain the correlations to be equal within the network, we obtain very similar results.[30] The correct estimation method depends on the nature of unobserved heterogeneity. If the unobserved heterogeneity is network-specific, then the estimates without unobserved heterogeneity are more accurate. If the unobserved heterogeneity is a separate function that multiplies across every network, then the estimates with unobserved heterogeneity are more accurate.

C. Estimation and Results of Semiparametric Models

We employ two semi-parametric models which do not use statistical distributions to estimate the baseline hazard. The Cox proportional hazards model builds an empirical likelihood function based on networks that have failed, while the piecewise-constant proportional hazards model estimates a

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[29] The likelihood ratio statistic between the two models, 28.24, is statistically significant.

[30] Prentice and Gloeckler (1978) and Meyer (1990) provide the theoretical basis for the relationship between discrete-time survival models and conditional log-log panel estimation. Jenkins (1995) demonstrates how to estimate discrete-time hazard models in a simple framework.

separate baseline hazard for each possible duration. Estimates from these models can be compared to the estimates from the parametric models to examine the effects of the parametric restrictions. Furthermore, the Cox model relies on the assumption of strict exogeneity to generate consistent estimates, while the piecewise-constant model does not. Therefore, by comparing the results from the Cox and piecewise-constant models, we can obtain an indication of any bias introduced by assuming strict exogeneity. In this application, the flexibility of the semiparametric methods comes with a cost. No programming networks exit during their ninth, fourteenth through seventeenth, or after their nineteenth year. The methods do not allow estimation of baseline hazard rates for periods where no networks failed.

Table 7 displays the results of the semiparametric estimation methods. The semiparameteric coefficients bear some similarity to the parametric results without unobserved heterogeneity. The piecewise-constant results are almost identical to the Weibull results with unobserved heterogeneity. This result indicates that the Weibull distribution provides a good fit for the underlying baseline hazard, and the addition of unobserved heterogeneity may generate more accurate results.

The Cox results depend on the assumption of strict exogeneity; a questionable assumption. However, the coefficients may still reasonably approximate the true underlying relationship between a network's survival probability and the covariates. An increase in one million subscribers generates a hazard ratio of 94%, so that one million subscribers decrease the probability of exit by 6%. Ten million subscribers generate a hazard probability of $e^{(10*-.06)} = e^{(-.6)} = .55$, so that ten million subscribers reduce the probability of exit by 45%. A spinoff network has a 70% greater chance of surviving in any given year, because $e^{-1.21} = 30$.

The piecewise-constant results do not depend on the assumption of strict exogeneity. Because we estimate a separate baseline hazard for each possible duration length, we estimate a completely flexible underlying baseline hazard.

The results from the piecewise-constant model indicate that an increase in one million subscribers generates a hazard ratio of 83%, so that one million subscribers decrease the probability of exit by 17%. Ten million subscribers generate a hazard probability of $e^{(10*-.17)} = e^{(-1.7)} = 18\%$, so that ten million subscribers reduce the probability of exit by 82%. A spinoff network has a 78% greater chance of surviving in any given year, because $e^{-1.5} = .22$. If a network began before 1984, then that network has 64% greater chance of surviving in any given year.

TABLE 7

SEMI-PARAMETRIC SURVIVAL ESTIMATES

(Z-statistics in parentheses)

	Cox Proportional Hazard (With Stratification by Sports and Shopping Genres)	Piecewise-Constant Hazard (No Stratification)
Millions of Subs	-0.06*** (4.96)	-0.17*** (6.73)
Missing Subs	-0.51** (2.21)	-2.10** (2.12)
Vertical Integration	0.00 (0.07)	-0.01 (1.15)
Spinoff	-1.21** (2.40)	-1.50*** (2.95)
Missing Vertical or Spinoff	0.26 (1.23)	-0.22 (1.22)
Born before 1984	-0.74 (1.62)	-1.08** (2.01)
Duration 2 years		-1.03*** (3.91)
Duration 3 years		-0.93*** (3.36)
Duration 4 years		-0.49* (1.91)
Duration 5 years		-0.82** (2.43)
Duration 6 years		-1.92*** (3.23)
Duration 7 years		-0.44 (1.25)
Duration 8 years		-0.60 (1.36)
Duration 10 years		-0.47 (3.47)
Duration 12 years		-0.35 (0.55)
Duration 13 years		-1.03 (0.98)
Duration 19 years		1.52 (1.29)
Constant		
Observations	305	305
Failures	96	96
Likelihood Ratio	-364.60***	-324.91***

