THE PERFORMANCE IMPLICATIONS OF DEPLOYING MARKETING ANALYTICS

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ABSTRACT

A few well-documented cases describe how the deployment of marketing analytics produces positive organizational outcomes. However, deployment of marketing analytics varies widely across firms and many C-level executives remain skeptical of the benefit they see from their marketing analytics efforts. We draw on upper echelons theory and the resource-based view of the firm to develop a conceptual framework that relates the organizational deployment of marketing analytics to firm performance and that also identifies the key antecedents of that deployment. Analysis of a survey of 212 senior executives of *Fortune* 1000 firms shows that firms realize favorable and, apparently sustainable, performance outcomes from greater use of marketing analytics. The analysis also reveals important moderators: greater industry competition and more rapidly changing customer preferences increase the positive impact of marketing analytics deployment on firm performance. The results are robust to the choice of performance measures, and a one-unit increase in degree of deployment on a 1-7 scale (which would move the average firm in our sample from the 50th to approximately the 65th percentile of deployment) is associated, on average, with an 8% increase in return on assets. The analysis also shows that support from the top management team, a supportive analytics culture, appropriate data, information technology support, and analytics skills are all needed for the effective deployment of marketing analytics.

Keywords: marketing analytics, marketing models, marketing ROI

1. Introduction

A recent Google search for "marketing analytics" returned more than 500,000 hits. Marketing analytics, a "technology-enabled and model-supported approach to harness customer and market data to enhance marketing decision making" (Lilien 2011, p. 5) consists of two types of applications: those that involve their users in a decision support framework and those that do not (i.e., automated marketing analytics). In the past half century, the marketing literature has documented numerous benefits of the use of such marketing analytics, including improved decision consistency (e.g., Natter et al. 2008), explorations of broader decision options (e.g., Sinha and Zoltners 2001), and an ability to assess the relative impact of decision variables (e.g., Silk and Urban 1978). The common theme in this literature is the improvement in the overall decision-making process (e.g., Russo and Schoemaker 1989, p. 137).

Rapid technological and environmental changes have been transforming the structure and content of marketing managers' jobs. These changes include (1) pervasive, networked, high-powered information technology (IT) infrastructures; (2) exploding volumes of data; (3) more sophisticated customers; (4) increasing demand by management for demonstrating positive returns on marketing investments; and (5) a global, hypercompetitive business environment. In this changing environment, opportunities seemingly should abound for deploying marketing analytics to increase profitability. Indeed, an entire stream of research in marketing documents the positive performance implications of deploying marketing analytics (e.g., Hoch and Schkade 1996; Kannan, Pope, and Jain 2009; Lodish et al. 1988; McIntyre 1982; Natter et al. 2008; Silva-Risso, Bucklin, and Morrison 1999; Zoltners and Sinha 2005).

However, there continue to be many skeptics of the "rational analytics approach" to marketing. For example, in a recent interview with one of the authors, the (former) head of product development at one of the world's leading car manufacturers claimed that "…marketing analytics-based results usually raise more questions than they provide answers," and he asserted that "the use of marketing analytics often slows you down." He also claimed that the "…performance implications of marketing analytics are at best marginal." When we inquired about documentation for his views, he referred us to Peters and Waterman's (1982) highly influential book, *In Search of Excellence* in which the authors denounce formal analysis for its abstraction from reality and tendency to bring about "paralysis through analysis" (p. 31), and argued that Peters and Waterman were correct in their observation. More recently (McKinsey & Co. 2009), a study of 587 C-level executives of large international companies revealed that only about 10% of the firms regularly employ marketing analytics. And Kucera and White (2012) note that only 16% of the 160 business leaders who responded to their survey reported using predictive analytics, even though those users "significantly outpace those that don't in two important marketing metrics[1]" (p. 1).

John Little diagnosed the issue more than 40 years ago as follows: "The big problem with … models is that managers practically never use them. There have been a few applications, of course, but the practice is a pallid picture of the promise" (Little 1970, p. B-466). In revisiting the issue, Little (2004, p. 1858) reports, "The good news is that more managers than ever are using models ... what hasn't changed is organizational inertia." Winer (2000, p. 143) concurs: "My contacts in consumer products firms, banks, advertising agencies and other large firms say that [model builders] are a rare find and that models are not used much internally. Personal experience with member firms of MSI indicates the same."

The low prevalence of marketing analytics use implies that many managers remain unconvinced about the benefits that accrue from that use. In addition, most research that

[1] The metrics are "incremental lift from a sales campaign" and "click through rate (for mass campaigns)." Those firms that use customer analytics also report significantly greater ability to measure customer profitability and lifetime value and also are more likely to have staff dedicated to data mining.

documents those benefits has focused on isolated firm or business unit "success stories," without systematically exploring performance implications at the firm level. Given the lack of compelling evidence about the performance implications of marketing analytics, the objective of this research is to study two questions: (1) Does widespread deployment[2] of marketing analytics within a firm lead to improved firm performance? And (2), If the answer to (1) is "yes," what leads to the widespread deployment of marketing analytics within firms? With the usual caveats and cautions particularly about making causal inferences from non-experimental data, we find that the answer to question 1 appears to be "yes," and hence, the answer to question 2 has high managerial relevance as well as academic importance.

To address these questions, we propose a conceptual framework that relies both on the resource-based view (RBV) of the firm (Barney 1991; Wernerfelt 1984) and upper echelons theory (Hambrick and Mason 1984) to model the factors that link marketing analytics deployment to firm performance, as well as the factors that drive the deployment of marketing analytics. We assess that framework with data drawn from a survey of 212 senior executives of *Fortune* 1,000 firms, supplemented by secondary source objective performance data for those firms. We find that deployment of marketing analytics has a greater impact on firm performance when the industry is characterized by strong competition and when customer preferences change frequently in that industry. We also find that top management team (TMT) advocacy and a culture that is supportive of marketing analytics are keys for enabling a firm to benefit from the use of marketing analytics and argue that the benefits realized by marketing analytics deployment should be sustainable.

[2] We use the term "deployment" or "to deploy" to mean "to put into use, utilize or arrange for a deliberate purpose" without reference to the financial, talent or technical investment that might be needed to enable that deployment.

We proceed as follows: We first present our conceptual framework and hypotheses, and then describe our data and our methodology. We then present our findings and discuss their theoretical and managerial implications, as well as the limitations of our research.

2. Conceptual Framework

The conceptual framework in Figure 1 depicts what we refer to as the marketing analytics chain of effects. It articulates our predicted relationships, including the hypothesized relationship between the deployment of marketing analytics and firm performance.

We propose that marketing analytics deployment, which we define as the extent to which insights gained from marketing analytics guide and support marketing decision making within the firm, has a positive impact on firm performance. However, this positive impact on firm performance is likely moderated by three industry-specific factors: (1) the degree of competition faced by the firm, (2) rate of change in customer preferences, and (3) prevalence of marketing analytics use within the industry. Further, we identify TMT advocacy of marketing analytics as a vital antecedent to the deployment of marketing analytics. We propose that a firm's TMT must not only commit adequate resources, in the form of employees' analytic skills, data, and IT, but also nurture a culture that supports the use of marketing analytics. Such a culture can ensure that the insights gained from marketing analytics get deployed effectively.

[Insert Figure 1 about here]

In the following, we first elaborate on the link between deployment of marketing analytics and firm performance. Next we consider the antecedents of the deployment of marketing analytics, i.e., the resources and organizational elements that we posit must be in place for marketing analytics to be deployed effectively.

2.1. The Performance Implications of Deploying Marketing Analytics

There is some literature (for the most part non-academic) that suggests that the use of marketing analytics can slow firms down, leading to missed opportunities that are seized by more agile and non-analytics oriented competition. For example, citing General Colin Powell's leadership primer, Harari (1996, p.37) proposes that, "excessive delays in the name of information-gathering breeds analysis paralysis", which leads to missed opportunities and hence subpar performance of firms. Peters and Waterman (1982) predict an analogous effect. Also, based on our discussions with executives, we find that many top managers share similar notions about the performance outcomes of using marketing analytics.

However, there are numerous firm-specific case studies that describe the positive performance impact of using marketing analytics. For example, Elsner, Krafft, and Huchzermeier (2004) show how Rhenania, a medium-sized German mail order company, used a dynamic, multilevel response modeling system to answer its most important direct marketing questions: When, how often, and to whom should the company mail its catalogs? The model helped the company increase its customer base by more than 55% and quadrupled its profitability in the first few years after its implementation, and the firm's president asserted that the firm was saved by deploying this system of marketing analytics.

Marketing analytics can also significantly improve a firm's ability to identify and assess alternative courses of action. For example, in the 1980's, Marriott Corporation was running out of good downtown locations for its new full-service hotels. To maintain growth, Marriott's management planned to locate hotels outside downtown areas to appeal to both business and leisure travelers. A marketing analytics approach called conjoint analysis helped the company design and launch its highly successful Courtyard by Marriott chain, establish a multibillion dollar business, and create a new product category (Wind et al. 1989).

In another example, Kannan, Pope, and Jain (2009) report how marketing analytics led to a better understanding of customers and to a better way of reaching them at the National Academies Press, which was concerned about the best way to price and distribute its books in print and in pdf format via the Internet. The firm built a pricing model that allowed for both substitution and complementarity effects among the two formats, and calibrated the model using a choice modeling experiment. The results permitted the company to launch its entire range of digital products with a variable pricing scheme, thereby maximizing the reach of its authors' work.

The common theme in the above firm-specific examples is that the deployment of marketing analytics helps firms develop and offer products and services that are better aligned with customer desires, which, in turn, leads to improved firm performance. Thus, we propose the following main effect:

> *H_1: The greater the deployment of marketing analytics, the better the firm's performance.*

2.1.1. Competitive Industry Structure. Most firms compete with numerous rivals (Debruyne and Reibstein 2005), though the degree of rivalry varies considerably across industries (DeSarbo, Grewal, and Wind 2006). The level of competition that a firm faces also has many concomitant effects, including the requisite degree of customer satisfaction that the firm must attain to operate successfully. For example, Anderson and Sullivan (1993) find that firms with less satisfied customers that face less competition perform about the same or even better than firms with more satisfied customers that operate in more competitive environments. Thus firms that confront more competition must strive for higher levels of customer satisfaction to perform well.

