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Forecasting advertising and media effects on sales: Econometrics and alternatives

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Abstract
The contribution of regression analysis (econometrics) to advertising and media decision-making is questioned and found wanting. Econometrics cannot be expected to estimate valid and reliable forecasting models unless it is based on extensive experimental data on important variables, across varied conditions. This article canvasses alternative, evidence-based methods that have been shown to be useful for forecasting problems. These methods are described with the hope that they are more widely used for marketing forecasting. The approaches include media and copy experiments, analyses of individual level single source data, and structured expert judgment.

Keywords
Econometrics, Advertising and media measurement, judgmental bootstrapping

Introduction

Managers are concerned with forecasting the effects of advertising and media decisions on sales. Econometrics is an umbrella term for a range of statistical techniques for developing causal models for that purpose; the term covers marketing mix modeling (MMM), media mix modeling, and attribution modeling. Underlying the various techniques of econometrics is the process of fitting a least-squares regression model to time-series or, less commonly, panel data. In marketing, econometrics is intended to answer forecasting questions, such as:

- How will changes in the marketing mix affect sales?
- What is the right amount to spend on media?
- Which medium or media combinations will be most effective or efficient?
- Is it better to schedule for flighting or continuity?

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- When will these ads wear out?
- How much economic activity is derived from advertising expenditure?
- Where should the next marketing dollar be spent?

Marketing analysts, then, use econometrics to estimate the relationship between one or more causal—sometimes referred to as explanatory or independent—variables and a dependent variable, the one being forecast. A typical dependent variable in marketing is sales, in terms of units or revenue. Causal variables can include price promotions, advertising spend by media type—TV, Facebook, search advertising, and so on—and other media metrics, such as the numbers of exposures/GRPs.

Econometrics is attractive to marketers because it offers the tantalizing prospect of being able to develop quantitative models of the underlying causal relationships from available data. Econometrics is also attractive because, given data, it will produce estimates of causal influences in the form of model parameters that have the appearance of being highly precise, and are therefore persuasive. An example of such a model parameter would be an advertising elasticity of demand of 0.726, which is interpreted to mean that an increase in radio advertising spend of, say, 10% will increase sales by 7.26%.

While managers might not *explicitly* use econometric models for forecasting—for example, "with our change in marketing mix expenditures, we expect to sell 95,000 extra units in July"—they certainly *implicitly* use them for forecasting when they take account of model parameters when making decisions or justifying business cases. For example, if an econometric model has an advertising elasticity of demand parameter of 0.726 for radio and of 1.271 for outdoor, shifting expenditure from radio to outdoor is an implicit acceptance of the model's forecasts. Logically, any business decision to do A is an implicit forecast that it will turn out to be more profitable than doing B, C, or D. Indeed, shareholders might want to know why their managers are paying often large sums for econometric modeling (e.g., Neff, 2011) if they are not using forecasts from the models to increase profits. And in the world of "big data," it might almost seem backward not to commission modeling work of apparently plentiful data.

Carefully designed experiments can provide the best estimates of the strength of causal relationships, but they are perceived to be impractical due to cost, time requirements or organizational difficulty. Instead, analysts are given the task of learning about those relationships from an expensive campaign after it has been run. Econometric analysis seems to offer a way to resolve competing theories about the relative contributions of different aspects of a campaign and the environment in which it was conducted. Unsurprisingly then, econometric modeling has become a popular tool for marketers to use to justify their marketing plans (McQuater, 2018; Moriarty & Joseph, 2013).

This article examines whether econometrics can be expected to provide useful forecasts for marketing managers for advertising and media decisions, and then describes alternative, evidence-based methods. We acknowledge that some of the issues relating to econometric modeling have been raised before, for example, Ehrenberg, Barnard, and Sharp (2000).

Econometric modeling: problems with complexity

Despite the popularity of econometric modeling, there are serious concerns about whether the method is suitable for developing forecasting models for complex uncertain situations, especially in the absence of experimental data (Armstrong, Green, & Graefe, 2015). Markets are complex phenomena involving many independent decisions and interactions taking place over time. As a consequence, causal relationships between marketing decisions—such as advertising spend allocations across media—and their effects are obscured. For example, was the sales gain due to the new advertising campaign, or the change in media mix, or the in-store display, or the price discounts? How much did each element in the marketing mix influence sales? And how much was due to retailer or competitors' actions, or the weather?

