Management Accounting Research xxx (xxxx) xxxx

Contents lists available at ScienceDirect

Management Accounting Research

journal homepage: www.elsevier.com/locate/mar

The interactive effect of competition intensity and customer service competition on customer accounting sophistication—Evidence of positive and negative associations

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ARTICLE INFO

Keywords:
Management accounting systems (MAS)
Competition intensity
Competition type
Customer service competition
Customer accounting
Customer profitability analysis

ABSTRACT

Recent research implies that the association between competition intensity and management accounting system (MAS) design varies with the type of competition involved, depending on the purpose of the MAS in focus. This study finds that competition intensity can be *positively* or *negatively* associated with customer accounting (CA) sophistication depending on the extent to which firms tailor their activities and offerings to meet individual customer needs (engage in a particular type of competition labelled 'customer service competition'). When customer service competition is high we predict there will be a positive relationship between competition intensity and CA sophistication, whereas when customer service competition is low this relationship is negative. Drawing on archival data and survey responses collected from 209 firms, we obtained results that support this hypothesis. The study provides the first empirical evidence of a crossover interaction effect between competition intensity and competition type on MAS design. Moreover, the study extends earlier work on CA by developing and finding empirical evidence supporting a model which provides a more nuanced understanding that explains why certain firms implement sophisticated CA practices while others are content with simpler CA.

1. Introduction

This study empirically examines the effects of competition intensity and customer service competition on customer accounting sophistication (CA). Mainstream management accounting research posits that firms deploy increasingly sophisticated management accounting systems (MASs) when competition intensifies (Al-Omiri and Drury, 2007; Cooper and Kaplan, 1988) and practitioner literature and textbooks echo this assertion (Krishnan et al., 2002). The effects of competition on MAS design has, however, been "the subject of conflicting prescriptions, theories, and empirical evidence" (Krishnan et al., 2002, p. 274). Analytical and experimental accounting research rooted in economic theory questions the putatively unambiguous nature of the effects of competition on MAS design. This suggests instead that these effects may vary depending on both the type and level of competition faced (Callahan and Gabriel, 1998; Hansen, 1998; Krishnan et al., 2002), and empirical studies have begun to provide evidence in support of this proposition (Krishnan, 2005; Chen et al., 2015).

The current study builds on this research and predicts that it is the type of competition (i.e. degree of *customer service competition*) that determines how competition intensity affects the degree of CA sophistication a firm adopts. We predict that competition intensity can be either *positively* or *negatively* associated with CA sophistication depending on the degree of the customer service competition firms face. In line with this prediction, we expect to find evidence of a crossover interaction effect, i.e., a relationship where the effect of one explanatory variable on the dependent variable is either positive or negative depending on the condition of another explanatory variable, and where there are no main effects (see Cohen et al., 2003, p. 286). In competitive contexts where customizing offerings in accordance with customer needs is extensive (i.e., when customer service competition is high), firms will invest in more highly sophisticated CA as competition intensifies. Under these conditions, sophisticated CA practices enhances a firm's ability to measure and manage the increasingly diverse resource costs incurred when extending its customization efforts. Thus, sophisticated CA helps firms manage the rising costs of retaining increasingly disloyal customers and thereby boosts profitability. In contrast, in competitive contexts where firms generally do not compete by customizing offerings according to individual customer needs (i.e., when customer service competition is low), the objective of containing

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https://doi.org/10.1016/j.mar.2019.07.001
Received 19 June 2017; Received in revised form 28 June 2019; Accepted 1 July 2019
1044-5005/

costs as competition intensifies will induce managers to prioritize their increasingly scarce resources and reduce CA investments. Consequently, we predict that as competition intensity rises CA sophistication will decline in competitive contexts characterized by low customer service competition.

In our empirical tests we choose the specific CA technique known as Customer Profitability Analysis (CPA) as the main variable, for three reasons: First, CPA is by far the most prevalent CA practice. This is demonstrated in Guilding and McManus's (2002) sample where CPA (segmented/individually) was significantly more widely used than Customer Lifetime Value (CLV) or customer asset valuation techniques. This is also the case in our sample where fewer than 10% of the respondents stated that their firms used some kind of CLV model. Second, profitability analysis is more closely related to more established research on MASs than CLV/customer asset valuation techniques or even customer satisfaction and other non-financial customer metrics. Third, given the scarcity of empirical research on the sophistication of CA in the mainstream MA literature, when we designed our study we decided to focus our attention on a specific CA technique where we could draw on prior research on cost-system sophistication from the product-costing literature.

We use an ordered logistic regression model to test our hypothesis using survey and archival data. The survey data were provided by commercial executives from 209 large Danish and Swedish firms while industry concentration data (the Herfindahl-Hirschman Index, HHI) were provided by the Danish and Swedish statistical bureaus. We provide empirical evidence of a significant crossover interaction effect between competition intensity and customer service competition on CA sophistication. This finding supports our theoretical predictions, that in competitive contexts characterized by high customer service competition, competition intensity is positively associated with CA sophistication, and in competitive contexts characterized by low customer service competition, competition intensity is negatively associated with CA sophistication. We also test the robustness of our findings regarding model estimation, model specification, the measurement of key constructs, and various subsample analyses. These additional analyses corroborate our main findings.

Our study makes two main contributions to the management accounting literature. First, this is the first study to provide empirical evidence of a crossover interaction effect between competition intensity and competition type on MAS design. Second, the study provides a more nuanced understanding than previous work on competition to explain why certain firms implement sophisticated CA while others implement simpler CA and why motivations for CA design choices differ across competitive contexts.

The remainder of the paper is organized as follows. Section 2 reviews prior literature, defines key constructs, and develops the hypothesis. We describe the method and research design in Section 3. Section 4 covers the empirical results, including both our main analyses and additional analyses as well as robustness tests. The conclusions and contributions are presented in Section 5.

2. Theoretical background and hypothesis

This section has two parts. First, we define our key constructs. Second, we review the literature on competition and MAS design, and develop our hypothesis linking competition intensity, competition type, and CA sophistication.

2.1. Definition of constructs

2.1.1. Competition intensity and competition type

In this study, we focus on how the interplay between competition intensity and competition type influences MAS design from a customer-focused perspective (i.e. CA). A well-established perspective on competition intensity sees competition intensity in terms of market structure, particularly regarding the number of firms competing in a market and the distribution of market shares across these firms. Previous research in the area has adopted this perspective on competition intensity (Krishnan, 2005; Chen et al., 2015). While competition intensity characterizes market concentration among firms in a market, it does not tell us much about *how* firms compete in that market. Competition type reflects the various parameters within which firms compete, which in the most general form can be classified as price or non-price features, such as product, quality, and service.

The literature offers little guidance on the conceptualization of a customer-focused competition construct. Nor does Khandwalla's (1972) well-known typology of price, product, and marketing competition offer much guidance on the issue. Firms' business environments and the competitive forces shaping these environments have arguably changed fundamentally since the early 1970s. Khandwalla's (1972) typology was heavily influenced by the dominant marketing approach at the time, the traditional marketing mix paradigm (product, price, place, promotion),[1] which was popularized during the 1960s (Kotler, 1967; McCarthy, 1960). This paradigm fits the servicing of mass markets well, which was evident for the transactional, product-oriented marketing approach that was deployed at the time. Since then the scope and content of the marketing mix has become broader and more complex (Nixon and Burns, 2012). Due to globalization, technological development, and the increasing range of products available to customers, firms are increasingly targeting more highly segmented (niche) markets and ultimately individual customers (Sheth et al., 2000). This has, among other things, shifted focus from a mass marketing paradigm towards a relationship marketing paradigm whereby niche segments or individual customers have become the center of attention in many industries (Grönroos, 1994).

Based on the relationship marketing paradigm we label our competition-type construct *customer service competition*, which we define as the propensity in firms to tailor their services to individual customer needs. In competitive contexts where firms compete more on the individualization of offerings such as customer relationship–based price differentiation, tailored direct marketing campaigns, differentiated sales visits, and individualized supply chain solutions, customer service competition is considered *high*. Competitive contexts where little or no differentiation regarding price, service levels etc. across customer relationships occurs features *low* customer service competition. Customer service competition can therefore represent a distinct form of non-price competition that is clearly distinguished from other forms, such as the product competition construct whereby firms differentiate perceived (brand) and real (quality) product attributes. Hence, firms in competitive contexts where product competition is high will attempt to acquire and retain customers in their markets by emphasizing the uniqueness of their products' attributes. Firms in competitive contexts characterized by high customer service competition will however attempt to acquire and retain customers by adapting their offerings (core products as well as customer-related services) to individual customers' needs and requirements.

2.1.2. Customer accounting sophistication

CA has been defined as "accounting practices directed towards appraising [the] profit, sales, or present value of earnings relating to a customer or group of customers" (Guilding and McManus, 2002, p. 48). This definition involves a dichotomy pitting current versus future profitability that reflects the generally accepted distinction in the marketing literature on customer profitability models between retrospective *Customer Profitability Analysis* and prospective *Customer Lifetime Value* models (Pfeifer et al., 2005). In this study, we focus on customer

[1] Khandwalla (1972) replicates 'price' and 'product' competition and refers to marketing competition as 'distribution and promotion' competition, thereby essentially covering the four Ps of the original marketing mix.

profitability models for the reasons highlighted in the introduction. Consequently, when we refer to CA hereafter we refer to specific customer profitability analysis (CPA) techniques.

