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Demand for Communications Services - Insights and Perspectives

Essays in Honor of Lester D. Taylor

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Prologue I: Research Demands on Demand Research

Overview

This should be the golden age of demand research. Many of the constraints of the past have relaxed when it comes to data collection. Yet the methodologies of demand analysis created by thought leaders such as Lester Taylor (1972, 1974; Houthakker and Taylor 2010) have not grown at the same pace and are holding back our understanding and power of prediction.

Demand research is, of course, highly important. On the macro-level, governments and businesses need to know what to expect by way of aggregate or sectorial demand, such as for housing or energy. On the micro-level, every firm wants to know who its potential buyers are, their willingness to pay, their price sensitivity, what product features they value, and what they like about competing products (Holden and Nagle 2001).

Yet it is always difficult to determine demand. It is easy to graph a hypothetical curve or equation in the classroom but hard to determine the real world nature of demand and the factors that go into it.

Demand analysis is particularly important and difficult for media and communications firms (Kim 2006; Burney et al. 2002; Green et al. 2002; Taylor and Rappoport 1997; Taylor et al. 1972). They must grapple with high investment needs ahead of demand, a rapid rate of change in markets and products, and an instability of user preferences. Demand analysis in the information sector must recognize the "public good" characteristics of media products and networks, while taking into account the effects of interdependent user behavior, the strong cross-elasticities in a market, as well as the phenomenon of supply creating its own demand.

There is a continuous back-and-forth between explanations of whether "powerful suppliers" or "powerful users" determine demand in the media sector. Research in the social sciences has not resolved this question (Livingstone 1993). On one side of this debate is the "Nielsen Approach," where the power is seen to lie with the audience. User preferences govern and it is up to the media companies to satisfy these preferences (Stavitsky 1995). Demand creates supply. The other side of the debate is the "Marketing" or "Madison Avenue Approach." In this view, the power to create and determine demand lies with the media communications firms themselves and the marketing messages they present (Bagdikian 2000). Supply creates demand.

In contrast to most other industries, demand measurement techniques affect firms' bottom lines, directly and instantly, and hence are part of public debate and commercial disputes. When, for television, a transition from paper diaries to automatic people meters took place in 1990, the effect of people meters on the bottom line was palpable. The introduction of people meters permanently lowered overall TV ratings by an average of 4.5 points. Of the major networks, CBS lost 2.0 points and NBC showed an average loss of 1.5 points. In New York City, Fox 5, UPN 9, and WB 11 showed large drops. Ratings for cable channels showed a gain of almost 20 percent (Adams 1994). In 1990, each ratings point was worth approximately $140 million/year. The decrease in ratings would have cost major networks between $400 and $500 million annually. Thus, demand analysis can have an enormous impact on a business in the media and communications sector.

The forecasting of demand creates a variety of issues. One can divide these problems into two broad categories. "Type I Errors" exist when the wrong action is taken. In medicine this is called a "false positive." Human nature mercifully contains eternal optimism but this also clouds the judgment of many demand forecasts. By a wide margin entrepreneurs overestimate the demand for products rather than underestimate it. Eighty percent of films, music, recordings, and books do not break-even. Observe AT&T's 1963 prediction that, "there will be 10 million picture phones in use by US households in 1980," yet in 1980 picture phones were little more than a novelty for a few and remained so for decades (Carey and Elton 2011). Another example of this type of error can be seen in the view summarized in 1998 by the *Wall Street Journal* that "The consensus forecast by media analysts is of 30 million satellite phone subscribers by 2006." In actuality, their high cost and the concurrent advancements in terrestrial mobile networks have relegated satellite phones to small niches only.

The second category of demand forecasting mistakes is a "Type II Error," when the correct action is not being taken. This is a "false negative." There are multiple historical examples in the media and communications sector. In 1939, the *New York Times* reported that television could never compete with radio since it requires families to stare into a screen. Thomas Watson, chairman of IBM, proclaimed in 1943, "I think there is a world market for maybe five computers." Today there are two billion computers, not counting smartphones and other "smart" devices. In 1977, Ken Olsen, President of the world's number two computer firm Digital Equipment Corporation, stated, "There is no reason anyone would want a computer in their home." A 1981 McKinsey study for AT&T forecast that there would only be 900,000 cell phones in use worldwide by the year 2000. In reality, in that year there were almost one billion cell phones in use and three billion in 2011.