Estimating the *long-run* relationships between ongoing major advertising spending alternatives and sales is particularly problematic because, for most brands, such spending will not have varied sufficiently or for long enough periods relative to other advertising spending. Moreover, any effects would likely be confounded by haphazard influences such as new products, price promotions, competitor actions, and economic conditions.

Frequent changes in variables—such as ad copy, ad length, and media schedules—can also present a problem for econometric modeling if, as is common, the data are aggregated. Ad copy varies in its ability to drive sales (Blair & Kuse, 2004; Lodish et al., 1995; Wood, 2009) and different media schedules differ notably in whom they reach, when, and how often. Thus, an econometric model estimated from aggregated data would be unlikely to provide valid forecasts for a specific ad and media schedule.

Developing an econometric model requires deciding which relationships are most important, and the nature of those relationships. Such decisions *should* be based on established knowledge. However, a lack of firm evidence, and hence subjective assumptions, are common. For example, there is no solid evidence-base about how quickly the effects of ad exposure decay and how this varies across conditions. Studies show widely differing estimates of such decay (Broadbent, Spittler, & Lynch, 1997; Ephron & Broadbent, 1999). This means an analyst constructing a model has to make a subjective choice about which decay rate they choose. Another example is the idea of using a "multiplier" to estimate the long-term advertising effect—estimates of these multipliers vary hugely (Webb, 2013). Modelers may acknowledge these subjective assumptions upon which their models are built, but it is not clear how the marketing decision maker should use that information, other than to hope that they do indeed apply to the situation under consideration.

In sum, the assumption that developing realistic—and hence, predictively valid—econometric models for advertising and media decision-making is in practice is rather heroic. Since the phrase "Marketing Mix" was first used in 1949 (Borden, 1964), there has been an appreciation that the list of causal variables and conditions can be very long, and can be different for different situations. Econometrics can only attempt to model the relationships that are represented in the dataset. Rarely will it be the case that all variables that are important and all possible variations in the relationships between them will be included in the data that are available to marketing analysts.

Best fit is over-fitted

> . . .econometrics is often viewed with nervousness and suspicion . . . [because] you can get multiple and even contradictory models from the same data set. (Louise Cook (2014), marketing mix modeler)

An under-appreciated fact of econometric modeling is that there will usually be several models that fit the available data to a similar extent using different coefficients (Lipovetsky, 2013). Analysts might reject models that violate prior knowledge or common sense—for example, a price rise causes sales to increase—and still have models to choose from. As a consequence, analysts have a great deal of freedom in choosing which results to present to marketing managers. In a discussion about the issue of reporting results with Sir David Spiegelhalter, President of the Royal Statistical Society, he replied, "yes, I am always slightly suspicious that people report the model with the coefficients they like best" (personal correspondence, 2015). To the manager, this practice should be very alarming—the final results may be highly influenced by the analyst's subjective choices.

An alternative approach is to pick the model that has the very best fit to the data available to the analyst. This is sometimes referred to as exploratory analysis. Statistical software packages make it easy for analysts to test (explore) many combinations of variables and variable transformations and to discover which model provides the best fit with the data. One approach to doing this that has been around since the early years of cheap computing, is stepwise regression. While the approach may seem sensible and a way to avoid a biased or arbitrary selection of a model, such a model cannot be counted on to provide the most accurate forecast of sales under the conditions prevailing over the forecast horizon.

Any data set has characteristics that are unique to the time and situation they relate to. Software algorithms for econometric models will try to fit as best they can to variation in that data that include random variations and the effects of other, unobserved, variables that are not in the dataset. As a consequence, last year's best fitting model is unlikely to be next year's best fitting model. And it is next year that the marketing manager needs to plan for. If one is thinking that perhaps the best fitting model might be good enough for forecasting, consider the test of exploratory data analysis described by Armstrong (1970). He found that he was able to identify a model with eight variables and an impressive fit ($R^2 = 0.85$) by following standard exploratory analysis procedures. The problem? The data were random numbers.

The more variables that are added to the model, the greater the certainty of discovering spurious relationships in random or irrelevant variations in the included variables; in other words, over-fitting. On the other hand, if important variables are omitted, then the model is likely to be an over-simplification. Econometrics does not have a solution to this "dammed if you do, dammed if you don't" problem (Ehrenberg et al., 2000).