Assuming that marketing analytics provide better insights about customer needs, firms in industries with greater competition should earn greater returns (because of more clearly targeted offerings resulting in (e.g.) greater customer satisfaction) than firms in less competitive industries. Thus, we propose:

> *H_2: The greater the level of competition among industry participants, the greater is the positive impact of the deployment of marketing analytics on firm performance.*

We note that if “analysis-paralysis” is a serious concern associated with the deployment of marketing analytics, then the corresponding negative performance implications should be even greater in competitive environments because competitors move more swiftly in such environments (e.g., DeSarbo, Grewal, and Wind 2006). Under these circumstances, we should see a negative interaction between marketing analytics deployment and firm performance (as opposed to our predicted positive interaction).

2.1.2. Customer Preference Changes. Customer preferences for product features, price points, distribution channels, media outlets, and other elements of the marketing mix change over time (e.g., Kotler and Keller 2006, p. 34). The rate of such change varies; fashions change seasonally, preferences for consumer electronics seem to change almost monthly (e.g., Lamb, Hair, and McDaniel 2009, p. 58), but preferences for construction equipment, hand tools, and agricultural products appear much more stable over time.

The more customers’ needs fluctuate, the greater is the uncertainty that firms face in making decisions, and the more critical it becomes to scan and interpret the changing environment (Daft and Weick 1984). Marketing analytics offer various means to help firms monitor the pulse of the market and provide early warning of preference changes. Also, a stable, predictable environment reduces the need for marketing analytics because such an environment requires a limited number of decision variables to manage for organizational success (Smart and Vertinsky 1984). Therefore, we propose:

> *H_3: The more rapidly customer preferences change in an industry, the greater is the positive impact of the deployment of marketing analytics on firm performance.*

2.1.3. Prevalence of Marketing Analytics Use. The prevalence of the use of marketing analytics within an industry may attenuate their positive performance implications. Porter (1996, p. 63) notes that as firms evolve, "staying ahead of rivals gets harder," partially due to the diffusion of best practices, facilitated for example, by inputs from strategy consultants. Competitors are quick to imitate successful management techniques, especially if they promise superior ways to understand and meet customers' needs. Such imitation eventually raises the bar for everyone (e.g., Chen, Su, and Tsai 2007; D'Aveni 1994; MacMillan, McCaffery, and Van Wijk 1985). Thus, the higher the overall use of marketing analytics, the lower the upside potential for a firm to increase its use. Hence, we propose:

> *H_4: The more prevalent the use of marketing analytics in an industry, the lower the positive impact of the deployment of marketing analytics on the performance of individual firms in that industry.*

To summarize (research question #1), we predict that the deployment of marketing analytics has positive performance implications in general[3] and that this effect is even stronger in industries characterized by strong competition and in which customer preferences change frequently and weaker in industries in which the deployment of marketing analytics is commonplace.

We next discuss the factors that lead to the deployment of marketing analytics.

2.2. Antecedents of the Deployment of Marketing Analytics

[3] A concave (downward sloping) response function would admit diminishing returns to deployment and would model a "paralysis of analysis effect". We report a test for such a possible effect in section 4.3.4 and do not find one.

Adapting a resource-based view (RBV) (Barney 1991; Wernerfelt 1984), Amit and Schoemaker (1993) propose that firms create competitive advantage by assembling their resources in a way so that they work together to create organizational capabilities. These capabilities refer to an organization's ability to assemble, integrate, and deploy resources in a way so that they become valuable business routines (e.g. Russo and Fouts 1997). Further, these capabilities can provide a sustainable competitive advantage when they are protected by isolating mechanisms that thwart competitive imitation (Rumelt 1984).

Building on the RBV literature, we argue that marketing analytics must be appropriately assembled and embedded within the fabric of the firm to be deployed effectively, potentially resulting in a sustainable competitive advantage. Further, we single out TMT advocacy of marketing analytics as a key driver of the process.

2.2.1. TMT Advocacy, Analytics Culture, and Sustainable Competitive Advantage. According to upper echelons theory (Hambrick and Mason 1984), organizations are a reflection of their TMT; thus for marketing analytics to become an integral part of a firm's business routines, and ultimately its culture, it must be strongly supported by the firm's TMT (Hambrick 2005).

We posit that a culture that is supportive of marketing analytics is critical for its effective deployment, because that culture carries the logic of how and why "things happen" (Deshpande and Webster 1989, p. 4). These norms are especially important since the person (or organizational unit) that carries out the marketing analytics (e.g., marketing analysts or researchers) frequently is not responsible for implementing the insights gained (e.g., executives in the marketing and other functions ; Wierenga and van Bruggen 1997; Carlsson and Turban 2002; van Bruggen and Wierenga 2010; Hoekstra and Verhoef 2011). An analytics culture provides decision makers with a pattern of shared values and beliefs (Ouchi 1981; Deshpande, Farley, and Webster 1993), which in turn, should positively influence the degree to which they incorporate the insights from marketing analytics in their decisions. Further, culture is sticky, difficult to create and even more difficult to change (e.g., Schein 2004), suggesting that it may protect against competitive imitation of a firm's analytics investments, delivering sustainable rewards from a firm's marketing analytics investments.

2.2.2. Analytics Skills. To deploy marketing analytics within a firm, the firm must also have access to people (either internally or among its partners) who know how to execute marketing analytics. Thus, the TMT must ensure that people with the requisite marketing analytics skills are present and available. Broadly, we distinguish between technical skills in marketing analytics and other individual-level, analytics-based knowledge structures that are more tacit (Grant 1991). The technical marketing analytics skills likely derive primarily from classroom learning and refer to the range of marketing models and related concepts that the analyst could deploy. In contrast, tacit marketing analytics knowledge includes skills acquired mostly through real-world learning.

We anticipate that higher levels of marketing analytics skills will increase the extent of marketing analytics deployment because people use the tools and skills they understand and are comfortable with (Lounsbury 2001; Westphal, Gulati, and Shortell 1997). Also, better skills should lead to more useful results from using those skills, facilitating the organization wide marketing analytics adoption process. Therefore, the analytics skills of a firm's employees should have both a direct, positive impact on the organizational deployment of analytics and an indirect effect on organizational deployment through the positive impact on analytics culture.

2.2.3. Data & IT Resources. The physical IT infrastructure and data resources of a firm are two other critical, tangible assets that the TMT must put in place to allow marketing analytics to be deployed effectively. Physical IT resources form the core of a firm's overall IT infrastructure and include computer and communication technologies and shared technical platforms and databases (Ross, Beath, and Goodhue 1996). Data result from measurements and provide the basis for deriving information and knowledge from marketing analytics (Lilien and Rangaswamy 2008). Marketing analytics are often based on vast amounts of customer data (Roberts, Morrison and Nelson 2004), which require sophisticated IT resources to effectively obtain, store, manipulate, analyze, and present the vast data. Hence, IT and data are closely related, tangible resources, such that one would be significantly less valuable without the other. Building on this mutual dependence, we posit that both IT and data resources are important prerequisites for conducting marketing analytics.

In summary (research question #2), we identify TMT advocacy of marketing analytics as an important precursor to the effective deployment of marketing analytics and propose that a firm's TMT must not only ensure that employees with the requisite analytics skills and an adequate data and IT infrastructure are in place, but also nurture a culture that supports the use of marketing analytics. Such a culture can ensure that the insights gained from marketing analytics get deployed effectively.

3. Data and Methods

3.1. Scale Development

We adapted existing scales when they were available. However, our study is amongst the first to explore the performance implications of marketing analytics empirically, and scales for several of our constructs were not available. We developed the missing scales, following a 4-phase iterative procedure as recommended in the literature (Churchill 1979): First, we independently generated a large pool of items for each of the constructs from an extensive literature review. Second, we engaged fifteen senior-level, highly regarded marketing academics to expand our list of items and evaluate the clarity and appropriateness of each item. Third, we personally administered pretests to six top managers to assess any ambiguity or difficulty they experienced in responding. Fourth, we did a formal pre-test with 31 senior managers. Because the fourth stage/pre-test revealed no additional concerns, we finalized the scale items that we list in the Appendix[4].

3.2. Data Collection Procedure

We conducted a mail survey among executives of *Fortune* 1000 firms. We first randomly selected 500 entries from the *Fortune* 1000 list and then leveraged our connections at two major U.S. universities to obtain the names of 968 senior executives (mainly alumni) working in these firms.

We addressed these respondents with personalized letters, in which we asked them to complete the survey in reference to either their strategic business unit (SBU) or their company, whichever they felt was more appropriate. We also provided a nominal incentive (US$1 bill, called a token of thanks, which emerged as the most effective incentive in a pretest). Of the 968 executives contacted, 36 returned the surveys and indicated they were not qualified to respond, and 20 surveys were returned because of incorrect addresses. We obtained 212 completed surveys (of 912 remaining), yielding an effective response rate of 23.25%. We controlled for possible nonresponse bias by comparing the construct means for early and late respondents (Armstrong and Overton 1977) but found no significant differences. As we show in Table 1,

[4] We note that we employed single-item measures for some of our constructs. Several researchers have shown that in certain contexts, measures that comprise one item generate excellent psychometric properties (e.g., Bergkvist and Rossiter 2007; Schimmack and Oishi 2005; Robins, Hendin, and Trzesniewski 2001; Drolet and Morrison 2001). In particular, single item measures have been found to be very useful when the construct is unambiguous (Wanous, Reichers, and Hudy 1997). Further, single-item measures are also useful when participants are busy (which certainly applies to top executives) and perhaps dismissive of and/or aggravated by multiple-item measures that, in their view, measure exactly the same construct (Wanous, Reichers, & Hudy, 1997). Such respondent behavior has been found to inflate across-item error term correlation (Drolet and Morrison 2001). Our pretests revealed that three of our constructs (i.e., competition, needs and wants change, and marketing analytics prevalence) are unambiguous in nature, leading us to employ single-item measures for them.

most (71%) of the respondents in our sample had titles of director or higher levels, which suggests they should be knowledgeable about their firms' capabilities and actions.