CA techniques are designed to create transparency regarding the revenues and costs involved in handling customer relationships across customer-related functions. This transparency can, in turn, facilitate resource allocation decisions regarding, for example, which customers to target and how to differentiate activities such as direct marketing investments, credit terms, sales force activities (e.g. sales visits), customer service activities, and delivery terms (e.g. minimum order sizes) across customer relationships. Innovations in management accounting techniques, most notably ABC (Cooper and Kaplan, 1991; Kaplan and Cooper, 1998), have been proposed as viable solutions to the challenge of estimating cost-to-serve for customer-level transactions (Goebel et al., 1998; Smith and Dikolli, 1995). Even though a full-scale ABC model is not always needed to support insightful customer management strategies (e.g., Storbacka, 1997; Mulhern, 1999), the vast majority of customer profitability model studies investigate the usefulness of the ABC technique for assigning costs to customer relationships in management accounting (e.g., Andon et al., 2003; McManus, 2007; Noone and Griffin, 1999) as well as in the marketing domain (e.g., Guerreiro et al., 2008; Helgesen, 2007; Niraj et al., 2001).

No conceptual framework that generates criteria for determining the level of sophistication of CA in estimating customer profitability has been posited in the literature. We therefore build on prior research on product-costing-system sophistication to develop a conceptualization of CA sophistication. Abernethy et al. (2001) were among the first to challenge the common perception that sophistication was merely a dichotomous choice between discrete alternatives (i.e., ABC vs. 'traditional' costing systems). Rather, sophistication was arguably to be seen as a nuanced phenomenon varying along several dimensions. A key dimension that has been pursued in subsequent research is the specific way in which a costing system handles overhead costs. This generated a sophistication spectrum with direct costing systems and simplistic, traditional costing systems with single plant-wide cost pools and allocation bases at the least sophisticated end and a multi-cost pool approach with many types of cost drivers at the most sophisticated end (Al-Omiri and Drury, 2007; Drury and Tayles, 2005). Brierley (2008) built on this idea of a spectrum of sophistication and devised a more comprehensive discussion of the concept of costing-system sophistication, drawing attention to the distinction between 'what [costs] to assign' (*Inclusion of All Costs Sophistication*) and 'how to assign' costs (*Overhead Assignment Sophistication*).

Following Brierley (2008), we conceptualize CA sophistication along these two main dimensions. First, the *Inclusion of All Costs* dimension ranges from merely accounting for the cost of goods sold (COGS) at the least sophisticated end to assigning all SG&A costs that are directly or indirectly caused by handling and interacting with customers along the value chain at the most sophisticated end. Second, the *Overhead Assignment* dimension addresses the method applied to assigning overhead costs that are caused by customer-related activities but cannot be traced directly to customers. Sophistication along this dimension is determined by the number of cost pools and cost drivers deployed (Al-Omiri and Drury, 2007). The more cost pools and cost drivers deployed to assign overhead costs that are not directly traceable to individual customers, the more sophisticated the CA.[2]

Hence, in line with research on product-costing-system sophistication, we propose that CA sophistication is determined along a spectrum. The least sophisticated model applies where customer profitability is approximated by sales or gross profits only. Expanding the range of costs by including customer-related SG&A costs adds sophistication, and increasing the number of cost pools and cost drivers when assigning indirect SG&A costs to customers adds further sophistication.

2.2. Literature review and hypothesis development

2.2.1. Competition and MAS design

Khandwalla (1972) was among the first to investigate the relationship between competition and MASs in accounting research. He argued that firms are exposed to three distinct types of competition—price, product, and marketing competition—and demonstrated that, even though all three types of competition had a positive impact on MAS use, there was a significant difference between the strength of the impact, with product and price competition being the most and least important types of competition, respectively.

The assertion of a general, positive association between competition and MASs was reiterated with the emergence of activity-based costing (ABC). Cooper (1988) and Cooper and Kaplan (1988) argued that the benefits of more accurate product cost and profitability information usually more than outweigh the costs of operating and maintaining more sophisticated costing and profitability systems. Since then, several empirical studies have investigated variants of this proposition. Increasing competition intensity has been shown to be associated with the adoption of a greater number of distinct types of MASs (Libby and Waterhouse, 1996; Williams and Seaman, 2001), increasing managerial use of benchmarking and monitoring information (Mia and Clarke, 1999), increased incidence and perceived usefulness of CA (Guilding and McManus, 2002), the deployment of more sophisticated product-costing systems (Al-Omiri and Drury, 2007), and the moderation of the ABC–financial performance relationship (Cagwin and Bouwman, 2002). However, other studies find no support for the notion of a relationship between competition and MAS design (e.g., Bjørnenak, 1997; Drury and Tayles, 2005; Schoute, 2009). Interestingly, even though most prior empirical research draws on Khandwalla's (1972) measurement model, none explores the multifaceted nature of competition by investigating various types of competition separately. Instead, they collapse several dimensions of competition (e.g. price, product, and promotion) into a single composite measure.

Another stream of research is based on ideas from economic theory (e.g. Joskow, 1983; Schmalensee and Willig, 1989), such as the structure–conduct–performance framework, which posits that "competition intensity has different effects on firm choices and outcomes in the presence of different types of competition" (Chen et al., 2015, p. 230). Thus, this literature suggests that the influence of competition on MASs is subtler than generally assumed in previous management accounting research. The theoretical reasoning based on these ideas helps to explain the mixed evidence on the association between competition and MASs (Krishnan et al., 2002; Krishnan, 2005).

Analytical and experimental studies have provided evidence highlighting the importance of distinguishing between competition intensity and competition type and studied the joint effect of these two dimensions of competition on MAS design. Callahan and Gabriel (1998) provide theoretical and experimental evidence suggesting that the value of more accurate product-cost information depends on a firm's competitive market structure (Cournot competition versus Bertrand competition) and product market strategy. These findings challenge the mainstream view that costing systems that provide materially more accurate or precise product-cost information have a value-enhancing effect on decisions (p. 419). Hansen (1998) demonstrates analytically how the relationship between demand for cost information (in terms of the investment in/design of cost accounting systems) and competition intensity varies with the level of competition (measured as the number of firms competing in a market). Experimental evidence has

[2] We note that adding cost drivers also provides the opportunity to apply a range of non-volume-based cost drivers. In the case of CA, deploying drivers that are unrelated to volume may be particularly effective in enhancing accuracy when estimating the resources consumed by individual customers. Hence, firms deploying multiple cost drivers in CA models are, as should be expected, doing so to increase measurement accuracy through the deployment of non-volume-based drivers such as number of sales visits, number of deliveries, etc.

subsequently provided support for this proposition (Krishnan et al., 2002).

More recently, empirical studies have emerged that expand on these ideas. Krishnan (2005) investigates the comparative effects of price and product (quality) competition on demand for accounting information among California hospitals. She explains how a positive association between competition intensity and demand for accounting information is present only when firms compete on *price* whereas competition intensity has no effect on demand for accounting information when firms compete on *product* (quality). Chen et al. (2015) investigate the impact of price and non-price competition on the incorporation of customer satisfaction targets in executive compensation packages in a cross-section of firms and find the association between competition intensity and the incorporation of customer satisfaction in such schemes to be stronger when firms compete on *non-price* parameters (e.g., quality, distribution etc.) than when firms compete on *price*.

2.2.2. Hypothesis development

As competition intensity increases, firms must examine the efficiency of their operational processes when facing worsening resource scarcity (Williams and Seaman, 2001). We propose that this stricter pursuit of effectiveness will also materialize when firms decide whether to implement sophisticated MASs. Hence, increasing competition intensity is expected to motivate managers increasingly to prioritize certain types of MASs. Prior research (e.g., Al-Omiri and Drury, 2007; Khandwalla, 1972) suggests that more sophisticated MASs will generally be prioritized when competition intensity is fierce. However, we propose that *resources will increasingly be allocated to the types of MAS that are relevant to firms' competitive contexts*. These investments will be made at the expense of investments in other, less relevant, MASs to optimize the return on the increasingly scarce resources available for investment. Managers may still use a broad range of management accounting controls, as proposed in prior research (e.g., Libby and Waterhouse, 1996), but these controls will be more carefully designed to align with demand for management accounting information to support planning, decision-making and evaluation needs (e.g., customer versus product profitability information).

We therefore hypothesize that the relevance of CA will depend on the degree of customer service competition encountered by firms in their competitive contexts. In competitive contexts where firms generally tailor offerings and services to meet individual customer needs (reflecting *high* customer service competition), increasing competition intensity makes the implementation of more sophisticated CA increasingly beneficial, for several reasons. Guilding and McManus (2002) argue that highly sophisticated CA practices are required to manage the greater variation in resource consumption and the derived costs across customers that arise as a consequence of the increased customization of offerings when competition intensifies in these markets. Moreover, customer retention becomes increasingly challenging as competition intensifies and the number of supply options increases. Consequently, firms operating in competitive contexts where customer service competition is high will need sophisticated CA to ensure that profitable customers are targeted for preferential treatment. Examples of preferential treatment include incentives such as loyalty bonuses, increasing attention from sales representatives and attractive supply chain solutions as a means of 'fencing in' attractive customers from the increasingly aggressive competition. This will, in turn, lead to reduced margins due to the increased resource investments required to enable such customization efforts to attract and retain customers combined with increasing cross-customer variation in resource consumption and cost-to-serve. Both effects emphasize the need for more sophisticated CA to identify the resources that are increasingly dedicated to differentiation activities across a firm's customer-facing functions and the consequential effects on costs and profits at the individual customer level.