Modeling blips instead of long-run sales

Econometric modeling identifies any variable that happens to co-vary with the dependent variable (sales, for example) as having an important relationship (large elasticity or effect size) with it. The blindness of econometrics to the difference between correlation and causation need not be a problem if the analyst does not expose the software to variables that are not known, *a priori*, to have a causal relationship with sales. For example, modeling the effects of price promotions can be quite straightforward because a short-term drop in price causes a large and instant uplift in sales and, as soon as the price deal ends, the uplift ends. Including variables with non-causal correlations with sales, on the other hand, can only lead to nonsensical forecasts.

For most established brands, particularly large ones, this month's sales figure has little to do with changes in marketing strategy this month, or in the preceding few months, or even years. Current sales are predominantly the result of marketing done over decades, such as by refreshing the brand memories of buyers who do not purchase in the category until long after their initial exposure. Given that most buyers in consumer packaged goods, for example, are very "light" or infrequent (J. Dawes & Trinh, 2017; Ehrenberg, 2000; Romaniuk & Sharp, 2016), the majority of consumers exposed to a brand's advertising will not buy within a short time period after exposure. Modelers accept that fact by modeling variations from a baseline of sales. That approach, however, can lead to the dangerous conclusion that the factors that cause short-term variations in sales are the same as those that are responsible for the brand's baseline sales. Moreover, if the brand owner sensibly uses a continuous advertising schedule, there will be little variation in ad spend, and therefore, it will be extremely difficult for a regression model to discern the short- or long-term sales effect of advertising.

As a consequence, even when the model variables are known to be causal, econometric modeling can lead the brand owner into taking actions that harm the baseline level of sales (e.g., Hickman, 2018). For example, suppose an analyst estimates a model that includes TV advertising, radio advertising, and social media advertising. The model coefficients indicate that social media advertising is the most cost-effective driver of incremental sales. The marketing manager concludes that advertising spend should be shifted to social media and away from other media. That conclusion would be wrong, however, because TV and radio advertising are essential for supporting baseline sales due to their broad reach and ability to refresh brand memories, which matter most over the long term.

Modeling confused and coincidental covariance

Even if the analyst avoids variables that are not already known to influence sales (but of course, they may not know if they do or do not!), the blindness of econometrics to the difference between correlation and causation *can* be a problem when the analyst attempts to estimate a model using data that were collected during a period that involved several different overlapping marketing activities. For example, suppose that a 4-week TV burst has come to an end and, while its longer-term after-effect plays out, a burst of print or outdoor advertising for the same brand is launched in conjunction with a social media campaign. Econometrics cannot properly disentangle the effects of the various activities and cannot therefore discern for how long or by how much the original campaign affected aggregate sales.

Furthermore, the problem with these simultaneously varying causal effects is compounded by the nature of the data that are available to marketing analysts. These are typically based on spend or rating points that do not identify which individuals have been exposed to which advertising. Some media are much better at hitting a broader audience that includes many light and non-brand buyers who will be critical for long-term brand growth (e.g., TV). Others only hit a select audience (e.g., loyalty program communications, or online ads targeted to those who recently searched for the brand or a competitor). There is a difference in the propensities of those audiences to buy the given brand that is unrelated to any advertising they receive (e.g., those who have searched for the brand or are in a loyalty program already have higher propensities to buy the brand).

Econometric modeling is further complicated for marketing analysts by differential exposures to advertising across media. For instance, most of those who are exposed to loyalty communications will also see a large TV campaign, but the reverse does not hold (Taylor et al., 2013). A consequence of differential exposure is that while the coefficients of an econometric model estimated on available data might suggest that advertising in one medium is much more efficient than advertising in other media, it may be that the apparently more efficient medium is already fully exploited in reaching, say, 0.1% of the market. In other words, spending more on that medium might have no effect on sales, even in the short run. Worse, a high estimate of the effect of spending in that medium may have arisen due to multicollinearity, rather than to any genuine causal relationship. Think again of social media, which is growing independently of advertisers spending: might it be that sales are increasing *along with* the increased volume of social chit-chat about products, rather than due to any marketing effort directed at social media. These arguments mean that an econometric model could produce findings that completely mislead the marketing team.

