# Forecasting in Marketing: Methods, Types of Data, and Future Research

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**Resumo**

Forecasts are fundamental to plan and deliver products and services. Despite such relevance, marketers have difficulty to choose which forecast method is the best for their organizations. One possible explanation for this is that marketing literature focuses on the explanation of which variables impact on marketing responses rather than the accuracy of predictions of those responses. Consequently, the literature is not clear about forecasting methods? classifications, approaches, complexity, requirements, and efficiency. This theoretical paper tries to improve this scenario, reviewing the state of the art about forecasting in marketing. More specifically, we focus on: different classifications and approaches used to study marketing responses, especially the ones based on statistics/mathematics and computer-intensive methods; the types of data used; and suggestions of future research aimed at improving forecasting marketing response. Besides simpler, easier to implement models, further research is necessary to develop forecasting techniques that give evidence of accuracy, uses aggregate or anonymized data, or that incorporates publicly available data. Of foremost importance are datasets that manufacturers of durable goods can use in models for their businesses, the exploration of location data, and the combination of different models and datasets.

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**Abstract:** Forecasts are fundamental to plan and deliver products and services. Despite such relevance, marketers have difficulty to choose which forecast method is the best for their organizations. One possible explanation for this is that marketing literature focuses on the explanation of which variables impact on marketing responses rather than the accuracy of predictions of those responses. Consequently, the literature is not clear about forecasting methods' classifications, approaches, complexity, requirements, and efficiency. This theoretical paper tries to improve this scenario, reviewing the state of the art about forecasting in marketing. More specifically, we focus on: different classifications and approaches used to study marketing responses, especially the ones based on statistics/mathematics and computer-intensive methods; the types of data used; and suggestions of future research aimed at improving forecasting marketing response. Besides simpler, easier to implement models, further research is necessary to develop forecasting techniques that give evidence of accuracy, uses aggregate or anonymized data, or that incorporates publicly available data. Of foremost importance are datasets that manufacturers of durable goods can use in models for their businesses, the exploration of location data, and the combination of different models and datasets.
**Keywords:** forecasting, marketing, analytics, theoretical paper

## 1. INTRODUCTION

Marketing responses comprise the consequences of consumers' actions in reaction to companies' marketing mix strategies. These responses can be measured in different ways, such as sales, brand choice, demand, or market share. To be able to predict next purchases is a valuable thing to marketing more than for other fields in social sciences (Chintagunta & Nair, 2011). However, the knowledge and the ability to forecast is not a skill of most marketing majors (Beal & Wilson, 2015), and selecting the most appropriate forecasting technique is challenging. The choice of the method is usually based on familiarity and not on what is more appropriate to the market under investigation or the data available (Canitz, 2016).

According to classical forecasting literature, the first criteria to select a method is related to the amount of objective data (Armstrong, 2001). This will define if it is to follow a qualitative/judgmental approach or a quantitative one. Regarding quantitative methods, Singh (2016) divides the research on forecasting into four types: behavioral-focused (judgmental adjustments to statistical forecasts); business performance focused (impact of forecasting practices on performance); statistics/mathematics-focused (time-series and causal); and big-data-based or computer-intensive (the newest research stream).

In this theoretical paper, we consider that judgments or domain knowledge should be used to add structure to forecasting models, but not to override the estimations after they are done. Domain knowledge improves forecast accuracy and reduces the need to do such adjustments (Chase Jr, 2013), and it can and should come from economic and marketing literature. Business performance is not analyzed either since the goal is not to discuss the advantages or difficulties to implement the process of forecasting in companies. For those reasons, in the remaining of this theoretical paper, the focus will be on statistics/mathematics and computer-intensive techniques.

In this paper, we describe the classification of methods and types of data used in marketing response models. Their relevance increased with the growing access to data from different contexts, which allowed the development of many different types of models, for different purposes and with different properties (Chintagunta & Nair, 2011). The manuscript unfolds as follows. First, we discuss the classification of marketing response methods, followed by a review of the techniques applied in practice and theory. This review is divided into two approaches, statistics/mathematics, and computer-intensive techniques. After that, we introduce the types of data used in marketing models. Finally, we present a methodological framework based on the literature reviewed, proposing some criteria to select forecasting methods. We also offer propositions of future research on forecasting.

## 2. CLASSIFICATIONS OF MARKETING RESPONSE METHODS

The types of marketing response analysis can be divided based on their goals (Chintagunta & Nair, 2011), which can be forecasting, measurement, and testing. Chintagunta and Nair (2011) subdivide such goals based on their respective models: descriptive models (for stable environments), structural models, and reduced-form causal effects. Descriptive models are the ones which focus on forecasting sales across time, based on variables that are available today (e.g. current marketing mix variables and sales). The emphasis is not on causality, given that these models cannot test theories about consumer or firm behavior. They can at the most show an econometric representation of the theory that may serve as the basis for such a causal test (Reiss, 2011).

