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**THE JOINT EFFECTS OF CUSTOMER PROFITABILITY
REPORTS AND SALES SUPPORT DIVERSITY IN EFFECTIVE
CUSTOMER PRICING**

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ABSTRACT

This paper experimentally investigates the value-enhancing effects of more accurate customer profitability analysis (CuPA) reports on customer pricing decisions and firm profitability when customers place different demands on the firm's support functions. Activity-based driven CuPA reports are contrasted against less accurate reports, either based on traditional volume-based costing or on aggregated feedback. Cost complexity of the environment was further varied by either low or high diversity in resource usage across customers depending on whether or not the most costly type of customer always consumed more resources in each of the various support functions of the firm. Results suggest that the diversity in resource requirements serves as an important 'contextual factor' for CuPA to have incremental value over the less accurate report types. Only when usage of sales support becomes more diverse, CuPA provides strong opportunities for learning resulting in more effective customer pricing and profit improvement. Results further show some profit benefits of volume-based costing reports. Even though cost allocations are more distorted, they still perform better than aggregated reports that do not allocate marketing overhead, but only in a more complex cost settings.

Keywords: Customer profitability, pricing, sales support diversity, decision making.

JEL-classification: C91, D83, M31, M41, M49

INTRODUCTION

Firms often construct customer-specific price offerings on the basis of related support services that customers require (Kaplan and Cooper, 1998). To this end, managers may use various types of customer accounting reports ranging from basic reports, that not perform any cost allocation or that use volume related cost drivers, to more accurate customer profitability analysis reports (CuPA) using ABC. Although CuPA better captures differences in related customer support (Foster, Gupta and Sjoblom, 1996), the effect of accounting data on customer pricing and profit performance has hardly been investigated (Foster and Young, 1997; Guilding and McManus, 2002).

Only recently, Narayanan (2003) analytically showed that more accurate ABC reports matter for price differentiation when firms face heterogeneous customers, in which some customers typically require more sales support than others. Instead of studying cost reports in isolation (Narayanan, 2003), we focus on a repeated pricing task in a heterogeneous customer base in which decision makers also utilize other types of feedback to improve task performance (Hirst, Lockett, and Trotman, 1999). Managers may already improve prices and profitability by using outcome feedback, market data, their experience, or their general knowledge of customers' usage of sales support (Bruns and McKinnon, 1993; Malmi, 1997). Studies in a production context showed that decision-makers with biased volume-based costing strongly improved judgment or profit performance, simply by using production properties feedback or by referring to their ABC-knowledge (Briers et al., 1999; Dearman and Shields, 2001). These studies raise doubt on the value of more refined costing, as participants with biased cost data can effectively improve performance via alternative feedback. However, no explicit comparison with ABC was made in any of these studies.

We therefore contrast more accurate CuPA reports with less refined systems that either use volume-based drivers, or that report customer data on an aggregated basis. We also create a setting in which decision makers receive additional feedback on the customers' usage of sales support. By focusing on a heterogeneous customer base in which some customers typically incur more costs than others, our main contribution is to propose 'support diversity' (Estrin, Kantor and Albers, 1994) as an important boundary condition for CuPA to enhance customer pricing and resultant profitability. Increased sales support diversity, typified by more costly customers that not necessarily use more resources in every sales support function, may make it difficult for subjects to refer to additional feedback for price setting. An unresolved issue is whether CuPA reports vis-à-vis less refined reports lead to incremental

profits in these more complex cost settings, as opposed to simpler settings with lower resource usage diversity (Gupta and King, 1997). In addition, we extend classical comparisons of accurate ABC reports vs. less refined volume based costing by introducing a third system that reports customer data on aggregated basis and by studying differences in learning processes between these various types of reports in repeated pricing decisions (Sprinkle, 2003; Luft and Shields, 2001).

HYPOTHESIS DEVELOPMENT

This section develops our experimental predictions. First we argue that more diverse usage of a firm's sales support will likely increase cost complexity. Next, we discuss how this affects customer pricing and profits under CuPA reports and two less refined reports that either use volume-based costing or aggregated feedback. Finally, we say something on the learning dynamics of cost reports in multi-period customer pricing.

Cost complexity through greater diversity in sales support

We will vary sales support diversity depending on whether or not the customers that consume more resources consistently use more support in every sales activity of the firm (Estrin, Kantor, and Albers, 1994). Managers in real life often have a fairly good understanding of how their customers consume resources (Bruns and McKinnon, 1993). To represent such information, our decision makers receive rank order information on the resource usage patterns of their customers, which often serves as a first rough estimation of costs (Malmi, 1997). If more costly customers always use more support in every sales activity (e.g. ordering, deliveries, etc.), resource consumption cues are deterministic (Luft and Shields, 2001). When, however, more costly types of customers vis-à-vis other customers only use a lot more support at some processes, but require a little bit less at others, the cost setting would be less predictable via the rank data of resource consumption patterns. Prior research has suggested that less consistent environmental cues may make decision improvement more difficult (Brehmer, 1980; Bonner, 1994; Hirst, Luckett and Trotman, 1999). Extrapolating this to our setting, we label our latter cost environment as more complex, and predict that in settings with greater resource diversity across customers, decision makers will be less successful in enhancing profits by merely differentiating customer prices on the basis of overall sales support:

H1: “Compared to simple cost settings, resulting profits are lower in a complex cost setting with greater sales support diversity across customers.”

Sales support diversity and the value of different types of accounting data

When studying various accounting reports, initial cost report differences may in fact not always persist. The feedback on a customers' resource usage may already provide more insight in the task (task properties feedback, Bonner and Walker, 1994) such that certain shortcomings of less refined cost systems can be addressed (Dearman and Shields, 2001). In Briers et al. (1999), participants with volume-based costing were able to recalculate their biased unit cost figures after receiving feedback on how products consumed resources. As a result, output decisions and profits were close to optimal. Apparently, subjects with volume based costing do not solely fixate on cost reports, but indeed effectively use their rank ordering data for profit improvement. In fact, one could question the value of more refined cost data such as CuPA reports in price discrimination, because contextual process feedback may serve as a substitute. But as Briers et al. (1999) did not directly compared results with ABC, there is no direct evidence that such a substitution effect would exist. Second, while their setting remained fairly simple, we in fact argue that cost reports differences may still be highly important in more complex cost settings¹.