[Insert Table 1 about here]

We also asked the respondents to report their confidence levels about the information they provided (Kumar, Stern, and Anderson 1993). The sample mean score was 5.59 (out of 7 [SD = .81]), indicating a high level of confidence. Moreover, we received multiple (either two or three) responses from 35 firms/SBUs in our sample.[5] [6]

3.3. Scale Assessment

We assessed the measure reliability and validity of our constructs using confirmatory factor analysis (Bagozzi, Yi, and Phillips 1991; Gerbing and Anderson 1988). We included all independent and dependent latent variables in one confirmatory factor analysis model, which provided satisfactory fit to the data (comparative fit index [CFI] = .97; root mean square error of approximation [RMSEA] = .05; 90% confidence interval [CI] of RMSEA = [.033; .068]). On the basis of the estimates from this model, we examined the composite reliability and discriminant validity of our constructs (Fornell and Larcker 1981). All composite reliabilities exceed the recommended threshold value of .6 (Bagozzi and Yi 1988); the lowest reliability is .75. The coefficient alphas of our constructs are all greater than .7. We also assessed discriminant validity using the criteria proposed by Fornell and Larcker (1981). The results show that the squared correlation between any two constructs is always lower than the average variance extracted (AVE) for the respective constructs, providing support for discriminant validity. Finally, the

[5] We received two responses for 33 firms/SBUs and three responses for 2 firms/SBUs. Because we had contacted 968 executives who worked for 500 randomly selected *Fortune* 1000 firms, we evidently contacted multiple executives working for the same firms/SBUs, which accounts for most of these multiple responses. In a few instances (n = 5), executives also invited their coworkers to participate in the survey.

[6] While this multiple-response sample is too small for a formal multitrait, multimethod assessment, it enabled us to assess if the respective respondent groups' means for the key constructs were statistically different (e.g., Srinivasan, Lilien and Rangaswamy 2002). T-tests indicated that none of the means were statistically significantly different.

correlations between the respective constructs are all significantly different from unity (Gerbing and Anderson 1988). Overall, the results indicate that our latent constructs demonstrate satisfactory levels of composite reliability and discriminant validity. We present the correlations among the constructs in Table 2 and the AVE and coefficient alphas in the Appendix along with the scale items.

[Insert Table 2 about here]

3.4. Descriptive Statistics

Table 3 contains descriptive statistics for our sample firms and indicates that the sample represents a broad range of firms. Table 4 lists the names of some sample firms. In Table 5 we provide the summary statistics and correlations of our variables, and in Table 6 we present histograms for our focal variables. As the histograms show, the sampled firms display a wide range of values for our focal variables. For example, on the seven-point scale measuring TMT advocacy of marketing analytics, approximately 18% of the sample firms fall into the 6–7 range and 16% in the 1–3 range (M = 4.5; SD = 1.7). Furthermore, with regard to analytics culture, approximately 25% of the sample firms fall into the 6-7 range, and just over 14% score in the 1–3 range (M = 4.6; SD = 1.6). We also asked the respondents (1) if their marketing analytics applications are primarily designed in-house or by outside experts and (2) if the primary day-to-day operations of marketing analytics are managed in-house or outsourced. Table 7 presents the responses to these questions and shows that the majority of firms design and manage their marketing analytics (applications) in-house. We also note the low percentage of respondents who did not know the answer to these questions, another sign that our respondents are quite knowledgeable about the domain under study.

[Insert Tables 3–7 about here]

3.5. Conceptual Model Testing Procedures

Our conceptual model proposes both direct and moderating effects (Figure 1). To model and test these effects simultaneously, we use structural equation modeling (SEM); recent methodological advances have made it feasible to include multiple interactions in a path model (Klein and Moosbrugger 2000; Muthén and Asparoughov 2003; Marsh, Wen and Hau 2004). We used Mplus Version 6.11 and estimated our model using the full-information maximum likelihood approach (Muthén and Muthén 2010, p. 71; Klein and Moosbrugger 2000).

4. Results

4.1. SEM Model Fit

Figure 2 summarizes the results of our SEM, showing two of the three interactions (i.e., competition and needs & wants change) as statistically significant. Since means, variances, and covariances are not sufficient statistics for our SEM estimation approach, our model does not provide the commonly used fit statistics (e.g., RMSEA, CFI). Instead, following Muthén (2010), we assessed fit in two steps. First we re-estimated our SEM without the interaction terms and compared that model with our original model via a chi-square difference test using the associated loglikelihoods (Muthén and Muthén 2011; Satorra and Bentler 1999). This test yielded a χ^2 difference of 28.124, which is highly significant (p <.0001; difference in df between models = 3) and clearly favors the model with interactions. Second, we (re) estimated the model without interactions with the conventional SEM estimation approach to derive the usual model fit statistics (e.g., RMSEA, CFI). This conventional model (without interactions) fits the data quite well (χ^2 = 243; CFI = .97; RMSEA = .04; 90% C.I. = [.03; .06]), and the paths are very similar to those of the moderated model. Based on these results, we conclude that the un-moderated model fits the data well and that the moderated model enhances the model fit.

[Insert Figure 2 about here]

4.2. Specific Model Paths and Hypothesis Test Results

All the paths from TMT advocacy to the respective subsequent latent constructs are positive and significant, suggesting that the TMT plays a key role in establishing an organizational setting in which marketing analytics can be deployed effectively. Also, as predicted, an analytics-oriented culture has a positive and significant effect on the deployment of analytics ($\beta = .317$, $p < .01$), in line with our proposition that strengthening a firm's analytics-oriented culture leads to an actual increase in the deployment of marketing analytics. In addition, we find that an increase in a firm's marketing analytics skills has both a direct and positive impact on the deployment of analytics ($\beta = .427$, $p < .001$) and a positive, indirect effect through analytics culture ($\beta = .120$, $p < .05$). That is, employees' marketing analytics skills directly influence the degree to which the firm uses analytics-based findings in marketing decision making; they also exert an indirect influence by enhancing the organization's analytics-oriented culture. We also find that the presence of a strong data and IT infrastructure promotes marketing analytics skills within the firm ($\beta = .621$, $p < .001$).[7]

As hypothesized in H_1, an increase in the deployment of marketing analytics leads to an increase in firm performance ($\beta = .106$, $p < .01$). Moreover, as hypothesized in H_2, we find a positive and significant deployment of analytics × competition interaction ($\beta =.081$, $p < .05$), which shows that the use of analytics is more effective in more competitive than in less competitive environments.[8] Similarly, in support of H_3, the use of analytics is more effective in environments in which customers' needs and wants change frequently ($\beta = .060$, $p < .01$). However, we do not find support for H_4, concerning the analytics × prevalence interaction ($\beta = –.034$, ns).

[7] Since data and IT go hand in hand, this may imply an interaction effect between the two in our model. As a robustness check, we added a fourth item to the "Data and IT" construct that captured the interaction between the data and IT items and then reran our model. The results did not change in any substantive way.

[8] The competition variable was skewed to the left. As a robustness check, we reran our analysis, substituting the competition variable with a dummy variable (1 = high competition [survey score of 6 or 7]; 0 = low competition [survey score between 1 and 5]). The outcomes did not change in any substantive way.

4.3. Robustness Checks

4.3.1. Validity of the Performance Measure/Monomethod Bias. Because our independent and dependent measures come from the same respondents, leading to the possibility of monomethod bias (Podsakoff et al. 2003), we collected performance data from independent sources to validate our performance measure. We obtained information on firm- and (less frequently) SBU-specific revenues, net income, earnings before interest, tax, depreciation, and amortization (EBITDA), total assets, and liabilities for as many firms as possible by retrieving their 10K and other filings with the U.S. Securities and Exchange Commission from the EDGAR database. We also consulted COMPUSTAT, Mergent Online and the firms' websites. With these financial data, we computed the respective unit's (i.e., firm or SBU) return on assets (ROA). These procedures yielded financial performance data for 68 of the 212 responses. After matching the time horizon of the performance measures, we computed a two-year average ROA for the two years preceding our primary data collection (e.g., Boulding, Lee, and Staelin 1994). We also standardized the ROA measure, according to each firm's respective competitors (from Mergent Online).

To address same-source bias, we used the objective performance data (i.e., ROA) from independent sources to reanalyze our conceptual framework. Given the small sample size (n = 68), however, testing all effects of our framework simultaneously in a single SEM as we did in our main analysis was not feasible due to a lack of statistical power. Instead, we broke the analysis into two parts: first we used a SEM to estimate the direct (un-moderated) effects in our conceptual framework. Second, we used an ordinary least squares (OLS) regression model to (re)examine the link between deployment of analytics and firm performance and to (re)test H_1–H_4. We substituted the ROA objective performance measure for the perceptual performance measure in both analyses.

The SEM results remain consistent using objective or subjective data; in fact the link from deployment to performance is even stronger with objective than with subjective data. We report the SEM results with objective data in Figure 3.

[Insert Figure 3 about here]

We report the regression results with objective data in Table 8 (model 1). We used a simple average of the items measuring deployment of analytics as our deployment construct in that analysis. We repeated the analyses using the factor scores from our SEM for our deployment construct. These two measures were highly correlated (correlation > .94), and none of our inferences were affected by the choice of deployment construct. Overall, the regression model is significant, and our inferences do not change.

[Insert Table 8 about here]

In summary, the signs of the SEM and regression model coefficients using objective data are consistent with those obtained using the survey-based data. However, the deployment of analytics × competition interaction does not reach significance in the regression model (t = 1.60), a result that could be a result of the small sample size for the objective data (n = 68).

4.3.2. Multiple Respondents for Some Firms. As noted, we have multiple respondents for 35 organizational units. To address potential issues of non-independence among the observations in our data, we averaged the responses of multiple respondents[9] of each firm (e.g., Homburg, Grozdanovic, and Klarmann 2007) and then re-estimated the SEM using individual responses as if we have only single responses (i.e., the average responses for those organizational units for which we have multiple responses). The results remain virtually the same, and our inferences do not change.

