ELSEVIER
Journal of Retailing xxx (xxx, 2014) xxx–xxx
Journal of Retailing

Research Note

Do Retailers Benefit from Deploying Customer Analytics?

Frank Germann[a,*], Gary L. Lilien[b,1], Lars Fiedler[c,2], Matthias Kraus[d,3]

[a] *Department of Marketing, 395 Mendoza College of Business, University of Notre Dame, Notre Dame, IN 46556, USA*
[b] *Department of Marketing, Smeal College of Business, Pennsylvania State University, 468 Business Building, University Park, PA 16802, USA*
[c] *McKinsey & Company, Inc., Am Sandtorkai 77, 20457 Hamburg, Germany*
[d] *McKinsey & Company, Inc., Sophienstraße 26, 80333 Munich, Germany*

Abstract

Prior research has documented a general positive relationship between the deployment of customer analytics and firm performance. In this research we focus on the retailing industry, an industry characterized by tight margins that lead to careful scrutiny of all business investments. Using survey data from 418 top managers based in the Americas, Europe Middle East and Africa (EMEA) and Asia, we show that of the eight industries in the study, firms in the retail industry have the most to gain from deploying customer analytics. However, we also find that not only do many retailers not perceive this potential gain, they do not invest in customer analytics at an economically appropriate level. Thus we identify a gap between perception and reality concerning the potential for customer analytics in the retail industry that has both theoretical and practical implications.

Keywords: Customer analytics; Performance implications of customer analytics; Survey data

Introduction

"Customer analytics" has become a pervasive buzzword in the business press, and many consultants and other intermediaries claim that firms have much to gain from the various analyses and business applications that use customer analytics. A Google search on January 20, 2014 of "customer analytics" returned over 5 million hits, with sponsored links from IBM, Accenture and Adobe and other consultants and research suppliers such as SAS, SAP and Deloitte displayed prominently.

With their many customers and large volume of customer-transaction data, retailers should be well positioned to benefit from deploying customer analytics effectively. Yet evidence suggests that many retailers under-utilize customer analytics. For example, a study by Ventana Research suggests that as many as 71 percent of retailers still use spreadsheets as their primary analysis tool (Cosentino 2012). Similarly, Bertolucci (2013) argues that small retailers in particular essentially ignore the potential benefits of deploying customer analytics.

Against this backdrop, we address two questions: First, do retailers realize benefits that justify investments in customer analytics? Through analysis of survey data from 418 top managers based in the Americas, Europe Middle East and Africa (EMEA) and Asia, we show that the answer to question #1 appears to be yes. Our second question concerns how retailers' customer analytics-based performance gains compare to those of firms in other industries. We find that of the eight industries surveyed, firms in the retail industry have the most to gain from increasing their deployment of customer analytics. Yet our findings also suggest that not only do retailers perceive customer analytics to be less effective than the average firm in our sample, they also deploy customer analytics less than the average firm. Thus, there appears to be a gap between perception and reality (Kayande et al. 2009) for retailers concerning the effectiveness of their investment in customer analytics.

We contribute to both the retailing as well as the customer analytics literature. To the best of our knowledge, this

* Corresponding author. Tel.: +1 574 631 4858; fax: +1 574 631 5255.
E-mail addresses: fgermann@nd.edu (F. Germann), GLilien@psu.edu (G.L. Lilien), lars_fiedler@mckinsey.com (L. Fiedler), Matthias_Kraus@mckinsey.com (M. Kraus).
[1] Tel.: +1 814 863 2782; fax: +1 814 863 0413.
[2] Tel.: +49 40 3612 1384; fax: +49 40 3612 1607.
[3] Tel.: +49 89 5594 8288; fax: +49 89 5594 8289.

http://dx.doi.org/10.1016/j.jretai.2014.08.002
0022-4359/

is the first study that explores whether and to what degree retailers can expect to benefit from deploying customer analytics. Given the significant investments necessary to deploy customer analytics (e.g., Germann, Lilien, and Rangaswamy 2013), and considering retailers' generally tight margins and resulting cost pressures (e.g., Gauri 2013), evidence of positive performance outcomes of analytics deployment would seem valuable for retailers. Moreover, while existing studies have scrutinized the performance gains firms can expect from deploying customer analytics (e.g., Brynjolfsson, Hitt, and Kim 2011; Germann, Lilien, and Rangaswamy 2013), these studies report aggregate, across industry performance effects. We argue and show empirically that performance effects vary systematically by industry and that retailers can expect to derive greater performance gains from using customer analytics than others.