On the other hand, in contexts where customer service competition is low, firms will reduce the resources allocated to implementing and maintaining sophisticated CA as they either deploy their detailed MASs to support other cost- or revenue-related management decisions (e.g., product or brand profitability techniques, sophisticated production cost controls) or invest in other efforts to achieve a competitive edge and thereby enhance their effectiveness as competition intensifies. Developing sophisticated CA is thus expected to be assigned low priority in this particular context.

This notion that firms prioritize distinct types of MASs and that some MAS types will thus be used less widely in certain competitive contexts corresponds well with findings reported in recent management accounting research. Bedford et al.'s (2016) review of the effects of strategic context on MAS usage suggests, for example, that prospector strategies are generally associated with decreasing use of subjective rewards and diagnostic controls and that defender strategies are associated with decreasing measure diversity and interactive control use. We argue similarly that increasing competition intensity can be associated with decreasing use of certain MAS types. More specifically, we propose that the usefulness of sophisticated CA will decrease with increasing competition intensity in competitive contexts where customer service competition is low.

These arguments lead to the following hypothesis:

H1. *In competitive contexts characterized by **high** customer service competition, competition intensity will be **positively** associated with CA sophistication, and in competitive contexts characterized by **low** customer service competition, competition intensity will be **negatively** associated with CA sophistication.*

3. Research method

3.1. Data

The current study was conducted to investigate the interactive effects of competition intensity and customer service competition on CA sophistication. A mixed-methods data-collection approach was deployed, combining primary and secondary data sources. Accounting data were gathered from official databases—NNE (Denmark) and Retriever (Sweden)—whereas industry concentration data were provided by the Danish and Swedish statistical bureaus (DST and SCB, respectively). Because information indicating CA sophistication is generally not publicly available, however, and since there is no readily available proxy for customer service competition, we conducted a survey to collect data pertaining to these variables and other (control) variables.

A survey instrument was developed and cross-sectional data were collected during the fall and winter of 2010/2011. We were interested in CA sophistication when it is developed for the specific purpose of resource allocation across customer relationships, so we wanted to target managers who were close to the decision-making process vis-à-vis customers. We therefore defined the target population (Van der Stede et al., 2005) as commercial directors (e.g., sales and marketing executives) or general managers involved in customer-related activities at large companies. These executives were expected to be best positioned to provide the most qualified information relating to CA sophistication and customer service competition. Additionally, we restricted our target population to large Danish and Swedish firms. Firms in our sample are either Danish/Swedish corporations (groups) or autonomous divisions of Danish, Swedish or foreign corporations operating as separate entities in the Danish/Swedish market.

To best reflect this target population of large Scandinavian firms, we collected contact information for commercial executives in the 1000 firms in Denmark and Sweden that earn the highest revenues. We based the Danish sampling frame on a list of the top 1000 firms in Denmark that is published annually by the Danish newspaper *Børsen*. For the Swedish sampling frame a consulting firm delivered the top 1000 list

Table 1
Sample by respondent characteristics.

	Commercial manager[1]	General manager[2]	Finance manager[3]	Other manager	Title not disclosed	Total
Panel A: Firm descriptives						
N (percentage split)	141 (67.5)	42 (20.1)	8 (3.8)	5 (2.4)	13 (6.2)	209 (100.0)
Mean revenue, DKK mio. (standard deviation)	3,269.6 (9,414.2)	3,502.1 (8,319.9)	3,912.3 (8,814.0)	1,109.8 (227.6)	1,131.6 (1,557.0)	3,156.3 (8,744.4)
Mean no. of employees (standard deviation)	1,201.6 (2,640.9)	1,033.0 (1,915.7)	4,100.1 (9,757.5)	201.0 (131.2)	490.9 (540.2)	1,210.5 (3,003.9)
Mean share of DK firms (standard deviation)	0.560 (0.498)	0.595 (0.497)	0.625 (0.518)	0.600 (0.548)	0.538 (0.519)	0.569 (0.496)
Mean share of B2B firms (standard deviation)	0.745 (0.438)	0.714 (0.457)	0.750 (0.463)	0.800 (0.447)	0.714 (0.457)	0.746 (0.436)
Panel B: Manager tenure						
Mean tenure in firm (N)	7.058 (139)	7.071 (42)	7.375 (8)	7.750 (4)	9.833 (12)	7.249 (205)
Mean tenure in industry (N)	14.860 (129)	16.282 (39)	11.625 (8)	15.500 (2)	18.222 (9)	15.187 (189)
Panel C: Key Constructs						
Mean CA Sophistication (standard deviation)	0.667 (0.867)	0.524 (0.773)	0.625 (0.518)	0.000 (0.000)	0.692 (0.947)	0.622 (0.841)
Mean Competition Intensity (standard deviation)	0.819 (0.170)	0.828 (0.175)	0.798 (0.335)	0.727 (0.379)	0.860 (0.132)	0.821 (0.183)
Mean Customer Serv. Comp. (standard deviation)	3.576 (0.236)	3.481** (0.256)	3.548 (0.166)	3.588 (0.164)	3.604 (0.144)	3.558 (0.233)

** Indicate significance at $p < 0.05$. 1) Commercial managers include the following titles: CMO, Marketing Executive, Sales or Marketing VP/Director/Manager or Business development Director/Manager. 2) General managers include the following titles: CEO, Business unit director, General Manager or Country Manager. 3) Finance managers include the following titles: CFO or Finance Manager.

(also based on revenue). For 455 firms it was not possible to contact the relevant target informants. This left us with a survey population of 1545 firms.

Prior to launch, the questionnaire was pre-tested on six academic colleagues and fourteen practitioners. This was to ensure that respondents had a consistent understanding of key terminology such as ‘resource allocation’ and ‘customer profitability analysis’ that was in line with the study’s definitions and to avoid any other misunderstandings that could lead to non-sampling errors such as response error (Dillman, 1999). Subsequently, the 1545 contacts in the survey population were e-mailed cover letters and a hyperlink to the online questionnaire.

Three rounds of follow-up emails were conducted to mitigate non-sampling error in the form of non-response bias. Personal phone calls were subsequently initiated to randomly selected firms from the survey population to increase the sample size. This yielded a sample of 255 informants. From the total sample, 46 responses were eliminated due to missing observations, yielding a final sample of 209 applicable responses corresponding to a response rate of 14%. All 209 informants in the net sample represented autonomous firms or business units conducting their own commercial activities and the observations are therefore regarded as independent and treated accordingly.

To determine whether there are any systematic biases related to the geographical composition of this sample and/or the types of respondents who participated, we investigated selected firm descriptives, respondent tenure, key constructs across respondent types (i.e., job title/position and function), and country (i.e., Denmark and Sweden). In Tables 1 and 2 we report the results of this investigation. In Table 1, Panel A we show that the vast majority of respondents are either commercial or general managers (87.6%), which corresponds well with our targeted commercial executives. The firms represented by commercial, general, or finance managers (91.4%) are fairly similar in terms of firm size (revenue), geography, and type of customer relationships (B2B share). In Table 1, Panel B we show that respondents are generally experienced, with a mean tenure of approximately 7 years and a mean industry tenure of approximately 15 years. Firm tenure is fairly similar across the respondents who agreed to disclose their job titles/positions (93.8%). Finally, in Table 1, Panel C we report observations suggesting that mean CA sophistication and mean customer service competition are lower for firms represented by general managers than for firms represented by commercial and finance managers; the difference for customer service competition is statistically significant ($p < 0.05$). To ensure that this difference did not confound our results we ran a robustness check of our main model including respondent-type dummies (commercial/general/finance) for the subsample of firms where the respondent agreed to disclose her/his job title/position (N = 196). Controlling for type of respondent in this way had no influence on our main results (not reported). We therefore conclude that bias related to respondent type is unlikely to affect our results.

The figures we report in Table 2 indicate that the Swedish firms in the sample are slightly larger in mean size than the Danish firms, although the difference is not statistically significant (Panel A). In Table 2, Panel B we document that mean CA sophistication is lower for the Swedish firms than for the Danish firms in the sample and this difference is statistically significant ($p < 0.10$). For reasons explained later in the control variables section, however, we control for country in our empirical model and any confounding effects of geographical differences in the sample are thus controlled for in our tests.

Our sample size of 209 responses is sufficiently large to achieve some degree of face validity (Van der Stede et al., 2005). However, despite the efforts made to increase our sample size, the response rate of 14% remains low compared with those reported by prior survey studies in management accounting. Van der Stede et al. (2005) note that response rates were already declining in management accounting and organization research in the mid-1990s and more recent studies in management accounting with survey populations and sampling frames that are similar to ours have achieved response rates that are comparable to our net response rate (e.g., Widener, 2007; Heinicke et al., 2016).

