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Stephan Leitner

Information Quality and Management Accounting

A Simulation Analysis of Biases in Costing Systems

Springer

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Foreword

Information generated by management accounting mainly serves two important roles: On the one hand, decision-makers are supplied with information that can be used as a basis to make well-founded decisions ("decision-facilitating information"). On the other hand, the managers' decision-making behavior is controlled by the specific use of the information provided by management accounting ("decision-influencing information"). Cost accounting systems, which play a very dominant role in the organizational practice, generate information for both functions.

In this context, the quality of the information which is provided by cost accounting systems and used for decision-facilitating as well as for decision-influencing purposes is an interesting point. Particularly the complexity of cost accounting systems used in practice indicates that there might be a number of sources for errors. These might, for instance, be errors in entering data or in the assignment of cost centers. With respect to information quality, these and other types of errors might be mutually correlated. Suboptimal decision-making and suboptimal controlling are among the consequences to be expected.

The present dissertation by Stephan Leitner particularly focuses on the question "which are the effects of biases on the quality of provided information in traditional costing systems." The findings are of high relevance for management science and, in particular, for management accounting research. In his dissertation, Leitner applies agent-based simulation as the research method which is a relatively new approach for this field. This makes it even more attractive for the scientific community. At the same time, the findings are of high relevance for the organizational practice. While cost accounting systems are among the widest spread types of management accounting systems, there is only little research on the quality of the provided information.

It can only be hoped that this dissertation attracts a broad interest in the scientific community as well as in the organizational practice.

Klagenfurt, Carinthia, Austria | Univ.-Prof. Dr. Friederike Wall

Preface

One of the main aims of management accounting is to provide managers with accurate information in order to provide a good basis for decision-making. There is evidence that data provided by management accounting systems (MAS) is distorted and the occurrence of biases in accounting information is widely accepted among users of MAS. At the same time, the intensity and the frequency of use of MAS in order to retrieve information as the basis for managerial decision-making increase. Consequently, the quality of the provided information is critical. The effects of biases in the provided accounting information might range from disruptions in operations to organizational extinction. In order to react appropriately to biases in the provided accounting information, knowledge of the impact of distortions in raw accounting data on the quality of the provided information is indubitably necessary. This emphasizes the need of research on biases in MAS and interactions among them and the respective impact on the quality of the provided information.

This book investigates the impact of a set of input biases in raw accounting data on the quality of the provided information in the case of traditional costing systems. The focus of this simulation study is twofold. On the one hand, the impact of traditional costing system sophistication on error propagation in the case of a set of input biases is investigated. On the other hand, the impact of single and multiple input biases on the quality of the information provided by traditional costing systems is discussed. In order to investigate the research questions, a simulation approach is applied.

Without the support of my doctoral supervisors, colleagues, friends, and family, it would not have been possible to finish my dissertation in the present state. They affected my motivation to write this dissertation in a positive way. Firstly, I would like to express my gratitude to my doctoral supervisors Univ.-Prof. Dr. Friederike Wall and Univ.-Prof. Dr. Franz Rendl for their continuous support, careful guidance, and valuable comments during all stages of my dissertation project. Moreover, I would like to thank my colleagues at the Alpen-Adria Universität of Klagenfurt for being so supportive. In particular, I would like to thank Alexandra and Katharina who were a great help in proofreading and gave valuable comments on earlier drafts of this dissertation. I would also like to thank them for being a source of

emotional support. Finally, I would like to thank my friends and my family for their understanding and support through all the ups and downs during the last years. They were an indispensable source of joy and happiness. Without their presence, I would not have made it this far.

Klagenfurt, Carinthia, Austria Dr. Stephan Leitner

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$A^{h,l}$	set of actions, agent h can select in order to fulfill task l
$a^{h,l,*}$	action desired by the principal to be selected by agent h in order to fulfill task l
$a^{h,l}$	action selected by agent h in order to fulfill task l
A	set of actions the agent can choose from (basic hidden action model)
a	action chosen by the agent in order to fulfill a task (basic hidden action model)
b_i^{dcp}	overhead rate for cost centers $m_i \in M^{dir^{dcp}}$
b_i^{mc}	overhead rate for cost centers $m_i \in M^{dir^{mc}}$
bc_i	i^{th} business case
BC	set of business cases
$costs_j^{prod,df,bench}$	benchmark costs at simulation run j, decision-facilitating perspective
$costs_{i,j}^{prod,di,bench}$	benchmark costs for cost center m_i at simulation run j, decision-influencing perspective
C_{in}^{dir}	set of input cost objects that contain information on direct costs
C_{in}^{indir}	set of input cost objects that contain information on indirect costs
c_{in_i}	i^{th} input cost object
C_{in}	set of input cost objects
c	index, interchangeably used
$cd_{i,j}^{ex}$	share of the j^{th} element of vector $\vec{g}$ that has to be allocated to cost center m_i, to be observed by agents
$\mathbf{CD}^{ex}$	matrix with allocation keys for allocation type 1, to be observed by agents
$cd_{i,j}$	share of the j^{th} element of vector $\vec{g}$ that has to be allocated to cost center m_i, introduced into the costing system by agents

CD	matrix with allocation keys for allocation type 1, introduced into the costing system by agents
$costs_i^{dir}$	total amount of direct costs per direct cost pool $k_i^{dir,group}$
$costs_i^{ent}$	entire costs allocated to direct cost center m_i
$costs_i^{prim}$	costs allocated to cost center m_i in allocation type 1
$costs^{prod,df}$	total cost per product, decision-facilitating information
$costs_i^{prod,di}$	overall costs for cost centers $m_i \in M^{dir}$, decision-influencing information
$costs_{i,j}^{sec}$	costs allocated from indirect cost center m_j to indirect cost center m_i in allocation type 2
dc_i	direct costs for product calculations incurred at cost center $m_i \in M^{dir^{dcp}}$
$\delta_{cd^{type:2},i,j,n}$	magnitude of input bias on the basis for allocation type 2 for cost driver r_i, providing cost center m_j and receiving cost center m_n
$\delta_{div,i}$	magnitude of input bias on differences in valuation for input cost object c_{in_i}
$\delta_{ico,i}$	magnitude of input bias on input cost objects for input cost object c_{in_i}
$EUCD_{n,q}^{df}$	Euclidean Distance, due to input biases n and q, decision-facilitating perspective
$EUCD_n^{df}$	Euclidean Distance, due to input bias n, decision-facilitating perspective
$EUCD_{n,q}^{di}$	Euclidean Distance, due to input biases n and q, decision-influencing perspective
$EUCD_n^{di}$	Euclidean Distance, due to input bias n, decision-influencing perspective
$\overline{e}_n^{mean,df}$	maximum mean absolute relative error due to input bias n, decision-facilitating perspective
$\overline{e}_n^{mean,di}$	maximum mean absolute relative error due to input bias n, decision-influencing perspective
$\overline{e}_{n,q}^{df}$	maximum relative error due to input biases n and q, decision-facilitating perspective
$\overline{e}_n^{df}$	maximum relative error due to input bias n, decision-facilitating perspective
$\overline{e}_{n,q}^{di}$	maximum relative error due to input biases n and q, decision-influencing perspective
$\overline{e}_n^{di}$	maximum relative error due to input bias n, decision-influencing perspective
$e_{n,q}^{mean,df}$	mean absolute relative error due to input biases n and q, decision-facilitating perspective
$e_n^{mean,df}$	mean absolute relative error due to input bias n, decision-facilitating perspective

$e_{n,q}^{mean,di}$	mean absolute relative error due to input biases n and q, decision-influencing perspective
$e_{n}^{mean,di}$	mean absolute relative error due to input bias n, decision-influencing perspective
$\underline{e}_{n}^{mean,df}$	minimum mean absolute relative error due to input bias n, decision-facilitating perspective
$\underline{e}_{n}^{mean,di}$	minimum mean absolute relative error due to input bias n, decision-influencing perspective
$\underline{e}_{n,q}^{df}$	minimum relative error due to input biases n and q, decision-facilitating perspective
$\underline{e}_{n}^{df}$	minimum relative error due to input bias n, decision-facilitating perspective
$\underline{e}_{n,q}^{di}$	minimum relative error due to input biases n and q, decision-influencing perspective
$\underline{e}_{n}^{di}$	minimum relative error due to input bias n, decision-influencing perspective
δ_{n}^{df}	difference between minimum and maximum mean absolute relative errors which are due to input bias n, decision-facilitating perspective
δ_{n}^{di}	difference between minimum and maximum mean absolute relative errors which are due to input bias n, decision-influencing perspective
$e_{j,n}^{df}$	relative error due to input biases n and q at simulation run j, decision-facilitating perspective
$e_{j,n}^{df}$	relative error due to input bias n at simulation run j, decision-facilitating perspective
$e_{i,j,n,q}^{di}$	relative error due to input biases n and q occurred at cost center m_i at simulation run j, decision-influencing perspective
$e_{i,j,n}^{di}$	relative error due to input bias n occurred at cost center m_i at simulation run j, decision-influencing perspective
$\underline{U}$	utility the agent can obtain from alternative contracts (basic hidden action model)
$f^{S}(\cdot)$	agent's compensaton function (basic hidden action model)
$f^{g}(\cdot)$	function that defines the agent's disutility of effort (basic hidden action model)
$f^{w}(\cdot)$	function that defines the outcome (basic hidden action model)
$f^{v}(\cdot)$	function that defines the agent's utility of compensation (basic hidden action model)
$f^{c}(\cdot)$	function that captures the observation of business cases and the generation of input cost objects
$f_{biased}^{c}(\cdot)$	function that captures the observation of business cases and the generation of input cost objects (in case of bias)