In a complex cost setting, customers diversely use a firm's support services. The quality of the contextual cues for taking corrective action diminishes (Brehmer, 1980). As a result decision makers will likely fixate more on cost report data (Hirst, Luckett and Trotman, 1999; Luft and Shields, 2001), making it more likely for differences between various accounting reports to appear (Ashton, 1976). In simpler cost settings, even decision makers with less refined cost reports would be able to estimate costs via consistent cues on how customers use sales support. Whether this sufficiently guides customer-specific price offerings, such that the effects of various kinds of cost reports become redundant, remains to be tested (Briers et al., 1999). It would require evidence of a joint interactive effect of sales support diversity and accounting report type, whereby the effects of accounting reports are more prevalent when the sales support diversity in the cost environment increases.

H2: “The effects of various kinds of accounting reports on profitability are dependent on the diversity in sales support of the cost setting.”

Consequently, we expect that the effects of accurate CuPA reports matters less when more costly types of customers use more support in every single sales support function (simple cost setting). But as cues on sales support become less consistent in complex cost settings other signals e.g. from the cost report, may matter for profit improvement

(Busemeyer, Swenson and Lazarte, 1986). CuPA reports issue more relevant customer cost data compared to less refined aggregated reports or volume-based costing reports (Gupta and King, 1997). Given that we expect greater cost report fixation in complex cost settings (Luft and Shields, 2001), profit benefits of CuPA reports should increase in settings with greater sales support diversity:

H2a: "Profit performance under CuPA reports vis-à-vis less refined cost reports increases in cost environments with more diversity in sales support."

A further test focuses on the differential impact between our two less refined cost reports. Unlike aggregated feedback that does not allocate customer costs, volume-based costing reports produce significant cost biases, which may be detrimental for customer specific price setting (Johnson and Kaplan, 1991). Nevertheless, compared to aggregated reports, volume-based cost reports contain bottom-line profit data on customers that is not only a result of a distorted (irrelevant) cost allocation, but in fact further includes (relevant) revenue data at the customer level. Iselin (1996) argues that performance improves with relevant accounting items on customer level (revenues), but may also sharply be reduced with irrelevant signals (distorted cost allocation). We would expect that if any of these cues dominate, differences between volume-based cost reports and aggregated reports should appear, but only in complex cost settings, where participants will rely more on their accounting report.

H2b: "Differences between volume-based cost reports and aggregated reports become more eminent, in cost environments with more diversity in sales support."

Prior to us, Gupta and King (1997) introduced resource diversity and product cost complexity in the study of more refined costing. They did not find that ABC would lead to higher profits in a more complex cost setting. However, the current study differs in many aspects from theirs. First, participants engage in a dynamic customer pricing task: they receive continuously updated cost reports and rank information after every trial, based on new prices they entered. Gupta and King's study was more static as participants made subsequent product cost forecasts, based on cost data and rank information that was issued only at the start of the experiment. Hence, subsequent decisions may have relied heavily on pure outcome feedback. Second, Gupta and King (1997) only found a main effect of accounting system, which

suggested that ABC is always highly beneficial, even in simple cost settings. Merely, having heterogeneous customers in terms of cost is not enough, as we expect CuPA to be beneficial only when heterogeneous customers make more diverse use of a firm's sales support². Finally, we extended the test by introducing a third report in which marketing overhead was not allocated. It allows us to test whether volume based cost reports have any benefit at all, compared to the argument of simply not allocating costs (Johnson and Kaplan, 1991).

Learning dynamics across report types

The multi-period pricing task, allows us to test whether *learning* across periods also differs across accounting reports (Hirst, Lockett and Trotman, 1999). Previous studies suggested that users of accounting reports resort to certain heuristics for adjusting their decisions (Dickhaut and Lere, 1983; Hilton, Swieringa and Turner, 1988). Nevertheless, these studies often do not identify differences in learning processes across various kinds of report types (Sprinkle, 2003). CuPA provides more accurate customer cost data than less refined costing data, and in simple settings this may serve as a better anchor point from which subsequent pricing decisions are made (Gupta and King, 1997). However learning effects across periods may quickly disappear as decision makers efficiently learn to price customers via more consistent cues on the sales support.

We therefore expect learning differences to occur in more complex cost settings. Effective customer pricing based on servicing costs first requires predictions of which customers require more support (cost uncertainty) to estimate the direction of price differences. This is difficult when customers use sales support in a diverse manner (Luft and Shields, 2001, 581). In general, such a setting would slow down learning (Bremher, 1980). Nevertheless, Busemeyer et al. (1986) argue that learning in terms of convergence to the optimum can still be improved via other relevant feedback. CuPA provides value by sooner resolving 'uncertainty' of cost behavior across customers (Narayanan, 2003), since it issues relevant activity data on customer-level while such data for resolving cost uncertainty is not readily available or more distorted under less refined cost reports (Luft and Shields, 2001). As a result we expect profit convergence under CuPA to become more efficient over time:

H3:"In settings with more sales support diversity across customers, resultant profits of repeated pricing better converge under CuPA (learning efficiency improves) than under less refined cost report types."

EXPERIMENT

In our experiment, participants set differentiated prices among a heterogeneous set of three customers A, B and C, based on variations in the servicing costs. The marketing environment was characterized by either high or low diversity in resource usage of customers across various sales support functions. Via Table 1, we first provide an overview of the underlying functions of our experimental setting, before we proceed to the discussion of our experimental factors. Subsequently, participants and experimental procedures are further described.

Insert Table 1 About Here

Experimental setting

The purpose of the task is to set prices for customers to increase customer and firm profitability³. Panel A of Table 1 shows that customer profitability in our underlying economic setting depends on a linear demand function, the cost of the unit sold to a customer and on the resources a customer consumes in four different sales activities. In fact, there is a unique price that maximizes customer profitability (equation 9), determined by solving the first order profit condition (equation 8) for that customer.