Structural models, on the other hand, use the theory to predict phenomena. These models combine theory and econometric specification to explain patterns in the data (Chintagunta & Nair, 2011). They combine marketing models of behavior with statistical assumptions to derive empirical models that can be estimated (Reiss, 2011). Discrete choice models are examples of structural models. They are among the most popular in marketing given that much of the data available consists of records of consumers making choices from a set of alternatives within a category. They can be causally interpreted but have limitations as well: (1) it is challenging to find the best combination of theory, data, and econometric specification; (2) they are time consuming; (3) it is difficult to build simple models that are realistic and can be estimated with the data available; (4) they usually present results that may be overly affected by strong assumptions; and (5) assumptions of distributions are made for computational convenience and most times do not have economic defense (Chintagunta & Nair, 2011; Reiss, 2011).

Finally, reduced-form causal models used for measurement and testing are diverse from structure models because they require fewer assumptions on distribution and specification (Chintagunta & Nair, 2011). However, they share some similarities, since both structural and reduced-form models imply causality and require theory.

Another way to classify models is by demand systems. Using this criterion, they can be divided into characteristics space and in product space. Demand in characteristics space assumes that consumers choose products by groups of characteristics. These models are flexible and usually outperform the models of the product space system. However, an issue is the assumption that consumers choose no more than one good (Nevo, 2011). Demand in product space, on the other hand, considers that consumers first decide by categories, then by segments, and finally by brands. Therefore, products, not characteristics, are grouped into these models. Product space systems are simpler to estimate, generally using linear methods, which save computational time. On the other hand, the products need to be classified into segments that are frequently hard to justify. Product space also assumes that consumers buy a number of products of all brands, when they, in reality, may consume more than one brand, but not all of them (Nevo, 2011).

One common disadvantage of both systems of models is that they are static and for many markets the demand is dynamic. This means that they do not consider the possibility of consumers' decisions in the present affecting the posterior decision, nor that the present decision is affected by expectations of the future (Nevo, 2011).

Another classification typology suggested by Roberts (1998) divides models by level (individual or aggregate) and by application (new or existing products). Models for new products at the individual level are used to predict or explain market share. Such models apply discrete choice analysis According to Roberts (1998), the focus of new products models has been on the aggregate-level through diffusion models. Since pre-launch forecasts are challenging, these studies are frequently done post-launch aimed at understanding the reasons that made the diffusion possible.

Post-launch models also apply discrete choice models at the individual level. The individual-level data comes from scanner data that is frequently used to analyze consumer preference and response to marketing instruments (Roberts, 1998). At the aggregate level, marketing has focused on the "study of advertising effects and other marketing mix variables on sales" (Roberts, 1998).

The classifications reviewed in this paper so far are broad, classifying methods that are applied with an aim to explain and to forecast. Armstrong's (2001) classification, on the other hand, focus on methods that have a forecasting goal and divides them based on knowledge of the relationships, type of data (time-series or cross-sectional), expectations of large changes, and domain knowledge. Armstrong (2001) also recommends the testing of different methods and, if they provide useful forecasts, the combination of those results. If they do not provide good results, one should simply use the best performing method. Figure 1 summarizes the techniques in a decision-tree format. However, the criteria proposed by the author misses to account the different goal of the techniques and does not include machine learning techniques.

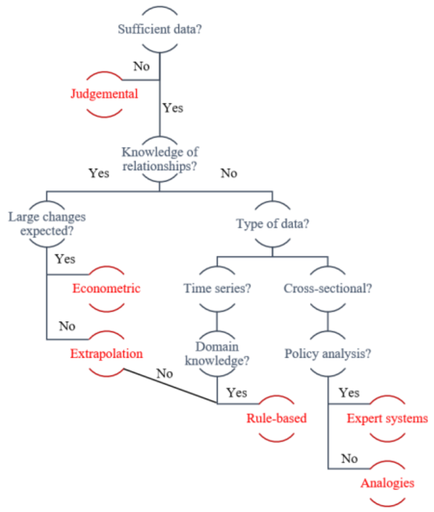


*Figure 1*. Criteria to select forecasting techniques. Adapted from Armstrong (2001)

Gentry, Calantone, and Cui (2006) suggests a different typology (Figure 2). According to then, although there are many different classifications, none is concise, exclusive, and exhaustive. These authors classify the forecasting methods along two continuums: from casual to naïve, and from opinion based to empirical. This classification creates 4 different categories of techniques: (1) predictions that are based on opinions that do not have explicit assumptions; (2) scripts or scenarios based on casual assumptions; (3) correlations or techniques that give back predictions based on the performance of another factor, with no casual assumptions; and (4) models that return predictions based on casual assumptions.