$f^{cd^{type:1}}(\cdot)$	function that captures agents observing keys for allocation type 1 and introducing observed information into the costing system
$f^{cd^{type:1}}_{biased}(\cdot)$	function that captures agents observing keys for allocation type 1 and introducing observed information into the costing system (in case of bias)
$f^{cd^{type:2}}(\cdot)$	function that captures agents observing cost driver activities for allocation type 2 and introducing observed information into the costing system
$f^{cd^{type:2}}_{biased}(\cdot)$	function that captures agents observing cost driver activities for allocation type 2 and introducing observed information into the costing system (in case of bias)
$f^{dcp}(\cdot)$	function that assigns direct cost pools to cost centers $M^{dir^{dcp}}$
$f^{dcp}_{biased}(\cdot)$	function that assigns direct cost pools to cost centers $M^{dir^{dcp}}$ (in case of bias)
$f^{g^h}(\cdot)$	function that gives the disutility for effort of selected actions in order to fulfill tasks for agent h
$f^k(\cdot)$	function that assigns cost categories to input cost objects
$f^k_{biased}(\cdot)$	function that assigns cost categories to input cost objects (in case of bias)
$f^{k,cat}$	function that classifies cost categories as direct and indirect, respectively
$f^{k,cat}_{biased}(\cdot)$	function that classifies cost categories as direct and indirect, respectively (in case of bias)
$f^{k,dir}(\cdot)$	function that builds direct cost pools
$f^{k,dir}_{biased}(\cdot)$	function that builds direct cost pools (in case of bias)
$f^l(\cdot)$	function that captures the assigment of tasks to agents
$f^{m,cat}(\cdot)$	function that categorizes cost centers into direct and indirect cost centers, respectively
$f^{m,cat}_{biased}(\cdot)$	function that categorizes cost centers into direct and indirect cost centers, respectively (in case of bias)
$f^{m^{dir},cat}(\cdot)$	function that builds subsets $M^{dir^{dcp}}$ and $M^{dir^{mc}}$
$f^r(\cdot)$	function that defines which cost drivers are the correct basis for allocation type 2
$f^r_{biased}(\cdot)$	function that defines which cost drivers are the basis for allocation type 2 (in case of bias)
$f^s(\cdot)$	function that determines differences in valuation for business cases
$f^{s,div}_{biased}(\cdot)$	function that determines differences in valuation for business cases (in case of bias, if the wrong magnitude of differences in valuation is calculated)
$f^{s,divnc}_{biased}(\cdot)$	function that determines differences in valuation for business cases (in case of bias, if no differences in valuation are considered)

$f^{S^h}(\cdot)$	compensation function for agent h
$f^{S^h,var}(\cdot)$	function that gives the variable compensation component for agent h
$f^{v^h}(\cdot)$	function that gives the utility of compensation for agent h
$f^{w^{ent}}(\cdot)$	function that gives overall outcome
$f^{w^{h,l}}(\cdot)$	function that gives the outcome of task l delegated to agent h
g_i	i^{th} element of vector $\vec{g}$
$\vec{g}$	vector that contains cost information of input cost objects that have assigned indirect cost categories
$\gamma_{acat,i}$	indicator for input biases on the assignment of cost categories, for input cost object c_{in_i}
$\gamma_{asgnm-cd^{type:2},i,j}$	indicator for input biases on the assignment of cost drivers for allocation type 2, i.e. indicates whether or not reallocation of cost from indirect cost center m_i to cost center m_j is based on the correct cost driver
$\gamma_{asgnm-dcp,i}$	indicator for input biases on the assignment of direct cost pools, i.e. indicates whether or not direct cost center m_i has assigned the correct direct cost pool
$\gamma_{catcategory,i}$	indicator for input biases on the categorization of cost categories for cost category k_i
$\gamma_{catcenter,i}$	indicator for input biases on the categorization of cost center for cost center m_i
$\gamma_{cd^{tpye:1},i,j}$	indicator for input biases on the basis for allocation type 1, for share of element g_j of vector $\vec{g}$ that should be allocated to cost center m_i
$\gamma_{cd^{tpye:2},i,j,n}$	indicator for input biases on the basis for allocation type 2, for cost driver r_i, the providing cost center m_j and the receiving cost center m_n
$\gamma_{dcp,i}$	indicator for input biases on the building of direct cost pools, i.e. indicates whether or not direct cost category k_i has assigned the correct direct cost pool
$\gamma_{divnc,i}$	indicator for input biases on differences in valuation, for input cost object c_{in_i} (if a differences in valuation are not considered)
$\gamma_{div,i}$	indicator for input biases on differences in valuation, for input cost object c_{in_i} (if a false extent of differences in valuation is calculated)
$\gamma_{ico,i}$	indicator for input biases on input cost objects, for input cost object c_{in_i}
$H^{acc-dep}$	set of managers of the accounting department
H^{dir}	set of managers of direct cost centers
H^{indir}	set of managers of indirect cost centers
H	set of agents
h	agent

i	index, interchangeably used
j	index, interchangeably used
$k_i^{dir,group}$	i^{th} direct cost pool
$K^{dir,group}$	set of direct cost pools
K^{dir}	set of direct cost categories
K^{indir}	set of indirect cost categories
k_i	i^{th} cost category
K	set of cost categories
L^h	set of tasks delegated to agent h
L	set of tasks
l	task
$M^{dir^{dcp}}$	set of direct cost centers with direct cost pool as basis for allocation type 3
$M^{dir^{mc}}$	set of direct cost centers with manufacturing costs as basis for allocation type 3
M^{dir}	set of direct cost centers
M^{indir}	set of indirect cost centers
m_i	i^{th} cost center
$MSE_{n,q}^{df}$	mean squared error, due to input biases n and q, decision-facilitating perspective
MSE_n^{df}	mean squared error, due to input bias n, decision-facilitating perspective
$MSE_{n,q}^{di}$	mean squared error, due to input biases n and q, decision-influencing perspective
MSE_n^{di}	mean squared error, due to input bias n, decision-influencing perspective
M	set of cost centers
$\nu_{n,q}^{di}$	measure for compensation among biases n and q, decision-facilitating perspective
$\nu_{n,q}^{di}$	measure for compensation among biases n and q, decision-influencing perspective
n	index, interchangeably used
$p_{n,q}^{over,df}$	probability of overcosting of input biases n and q, decision-facilitating perspective
$p_n^{over,df}$	probability of overcosting of input bias n, decision-facilitating perspective
$p_{n,q}^{over,di}$	probability of overcosting of input biases n and q, decision-influencing perspective
$p_n^{over,di}$	probability of overcosting of input bias n, decision-influencing perspective
$p_{n,q}^{under,df}$	probability of undercosting of input biases n and q, decision-facilitating perspective
$p_n^{under,df}$	probability of undercosting of input bias n, decision-facilitating perspective

$p_{n,q}^{under,di}$	probability of undercosting of input biases n and q, decision-influencing perspective
$p_{n}^{under,di}$	probability of undercosting of input bias n, decision-influencing perspective
p_{acat}	probability of occurrence for input biases on the assignment of cost categories
$p_{asgnm-cd^{type:2}}$	probability of occurrence for input biases on the assignment of cost drivers for allocation type 2
$p_{asgnm-dcp}$	probability of occurrence for input biases on the assignment of direct cost pools
$p_{catcenter}$	probability of occurrence for input biases on the categorization of cost centers
$p_{cd^{type:2}}$	probability of occurrence for input biases on the basis for allocation type 2
$p_{catcategory}$	probability of occurrence for input biases on the categorization of cost categories
p_{dcp}	probability of occurrence for input biases on the building of direct cost pools
p_{divnc}	probability of occurrence for input biases on differences in valuation (if a differences in valuation are not considered)
p_{div}	probability of occurrence for input biases on differences in valuation (if a false extent of differences in valuation is calculated)
p_{ico}	probability of occurrence for input biases on input cost objects
P	principal
$p_{cd^{type:1}}$	probability of occurrence for input biases on the basis for allocation type 1
p_s	probability of occurrence for differences in valuation
$\mathbf{Q}$	matrix that contains costs allocated in allocation type 1
$q_{i,j}$	element of matrix $\mathbf{Q}$, share of g_j allocated to cost center m_i
R	set of cost drivers
$\rho_{n,q}^{df}$	measure for interactions among biases n and q, decision-facilitating perspective
$\rho_{n,q}^{di}$	measure for interactions among biases n and q, decision-influencing perspective
$r_{i,j,n}^{ex}$	element of matrix R^{ex}, amount of cost driver r_i provided by cost center m_j and received by cost center m_n, to be observed by agents
$\mathbf{R}^{ex}$	matrix with cost driver activities for allocation type 2, to be observed by agents
$r_{i,j,n}$	element of matrix R, amount of cost driver r_i provided by cost center m_j and received by cost center m_n, observed and introduced into the costing system by agents