Following from previous discussions, we will define a simple and a more complex cost environment. Due to our primary focus on a heterogeneous customer base, we introduced large cost differences across customers in both these cost settings. The parameters in Panel B of table 1 show that variations in cost-to-serve mainly stem from customers consuming different amounts of resources in four sales activities. The cost of goods sold barely differs across customers. In both environments customer B incurs the highest servicing cost followed by customers A and C. Participants had to differentiate prices across customers based on servicing costs. Panel B shows that actual cost-to-serve differences are reflected in the optimal price pattern ($P_B > P_A > P_C$). Note that in both the simple and the complex environment unit costs and optimal prices and resulting profits are nearly identical. The only difference is the choice of the resource consumption parameters. In the simple cost environment, customer B always uses the most resources in each of the four sales activities, followed by A and C. Conversely, in the complex cost setting, there is greater diversity of resource usage across the four different sales support functions (e.g. only in sales activity 4 customer B uses the most

activities, in sales activity 3 it is ranked second, while in sales activity 1 and 2 it consumes the least resources). Even though environments are nearly identical, the ABC literature defines more diversity in sales support functions as a more complex cost environment (Estrin, Kantor and Albers, 1994).

Experimental factors

Two factors were manipulated between subjects. Participants were first of all assigned to one of our two cost settings (simple vs. complex). We did not provide the actual data of Table 1. Instead we only showed them rank data on the customers' resource consumption patterns of their assigned environment, representing the general knowledge that managers have about their customer base (Malmi, 1997). We further manipulated accounting report type as a second factor. Participants received one out of three, but still imperfect, accounting reports. Even a CuPA report made still a small aggregation error, following the general idea that even more refined cost reports tend to imperfectly capture the true costs (Datar and Gupta, 1994).

We will first discuss the factor **accounting report type**. Appendix A shows the three possible report types, which were issued before participants commenced their task. Reports are updated after each new pricing decision entered by a participant. One report type is a *more accurate* customer profitability analysis (CuPA) report that allocates the cost of sales activities via the customer's resource usage across the various sales support functions. The aggregation error stems from combining sales activities 1 and 2 into a single cost pool⁴. Ergo, a CuPA report had three cost pools or support activities, which we labelled for convenience as order processing (SA1 and SA2), internal logistics (SA3) and delivery (SA4). Drivers were the number of orders (ru2), stock pickings (ru3) and deliveries (ru4) used at each process. Appendix A shows that a CuPA report closely approximates actual customer profitability data.

The other two are *less accurate report* types. One report is based on traditional volume-based costing (VBC). Compared to actual data this report produces highly biased cost and profit data (see Appendix A). It in fact gathers all sales activity costs into a single cost pool that is then allocated via the typical volume driver 'sales'. The other report is denoted as total aggregated feedback (AGGR). It displays total sales, revenues, costs including total sales activity costs and profits. But, the report did not further allocated cost and profits to customers. Compared to traditional costing, this report type at least does not produce biased cost and profit information (Appendix A).

The second factor is the sales support diversity in the **cost environment**. Subjects received rank order data on the resource usage of customers in either the simple or the more complex cost environment, as displayed in Table 2. All subjects were told that customers consumed various amounts of orders, stock pickings and deliveries in the process of serving a customer. We only mentioned the ranks for three support functions, not only because CuPA uses the same three pools, but also again inspired by the fact that managers have some insights on resource usage of customers, rather than perfect data on all activities. In the simple environment there is low diversity in resource usage, because the most costly customer B always uses more activities in every support function. Participants can more easily infer important cost variations across customers. Conversely, complex cost settings are typified by increased support diversity. Rank data are then less effective in discriminating among cost-to-serve differences across customers since the most costly customer requires more resources in some process while requiring the least vis-à-vis others at other processes (see Table 2). Hence, only CuPA reports may be beneficial for improving prices and resulting profits when cost settings are typified by greater sales support diversity.

Insert Table 2 About Here

Participants and procedures

A total of 170 students –median age of 22- from a master level cost accounting course at a West-European university enrolled for the computerized experiment⁵. The course had covered traditional cost systems, ABC and customer profitability analyses. Participants were randomly assigned to one of the six treatment groups when entering the PC-room. Sessions lasted for one hour. To induce motivation, subjects were notified in advance that the best six players - with the highest overall profit - would receive a 20 € gift coupon exchangeable against CD's or books⁶.

Before starting the experiment, subjects reviewed instruction screens describing the case company and their pricing task. Participants were instructed to improve the profits of the case company by differentiating prices across the firm's customer base. Participants were provided with an initial cost report (see appendix A) and the product rank data of Table 2 of their respective environments. They were explicitly told that cost varied across customers due to the different usage of orders, stock pickings and deliveries. They were told that there was ample room to improve prices and resulting profitability, but did not know the maximum

profit level, nor did they receive data on the level of complexity and the parameters of their environment.

The task was performed over ten trials. In each trial, prices for customer A, B and C had to be set within a price bracket of €100 and €160. In addition to the total realized profit, subjects received an updated cost report (AGGR, VBC, CuPA) after each pricing decision. The rank information on the customer's resource usage (either of the simple or complex cost environment) was also shown in each trial. Price choices and profit performance of the last five trials always remained on screen. After finishing the task, subjects filled out an exit questionnaire containing several items (on a five-point scale). It confirmed that participants were highly motivated (average: 4.25). Importantly no significant differences were detected for accounting report type ($F_{(2,164)} < 1$, ns) and cost complexity ($F_{(1,164)} < 1$, ns).

DISCUSSION OF RESULTS

Manipulation checks

Items in the exit questionnaire tested subjects' perceived value of the supplementary rank information and their perceived benefit of cost data on customers. Concerning rank information, the analysis revealed that participants in a simple cost environment, indeed considered the rank information more useful for identifying the costly customer ($F_{(1,164)} = 34.85$, $p < .01$) and considered it as more relevant for the pricing decisions ($F_{(1,164)} = 34.55$, $p < .01$) compared to people in a complex cost environment. A main effect of accounting report type was not detected for these items. In sum, these analyses indicate that the perceived complexity was indeed higher in a cost environment with greater resource diversity across customers.