We proceed as follows: We first discuss why retailers should expect to benefit from deploying customer analytics. We then describe our data and methodology and present our findings. We conclude with a discussion of our findings, what they mean for retailers, the limitations of our research, and potential for further work.

Why Retailers Should Expect to Benefit from Deploying Customer Analytics

Leeflang and Wittink (2000) suggest that the effective use of customer analytics depends both on customer data availability as well as on access to appropriate estimation methods. Data is usually needed to perform customer analytics, and estimation methods are needed to link data to models. Kayande et al. (2009) propose that the use of customer analytics is especially effective when the customer data available are voluminous and beyond human processing capabilities, and when customer analytics-based methods are used to help make repetitive decisions. Using the same customer analytics-based methods repeatedly not only helps justify the costs associated with method development but also provides a feedback mechanism that can be used to continuously calibrate and improve the methods.

Building on this literature, and adopting a contingency perspective (Lawrence and Lorsch 1967; Zeithaml, Varadarajan, and Zeithaml 1988), we posit that firms that operate in industries in which (1) much customer data is available, (2) appropriate customer analytics-based methods exist, and (3) customer analytics-based methods are frequently used to support repetitive decisions, should benefit more from customer analytics use than industries without such characteristics. Moreover, we argue that these three factors fit the retailing industry particularly well.

Data

Retailers have access to a great deal of meaningful customer data, both online and offline (e.g., Kayande et al. 2009; Van Bruggen and Wierenga 2000). Traditional brick-and-mortar retailers have access to scanner data that can reveal meaningful insights. For example, in 2004, analyzing its scanner data, Wal-Mart discovered that storm warnings trigger a significant increase in the sales of certain products such as Pop-Tarts, whose sales on average increase by 700 percent shortly before a hurricane (note: only beer sees a bigger sales spike when a hurricane is about to hit (Fiedler et al. 2013)). Retailers like Wal-Mart can use such analytics-based insights to increase the stock of their most popular items and place them strategically in the store to best leverage the (anticipated) increase in demand.

As another example consider the NFLshop.com. Based on customer feedback data, the NFLShop.com realized during the 2012 holiday season that women were dissatisfied with their shopping experience. The retailer had incorrectly assumed that female shoppers were visiting the site to purchase gifts for their significant (male) others. Yet, their data showed that many women were visiting the online store to make purchases for themselves. Based on this insight, the NFLShop.com increased its catalog circulation to women and aired a TV ad targeted at women, among other things, resulting in a year-over-year online sales increase of 25 percent (Thau 2013).

In summary, most retailers have access to a great deal of customer data. Using this data in conjunction with customer analytics-based methods (discussed next) retailers should be able to gain meaningful customer insights, engage with customers on a meaningful level, and ultimately benefit financially.

Customer Analytics Methods

Numerous customer analytics-based methods exist that can benefit retailers. A pioneering example is Guadagni and Little's (1983) seminal paper, in which the authors used a multinomial logit model to help retailers (and manufacturers) understand how marketing mix decisions – price and promotion decisions in particular – influence the sales and market shares of the products they sell. Much work in customer analytics in the retail domain has followed Guadagni and Little's (1983) contribution; we highlight a few here.

One influential research stream is the work on customer relationship management (CRM) and customer lifetime value (CLV). Kumar and Petersen (2012, p. 202 ff.), for example, demonstrate the power of the CLV metric in maximizing retailer's profitability and propose an approach to implementing a CLV management framework. Thanks in large part to such work, a number of retailers today are seeing the benefits of establishing CRM and CLV systems and strategies.

Bucklin and Gupta's (1999) research sought to "uncover key questions practitioners would like to answer with scanner data. . .and then compare and contrast practitioners' views. . .with academic research" (p. 247). They identified research opportunities that were viewed as unresolved by both groups. Since then, much meaningful research has taken place in the scanner data domain both by academics (e.g., Bronnenberg, Kruger, and Mela 2008) as well as by practitioners/intermediaries (e.g., Information Resources, Inc.; Nielsen, North America), and retailers have been among the primary beneficiaries.

Repetitive Decisions

Retailers make many of the same decisions repeatedly. For example, managers in retail grocery chains must set prices daily for thousands of products, integrating information about retail price elasticities amid uncertain competitive reactions (Kayande et al. 2009). Although as many as 94 percent of grocers may use gut feeling for making pricing decisions (e.g., Reda 2003), powerful customer analytics methods exist that those grocers could use to optimize their daily, repetitive prizing task (Montgomery 2005).