$\mathbf{R}$	matrix with cost driver activities for allocation type 2, introduced into the costing system by agents
$soph^{cat}$	cost category sophistication
$soph^{cent}$	cost center sophistication
S_0^h	fixed compensation component for agent h
s_i	rate of differences in valuation for the i^{th} input cost object
Θ	set of random states of nature (basic hidden action model)
θ	random state of nature (basic hidden action model)
θ^l	state of interactions for task l
$U^H(\cdot)$	agent's utility function (basic hidden action model)
$U^P(\cdot)$	principal's utility function
$U^{A^h}(\cdot)$	agent's h utility function
$U[\underline{a}_{bc};\overline{a}_{bc}]$	interval for the generation of business cases
$U[\underline{a}_{cd^{type:2}};\overline{a}_{cd^{type:2}}]$	interval for the magnitude of bias for input biases the basis for allocation type 2
$U[\underline{a}_s;\overline{a}_s]$	interval for differences in valuation
$U[\underline{a}_{div};\overline{a}_{div}]$	interval for the magnitude of bias for input biases on differences in valuation
$U[\underline{a}_{ico};\overline{a}_{ico}]$	interval for the magnitude of bias for input biases on input cost objects
$U[\underline{a}_{prod};\overline{a}_{prod}]$	interval for the generation of direct costs for product calculations
$U[\underline{a}_{cd^{type:2}};\overline{a}_{cd^{type:2}}]$	interval for the generation of cost drivers
W	outcome (basic hidden action model)
W_{true}^{ent}	overall outcome, provided by sources other than the costing system
W^{ent}	overall outcome, provided by the costing system
$W^{h,l}$	outcome of task l delegated to agent h

Chapter 1
Introduction

Abstract The introduction is organized in four sections. Section 1.1 outlines the research problem and elaborates the research questions which are investigated in the current simulation study. Section 1.2 presents prior research on the effects of biases in raw accounting data on the accuracy of provided decision-influencing and decision-facilitating information. Section 1.3 gives the rationale for the choice of research method. Finally, Sect. 1.4 outlines the structure of the chapters of this simulation study.

1.1 Research Problem and Research Questions

In its most simple form, the purpose of management accounting can be defined as collecting and recording useful accounting and statistical data as well as reporting them to decision-makers (Crossman 1958; Singer 1961; Feltham 1968; Bruns and McKinnon 1993; Brignall 1997; Bouwens and Abernethy 2000; Chenhall 2003; Cassia et al. 2005; Horngren et al. 2005). The environment in which management accounting takes place, appears to have changed within the last decades. As a response to increased turbulence, competition and uncertainty, advances in information technology and new management accounting practices, a wide variety of management accounting systems (MAS) has evolved in order to fulfill the basic function of information provision (Ezzamel et al. 1996; Bouwens and Abernethy 2000; Burns and Scapens 2000; Garg et al. 2003; Heidmann et al. 2008). While, due to these changes, MAS increase in complexity, the intensity and frequency of use of MAS increase, too (Paradice and Fürst 1991; Chong 1996). Many managerial decisions are based on information provided by MAS (Horngren et al. 2002; Garg et al. 2003). Hence, one of the main scopes of MAS can be defined as providing decision-makers with information that reflects the real world (Cooper and Kaplan 1988; Orr 1998). Consequently, the quality of information provided by MAS is critical (Paradice and Fürst 1991).

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MAS are unlikely to be free of error in application (Orr 1998; Labro and Vanhoucke 2007, 2008; Banham 2002). There is evidence that data used for decision-making is affected by errors-rates that range from 5 to 10 % (Madnick and Wang 1992; Orr 1998; Banham 2002). Redman (1996; 1998) reports even higher error-rates that range up to 30 %. Defective information provided by MAS and used as a basis for decision-making potentially leads to suboptimal or wrong decisions or even to failing to recognize the need to make a decision, where the respective impacts potentially range from disruptions in operations to organizational extinction (Fox 1961; Cooper and Kaplan 1988; Wang and Strong 1996; Orr 1998; Biros et al. 2002; Ballou et al. 2003; Lillrank 2003; Tee et al. 2007). Usually, MAS serve many purposes within organizations and provide information to a wide variety of decision-makers with potentially different interests. According to Christensen (2010) this multiplicity of purposes MAS serve and the various needs of information recipients, lead to biases in provided information (e.g. information provided by MAS might serve decision-facilitating and decision-influencing purposes, cf. Demski and Feltham 1976, cf. also Sect. 2.2.2). Although there is little information on the effects of biases in MAS on provided information, the occurrence of biases is widely accepted among users of MAS (cf. Labro and Vanhoucke 2007) and users of information provided by MAS perceive provided information as a good basis for cost management and the achievement of cost transparency (cf. Friedl et al. 2009). In order to react appropriately to biased data in MAS and to generate a good basis for managerial decision-making, knowledge of the impact of biases on provided information and knowledge on the interactions among biases within costing systems is indubitably necessary (Labro and Vanhoucke 2007; Tee et al. 2007). This emphasizes the need for research on the nature and extent of biases in the context of MAS (cf. also Christensen 2010).

MAS capture a wide variety of different accounting systems. In particular, cost accounting systems, capital budgeting and capital accounting systems can be subsumed under MAS (Ewert and Wagenhofer 2008, for a more detailed classification cf. Sect. 2.3). This simulation study focuses on biases in cost accounting systems because, on the one hand, cost accounting systems appear to be characterized by a larger number of arithmetic operations than capital budgeting systems and capital accounting systems. On the other hand, due to the integration into the organizational processes, a larger number of agents might interact with cost accounting systems than with capital budgeting and capital accounting systems. This might lead to a larger magnitude of biased data to be introduced into the cost accounting system.

Cost accounting systems can be further subdivided on the basis of their level of sophistication. The types job costing system and activity based costing system might be viewed as the ends of a continuum. These classifications are mainly build on the basis of allocation procedures. Mixed forms along the continuum are, of course, possible (e.g. Gosselin 1997; Clarke et al. 1999; Brown et al. 2004; Al-Omiri and Drury 2007; Brierley 2008, for a more detailed elaboration cf. Sect. 2.3.2.1). Among the wide range of different conceptions of costing systems, this simulation study investigates effects of biases in traditional costing systems (for the characterization of the costing system cf. Sect. 4.1). There is empirical evidence that traditional costing systems are widely applied in organizational practice while newer conceptions (i.e., activity based costing systems) show a much lower application rate (Drury and Tayles 1998; Garg et al. 2003). Empirical findings suggest that the sophistication within the traditional form of costing systems increases, e.g., the number of cost centers or the number of cost categories increases in order to map organizational processes on a more detailed level (Friedl et al. 2009). However, whether or not this increasing sophistication affects the quality of the provided information is widely unclear.

This simulation study investigates effects of biases on the quality of provided information in traditional costing systems whereby different sources for biasing behavior are investigated, i.e., intended and unintended biasing behaviors are considered (for detailed elaborations on behavioral assumptions cf. Sects. 3.1.2 and 4.2). In addition to different sources of biasing behavior, this simulation study considers different purposes of information provided by traditional costing systems. Effects from the perspective of the decision-influencing role as well as from the perspective of the decision-facilitating role of provided information are analyzed (cf. Sect. 2.2.2).

In particular, this simulation study investigates the following research questions which are based on the elaborations outlined above:

1. How does the level of (traditional) costing system sophistication affect the quality of decision-influencing and decision-facilitating information provided by costing systems in case of intended and unintended biases in input data?
2. What are the effects of intended and unintended single biases in input data on the quality of decision-influencing and decision-facilitating information provided by (traditional) costing systems?
3. What are the effects of interactions among multiple intended and unintended biases in input data on the quality of decision-influencing and decision-facilitating information provided by (traditional) costing systems?

1.2 Prior Research

Effects of biases in data on information provided by MAS as well as the effects of costing system sophistication on error propagation have rarely been investigated in prior research. This section aims at giving an overview of prior research relevant to the research questions outlined above.

Kaplan and Thompson (1971) apply a linear programming model and analyze cost allocation methods with respect to relative profitability of products not being distorted, i.e., they analyze whether or not before and after cost allocation procedures the same optimal product mix decisions would be made. They suggest an allocation method that fulfills this demand and, additionally, helps in recognizing scarce resource utilization and interactions among product profitability reporting.

In his investigation, Noreen (1991) focuses on activity based costing systems. Specifically, this study aims at finding conditions under which activity based costing systems provide accurate information. Noreen (1991) applies an analytical approach and does not consider various agents interacting with the system. He finds that activity based costing systems provide accurate information if (1) total costs can be partitioned into cost pools whereby each cost pool depends on one activity only, (2) each cost pool is strictly proportional to the level of the respective activity and (3) each activity can be partitioned into elements that depend solely upon each product, i.e. the total activity results as sum of activity measures assigned to individual products. Hence, according to Noreen (1991), the conditions under which undistorted information might be provided are very restricted.