Regarding the role of specific cost accounting data, customers with VBC had a feeling that their reported unit cost was more biased than participants using ABC, irrespective of the cost environment ($F_{(1,110)} = 6.99$, $p < .01$)⁷. We have thus created a strong test for the value of more refined CuPA reports in a complex cost setting. If we would observe any benefit of CuPA-reports, we can rule out the alternative explanation that CuPA renders benefits, merely due to the fact that participants with VBC were unaware of cost distortions.

Profit effects of sales support diversity and accounting report type

This section analyses effects of resource usage diversity in the cost environment and accounting report type on performance. The mean relative distance against optimal profit (Mean % dev. π_i^*) over ten trials is the dependent variable in an ANOVA model⁸. Complexity of the cost environment (E), accounting report (R) and their interactions are the between subject factors. We note that the lower the ‘ %dev. π_i^* ’, the closer participants are to optimal profit. Results are summarized in Table 3.

Insert Table 3 About Here

First, in Panel B of Table 3 we observe a significant effect of the environment (E). The means in Panel A of Table 3 show that profits deteriorate when participants operate in a complex cost settings. Participants are generally further removed from the optimum than in a simpler cost environment. This supports H1, suggesting that when heterogeneous customers make diverse use of the firms’ support functions customer pricing and resultant profit improvement becomes difficult. Secondly, the main effect of accounting report (R) is significant, together with the interaction of report type and complexity of the cost environment (RE). It indicates that differences in accounting reports depend on the complexity of the cost setting (Panel B of Table 3). The means in Panel A show that the effects of various accounting reports are more prominent in a cost setting with greater sales support diversity, as was predicted by H2. With more support diversity across customers, subjects have difficulties to use the sales support rank data for profit enhancement, and hence profits are more affected by report type.

To test, however, whether profit benefits of more refined accounting reports such as CuPA increase vis-à-vis that of less refined accounting reports in a more complex cost setting we focus on pairwise comparisons. When we compare the value of CuPA against VBC, differences in means (Panel A) suggest that CuPA only performs 4.44% better than VBC in a simple cost setting, while profit benefits in a complex cost setting are much higher (11.58%). The pairwise interaction at the right hand sight of Panel B in Table 3 is significant at the 5%-level, suggesting that resultant profits from customer pricing under CuPA compared to VBC significantly increase with cost complexity (increase of 7.14% = 11.58%-4.44%). Similarly, the pairwise interaction RE_{CuPA_AGGR} is significant. It supports that CuPA also performs much better in complex settings, where customers make divers use of sales support, when compared

to aggregated reports ($12.74\% = 17.43\% - 4.67\%$). The combined interaction of CuPA versus the two less refined costing techniques is further significant. In sum, we can argue H2a is supported. The value of CuPA against less refined cost reports increase as heterogeneous customers make diverse use of a firm's support functions.

Finally, when comparing VBC reports producing biased cost data with the report where marketing overhead is not allocated (AGGR), the means of Panel A show that in settings with low diversity across customers, both reports result in similar profits, whereas in complex cost settings differences between the two reports become apparent (H2b). This is evidenced by the pairwise interaction of Panel B, that is just marginal significant. Although H2b was a non-directional hypothesis, the results show that customer data under VBC do seem to have some benefit when the cost environment is typified by greater diversity in sales support across customers.

Report types and their learning effects across cost environments

In this section we report ANOVA-models separately for both cost environments (E), each with $\%dev.\pi_i^*$ as the dependent variable, accounting report (R) as the between-subjects variable, and trial (T) and its interaction with report type (TR) as within-subjects variables. All possible contrasts between the three accounting reports are also tested. Introducing trial as within-subjects allows us to test whether learning in terms of profit convergence—as represented by $\%dev.\pi_i^*$ - differs across accounting reports (H3). The separate analysis by cost setting allows for an explicit check of whether accounting reports are redundant for learning in simple settings. If so, we should only observe differential effects of report type across trials (learning) in complex cost settings with greater sales support diversity⁹. Results are reported in Table 4.

Insert Table 4 About Here

Panel B of Table 4, indicates that in a simple cost environment, only a main effect of trial was found suggesting that all participants tend to learn. Learning does not differ across accounting reports as report type and the trial*report interaction are not significant. When studying individual contrast effects, interactions of trial and report type are never significant suggesting that learning rates are indeed highly comparable across report types in simple cost settings, presumably because sales support feedback is already descriptive for customer pricing. Nevertheless, more refined cost reports are not completely redundant because the

main contrast effect for CuPA reports versus other reports was still marginal significant, indicating that CuPA, gives a small head start, from which further decisions are likely anchored on (Gupta and King, 1997).

Panel B of Table 4 shows that trial, report and their interaction are significant in a complex cost setting. The individual contrast effects of report type for CuPA versus either VBC or AGGR reports are significant. More importantly the interactions of both contrasts with trial are significant. These specific interactions support the hypothesis (H3) that in cost settings, with greater resource usage diversity across customers, the learning process resulting in convergence to optimal profits is more effective with CuPA compared to with the less refined cost reports. This is evidenced in the figure of Panel A of Table 4, where CuPA leads to faster profit convergence in the initial phases of the experiment compared to the other reports, but only in complex cost settings. We provide new evidence suggesting that refined CuPA reports in fact enable more effective learning in pricing tasks where customers make diverse use of sales support. Finally, contrast effects further show that the small benefit of VBC versus AGGR reports in cost environments with greater sales support diversity is not explained by differences in learning rates. There is however a marginal main contrast effect; VBC only provides a small advantage that is maintained throughout the task.

Supplementary analyses

We performed a few sensitivity analyses to check whether the prices charged to customers differed across report type. In Table 5 we show the contrast estimates for the ANOVA-models with the metrics %dev.P_A, %dev.P_B and %dev. P_C, representing the mean price differences for customers A, B, and C from the optimal price¹⁰. In addition a few other analyses are tested which are further discussed below.

Insert Table 5 About Here

CuPA reports versus less refined accounting reports

Results of Table 5 show that in a simple cost setting, the marginal profit effect of CuPA vis-à-vis less refined accounting reports (see Table 4) is due to significant price effects for customer B and customer C (high and low cost-to-serve customers) and not for customer A. Although customer rank data of sales support is deterministic, CuPA apparently still adds some value by indicating how far one can go for the least and most costly-to-serve customers.