If a brand owner wants to increase sales over the long term, they need to use media that allow broad reach, with continuity (Sharp, 2017). The reason is that marketing messages can only influence the people that they reach, and brand sales usually come from a very broad base of consumers who generally do not have distinguishing characteristics other than they buy the product category (e.g., Uncles, Kennedy, Nenycz-Thiel, Singh, & Kwok, 2012). Therefore, reaching large numbers of potential buyers is usually not optional. Second, buyers are thinly spread out in time. Many do not buy a typical product category from one month to another—for example, average annual purchase rates for CPG categories are surprisingly small, for example, coffee—seven; toothpaste—six; and yogurt—11 occasions per year (J. Dawes, Meyer-Waarden, & Driesener, 2015)—let alone less frequently bought products such as say, car tires or insurance policies. Therefore, continuity is needed to spread out advertising exposures to maximize the number of consumers who have at least one opportunity-to-see in any given time period (McDonald, 1997). In turn, this approach offers the advertiser the chance to link their brand in as many collective memories as possible, to be eventually activated when consumers eventually buy the category. By contrast, the emphasis on short-term sales response and Return on Investment (ROI) that econometric models tend to encourage leads to advertising and media decisions that are likely to harm longer-term profitability (e.g., Moriarty & Joseph, 2013).

Conclusions on suitability of econometrics for marketing analysis

When academics and consultants use statistical techniques to fit a model to noisy and error-ridden data, they neglect the hard work of doing the science that is needed to properly estimate causal impacts. Even when important causal variables are identified a priori, econometrics cannot estimate the relative strengths of advertising across various media in causal marketing mix models of aggregate sales, unless there are many data for all possible combinations of variable values. For practical marketing mix problems, then, econometric models are unlikely to sufficiently generalize that they will produce reliable forecasts of the effects of changes in spend.

In the absence of experimental data, where the values of causal variables can be controlled and varied such that sufficient data are generated to properly estimate the effects of individual variables (e.g., TV spend) and interactions between variables (e.g., TV spend and point-of-sale spend), there is little reason to think that estimated relationships will be valid, even for short-run econometric models.

One might claim the problems with econometrics for marketing analysis would not matter if the models were useful for forecasting. The evidence that we have is that they are not. Econometric models fail when used for prediction tasks relative to simpler alternatives (e.g., Armstrong, 2001a; Dana & Dawes, 2004; J. Dawes, 2004).

Coping with complexity: simple evidence-based alternatives to econometrics

> I do not know of a complicated model in any area of science that performs well in explanation and prediction and have challenged many audiences to give me examples. So far, I have not heard about a single one. (Professor A. Zellner, founder of the Journal of Econometrics (García-Ferrer, 1998))

We contend that managers should stop relying on econometric analyses of aggregate sales data to allocate media spend. The data that underpin these studies does, however, often include important information that marketers need to use in their planning, and often these studies are the only times that the marketers acquire this information. Therefore, solid descriptions of this information are needed to understand the likes of seasonality in the category and fundamental patterns in buying (e.g., which brands and variants are popular, the relative incidence of light, medium and heavy buyers, and so on). Combining this descriptive knowledge with information about which media can reach and influence which parts of the buyer population, at what costs, is then critical.

To go further than the descriptive documentation of buying and media scenario number crunching, alternatives methods to consider are experiments, single source studies, and structured expert judgment. Marketers would be well advised to draw on the lessons and approaches from forecasting researchers. We now discuss these alternatives.

Run media and copy experiments

If managers want to know which media investments to make, they should implement spending *experiments* over the medium to long term. For example, to run experiments that systematically up-weight or down-weight total media spend and relative allocations over a periods of months to a year or more, across multiple markets. This time period is needed to identify how the chosen spending allocation affects the brand's medium-term sales trajectory. Ideally, the business would set out to become an active learner, running multiple experiments over time, thus building what has been called a Many Sets of Data (MSoD) approach to build generalized, robust knowledge (Ehrenberg, 1990).

Of course, a marketplace cannot be controlled in the same manner as a scientist's laboratory. However, if a sufficient number of experiments are conducted, and the major uncontrollable marketplace occurrences of each are noted, a good indication of how media allocations affect brand sales can be gleaned. The idea is certainly feasible—Ackoff and Emshoff (1975a, 1975b) did basic versions of such experiments for Anheuser as far back as the 1960s-1970s. With the advent of much digital media delivery (e.g., for television and other video, social and radio listening) facilitating better measurement, split-cable tests (for media and copy) should become a norm for marketers who want to be evidence-based in their media decision-making. Indeed, there are books available on the subject of how practitioners can run split-sample advertising tests (e.g., Eisenberg, Quarto-vonTivadar, & Davis, 2009). It is also the case that media and copy experiments can be run within a given country-market, in different geographies. This would allow for a much quicker "test and learn" regime with different media weights or copy run simultaneously. Such experimentation would allow for short and longer-term effects to be revealed.

