Customer Analysis and Financial Performance: Empirical Evidence from the Polish Insurance Market

CONFERENCE PAPER · SEPTEMBER 2015

DOI: 10.13140/RG.2.1.1985.2246

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The paper was accepted for the 6th EMAC Regional Conference in Vienna, September 16-18, 2015

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CUSTOMER ANALYSIS AND FIRM PERFORMANCE: EMPIRICAL EVIDENCE FROM THE POLISH INSURANCE MARKET

Abstract

The paper outlines the outcomes of an empirical investigation of the links between involvement of insurance firms in customer analysis and their financial performance. The data were collected through a CAWI survey of independent insurance agents in Poland (n=590). Statistical methods included exploratory factor analysis and structural equation modeling. In keeping with the customer lifetime value model and loyalty management theory the concept of customer analysis was operationalized as a second-order reflective construct, expressed through five first order subconstructs. Financial performance was measured with an index of five self-reported metrics. The findings lent support to the hypothesis of a positive association between engaging in customer analysis and financial performance.

Keywords: customer analysis, customer research, customer lifetime value, financial performance, insurance industry, Poland.

Theoretical background

Customer analysis (CA), encompassing customer data collection, profitability measurement and lifetime value estimation, is a crucial component of several well-known marketing concepts, such as customer relationship management (Reinartz et al., 2004), customer lifetime value management (Doligalski & Tomczyk, 2014; Tomczyk, 2014; Akroush et al., 2011) customer equity management (Bruhn et al., 2008) and interaction orientation (Ramani&Kumar, 2008). As such, CA components often appear in marketing studies as elements of other constructs or conceptual systems, but comprehensive research that centers on how companies' involvement in CA is linked with financial performance (FP) is scarce. Out of a few quantitative studies that addressed this topic, mild positive effects were reported by Akroush et al.(2011), who found that collecting information about key customers by banks and insurance firms had a weak but statistically significant association with financial performance. According to another study, collecting and processing data about customer profitability was a crucial component of how the utility of CRM systems was viewed by managers (Bruhn et al., 2008); there the CRM value was strongly dependent on perceived benefits from the use of the system, which involved the amount of generated profits. In contrast, negligible or no effects on earnings of various aspects of CA were noted by Ramani and Kumar (2008). On the whole, it seems that the problem of links between CA and FP is not sufficiently investigated, as evidenced by the ambiguity of findings and the lack of works that take a systematic and complete view of CA. Thus, it can be argued that the current study makes a contribution address this gap in marketing theory.

In the current study, following guidelines from the literature and our own observations, we conceptualized CA as a second order reflective construct with five first order latent variables derived from marketing and consumer behavior theory. In particular, we made use of the customer lifetime value model and loyalty management theory.

CA represents a key element in the measurement of customer lifetime value (CLV), which is based on estimating a current amount of net benefits accrued by a company over the length of its relationship with a customer (Doligalski, 2015; Borle et al., 2008). The key value streams here comprise cash flows (Gupta & Lehmann, 2003), which are a discounted difference between revenues and marketing costs incurred to maintain the relationship with a customer (Berger & Nasr, 1998). The need for measuring financial costs and benefits gave rise to the first two CA components, named **Customer Costs (COS)** and **Revenues and Earnings (REV)**. Since the CLV identification based on expected costs and earnings enables a more advanced marketing practice of differentiating customer groups, we came up with **Customer Segmentation (SEG)** as another component of the CA construct.