Babad and Balachandran (1993) investigate optimization methods of cost drivers in activity based costing systems with respect to cost and loss of accuracy of provided information. They argue that in the context of activity based costing systems there are two main questions, i.e., to determine the number of cost drivers and to select the representative cost driver. In their paper, they suggest ways of how to cope with these questions. In their investigation, they apply an integer programming method.

Gupta (1993) investigates how the degree of heterogeneity in products, in allocation measures and in resource usages across activities affect costs allocated to products at different levels of aggregation. Therefore, an analytical approach is applied which, in a second step, guides an empirical analysis. Gupta (1993) analytically and empirically tests how costs allocated to products change with different levels of aggregation and what these differences in costs might be due to. Gupta (1993) shows that there are positive correlations between the level of heterogeneity and the level of differences in costs allocated to different products at different aggregation levels.

Hwang et al. (1993) develop a model of a two-stage cost allocation process and derive an expression of the firm's economic loss from distortions in provided product costs. Furthermore, they provide a heuristic to choose the best possible allocation base for each overhead cost pool.

Datar and Gupta (1994) also apply an analytical approach and focus on activity based costing systems. They argue that intuition suggests that multiple cost pools and multiple cost drivers better reflect the real world and lead to better information being provided by the costing systems. They investigate effects on quality of provided information of a higher sophistication of the activity based costing system in interrelation with errors (1) in the specification of costs, (2) in the aggregation of costs, (3) in the measurement of overhead costs, and (4) in the measurement of product specific units of allocation bases. They find that a more sophisticated specification of cost allocation bases and a higher number of cost pools potentially increases specification and aggregation errors and that reducing specification and aggregation errors potentially leads to increased measurement errors.

Christensen and Demski (1997) analytically investigate the ability of various accounting procedures to provide relatively accurate information on marginal costs in a multi product-setting. They find that this ability strictly depends on the underlying technology and varies among products. Due to the fact that errors vary across products they argue that in this context the question emerges where in the product space to tolerate large costing errors in order to assure small errors in cost information of other products.

Homburg (2001) applies a mathematical model in order to support cost driver selection in activity based costing systems with respect to accuracy of provided information. He argues that prior research focuses on the replacement of one cost driver by another cost driver and suggests that cost drivers might also be replaced by combinations of other cost drivers.

Labro and Vanhoucke (2007) investigate biases in activity based costing systems. They apply a simulation approach in order to investigate aggregation errors, measurement errors and specification errors at the resource cost pool as well as on the activity cost pool level. In addition, they investigate interactions among these types of biases and their effects on costing system accuracy. They find that partial improvement usually increases overall accuracy of provided information and that errors in the second allocation step affect accuracy more strongly than errors in the first allocation step. The investigation of Labro and Vanhoucke (2007) cover biases in activity costing systems only. Traditional costing systems remain unconsidered.

In an experimental setup, Cardinaels and Labro (2008) focus on time estimates in the context of costing systems and investigate effects of (1) the aggregation level of costing system activities, (2) the extent of coherence among the tasks that require time estimates, and (3) the knowledge about the fact that time estimates will be required ex-ante to task execution. They find that an increasing aggregation of activities leads to a decreasing number of measurement errors. Furthermore they find a strong overestimation bias if time-estimates are given in minutes.

Labro and Vanhoucke (2008) focus on diversity in resource consumption patterns. They analyze situations in which increased sophistication of the costing system pays off with respect to accuracy of provided information. In their investigation, they apply a simulation approach and show that not all situations that are characterized by a high diversity in resource consumption induce the need of a more sophisticated costing system. Surprisingly, they find that in some setups which are characterized by high diversity, costing system refinement affects accuracy of provided information negatively.

Balakrishnan et al. (2011) investigate heuristics in the context of product costing systems design with respect to accuracy of provided information whereby they focus on rules for grouping resources into cost pools and determining drivers for cost pools. In their investigation they apply a simulation approach, Balakrishnan et al. (2011) argue that correlation based rules (i.e., to combine similar resources) are superior to size based rules (i.e., to focus on most expensive resources) and provide guidance how to implement these rules.

As outlined above, prior research mainly focuses on activity based costing systems. There is only little research that focuses on traditional costing systems or on the interrelation of costing system sophistication and error propagation in the case of traditional costing systems.

1.3 Rationale for the Choice of Research Method

In order to face the complexity of the research questions outlined above, a simulation approach is applied. Costing systems can be characterized as a set of interacting components whereby some of the components are more influential with respect to outcome than others (cf. also Sect. 4.1). In addition, none of the components usually controls the behavior of the whole costing system. Due to the wide integration into organizational processes (e.g., costing systems might map organizational transformation processes) there are a large number of agents that interact with the costing system at different steps of these processes. This increases the complexity of the research problems.

On the one hand, there are interactions among components of the costing system. On the other hand, there are interactions of various agents with the costing system. Simple patterns of repeated interactions among components and repeated individual interactions might lead to situations that are nearly impossible to predict. Applying an analytical approach or formal modeling to the research problem outlined above would exceed the boundaries of these research methods (Gilbert 1995). In addition, there are various behavioral assumption which the agents' behavior is based on, i.e., this simulation study considers biasing behavior which might be unintended and intended, respectively. In this simulation study the accuracy of information provided by costing systems is inextricably linked to individual judgements, decisions, actions and abilities of the interacting agents (cf. also Sprinkle 2003). The consideration of different types of agents' actions based on varying behavioral assumptions would lead to intractable dimensions of formal modeling (Davis et al. 2007). Simulation approaches, on the contrary, are widely believed to be powerful approaches in order to face such complex research questions (Resnick 1999). Simulations allow for analyzing macro level complexities that result out of micro level interactions (Ma and Nakamori 2005), i.e., applying a simulation approach potentially helps in generating knowledge about individual behavior and the respective outcome on the overall system level (North and Macal 2007). For the context of costing systems this means that a simulation approach gives the possibility to analyze effects of biasing behavior, from an intended as well as from an unintended perspective, on the quality of the information provided.

Estimating effects of costing system sophistication and effects of biasing behavior on the quality of the information provided by costing systems is particularly difficult in empirical research. Independent variables under research might be contaminated themselves because their effects cannot be necessarily disentangled from other effects. In addition, independent variables under research might be contaminated, i.e., they probably contain systematic noise due to imprecise measurement (Sprinkle 2003). Besides these concerns, on the one hand, due to organization specific characterizations of costing systems it is nearly impossible to empirically compare different levels of costing system sophistication. On the other hand, determining a true costing benchmark in order to calculate output error and, hence, evaluating the quality of the provided information as well as studying controlled characterizations of biasing behavior also appears to be nearly impossible if empirical research approaches are applied. Controlled simulation experiments, on the contrary, allow for comparing the impact of input biases on information quality in the case of different levels of costing system sophistication and also give the possibility to study cause-effect relationships under uncontaminated conditions (Kerlinger and Lee 2000).

Consequently, due to dimensions of formal modeling and limitations of empirical research, a simulation approach appears appropriate in order to face the research questions outlined above.

1.4 Structure of Chapters

The remainder of this simulation study is organized in 8 further chapters (for an overview of the structure of chapters cf. Fig. 1.1).

Chapter 2 focuses on management accounting within the organizational context. The first section of Chap. 2 elaborates the (changing) roles of management accounting in organizations. The second section outlines the different roles of information provided by management accounting, Finally, Chap. 2 provides a classification of (management) accounting systems and locates costing systems within this classification.

Chapter 3 provides the conceptual and the theoretical framework. The first section elaborates the conceptual framework, i.e., the understanding of the terms bias and error in different research contexts are analyzed and potential sources for biasing behavior are provided. In the second section, agency theory and especially the hidden action problem are introduced as the theoretical basis.

Chapter 4 introduces the simulation model in three steps. First, the computational model of the costing systems is formalized. Second, the model of the agents' behavior is introduced and potential biases are deduced. Third, the elaborated types of biases are incorporated into the computational model of the costing system.

Chapters 5–7 focus on the research questions outlined above. Chapter 5 presents results on the sensitivity of biases to different levels of costing system sophistication. Chapter 6 investigates the effects of single input biases on the quality of provided decision-influencing and decision-facilitating information. Chapter 7 focuses on multiple input biases and presents results on interaction and compensation among various types of input biases.

Chapter 8 discusses the results presented in Chaps 5–7 and aims at deriving implications for the design of costing systems and the building of organizational data quality policies. Furthermore, Chap. 8 discusses limitations of this simulation study and suggests avenues for future research. Finally, Chap. 9 concludes this simulation study.