[9] The t-tests of the key variables across these respondents' reports indicated that the respective means were not statistically different.

4.3.3. Multigroup Analysis — B2B vs. B2C. There are many differences between business-to-business (B2B) and business-to-consumer (B2C) firms (see Grewal and Lilien 2012) that might lead one to expect that there would be differences in the role and impact of marketing analytics within B2B and B2C firms. To assess this possibility, we performed a multigroup confirmatory factor analysis to compare the factor loadings of B2B with B2C firms. To test for partial measurement invariance across groups, we compared a model in which all parameters could be unequal across the two groups with one in which we constrained the factor loadings to be equal. The model with all parameters freely estimated fit the data well ($\chi^2(252) = 321.541$; CFI = .97; RMSEA = .05), as did the partial invariance model with factor loadings constrained to be equal ($\chi^2(270) = 336.227$; CFI = .97; RMSEA = .05). Furthermore, the χ^2 difference test indicated that the two models were not statistically significantly different (χ^2 diff. (18) = 14.7, p = .68) thereby supporting the generality of our findings across different types of firms.

4.3.4. Robustness of the Deployment to Performance Link. Our study reveals a statistically significant positive relationship between deployment of marketing analytics and firm performance (both subjective and objective). This result is also managerially very significant, and therefore, we subjected this relationship to additional scrutiny via, (1) testing for the linearity of this relationship, (2) assessing effects of various controls, (3) subjecting it to a reverse-causality test, (4) assessing the contemporary versus carryover effects of deployment on performance, (5) testing for the effects of unobserved heterogeneity, and (6) assessing the unidimensionality of our performance construct. We elaborate on these below.

First, using an OLS regression model similar to the one reported in Table 8 but using the full survey data (n = 212), we included a quadratic term in the equation to check whether the deployment of analytics effect is curvilinear. The squared term was not statistically significant, suggesting no curvilinear effect, at least within the range of our data.

Second we included organization size (number of employees) and industry dummy variables as controls in this regression model. Firm size could account for the fact that larger firms could benefit from economies of scale and scope, making their use of analytics more effective. Industry dummies could account for differences in industry segments. We used standard industrial classifications to group the sample firms into five categories (see Table 3): services, manufacturing, finance/insurance, trade, and construction/mining. The size and industry dummy variables had neither a main nor a moderating effect on the relationship between analytics deployment and firm performance and our inferences did not change. Thus our results appear robust to firm size and industry segment.

Third, it might be that firms that perform well have more slack and hence more resources to deploy marketing analytics than those that perform poorly, implying that firm performance may affect the deployment of marketing analytics, and not vice versa. To (at least partially) assess this potential reverse-causality issue, we collected additional objective performance data for the year following our survey. We followed the same procedure as outlined earlier to collect the additional objective performance data and then calculated the two-year average ROA using the newly collected data as well as the data for the year preceding our primary data collection. We then used this new objective performance data to reanalyze our conceptual model. As before, we relied on SEM to estimate the direct (un-moderated) effects in our conceptual model and used OLS regression to examine the link between deployment of marketing analytics and firm performance. We report the SEM results in Figure 4 and include the regression results in Table 8 (model 2). As the results show, the outcomes did not change in any substantive way providing some support for the notion that marketing analytics deployment is an antecedent of firm performance and not vice versa.[10]

[Insert Figure 4 about here]

Fourth, to assess the timing of the performance effects of deployment of marketing analytics, we combined the two objective performance measures we obtained as follows:

$(\lambda \; x \; Performance_{Time\ 1}) + ([1 - \lambda] \; x \; Performance_{Time\ 2})$,

where λ can range from 0 to 1, $Performance_{Time\ 1}$ is our initial objective ROA measure and $Performance_{Time\ 2}$ is the ROA measure with a one year lag. We then re-estimated our OLS regression model, with the resulting linear combination values as the dependent variable (with λ varying in increments of 0.1 from 0 to 1), and assessed which linear combination yields the best fitting model as determined by Adj. R^2. Figure 5 shows the model results.

[Insert Figure 5 about here]

The results reveal the highest Adj. R^2 for $\lambda = .4$, (this is the maximum likelihood estimate for λ assuming Normal distribution of the error terms of the OLS regression) suggesting that the performance effects of the deployment of analytics appear to be seen both immediately and with some carryover. This finding further reduces the likelihood of a reverse-causality effect, with the effects slightly stronger in *Time 2* than in *Time 1* (A value of $\lambda = .5$ would indicate the short-term and longer-term effects are the same).

Fifth, we estimated a mixture regression model (DeSarbo and Cron 1988) to explore the possibility of unobserved heterogeneity among firms. The lowest Bayesian information criterion emerged for a one-class model (consistent with our multi-group analysis above), which suggests

[10] We also used the yearly ROA objective performance measures instead of the two-year average measures in our analyses. Our inferences did not change.

that unobserved heterogeneity was not relevant for our model. Thus our findings seem to be generalizable to *Fortune* 1,000 firms.

Sixth, the correlations among the subjective performance measures (items 16 – 18 in Table 5) suggest that our performance construct may not be unidimensional: the correlation between profits and return on investment (ROI) is quite high (r = .832) whereas the correlation between sales growth and profits (r = .451) and sales growth and ROI (r = .496) is significantly lower. Thus, we analyzed deployment of analytics' effect on performance separately for sales growth and profits/ROI. The main effect of deployment of analytics on performance in the SEM increased in both instances, i.e., when using the single item sales growth measure only (β = .171 vs. .106) and when using the construct comprised of the profits and ROI items (β = .198 vs. .106). Further, when employing sales growth as the outcome measure, competition no longer emerges as a significant moderator of analytics deployments' effect on performance ($\beta_{\text{deployment x competition}}$ = .063 vs. .081; the interaction between needs & wants change and deployment of analytics remains marginally significant: $\beta_{\text{deployment x needs \& wants change}}$ =.076 vs. .06)). In contrast, both interactions, i.e., competition*deployment of analytics and needs and wants change*deployment of analytics become stronger when including the profits/ROI performance variables in the SEM ($\beta_{\text{deployment x competition}}$ = .149 vs. .081 and $\beta_{\text{deployment x needs \& wants change}}$ =.113 vs. .06). All other paths remain virtually the same in the respective models.

Thus, while the use of marketing analytics seems to affect sales growth, profits and ROI positively, our analysis suggests that the deployment of analytics may have a somewhat stronger effect on profits/ROI than on sales growth. We offer the following possible explanations for this finding: First, many marketing analytics applications are geared toward identifying the most profitable customer segment(s) (e.g., Reinartz and Kumar 2000), applications designed to improve profits and ROI as opposed to sales. Second, as our sample is drawn from the *Fortune*

1,000—all large firms, the scale of those firms normally prevent them from growing as quickly as smaller firms. Thus, this finding may be specific to our sample and should be explored more broadly.

4.3.5. Deployment of Analytics as Mediator. Our conceptual model assumes that deployment of analytics mediates the effect of analytics culture and analytics skills on firm performance. To test this assumption, we conducted a formal test of mediation following the procedure recommended by Baron and Kenny (1986). We used both of the objective performance measures (i.e., $Performance_{Time\ 1}$ and $Performance_{Time\ 2}$ as described above) as the respective dependent variables, deployment of analytics as the mediator, and analytics skills or analytics culture as the respective independent variables. Deployment of analytics emerges as a mediator for both independent variables irrespective of objective performance measure used.

5. Discussion and Conclusion

Our objective has been to determine whether the deployment of marketing analytics provides a financial return, and to identify the factors that lead firms to deploy marketing analytics. Our findings address these two research issues and provide insights of value both to marketing theory and to marketing practice.

5.1. Theoretical Implications

Our study helps explain both what drives the adoption of marketing analytics and why that adoption leads to positive financial returns.

We find support for our hypotheses that the positive effect of marketing analytics deployment on firm performance is moderated by the level of competition that a firm faces, as well as by the degree to which the needs and wants of its customers change over time. However, in contrast with our hypothesis, the prevalence of marketing analytics in a given industry does not moderate the effect of marketing analytics on firm performance. We suggest a possible explanation for this (non)result: consistent with the findings from McKinsey & Co. (2009), the prevalence of marketing analytics use in the industries that we examined is relatively low. That is, the average response of executives who participated in our survey to the question "marketing analytics are used extensively in our industry" was 3.4 (seven-point scale [min = 1; max = 6; SD = 1.6]). Perhaps the moderating effect of marketing analytics' prevalence does not emerge until the industry-wide use of marketing analytics reaches a higher level than evidenced in our sample. Our data simply may not provide the necessary range to manifest such an effect,[11] an issue we plan to examine in more detail in the future.

We posit and show empirically that a firm's TMT must ensure that the firm (1) employs people with requisite analytics skills, (2) deploys a sophisticated IT infrastructure and data, and (3) develops a culture that supports marketing analytics, so that the insights gained from marketing analytics can be deployed effectively within the firm.

The people who perform marketing analytics (e.g., marketing analysts) frequently are not the people who implement the insights gained from marketing analytics (e.g., marketing executives), but both groups should support the use of marketing analytics if the firm is to have a strong marketing analytics-oriented culture (Deshpande, Farley, and Webster 1993). Therefore, a suitable analytics culture that promotes the use of marketing analytics is a critical component of our framework. And the centrality of an analytics culture, which is sticky and hard to change or replicate, suggests that the deployment of marketing analytics has the necessary properties of a firm capability that can lead to a sustainable competitive advantage (Barney 1991).

5.2. Managerial Implications

Our findings offer several useful implications for managerial practice. First, the low prevalence of marketing analytics use indicates that few managers are convinced of the benefits

[11] We also examined curvilinear effects of marketing analytics prevalence but did not find a significant effect.

of marketing analytics. Yet our results suggest that most firms can expect favorable performance outcomes from deploying marketing analytics. Moreover, these favorable performance outcomes should be even greater in industries in which competition is high and in which customers change their needs and wants frequently.