* - significant at 10% level, ** - significant at 5% level, *** - significant at 1% level

D. Discussion of Results

This study concludes that the piecewise-constant model generates the most reliable results. The piecewise-constant hazards model allows for a completely flexible hazard form and does not rely on the assumption of strict exogeneity. Therefore, the discussion of results uses the piecewise-constant estimates.

As mentioned before, an increase in one million subscribers generates a hazard ratio of 83%, so that one million subscribers decrease the probability of exit by 17%, and ten million subscribers reduce the probability of exit by 82%. If the observation on the number of subscribers is missing, then the hazard ratio is 0.12, so the probability of exit is 88% lower than the probability of exit if we observed zero subscribers. Therefore, observing 12.35 million subscribers confers the same probability of exit as not being able to observe subscribers.

As before, we use the estimates from the Cox model and the piecewise-constant model to generate 70% survival probabilities over five and 10 years, as shown in Table 9, using typical subscriber growth rates.[31] Again, we assume that the network began after 1984; is not vertically integrated; is not a spinoff; and has no missing values for the number of subscribers, the degree of vertical integration, or spinoff status. In addition, the network genre is neither sports nor shopping. Table 10 reports the subscriber profile required to reach a 90% survival probability.

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[31] These values are simply used to illustrate how to generate survival profiles and are not intended to suggest appropriate values for the calculation.

TABLE 8

SUBSCRIBER PROFILES FOR 50% SURVIVAL PROBABILITY OVER 5 AND 10 YEARS

Cox Proportional Hazards 5 Years		Cox Proportional Hazards 10 Years		Piecewise-Constant Hazard 5 Years		Piecewise-Constant Hazard 10 Years	
Year	Subscribers (in millions)	Year	Subscribers (in millions)	Year	Subscribers (in millions)	Yea r	Subscribers (in millions)
1	0	1	1.43	1	3.63	1	3.99
2	0	2	2.05	2	5.39	2	5.92
3	0	3	2.77	3	7.28	3	8.00
4	0	4	3.53	4	9.29	4	10.21
5	0	5	4.45	5	11.71	5	12.87
		6	5.48			6	15.85
		7	6.62			7	19.12
		8	7.66			8	22.14
		9	8.94			9	25.82
		10	9.47			10	27.35

TABLE 9

SUBSCRIBER PROFILES FOR 70% SURVIVAL PROBABILITY OVER 5 AND 10 YEARS

Cox Proportional Hazards 5 Years		Cox Proportional Hazards 10 Years		Piecewise-Constant Hazard 5 Years		Piecewise-Constant Hazard 10 Years	
Year	Subscribers (in millions)	Year	Subscribers (in millions)	Year	Subscribers (in millions)	Yea r	Subscribers (in millions)
1	5.87	1	6.52	1	5.90	1	6.06
2	8.38	2	9.31	2	8.75	2	8.99
3	11.33	3	12.59	3	11.83	3	12.15
4	14.46	4	16.06	4	15.10	4	15.50
5	18.23	5	20.24	5	19.03	5	19.54
		6	24.93			6	24.06
		7	30.08			7	29.04
		8	34.83			8	33.62
		9	40.62			9	39.21
		10	43.03			10	41.53