A low response rate is not problematic per se, but the associated risk of non-response bias in the sample warrants a thorough analysis (Van der Stede et al., 2005). Inspired by Heinicke et al. (2016), we perform several non-response bias analyses, the results of which can be seen in Table 3. First, a chi-square goodness-of-fit test reveals that the size distribution of our sample is not significantly different from that of the population as a whole (Panel A). Additionally, we observe that profitability as measured by ROS and ROA, respectively, is also similar to what occurs in the survey population with no significant differences registered (Panel B). The results we report in Panel C show that there are no significant differences between early and late respondents (median split) for the mean values of the study’s key constructs.[3] Overall, these analyses generally support the assumption that our sample is representative of our survey population and the likelihood of non-response bias is low. Finally, in Table 3, Panel D the median values

[3] We also split the sample into the ‘earliest’ responding quartile (1 day) and the ‘latest’ responding quartile (14 days or more). This analysis provided the same results as the median split analysis.

Table 2
Sample by country characteristics (DK vs. SE).

	Denmark (DK)	Sweden (SE)	Total
Panel A: Firm descriptives			
N (percentage split)	119 (56.9)	90 (43.1)	209 (100.0)
Mean revenue, DKK mio. (standard deviation)	2,699.1 (6,386.64)	3,760.8 (11,134.4)	3,156.3 (8,744.4)
Mean no. of employees (standard deviation)	994.2 (2,978.5)	1,496.6 (3,030.0)	1,210.5 (3,003.9)
Mean share of B2B firms (standard deviation)	0.748 (0.436)	0.744 (0.439)	0.746 (0.436)
Panel B: Key Constructs			
Mean CA Sophistication (standard deviation)	0.706 (0.857)	0.511* (0.811)	0.622 (0.841)
Mean Competition Intensity (standard deviation)	0.809 (0.204)	0.836 (0.150)	0.821 (0.183)
Mean Customer Serv. Comp. (standard deviation)	3.540 (0.231)	3.582 (0.236)	3.558 (0.233)

* Indicate significance at $p < 0.10$.

we report reveal that the average firm in the sample have revenues of approximately DKK 850 mill. and carries 380 employees and in Panel E we present the industry distribution of our sample.

Another concern in survey-based research is common method bias, particularly common rater effects that arise when the same respondent provides input pertaining to both the dependent and independent variable(s) (Podsakoff et al., 2003). Competition intensity is measured via data collected from secondary sources (HHI) and common method bias is therefore not an issue. Customer service competition is measured based on survey responses, but the measures are aggregated at the industry level and at an entirely different scale from that of CA sophistication. Moreover, the questions were ordered such that informants were unlikely to be able to identify our underlying model when completing the questionnaire. Consequently, the risk of common method bias appears negligible.

3.2. Main measures

The measures used in the study were, wherever possible, drawn from previous research. We describe the measures used below.

3.2.1. CA sophistication

We constructed an ordinal three-point scale to measure the dependent variable, CA sophistication, based on the conceptualization of this construct as presented in Section 2.[4] The measure was created through a two-step procedure (see Supplementary material for an extract of the questionnaire). First, firms using CPA for resource allocation purposes were identified (Q1–Q3). Subsequently, in Q4, all respondents who identified themselves as CPA users in questions Q1–Q3 (n = 81) were asked to report the range of financial information included in their CPA measures (revenue and/or COGS and/or SG&A) as well as the method used for assigning SG&A costs to customers. The remaining respondents (n = 128) were considered non-users and were redirected to other questions and therefore were not given the opportunity to answer Q4 in the questionnaire.

The scale ranges from ‘0’ to ‘2’ across non-users (the least sophisticated), basic users, and advanced users (the most sophisticated). ‘0’ includes all non-users of CA (as explained above, n = 128). ‘1’ denotes basic CA in firms that have started measuring some variation in customer profitability by including profitability-related elements that are directly caused by serving customer relationships but have not addressed the issue of SG&A overhead assignment in great detail. This category includes all firms that indicated in Q4 that they regularly measure at least one of the following components at the customer level: Sales (Q4, a) and gross profit (Q4, b), direct SG&A costs (Q4, c), or indirect SG&A costs *assigned* via *a single cost driver* (Q4, d). Finally, ‘2’ denotes more advanced CA in which firms, in addition to measuring customer revenue and all direct product and SG&A costs at the customer level (Q4 a–c), assign indirect SG&A costs to customers using multiple cost drivers and cost pools (Q4 e), as is the case, e.g., in an ABC system. Using the number of cost pools and cost drivers as a proxy for cost-system sophistication aligns with procedures followed in prior research on the antecedents of product-cost-system sophistication (Al-Omiri and Drury, 2007; Drury and Tayles, 2005; Schoute, 2009).

On this CA sophistication scale, a shift from ‘0’ to ‘1’ constitutes progress towards greater CA sophistication, as the decision to use something rather than nothing can be seen as a careful decision made to change how resources are allocated when adopting a more customer-oriented profitability perspective. Moreover, a shift from ‘1’ to ‘2’ constitutes another distinct shift in the level of sophistication as the decision to start measuring SG&A overhead costs via multiple cost pools and cost drivers reflects a desire to more accurately estimate customers’ consumption of shared resources across customer-facing functions. Such information is typically not available in traditional cost systems (as opposed to the information required to implement a ‘level 1’ CA). Therefore, firms will need to implement new and more sophisticated systems and processes such as ABC systems or the equivalent that enables them to assign SG&A overhead resource costs to customers via multiple cost pools/drivers.

3.2.2. Competition intensity

We use the Herfindahl-Hirschman Index (HHI) per industry (using the 4-digit NACE industry code)[5] to measure competition intensity. Data were acquired from the Danish and Swedish governments’ statistical bureaus, *Statistics Denmark (DST)* and *Statistics Sweden (SCB)*. These data include both publicly listed and privately held firms across industries.

HHI measures concentration within an industry and is calculated as the sum of the squared market shares across firms within an industry as follows: $HHI = \Sigma_i (s_i)^2$, where s_i is the percentage market share based on revenues of firm *i* and then summed over the total number of firms in the industry.[6] To facilitate interpretation, we reverse-coded HHI to

[4] Additional levels of sophistication could be added by differentiating between varying levels of cost pools and cost drivers used in the cost model (e.g., Al-Omiri and Drury, 2007). It would be impossible, however, to establish a progressive linear scale on a general basis because the’ optimal’ number of cost pools and cost drivers can be expected to vary substantially depending on the business model, cost structure, and customer portfolio served by a given firm.

[5] “NACE” codes indicate sector according to the General Industrial Classification of Economic Activities. A complete list of NACE codes can be found on the European Commission’s homepage: http://ec.europa.eu/competition/mergers/cases/index/nace_all.html

[6] HHI is sometimes normalized to mitigate potential issues arising because the range of the HHI measure varies with the size of the industry, as industries with few internal competitors will have a minimum HHI greater than zero. Normalized HHI (HHI*) is calculated as follows: $HHI^* = ((H-1/N))/(1-1/N)$. We decided to use the standard HHI measure as the practical issue is limited in our sample because 93% of the sample firms compete with 20 or more firms in their industries. However, we tested our main model using inverse HHI* as our measure of competition intensity and found results consistent with using HHI.

Table 3
Test of non-response bias and sample structure.

Panel A: Representativeness of the received sample

Revenue in Mill. DKK	Received questionnaires (% of total)	Expected questionnaires (% of total)
0–999	122 (58.4)	117 (56.0)
1000–2499	43 (20.6)	49 (23.3)
2500–4999	22 (10.5)	20 (9.7)
5000–9999	9 (4.3)	12 (5.6)
10000–20000	6 (2.9)	6 (2.9)
20000 <	7 (3.3)	5 (2.5)
Total	209	
Chi-squared test statistic	2.38	
Degrees of freedom	5	
p value	0.80	

Panel B: Non-response analysis for firm financial characteristics (mean values)

Variable	Respondents	Addressed non-respondents	Survey population[1]	Mann-Whitney-*U*-test
Revenue in Mill. DKK	3265.1 (n = 209)	3107.7 (n = 1791)	3124.1 (n = 2000)	Z = 0.118 (*p* = 0.91)
RoS in%	2.13 (n = 209)	2.66 (n = 1761)	2.61 (n = 1970)	Z = -0.484 (*p* = 0.63)
RoA in%	2.71 (n = 209)	3.11 (n = 1761)	3.06 (n = 1970)	Z = -1.398 (*p* = 0.16)

Panel C: Comparison of constructs for early and late respondents

Construct/Variable	Mean rank of values Early respondents; median split (n = 108)	Mean rank of values Late respondents; median split (n = 101)	Mann-Whitney-*U*-test
CA Sophistication	109.07	100.64	Z = 1.159 (*p* = 0.25)
Competition intensity	105.53	104.43	Z = 0.131 (*p* = 0.90)
Customer service comp.	111.36	98.20	Z = 1.595 (p = 0.11)