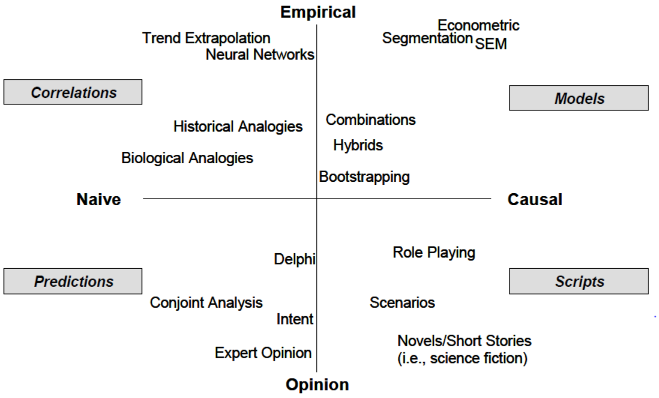


*Figure 2.* Typology of methods (Gentry et al., 2006)

Extrapolation methods and neural networks (just one of the machine learning techniques available) are classified by the authors as correlations. This can create confusion regarding the definitions of those techniques that apply more than correlations to return predictions. Extrapolation methods are easy to implement, highly accurate techniques that may (or may not) consider seasonality, trends, and cycles (Armstrong, 2001). Gentry et al. (2006) justify this definition by the lack of explicit causal assumptions, however, the extrapolation methods do not lack an assumption. The assumption is of stability, or that the variables will continue to behave as they did in the past. The authors lastly call these methods “black boxes”, because one cannot interpret parameters the same way as in an econometric model. This statement misses informing that some machine learning techniques return the importance of variables, for example, giving the researcher more than the prediction and accuracy rate (which is not less than other models, just different in its goal).

## 3. STATISTICS/MATHEMATICS-FOCUSED METHODS

Statistics/mathematics-focused forecasting techniques used in practice can be divided into three streams: time-series (also called extrapolation methods), causal, and weighted combined forecasting (Chase Jr, 2013). Weighted combined forecasting combine methods (i.e., time series, causal, and/or judgmental) and create a single forecast by giving each result an equal or different weight. This combination outperforms most single forecasts since biases among methods will compensate one another (Chase Jr, 2013).

Time-series techniques identify patterns (trend, seasonality, cyclical, and randomness) and make predictions for the future. They have higher predictive accuracy in stable markets. Some examples of time-series are moving average, simple exponential smoothing, Holt’s two parameters, and Winters’ three parameters. Time-series are simple to develop and require a minimal amount of data, however, they are unable to predict sudden changes in demand. ARIMA (Autoregressive integrated moving average) models are a more advanced class of time-series technique that combine regression elements. These modes are more accurate in long term predictions. ARIMA can model trend/cycle, seasonality, as well as other factors influencing demand or sales (explanatory variables) but require more data and are more complex to develop (Chase Jr, 2013).

Causal techniques assume that future sales are related to changes in other variables (price, promotions, among others). Examples are regression and ARIMAX (an extension of ARIMA). These techniques require more data and are more complicated to develop (Chase Jr, 2013). On the other hand, they can include intervention variables (using dummy variables).

Practitioners still practice simpler forecasting methods, favoring forecast accuracy than the ability to explain which variables impact the increase or decline of marketing response. One reason is that the models that result from marketing research are hard to implement in practice. This is a significant challenge for structural models, because “the large number of observations in practice, the large array of state and control variables, and the frequency of decision making can render the application of structural models infeasible” (Mela, 2011). Another reason for the choice of time-series models by practitioners is the availability of data. Most companies do not have access to detailed individual consumer information, nor market data regarding sales of competitors. In these contexts, it is very challenging to apply current marketing response models.

In marketing, structural models are the most used approach, using econometric techniques that focus on explanation, not on forecasting. There are also some models that apply a reduced form (e.g. Briesch, Dillon, & Fox, 2013; Chung, Derdenger, & Srinivasan, 2013) or a combination of reduced form and structural model (e.g. Chung et al., 2013). Some studies apply structural models with a Bayesian approach (e.g. Aribarg, Arora, & Kang, 2010; Arora, Henderson, & Liu, 2011; Che, Chen, & Chen, 2012; Chung & Rao, 2012; Feit, Wang, Bradlow, & Fader, 2013; Rooderkerk, Van Heerde, & Bijmolt, 2011; Zhao, Yang, Narayan, & Zhao, 2013; Zhao, Zhao, & Helsen, 2011).

For that reason, another important distinction must be made between the use of classical and Bayesian statistics. This is important particularly in situations with limited information (Rossi & Allenby, 2003). Bayesian statistics are commonly used in marketing, partially due to computing developments that have made it accessible (Allenby, Bakken, & Rossi, 2004). For example, Markov Chain Monte Carlo (MCMC) simulation made it easier to estimate complex models of behavior that would not be possible with other methods (Allenby et al., 2004).

The Bayesian approach has some advantages, such as: it is able to reflect heterogeneity in consumer preferences; the developed models are more realistic; it allows disaggregate analysis; the Hierarchical Bayes methods have predictive superiority due to avoiding the restrictive analytic assumptions that alternative methods impose; it allows studies of high-dimensional data and complex relationships; and instead of point estimate of values for each respondent, it ends up with a distribution of estimates for each respondent (for a more comprehensive review see Allenby et al., 2004; Rossi and Allenby, 2003). This distribution can be informative about uncertainty, but on the other hand, makes the analysis more complex.