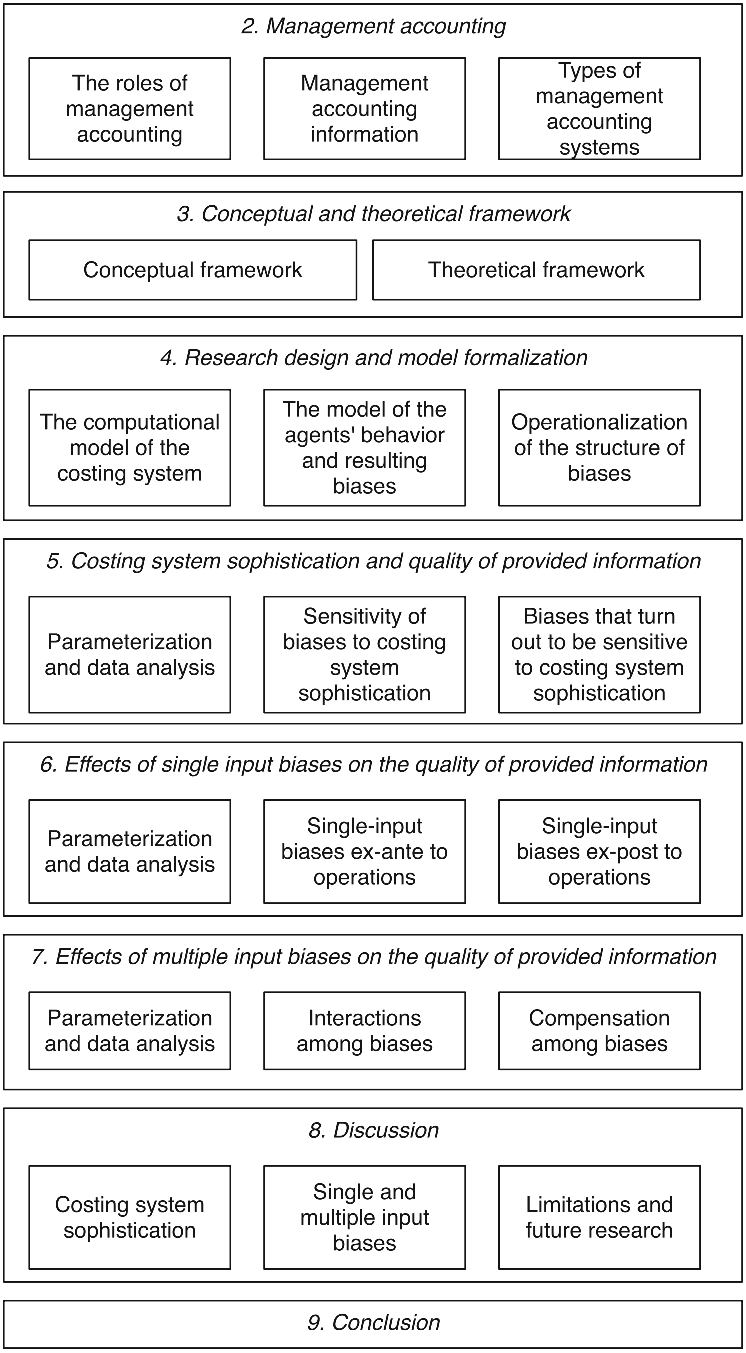

Fig. 1.1 Structure of chapters

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Chapter 2
Management Accounting

Abstract This chapter focuses on management accounting. Section 2.1 outlines the various (changing) roles that management accounting captures. Section 2.2 on the one hand elaborates an understanding of management accounting information and on the other hand gives information on the different roles of management accounting information within organizations. Finally, Sect. 2.3 categorizes accounting systems, gives further information on the various types and the respective fields of application of accounting systems within organizations and locates costing systems within this categorization.

2.1 The Roles of Management Accounting

In its most simple form, management accounting can be defined as collecting and recording useful accounting and statistical data as well as reporting them to decision makers (Crossman 1958; Singer 1961; Feltham 1968; Bruns and McKinnon 1993; Horngren et al. 2005). Early studies place management accounting in a service function with the scope to provide all levels of management with high-quality scorekeeping, attention-directing and problem-solving information (Simon et al. 1954). Crossman (1958) argues that management accounting provides management with data in order to establish policies, develop plans and control operations. Furthermore, in his definition Crossman (1958) includes analysis and interpretation and representation of data in accordance with the recipient's needs. Additionally, there is a separate division within management accounting which captures cost accounting, cost analysis, cost control and cost reduction (Crossman 1958). Singer (1961) and Bruns and McKinnon (1993) point out that management accounting captures collecting (financial) information which is useful. Usefulness in this context refers to decision-making relevance. In his elaborations Feltham (1968) focuses on the aspect of supplying management with information. He argues that management accountants play a keyrole in deciding which information should be produced. Bruns and McKinnon (1993) additionally argue that providing management with information captures two aspects, i.e., (1) the communication of information and

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(2) the control of the systems and processes by which information reaches the recipients, i.e., the managers. Furthermore, Bruns and McKinnon (1993) point out that information does not necessarily have to be solely quantitative as considered in early definitions of management accounting (e.g. Singer 1961) and that management accounting also captures the consideration of the nature of managerial work and the psychological processes inherent in decision-making (Brignall 1997).

There is evidence that the traditional accounting functions remain popular but, at the same time, management accounting transforms into new roles (Burns and Vaivio 2001; Burns and Yazdifar 2001). The literature provides a set of more comprehensive roles which management accounting should be aspiring. According to Cooper and Dart (2009) these roles are to be modern and business-oriented (Granlund and Lukka 1998b), to be an internal business consultant (Burns and Vaivio 2001), to be a strategic management consultant (Holtzman 2004) or to be a hybrid accountant (Burns and Baldvinsdotti 2005).

Granlund and Lukka (1998b) investigate management accounting practices in Finnish organizations. They argue that management accounting evolves as a more business oriented function, i.e., in addition to principals of financial analysis, management accounting captures good knowledge of the business the firm operates in, fluent communication skills and knowledge of (change) project management.

Burns and Vaivio (2001) refer to Coad (1999) and argue that the modern management accountant's role has changed from controller to business supporter or internal business accountant. Specifically, they mean that the management accountant nowadays is involved in topics such as strategy, information system implementation and change management. In addition to the role of internal business consultant, Coad (1999) refers to Kaplan (1995), Evans and Ashworth (1996) and Cooper (1996a,b) and argues that management accountants nowadays need to be skilled in the design of cost management systems and be involved in business decision processes.

Holtzman (2004) analyzes the change (management) accounting firms have undergone during the twentieth century and claims that management accountants have transformed from an information processing entity to strategic business advisors. Holtzman (2004) argues that changes in the environment (e.g., advanced communication technology) have led accounting firms to provide new services to its customers which, in consequence, has led to a redefinition of the management accountants' role within organizations.

Burns and Baldvinsdotti (2005) analyze the emergence of team-oriented management accounting roles and argue that nowadays management accountants need to have hybrid skills. Specifically, Burns and Baldvinsdotti (2005) argue that apart from the traditional roles, management accounting is becoming wider involved in integrated business situations, agendas and decision-making forums.

Järvenpää (2001) elaborates characteristics of the "new" hybrid management accountant. Analytical skills, instrumental accounting competence and independency remain of equal importance, while communication skills, cooperation and interpersonal skills, wide business management skills and the ability to understand large entities gain importance.

Byrne and Pierce (2007) investigate new characteristics of management accounting and distinguish skills at the individual level and roles at the activity level. At the skill-level they argue that management accountants inter alia need to have business knowledge, communication skills, IT- and technical skills and monitoring skills. Additionally, management accountants are characterized by flexibility, organizational influence and personal qualities. For the activity level, Byrne and Pierce (2007) argue that the management accountant faces the challenge of providing information and supporting decision-making and planing. Additionally, management accounting is characterized by providing management with periodic performance reporting and ad-hoc analyses, instructing operational managers, supporting business administration and being involved in project management.

Kelly and Pratt (1992) argue that management accounting fulfills a multiplicity of purposes and analyze actions in which management accountants are involved. For a systematization of roles they refer to Burchell et al. (1980) who define the following eight roles: (1) a rational/instrumental role, (2) a symbolic role, (3) a ritualistic role, (4) a mythical role, (5) a political/bargaining role, (6) a legitimating/retrospective rationalizing role, (7) a disciplinary role and (8) a repressing/dominating/ideological role. For the (1) rational/instrumental role, Kelly and Pratt (1992) argue that managers suffer from bounded rationality (Simon 1957) and, according to Simon et al. (1954), management accounting is in charge of providing scorekeeping, problem-solving and attention-directing information in order to induce rational decision-making. For the (2) symbolic role, Kelly and Pratt (1992) refer to Feldman and March (1981) and argue that management accounting is in charge of signaling others (within and outside the organization) that decisions are made rationally and that decision-makers are accountable for their decisions. The (3) ritualistic role refers to management accounting being responsible for setting rules and fixing parameters for processes within organizations. Specifically, this role focuses on relationships between collaborators within an organization, rather than the original activity of the organization itself. These relations are regarded to be ritualistic and management is in charge of controlling these interactions, fixing rules and setting parameters for interaction (Gambling 1987; Kelly and Pratt 1992). In order to outline the (4) mythical role of management accounting, Kelly and Pratt (1992) refer to Meyer (1983) and argue that the mythical role of accounting refers to the purpose of reducing complexity of comprehensive situations, i.e., management accounting is in charge of providing some solution to bounded rationality. In addition, Kelly and Pratt (1992) differentiate between the (3) ritualistic role and the (4) mythical role. They argue that the (3) ritualistic role focuses on controlling the behavior of those who are involved in rituals, while the (4) mythical role serves decision-makers. For the (5) political/bargaining role of management accounting, Kelly and Pratt (1992) state that organizations are a composition of individuals with potentially divergent interests where political processes are a feature of organizational life. They refer to Burchell et al. (1980) and argue that it is within the scope of management accounting to design information and accounting systems in order provide information to manage these political processes. For the (6) legitimating/retroperspective role, Kelly and Pratt (1992) claim that managers face complex decision-problems.