As another example, consider Kroger. Most of Kroger's customers have the Kroger shoppers' card, allowing Kroger to track which customers purchase what kind of products.[4] Merging shoppers' card data with scanner data provides Kroger with customer insights and opportunities to engage with the customers in a meaningful way: for example, rather than sending the same coupons to all customers, Kroger sends customized coupons for products that customers have purchased in the past (based on shoppers' card data) as well as products that customers are most likely to be interested in purchasing in the future, based both on shoppers' card data and scanner data for all their customers. Thanks to its customer analytics-based methods, Kroger generates and sends its coupons automatically and frequently.

Thus, considering that (1) retailers have access to a large volume of customer data, (2) powerful customer analytics methods tailored to retailers are available, and (3) customer-analytics based methods exist for many retailing decisions that are made on a regular basis, we hypothesize:

H1. Retailers' financial performance will increase as their customer analytics deployment increases.

The above discussion also suggests that retailers should benefit more from deploying customer analytics than firms in most other industries. First, thanks to, for example, detailed scanner data, retailers have access to more customer data than firms in many other industries (e.g., Van Bruggen and Wierenga 2000). Second, due in large part to research programs such as the one initiated by Bucklin and Gupta (1999), more and perhaps better customer analytics-based methods exist in the retailing industry than in many other industries. Third, many of the existing customer analytics-based methods in the retailing space can be used to support repetitive decision making. Indeed, powerful customer analytics-based methods exist to aid retailers make daily prizing decisions or to help them decide who to send coupons to and what type of coupons to send (e.g., Bronnenberg, Kruger, and Mela 2008; Montgomery 2005). In contrast, to the best of our knowledge, customer analytics-based methods used to aid repeated decision-making are significantly sparser in many other industries. Thus, we hypothesize:

H2. Retailers' will benefit more from increases in customer analytics deployment than will firms in most other industries.

[4] These insights are based on conversations between the authors and Kroger personnel.

Table 1
Profile of respondents.

Position	Number of respondents	Percentage
Chief Executive Officer (CEO)	70	17
Chief Marketing Officer (CMO)	56	13
Head of Marketing	93	22
Chief Sales Officer (CSO)	25	6
Head of Sales	36	9
Chief Commercial Officer	22	5
Chief Marketing and Sales Officer	24	6
Head of CRM	18	4
Other	74	18
Total	418	100

Data and Methodology

Data Collection Procedure and Scales

With the support and sponsorship of McKinsey and Company, we conducted a worldwide online survey among senior executives in three regions – the Americas, Europe, Middle East and Africa (EMEA), and Asia. We addressed the respondents using personalized emails, 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.

Of the 5,205 executives contacted, 418 participated in the survey, yielding an effective response rate of 8.03 percent. As we show in Table 1, over 80 percent of the respondents were division heads or higher, suggesting that they should be knowledgeable about their firms' capabilities and actions. We also asked the respondents to report their confidence levels with the information they provided (Kumar, Stern, and Anderson 1993). The sample mean was 5.58 (out of seven [SD = 1.12]), indicating a high level of confidence.

The respondents answered a variety of questions, of which two sets are of particular importance here – (1) customer analytics deployment and (2) firm performance. We adapted those scales from Germann, Lilien, and Rangaswamy (2013), listed in the Appendix. The coefficient alphas of the two constructs are both greater than 0.8, suggesting internal consistency and reliability (Bagozzi, Yi, and Phillips 1991). We investigated possible nonresponse bias by comparing the construct means for early and late respondents (Armstrong and Overton 1977) and found no significant differences.

Descriptive Statistics

Table 2 shows some descriptive statistics of our sample firms and indicates that the sample represents a broad range of firms, industries, and regions. Table 3 provides summary statistics and correlations of our focal variables.

For our subsequent analysis, we average the variables that form our two focal constructs, that is, customer analytics deployment and firm performance. Our sample firms display a wide range of values for these two constructs: on the seven-point scale measuring customer analytics deployment, approximately

Table 2
Sample firm profiles.

	Number of respondents	Percentage
Regions		
Americas	122	29
EMEA	162	39
Asia	134	32
Total	418	100
Industries		
Banking	59	14
Insurance	22	5
Media, Entertainment and Information	32	8
Retailing	38	9
Hospitality	14	3
Telecom	42	10
Energy	64	15
Other	147	35
Total	418	100
Employees		
≤ 500	67	16
501–1,000	55	13
1,001–5,000	111	27
5,000–50,000	130	31
> 50,000	55	13
Total	418	100

Note: The profile pertains to either the business unit or the overall company associated with our respondents, depending on which UNIT the respondents selected when completing the survey.