TABLE 10

SUBSCRIBER PROFILES FOR 90% SURVIVAL PROBABILITY OVER 5 AND 10 YEARS

Cox Proportional Hazards 5 Years		Cox Proportional Hazards 10 Years		Piecewise-Constant Hazard 5 Years		Piecewise-Constant Hazard 10 Years	
Year	Subscribers (in millions)	Year	Subscribers (in millions)	Year	Subscribers (in millions)	Year	Subscribers (in millions)
1	18.43	1	18.52	1	10.73	1	10.75
2	26.34	2	26.46	2	15.91	2	15.94
3	35.61	3	35.77	3	21.51	3	21.55
4	45.45	4	45.65	4	27.45	4	27.51
5	57.27	5	57.53	5	34.59	5	34.66
		6	70.84			6	42.68
		7	85.50			7	51.51
		8	99.00			8	59.65
		9	115.45			9	69.56
		10	122.29			10	73.68

Generally, a reasonable observer expects a network to have a positive number of subscribers, but the number of subscribers is set equal to zero when we observe no subscribers. The coefficients on the missing subscriber dummy variables therefore represent joint functions of both

(1) A possible set of completely unobservable network characteristics that determine both the observability of the characteristic in question and the network's probability of exit;

and

(2) the expectation of the observations' true values conditional on the observations being missing.

Absent prior assumptions about (1) and (2), the effects of each cannot be explicitly estimated. However, the effects of (1) increase a network's estimated marginal probability of exit, and the effects of (2) may increase or decrease a network's estimated marginal probability of exit.

Earlier estimates show that not observing subscribers produces the same hazard as observing 12.35 million subscribers. This result raises several possibilities. Unobservable characteristics that reduce the ability to observe the number of subscribers may not affect the network's exit probability. The mean number of subscribers conditional on not observing the number of subscribers would then be nine million. Unobservable characteristics that reduce the ability to observe the number of subscribers may increase the likelihood of exit. This result would occur, for example, if a network's failure to inform the *Cable Factbook* of their subscriber base correlated negatively with a network's managerial competence, so that managers who incur higher costs in reaching subscribers are also less likely to inform the *Cable Factbook* of their subscriber levels. The mean number of subscribers conditional on not observing the number of subscribers would then be greater than 12.35 million. Finally, unobservable characteristics that reduce the ability to observe the number of subscribers may decrease a network's exit probability. This outcome would occur if, for example, following a niche strategy that makes a network less likely to report their subscribers to the *Cable Factbook*. Because regional networks are excluded from the sample, this niche strategy could involve targeting smaller populations that generate more advertising revenue per subscriber or targeting smaller populations that cost less to reach per subscriber.

A spinoff network has a 78% greater chance of surviving in any given year, because $e^{-1.5} = .22$. This result may indicate that spinoff networks have significantly lower costs, because the spinoff network can recycle programming from the parent network. This may also indicate that a spinoff network increases the parent network's subscribers, which leads the parent network to support the spinoff network. Finally, a spinoff network, when combined with channel bundling, may enable the cable operator to exclude entry by the parent network's competitors and split the profits with the parent network. If a network began before 1984, then that network has a 64% greater chance of surviving in any given year.

Like the coefficient on the missing subscribers dummy variable, two factors drive the coefficient on the missing vertical or spinoff dummy variable, namely,

(1) A possible set of completely unobservable network characteristics that determine both the observability of the spinoff status and vertical integration and the network's probability of exit;

and

(2) the expectation of the observations' true values conditional on the observations being missing.

This coefficient is not significant in the piecewise-constant estimation.

IV. Conclusion

This study analyzes the survival of multi-channel video programming networks using the tools of survival analysis. Using the estimates from a piecewise-constant model, the study finds that a network growing at the average rate requires over 19 million subscribers at the end of five years to have a 70% probability of survival over its first five years, and over 41.5 million subscribers to have a 70% probability of survival over its first ten years. Recall, however, that a network requires far fewer subscribers for survival if it acquires all of those subscribers from day one. According to the piecewise-constant estimates, a network requires only 10.18 million subscribers from day one to have a survival probability of 70% over its first five years, and 13.94 million subscribers from day one to have a survival probability of 70% over its first ten years. Thus, Comcast, which reaches over 21 million subscribers,[32] could confer a 70% chance of survival on that cable network over the cable network's first 10 years by agreeing to carry a cable network to half of its subscriber base from the network's first day. Echostar, which reaches slightly less than 10 million subscribers, would be unable to confer a 70% chance of survival to a cable network over that cable network's first 5 years.[33]