Invest in individual level cross media single-source data

Advances are being made in the collection and analysis of single source data—matching ad exposures to individual-level purchase records (e.g., Poltrack, Doud, & Wood, 2014). Single-source is arguably most appropriate for consumer goods, where it is more likely that an adequately large number of consumers (with ad exposure tracking) will purchase in a time period such as a month within advertising exposure.

Single source studies can identify short-term advertising effects at the individual level *even if there is no aggregate level effect* on brand sales due to competitor actions. Documentation of the approach and its challenges is provided by Taylor et al. (2013). Despite single-source data being complex and expensive, it yields knowledge that typical econometric studies cannot. We encourage marketers to lobby large research providers to invest more into single-source consumer panels. There are many consumer panels run in dozens of countries, but what is needed is to recruit subsets of these panels with media recording devices so that ad exposure and purchasing behavior can be matched.

Develop and test a structured judgment approach

Managers already know a lot about the effects that changes in the marketing mix are likely to have, from accumulated experience. Moreover, much of this knowledge is difficult or impossible to include in econometric models. Indeed, it is likely that even where the econometrics models attempt to include the relationships that managers know are important, those relationships will be badly estimated due to the non-experimental nature of the data available. So rather than using econometrics, we can use managerial knowledge in a structured way to aid forecasting. It is important it is structured, as unaided judgments are typically unreliable. For a recent advertising example that demonstrates how poor marketers are at using their unaided judgments to make advertising decisions, see Hartnett, Kennedy, Sharp, and Greenacre (2016).

Research on forecasting has identified a useful method for capturing management knowledge about causal relationships. It is known in the forecasting literature as "judgmental bootstrapping." Armstrong (2001b) reviewed the evidence on this method, and found that it almost always improved forecast accuracy and usually substantially compared to experts' unaided judgments. For example, Ashton and Stacey (1995) found reductions in average and maximum errors for forecasts of advertising sales in *Time* magazine.

The method has been around since at least 1917 when it was applied to predicting corn yield from spring inspection of crops, but has been surprisingly underused. The term judgmental bootstrapping was coined by R. M. Dawes (1971) when he reviewed the research to suggest that forecasters could metaphorically pull themselves up by their own bootstraps. The idea behind the method is to estimate a model of an expert's forecasting process. It turns out that forecasts from bootstrap models are more accurate than forecasts from the experts when they use their unaided judgment.

As a concept, the process of estimating judgmental bootstrap models is simple. In the case of brand sales, one would ask experts to make forecasts of sales for many different media mix combinations. Then, estimate an equation that relates the forecasts to the causal variables including spend in each media, used by the experts.

The first step is to prepare a comprehensive set of media mix proposals encompassing all plausible combinations of media and other important variables—including expected economic conditions—that experts believe affect sales. Second, ask five or more experts with diverse but relevant knowledge to forecast the change in brand sales for each of the proposals. Third, develop a model by estimating the relationships between the experts' brand sales forecasts and the variables that they used to make their forecasts. For example, imagine a team of six experts asked to evaluate 20 proposals. The proposals incorporate four media, each with five spending levels: TV, radio, print, online/search. The experts use their knowledge to predict the resultant brand sales for the quarter and for the coming year. The end result is that the process reveals, in the form of model parameters or coefficients, the experts' beliefs about the relative effects of changes in media spend and other variables. The model can then be used to forecast the effect of new media mix proposals. Importantly, the predictions and outcomes can be compared after a period of time. Furthermore, since the process and all variables are fully known and transparent, managers can learn and refine their knowledge from further iterations of this technique.

This idea sounds so simple that one could be forgiven for thinking it could not possibly work for purposes such as allocating spending across media for a brand. However, what this approach does is effectively capture the accumulated domain knowledge of experts in a structured way. There are certainly examples of how structured expert judgment has been successfully employed, in fields such as tourism demand forecasting (Croce & Wöber, 2011). Therefore, judgemental bootstrapping—or put another way, structured expert judgment—offers a real alternative upon which sound media spending decisions can be made.