One important difference between classical and Bayesian statistics is that the former says nothing about how to incorporate different sources of data, such as expert’s information and other data sets (Rossi & Allenby, 2003). That is important because merging information acquired from different data sets is challenging for marketing practitioners (Rossi & Allenby, 2003).

Descriptive models can also be applied in marketing, however, the field does not have as many published papers that applied these methods, when compared to the other types of methods discussed in this paper (Dekimpe & Hanssens, 2000). Wedel and Kannan (2016) review the techniques applied in marketing (Figure 3) and ignore time-series models or machine learning techniques. They concentrate their analysis on econometric models explaining choices (and for segmentation, that is beyond the scope of this manuscript).

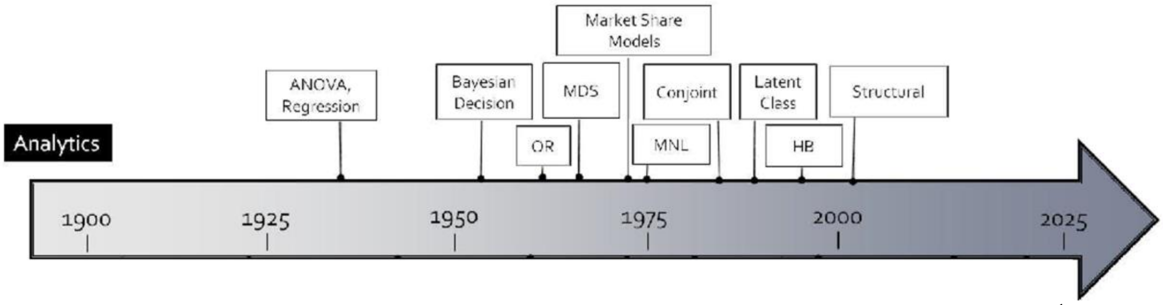


*Figure 3.* Techniques applied in marketing. Adapted from Wedel and Kannan (2016)[1]

Marketing has not given much attention to data-driven approaches as time-series (Dekimpe & Hanssens, 2000). This may have a connection with a lack of skilled researchers to apply these techniques (Beal & Wilson, 2015). The same logic can explain the lack of publications on marketing journals using machine learning to forecast marketing responses. This is a symptom of the lack of emphasis in analytics skill on business, especially marketing academic curriculum. Therefore, the ability to work with big data is not common among marketing researchers (Feit et al., 2013), and marketing should strive to gain knowledge in computer science. Computer-intensive methods (i.e. machine learning techniques) will be discussed in the next section.

## 4. COMPUTER-INTENSIVE METHODS

Methods applied to study marketing response are related to the characteristics of the variables and data sets that became available to marketing scientists. As scanner data enabled marketing to apply structured causal models from fields like transportation science and economics, now big data makes it possible to apply methods from machine learning (Chintagunta, Hanssens, & Hauser, 2016).

Big-data is related to new types of variables, and the size of data sets used, but also to the different methods applied. With bigger data sets and a higher number of different attributes applied in marketing studies, analysis using conventional statistical methods became impractical or even infeasible because of computer constraints (Fildes, Nikolopoulos, Crone, & Syntetos, 2008).

Computer-intensive methods apply statistical and machine learning algorithms for discovering valid, novel and potentially useful predictive information from large data sets in unstructured problems. Statistics is the intellectual base of these applications, given that finding useful patterns from data for prediction has long been a statistical challenge (Fildes et al., 2008).

Most studies applying machine learning focus on segmenting or classifying customers, such as CRM related topics (up/cross-selling, churn analysis, credit scoring). One example of this application is the study of Sundsøy et al. (2014) that compared different machine learning algorithms to the judgment of the marketing team in identifying customers that were more likely to buy mobile internet service.

Ali et al. (2009) and Sun et al. (2008) are two examples of sales forecasting studies that used machine learning techniques. Although these studies are related to the marketing area they were not published in marketing journals. Ali et al. (2009) forecast sales of a grocery store, in the presence of promotions. The authors compared different methods of forecasting, such as exponential smoothing, stepwise linear regression, support vector regression (the regression version of support vector machines), and CART (regression trees). They found that, for periods with no information about marketing instruments (in this case, the promotions), time series techniques performed better. In this case, machine learning techniques only matched the performance of other models (Ali et al., 2009). The reason is that time-series techniques perform well if sales are stable, which corroborate to one of the advantages of these techniques mentioned previously. For periods with promotions, on the other hand, regression trees performed better. However, regression trees are a more complex technique that demand more intense data manipulation. Ali et al. (2009) propose a combination of these techniques in a forecasting system, applying time-series for periods when there is no promotion and regression tree model in periods with promotions.

Sun et al. (2008) applied a neural network technique called extreme learning machine to forecast sales in fashion retailing. The advantages of that technique are the higher generalization performance and that it avoids difficulties of other learning methods (stopping criteria and long computation time, for example). The disadvantage is that its results are different from time to time because the input weights and hidden biases are randomly chosen (Sun et al., 2008).