As the complexity in resource usage increases across customers, effects of CuPA reports compared to other reports strongly increases. All contrast estimates with CuPA are significant for all three customers and size effects of price differences are stronger than in a simple cost setting (see Table 5).

We further tested whether learning to predict ‘the correct price direction’ differed across accounting report type. Correctly predicting meant setting $P_B > P_A > P_C$, because customer B needed the highest price to cover the stronger sales support costs that this customer required¹¹. In simple cost settings, average prices set under CuPA revealed in 93.1% of the cases a correct prediction, which was not significantly different from VBC (78.6%, χ^2 : 2.44, $p > .11$) or AGGR (85.7%, χ^2 : 0.48, $p > .49$) supported price setting. In a complex cost setting correctly predicting the relation slightly decreased under CuPA to 82.1%, but this was, however, much better than under VBC (43.7%, χ^2 : 9.05, $p < .01$) or AGGR (35.7%, χ^2 : 12.25, $p < .01$). These results confirm that CuPA enables better learning when the resource usage environment is more complex (H3). In simple settings its value is limited, presumably because participants learn to predict price directions via the additional customer-level rank data on required sales support.

VBC versus aggregated reports

Previous tests that compared volume-based costing with aggregated feedback reported a marginal profit benefit of VBC, but only in a complex setting (see Table 4). Table 5 indicates that this can only be explained by a significant price effect for customer C, in a complex cost environment, whereby VBC is closer to the optimal price.

A likely explanation is that bottom-line information in a VBC report for customer C should have given some advantage compared to a report without a cost allocation, in spite of the fact that allocated customer data is highly distorted. In fact, when prices for customer C were too high ($P_C \geq 144$) or too low ($P_C \leq 104$), VBC reports produced an ‘accounting loss’ for this particular customer. Subjects stopped charging these sub-optimal prices for customer C under VBC, presumably because they want to avoid these reported accounting losses. It strongly resembles “loss aversion” labeled by Tversky and Kahneman (1991) as a preference for avoiding losses. Kachelmeier (1996) has shown that it may be triggered by cosmetic accounting variations that produce these losses. We ran a test to which extent participants charged sub-optimal prices for customer C. Extreme prices ($P_C \geq 144$ or $P_C \leq 104$) were charged in complex cost settings, in 3.21% of all participants/trial observations under VBC whereas under AGGR this was the case for 20.36% (χ^2 : 9.05, $p < .01$). Further tests supported that the

marginal profit result of Table 4 is indeed explained by participants with VBC better avoiding losses for customer C¹². In sum, when the complexity in sales support diversity increases, accounting losses under VBC can limit the participant's search field for particular customers. The effect did not play in simple cost settings as all participants learned to avoid extreme prices via the informative cues on sales support.

CONCLUSIONS

Research on the role of customer accounting for marketing decision-making and firm profitability has remains scarce (Guilding and McManus, 2002). We provide experimental evidence in a repeated customer pricing task in which customer profitability analysis (CuPA) reports are contrasted with less refined accounting reports based on volume-based costing or aggregated customer support data. Just as in actual business settings, decision makers had further access to contextual cues of sales support (Malmi, 1997).

Our study suggests that it is not sufficient to have heterogeneous customers in terms of sales support (Lere, 2000; Narayanan, 2003), but proposes that the degree of cost complexity, typified by greater diversity in sales support usage, is an important contextual factor that explain whether CuPA assists in enhancing customer price setting and firm profits. Results indicate that in complex cost settings, where more costly types of customers do not consistently consume more resources in every sales activity, the use of contextual cues of on sales support usage is difficult, such that profits tend to decrease. Nevertheless, especially here, CuPA reports enhanced profit performance because of accelerated learning vis-à-vis less refined accounting reports.

Our results elaborate and refine the conclusions of Gupta and King (1997), who found that the benefit of more accurate reports did not vary with the complexity of the cost setting. While they focused on a more static product cost forecasting task where cost information was only available in initial trials, we introduce a more dynamic price setting tasks. Our subjects base prices on continuously updated cost reports and on rank ordering information of sales support. The Gupta and King study (1997) may have been less efficient for promoting learning, causing initial cost report variations to persist, irrespective of the type of cost environment. Our dynamic setting fostered learning in simple cost settings, such that cost report induced variations are sharply reduced. Conversely, in complex cost settings, learning is difficult and only then more accurate CuPA reports are highly beneficial for further profit improvement.

We further add an argument to the issue whether a more distorted volume-based cost (VBC) allocation of marketing overhead, does provide any benefit compared to simply reporting customer data on an aggregated basis. Results indicate that VBC reports result in small profit benefits compared to aggregated reports, but only in complex cost settings. Unlike aggregated feedback, VBC produced distorted accounting losses for a particular customer, which served as a signal for participants to avoid highly sub-optimal prices for that customer. As such distorted accounting losses under VBC are in fact a beneficial application of participants' general aversion to loss-making scenarios (Tversky and Kahneman, 1991). Nevertheless, we believe it is worthwhile for future research to explore settings in which distorted accounting losses may be dysfunctional for further profit improvement.

We conclude by mentioning some limitations of the current experiment that may be addressed in follow-up work. Although, our participants perceive settings in which customers made diverse use of sales support, already as more complex, we admit that complexity is a multi-dimensional concept that can be operationalized in many divergent manners. From the view of a cost accountant, introducing the problem of capacity costs (Buchheit, 2003), adding more support functions and divergent prices per units of resources consumed (Anderson, 1995), can further add to complexity. Other specific actions, e.g. customer acquisition and retention programs, marketing budget allocations, could be more complex in nature than customer pricing and the relation with other performance metrics (e.g. market share) could be addressed. An appealing question is to test if our findings extend to these more complex and cognitively demanding environments. Our experiment maintained a focus on repeated decision-making to show that learning efficiency under higher levels of complexity may differ across report type. For reasons of experimental control, our decision-maker had, however, full discretion on customer prices and access to sales support cues as only one source of additional feedback. One could test the value of various accounting reports in markets where competitive feedback is available as an additional source for profit improvement (Briers et al., 1999). Besides customer pricing, other strategic considerations such as the type of cost signal that is issued to competitors (Callahan and Gabriel, 1998), the amount of resources invested into more refined costing when other players enter the market (Krishnan, Luft and Shields, 2002) could benefit from studying learning across accounting reports in a repetitive decision framework.