Panel D: Sample descriptives

	Revenue in Mill. DKK (n = 209)	Number of employees (n =209)
Mean	3,265.1	1,210.5
Median	848.6	380
Min	138.6	20
Max	96,008.3	28,165
Standard deviation	9,291.7	3,003.9

Panel E: Industry structure of sample

Industry Description	% of sample
Industrial products	31.1
Construction & building materials	11.0
Transportation	10.5
IT & Telecom	9.1
Consumer products	9.1
Services	8.6
Chemicals	4.8
Retail	3.8
Energy	3.8
Financial institutions	2.9
Other	5.3

1) We were unable to retrieve financial data to compute ROS and ROA for 30 of the 1791 non-responding firms.
Note: In the table we report the results of the chi-square statistics for the test of distributional adequacy (size) of the received sample. No significant differences were found ($p < 0.10$).
Note: In the table we report variable means as well as the results of the Mann-Whitney-U-Test for the comparison of means of selected financial characteristics (revenue, ROS, ROA). No significant differences ($p < 0.10$) were found.
Note: In the table we report variable means as well as the results of the Mann-Whitney-U-Test for the comparison of means of variables between respondents and addressed non-respondents (median split). No significant differences ($p < 0.10$) were found. The results are not sensitive to comparing the 25%-quartile (1 day) with the 75%-quartile (14 days).
Note: In the table we report some characteristics of the sample in terms of mean, min and max of sales (in mDKK) and number of employees. We also report the industry distribution of our sample.

measure competition intensity as 1 – HHI. Additionally, we performed a square root transformation of the reverse-coded HHI as we do not know the form of the relationship between competition intensity and CA model sophistication (DeFond and Park, 1999).[7]

HHI is a widely accepted measure of industry competition intensity and has been used in numerous prior accounting studies (e.g., Chen et al., 2015; DeFond and Park, 1999; Krishnan, 2005; Patatoukas, 2012). Moreover, using HHI responds to calls in prior studies of the relationship between competition and CA to apply more objective measures of competition (Guilding and McManus, 2002, p.57).

3.2.3. Customer service competition

To the best of our knowledge no well-established measure of customer service competition is available in the accounting literature. We therefore adopted a multi-item measurement scale from the marketing literature developed by Holm et al. (2012) to measure the extent to which firms differentiate customer-related activities according to customer needs, for example through product customization, and/or the differentiation of commercial terms (e.g., price), delivery terms, customer service levels, and so on, across customers. Informants responded using 5-point Likert scales (survey items are outlined in Supplementary material, Section 2, Q7). There is considerable variation across all six items where mean scores generally fall between ‘3’ and ‘4’, ranging from 3.41 to 3.84, suggesting that individual-level customer differentiation is generally slightly above average among firms in the sample (not reported).

Confirmatory factor analysis (CFA) was performed to test for the one-dimensionality of the scale items (Maas and Matejka, 2009). We excluded the first two items in our measurement scale because their factor loadings were below 0.50 (Hair et al., 1998) and found an acceptable fit (Normed $\chi^2 = 3.93$ / p = 0.14, SRMSR = 0.03, RMSEA = 0.07, GFI = 0.99, AGFI = 0.95, NNFI = 0.98) across the remaining four items. Additionally, the reliability of the construct is satisfactory, with a Cronbach’s Alpha of 0.73 (Nunnally, 1978).

Customer service competition as perceived by individual firms was computed as the equally weighted average of scores on the four items. Subsequently, the industry-level degree of customer service competition was measured at the aggregate industry level by calculating industry averages across the sample.[8]

3.2.4. Control variables

3.2.4.1. Firm size. The size of an organization has consistently been incorporated in studies of MAS sophistication, including studies of ABC and balanced scorecard (BSC) adoption (Al-Omiri and Drury, 2007; Hoque and James, 2000; Malmi, 1999), as larger firms are generally expected to use more sophisticated MASs. We therefore included size, measured as the natural logarithm (Ln) of a firm’s number of employees, as a control variable in our model.[9]

3.2.4.2. Firm growth. A relationship between a firm’s stage of maturity (and thereby growth prospects) and MAS sophistication has been demonstrated in prior research. Some claim that new cost information is more beneficial when limited growth prospects cause firms to focus more intently on cost (Anderson and Young, 1999). Davila and Foster (2005) specifically show that CPA is one of the last accounting techniques to be adopted in startup companies, suggesting that in earlier, high-growth stages CA profitability sophistication is expected to be lower than in later stages when growth levels off. We therefore controlled for growth measured as the compound annual growth rate in sales during the last three years as reported in firms’ annual accounts.

3.2.4.3. Country. The institutional contexts in Denmark and Sweden are in many ways rather similar. However, differences in accounting traditions have been highlighted (Jönsson and Mouritsen, 2005; Näsi and Rohde, 2006). To mitigate confounding effects related to the country in which a firm operates, we controlled for country of origin in our model.

3.2.4.4. Customer relationships (B2B). Differences in CA sophistication may be explained by demand-related rather than supply-related factors. More specifically, markets characterized by business-to-business (B2B) relationships vary in a number of ways from markets where suppliers have more limited direct contact with the end-users of their products. We control for any confounding effects of the main customer relationship types in participating firms’ markets by incorporating a dummy variable taking the value ‘1’ if a firm has some kind of B2B-relationship with some or all of their customers and ‘0’ if that is not the case.

3.2.4.5. Industry. In addition to competitive forces, there are several other plausible systematic differences in CA sophistication across industries. Messner (2016) argues that in addition to contextual factors core organizational practices may also shape differences in MAS usage across industries. In our case, one may expect customer orientation to be more profound in industries where customer insights play an important role (e.g., fast-moving consumer goods). Similarly, it is reasonable to believe that more advanced management information systems are applied in industries where employees generally possess higher-level technical educations (e.g., pharmaceuticals). We therefore also include industry fixed effects in our model.

3.3. Empirical tests and analyses

To test our hypothesis, we specified an ordered logistic regression model with CA sophistication as our dependent variable using maximum-likelihood estimation. The ordered logit model assumes a probability distribution of the continuous variable that underlies our observed CA sophistication variable, thereby explicitly recognizing the categorical nature of our measure and avoiding arbitrary assumptions about its scale (Jones and Hensher, 2004).

The model is estimated as follows:[10]

$$\textit{Sophistication} = \alpha + \beta_1\ \textit{Competition Intensity} + \beta_2\ \textit{Customer Service Competition} + \beta_3\ \textit{Competition Intensity x Customer Service Competition} + \beta_4\ \textit{Firm Size} + \beta_5\ \textit{Firm Growth} + \beta_6\ \textit{Country} + \beta_7\ \textit{B2B} + \beta_i\ [\textit{Industry}_i] + \varepsilon \quad (1)$$

Potential endogeneity issues are substantially mitigated in our model as all independent test variables are measured at the industry level whereas the dependent variable is measured at the individual firm level. Individual firms are unlikely to exert significant influence on industry competition intensity or type so reverse causality is unlikely.

We followed prior research on regression models with interaction effects (e.g., Hartmann and Moers, 1999) and simultaneously tested for main effects and interaction effects. All continuous independent

[7] Tests performed without this square root transformation yielded consistent results.

[8] We use a Danish industry classification of 12 industries. This comparatively highly aggregated level is necessary to cover a sufficient number of firms within each industry classification because we have a sample of only 209 responses on which to base our industry averages.

[9] Size is also commonly measured by either revenues or total assets. In line with Hoque and James (2000) we also ran our main model with revenues and total assets, respectively, as our proxy for size. This did not change our results and we therefore report only the results obtained using number of employees.

[10] We acknowledge potential issues interpreting interaction terms in logistic regression models. We therefore test the robustness of our results regarding this factor in the robustness tests and additional analyses and report the results in the first part of Section 4.

Table 4
Descriptive statistics.

	Full sample				CA users				Firms that do not use CA				Mann-Whitney-U-test
Variable	n	Mean	Median	S.D.	n	Mean	Median	S.D.	n	Mean	Median	S.D.	
SOPHISTICATION	209	0.62	0.00	0.84	81	1.60	2.00	0.49	128	–	–	–	–
COMPETITION INTENSITY	209	0.90	0.94	0.13	81	0.89	0.93	0.14	128	0.90	0.94	0.12	Z = -0.477 (p = 0.634)
CUSTOMER SERV. COMPETITION	209	3.56	3.58	0.23	81	3.58	3.58	0.22	128	3.54	3.53	0.24	Z = 0.938 (p = 0.348)
FIRM SIZE	209	6.00	5.94	1.34	81	6.16	6.10	1.31	128	5.90	5.88	1.35	Z = 1.337 (p = 0.181)
FIRM GROWTH	209	1.39	1.39	12.64	81	−0.83	−0.94	12.61	128	2.80	1.84	12.51	Z = -1.446 (p = 0.148)
COUNTRY (DK)	209	0.57	1.00	0.50	81	0.65	1.00	0.48	128	0.52	1.00	0.50	Z = 1.967** (p = 0.049)
B2B	209	0.75	1.00	0.44	81	0.79	1.00	0.41	128	0.72	1.00	0.45	Z = 1.151 (p = 0.250)

** Indicates significance at $p < 0.05$.
Note: Square-root-transformed competition intensity is reported here.

Table 5
Correlations matrix (Pearson).