More recently Liu, Singh and Srinivasan (2016) used big data from different sources (Twitter, Google Search, IMDB reviews, among others) to predict TV shows ratings. Cloud computing was applied, so it would be possible to process a large amount of data and to prepare the unstructured data was used text mining (machine learning technique). Alternative machine learning models were tested, but they were outperformed by the structured model chosen by the authors.

Although some efforts were already made in marketing to apply computer-intensive methods on marketing response forecasting, there is still space for evolution (Cui & Curry, 2005; Wedel & Kannan, 2016). To do so marketing researchers need to learn about (or associate with) other disciplines, like data science and machine learning (Chintagunta et al., 2016).

Finally, is important to keep in mind that the method should be chosen after the research problem is defined and the data to solve is accessible. These two criteria should determine the model and not the opposite (Reiss, 2011). The next section will review the types of data commonly used in marketing literature.

## 5. TYPES OF DATA USED

Choosing the data is related to the theory and the research problem wished to address. Researchers study the theory, the market, and develop a model based on assumptions. From this model, researchers know what data they need to gather. Mela (2011) outlines a process to data procurement for structural models that consist in determining the data necessary to the research problem, finding the source (or sources) of data and then negotiate, acquire, and check the data. Research problems can also be derived from access to new types of data that were not available before. New types of data can bring new opportunities to apply marketing theory.

In forecasting practice, according to Chase Jr (2013), the most common data sources used are customer orders, customer shipments (or replenishment), point-of-sales data, promotions, price, Consumer Price Index, gross national product growth, and Consumer Confidence Index. The marketing literature, on the other hand, focuses on marketing instruments, such as promotions, price, and their relation to sales or market share. The basic model studied in marketing, according to Fildes et al. (2008), can be represented as:

$$\textit{Marketing response}_{ijt} = f\,(\textit{marketing instruments}; \text{seasonality}; \text{exogenous factors}) \qquad (1)$$

where $i$ = brand or SKU, $j$ = store, $t$ = time, *Marketing response* = sales or market share, and *marketing instruments* = price, promotion, competition, among others.

Marketing theory has many potential explanatory variables to put on this basic model (Fildes et al., 2008). Researches should caution that a greater number of variables in a model can explain better, but make the model lose forecasting performance (Chase Jr, 2013). For that reason, it is recommended to keep the model specification simple. That is not a preoccupation in marketing models since marketing has historically focused on explanation and not on forecasting performance. Consequently, models are very complex, hard to apply in practice, and there is still a lack of evidence concerning the impact of marketing variables to increase accuracy (Fildes, Ma, & Kolassa, 2018; Fildes et al., 2008)

Models that include marketing variables are econometrically endogenous. Therefore, the correction of such endogeneity is one of the contributions that authors seek. One way to address this issue is to use instrumental variables. But they are hard to choose, to justify, and do not correct fully the problem. Instrumental variables correct the intercept endogeneity, but not the slope endogeneity. This weakness has not been observed by marketing researchers (Luan & Sudhir, 2010). Luan and Sudhir (2010) define slope endogeneity as "private information possessed by managers about the heterogeneous effects of marketing-mix variables on sales".

Reiss (2011) explains an experimental approach in marketing responses studies to overcome problems with endogeneity bias. There is a bias when omitted variables (unobserved factors) are correlated with the error and one or more independent variables in a regression (Rossi, 2014). The idea is to run experiments manipulating one variable (price, for example) independently of the others (e.g.; promotions), controlling this issue. This approach includes lab experiments, randomized field experiments, natural experiments, and instrumental variables (IV) methods.

Marketing researches prefer the more realistic field experiments that have external validity but is more difficult to control for confounds (Reiss, 2011). Natural experiments are still rare in marketing but are commonly applied in economics (Chen, Wang, & Xie, 2011). These types of experiments investigate the effects of variables not in control of the researches, such as government intervention or policy changes, for example (Chen et al., 2011; Reiss, 2011). Instrumental variables are observables variables that are correlated with X variable but are not a part of the structural equation, not affecting Y (Rossi, 2014). Instrumental Variables and experiments do not solve this problem without support from theory (Reiss, 2011). The researcher should not use invalid or week IVs. If there is concern about an unobserved variable, it should be measured (Rossi, 2014).

Another way to correct endogeneity is "to address the codetermination is to impose restrictions from an assumed model of supply […] into the demand estimation step" (Chintagunta & Nair, 2011). Even if this is one way to address the issue, the authors consider that models in marketing literature are better at explaining demand than supply data and propose this as an area for future research. They also alert that supply-side models are harder to estimate with the current data and computing power (Chintagunta & Nair, 2011).

In marketing literature, there is also an emphasis on disaggregate analysis. This is due to the fact that the area has access to consumer panels linked with data on marketing instruments (Chintagunta & Nair, 2011). This means that the models in marketing deal with censored or truncated data (many zeros in the data). Also, it means that models on marketing are linked to economic theory, structural work, with emphasis on heterogeneity across consumers and considers that products are also differentiated (Chintagunta & Nair, 2011).