We advise caution when drawing inferences from survival analysis. By definition, survival examines the exit decisions of firms that have already entered the market. Firms considering whether to exit the market have already incurred sunk entry costs, and therefore decide whether to exit based on expected quasi-rents. Firms considering whether to enter the market have not yet incurred sunk entry costs, and therefore decide whether to enter based on expected profits. The sunk entry costs are the gap between expected profits and expected quasi-rents. Dixit (1989) points out that even small sunk entry costs drive a significant wedge between entry and exit decisions, and cable entrants face at least some sunk entry costs in the form of launch fees and up-front marketing investments. In addition, the underlying model of cable network survival that drives survival analysis assumes an exogenous probability of exit given by nature. If firm survival does not follow this pattern, then other models of firm survival may be more appropriate.

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[32] For this analysis, we assume that Comcast reaches 21 million subscribers, because NCTA reports that Comcast reached approximately 21 million subscribers through its owned and managed systems as of December, 2003. When we include all subscribers that could be attributed to Comcast under FCC attribution rules, Comcast has 26 million attributable subscribers. *See* Letter from Peter H. Feinberg, Associate General Counsel, Comcast Cable Communications, LLC, to Marlene H. Dortch, Secretary, FCC, MM Docket No. 92-264 at 2 (Sept. 22, 2004).

[33] The best Echostar could offer is a 45% chance of survival over a cable network's first ten years.

This study therefore raises an important question for future research. If we assume that different potential entrants have some range of beliefs about their potential networks' profitability, with some potential entrants being overly pessimistic and others overly optimistic about future profit streams, then we expect the overly optimistic potential entrants to enter the market. If entrants face sunk entry costs, then some networks may continue operations because they are marginally profitable, i.e., make some positive quasi-rent, even though the entry decision turned out to be unprofitable. Overly optimistic beliefs amplify this phenomenon. Future research should focus on finding the marginal networks, i.e., those who believed upon entry that they would make zero economic profits,[34] and discover the subscriber levels those cable networks require to continue. In addition, future research should consider other underlying models of cable network survival and should estimate these models.

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[34] Of course, zero economic profits simply means that the cable network's accounting profits equal the average return on all other investments of similar risk, so non-economists should not interpret "zero economic profits" as meaning that the cable network makes zero dollars.

References

Chung, C. F., P. Schmidt, and A. D. Witte. 1991. Survival analysis: a survey. *Journal of Quantitative Criminology* 7: 59- 98.

Cox, D. R. 1972. Regression models and life tables. *Journal of the Royal Statistical Society.* Series B 34: 187-220.

DeVany, A., and W. D. Walls. 1996. Bose-Einstein dynamics and adaptive contracting in the motion picture industry. *Economic Journal* 106:1493-1514.

———. 1997. The market for motion pictures: rank, revenue and survival. *Economic Inquiry* 35:783-797.

Dixit, Avinash. 1989. Entry and exit decisions under uncertainty. *Journal of Political Economy* 97:620-638.

FCC Video Competitions Reports. Various years.

Fisher, F. M., and J. J. McGowan. 1983. On the misuse of accounting rates of return to infer monopoly profits. *American Economic Review* 73:82-97.

Ham, J. C., and R. J. Lalonde. 1996. The effect of sample selection and initial conditions in duration models: evidence form experimental data on training. *Econometrica* 64:175-205.

Jenkins, S. P. 1995. Easy estimation methods for discrete-time duration models. *Oxford Bulletin of Economics and Statistics* 57:129-138.

Kalbfleisch, J. D., and R. L. Prentice. 1980. *The statistical analysis or failure time data.* New York: Wiley.

Kagan, Research. 2002. *Economics of basic cable networks 2003*. Carmel, CA: Kagan Research.

Kranenburg, H. L. Van, F. C. Palm and G. A. Pfann. 2002. Exit and survival in a concentrating industry: the case of daily newspapers in the netherlands. *Review of Industrial Organization* 21:283-303.