Once decisions are made, the decision-makers expect feedback on decisions, i.e., information on rationality of decisions based on previously defined criteria, whereby management accounting is in charge of providing this information. The (7) disciplinary role of management accounting captures the control of behavior and social practices within organizations. Kelly and Pratt (1992) refer to Knights and Collinson (1987) and argue that the disciplinary role of management accounting aims at supporting management in controlling labour. In addition, Cooper et al. (1981) show that this role of management accounting does not solely capture behavior control but also the control of agendas and issues. Finally, for the (8) repressing/dominating/ideological role, Kelly and Pratt (1992) argue that managers are in charge of protecting the interests of the owners of the organization. This involves understanding the relationship between managers, shareholders, capital and labour. Kelly and Pratt (1992) note that the words repressing, dominating and ideological, which are mainly used in a societal perspective of management accounting, might give way to terms like control, management and objectives. In order to monitor performance with respect to the owners' interests, surveillance systems need to be installed which are under the management accounting's area of responsibility.

The elaborations outlined above on the (changing) roles of management accounting are reflected in the literature on empirical research on management accounting tasks. In their investigation, Burns and Yazdifar (2001) analyze the changes in management accounting between 1995 and 2000. Inter alia their investigation includes tasks that were vitally important for management accountants within this period. The top three tasks are business performance evaluation, cost/financial control and interpreting/presenting management accounts. This is (at least partly) consistent with both the earlier and the newer conceptualizations of management accounting. Representing and providing management accounts is contained in early elaborations on management accounting (cf. inter alia Crossman 1958; Singer 1961; Feltham 1968). The task listed in the first place, i.e. business performance evaluation, is also captured by the political and the repressing/dominating/ideological role as elaborated by Kelly and Pratt (1992), cost/financial control is also considered in elaborations on the roles of management accounting (cf. inter alia Crossman 1958; Granlund and Lukka 1998a). Burns and Yazdifar (2001) rank the implementation/design of new information systems seventh in their list of top management accounting tasks. In elaborations on management accounting tasks (as outlined above) this feature has a prominent position. Bruns and McKinnon (1993), Burns and Vaivio (2001), Coad (1999), Kaplan (1995), Evans and Sridhar (1996), Cooper (1996a,b), Byrne and Pierce (2007) and Kelly and Pratt (1992) explicitly list information systems' design as a typical management accounting task. In their analysis of management accounting tasks, Russell et al. (1999) list five work activities that have gained more attention in the previous years, i.e., internal consulting, long-term/strategic planning, computer systems and operations, management of the accounting function, process improvement and performing economic analysis. As in case of the investigation of Burns and Yazdifar (2001), findings presented by Russell et al. (1999) are also reflected in the conceptualizations of management accounting outlined above. The internal consulting function is considered in the elaborations of Burns and Vaivio (2001), the long-term perspective is captured by the conceptualization of Holtzman (2004) and the management of the accounting function is covered by control of accounting processes (Bruns and McKinnon 1993), management skills and the ability to understand large entities (Järvenpää 2001) and the ritualistic role of management accounting (Kelly and Pratt 1992). As in the investigation of Burns and Yazdifar (2001), the study presented by Russell et al. (1999) suggests that management accounting systems play an important role in the context of management accounting tasks. In the investigation carried out by Cooper and Dart (2009) the top five activities associated with management accounting are the preparation and interpretation of management accounting information, the communication and presentation of financial information, leadership, development and implementation of management accounting systems and managing staff. Hence, similar to studies conducted by Burns and Yazdifar (2001) and Russell et al. (1999), tasks associated with collecting, generating and reporting information appear to be an important feature of management accounting.

2.2 Management Accounting Information

The elaborations on the roles of management accounting within organizations indicate that one major feature of management accounting is to provide decision makers with information (cf. Sect. 2.1). In this section various roles of management accounting information are described. First, Sect. 2.2.1 focuses on the distinction between management accounting data and management accounting information. In Sect. 2.2.2, the two roles of management accounting information, i.e., the decision-facilitating and the decision-influencing role, are outlined and differentiated from each other.

2.2.1 Management Accounting Data and Information

Liebenau and Backhouse (1990), Checkland and Holwell (1998) and McKinney and Yoos (2010) argue that there is no generally accepted definition of the terms data and information but there are clusters of ideas of what these terms might mean. According to Avison and Fitzgerald (1995), information has a meaning and stems from summarized data that is presented in a way that is useful to the information recipient, while data are described as unstructured facts. Laudon and Laudon (1991) refer to data as raw facts while they define information as data that has been shaped into a meaningful and useful form. Martin and Powell (1992) describe data as raw material of organizational life (i.e. numbers, words, symbols and syllables), while information is defined as processed data. Specifically, Martin and Powell

(1992) add that information is useful in managerial decision-making. From a more technical point of view, Ferstl and Sinz (2008) and Bauer and Goos (1991) argue that, in the context of information systems, data stands for a sequence of characters. This sequence of characters is interpreted according to a specific routine in order to generate information. Hansen and Neumann (2001) define data as the basis for information whereby information is also useful for the recipient. Hildebrand (1995) also reviews various definitions for the terms data and information and concludes that there is no perfect definition. Heinrich (1992) refers to information as knowledge about past, present and future states and events of the real world whereby knowledge is defined as information that is used in order to achieve objectives (cf. also Wittmann 1959).

Checkland and Holwell (1998) argue that the most common elements in definitions for the term data are raw facts and raw material. Definitions of information frequently contain the words shape, interpret, transform and process whereby all definitions of information describe data as the starting point in order to generate information. Eschenröder (1985) and Hildebrand (1995) additionally argue that in the economic context, information is associated with costs.

Buhaisi (2011) argues that accounting information assists managers in planning, evaluating and controlling operations. Several authors argue that accounting information should facilitate efforts in the controlling of costs, the improvement of productivity and the improvement of organizational processes (e.g. Johnson and Kaplan 1987; Demski 2008; Buhaisi 2011). Additionally, Buhaisi (2011) refers to Chadwick (1993) who outlines that accounting information captures all information which assists management in achieving objectives, formulating policies, monitoring and assessing performance, evaluating alternative scenarios, making plans, controlling operations, taking account of behavioral factors and a variety of other problems. Hansen and Mowen (1994) review which trends the outlined changes in the management accounting profession might be due to and conclude that (1) just-in-time manufacturing and emphasis on quality, (2) a higher diversity in product ranges and short product-life-cycles and (3) advances in information technology and computer integrated manufacturing are the main factors that drive the changes outlined above.

In accordance with the understanding of data and information outlined above, in this simulation study, agents interact with MAS and enter data into these systems. The MAS transforms data into information. Hence, MAS represent the transformation-procedure from data to information and MAS provide decision-makers with information which is useful for managerial decision-making. In the accounting literature, it is widely accepted that accounting information can serve two distinct roles (cf. Wall and Greiling 2011). In line with the distinction originally made by Demski and Feltham (1976) the roles of accounting information are typically divided into the (1) decision-facilitating and the (2) decision-influencing role. These two roles are outlined in Sect. 2.2.2.

2.2.2 The Decision-Facilitating and the Decision-Influencing Role of Accounting Information

According to Demski and Feltham (1976), *decision-facilitating information* is given to the decision-maker ex-ante to the decision. Hence, decision-facilitating information is a direct input into the decision-making process and is expected to help the decision-maker to make better decisions (Evans et al. 1994; Wall and Greiling 2011). According to Sprinkle (2003), the purpose of this type of information is to reduce the ex-ante uncertainty of the decision at hand (cf. also Demski and Feltham 1976; Tiessen and Waterhouse 1983), to revise the decision-makers beliefs (cf. also Baiman 1982) and assist in problem-solving (cf. also Simon et al. 1954; Emsley 2005). Sprinkle (2003) adds that the use of decision-facilitating information improves the decision-maker's knowledge and, hence, enhances their ability to make decisions that also meet the organizational objectives. This type of information plays a role in judgements and decisions that concern both the past (e.g., performance evaluation) and the future (e.g., planning). Sprinkle (2003) argues that performance evaluation in the context of decision-facilitating information is different from managerial performance evaluation. In particular, he argues that decision-facilitating information might also be used to asses prior choices and decisions with the aim of improving future performance.

Decision-influencing information, on the contrary, is provided ex-post to the selection and implementation of the decision. Decision-influencing accounting information is used to overcome organizational control problems due to selfish behavior (Jensen and Meckling 1976; Baiman 1982), i.e. it helps to ensure that decision-makers exhibit behavior that is oriented toward the organizational objectives (Sunder 1997; Indjejikian 1999; Sprinkle 2003). This type of accounting information is used to evaluate the decision-maker's choices ex-post to decision-making (cf. also Demski and Feltham 1976; Tiessen and Waterhouse 1983), to evaluate performance (cf. also Baiman 1982) and fulfill the scorekeeping function (cf. Simon et al. 1954), i.e. decision-influencing information also captures information used for compliance reporting (Emsley 2005). Hence, decision-influencing accounting information also supports the attention-directing function of information. The use of the decision-influencing information aims at affecting the decision-maker's behavior, i.e., via monitoring of behavior and measurement and evaluation of performance, which subsequently are rewarded or penalized, individual behavior is affected (Sprinkle 2003; Wall and Greiling 2011). The performance evaluation purpose of decision-facilitating information, on the contrary, aims at making better decisions in the future by evaluating performance of past decisions. Evans et al. (1994) argue that basing the decision-maker's compensation on decision-influencing information, i.e., information on the performance of the previously made and implemented decision, might more efficiently induce the manager to make decisions that are congruent with the owner's objectives.