Mela (2011) divide the types of data by firm property data, free public data, and commercially available market research. Commercially available data, such as scanner data, is often expensive, however, is much quicker to obtain and easier to use (Mela, 2011). Firm property data is of great importance not only because it is rich but also because it is rare to have access. Also having access to people directly involved in the decision making on the firms can bring insights into the "rules of the game" (Mela, 2011). Those are important to specify the model. Public data, such as word of mouth on social media or census data, and commercially available data share the disadvantage of being less customized to the research problem.

Some of the variables applied to the basic model (1) that can be found in the marketing literature are: price, discounts, sales, market share, demographics (income, household size), attributes of products and services, competition, periods (of stockouts, of release of products, or of product-harm crisis), promotion (advertising expenditures, earned media, celebrity endorsements), geographical distance (based on zip-codes), number of alternatives, number of points-of-sales, word-of-mouth data (volume, variance and valence of posts from experts, peers, and critics), among others.

As mentioned before, methods applied in marketing response studies are related to the characteristics of the variables and data sets that became available to marketing scientists. As developments are still occurring in big data, allowing access to structured and unstructured data, many recent studies apply it to study marketing response.

The bigger influx of information, though, is for those businesses that are already online. The connection between online and offline behavior is still a challenge (Liu et al., 2016), but there are some studies that attempt to find this relation. Chevalier and Mayzlin (2006) and Zhao et al. (2013) developed models to predict book sales with data from online book reviews. Dewan and Ramaprasad (2014), and Dhar and Chang (2009) studied the effect of blog posts and social network on sales of these music's singles and albums. Xiong and Bharadwaj (2014) used prerelease buzz to forecast video games sales. Godes and Mayzlin (2004) and Liu et al. (2016) investigate the effect of user-generated content on TV ratings. Lastly, another relation investigated by authors is between word of mouth and sales in the movie industry (Chintagunta, Gopinath, & Venkataraman, 2010; Dellarocas, Zhang, & Awad, 2007; Gopinath, Chintagunta, & Venkataraman, 2013; Karniouchina, 2011; Liu, 2006; Moon, Bergey, & Iacobucci, 2010; Onishi & Manchanda, 2012).

In the next section, we propose a methodological framework based on the literature reviewed and develop a set of propositions of future research to contribute to the forecasting research.

## 6 FUTURE OF FORECASTING IN MARKETING

Some studies on marketing response have also contributed to improvements in methods. They have proposed different approaches (often Bayesian) or modified model versions to accommodate the data available or to solve problems of endogeneity in structural models (e.g. Luan & Sudhir, 2010; Narayanan & Nair, 2013; Petrin & Train, 2010). Such studies also aspire for substantive contribution applying marketing theory to econometric models, such as brand awareness, choice complexity, satisfaction, word of mouth, conjoint purchase, or promotion expenditures. Still, there is a need for studies with a focus on forecasting that combines the advantage of descriptive models to be easy to apply with the capacity of structural models to give evidence of variables that impact on marketing response. Also, models and methods that ensure consumer privacy are, and will continue to be, on focus for companies and need to be addressed by researchers.

Most of the papers published study marketing response using structural models. These models have many benefits, but they also bring some challenges. The key challenge is to develop structural models that provide realistic descriptions of the environments in which firms market their products and services (Reiss, 2011). Models like the basic marketing response (1) are not usually adopted by firms. As Fildes et al. (2008) sustain, the evidence of improved accuracy of such a model is lacking. This is because there is a need for simpler operational models that include marketing variables and that are downwardly compatible in the product hierarchy (e.g., from category to brand to SKU). In short, forecast accuracy and the level of complexity valuable in modeling the problem are under-researched (Fildes et al., 2018).

In Figure 4 we purpose a methodological framework based on our experience and the literature reviewed to help future researches and practitioners to select the methods to apply.