Lancaster, T. 1979. Econometric methods for the duration of unemployment. *Econometrica* 47:939-956.

———. 1990. *The econometric analysis of transition data*. Cambridge: Cambridge University Press.

Meyer, B. D. 1990. Unemployment insurance and unemployment spells. *Econometrica* 58:757-782.

NCTA. *Cable Developments*. Various years.

Prentice, R., and L. Gloeckler. 1978. Regression analysis of grouped survival data with application to breast cancer data. *Biometrics* 34:57-67.

Simonoff, J., and L. Ma. 2003. An empirical study of factors relating to the success of broadway shows. *Journal of Business* 76:135-150.

Spence and Owen. 1977. Television programming, monopolistic competition, and welfare. *The Quarterly Journal of Economics* 91:103-126.

Warren, Albert. Various years. *The television and cable factbooks.* Washington, D.C.: Warren Communications.

Wooldridge, Jeffrey M. 2002. *Econometric analysis of cross section and panel data.* Cambridge: MIT Press.

APPENDIX 1
LIST OF SAMPLED CABLE NETWORKS

Channel	Start year	End year	Subscribers Missing	Vertical Integration Missing	Spinoff Status Missing
A&E	1984	-	0	0	0
ABN/Biznet	1982	1994	1	1	1
Access Entertainment	1998	1999	1	1	1
ACTS Satellite Network	1984	-	1	0	0
ActTV	1997	-	1	1	1
AETN	1984	1985	1	1	1
Agrisat	1987	1990	1	0	0
AIT	1984	1987	1	1	1
All News	1990	2001	1	0	0
Alternate View	1989	1995	0	0	0
AMC	1985	-	0	0	0
AMC's American Pop	1998	-	1	0	0
America One	1995	-	1	0	0
American Independent Network	1994	-	1	0	0
American Political Channel	1995	1998	1	1	1
American Sports Classics	1997	1999	1	0	0
Americana	1994	1995	0	0	0
America's Collectibles	1993	-	1	0	0
America's Shopping Channel	1984	1990	1	0	0
America's Store/Spree	1995	-	1	0	0
America's Talking/MSNBC	1994	-	0	0	0
America's Value Network	1987	1989	1	0	0
America's Voice/NET	1994	-	0	0	0
Animal Planet	1996	-	0	0	0
Arabic	1991	-	1	0	0
Arena	1997	1999	1	1	1
Art & Craft	1997	1999	1	1	1
Arts and Antiques	1994	1998	1	1	1
Asian American	1992	1998	1	1	1
AsiaNet	1993	-	1	0	0
ASN	1985	1987	1	0	0
ATN	1996	1998	0	0	0
AVN	1990	1993	1	0	0
Baby Bear	1995	1997	1	0	0
Baby TV	1999	-	1	0	0
BBC	1998	-	0	0	0
Behavior Communications	1999	-	1	1	1
BET	1980	-	0	1	0
BET on Jazz	1996	-	0	0	0
BET-HSN	1996	1999	1	0	0
Better Health	1996	2000	0	1	1
Biograpy Channel	1998	-	1	0	0
Black Shopping	1997	1998	1	1	1
Bloomberg	1994	-	1	0	0
B-Movie	2000	-	0	1	1
Boomerang	2000	-	1	1	1
Box	1986	-	1	0	0