APPENDIX A

This appendix displays the different accounting reports subjects receive at the start of the experiment. These reports are automatically updated and issued after each pricing decision. We only show analysis for a simple cost environment. Analysis for the complex cost setting is similar. Since we want to have an idea how closely each cost report approximates actual cost, Panel A of table A1 displays the actual figures based on the information in Table 1.

Insert Table A1 here

Panel A clearly shows that prices are not in line with actual cost-to-serve (customer B uses the most support but receives the lowest price). Participants do not receive actual data, but differentiate prices among customers using imperfect accounting reports, that are displayed in Panel B of Table A1. Participants using an **aggregated report** receive only the total revenue, the total costs, including total sales costs, and profit information but they do not receive any information on customers (see column A). It is important to note that just like all other participants they receive a general definition of sales costs. A **volume-based costing (VBC) report**, gathers the cost of all four sales activities (=10.828.424) into a single cost pool. This cost pool is allocated to customers via the driver ‘sales’ which does not capture the actual resource consumption patterns of customers (Selnes, 1992). In fact, VBC cues produces a highly biased cost picture compared to actual data. By fixating on these biased figures, participants may perform worse than under aggregated reports were such figures are not available. Nevertheless, the extra customer’ cues may contain also some relevant components.

Participants with a **customer profitability analysis (CuPA) report** receive more accurate cost figures. The typical sales costs are allocated to customers according to their resource usage. CuPA reports, however, make a small aggregation error since the cost of sales activity “SA1” and “SA2” are aggregated into a single cost pool which is allocated to customers using the number of orders as cost driver (footnote c of Table A1). Since the aggregation error is small, the cost per unit and the profitability per customer under CuPA (last column of Panel B) strongly resembles actual figures of Panel A. Participants using more refined CuPA reports for price differentiation should outperform participants with less refined reports, especially in complex cost scenarios where it is more difficult to learn from additional information on sales support, due to the fact that customers make diverse use of sales support.

ENDNOTES

1. There exists limited evidence that market discipline may eliminate the impact of report choices on variable vs. absorption costing (Waller, Shapiro and Sevcik, 1999). But, it has not yet been shown in single settings that the use of 'process feedback' can make cost report choice in terms of increased accuracy versus distorted reporting, less important. In addition, the conditions under which process feedback may or may not assist the decision maker, remains unresolved. Cost complexity (as defined in Gupta and King, 1997) may be a factor that negatively affects the value of process feedback for profit improvement, such that more accurate costing becomes important again.
2. Gupta and King (1997) use the term heterogeneity in resource usage to also describe that the level of support of a product varies strongly in each kind of support function. This term causes some confusion. Customers or products may be heterogeneous in terms of cost simply because certain types of customers or products generally use more support in every support function (Cooper, 1988, Lere, 2000). Diversity across support functions is then still low. Higher levels of diversity in Gupta and King (1997) and in our study represent settings in which products or customers, that are overall more costly, still use less support vis-à-vis other products or customers in some support functions.
3. Subjects will act as managers of firms with complete discretion on prices, comparable to setting of Narayanan (2003). We mainly focus on process feedback (sales support). Therefore, competitors and market feedback (Callahan & Gabriel, 1998; Waller, Shapiro & Sevcik, 1999) were not considered.
4. The aggregation error remained small, since resource usage in SA1 strongly resembles that of SA2.
5. Note that we only used 169 observations in subsequent analyses, due to one significant outlier. One participant in the cell "VBC/simple cost setting" was four times the standard deviation removed from the mean. On the basis of the Grubb's test for outlying observations, one can reject with 99% confidence that the performance of this participant comes from the same distribution as that of other participants in that cell. Analyses in the other cells did not reveal any other outliers of this kind.
6. In reality we rewarded the best player in each of the six treatments with a coupon. The average realized profit of all experimental trials was taken as a reward, in order to restrict people from taking risky decisions for one of the trials. McIntyre and Ryans (1983) use a similar compensation scheme.
7. Managers often call into question the wisdom of investing in more refined costing systems (Malmi, 1997; Narayanan and Sarkar, 2002), because they can address distortions introduced in existing VBC-cost systems via their general accounting knowledge (Dearman and Shields, 2001). Our test may indicate whether more

refined costing still provides benefits in complex cost settings, even if participants are aware that VBC produces biased cost data. Note, that analyses were only run for VBC and CuPA reports, because aggregated data does not display any cost data on customer-level.

8. $\%dev.\pi_i^* = (\pi^* - \pi_i)/\pi^*$ where π^* is the optimal profit and π_i is the average realised profit over the 10 trials for each participant i . The optimal profit π^* can be found in Table 1.
9. While interactions in the previous section showed increased value of cost reports (especially CuPA reports) in complex cost settings, they do not explicitly test for redundancy in simple settings.
10. $dev.P_{Ai}^* = \text{abs}(P_A^* - P_{Ai})/P_A^*$ with P_A^* the optimal price for customer A (see Table 1) and P_{Ai} the participant's mean price over 10 trials. The absolute value is taken because prices above and below optimum are possible. Similar formulas for PB and PC. Lower scores represent better performance.
11. Predicting the right direction was coded as 1 if average prices were such that $P_B > P_A > P_C$ and zero otherwise. Because of this zero/one dummy the use non-parametric testing is advisable for pairwise comparisons across report types (cfr. Kruskal-Wallis test).
12. In order to test whether the phenomenon of "loss aversion" explained the differences in profits between VBC and AGGR reports in Table 4, a variable "LOSS" was created (with LOSS is 1 if $P_C \geq 144$ or $P_C \leq 104$ and 0 otherwise). We explore whether "LOSS" is a 'mediating' variable between the dependent variable "%dev. π " and the contrast "Report_(VBC/AGGR)" in a complex cost setting. We therefore examined the criteria proposed by Baron and Kenny (1986) that stated that if the mediator is added to the model, it should have an effect on the dependent variable while the contrast effect should be reduced to non-significance. The test strongly supported the mediation hypothesis. With "LOSS" added to the general model, the marginal significant effect of "Report_(VBC/AGGR)" on profits (panel B of table 4) was reduced to non-significance ($F=0.78$, $p>0.38$) while the effect of "LOSS" remained highly significant ($F=5.95$, $p<.02$).