25 percent of the sample firms fall within the 6–7 range and 20 percent within the 1–3 range ($M = 4.6$; SD = 1.51). Further, with regard to firm performance, approximately 21 percent of the sample firms fall within the 6–7 range and approximately eight percent score within the 1–3 range ($M = 4.8$; SD = 1.18). The individual variables that form the constructs are all approximately normally distributed as well.

Model

To test our hypotheses, we used a hierarchical Bayesian regression model with a shrinkage specification to allow for industry-specific regression coefficients. This model is a popular marketing tool to model heterogeneity (Rossi and Allenby 2003); we use it here as we seek implications of customer analytics deployment that may differ by industry. Our model takes the following form:

$$Firm\ Performance_{ij} = \beta_{0j} + \beta_{1j} Customer\ Analytics_{ij} + \in_{ij} \tag{1}$$

where $Firm\ Perfomance_{ij}$ is the performance of firm i in industry j, β_{0j} is the random intercept to be estimated per industry, β_{1j} is the random slope to be estimated per industry, $Customer\ Analytics_{ij}$ is firm i's (in industry j) score on the deployment of customer analytics variable, and ϵ_{ij} is distributed normally with homogeneous variance across industries, that is $\in_{ij} \sim N(0, \sigma^2)$. Heterogeneity is modeled as $\beta_j \sim N(\bar{\beta}, \sum)$. We note that there are a number of other potential variables we could have included in the model; however in the interest of maintaining a clear simple narrative (e.g., Lehmann, McAlister, and Staelin 2011), we did not include these additional variables in our main model, but address the issue of missing variables as a robustness check below.

We estimated our model using 10,000 Markov chain Monte Carlo (MCMC) draws, using the first 5,000 draws as the burn-in period and the remaining 5,000 for estimation.

Results

Empirical estimates of the association between customer analytics deployment and firm performance show that, on average, all industries benefit financially from deploying customer analytics, with an overall average effect of about 0.29. Thus, a one-unit increase in the deployment of analytics (on a scale from 1 to 7) is, on average, associated with a 0.29 unit increase in firm performance across all regions (also on a scale from 1 to 7).

Fig. 1 shows the posterior means of customer analytics' effect on firm performance by industry. An analysis of the posterior distribution of the retailing industry's coefficient indicates that the probability that it is greater than zero is more than 0.99, providing strong empirical support for H1. Also, while all industries seem to benefit from using customer analytics, Fig. 1 suggests that some benefit considerably more than others, demonstrating heterogeneity in the deployment-performance link across industries. Moreover, Fig. 1 suggests that firms in the retailing industry have more potential for financial gain from increasing customer

Table 3
Correlations and summary statistics for items on customer analytics use and firm performance.

Variables	Correlations					
	1.	2.	3.	4.	5.	6.
1. In our firm/BU, we extensively use customer analytics	1					
2. Virtually everyone in our firm/BU uses customer analytics-based insights	.664	1				
3. When making decisions, we back arguments with analytics-based facts	.718	.755	1			
4. Please describe the performance of your business: Total Sales Growth	.277	.277	.328	1		
5. Please describe the performance of your business: Profit	.283	.266	.290	.590	1	
4. Please describe the performance of your business: return on Investment	.300	.294	.299	.625	.758	1
Summary statistics						
Mean (out of seven)	4.83	4.15	4.82	4.76	4.87	4.76
Standard deviation	1.62	1.81	1.61	1.36	1.35	1.32

Please cite this article in press as: Germann, Frank, et al, Do Retailers Benefit from Deploying Customer Analytics? *Journal of Retailing* (xxx, 2014), http://dx.doi.org/10.1016/j.jretai.2014.08.002