Channel	Start year	End year	Subscribers Missing	Vertical Integration Missing	Spinoff Status Missing
Box Country	1997	-	0	0	0
Box Edge	1999	-	1	0	0
Box Pulse	1999	-	1	0	0
Box Set	1999	-	1	0	0
Box Urban	1999	-	1	0	0
Boyz	2000	-	1	0	0
Bravo	1980	-	0	0	0
Business Vision	1996	-	1	0	0
C-3D	1999	-	1	1	1
Cable Newspaper	1984	1985	1	1	1
Cable Sports Net	1984	1985	1	1	1
Cable Value Network	1986	1992	1	0	0
Camnet/Nancys	2000	-	1	0	0
Canal de Noticias	1993	1997	1	1	0
Cancom	1987	-	1	0	0
Carribean Satellite	1993	1995	1	1	1
Cartoon	1993	-	0	0	0
Catalog Channel	1999	-	1	1	1
CBS Eye On People/Discovery People	1999	-	0	1	1
CBS Telenoticias	1995	1999	1	1	1
Channel America	1988	1998	1	0	0
Channel Black	1984	1985	1	0	0
Channel Earth	1997	1999	1	1	1
Channel Korea	2000	-	1	1	1
Children's	1995	-	1	1	1
Chinese Communication Channel	1989	1999	1	1	1
Classic Music	1996	1999	1	1	1
Classic Sports	1995	1999	1	0	0
CNBC	1989	-	0	0	0
CNN	1980	-	0	1	0
CNN en Espanol	1999	-	0	0	0
CNN International	1995	-	0	0	0
CNNfn	1996	-	0	0	0
CNNsi	1996	-	1	0	0
Collectible Showcase	1987	1988	0	0	0
Comedy Central	1989	-	1	0	0
Computer Television	1996	1999	1	0	0
Consumer Discount	1987	1989	1	1	1
Consumer Resource/FYI	1995	-	1	1	1
Country Music Television	1983	-	1	1	0
Courtroom	1991	-	0	0	0
Cowboy	1990	1992	0	1	1
Crazy Eddie	1987	1990	1	0	0
Crime	1993	-	1	0	0
C-SPAN	1979	-	0	1	1
C-SPAN II	1986	-	1	1	1
Cupid	1994	-	1	1	1

Channel	Start year	End year	Subscribers Missing	Vertical Integration Missing	Spinoff Status Missing
CVN	1996	-	1	0	0
Dating Channel	1995	2000	1	0	0
Deep Dish	1986	-	1	0	0
Deutsche Welle	1991	-	1	1	1
Discovery	1985	-	1	1	0
Discovery Civ	1997	-	1	0	0
Discovery Kids	1997	-	1	0	0
Discovery Living Channel	1999	-	1	1	1
Discovery Music	1985	1989	1	0	0
Discovery Science	1997	-	1	0	0
Discovery Showcase	1996	-	1	0	0
Disney	1983	-	0	0	0
Do-It-Yourself	1999	-	0	0	0
Dream	1995	-	0	1	1
E!	1987	-	1	1	1
Ecology Channel	1995	-	1	0	0
ESPN	1979	-	0	0	0
ESPN News	1996	-	0	0	0
ESPN2	1994	-	0	0	0
Eternal Word	1981	-	0	0	0
Eye on People	1997	1998	1	1	1
Family Channel	1977	-	0	1	0
FamilyNet	1980	1996	1	0	0
Fashion Channel	1988	1993	0	1	1
Fashion Network	1996	-	1	1	1
Fifth Avenue	1998	-	1	1	1
Fight Channel	1999	-	0	1	1
Filipino	1996	-	0	0	0
Financial	1981	1991	0	1	1
Fit TV/America's Health/Health Network	1994	-	1	0	0
Football Network	1998	-	1	0	0
Fox Kids	1998	1999	1	0	0
Fox Sports Americas	1995	-	1	0	0
Fox Sports Net	1997	-	0	0	0
Fox Sports World	1997	-	1	0	0
FoxNews	1996	-	0	0	0
Free Speech	1989	-	1	0	0
FX	1994	-	1	0	0
FXM	1995	1998	1	0	0
Game Show	1995	-	0	0	0
Gay	1993	-	1	0	0
Girlz	2000	-	1	1	1
Global Shopping	1997	1997	0	0	0
Golden American	1993	1998	1	1	1
Golf Channel	1997	-	1	0	0
Goodlife TV Network	1984	-	1	0	0
Gospel Music	1996	1998	1	0	0