	1.	2.	3.	4.	5.	6.	7.
1. SOPHISTICATION							
2. COMPETITION INTENSITY	−0.05						
3. CUSTOMER SERV. COMPETITION	0.09	−0.02					
4. FIRM SIZE	0.07	−0.09	0.10				
5. FIRM GROWTH	−0.11	−0.07	−0.18***	−0.02			
6. COUNTRY (DK)	0.12*	−0.08	−0.09	−0.16**	−0.08		
7. B2B	0.05	0.06	0.35***	−0.03	−0.14**	0.00	

***, **, * Indicate significance at $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

variables were mean-centered so that each of the main effects was examined as the effect of the predictor on the dependent variable when the predictor with which it interacts equals its mean (Aiken and West, 1991). This ensures that the (expected lack of a) main effect of *Competition Intensity* on *Sophistication* can be interpreted (Hartmann and Moers, 1999), and mitigates potential multicollinearity issues (Cohen et al., 2003).

We hypothesize a crossover interaction effect (see Cohen et al., 2003) as we expect a positive (negative) association between competition intensity and CA sophistication for high (low) levels of customer service competition. A significant coefficient on the interaction effect combined with non-significant first-order effects of competition intensity and customer service competition on CA sophistication will, by default, indicate a crossover relationship (see Fig. 2 for a graphical representation of the hypothesized model). This approach is consistent with Zatzick et al. (2012), who find support for the proposition that total quality management (TQM) affects performance positively at low levels of differentiation strategy and negatively at high levels of differentiation strategy by interpreting a significant interaction term in their regression model.

4. Empirical results

4.1. Descriptive statistics

Table 4 displays descriptive statistics for the full sample (N = 209) as well as for the respective subsamples of CA adopters (N = 81) and non-adopters (N = 128). First, the results show that just fewer than 40% of the firms in our sample have adopted CA. Regarding our competition-intensity measure (inverse HHI), the relatively high median suggests that the typical firm in the sample operates in a rather fragmented market, albeit with some variation in the data. This high mean inverse-HHI level corresponds with what is reported in prior empirical accounting research (e.g., Chen et al., 2015; DeFond and Park, 1999).

In Table 5 we present bivariate correlations between model variables. We observe that no significant correlation is found between either of the main test variables (competition intensity or customer service competition) and the dependent variable. Hence, these preliminary indications suggest that there is no direct effect of either of these variables on CA sophistication. Another interesting observation is that competition intensity and competition type are uncorrelated (ρ = -0.02), suggesting that the two empirical measures are not related. Finally, even though some of the model variables are correlated to a statistically significant extent, none of these bivariate correlations is at a critical level and these correlations therefore are not expected to confound our main analyses.

4.2. Hypothesis test

In Table 6 we present the results of estimating our hypothesized logistic regression model using Eq. (1). We deploy a hierarchical modelling approach in two steps and control for industry fixed effects in both. First, we include only *Competition Intensity* and the control variables (column 3). Second, we add *Customer Service Competition* and the interaction term *Customer Service Competition* × *Competition Intensity* to the model (column 4).

The results reported in column (3) show that the main effect of *Competition Intensity* is not significant (p = 0.68). This remains the case in the second step, as seen in column (4) (p = 0.53). The coefficient on the *Customer Service Competition* × *Competition Intensity* interaction variable is positive and significant ($p < 0.05$), as expected. Moreover, model fit improves when *Customer Service Competition* and the interaction term are added to the model. Among the control variables, only *Firm Size* is statistically significant.

All these results support our main hypothesis that increasing competition intensity is associated with increasing (decreasing) CA sophistication when customer service competition is high (low).[11]

One potential concern with the results derived from our logistic regression model is that score tests for the proportional-odds

[11] Subgroup regression analysis (see Hartmann and Moers, 1999), where the sample was split around the median *Customer Service Competition* and a dummy taking the values '-1' (low) and '+1' (high) was used instead of the continuous *Customer Service Competition* measure, yielded the same results, i.e., a significant positive coefficient on the interaction effect and non-significant first-order effects of both competition constructs.

Table 6
Ordered logistic regression model to test the joint effects of customer service competition and competition intensity on Customer Accounting (CA) sophistication.

(1) Variable	(2) Pred. sign	(3) Base model with competition intensity only: Coefficient (z-stat.)	(3) p-value	(4) Expanded model with interaction added: Coefficient (z-stat.)	(4) p-value
COMPETITION INTENSITY	Not significant	−0.48 (0.17)	0.68	−0.80 (0.40)	0.53
CUSTOMER SERV. COMP.	Not significant			−2.77 (0.20)	0.65
CUSTOMER SERV. COMP. * COMPETITION INTENSITY	+			**13.22 (4.41)**	**0.02****
FIRM SIZE	+	0.20 (2.84)	0.09*	0.22 (3.18)	0.07*
FIRM GROWTH	–	−0.01 (1.16)	0.28	−0.01 (1.14)	0.29
COUNTRY (DK)	+/-	0.40 (1.57)	0.21	0.40 (1.48)	0.22
B2B	+/-	0.17 (0.19)	0.67	0.11 (0.08)	0.78
Industry fixed effects		YES		YES	
Wald χ^2		23.91		26.99	
Pseudo R^2		0.19		0.22	
N		209		209	

**, * Indicate significance at $p < 0.05$, and $p < 0.10$, respectively (one-tailed tests for hypothesized interaction effect; two-tailed otherwise).

assumption (untabulated) suggest that this assumption concerning the slope across the categories for our dependent variable is violated ($p < 0.01$). In models where the number of explanatory variables is large and/or in models where there is at least one continuous variable the proportional-odds assumption is anti-conservative and thus tends to reject the assumption too frequently (Allison, 1999; Brant, 1990). To rule out the possibility that our main results are driven by the violation of this assumption, however, we test various model specifications to identify the cause of the violation. These tests show that the violation is caused by the controls for industry fixed effects, more specifically the 'Transportation' industry dummy. We therefore ran a partial proportional-odds model while relaxing the assumption that the 'Transportation' industry dummy must be proportional. We also ran a revised model where we eliminated the 'Transportation' dummy completely. Finally, we performed stepwise selection of industry dummies while retaining only the (three) industries that were shown to have a significant effect on *Sophistication* (not reported). The main results we report in Table 6 did not change in any of these tests and are therefore unlikely to be biased by the potential violation of the proportional-odds assumption in our main model.

4.3. Additional analyses and robustness tests

4.3.1. Interpretability of the interaction effects in the empirical model

Scholars continue to debate the interpretation of interaction effects in non-linear models, such as logistic regression models. Ai and Norton (2003) demonstrate that the coefficient on an interaction term in a logit model does not necessarily have either the same sign or the same significance level across the range of predicted values for the dependent variable. This reflects the non-linear nature of the relationship between predicted probabilities and predictor variables. Greene (2010) concurs but questions whether tests pertaining to partial effects and interaction terms proposed by Ai and Norton (2003) and Norton et al. (2004) are sufficiently informative, arguing for the usefulness of graphical presentations in analyzing the implications of the interaction term. Kolasinski and Siegel (2010) dismiss the issue raised by Ai and Norton (2003) for practical research purposes, demonstrating that the issue is relevant mainly for extreme probabilities (close to 0 or 1). Moreover, they also show that the coefficient on the interaction term in non-linear regression models can still provide economically meaningful interpretations when one is interested in proportional rather than marginal change effects.

Given this controversy, we performed two additional analyses to test the robustness of our findings derived from estimating the logit regression model with an interaction term in Eq. (1). First, we followed Greene's (2010) suggestions and developed two graphical analyses (see also Keune and Johnstone, 2012). Fig. 1 plots z-statistics for the total interaction effect of *Customer Service Competition* × *Competition Intensity* for the model in Eq. (1) for each CA sophistication observation in the sample. The z-statistics are positive across the entire sample and generally fall within the statistically significant range. Hence, there is no indication of a shift in sign from positive to negative at multiple predicted probability levels, and these results are therefore consistent with the significant positive coefficient on the interaction term *Customer Service Competition* × *Competition Intensity* in our main model in Eq. (1).

Following Greene (2010) we also plotted the predicted probabilities regarding the deployment of CA (i.e., *Sophistication* = '1' or '2') as a function of competition intensity and at varying levels of customer service competition (see Fig. 2). The bold black line illustrates predicted probabilities when customer service competition is one standard deviation above the mean, whereas the dotted black line illustrates predicted probabilities when customer service competition is one standard deviation below the mean. This chart again lends support to our hypothesized crossover interaction effect. More specifically, we observe a positive association between CA sophistication and competition intensity when customer service competition is high and a negative association when customer service competition is low.

4.3.2. Linear probability model

In addition to the graphical analyses whose results are reported in Figs. 1 and 2, we specified a linear probability model by testing the main model in Eq. (1) via OLS estimation. When incorporating a discrete dependent variable, linear regression models can be problematic. We therefore included this estimation to analyze the sign and significance of the interaction effect in a model generally free of the same potential issues when interpreting interaction effects as there are in nonlinear models. In Table 7 we report the results obtained with this model. These results are consistent with our main findings with regards to the interaction of *Customer Service Competition* × *Competition Intensity* as well as to the other effects in the model. Furthermore, we also estimated the linear probability model for all of the succeeding robustness tests. These findings generally corroborate our main findings (not reported).