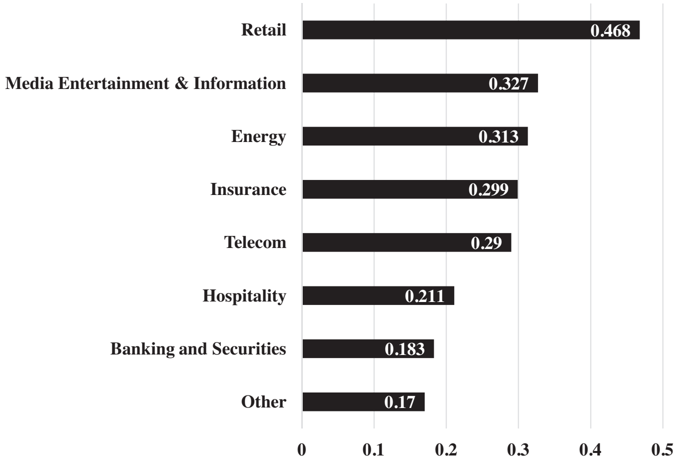

Fig. 1. Estimates of the association between customer analytics deployment and firm performance by industry. *Note*: All coefficients are greater than zero with a probability of more than .95.

analytics than firms in any of the other seven industries. Indeed, an analysis of the posterior distributions by industry shows that the retailing industry's coefficient is greater than the remaining industries' average coefficient with a probability of more than 0.99. Thus, our results provide empirical support for H2.[5]

Robustness Checks

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. Using Mergent Online and following the procedure outlined by Germann, Lilien, and Rangaswamy (2013), we computed the return on assets (ROA) for as many of the firms as possible (for the year 2012). This procedure yielded objective ROA data for 32 of the 418 firms.[6] We then regressed the (sub-) sample firms' objective performance score on the average of the three items that form the deployment of customer analytics scale (see Appendix) using Ordinary Least Squares (OLS) regression. The regression model was significant (F-value $(1, 30) = 9.076$; $R^2 = .23$; *Adj.* $R^2 = .21$), and higher levels of deployment of customer analytics are associated with an increase in objective firm performance ($\beta_{\text{Deployment of Customer Analytics}} = .584$, $t = 3.013$, $p < .01$). We repeated this analysis using a structural equation model (SEM) that included all three deployment of customer analytics scale items as well as the objective performance measure with very similar results and found our inferences are robust to model type, OLS or SEM.

Omitted variables. Our model is a nested version of the model used by Germann, Lilien, and Rangaswamy (2013). Besides the direct path from analytics use to performance that we estimate, Germann, Lilien, and Rangaswamy (2013) also included (1) industry competitiveness, (2) customers' needs and wants change, and (3) industry prevalence of analytics use as moderators in their model.[7] To address a potential omitted variable bias in our main results, we reran our model and included these additional three variables as controls. The results did not change in any meaningful way and confirmed that retail firms derive more benefit from using analytics than firms in any other industry.[8]

Endogeneity of customer analytics use. Our analysis does not preclude the possibility that the quality of firm management drives both analytics use in the firm and firm performance. To address this potential endogeneity issue, we sought an instrument that is correlated with analytics use in the firm but not with management quality (Wooldridge 2003, p. 462). The survey asked respondents (on a 1–7 scale) to report the degree to which "customer analytics is used extensively in our [their] industry." That item is significantly and positively correlated with analytics use in the firm ($r = .6$) and it seems reasonable to assume that analytics use in the industry would not be significantly correlated with the management quality of the firm. Using all 418 observations, we next conducted a residual test (e.g., Wooldridge 2003, p. 596) and added the residual from the regression of customer analytics use on customer analytics use in industry (i.e., our instrument) into our main model, that is, the regression of firm performance on customer analytics use. The estimate for this residual was not significant, suggesting that analytics use is not endogenous.

Discussion and Conclusions

Our results suggest that, of the industries examined, retailers seem to benefit the most from increases in deployment of customer analytics. One might then assume that retailers would both perceive this potential and invest accordingly. Neither seems to be the case.

Post Hoc Analysis

Fig. 2 (Histogram A) shows the average response (per industry, on a 7-point scale) to the three items that form the deployment of customer analytics scale (see Appendix). Retailers, on average, deploy customer analytics slightly less than the average non-retail firm in our sample ($\bar{x}_{analytics\ use\_retailers} = 4.55$ vs. $\bar{x}_{analytics\ use\_all\ other\ firms} = 4.64$). Respondents from the

[5] We also estimated region-specific posterior means of customer analytics' effect on firm performance. The results suggest that customer analytics' positive and significant effect in the retailing industry holds across all three regions, having the greatest effect of all industries in the Americas and EMEA, and a close second (behind the insurance industry) in Asia. The retailing industry's coefficient is greater than zero with a 0.99 probability in all three regions.

[6] Due to data availability constraints in EMEA and Asia, most of the subsample firms are from the Americas.