Channel	Start year	End year	Subscribers Missing	Vertical Integration Missing	Spinoff Status Missing
Great American Country	1996	-	0	0	0
HA!	1990	1993	1	0	0
Headline news	1981	-	0	1	0
Health and Fitness	1993	1997	1	0	0
History	1995	-	0	0	0
History International	1999	-	1	1	1
Hit Video USA	1986	1995	1	0	0
Home and Garden	1995	-	0	0	0
Home Improvement	1994	-	1	0	0
Home Shopping Network	1985	-	1	0	0
Home Shopping Network II	1986	1997	1	0	0
HomeMed Channel	1996	-	1	0	0
HTV	1997	-	1	0	0
ICG Netcom.	1999	-	1	1	1
Idea Channel	1992	-	1	0	0
Infomerica TV	1996	-	1	1	1
International	1988	-	1	0	0
Intro	1994	-	1	1	1
IntroNet	1994	-	1	0	0
Jones Computer	1994	1997	0	0	0
Kaleidoscope	1990	-	1	0	0
Keystone	1988	1997	1	1	1
KIDZTIME TV	1996	1999	1	0	0
Korean	1986	-	1	0	0
Las Vegas	1996	-	1	0	0
Las Vegas Shopping	1995	1997	1	0	0
Learning	1979	-	0	0	0
Lifetime	1984	-	0	0	0
Lifetime Movie Network	1999	-	1	0	0
Lottery	1995	-	1	0	0
M2: Music Television	1999	-	0	1	1
Maranatha	1985	1987	1	1	1
MBC Gospel Network	1999	-	1	0	0
Merchandise	1994	1997	1	0	0
Military	1994	2000	1	0	0
Mind Extension University	1988	2000	0	0	0
Monitor Channel	1991	1992	0	0	0
MOR	1993	2000	1	0	0
Motivation	1985	1988	1	0	0
MSN Info	1984	1986	0	1	1
MTV	1981	-	0	1	0
MTV Latino	1994	-	1	0	0
MTV2	1996	-	1	0	0
Muchmusic	1994	-	1	0	0
My Pet	1997	-	0	0	0
NASA	1991	-	1	0	0
National & International Singles TV	1998	-	0	0	0

Channel	Start year	End year	Subscribers Missing	Vertical Integration Missing	Spinoff Status Missing
National Christian1	1980	1986	0	0	0
National Christian2	1987	1993	1	0	0
National College Television	1991	1992	0	1	1
National Jewish	1981	-	1	1	1
National Journal	1998	-	1	1	1
National Shopping Club	1988	1989	1	1	1
National Weather	1991	2000	1	0	0
Nationality Broadcasting	1985	-	0	1	1
NBA.com	2000	-	1	1	1
Network One	1989	-	1	0	0
NewSport	1994	1998	1	0	0
NewsTalk	1994	1998	1	0	0
NewsWorld	1998	-	0	1	1
Nickolodeon	1979	-	0	1	0
Noggin	1999	-	1	0	0
OASIS	1998	-	1	0	0
Odyssey	1985	1987	0	1	0
Odyssey	1988	-	0	0	0
ORB TV	1995	-	1	1	1
Outdoor1	1994	-	0	0	0
Outdoor Life	1995	-	0	0	0
Outdoor, Motorsports, Collectibles	1994	-	1	0	0
Outlet Mall Network	1997	2000	1	1	1
Ovation	1996	-	1	0	0
Oxygen	2000	-	1	0	0
Pacific	1984	1987	0	1	1
Pandamerica	1995	-	1	0	0
PBS Kids	1999	-	1	1	1
Peoples Network	1995	-	1	0	0
Performance Showcase	1998	-	1	1	1
Pet	1995	-	1	1	1
Praise Television	1996	-	1	0	0
Prime of Life	1984	1986	1	1	1
Product Information	1996	-	0	0	0
Promoter	1990	-	1	0	0
PTL	1979	-	0	1	1
Public Interest	1979	-	1	0	0
Q2	1994	-	1	0	0
QVC	1987	-	0	0	0
QVC Fashion	1994	1995	0	0	0
Radar Channel	1997	-	1	0	0
Radio Television Portugal	1992	-	1	0	0
RAI Italia	1987	-	1	1	1
RAP-TV	1999	-	1	1	1
Recovery	1994	-	1	0	0
RFD-TV	1989	1992	1	0	0
Romance Classics/We	1994	-	1	0	0