Major Stages of Demand Analysis

When it comes to demand analysis the two major stages are data collection and data interpretation. Data used to be gathered in a leisurely fashion with interviews, surveys, focus groups, and test marketing. Television and radio audiences were tracked through paper diaries. This data sample was small yet expensive, unreliable, and subject to manipulation. Four times a year, during the "sweeps" periods, the audiences of local stations were measured based on samples of 540 households subject to a barrage of the networks' most attractive programs. Other media data was collected through the self-reporting of sales. This is still practiced by newspapers and magazines, and is notoriously unreliable. For book best-seller lists, stores are sampled. This, too, has been subverted. Two marketing consultants spent 30,000 dollars in purchases of their own book and were able to profitably propel it into the bestseller list. For film consumption attendance figures are reported weekly. According to the editor of a major entertainment magazine, these numbers are "made up—fabricated every week." In parallel to these slow and unreliable data collection methods, analytical tools were similarly time-insensitive: they were lengthy studies using methodologies that could not be done speedily. In fact, many academic demand models could never be applied realistically at all. They included variables and information that were just not available. And the methodologies themselves had shortcomings.

Estimation Models

The major methodological approaches to demand estimation include econometric modeling, conjoint analysis, and diffusion models. Econometric estimations are usually created with economic variables for the elasticities for price, income, as well as socio-demographic control variables (Cameron 2006). The price of substitutes is often used. There are generic statistical problems to any econometric estimation, such as serial correlation, multicollinearity, homoscedasticity, lags, and exogeneity (Farrar and Glauber 1967). Moreover, predicting the future requires the assumption that behavior in the future is similar to behavior in the past.

One needs to choose and assume a specific mathematical model for the relationship between price, sales, and the variables. If the specification is incorrect the results will be misleading. Examples of this are several demand estimation models for newsprint, the paper used by daily newspapers. This demand estimation is of great importance to newspaper companies who need to know and plan for the price of their main physical input. It is also of great importance to paper and forestry companies who must make long-term investments in tree farming.

Here is how the different models described the past and project the future (Hetemäki and Obersteiner 2002), and a comparison with subsequent reality. One model is that of the United Nation's Food and Agriculture Organization (FAO).

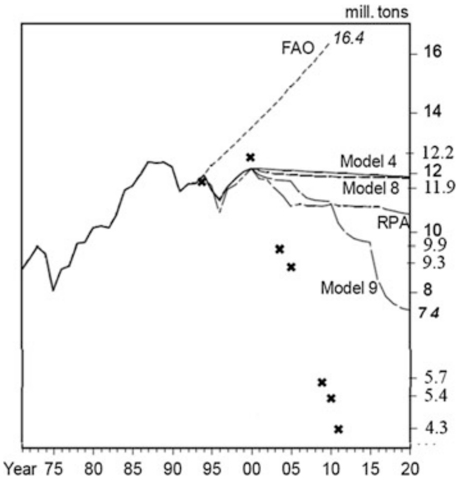

Fig. 1 Forecasts for Newsprint Consumption in the US, 1995–2020—Various Models (Hetemaki and Obersteiner 2002)

Another is that of the Regional Planning Association (RPA). And there are seven other models.

As one can see, the models, though using the same past data from 1970–1993, thereafter radically diverge and predict, for 2010, in a range from 16.4 million tons to about 11 million tons. The gap widens by 2020 to over 130 %, making them essentially useless as a forecasting tool for decision makers in business and policy. On top of that, none of the models could predict the decline of newspapers due to the internet, as shown by the ‘x’ markings on the graph. The actual figures were, for 2010, 5.4 million and for 2011, about 4.3 million—literally off the chart of the original estimates. The worst of the predictions is the UN’s authoritative prediction which is a basic input into many countries’ policy making, as well as for global conferences assessing pressure on resources.

Econometric models have also been employed by the film industry. They have tried to create some black-box demand models to aid in the green-lighting of film projects. Essentially, coefficients are estimated for a variety of variables such as genres, e.g., science fiction; stars, e.g., Angelina Jolie; plot, e.g., happy endings, directors, e.g., Rob Reiner, and other factors. These models include the Motion Picture Intelligencer (MIP), MOVIEMOD, and others (Eliashberg et al. 2000; Wood 1997). Such models are proprietary and undisclosed, but even after employing them, films still bomb at an 80 % rate.

A second traditional empirical methodology for demand analysis has been conjoint analysis (Green and Rao 1971; Allison et al. 1992). This method permits the researcher to identify the value (utility) that a consumer attaches to various product attributes. The subject is asked to select among different bundles of attributes and one measures the trade-off in the utility of such attributes. There is not much theory in conjoint analysis, but it is a workable methodology.

An example is an attribute-importance study for MP3 players. On a scale of 1–10, people's preference weights were found to be quality: 8.24; styling: 6.11; price: 2.67; user friendliness: 7.84; battery life: 4.20; and customer service: 5.66.

These weights enable the researcher to predict the price which the consumer would pay for a product of various combinations of attributes (Nagle and Holden 1995). There are computer packages that generate an optimal set of trade-off questions and interpret results. But the accuracy of this technique is debatable. People rarely decompose a product by its features and are likely to be more affected by generic perspectives such as brand reputation or recommendations, not by feature trade-offs.