The objective performance data, as a dependent variable in our regression model, enable us to quantify the actual performance implications of, say, a one-unit increase (on a scale from 1 to 7) in marketing analytics deployment. For an average firm that operates in an industry with average competition and average changes in customer needs and wants, a one-unit increase in the deployment of marketing analytics (i.e., an increase in stated deployment from the 50th percentile to approximately the 65th percentile) is associated with an 8% increase in ROA. For an average firm in our sample that operates in competitive industries with frequently changing customer needs and wants, this one-unit increase (i.e., an increase in stated deployment from the 50th percentile to approximately the 70th percentile) is associated with a 21% average increase in ROA.[12] The 8% increase in ROA implies an average increase of about $70 million in net income for the firms in our sample; the 21% increase means more than $180 million more in net income.[13]

Second, if implemented properly, the use of marketing analytics may be a source of a sustainable competitive advantage for a firm. Our study should help managers avoid what seems to be a common misconception, i.e., that hiring marketing analysts who know how to perform marketing analytics will be sufficient for their firm to benefit from marketing analytics. In contrast, we find that TMT involvement and a suitable analytics culture that further supports the

[12] Assuming a firm's ROA is 5%, a one-unit increase in the deployment of analytics should on average be associated with an increase in ROA of about 1% (i.e., 5% × 1.21 ≈ 6%).
[13] We used our first objective performance measure in this analysis (i.e., the performance measure used in regression 1 in table 8). The average net income of the firms in our sample was $922,200,000. We note that we repeated the analysis using our second objective performance measure and our results did not change in any significant way.

use of marketing analytics (along with the appropriate IT and data infrastructure) are necessary for the firm to see the benefits of greater deployment.

5.3. Limitations and Further Research

While we believe we have broken some new ground with this work, there are clear limitations, several of which provide avenues for future research. First, while our robustness analysis shows that the effects we report can be translated into real financial returns, our main measures are attitudinal, not objective. In addition, we do not examine the actual return a firm could expect from its investment in marketing analytics. Thus, it might be useful to get objective data on the costs and benefits that we measure subjectively in this research.

Second, our findings are correlational, not causal. For example, we find that an increase in analytics skills and culture *ceteris paribus* is associated with the deployment of analytics, which in turn is associated with higher firm performance. We cannot make direct causal claims about these relationships though. Future research could be based on longitudinal data for a sample of firms to track changes in the precursors of the deployment of marketing analytics to determine how they affect deployment and how changes in deployment affect firm performance. Such research should be feasible because many firms are still in the early stages of deploying marketing analytics.

Third, our results are based on the overall deployment and impact of marketing analytics. Additional research is needed to understand the returns associated with different types of analytics (e.g., embedded automated models versus decision support), as well as from various aspects of analytics implementation such as the nature of the decisions/actions supported by analytics (e.g., segmentation, targeting, forecasting, pricing, sales), and the penetration of marketing analytics into non-marketing decisions and actions.

Fourth, our results are based on, and limited to, very large U.S. firms. It would be useful to extend this work to other geographies and to the much larger universe of medium-sized and small firms.

Despite these limitations, we believe that beyond their theoretical interest, our framework and findings should prove useful for managers who are looking to justify investments in marketing analytics, or are seeking a framework to help them deploy those investments most effectively. Our results also provide a bit of a cautionary tale: Without TMT advocacy and support, the necessary investments in data, analytic skills, and a supportive analytics culture are unlikely to occur. We hope that the modest step we have taken here to address the performance implications of marketing analytics will prove provocative and spawn additional research in this important area.

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Table 1
Profile of *Fortune* 1000 Firm Respondents

Position	Number of Participants	Percentage
President, CEO	7	3
EVP, (Sr.) VP, CMO, CFO, COO	78	37
(Sr.) Director, Executive Director	65	31
(Sr.) Marketing Manager	47	22
Other (e.g., Marketing Strategist)	15	7
Total	**212**	**100**

Table 2
Construct Correlations

Constructs	Correlations 1	2	3	4	5	6
1. TMT Advocacy	**1.000**	0.649	0.570	0.188	0.476	0.047
2. Analytics Culture	**0.806 (0.03)**	**1.000**	0.681	0.176	0.543	0.033
3. Marketing Analytics Skills	**0.755 (0.04)**	**0.825 (0.03)**	**1.000**	0.318	0.608	0.070
4. Data and IT	**0.434 (0.07)**	**0.419 (0.07)**	**0.564 (0.06)**	**1.000**	0.196	0.107
5. Deployment of Analytics	**0.690 (0.05)**	**0.737 (0.04)**	**0.780 (0.03)**	**0.443 (0.06)**	**1.000**	0.062
6. Firm Performance	**0.216 (0.07)**	**0.181 (0.08)**	**0.265 (0.07)**	**0.327 (0.08)**	**0.248 (0.07)**	**1.000**

Note: The correlations and their standard errors (in brackets underneath) are shown in bold and the squared correlations are shown in plain text.

Table 3
Sample Firm Profiles

Industry Groups	**#**	**%**
Services	88	41.5
Manufacturing	65	30.7
Trade	22	10.4
Construction and Mining	7	3.3
Finance and Insurance	30	14.1
Total	**212**	**100**
Sales	**#**	**%**
< $1 Million	5	2.4
$1 Million - $10 Million	14	6.6
$10 Million - $100 Million	23	10.8
$100 Million - $1 Billion	57	26.9
$1 Billion - $5 Billion	74	34.9
> $5 Billion	39	18.4
Total	**212**	**100**
Number of Employees	**#**	**%**
0-100	20	9.4
101-1,000	37	17.5
1,001-10,000	39	18.4
10,001-100,000	60	28.3
100,001-200,000	32	15.1
> 200,000	24	11.3
Total	**212**	**100**

Note: The profiles pertain to either the strategic business unit (SBU) or the overall company of our respondents, depending on which UNIT the respondents selected when completing the survey.

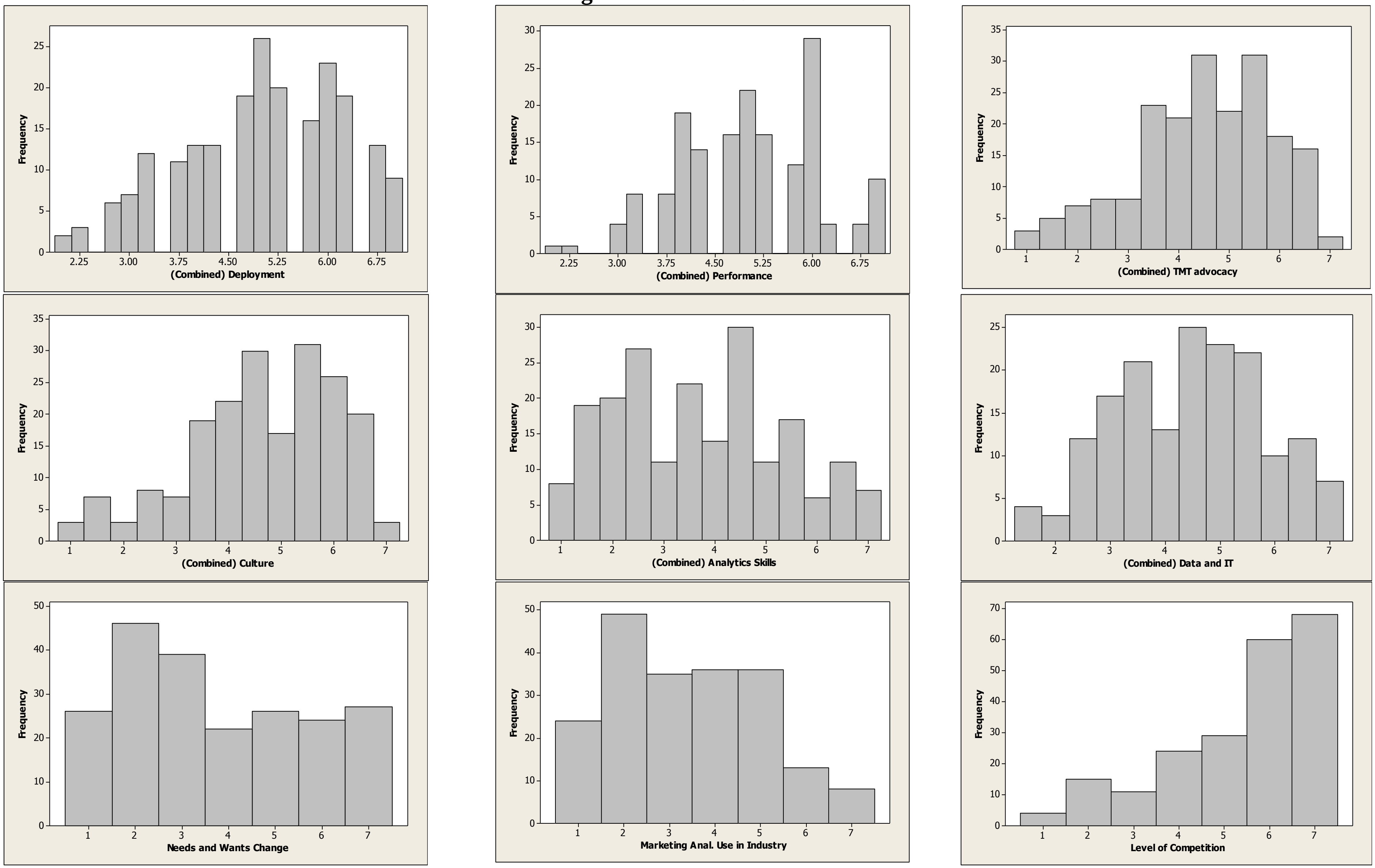
Table 4
Sample Firms (Partial List)

- IBM
- Honeywell
- American Express
- Marriott International
- Raytheon
- Capital One
- DuPont
- Hewlett-Packard
- Ford Motor Co
- Pfizer
- AT&T
- Xerox
- Johnson&Johnson
- Progressive
- Boeing
- Amazon.com
- ConAgra Foods
- Apple
- Oracle
- Kraft Foods
- FedEx
- Sears Holdings
- JP Morgan Chase
- UPS
- Deere & Company
- Alcoa
- Aramark
- Citigroup
- Baxter International
- General Mills
- 3M
- Motorola
- Starbucks
- Verizon
- Charles Schwab
- Dick’s Sporting Goods
- Harley-Davidson
- Hershey