2.3 Types of Management Accounting Systems

According to Horngren and Harrison (1992) and Weygandt et al. (1993), the scope of MAS is to produce (financial) reports which are used by managers in order to make decisions. MAS can be both, computerized systems and manual systems. Typically, each organization designs its system in order to achieve organizational objectives such as control and acceptable cost-benefit relationship.

The tasks which MAS serve appear to be a firm basis in order to categorize types of MAS systematically (Seicht 1990; Möws 1991; Ebert 2000; Horngren et al. 2005; Ewert and Wagenhofer 2008). Illetschko (1984), Seicht (1990) and Ebert (2000) distinguish between (1) financial accounting systems, (2) cost accounting systems, (3) budgeting systems and (4) systems that capture business statistics. At the same time, Illetschko (1984) adds that MAS might also be categorized on the basis of their purposes within an organization and lists three possible clusters of MAS-types, i.e. MAS for (1) control purposes, (2) planning purposes and (3) the provision of information. Horngren et al. (2005) provide a more detailed list of MAS-purposes. In particular, they list five purposes for which accounting systems potentially provide information, i.e., (1) the formulation of overall strategies and long-range plans, (2) resource allocation decisions, (3) cost planning and cost control, (4) performance measurement and evaluation of people and (5) meeting external regulatory and reporting requirements. At the same time, Horngren et al. (2005) add that all these purposes require a different representation or reporting mode. Horngren et al. (2005) distinguish between management accounting systems for decision making (i.e., cost accounting systems, capital budgeting systems), planning and budgetary control systems and management control systems. Furthermore, MAS can be differentiated on the basis of information recipients, i.e. internal and external accounting systems (Hummel and Männel 1986; Kilger 1992; Schneider 1997; Ebert 2000; Möller et al. 2005; Ewert and Wagenhofer 2008; Götze 2010). Based on the recipients of the provided information, Hansen and Mowen (1994) distinguish between financial and management accounting systems, whereby financial accounting systems capture information systems that primarily serve external information recipients and management accounting systems provide information for internal recipients. Additionally, Schneider (1997), Möws (1991) and Möller et al. (2005) distinguish between MAS on the basis of time-relation, i.e. MAS that are oriented towards the past (financial accounting, cost accounting, calculation for control purposes) and MAS that are oriented towards the future (financial planning, cost planning, calculation for planning purposes). Furthermore, Möws (1991) differentiates the determination of (financial) information and analysis. For the process of determination of information, Möws (1991) lists financial and cost accounting systems while analysis is captured by business statistic systems. Ewert and Wagenhofer (2008) also distinguish between internal and external accounting systems whereby financial accounting systems serve external accounting purposes and costing systems and capital budgeting and accounting systems are categorized as internal accounting systems. It might be assumed that business statistics are implicitly included in the other types of accounting systems.

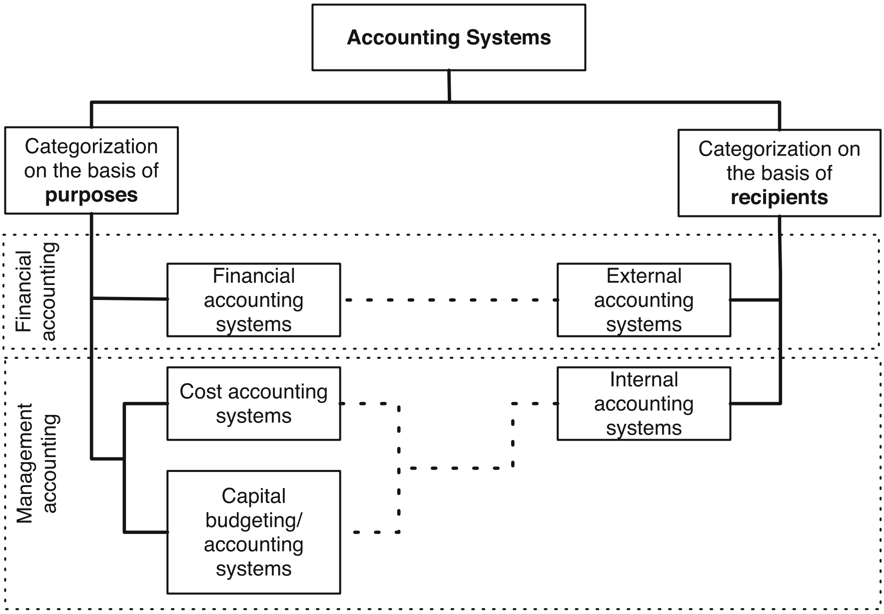

Fig. 2.1 Classification of accounting systems

Based on the approaches to classify MAS outlined above, the classification applied in this study distinguishes between MAS on the basis of information recipients and purposes of MAS. On the one hand, accounting systems are categorized as internal and external systems, respectively, where information systems for external purposes are financial accounting systems and information systems for internal purposes are MAS. On the other hand, this study distinguishes between financial accounting systems, cost accounting systems and capital budgeting and capital accounting systems (cf. also Fig. 2.1). This categorization follows Ewert and Wagenhofer (2008) and assumes business statistics to be implicitly included in the other types of MAS. In addition, planning systems, as considered in the categorization of Seicht (1990), are considered to be a function of all types of accounting systems, i.e., all types of accounting systems can be extended by ex-ante planning. This follows the argumentation of Illetschko (1984). Financial accounting systems are classified as external accounting systems while cost accounting systems and capital budgeting systems are subsumed under management accounting systems which primarily provide information for internal recipients. Hansen and Mowen (1994) add that both financial and management accounting systems are part of an entire accounting system whereby all information is often derived from the same set of data, which in many cases is data for external accounting purposes (with is often adapted for internal accounting purposes). Many organizations expand the existing data set in order to satisfy the needs of internal information recipients. For the characterization of the accounting system applied in this simulation study cf. Sect. 4.1.

2.3.1 Financial Accounting Systems

Financial accounting systems primarily produce information for external recipients. Morse et al. (1988), Seicht (1990) and Hansen and Mowen (1994) compare MAS to financial accounting systems and characterize financial accounting systems as (1) an externally focused system, (2) oriented towards externally imposed rules (determined by law and generally accepted accounting principles while the characterization of MAS is aligned to the specific needs of the organization), (3) oriented towards the past, (4) a system that evaluates and gives information on the organization as a whole, (5) a self-contained system and (6) a system that focuses on financial operations while MAS also focus on the organizational transformation processes. Morse et al. (1988) outline that financial accounting systems are information processing systems that primarily generate general-purpose reports for the respective organization. In particular, these are reports on financial operations, i.e., (1) income statement and (2) statement of cash-flows, and reports of financial position, i.e., (3) balance sheet. Additionally, financial accounting systems keep track of the organization's assets, obligations and the payment of debts (Morse et al. 1988; Wagenhofer and Ewert 2002). Wagenhofer and Ewert (2002) add that organizations that are listed on the stock exchange are required to provide interim reports. In addition, listed organizations often provide ad-hoc reports on effects that might affect the share prices.

The (1) income statement shows revenues and expenses during a specific period of time and any gains or losses within this time period. The (2) statement of cash-flows summarizes inflows and outflows of cash and the (3) balance-sheet reports the economic health of an organization at a specific point of time, i.e., it shows assets and claims on assets (Morse et al. 1988; Wagenhofer and Ewert 2002; Ewert and Wagenhofer 2008).

Although financial accounting gives a comprehensive overview, it has little value in day-to-day operations. Due to the fact that it is oriented towards the past, information is too aggregated and it is not action-oriented, managers often find little value in financial accounting information (Morse et al. 1988). Of course, for the originally intended information recipients of financial accounting systems, the provided information shows a certain usefulness in decision-making, e.g., provided information helps potential future shareholders to make better informed decisions about whether or not to purchase shares (Wagenhofer and Ewert 2002).

2.3.2 Management Accounting Systems

In contrast to financial accounting systems, MAS provide information for decision-makers within organizations and capture orientation towards the past and towards the future. In contrast to financial accounting systems, Morse et al. (1988), Seicht (1990) and Hansen and Mowen (1994) characterize MAS as (1) internally focused with (2) no mandatory rules, (3) it focuses also on the future, (4) it allows for internal evaluation of segments (also under the aspect of behavioral controlling), (5) it provides detailed information and (6) MAS are typically broad and multidisciplinary systems.

MAS can be subdivided into cost accounting systems and capital planning and budgeting systems, respectively. Sections 2.3.2.1 and 2.3.2.2 differentiate between cost accounting systems and capital planning and budgeting systems.