[7] Like Germann, Lilien, and Rangaswamy (2013), we asked respondents to respond (on a 1–7 scale) in our survey to the following three items: (1) We face intense competition, (2) Our customers' needs and wants change frequently, and (3) Customer analytics is used extensively in our industry.

[8] In fact, the coefficient of the retailing industry even increased in this analysis to .69 (and the probability that the coefficient is greater than zero remained at more than 0.99).

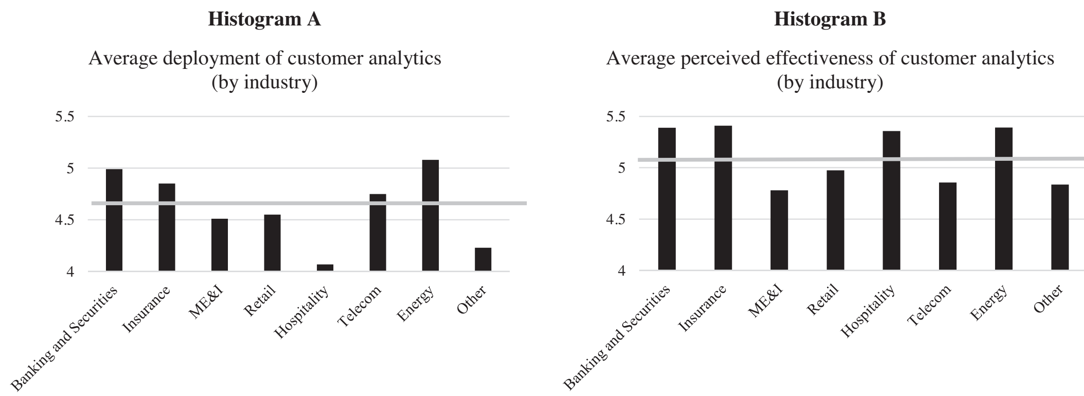

Fig. 2. Histogram A: Average deployment of customer analytics (by industry). Average response on a 7-point scale (1 – disagree to 7 – agree) per industry to the three deployment of customer analytics items. The gray line shows the average ($\bar{x} = 4.64$) across all non-retailing industries. ME&I stands for Media Entertainment and Information. The three items are listed in the Appendix. Histogram B: Average perceived effectiveness of customer analytics (by industry). Average response on a 7-point scale (1 – disagree to 7 – agree) per industry to the following question: "The use of customer analytics contributes significantly to our firm's/business unit's performance." The gray line shows the average ($\bar{x} = 5.15$) across all non-retailing industries.

banking and securities, insurance, telecom, and even the energy industries, on average, seem to use customer analytics more than do respondents from the retailing industry.

Perhaps accordingly, retailers also seem to perceive that deploying customer analytics contributes less to their performance than the average firm in our sample. Histogram B in Fig. 2 shows the response (again per industry, on a 7-point scale) to the following additional question captured in the survey: "The use of customer analytics contributes significantly to our firm's/business unit's performance." On average, retailers perceive analytics' effectiveness to be slightly lower than the average non-retail sample firm does ($\bar{x}_{analytics\,effectiveness\_retailers} = 4.97$ vs. $\bar{x}_{analytics\,effectiveness\_all\,other\,firms} = 5.15$). Note again that respondents from the banking and securities, insurance, hospitality and energy industries, on average, perceive customer analytics to be more effective than do respondents from the retailing industry.

The survey also asked respondents about their customer analytics investments and how they have changed year-over-year. Fig. 3 shows average responses (again per industry, on a 7-point scale) to the question "Compared to the last 12 months and considering the coming 12 months, how have your firm's/business unit's one-time expenses for customer analytics changed (in percent)?" The results suggest that many firms have made noteworthy investments in customer analytics from 2012 to 2013: firms (excluding retailers) increased their onetime investments in customer analytics by 16.0 percent on average year-over-year. In contrast, while retailers are indeed investing in their customer analytics capabilities, with a year-over-year percentage-change in onetime investments of 13.8 percent, they trail the overall average by over two percent.