Channel	Start year	End year	Subscribers Missing	Vertical Integration Missing	Spinoff Status Missing
Russian Television	1991	-	1	0	0
Satellite Program	1979	1986	0	1	1
Sci-Fi	1991	-	1	0	0
SCOLA	1994	-	0	0	0
Shalom USA	1990	-	1	0	0
Shepherds Chapel	1987	-	1	0	0
Shop at Home	1986	-	1	1	1
Shop TV	1987	1990	1	1	1
Shopping Line	1987	-	1	1	1
Silent Network	1984	1995	0	0	0
Single Vision	1995	-	1	0	0
Sky Merchant	1999	2000	1	1	1
SoapNet	2000	-	1	1	1
Speedvision	1996	-	1	0	0
Sporting Channel	1994	-	1	0	0
Sportstime	1985	1985	0	1	1
Sportsvision	1985	1986	0	1	1
S-TV The Surfing Channel	1998	1999	1	1	1
Style	1999	-	0	0	0
Sur	1993	-	1	0	0
Talkline	1981	-	1	1	1
TCM	1994	-	1	0	0
Telemundo	1987	-	1	1	1
Telenoticias	1996	1997	1	1	1
Television Food Network	1994	-	0	0	0
Telshop	1986	1992	1	1	1
Tempo Galeria	1987	1988	1	1	1
Tempo Television	1979	1988	1	1	1
The Computer Network	1996	1999	1	1	1
The Nashville Network	1983	-	0	0	0
TNT	1989	-	0	0	0
Toon Disney	1998	-	0	0	0
Total Communication	1995	-	1	0	0
Travel Channel	1987	-	1	0	0
Trinity	1973	-	0	0	0
Trio	1998	-	0	1	1
Tropical Television Network	1996	2000	1	0	0
TV Bingo	1994	-	1	0	0
TV Land	1996	-	0	0	0
TV5	1998	-	0	1	1
TVG	1999	-	1	1	1
U-Network	1994	-	0	0	0
United Satellite	1985	1988	0	0	0
USA	1977	-	0	0	0
ValuVision	1991	-	1	1	1
Vector	1984	1991	0	1	1
VH-1	1985	-	1	0	0

Channel	Start year	End year	Subscribers Missing	Vertical Integration Missing	Spinoff Status Missing
VH1 Classic	1998	-	0	0	0
VH1 Music First	1998	-	0	0	0
VH-1 Soul	1998	-	0	0	0
Via	1994	2000	1	0	0
Video Catalog	1991	-	1	0	0
Video Concert Hall	1984	1993	1	1	1
Video Shopping Mall	1986	1993	1	1	1
VIVA	1993	1998	1	0	0
Weather Channel	1982	-	0	0	0
Weatherscan	1998	-	1	1	1
Weird TV	1994	1997	1	0	0
WGN	1978	-	0	0	0
Wingspan, Air and Space Channel	1998	-	1	1	1
Wisdom Network	1997	-	1	1	1
WOR	1979	1997	0	1	1
World Cinema	1999	-	1	1	1
World Fight Channel	1999	-	1	1	1
Worship	1992	-	1	1	1
WPIX	1984	-	0	1	1
WTBS	1976	-	0	0	0
Youth Sports Broadcasting Channel	1999	-	1	1	1
ZDTV	1998	-	1	1	1
ZTV	1993	2000	1	0	0

APPENDIX 2

THE AVERAGE NUMBER OF SUBSCRIBERS BY AGE AND THE IMPLIED RATE OF YEAR-TO-YEAR GROWTH

Subscribers (in millions)	Age	Implied Growth Rate
2.17	1	-
3.51	2	48.26%
4.99	3	35.18%
6.59	4	27.64%
8.54	5	26.01%
10.76	6	23.14%
13.24	7	20.69%
15.50	8	15.79%
18.31	9	16.62%
19.42	10	5.92%
22.14	11	13.09%
25.09	12	12.52%
28.36	13	12.24%
30.57	14	7.52%
32.88	15	7.27%
35.45	16	7.54%
37.43	17	5.44%
38.91	18	3.86%
42.69	19	9.28%