Summary and recommendations

While econometric modeling is commonly used, its use is unlikely to help managers make better decisions in complex situations involving more than a handful of important variables. We contend it is of limited use in allocating media investment in today's complex media environment; given also the many and varied tactics of advertising. Econometrics tends to produce results that depend on a specific dataset that is unlikely to generalize to the future or to other market contexts. A number of alternatives are proposed: experiments, single-source, and a structured method for capturing expert knowledge, called judgemental bootstrapping. While one of these approaches, single-source, is more likely to be available to larger firms in frequently bought categories, experiments and judgemental bootstrapping are realistic tools for small to medium-sized brands.

We suggest that the transparent and readily understandable nature of the judgmental bootstrapping method and its close relationship to current practice make it an attractive replacement for the use of expensive econometric modeling exercises. We encourage marketers and brand managers to volunteer to adopt this approach, and to report their experiences in the public domain.

We also recommend validation tests against in-market results compared to current practice. This might involve asking the econometric modelers and the managers that use the modelers' outputs to make sales predictions for each media allocation decision. The accuracy of these forecasts could then be compared with those from judgmental bootstrap models and/or the index method that had been independently estimated and withheld from the econometricians and managers. We encourage comparisons with single source data/analysis and experimentation to continue to improve knowledge on the effects of media mix on brand sales. There is much research still to be done to determine how best to measure advertising and media and to improve marketing decision-making, which has been highlighted as the next big research frontier (Wierenga, 2011).

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References

Ackoff, R. L., & Emshoff, J. R. (1975a). Advertising research at Anheuser-Busch, Inc. (1963-68): Part I. *Sloan Management Review*, *16*(2), 1–15.

Ackoff, R. L., & Emshoff, J. R. (1975b). Advertising research at Anheuser-Busch, Inc. (1968-74): Part II. *Sloan Management Review*, *16*(3), 1.

Armstrong, J. S. (1970). How to avoid exploratory research. *Journal of Advertising Research*, *10*(4), 27–30.

Armstrong, J. S. (2001a). Evaluating forecasting methods. In J. S. Armstrong (Ed.), *Principles of forecasting a handbook for researchers and practitioners* (pp. 443–472). Boston, MA: Kluwer Academic.

Armstrong, J. S. (2001b). Judgemental bootstrapping: Inferring experts' rule for forecasting. In J. S. Armstrong (Ed.), *Principles of forecasting: A handbook for researchers and practitioners* (pp. 171–192). Norwell, MA: Kluwer Academic.

Armstrong, J. S., Green, K. C., & Graefe, A. (2015). Golden rule of forecasting: Be conservative. *Journal of Business Research*, *68*, 1717–1731.

Ashton, W. B., & Stacey, G. S. (1995). Technical intelligence in business: Understanding technology threats and opportunities. *International Journal of Technology Management*, *10*, 79–104.

Blair, M. H., & Kuse, A. R. (2004). Better practices in advertising can change a cost of doing business to wise investments in the business. *Journal of Advertising Research*, *44*, 71–89.

Borden, N. H. (1964). The concept of the marketing mix. *Journal of Advertising Research*, *4*, 7–12.

Broadbent, S., Spittler, J. Z., & Lynch, K. (1997). Building better TV schedules: New light from the single source. *Journal of Advertising Research*, *37*(4), 27–31.

Cook, L. (2014, February). Econometrics: Get the best from econometric modelling. *Admap Magazine*, pp. 1–6.

Croce, V., & Wöber, K. W. (2011). Judgemental forecasting support systems in Tourism. *Tourism Economics*, *17*, 709–724.

Dana, J., & Dawes, R. M. (2004). The superiority of simple alternatives to regression for social science predictions. *Journal of Educational and Behavioral Statistics*, *29*, 317–331.

Dawes, J., Meyer-Waarden, L., & Driesener, C. (2015). Has brand loyalty declined? A longitudinal analysis of repeat purchase behavior in the UK and the USA. *Journal of Business Research*, *68*, 425–432.

Dawes, J. (2004). Price changes and defection levels in a subscription-type market: Can an estimation model really predict defection levels? *The Journal of Services Marketing*, *18*, 35–44.

Dawes, J., & Trinh, G. (2017, September 24). *Category and Brand Purchase Rates (Still) Follow the NBD Distribution*. Available at SSRN: https://ssrn.com/abstract=3042332 or http://dx.doi.org/10.2139/ssrn.3042332

Dawes, R. M. (1971). A case study of graduate admissions: Application of three principles of human decision making. *American Psychologist*, *26*, 180–188.