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TABLE 1

The experimental setting

Panel A: Underlying functions in the experiment^a

Demand: $Q_i = a_i - b_i P_i$ (1)

Cost functions:

Cost of goods sold: $CGS_i = pc_i Q_i$ (2)

Sales activity 1: $SA1_i = (ru1_i/1000) dr1 Q_i$ (3)

Sales activity 2: $SA2_i = (ru2_i/1000) dr2 Q_i$ (4)

Sales activity 3: $SA3_i = (ru3_i/1000) dr3 Q_i$ (5)

Sales activity 4: $SA4_i = (ru4_i/1000) dr4 Q_i$ (6)

Cost per unit: $C_i = pc_i + \sum_{j=1}^4 (ru_{ij}/1000) * dr_j$ (7)

Customer profitability: $\pi_i = (P_i - C_i) Q_i = (P_i - pc_i - \sum_{j=1}^4 (ru_{ij}/1000) * dr_j) (a_i - b_i P_i)$ (8)

Optimal price: $P_i^* = \frac{a_i + b_i (pc_i + \sum_{j=1}^4 (ru_{ij}/1000) dr_j)}{2b_i}$ (9)
(solve first order condition for 8)

Panel B: Parameters and optimal solution for each customer in each environment^b

		SIMPLE Low support diversity			COMPLEX High support diversity		
		CUST. A	CUST. B	CUST. C	CUST. A	CUST. B	CUST. C
Parameters							
Demand	a	200000	330000	295000	200000	330000	295000
	b	1240	1790	2050	1240	1790	2050
Purchase cost	pc	55	54.5	56	55	54.5	56
Resource usage dr1=1500; dr2=3000; dr3=1500; dr4=2000	ru1	3.4	4	3	3	2	3
	ru2	3	5	2.5	4	3	5
	ru3	8	11	6	13	11	2
	ru4	9	13	5.75	4	17.5	5
Cost per unit	C	99.1	118.0	88.5	99.0	118.0	88.5
Optimal solution							
Price	P*	130.2	151.2	116.2	130.1	151.2	116.2
Customer profit	π^*	1198967	1970487	1573083	1202826	1970487	1573083
Firm profitability			4742537			4746396	

^a With i = customers A, B, C; For each customer Q_i represents the demand of the product; a_i and b_i the demand parameters; P_i the price charged; pc_i the purchasing cost of the product sold; $ru1_i$ until $ru4_i$ the average no. of resources used for 1000 units sold; $dr1$ till $dr4$ driver rates per resource consumed.

^b Optimal prices for each customer can be found by setting the first derivative of the customer profits (equation 8, panel A) to zero: $2b_i P_i + a_i + b_i pc_i + b_i \sum ru_{ij} * dr_j = 0$. Solving this equation for P_i results into the optimal solution of equation 9. This price maximizes customer profitability since the second^d derivative of equation 8 is < 0 (second order condition for a maximum).

TABLE 2

Displayed tables on a customer's resource usage patterns ^a

Simple cost environment with low sales support diversity across customers				Complex cost environment with high sales support diversity across customers			
↓ ↓							
Resources	A	B	C	Resources	A	B	C
Orders	2	1	3	Orders	2	3	1
Stock Pickings	2	1	3	Stock Pickings	1	2	3
Deliveries	2	1	3	Deliveries	3	1	2

^a Rank 1 stands for the highest resource usage at a particular support activity, 2 for the second most; 3 for the least resources. Only in a simple cost setting, the most costly type of customer B consistently uses more support at every sales support process.

TABLE 3

Summary statistics and ANOVA-analysis on the mean %dev.p^a

Panel A: Summary statistics of the mean % dev.π

	AGGR	VBC	CuPA
Simple Cost	0.25%	4.69%	4.44%
mean % dev. π	13.69%	13.44%	9.00%
# subjects (n)	28	28	29
Complex Cost	5.85%	17.43%	11.58%
mean % dev. π	31.18%	25.33%	13.75%
# subjects (n)	28	28	28

Panel B: Full ANOVA-model^b and contrast estimates of pairwise interactions^c

	F-value	p-value	<i>Pairwise interactions</i>	
			Estimate	p-value
Environment (E)	44.89	0.0001 ^{***}	RE_{CuPA_Other}	9.94% 0.0034 ^{***}
Report (R)	15.17	0.0001 ^{***}	RE_{CuPA_AGGR}	12.74% 0.0013 ^{***}
Interaction (RE)	4.73	0.0101 ^{**}	RE_{CuPA_VBC}	7.14% 0.0437 ^{**}
F-model	16.93	0.0001 ^{***}	RE_{VBC_AGGR}	5.60% 0.0906 [*]
R-square	34.2%			

^a Mean % dev.π =relative distance of a participants' mean realized profit (10 trials) to the optimal profit

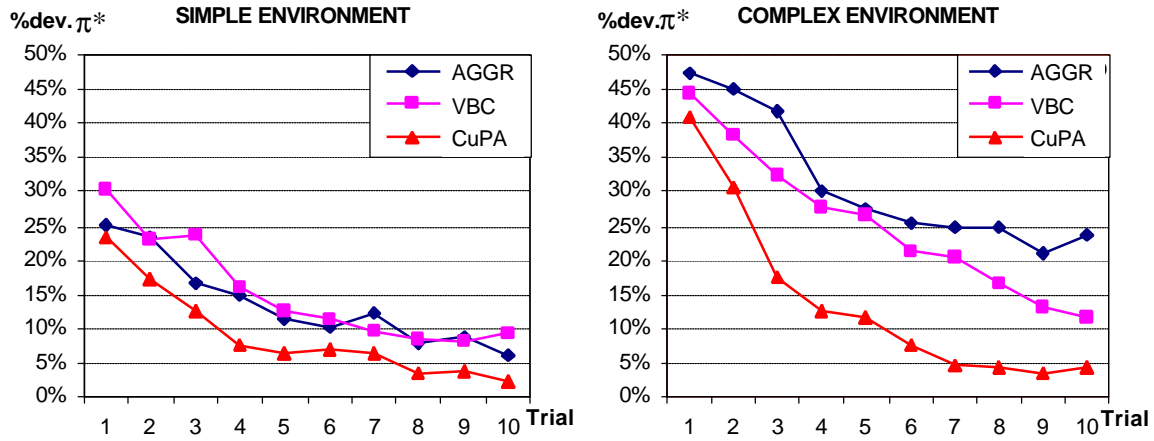
^b Anova with the mean %dev.π as the dependent, and main and interactive effects of Report (0=AGGR; 1=VBC; 2=CuPA) and complexity of the cost Environment (Low support diversity=0, High =1).