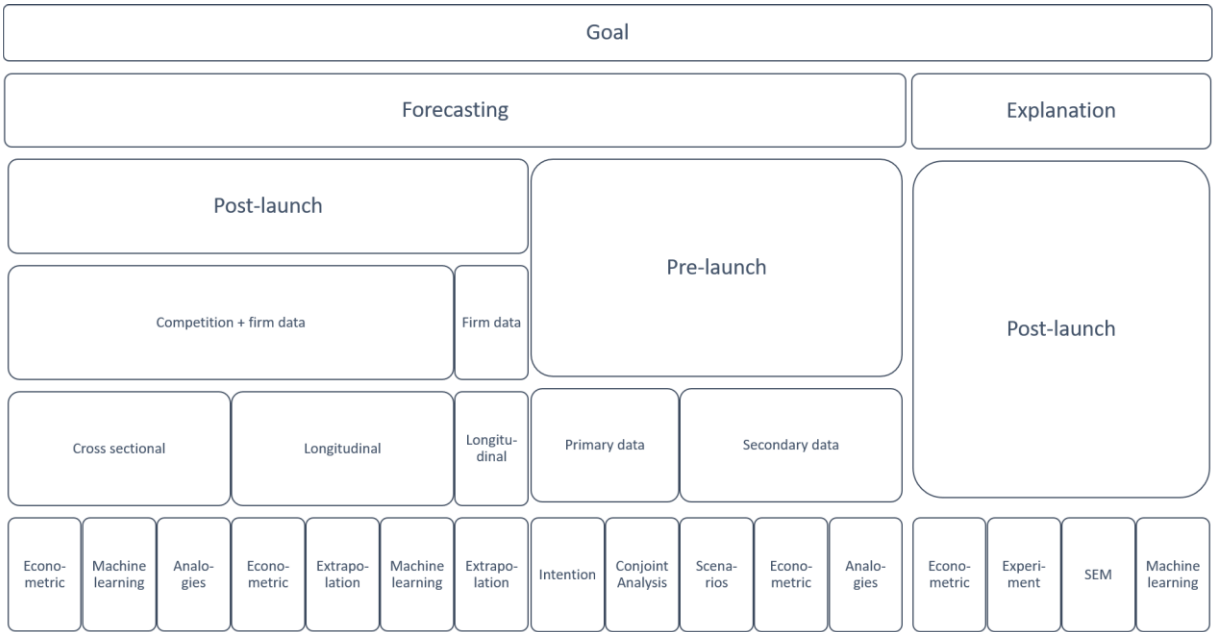

*Figure 4.* Proposed criteria to select market response methods

Econometric models that appear in Figure 4 are the ones reviewed, mostly structural, using Bayesian or Classical inference. SEM stands for "structural equations modelling". Combinations, such as ensembles or rule-based forecasting are not on the criteria since they imply the choice of more than just one method. Also, judgmental methods were not on the scope of the paper and were not included.

One of the opportunities for future researches on marketing response forecasting is the use of different computer-intensive methods, such as support vector machines and neural networks (Fildes et al., 2008). However, in general, marketing academia is not providing professionals with the necessary analytical skills (Kerwin, & Zmuda, 2013; Leeflang, Verhoef, Dahlström, & Freundt, 2014). Companies need to be able to predict and be ever more accurate and, because of the hype around machine learning accurate results, marketing practitioners are being pressured not only to understand what machine learning is, they also need to know how to work with it.

The combination of data from new sources is another opportunity. Especially real-time data that is already used in "areas as diverse as stock-price trading, electricity load forecasting […] and could be applied more widely" (Fildes et al., 2008). These new sources of data need to be combined because databases do not have all the information about a customer's behavior, even the best ones (Chen & Steckel, 2012). It remains an opportunity to combine data such as purchase, sensor, market, temporal (weather, traffic, etc.) and unstructured from social/mobile/digital/e-commerce (Chase Jr, 2013). This is important for products that are not frequently purchased (durables), for example, that do not have rich data sets like those from package consumer goods (Chen & Steckel, 2012).

However, ensuring anonymity is vital since companies are now facing new privacy regulations and discussions about leaks and unfair use of data are frequent on media. For example, it has been proved that metadata is able to uniquely identify individuals, and that "knowing four random spatiotemporal points […] is enough to uniquely reidentify 90% of the individuals and to uncover all of their records" (De Montjoye, Hidalgo, Verleysen, & Blondel, 2013). This points to the importance to adapt marketing response models to work with aggregate data, maintaining the same predictive power (Wedel & Kannan, 2016).

Not only data but also methods tend to be combined to improve accuracy (i.e. ensemble models). The more the data and the methods differ, the greater the expected improvement in accuracy of the ensemble, if compared with the result of a single method forecast (Armstrong, 2001; Fildes et al., 2008). Such diversity can be achieved by combining the predictions obtained by methods applied in different samples (bagging is the most known example). Another possibility to increase diversity is to use different sets of variables (random forest or LASSO techniques can help select the set of variables), to use hybrid (stacking) or non-hybrid (bagging or boosting) methods, also ensemble with different combination rules, known as the weight functions (De Bock, Coussement, & Van den Poel, 2010).

Methods to be combined can be qualitative (judgmental), adding adjustments to the results of quantitative models, or by combining different expert and salesforce predictions. They can also be quantitative, with different machine learning or time series models, for example, combined. Ensemble methods are used in forecasting competitions, such as M4 competitions and Kaggle, with very good results.

Nevertheless, one important question that still needs to be answered is the real necessity of spending resources gathering and analyzing the vast amount of data that is now collected from consumers. With new sources and a bigger volume of data, researchers and companies face now an unfamiliar problem of selecting the variables to use and at what level of aggregation (Dekimpe & Hanssens, 2000). For theoretical purposes, it may be interesting to explore and explain the impact of any available variable on sales. However, for companies' managers that need to make better and faster decisions, it is more vital to know which variables will improve the predictive power of models and focus on them.

Concerning which variables are important to analyze, location is returning to the focus of researchers. This type of data is abundant nowadays because of mobile devices and applications (apps) that keep location metadata stored. They have been used, for example, to predict population movements (Lu, Wetter, Bharti, Tatem, & Bengtsson, 2013). Also, data from satellite on the location of night lights have been used as an alternative to measure economic growth (Henderson, Storeygard, & Weil, 2012).