The above financial metrics fail to capture less quantifiable but still very relevant benefits from the company-customer relationship (Bauer et al., 2003; Bauer & Hammerschmidt, 2005). CLV is, inter alia, a function of loyalty (Keane & Wang, 1995). Loyalty management calls for information about customer behavior, preferences and referrals, as well as estimation of non-monetary values of key streams delivered to the company during its relationship with the customer (e.g. recommendations, image benefits, behavioral patterns and other insights gained from customers). Thus, we introduced in our model the subconstruct **Intangible Benefits and Customer Behavior (INT).**

Quantifiable benefits and knowledge of customer intangible benefits and behavior are not sufficient to fully assess the CLV potential. To supplement their existing customer records, companies need to look at prospective clients in terms of characteristics of desired products and services (Doligalski, 2015), likelihood of purchasing (Dwyer, 1989) and future benefits from customer retention (Rosset et al., 2003). This aspects of CA were operationalized as the last element of our measurement model labeled **Prospective Customers (PRO).** The specific content of the items used for measuring each of the five subconstructs were given in Table 1 in the results section.

Research objectives and method

The study aims to explore the relationship between involvement of insurance service providers in customer analysis and their performance. Based on the presented literature review we hypothesized that **higher extents of customer analysis would correspond with better financial outcomes**. By the same token, **low levels of customer research would characterize relatively underperforming firms**.

To test the hypothesis of a positive link between customer analysis and financial performance we collected data from insurance salespersons who operated as independent intermediaries. They were micro-entrepreneurs, catering to both B2B and B2C markets, selling all kinds of popular insurance policies (life and non-life). On the whole, 590 questionnaires with complete response sets were collected through CAWI method in October and November 2012. The sample was drawn from a larger database that included insurance providers from across the whole country, which could be considered an adequate representation of this part of the insurance industry in Poland.

The questionnaire had 18 Likert scale items for measuring various aspects of customer analysis practices. The particular statements were adopted from previous studies on similar topics to encompass all salient aspects of CA that were applicable to insurance intermediaries.

The two techniques used in statistical analysis included exploratory factor analysis (EFA) and structural equation modeling (SEM), available in SPSS 22 and AMOS 22.

Research Outcomes

In our statistical data processing the first step involved an EFA with maximum likelihood as the estimation method and oblique rotation of the factor matrix. The EFA solution confirmed our initial theory-driven assumptions that the Likert scale items are manifest variables for five distinct hidden variables that represented different focus areas of customer analysis (we chose not to provide detailed outputs of the EFA due to space constraints in the paper). The specific meaning of each hidden variable can be gleaned from Table 1 by looking at their associated items. The pattern of hidden and manifest variables, as set out in Table 1, was replicated in the subsequent structural equation model that was developed to test the hypothesis of a positive relationship between customer analysis and financial performance.

Table 1: Operationalization of Customer Analysis in the current study

Focus areas (subconstructs) of Customer Analysis	Item designation	Item content
Customer Costs (COS)	COS1	We collect information about costs of acquiring each customer
	COS2	We collect information about costs of servicing each customer
	COS3	We estimate acquisition costs of each customer
	COS4	We estimate future costs of servicing each customer
Revenues and Earnings (REV)	REV1	We gather information about revenues from providing service to each customer
	REV2	We estimate future revenues from selling to each customer
	REV3	We estimate expected profits from each customer
Intangible Benefits and Customer Behavior (INT)	INT1	We collect information about referrals and recommendations from each customer
	INT2	We collect information about preferences of each customer
	INT3	We try to learn behavioral patterns of our customers
	INT4	We assess the value of information provided by customers
	INT5	We identify the value of image gains from selling to a given customer
Customer Segmentation (SEG)	SEG1	We categorize our customers according to estimated future benefits from cooperation
	SEG2	We make our decisions to cooperate with customers based on

		estimated amounts of future benefits
	SEG3	We resign from servicing those customers who fail to bring in expected benefits
Prospective Customers (PRO)	PRO1	We determine the likelihood of acquiring each customer
	PRO2	We estimate the length of likely cooperation with each customer
	PRO3	We evaluate likely benefits from cooperating with each customer

Source: Own elaboration

The structural equation analysis conceptualized involvement in customer research as a second order reflective construct expressed through five first order subconstructs, as specified in Table 1.