^c We performed contrasting coding on cell differences. Estimates rather than F-values are reported to allow judgment of the size-effect of the differential impact of accounting reports across environments. *, **, ***, significant at 10%, 5% or 1 % respectively.

TABLE 4

Learning effects by cost environment across the various report types

Panel A: Trial by trial %dev. π for each experimental cell



Panel B: ANOVA by environment on the dependent ‘%dev. π ’; report type as within-subjects; trial as repeated measure; and contrasts for pairwise comparison^a

	Simple Cost (E=0)		Complex Cost (E=1)	
	F-value	P-value	F-value	P-value
Between-subjects				
Report (R)	2.01	0.1405	15.24	0.0001***
Within-subjects				
Trial (T)	57.59	0.0001***	78.06	0.0001***
Trial*Report (TR)	1.07	0.4289	1.89	0.0139**
Contrast-effects				
$R_{(AGGR/CuPA)}$	2.83	0.0964*	29.41	0.0001***
$Trial * R_{(AGGR/CuPA)}$	0.52	0.8575	2.46	0.0093***
$R_{(VBC/CuPA)}$	3.16	0.0792*	12.98	0.0005***
$Trial * R_{(VBC/CuPA)}$	1.06	0.4572	1.95	0.0430**
$R_{(AGGR/VBC)}$	0.01	0.9251	3.32	0.0723*
$Trial * R_{(AGGR/VBC)}$	1.65	0.1557	1.28	0.2462

^a Trial was added as repeated measure to represent learning in terms of how well participants converged to optimal profits as measured by the trial by trial %dev. π . The contrast $R_{(.,.)}$ is between-subjects and $Trial * R_{(.,.)}$ is within-subjects. The latter tests for differences in convergence rates across cost reports (which are also graphically shown in Panel A). *, **, ***, significant at 10%, 5% or 1 % respectively.

TABLE 5:

Additional analyses: pairwise report comparison of price deviations of P_A, P_B, P_C ^a

Contrast estimates	Simple Cost (E=0)			Complex Cost (E=1)		
	%dev. P_A	%dev. P_B	%dev. P_C	%dev. P_A	%dev. P_B	%dev. P_C
Report _{AGGR_CuPA}	-0.86%	-2.37% ^{**}	-2.31% ^{**}	-1.93% ^{**}	-6.11% ^{***}	-8.09% ^{***}
Report _{VBC_CuPA}	-0.42%	-2.63% ^{**}	-3.10% ^{***}	-1.79% ^{**}	-5.77% ^{***}	-4.03% ^{**}
Report _{AGGR_VBC}	-0.45%	0.26%	0.79%	-0.14%	-0.34%	-4.05% ^{**}

^a We ran three ANOVA models by cost environment on the dependents %dev. P_A , %dev. P_B , %dev. P_C , (respectively the mean relative distance to optimal prices for customer A, B and C) and report type as independent factor. Contrast estimates are reported to allow judgment of the size effect of pairwise differences across report types. *, **, ***, significant at 10%, 5% or 1 % respectively.

TABLE A1

Actual data at the start versus the three accounting reports (cfr. simple environment)

Panel A: Actual figures for the starting prices, calculated via functions of table 1

Actual items	TOT	A	B	C
Starting prices	-	119	117	131
Sales volume	199460	52440	120570	26450
Revenues	23812000	6240360	14106690	3464950
Cost of goods sold	10936465	2884200	6571065	1481200
Cost sales activities	10828424	2312604	7656195	859625
SA1	1109889	267444	723420	119025
SA2	2478885	471960	1808550	198375
SA3	2856735	629280	1989405	238050
SA4	4382915	943920	3134820	304175
Profit	2047111	1043556	-120570	1124125
Unit Cost	-	99.1	118.0	88.5

Panel B: The different possible accounting report types issued to the participants

Aggregated report ^a		VBC report ^b			CuPA Report ^c		
Column A		= info below + column A			= Info below + Column A		
Income statement	TOT	A	B	C	A	B	C
Price	-	119	117	131	119	117	131
Sales volume (Q)	199460	52440	120570	26450	52440	120570	26450
Revenues	23812000	6240360	14106690	3464950	6240360	14106690	3464950
Cost of goods sold	10936465	2884200	6631350	1481200	2884200	6631350	1481200
Cost sales activities	10828424	2846899	6545588	1435936	2256474	7742530	829420
Profit	2047111	509261	990037	547814	1099686	-206905	1154330
Unit Cost	-	109.3	108.8	110.3	98.0	118.7	87.4

^a Cost sales activities stands =cost of order processing, stock picking and delivery. This description was issued to participants and it was suggested that certain customers required more support than others.

^b Cost Pool

TOT (panel A)	Driver	A	B	C
10828424	Sales volume	2846899	6545588	1435936

Allocated via sales volume e.g. Cust. A is assigned: $[52440 (Q_a)/199460 (Q_{tot})] * 10828424 = 2846899$

^c Cost Pools

TOT (panel A)	Driver	A	B	C
3588774	ru2; orders	683274	2618305	287195
2856735	ru3; stock pickings	629280	1989405	238050
4382915	ru4; deliveries	943920	3134820	304175
10828424		2256474	7742530	829420

Allocated via the no. of orders, stock pickings and deliveries e.g. number of orders for customer A = $(3/1000) * 52440 = 157,32$; for B = $(5/1000) * 120570 = 602,85$; for C = $(2,5/1000) * 26450 = 66,125$ → Total orders = 826,295; Customer A is assigned: $(157,32/826,295) * 3588774 = 683274$. Similar analysis for customer B and C; cost pools 2 and 3.