The third major empirical method for demand analysis is an epidemic diffusion model. Such a model is composed of a logistic function such as $y(t) = 1/(1 + c\,e^{-kt})$. This technique, like the others, has its own inherent problems (Guo 2010). It is difficult to find the acceleration point and the "saturation level." Comparisons of the product are made and forecasted with some earlier product that is believed to have been similar.

Thus, in the past, demand analysis was constrained by weak data and clunky analytical models. Recently, however, things have changed on the data collection end. Data have ceased to be the constraint that it once was as more advanced collection tools have emerged. First, there are now increasing ways to measure peoples' actual sensory perceptions to media content and to products more generally. "Psycho-physiology" techniques measure heart rate (HR), brainwaves (electroencephalographic activity, EEG), skin perspiration (electrodermal activity, EDA), muscle reaction (electromyography, EMG), and breathing regularity (respiratory sinus arrhythmia, RSA) (see Ravaha 2000; Nacke et al. 2010). These tools can be used in conjunction with audience perception analyzers, which are hand-held devices linked to software and hardware that registers peoples' responses and their intensity.

Second, the technology of consumer surveying has also improved enormously. There are systems of automated and real-time metering. Radio and television listening and channel-surfing can be followed in real-time. Measuring tools are carried by consumers, such as the Passive People Meter (PPM) (Arbitron 2011; Maynard 2005). The TiVo Box and the cable box allow for instant gathering of large amounts of data. Music sales are automatically logged and registered; geographic real-time data is collected for the use of the internet, mobile applications, and transactions (Roberts 2006; Cooley et al. 2002). Mobile Research, or M-Research, uses data gathered from cell phones for media measurement and can link it to locations. Radio-frequency identification (RFID) chips can track product location (Weinstein 2005). Even more powerful is the matching of such data. Location, transaction, media consumption, and personal information can be correlated in real-time (Lynch and Watt 1999). This allows, for example, the measurement in real-time of advertising effectiveness and content impact, and enables sophisticated pricing and program design.

Thus, looking ahead, demand data measurement will be increasingly real-time, global, composed of much larger samples, yet simultaneously more individualized.

This will allow for increasing accuracy in the matching of advertising, pricing, and consumer behavior.

Of course, there are problems as data collection continues to improve (O'Leary 1999). The first challenge is the coordination and integration of these data flows (Clark 2006). This is a practical issue (Deck and Wilson 2006). Companies are working on solutions (Carter and Elliott 2009; Gordon 2007). Nielsen has launched a data service (Gorman 2009), Nielsen DigitalPlus, which integrates set top box data with People Meter data, transaction data from Nielsen Monitor Plus, retail and scanning information from AC Nielsen, and modeling and forecasting information from several databases (Claritas, Spectra, and Bases.) Nielsen intends to add consumers' activities on the internet and mobile devices into this mass of data.

The second challenge is that of privacy: the power of data collection has grown to an extent that it is widely perceived to be an intrusive threat (Clifton 2011; Matatov et al. 2010; Noam 1995). So there will be further legal constraints on data collection, use, matching, retention, and dissemination.

The third problem is that when it comes to the use of these rich data streams, academic and analytical research are falling behind (Holbrook et al. 1986; Weinberg and Weiss 1986). When one looks at what economists in demand research do these days, judging from the articles' citations, they still show little connectedness to other disciplines or to corporate demand research. There is a weak appreciation of the literatures of academic marketing studies, of information science on data mining (Cooley 2002), of the behavioral sciences (Ravaha et al. 2008), of communications research (Zillman 1988; Vorderer et al. 2004), and even in the recent work by behavioral economists (Camerer 2004). There is little connection to real-world demand applications—the work that Nielsen or Simmons or the media research departments of networks do (Coffey 2001). Conversely, the work process of Nielsen and similar companies seems to be largely untouched by the work of academic economists, which is damning to both sides.

The next challenge is therefore to create linkage of economic and behavioral data. Right now there is no strong link of economic behavioral models and analysis. Behavioral economics is in its infancy (Kahneman 2003, 2012), and it relies mostly on individualized, traditional, slowpoke data methods of surveys and experiments. The physiologists' sensor-based data techniques, mentioned above, have yet to find a home in economic models or applied studies. There is also a need to bridge the academic world of textbook theory of consumer demand with the practical empirical work of media researchers.

Thus, the biggest challenge in moving demand studies forward is the creation of new research methodologies. The more powerful data collection tools will push, require, and enable the next generation of analytical tools. One should expect a renaissance in demand analysis. Until it arrives one should expect frustration.

In short: What we need today, again, is a Lester Taylor.

Eli Noam

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