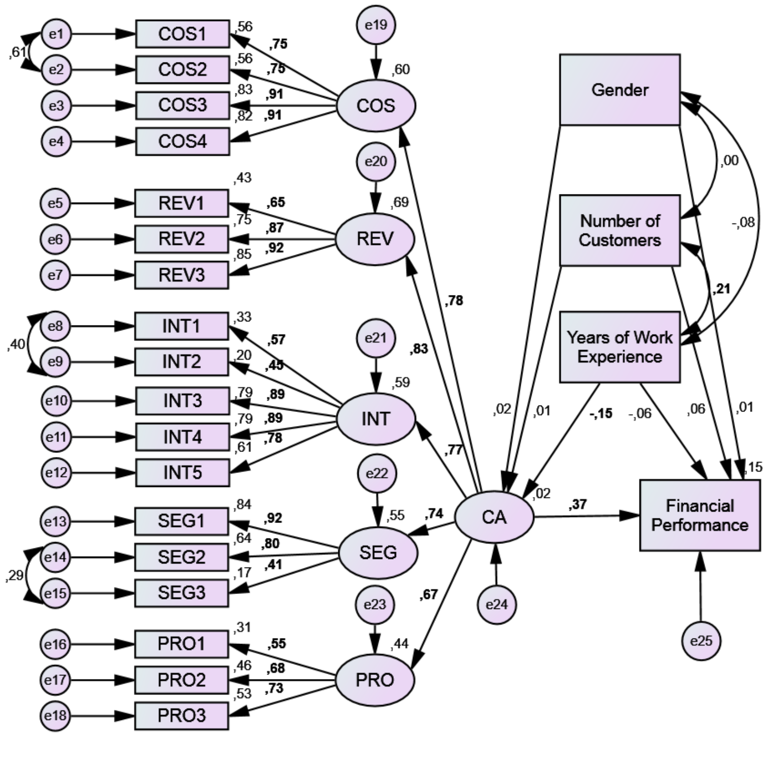
To measure financial performance we used a composite variable obtained by taking an arithmetic average of scores on the five Likert type items: (1) Mean earnings per customer that we have obtained this year are greater as compared to the previous year; (2) We expect that the mean earnings per customer will be higher the next year as compared to the present one; (3) The average monthly commission that we earned this year was greater than the last year; (4) Our total profits this year were greater than the previous year's profits; and (5) In the current calendar year we managed to reach our profit targets.

As such, the financial outcomes were considered a formative construct and computing a mean is one of the common ways to incorporate this type of variable in structural equation models (Temme et al., 2014).

In addition to the outcome and predictor variables the structural model also controls for possible extraneous variables, such as gender of the firm's owner, number of serviced customers and years of work experience of the firm's owner.

The model's structure and its standardized parameters are depicted in Figure 1.

Figure 1: Structural equation model for relationship between CA and FP
(significant standardized regression weights were marked in bold)



Source: Own elaboration

To assess the model fit with the empirical data a number of typical diagnostic metrics was obtained and set out in Table 2.

Table 2: Overall diagnostics for the structural model

Metric	Value	Threshold for a well-fitting model
Chi-square/df (relative chi-square)	2.942	<2 for good fit, <3 for acceptable fit
p-value for the model	<0.001	>0.05
GFI (goodness of fit index)	0.918	≥0.9
CFI (comparativefitindex)	0.941	≥0.9
AGFI (adjusted goodness of fit index)	0.897	≥0.8
RMSEA (root mean square of approximation)	0.057; HI90=0.063	≤0.05 for good model fit; ≤0.08 for adequate fit; in addition, the upper 90% confidence limit (HI 90) should be no more than 0.08 for a well-fitting model

Source: Own elaboration. Cutoff points based on Garson (2012).

The table suggests that according to most of the metrics the model fits the empirical data adequately. The only exception being the chi-square test, which is significant and leads to rejecting the null hypothesis of the lack of differences between the observed covariance matrix and the one recreated from the model. However, for large sample sizes, which result in increased sensitivity of all statistical tests, this measure is considered unreliable and could be disregarded if other metrics imply a well-fitting solution, which was the case with the current analysis (Byrne 2010, pp 76-77; Bowen, Guo 2012, p. 142).