Table 5
Correlations and Summary Statistics

	Correlations																							
Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
1. TMT attitude toward marketing analytics	1.000																							
2. Annual reports highlight use of marketing analytics	0.579	1.000																						
3. TMT expects quantitative analyses	0.578	0.778	1.000																					
4. If we reduce marketing analytics use, profits will suffer	0.379	0.558	0.601	1.000																				
5. Confident that use of marketing analytics improves cust. satisfaction	0.492	0.641	0.635	0.697	1.000																			
6. Most people are skeptical of any kind of analytics-based results (R)	0.401	0.552	0.581	0.676	0.713	1.000																		
7. Appropriate marketing analytics tool use	0.497	0.546	0.600	0.630	0.637	0.561	1.000																	
8. Master many different marketing analysis tools and techniques	0.466	0.569	0.591	0.648	0.615	0.558	0.837	1.000																
9. Our people can be considered experts in marketing analytics	0.572	0.599	0.642	0.621	0.648	0.637	0.736	0.738	1.000															
10. We have a state-of-art IT infrastructure	0.283	0.281	0.264	0.300	0.331	0.283	0.431	0.343	0.361	1.000														
11. We use IT to gain a competitive advantage	0.190	0.230	0.285	0.220	0.180	0.103	0.315	0.312	0.320	0.344	1.000													
12. In general, we collect more data than our primary competitors	0.269	0.268	0.349	0.326	0.319	0.253	0.432	0.422	0.420	0.392	0.637	1.000												
13. Everyone in our UNIT uses analytics insights to support decisions	0.459	0.537	0.586	0.577	0.624	0.560	0.649	0.639	0.645	0.312	0.248	0.352	1.000											
14. We back arguments with analytics based facts	0.404	0.436	0.516	0.460	0.498	0.444	0.586	0.598	0.562	0.234	0.205	0.314	0.813	1.000										
15. We regularly use analytics in the following areas	0.335	0.550	0.502	0.442	0.598	0.460	0.489	0.517	0.509	0.310	0.205	0.354	0.542	0.479	1.000									
16. Firm performance - total sales growth	0.077	0.007	0.006	0.089	0.124	0.062	0.100	0.149	0.147	0.207	0.156	0.206	0.172	0.148	0.174	1.000								
17. Firm performance - profits	0.293	0.150	0.186	0.106	0.113	0.167	0.193	0.203	0.230	0.343	0.218	0.242	0.197	0.172	0.222	0.451	1.000							
18. Firm performance - return on investment	0.276	0.158	0.182	0.134	0.136	0.216	0.204	0.197	0.236	0.313	0.204	0.193	0.208	0.188	0.181	0.496	0.832	1.000						
19. We face intense competition	-0.060	-0.115	-0.060	-0.058	-0.078	-0.082	-0.050	-0.058	-0.113	-0.042	-0.034	-0.017	-0.118	-0.154	-0.117	0.018	-0.068	-0.097	1.000					
20. Our customers needs and wants change frequently	-0.090	-0.083	-0.103	-0.130	-0.172	-0.084	-0.040	-0.057	-0.042	0.051	0.013	0.005	-0.092	-0.060	0.022	0.031	0.020	0.005	0.167	1.000				
21. Marketing analytics are used extensively in our industry	-0.052	0.126	0.101	0.069	0.061	0.069	0.014	0.032	0.049	-0.063	0.033	0.117	0.079	0.097	0.115	-0.032	-0.023	-0.011	0.007	0.052	1.000			
22. Size	-0.005	0.017	0.057	0.081	0.084	0.043	0.069	0.067	0.091	0.044	0.012	0.007	-0.006	-0.030	-0.024	-0.012	-0.157	-0.162	0.146	0.177	-0.070	1.000		
23. Objective ROA (Time 1)	0.278	0.276	0.334	0.168	0.288	0.287	0.320	0.283	0.294	0.056	0.291	0.279	0.342	0.397	0.444	0.275	0.318	0.375	0.061	-0.037	0.177	0.048	1.000	
24. Objective ROA (Time 2)	0.276	0.300	0.270	0.151	0.229	0.244	0.219	0.187	0.258	0.060	0.204	0.145	0.347	0.323	0.362	0.217	0.341	0.371	0.082	-0.003	0.230	0.001	0.508	1.000
Summary Statistics																								
Mean	3.571	5.029	5.014	4.699	4.714	4.455	3.596	3.790	3.720	4.696	4.219	4.505	5.241	4.580	5.189	4.839	5.196	5.006	5.422	3.743	3.408	3.561	4.962	4.674
Standard Deviation	1.705	1.506	1.419	1.589	1.511	1.618	1.860	1.704	1.771	1.576	1.755	1.744	1.422	1.383	1.435	1.208	1.268	1.262	1.635	1.966	1.638	1.467	1.541	1.234

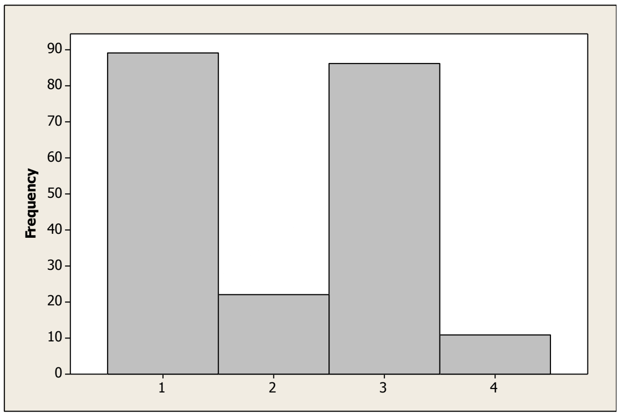
Table 6
Histograms of Focal Variables



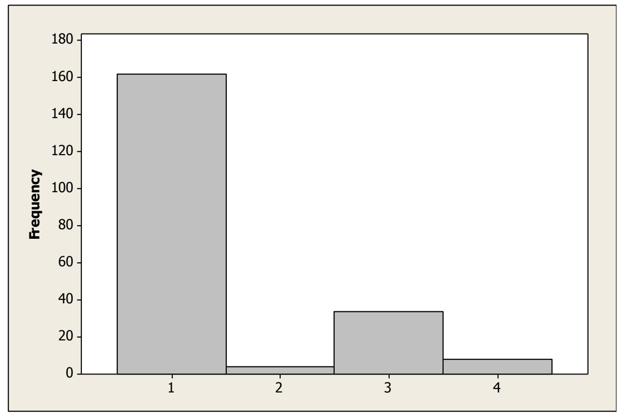
Note: (Combined) signifies that the graph reports the average scores of the variables that form the respective latent variables. As the histograms illustrate, the firms in the sample display a wide range of values on our focal variables.

Table 7
Locus of Marketing Analytics Development and Execution

"Are your marketing analytics applications designed primarily in-house, or by outside experts/consultants?"



"Are the primary DAY-TO-DAY OPERATIONS of the marketing analytics managed in-house, or are they out-sourced?"



1 = Primarily in-house; 2 = Primarily external; 3 = Combination of in-house and external; 4 = Don't know

Table 8
The Effect of Analytics Deployment on (Objective) Firm Performance (=DV)

	Model 1: Objective ROA #1		Model 2: Objective ROA #2	
Predictor Variable	**Parameter Estimate**	**t-Value**	**Parameter Estimate**	**t-Value**
Main Effects				
Deployment of Analytics	.45**	3.06	.24*	2.08
Needs & Wants Change	.04	.46	.06	.83
Competition	.11	1.09	.10	1.26
Analytics Prevalence	.08	.87	.11	1.43
Interactions				
Depl x Competition	.12	1.60	.11†	1.79
Depl x Needs & Wants Change	.13*	2.15	.13**	2.68
Depl x Prevalence	.03	.46	-0.04	-0.63
Other				
Constant	5.00	29.14	4.75	35.58
R^2	32.5%		36.3%	
Adjusted R^2	24.7%		28.9%	
F-Value (7,60)	4.14		4.89	
F-Probability	<.001		<.001	

Note: For ease of interpretation, we mean-centered the focal variables (i.e., deployment of analytics, needs and wants change, competition, and analytics prevalence) before creating the interaction terms (Echambadi and Hess 2007). **t ≥ 2.576, *p* < .01; *t ≥ 1.96, *p* < .05; †t ≥ 1.645, *p* < .10.