4.3.3. Alternative measures of the dependent variable

Another potential concern with the model specified in Eq. (1) is the construct validity of our measure of CA model sophistication. To investigate any potential issues in this regard we performed two additional tests with alternative measures of CA sophistication and usage. First, we applied a binary measure of CA model adoption ('1' = use CA; '0' = do not use CA) as the dependent variable and tested the association of this variable with our independent variables in a binary logit regression model. This binary measure (user vs. non-user) is arguably simpler than the sophistication scale we have developed, which has the advantage of providing a more effective classification of firms but also the downside of not capturing various degrees of CA sophistication

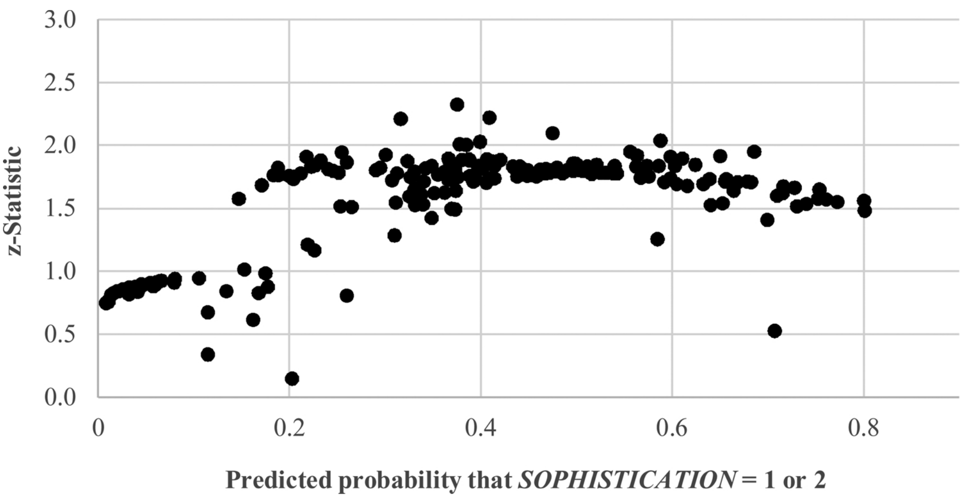

Fig. 1. z-Statistics for CUSTOMER SERVICE COMPETITION × COMPETITION INTENSITY.

satisfactorily. Second, we used the extent of CA usage across departments and divisions within an organization as a proxy for sophistication. The logic governing this tactic is that the more widely the CA is used across an organization the higher the degree of sophistication is generally expected to be. For this test, we asked survey respondents to report the span of CA usage across their firms on a categorical scale ranging from ‘1’ (used in one division/department) to ‘4’ (used across the entire organization). The scale can be found in Supplementary material (Q5). Subsequently, we created a 3-point scale whereby ‘0’ represents non-users of CA; ‘1’ represents firms that use CA in parts of their organizations, consolidating responses ‘1’, ‘2’ and ‘3’ from the questionnaire; and ‘2’ represents firms that have implemented CA across their entire organizations (‘4’ in the questionnaire).

The results of both tests are reported in Table 8. Both hypothesized effects are prevalent in the binary user/non-user model (column 3) as well as in the ordered logit model, with the extent of CA usage as the dependent variable (column 4). The coefficient on the interaction term *Customer Service Competition × Competition Intensity* is statistically significant in both tests ($p < 0.05$), whereas the first-order effect of *Competition Intensity* is not statistically significant. Moreover, the parameter estimates for the control variables are in line with the main analyses, whose results are reported in Table 6. These tests, therefore, also corroborate our main findings.

4.3.4. Subsample analyses

An underlying assumption of our theoretical framework and hypotheses is that managers act rationally and autonomously to adapt the sophistication of their CA practices to the competitive contexts in which they operate. This perspective can, however, be challenged. Abrahamson (1991) suggests that non-rational motives such as the impulse to follow fads or fashion as well as forced selection by authorities outside a firm or business unit (most notably corporate headquarters) may substantially influence the adoption and design of managerial innovations such as CA. To mitigate the confounding effects of these adoption motives on CA design choices, we asked respondents whether external consultants and/or corporate headquarters were involved in the decision to implement CA in their organizations (see questionnaire in Supplementary material, Q6). Based on this, we performed three subgroup analyses, as reported in Table 9. First, we ran our ordered logistic regression model in Eq. (1) on the subgroup of firms that reported that they were not influenced by external consultants during the process of implementing their CA models (see column 3 in Table 9). Second, we ran the model on the subgroup of firms that were not influenced by corporate headquarters during the process of implementing their CA models (see column 4 in Table 9). Third, we ran the model on the subgroup of firms that reported that they were influenced by neither external consultants nor corporate

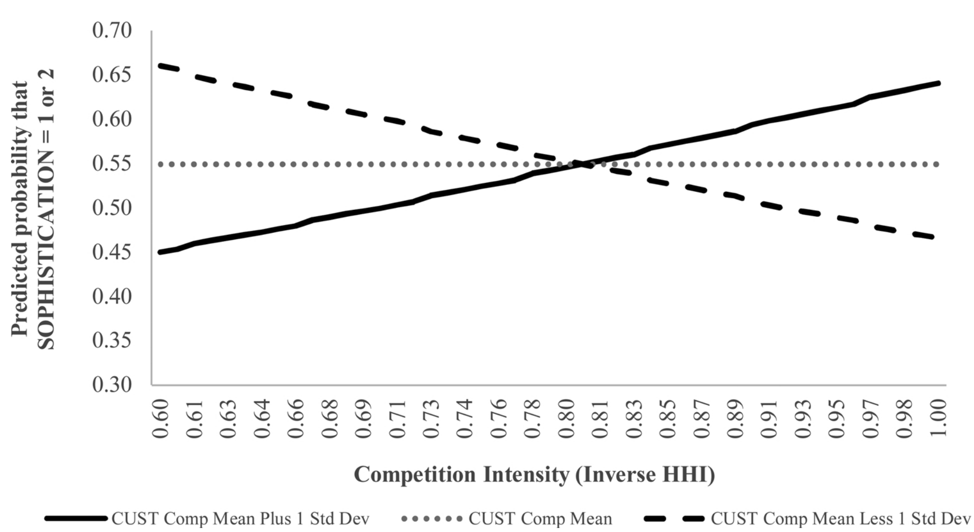

Fig. 2. Illustration of CUSTOMER SERVICE COMPETITION × COMPETITION INTENSITY interaction effect.
Note: For ease of interpretation we report unadjusted competition intensity rather than the square-root-transformed measure used in our regression models.

Table 7
OLS regression model to test the joint effects of customer service competition and competition intensity on Customer Accounting (CA) sophistication.

(1) Variable	(2) Pred. sign	(3) Base model with competition intensity only Coefficient (t-stat.)	p-value	(4) Expanded model with interaction added Coefficient (t-stat.)	p-value
COMPETITION INTENSITY	Not significant	−0.17 (-0.32)	0.75	−0.27 (-0.63)	0.53
CUSTOMER SERV. COMP.	Not significant			−1.41 (-0.82)	0.42
CUSTOMER SERV. COMP. * COMPETITION INTENSITY	+			**5.04 (2.85)**	**< 0.01*****
FIRM SIZE	+	0.07 (1.66)	0.09*	0.07 (1.75)	0.08*
FIRM GROWTH	–	−0.00 (-0.91)	0.37	−0.00 (-0.85)	0.40
COUNTRY (DK)	+/-	0.12 (1.01)	0.32	0.10 (0.87)	0.39
B2B	+/-	0.03 (0.20)	0.84	0.01 (0.06)	0.95
Industry fixed effects		YES		YES	
F Value		2.01		2.13	
Adj. R^2		0.07		0.09	
N		209		209	

***, * Indicate significance at $p < 0.01$, and $p < 0.10$, respectively (one-tailed tests for hypothesized interaction effect; two-tailed otherwise). Note: Heteroscedasticity-consistent standard errors applied.

headquarters during the process of implementing their CA models (see column 5 in Table 9).

As the figures we present in Table 9 demonstrate, the results are generally consistent with our main results: the coefficient on the interaction term *Customer Service Competition* × *Competition Intensity* is positive and significant in all three tests and the first-order effect of competition intensity is nonsignificant.

5. Conclusion and contributions

This study builds on prior research highlighting the importance of distinguishing between competition intensity and competition type when studying MAS design. Consistent with our theoretical predictions, we find competition intensity to be positively (negatively) associated with CA sophistication when customer service competition is high (low), where customer service competition reflects the degree to which firms compete on customizing their offerings in accordance with customer needs.

Our study makes two main contributions to current knowledge. First, this is the first study to provide empirical evidence of a crossover interaction effect between competition intensity and competition type. Taken together, our findings and those of prior studies support the notion that the type and purpose of MASs and the competitive context are critical for understanding what types of competition are important and how their interaction with competition intensity influences MAS design.