In marketing literature location data (although not metadata or satellite data, but zip codes and distances to stores/services) was used in marketing response models about hotels (Zhang & Kalra, 2014), gas stations (Chan, Padmanabhan, & Seetharaman, 2007), fuel adoption (Shriver, 2015), drug prescriptions (Stremersch, Landsman, & Venkataraman, 2013), solar panels (Bollinger & Gillingham, 2012), organic products (Sridhar, Bezawada, & Trivedi, 2012), and the car industry (Albuquerque & Bronnenberg, 2012; Bucklin, Siddarth, & Silva-Risso, 2008; Narayanan & Nair, 2013).

There is still potential to explore location information such as studying similarities among customers preferences based on geographic location (Chung & Rao, 2012) or migration patterns influence on their purchases (Bronnenberg, Dubé, & Gentzkow, 2012), for example. Wedel and Kannan (2016) state that location is a data source still to be explored by marketing.

A good example of the use of location in models is Bucklin, Siddarth and Silva-Risso (2008) study. They created a choice model with three measures of car dealers' concentration, accessibility, and spread, based on the geographic locations of buyers and new car dealers. The authors found that these three measures were significantly related to new car choice, helping firms to decide the effects of opening or closing points-of-purchase. The authors state that marketers need to be able to understand how changes in distribution (e.g., the size and structure of a dealer network) can affect the demand. They argue that only product, price, and promotion variables were incorporated as attributes in utility before their paper. However, the empirical relationship between market share (or sales) for a product and its level of distribution intensity is still an open question for the future research on consumer durables (Bucklin et al., 2008).

Even if new methods are not applied, there is still a chance for improvement in structural models that are the most commonly applied in marketing literature. Chintagunta and Nair (2011) suggest three new directions: dynamics, use of data on unobservable (primary data), and nonparametric approaches. Dynamics means models that consider purchase on present impacts purchase in the future, such as storability and durability. To model non-frequently purchased products such as durables is a challenge, not only because of its dynamics but also because scanner data are not so common for these products (Zhao et al., 2011). The decisions concerning these types of products are also more sophisticated (involving more people and more time to decide), although empirical research on the subject is not frequent in marketing (Ni, Neslin, & Sun, 2012). Therefore, a thorough understanding of consumer decisions about durables will not only help to develop and test both economic and consumer behavior theories but also will have important implications for managerial decisions.

Experience goods are also a dynamic problem because "purchase today provides a signal about quality, which updates the future information set" (Chintagunta & Nair, 2011). To close the discussion of dynamics issues, complementarities refer to products that are purchased only after another one is, so the choice of the complementary product is dependent on the choice of the first product (common in technological products due to compatibility issues).

Another direction is related to improve models with primary data that reduce possible confounds, such as experiments. A final direction, also mentioned by Chintagunta and Nair (2011), is the use of nonparametric approaches due to the increased access to larger data sets. Some of these directions are overlapped, since dynamic problems such as intermittent demand (periods of no demand followed by periods of highly variable demand, which introduces lumpiness), can be improved by nonparametric approaches (Fildes et al., 2008). Allenby, Garratt and Rossi (2010) warn that current research is dominated by linear utility specifications and that it is necessary for structural models to use utility specifications that have more realistic assumptions. To sum up, the gaps to be explored in future research are:

- Development of simpler to implement and more realistic models;
- New approaches on correcting for endogeneity;
- The increasing integration of computer science knowledge;
- Incorporation of new sources of data;
- Development of new models with location/geographical variables;
- Combination data sets and methods;
- Improvement of models based on primary data;
- The consideration of the dynamic type of goods: durable, experience goods, and complementarities;
- Use nonparametric approaches and more realistic assumptions on utility specifications.

We showed that marketing literature focuses more on explanation and marketing practice has a higher accuracy / easy to implement orientation. One way of ending this contrasting focus is to use big data/computer-intensive methods. Marketing is the discipline responsible to understand and share customer knowledge with companies and society in general. Computer-intensive methods (combined or not with access to big data) unlocks possibilities not only to deepen such knowledge but also to predict it. Prediction of market response – i.e. sales, market share, demand – has developed in academia and in practice. Most of this development is now happening in other fields.

Marketing response models studied in marketing are mostly cross-sectional, hard to implement and since their focus is on explanation, they are less helpful when practitioners are planning future strategy. Companies rely on simpler models that give them a satisfactory level of accuracy and are easy to implement. Marketing should take the models that are used in practice and add marketing variables to improve it. For that, our field needs to integrate computer science knowledge to its reality. This even more important if the field wants to take advantage of big data. Marketing needs to change graduate and postgraduate curriculum. This will prepare market professional and researchers to the future of the field. It will provide them with the skills necessary to deal with new data sources and the methods most suitable to work with them. As for research, the focus on explanation should be divided or accompanied by a prediction application. In short, combining big data-based methods is still a major trend for future research in marketing forecasting.

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[1] On Figure 3, MDS stands for "multidimensional scaling"; OR, for "operations research"; MNL, for "multinomial logit"; and HB, for "Hierarchical Bayesian".