The next table centers on individual subconstructs and offers insights into their internal reliability (Cronbach's Alpha), convergent validity (AVE, or average variance extracted) and discriminant validity (MSV, or maximum shared variance).

Table 3: Reliability and validity measures of component constructs in the structural model

Construct	Cronbach's Alpha	AVE	MSV
Costs	0.911	0.693	0.436
Revenues and Earnings	0.848	0.537	0.436
Intangible Benefits and Customer Behavior	0.854	0.544	0.423
Customer Segmentation	0.772	0.550	0.372
Prospective Customers	0.715	0.433	0.314

Source: Own elaboration

All subconstructs display sufficient internal validity with Cronbach's alphas greater than 0.7 (Malhotra, 2014, p. 287). In terms of convergent validity four hidden variables had AVE values above a threshold of 0.5 (Hair et al., 2010). The subconstruct Prospective Customers has the AVE metric lower than 0.5, which suggests that above half of the variance in manifest variables was accounted for by other factors, not included in the model. One such factor could be the marketing strategy followed by a company, which might be fairly independent from what companies do in the area of customer research. Such a low value of AVE may justify removing the construct from the solution, but seeing that collecting and processing information from would-be clients seems to be a useful complement of the other areas of customer analysis, we decided to keep it. In terms of discriminant validity, which considers if factors were explained better by their own indicators than the indicators for other factors, the metrics do not signal any marked problems, with MSV values being lower than AVE for each of the constructs (Hair et al., 2010).

It can be noted that the path diagram has three correlated error terms, which was done to obtain gains in the model fit. This is an acceptable practice if the linked error terms are for manifest variables under the same construct, but not across different constructs (Mulaik, 2009, pp. 342-345).

On the whole, the model seems to be an adequate representation of empirical data and could provide a basis for hypothesis tests and interpretations.

Looking at the regression weights between CA, FP and the three extraneous variables, it is clear that CA had a mild but significant influence on FP. The standardized regression weight of 0.36 implies that this factor explained about 14% of variance in financial outcomes, with the rest of variability (86%) accounted for by other determinants not subsumed within the model. In addition it seems that the positive impact of CA was fairly independent of the salient characteristics of businesses and their owners, as only Years of Work Experience was slightly negatively associated with CA. This suggests that there might have been some substitution of professional experience for actual research, especially among older respondents, but this does not change the general conclusion of the positive link between CA and performance. In consequence, **the study provides support for the hypothesis that increased involvement in customer analysis corresponds with enhanced financial outcomes.**

Discussion and limitations

According to our findings, CA is positively correlated with FP. This is an important observation, as it justifies activities in the area of CA. The further research may investigate which specific practices and techniques comprising CA are most effective at improving FP. CA allows customer segmentation, and consequently key customer focus (Sin, 2005). This facilitates adopting various measures aimed at customers of unsatisfactory or even negative profitability, which can include relationship termination (Pepers & Rogers, 2011). Interestingly, in contrast to our findings key customer focus had no significant influence on business performance among Jordanian banks and insurance companies (Akroush et al., 2011). This discrepancy could point at cultural differences (both of a national and organizational kind) and varying CA implementation effectiveness as moderating factors in the CA – FP relationship, which could be explored in follow-up studies.

In interpreting our results, one should take note of the limitations to generalizability that stem from the specific industry and the national context of the research. Sales of insurance products are characterized by a diverse level of customer service. This leads to the situation in which customers purchasing the same product can generate various levels of costs. In other sectors this kind of costs may be lower and more equally distributed among customers, which may amount to smaller benefits resulting from CA.

Although the presented model proposes that greater involvement in CA leads to FP improvement, the reverse causal relationship is also plausible due to the presence of a feedback loop (Rosenberg, 2007). Accordingly, better FP may lead to deeper involvement in customer relations, including an increased use of CA. In our opinion, however, the strength of such reversed causal link is rather negligible as compared to the primary effect.

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