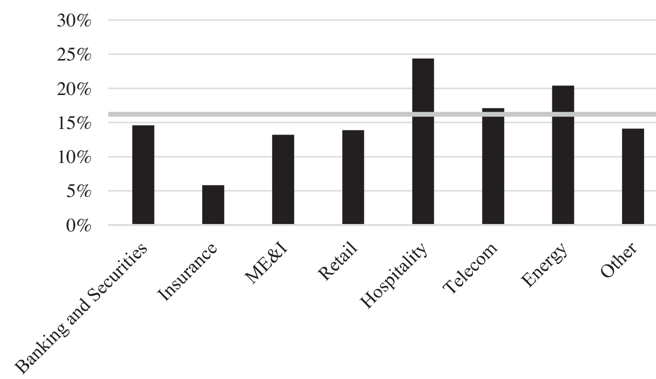

Fig. 3. Average one-time investment changes in overall analytics (year-over-year and by industry). Average response on a 7-point scale (1 – disagree to 7 – agree) per industry to the following question: "Compared to the last 12 months and considering the coming 12 months, how have your firm's/business unit's one-time expenses for customer analytics changed (in percent)?" The gray line shows the average ($\bar{x} = 16\%$) across all non-retailing industries. ME&I stands for Media Entertainment and Information.

Limitations

Although we believe that we have broken some new ground with this work, there are clear limitations. First, our main measures are perceptual, not objective. While we use existing scales and multiple items to measure our two focal variables, our analysis assumes that each industry respondent perceives the survey questions to have the same meaning. Hence, we cannot rule out the possibility that respondents from different industries understand and answer survey questions differently, an issue that could be addressed in future research. (We note, however, that qualitative interviews with respondents from different industries did not reveal any industry-specific biases as far as responding to analytics-related survey questions is concerned). Second, we do not examine the actual financial return that a firm could expect from its investments in customer analytics. Third, our findings are correlational, not causal: while we find that an increase in customer analytics is associated with higher firm performance, we cannot make direct causal claims regarding this relationship. Also, given the nature of our (cross-sectional) data, we cannot rule out potential reverse-causality issues. We note, however, that there is a growing body of case evidence that suggests that the use of analytics leads to performance gains and not vice versa (e.g., Davenport and Harris, 2007; Kumar et al. 2014). Moreover, Brynjolfsson, Hitt, and Kim (2011) find evidence that the effect of analytics use on firm performance appears to be causal, and not driven by the possibility that high performing firms may have a greater propensity to invest in analytics use in the absence of real benefits. Future research using a longitudinal approach would be useful to focus on how changes in the deployment of customer analytics affect (subsequent) firm performance.

Implications and Conclusions

We have found that not only do retailers seem to benefit from deploying customer analytics but that the benefits they can obtain are greater than what firms in other industries can obtain. Given the discussion above, these results might come as a surprise to some retailers, who neither seem to perceive this potential benefit nor seem to be willing to invest at a level that is in line with that benefit. We hope our research encourages retailers to change their beliefs about customer analytics, and that it also encourages academics to further explore the antecedents and impact of customer analytics in the retail sector.

Acknowledgments

The authors thank Gerrit van Bruggen, Peter Ebbes, Timothy Gilbride, Ujwal Kayande, and Raji Srinivasan for helpful comments on an earlier version of this article. They also thank Jesko Perrey, Director and Global Knowledge Leader of the Marketing and Sales Practice at McKinsey & Company for his helpful support.

Appendix. Scale items

Measure	Items (1–7 scale)
Deployment of customer analytics $\alpha = .88$	1. In our firm/business unit, we extensively use customer analytics
	2. Virtually everyone in our firm/business unit uses customer analytics-based insights to support decisions
	3. When making decisions, we back arguments with customer analytics-based facts
Firm performance $\alpha = .85$	Please describe the performance of your firm/business unit in the following areas relative to your average competitor (consider the immediate past year in responding to these items)
	4. Total Sales Growth
	5. Profit
	6. Return on Investment

Source of scales: Germann, Lilien, and Rangaswamy (2013).

References

Armstrong, J. Scott. and Terry S. Overton (1977), "Estimating Non-Response Bias in Mail Surveys," *Journal of Marketing Research,* 14 (3), 396–402.

Bagozzi, Richard P., Youjae Yi and Lynn W. Phillips (1991), "Assessing Construct Validity in Organizational Research," *Administrative Science Quarterly,* 36 (3), 421–58.

Bertolucci, Jeff (2013), "Big Data For Mom-And-Pop Shops," *Information Week,* (April), www.informationweek.com

Bronnenberg, Bart J., Michael W. Kruger and Carl F. Mela (2008), "The IRI Marketing Data Set," *Marketing Science,* 27 (4), 745–8.

Brynjolfsson, Erik, Lorin M. Hitt and Heekyung Hellen Kim (2011), *"Strength in Numbers: How Does Data-Driven Decision-making Affect Firm Performance?" Working Paper,*.