Second, by drawing on the recent literature on competition and MASs and by rethinking earlier theoretical reasoning regarding the association between competition and CA, we extend earlier work on CA. Specifically, we posit a crossover interaction effect between competition intensity and competition type (customer service competition), not an inverted U-shaped relationship as proposed in previous research (Guilding and McManus, 2002), and find empirical evidence supporting our model. We therefore provide a more nuanced understanding than previous work on competition to explain why certain firms implement sophisticated CA while others implement simpler CA and why motivations for CA design choices differ across competitive contexts.

The current study yields several implications for management accounting research. Our findings and prior studies (Krishnan, 2005; Chen et al., 2015) suggest that the assumption in mainstream research that increasing competition intensity generally leads to the use of increasingly sophisticated MAS design needs to be qualified. This in turn suggests that relying on unidimensional conceptualizations of competition (typically in terms of competition intensity) is suboptimal. Given the importance of understanding demand for management accounting information for various purposes and how it relates to MASs, there is a need for more research describing the joint effects of competition intensity and competition type on the design of various types and purposes of MASs in distinct competitive contexts. An important part of this research agenda would involve disentangling competition types at more disaggregated levels and studying specific management accounting practices. Such an approach could potentially also help reconcile the mixed evidence pertaining to the association between competition and MASs reported in prior management accounting

Table 8
Alternative measures for the dependent variable to test the joint effects of customer service competition and competition intensity on Customer Accounting (CA) sophistication (Logit regression models).

(1) Variable	(2) Pred. sign	(3) Binary (user/non-user) Coefficient (z-stat.)	p-value	(4) Extent of CA usage across organization Coefficient (z-stat.)	p-value
COMPETITION INTENSITY	Not significant	−0.78 (0.31)	0.58	−0.69 (0.28)	0.60
CUSTOMER SERV. COMP.	Not significant	−2.25 (0.13)	0.72	−2.69 (0.19)	0.66
CUSTOMER SERV. COMP. * COMPETITION INTENSITY	+	**15.32 (4.45)**	**0.02****	**14.82 (4.97)**	**0.01****
FIRM SIZE	+	0.25 (3.82)	0.05*	0.23 (3.46)	0.06*
FIRM GROWTH	–	−0.02 (2.37)	0.12	−0.03 (3.56)	0.06*
COUNTRY (DK)	+/-	0.22 (1.61)	0.20	0.25 (2.36)	0.13
B2B	+/-	0.13 (0.41)	0.52	0.11 (0.35)	0.56
Industry fixed effects		YES		YES	
Wald χ^2		27.58		28.44	
Pseudo R^2		0.26		0.24	
N		209		209	

**, * Indicate significance at $p < 0.05$, and $p < 0.10$, respectively (one-tailed tests for hypothesized interaction effect; two-tailed otherwise).

Table 9
Ordered logistic regression model to test the hypothesized relationships in reduced samples excluding influence from headquarters and/or external consultants.

(1) Variable	(2) Pred. sign	(3) Subsample excl. firms influenced by consultants: Coefficient (z-stat.)	p-value	(4) Subsample excl. firms influenced by headquarters: Coefficient (z-stat.)	p-value	(5) Subsample excl. firms influenced by consultants and/or headquarters: Coefficient (z-stat.)	p-value
COMPETITION INTENSITY	Not significant	−0.58 (0.17)	0.68	0.13 (0.01)	0.93	−0.27 (0.03)	0.87
CUSTOMER SERV. COMP.	Not significant	−0.16 (0.04)	0.84	0.44 (0.30)	0.58	0.34 (0.12)	0.73
CUSTOMER SERV. COMP. * COMPETITION INTENSITY	+	**8.70 (2.04)**	**0.08***	**10.53 (2.63)**	**0.05***	**11.71 (2.73)**	**0.05****
FIRM SIZE	+	0.16 (1.61)	0.20	0.25 (3.55)	0.06*	0.36 (5.63)	0.02**
FIRM GROWTH	–	−0.01 (1.09)	0.30	−0.01 (0.28)	0.60	−0.00 (0.01)	0.93
COUNTRY (DK)	+/-	0.37 (4.36)	0.04**	0.51 (7.39)	< 0.01***	0.66 (9.07)	< 0.01***
B2B	+/-	0.03 (0.02)	0.90	0.07 (0.11)	0.74	0.09 (0.14)	0.71
Industry fixed effects		NO		NO		NO	
Wald χ^2		8.44		12.17		14.17	
Pseudo R^2		0.07		0.10		0.14	
N		173		172		151	

***, **, * Indicate significance at $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively (one-tailed tests for hypothesized interaction effect; two-tailed otherwise). *Note:* We run these models without industry fixed effects to avoid over-specification for these (smaller) subsamples. None of the industry fixed effects was significant in any of these models when they were originally included.

research (as noted by Krishnan, 2005).

In addition to implications for research, our findings also have implications for management accounting practice literature and textbooks, which typically also echo the idea that increasing competition requires more sophisticated MASs. Krishnan et al. (2002) explain that this view is based on intuitive ‘theories’ rather than on scientific research. Indeed, our findings support calls (Krishnan, 2005; Chen et al., 2015) for a more nuanced picture of the association between competition and the design of MASs in the practice literature and textbooks.

Our findings also have implications for CA practice. For example, the response from large management accounting professional associations to the emergence of customer service competition has generally been to call for larger investments in customer profitability measurement models (e.g. CIMA, 2008, 2009, 2013; IMA, 2010). Our findings challenge the notion that sophisticated CA practices are “becoming a must-have inside many organizations” (CIMA, 2008, p. 30). CA practices certainly have their merits in competitive contexts where customization of offerings, prices, and service levels vis-à-vis customer needs are key competitive parameters. Managers of firms in competitive contexts where competitive advantage derives mainly from product differentiation and/or the ability to deliver products/services at the lowest price could benefit, however, from prioritizing other MASs to a greater extent than from adopting sophisticated CA practices.

Our study is subject to several limitations. First, two of our main measures rely on self-reported survey data. CA sophistication is arguably a multifaceted construct. Our measure of CA sophistication is, though, rooted in prior costing research and our results hold when we test the robustness of our CA sophistication measure. Regarding our customer service competition measure, there is no proxy available in the accounting literature so we relied on a multi-item construct that was developed in the marketing literature. Future CA research could further validate this construct.

Second, HHI’s assumptions about the nature of competition intensity are potentially problematic, in part because markets with similar HHI scores may have varying competitive dynamics that reflect differences in relationships between actors in the marketplace (Krishnan, 2005) and in part because HHI ignores geographical differences in competition. Insofar as HHI is one of the most popular measures of competition intensity and is used by antitrust agencies such as the U.S. Department of Justice and the Federal Trade Commission (Krishnan, 2005), however, we feel comfortable using this measure.

Third, the industrial organization literature finds that competition intensity and competition type are interrelated. This poses a challenge to any attempt to identify the separate effects of these dimensions of competition empirically. In our dataset, there is no significant correlation between measures of intensity and type of competition. Although this does not rule out the possibility that intensity and type of competition are interrelated in some way, it is at least an indication that these two empirical constructs are not picking up the same variation in the data. Moreover, this limitation applies generally to the emerging stream of research investigating the interactive effect of competition intensity and competition type on MAS design (e.g. Krishnan, 2005; Chen et al., 2015).

Fourth, while we focus on customer profitability measures and, in particular, on cost, we do not discuss issues related to measuring customer revenues. Perhaps more importantly, we ignore the use of non-financial customer performance measures either as a substitute for or as a supplement to profitability-based CA (see McManus and Guilding, 2008). We decided to remain within the traditional domain of cost accounting in this early phase of research on CA sophistication and competition. However, future research could expand the research scope, for example by drawing on prior accounting research by Ittner and Larcker (1998, 2008) on customer satisfaction metrics and performance management or by seeking inspiration in the marketing literature (see McManus and Guilding (2008) for a literature review and a discussion of the merits of combining the marketing and accounting literatures on this matter).

Despite these limitations, we believe our results generate novel insights into the interactive effects of competition intensity and competition type on MAS design.

Acknowledgements

We appreciate helpful comments and input on earlier versions of this paper from Markus C. Arnold, Clara Xiaoling Chen, Henri Dekker, Ranjani Krishnan, F. Asis Martinez-Jerez, Kenneth Merchant, Ismir Mulalic, Lynette Ryals, Mikko Sandelin, Naomi Soderstrom, and participants at the 40th EAA Annual Congress in Valencia, Spain, 2017, the AAA Annual Meeting in Atlanta, Georgia, USA, 2014, the 12th EIASM Manufacturing Accounting Research Conference (MAR) in Copenhagen, Denmark, 2014, the 11th Annual Conference for Management Accounting Research (ACMAR) in Vallendar, Germany, 2014, as well as workshop participants at Aalborg University and Copenhagen Business School. Morten Holm acknowledges financial support from VISMA A/S and QVARTZ. The authors would also like to thank Jacqueline Rosberg and Narin Celiker for competent research assistance. Finally, we greatly appreciate the comments and help received from the editor, Margaret Abernethy, and the two anonymous reviewers. The responsibility for

any remaining errors or mistakes is the authors' alone.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.mar.2019.07.001.

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