Ehrenberg, A. (1990). A hope for the future of statistics: MSOD. *The American Statistician*, *44*, 195–196.

Ehrenberg, A. (2000). Repeat-buying: Facts, theory and applications. *Journal of Empirical Generalisations in Marketing Science*, *5*, 392–770.

Ehrenberg, A., Barnard, N. R., & Sharp, B. (2000). Decision models or descriptive models? *International Journal of Research in Marketing*, *17*, 147–158.

Eisenberg, B., Quarto-vonTivadar, J., & Davis, L. T. (2009). *Always be testing: The complete guide to Google website optimizer*. Indianapolis, Indiana: John Wiley.

Ephron, E., & Broadbent, S. (1999, January). Two views of TV scheduling: How far apart? *Admap Magazine*. Retrieved from http://www.forumsostav.ru/

García-Ferrer, A. (1998). Professor Zellner: An interview for the international journal of forecasting. *International Journal of Forecasting*, *14*, 303–312.

Hartnett, N., Kennedy, R., Sharp, B., & Greenacre, L. (2016). Marketers' intuitions about the sales effectiveness of advertisements. *Journal of Marketing Behavior*, *2*, 177–194.

Hickman, A. (2018). *Digital giants are "Weaponising" attribution and it's driving short-termism*. Retrieved from http://www.adnews.com.au/news/digital-giants-are-weaponising-attribution-and-it-s-driving-short-termism

Lipovetsky, S. (2013). How good is best? Multivariate case of Ehrenberg-Weisberg analysis of residual errors in competing regressions. *Journal of Modern Applied Statistical Methods*, *12*, 242–255.

Lodish, L. M., Abraham, M., Kalmenson, S., Livelsberger, J., Lubetkin, B., Richardson, B., & Stevens, M. E. (1995). How TV advertising works: A meta-analysis of 389 real world split cable TV advertising experiments. *Journal of Marketing Research*, *32*, 125–139.

McDonald, C. (1997). From "frequency" to "continuity": Is it a new dawn? *Journal of Advertising Research*, *37*, 21–25.

McQuater, K. (2018). *How Diageo is emphasising data in marketing decisions*. Retrieved from https://www.research-live.com/article/news/how-diageo-is-emphasising-data-in-marketing-decisions/id/5035932

Moriarty, P., & Joseph, J. (2013). *Marketing mix modeling on trial*. Chicago, IL: IRI.

Neff, J. (2011). P&G shifts marketing-mix biz to Nielsen, Demandtec for Faster Roi Reads, 8 = AdAge, March Aug 12, USA, Retrieved from http://adage.com/article/news/p-g-shifts-marketing-mix-biz-nielsen-demandtec/229235/.

Poltrack, D., Doud, J., & Wood, L. (2014). OBJ at last, long term ad effectiveness measurement, the single source solution. In *Audience measurement 2014*. New York, NY: The Advertising Research Foundation.

Romaniuk, J., & Sharp, B. (2016). *How brands grow: Part 2*. South Melbourne, Victoria, Australia: Oxford University Press.

Sharp, B. (2017). *Marketing: Theory, evidence, practice*. Melbourne, Victoria, Australia: Oxford University Press.

Taylor, J., Kennedy, R., McDonald, C., Larguinat, L., El Ouarzazi, Y., & Haddad, N. (2013a). Is the multi-platform whole more powerful than its separate parts? Measuring the sales effects of cross-media advertising. *Journal of Advertising Research*, *53*, 200–211.

Uncles, M., Kennedy, R., Nenycz-Thiel, M., Singh, J., & Kwok, S. (2012). In 25 years, across 50 categories, user profiles for directly competing brands seldom differ: Affirming Andrew Ehrenberg's principles. *Journal of Advertising Research*, *52*, 252–261.

Webb, J. (2013, November 29). Discovering the long term effects of your advertising. *HuffPost*. Retrieved from https://www.huffingtonpost.co.uk/jon-webb/marketing-long-term-effects_b_4355171.html

Wierenga, B. (2011). Managerial decision making in marketing: The next research frontier. *International Journal of Research in Marketing*, *28*, 89–101.

Wood, L. (2009). Short-term effects of advertising: Some well-established empirical law-like patterns. *Journal of Advertising Research*, *49*, 186–192.