Figure 1
Conceptual Framework

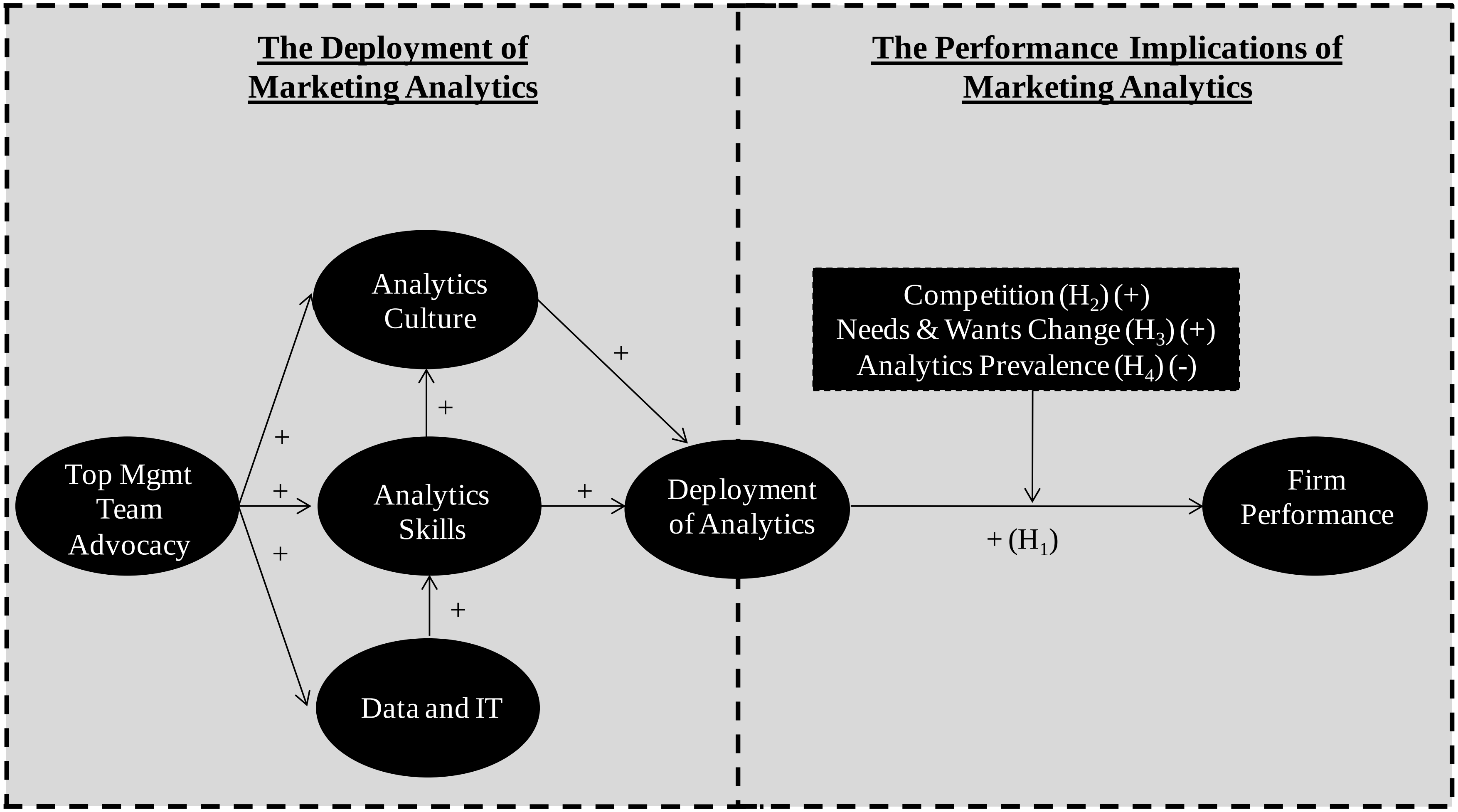
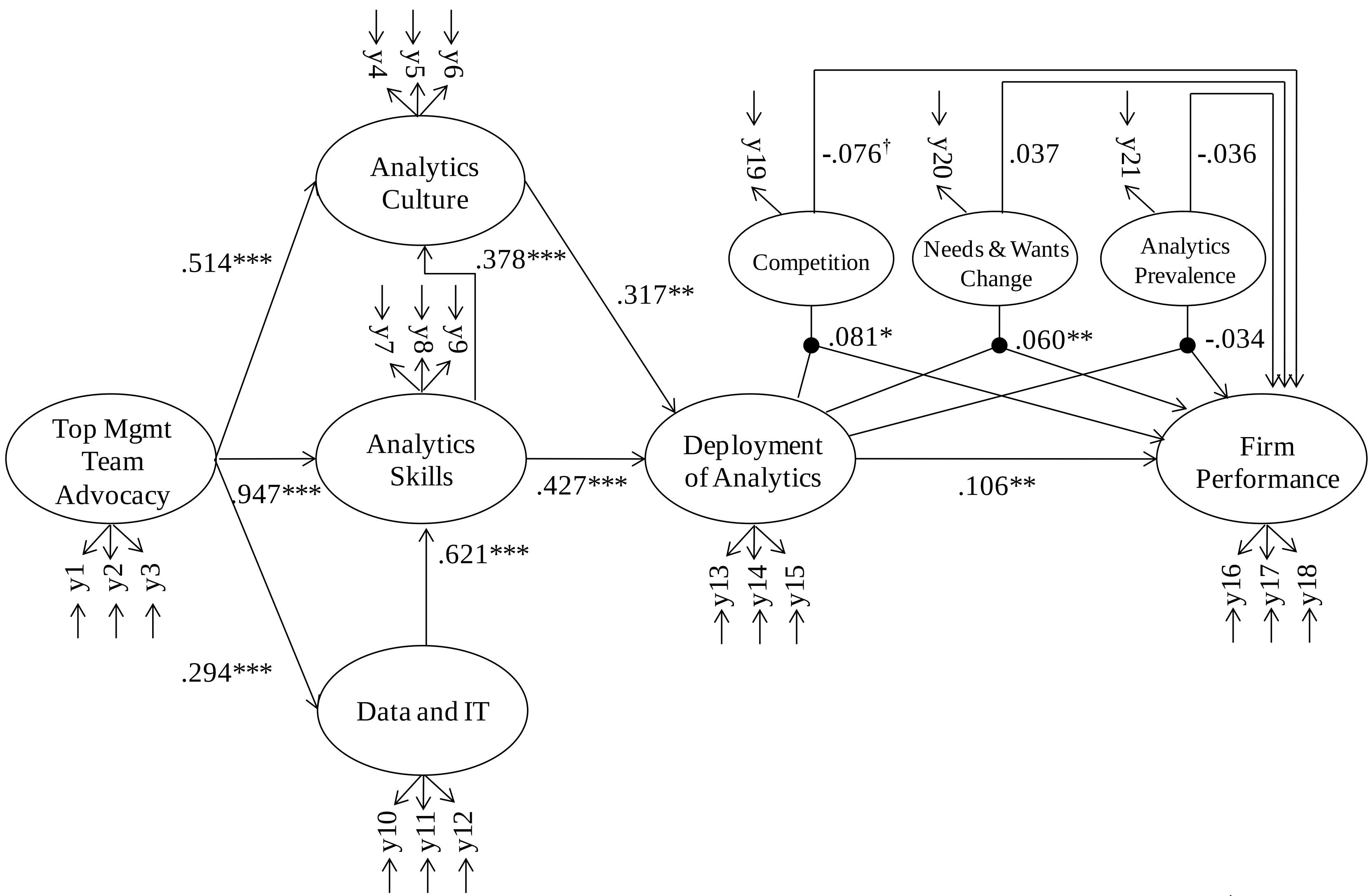
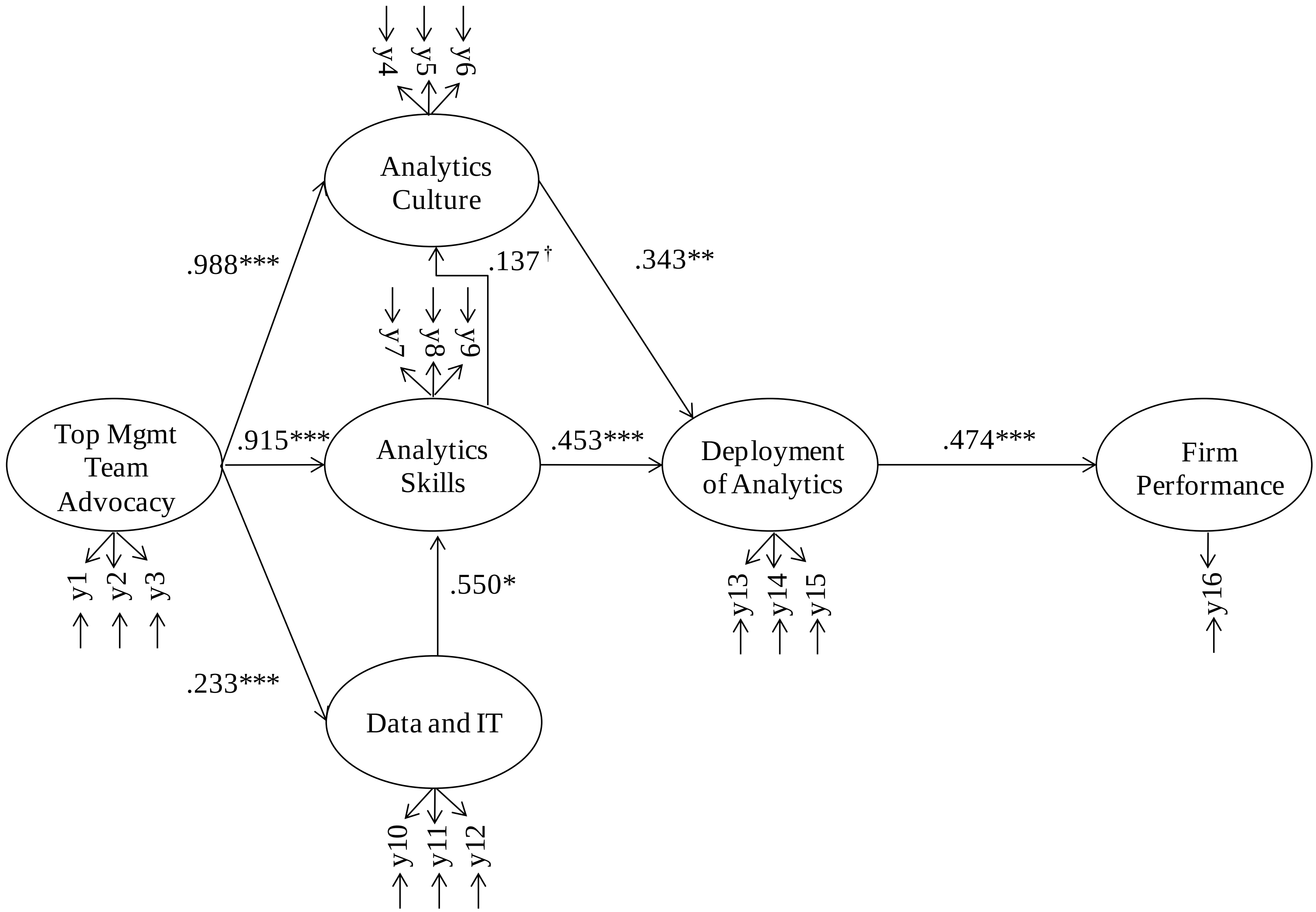