Bucklin, Randolph E. and Sunil Gupta (1999), "Commercial Use of UPC Scanner Data: Industry and Academic Perspectives," *Marketing Science,* 18 (3), 247–73.

Cosentino, Tony (2012), *Shifts in Retail Demand New Analytics,*. Available at http://www.ventanaresearch.com/blog/commentblog.aspx?id=3425 (accessed 20.01.14)

Davenport, Thomas H. and Jeanne G. Harris (2007), *Competing on Analytics: The New Science of Winning,* Boston, MA: Harvard Business School Press.

Fiedler, Lars, Frank Germann, Matthias Kraus and Jesko Perrey (2013), "Koenig Kunde – Kapital Kundenwissen," *Akzente,* 3, 24–9.

Gauri, Dinesh (2013), "Benchmarking Retail Productivity Considering Retail Pricing and Format Strategy," *Journal of Retailing,* 89 (1), 1–14.

Germann, Frank, Gary L. Lilien and Arvind Rangaswamy (2013), "Performance Implications of Deploying Marketing Analytics," *International Journal of Research in Marketing,* 30 (2), 114–28.

Guadagni, Peter M. and John D.C. Little (1983), "A Logit Model of Brand Choice Calibrated on Scanner Data," *Marketing Science,* 2 (3), 203–38.

Kayande, Ujwal, Arnaud De Bruyn, Arvind Rangaswamy and Gerrit Van Bruggen (2009), "How Incorporating Feedback Mechanisms in a DSS Affects DSS Evaluations," *Information Systems Research,* 20 (4), 527–46.

Kumar, Nirmalya, Louis W. Stern and James C. Anderson (1993), "Conducting Inter-organizational Research Using Key Informants," *Academy of Management Journal,* 36 (6), 1633–51.

Kumar, V. and Andrew J. Petersen (2012), *Statistical Methods in Customer Relationship Management,* West Sussex, UK: John Wiley & Sons Ltd.

Kumar, V., Amalesh Sharma, Naveen Donthu and Carey Rountree (2014), "Implementing Integrated Marketing Science Modeling at a Non-Profit Organization: Balancing Multiple Business Objectives at Georgia Aquarium," *Marketing Science,*, (forthcoming).

Lawrence, Paul R. and Jay W. Lorsch (1967), *Organizations and Environment,* Boston: Harvard University.

Leeflang, Peter S.H. and Dick R. Wittink (2000), "Building Models for Marketing Decisions: Past, Present and Future," *International Journal of Research in Marketing,* 17 (2–3), 105–26.

Lehmann, Donald R., Leigh McAlister and Richard Staelin (2011), "Sophistication in Research in Marketing," *Journal of Marketing,* 75 (4), 155–65.

Montgomery, Alan L. (2005), "The Implementation Challenge of Pricing Decision Support Systems for Retail Managers," *Applied Stochastic Models in Business and Industry,* 27 (4–5), 367–78.

Podsakoff, Philip M., Scott B. MacKenzie, Jeong-Yean Lee and Nathan P. Podsakoff (2003), "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies," *Journal of Applied Psychology,* 88 (5), 879–903.

Reda, Susan (2003), "Despite Early Positive Results, Retailers haven't Jumped on Analytics Bandwagon," *Stores,* 85 (3), 34.

Rossi, Peter E. and Greg M. Allenby (2003), "Bayesian Statistics and Marketing," *Marketing Science,* 22 (3), 304–28.

Thau, Barbara (2013), "Can 'Predictive Analytics' Help Retailers Dodge a J.C. Penney-Style Debacle?," *Forbes.com,*,. Available at http://www.forbes.com/sites/barbarathau/2013/04/22/can-predictive-analytics-help-retailers-dodge-a-j-c-penney-style-debacle (accessed October 2013)

Van Bruggen, Gerrit H. and Berend Wierenga (2000), "Broadening the Perspective on Marketing Decision Models," *International Journal of Research in Marketing,* 17 (2–3), 159–68.

Wooldridge, Jeffrey M. (2003), *Introductory Econometrics,* 2nd ed. Mason, OH: Thomson South-Western.

Zeithaml, Valarie A., P. Rajan Varadarajan and Carl P. Zeithaml (1988), "The Contingency Approach: Its Foundations and Relevance to Theory Building and Research in Marketing," *European Journal of Marketing,* 22 (7), 37–64.