Figure 2
Structural Equation Model Results



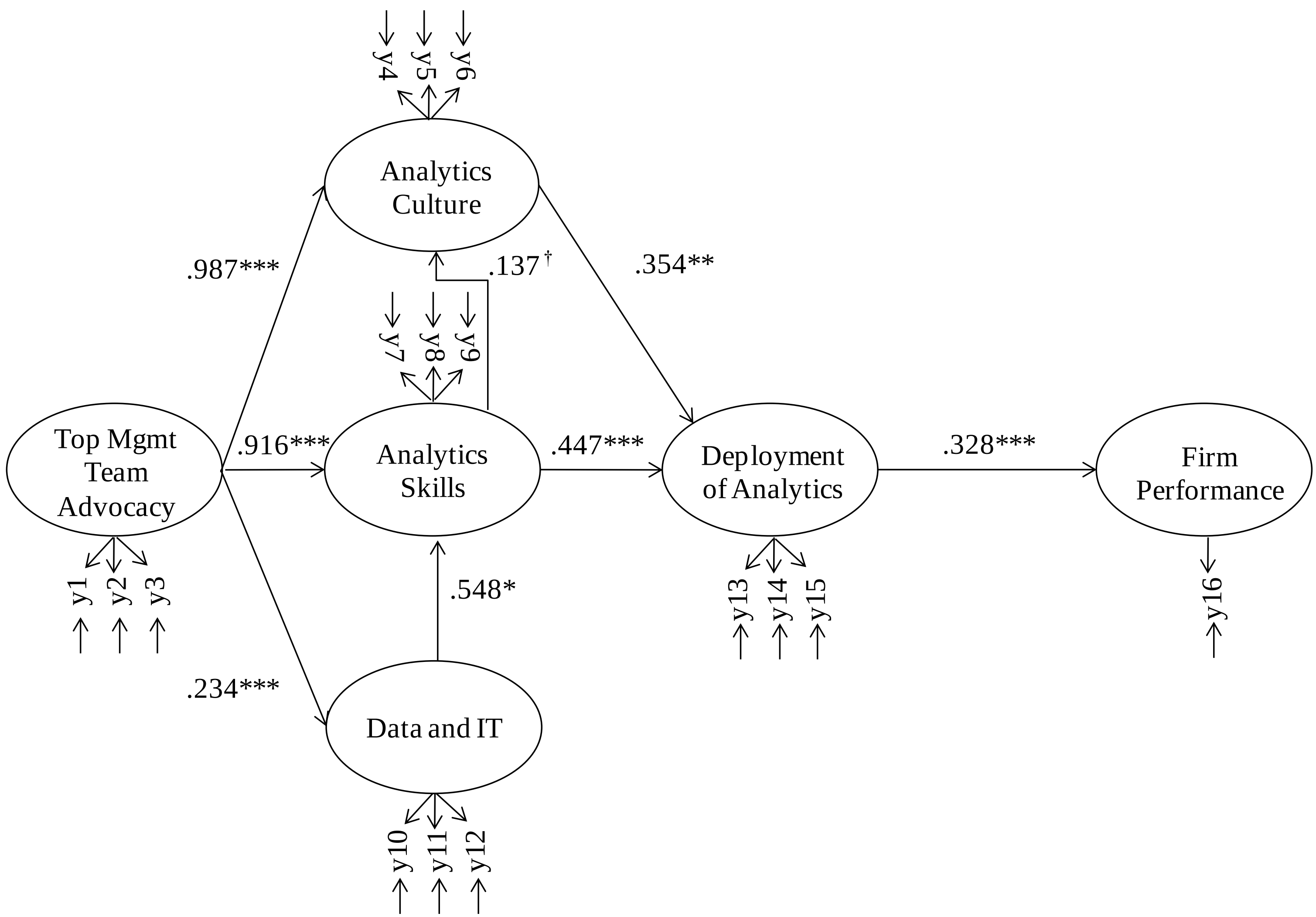
We used full information maximum likelihood to estimate the model (n = 212); *** t ≥ 3.291, *p* < .001; **t ≥ 2.576, *p* < .01; *t ≥ 1.96, *p* < .05; †t ≥ 1.645, *p* < .10.

Figure 3
Structural Equation Model Results Using Objective Performance Data #1



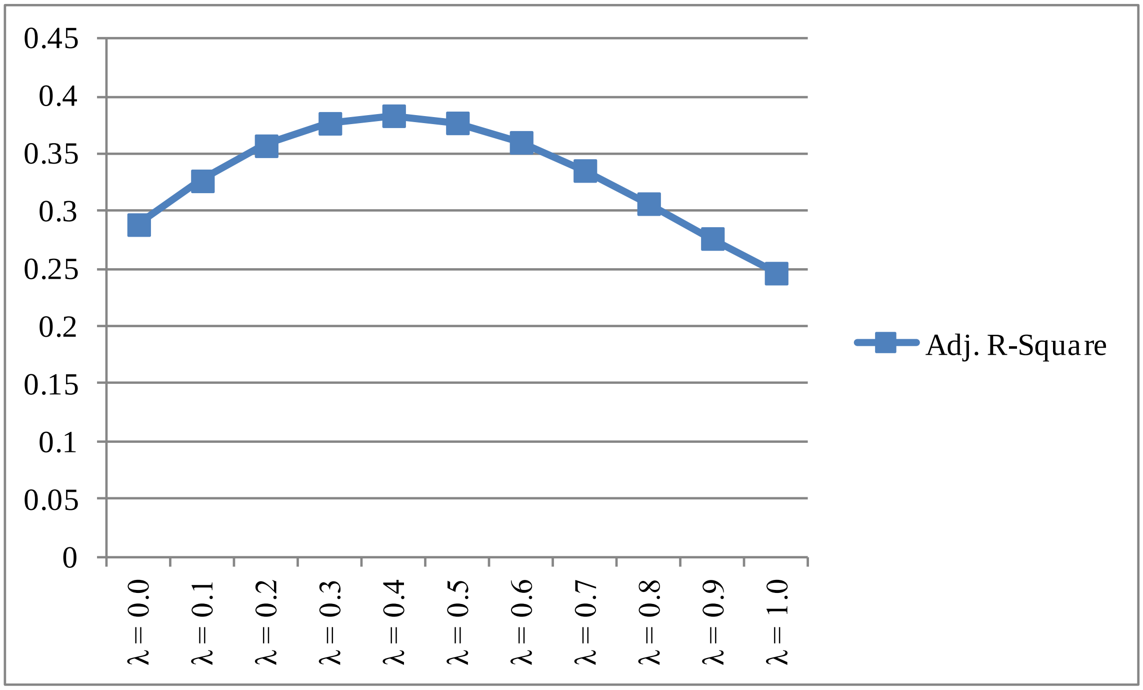
Overall, the model fits the data reasonably well; n = 68; χ^2 = 158.153; CFI = .922; RMSEA = .096, 90% confidence interval of RMSEA = [.068; .123].
*** t ≥ 3.291, *p* < .001; **t ≥ 2.576, *p* < .01; *t ≥ 1.96, *p* < .05; †t ≥ 1.645, *p* < .10.

Figure 4
Structural Equation Model Results Using Objective Performance Data #2



Overall, the model fits the data reasonably well; n = 68; χ^2 = 149.744; CFI = .932; RMSEA = .089, 90% confidence interval of RMSEA = [.060; .117].
*** $t \geq 3.291$, $p < .001$; **$t \geq 2.576$, $p < .01$; *$t \geq 1.96$, $p < .05$; †$t \geq 1.645$, $p < .10$.

Figure 5
Contemporary versus Carryover Effects on Firm Performance



This linear combination analysis shows that the highest Adj. R^2 occurs for λ = .4. This suggests that the deployment to performance link is strongest with an objective performance variable that gives 40% of the weight (λ = .4) to contemporary effects on firm performance and 60% to carryover effects.

APPENDIX
Scale Items

Measure	Items*
Top Management Team Advocacy α = .84 Average Variance Extracted (AVE) = 0.659	1. Our top management has a favorable attitude towards marketing analytics. 2. Our annual reports and other publications highlight our use of analytics as a core competitive advantage. 3. Our top management expects quantitative analysis to support important marketing decisions.
Analytics Culture α = .87 AVE = 0.692	4. If we reduce our marketing analytics activities, our UNIT's profits will suffer. 5. We are confident that the use of marketing analytics improves our ability to satisfy our customers. 6. Most people in my unit are skeptical of any kind of analytics-based results (R).
Marketing Analytics Skills α = .90 AVE = 0.777	7. Our people are very good at identifying and employing the appropriate marketing analysis tool given the problem at hand. 8. Our people master many different quantitative marketing analysis tools and techniques. 9. Our people can be considered as experts in marketing analytics.
Data and IT α = 0.72 AVE = 0.503	10. We have a state-of-art IT infrastructure. 11. We use IT to gain a competitive advantage. 12. In general, we collect more data than our primary competitors.

* The item numbers presented here correspond with those used in Table 5 & Figures 2 – 4.

APPENDIX A
Scale Items (continued)

Measure	**Items**
Deployment of Analytics α = .82 AVE = 0.657	13. Virtually everyone in our UNIT uses analytics based insights to support decisions. 14. In our strategy meetings, we back arguments with analytics based facts. 15. We regularly use analytics to support decisions in the following areas (average score across 12 areas to choose from [pricing, promotion and discount management, sales-force planning, segmentation, targeting, product positioning, developing annual budgets, advertising, marketing mix allocation, new product development, long-term strategic planning, sales forecasting] + 2 open ended areas).
Firm Performance α = .81 AVE = 0.639	Please circle the number that most accurately describes the performance of your UNIT in the following areas relative to your average competitor (1 = well below our competition; 7 = well above our competition) Please consider the immediate past year in responding to these items. 16. Total Sales Growth. 17. Profit. 18. Return on Investment.
Competition	19. We face intense competition.
Needs and Wants Change	20. Our customers are fickle—their needs and wants change frequently
Industry Prevalence	21. Marketing analytics are used extensively in our industry.