2.3.2.1 Cost Accounting Systems

Cost accounting systems are primarily applied in the context of planning, evaluation and coordination of decisions within organizations whereby these decisions are typically short-dated (Ewert and Wagenhofer 2008). In contrast to financial accounting systems (which are primarily based on revenues and expenses), information provided by cost accounting systems is based on the consumption and production of goods and services within certain time periods (Seicht 1990; Ebert 2000; Ewert and Wagenhofer 2008).

Ebert (2000) characterizes cost accounting systems as the set of methods and systems that aim at determining, allocating and evaluating costs and performance (in terms of provided goods and services) that result out of operations in order to provide information for decision-influencing and decision-facilitating purposes. Möws (1991) gives a more detailed view on the purposes of cost accounting systems, i.e. (1) determining short-dated profit or loss, (2) determining valuations that are also used for financial accounting purposes, (3) evaluating economic efficiency and (5) providing information for decision-making. In his elaborations Möws (1991) does not consider the decision-influencing purpose of cost accounting information. For (1) determining short-dated profit or loss, Möws (1991) argues that the determination of profit or loss can typically be found in the area of responsibility of financial accounting. Due to the fact that decision-makers typically need this information for short-dated periods (and financial accounting normally performs this task annually), cost accounting is also in charge of providing this information for periods which are shorter than 1 year. In addition, cost accounting systems provide this information not only at the organizational level but also on the product, product-group of organizational-unit level. In some cases financial accounting and cost accounting are interrelated, i.e., (2) cost accounting determines valuations that are used for financial accounting purposes (Möws 1991; Wagenhofer and Ewert 2002). This for example captures the valuation of unfinished and finished goods at production costs. With respect to (3) the evaluation of economic efficiency, in contrast to financial accounting systems, cost accounting systems typically differentiate between operational and non-operational profit or loss and are based on the consumption and production of goods and services. Finally, Möws (1991) argues that cost accounting is in charge of providing information for decision-making whereby this purpose appears to be multi-facetted. Specifically, Möws (1991) lists that cost accounting information might be used for determining (1) prices for both sales and intra company accounting for goods and services, (2) (short-dated) upper and lower limits for sales prices, (3) the economic order quantity, (4) the optimized production program, (5) the optimal replacement-time for assets. Thus, cost accounting information appears to be widely used in organizational decision-making. Additionally, Ebert (2000) and Ewert and Wagenhofer (2008) argue that cost accounting information might also be used for decision-influencing purposes (cf. also Sect. 2.2.2), i.e., to motivate individuals towards organizational objectives. In order to characterize costing systems, Götze (2010) refers to Hummel and Männel (1986) and argues that costing systems are (1) an element of internal accounting, (2) are based on imputed numbers, (3) have a short-dated perspective, (4) provide an income statement and (5) are provided regularly and voluntarily. In order to outline the purposes of costing systems, Götze (2010) additionally refers to Schweitzer and Küpper (2008) and summarizes the respective tasks as (1) mapping and documenting the whole organizational production process, (2) providing information for planning and control purposes, (3) providing information for behavioral management and (5) providing a valuation base for processed and finished goods as well as for assets. In his elaborations on costing systems' characteristics, Zimmerman (2011) is partially in line with the characterizations of costing systems outlined above. He argues that costing systems (1) provide information necessary to assess profitability of products or services, to set optimal prices and market the products or services, (2) provide information in order to detect information on inefficiencies and ensure minimal cost of production, (3) if combined with reward schemes, provide incentives for managers to behave in the organization's interest, (4) support financial and tax accounting functions and (5) contribute more to firm value than they cost. Hence, Zimmerman (2011) considers the decision-facilitating and the decision-influencing perspective, the interrelation of financial and cost accounting systems and additionally adds a cost-benefit perspective.

Horngren et al. (2005) distinguish between two basic types of costing systems, i.e., (1) job costing systems and (2) process costing systems. At the same time they add that organizations do not apply neither pure job costing systems nor pure process costing systems. Organizations rather combine elements of both types in order to build an organization-specific costing system. For (1) job costing systems, costs are assigned to distinct units or batches of products whereby the specific product is often custom-made. In case of (2) process costing systems, the costs of products or services are determined on the base of broad averages. Process costing systems are typically applied for mass-produced goods while job costing systems are applied for cases in which goods are produced for a specific customer.

Types of costing systems can also be divided into full costing systems and marginal costing systems. In addition, costing systems can be used for ex-post cost determination or ex-ante cost planning (cf. inter alia Seicht 1990; Ebert 2000). Marginal costing systems consider the cost structure, i.e., marginal costing systems differentiate fixed and variable cost components while full costing systems totally exclude the cost structure from consideration. In case of full costing systems, all costs, i.e., fixed and variable costs, are considered in cost allocation and are allocated to products and services. In case of marginal costing systems, only the variable costs are considered in cost allocation. Fixed costs are directly transferred to the calculation of income (Möws 1991). These two typologies are extreme characterizations whereby mixed forms of costing systems are possible. Both types of costing systems can be extended by ex-ante planned costs. Consequently, if ex-ante planned costs are available, these costing systems allow for evaluation of deviations from planned costs. Ebert (2000) argues that the advantages of full costing systems lie in the simplifications and acceleration of cost allocation and information provision. In contrast to marginal costing systems, full costing systems do solely allow for a simple calculation of deviations from planned costs while marginal costing systems give the possibility of a more detailed evaluation.

Another categorization of costing systems which is widely applied in literature is the division into sophisticated (i.e., activity based costing) and non-sophisticated costing systems (i.e., product costing systems, other types than activity based costing systems) (e.g. Gosselin 1997; Clarke et al. 1999; Brown et al. 2004; Al-Omiri and Drury 2007; Brierley 2008). Not at least because of the categorization of product costing systems (i.e., other types than activity based costing systems) this categorization appears to be very narrow and simple (Al-Omiri and Drury 2007; Brierley 2008). Amongst others, Abernethy et al. (2001) and Al-Omiri and Drury (2007) have elaborated a more detailed differentiation of types of costing systems.

The basis for the level of sophistication as elaborated by Abernethy et al. (2001) is three-dimensional. They argue that there are two extreme characterizations, i.e., (1) lowly sophisticated costing systems that consider one organization wide cost pools that use cost drivers at the unit-level and apply responsibility based cost pools and (2) highly sophisticated costing systems that are characterized by many cost pools, hierarchical cost drivers and activity cost pools. As in case of the distinction by Horngren et al. (2005), these two types of costing systems are best viewed as ends of a continuum where many organizations might combine elements of both characterizations. Al-Omiri and Drury (2007) similarly distinguish between highly and lowly sophisticated costing systems. Specifically, they argue that lowly sophisticated systems are simple direct costing systems while highly sophisticated costing systems are activity based costing systems. They determine the level of sophistication on the base of the number of cost pools and cost drivers, the method of cost allocation in the first step (allocation to cost pools) and the allocation method in further steps of cost allocation (e.g. whether the allocation is based on transaction or duration drivers).

2.3.2.2 Capital Budgeting and Capital Accounting Systems

The purpose of this final cluster of internal accounting systems is twofold. On the one hand, capital budgeting systems support decision-makers in assessing potential investments with respect to cost effectiveness. On the other hand, capital accounting systems support decision-makers in controlling and planning liquidity (Ewert and Wagenhofer 2008).

Capital budgeting systems support management in making decisions in the context of capital investment decisions. In particular, capital budgeting systems help to determine whether or not a capital investment will earn back the original outlay and in addition provide a reasonable return. This type of decisions usually involves large amounts of organizational resources at risk and, at the same time, affects the future development of the organization (Morse et al. 1988; Zimmerman 2011). Horngren et al. (2002, 2005) additionally state that capital budgeting systems usually focus on capital investment decisions that span many years. This differentiates capital budgeting systems from income determination and planning which usually focus on the current period. Capital investment decisions usually involve cash inflows and outflows that accrue at different points in time which are usually answered by adding accrued interest of discounting of cash-flows (Möller et al. 2005). For the process of capital budgeting, Clive et al. (1990) refer to King (1975) and argue that the capital budgeting process consists of six steps, i.e. (1) project generation, (2) estimation of cash-flows, (3) progress through the organization, (4) analysis and selection of projects, (5) authorization of expenditures and (6) post-audit investigations. In the step of (1) project generation, potential investments are selected for which in step (2) potential cash-flows are estimated. In step (3), i.e., progress through the organization, Clive et al. (1990) argue that certain projects require approval of top-management (cf. also Scapens et al. 1982). In step (4), i.e., analysis and selection of projects, the selected projects are evaluated with respect to the fact that cash inflows and outflows usually realize at different points in time. Step (5), authorization of expenditures, captures the final decision (usually made by top management) on whether or not to invest into the selected project. Finally, step (6) captures a post-audit investigation, i.e., after a certain period of time actual results might be gained which potentially provide input for control purposes. Capital budgeting systems particularly support management in step (4), i.e., the analysis and selection of projects.

Capital accounting systems support management in planning and controlling liquidity. In the context of capital accounting systems another interrelation of external and internal accounting envisions, i.e., capital budgeting systems are also used for external accounting purposes (Ewert and Wagenhofer 2008). In particular, the cashflow-statements are similar to capital budgeting systems (cf. also Sect. 2.3.1). In addition, capital budgeting systems consider the planning of cash inflows and outflows, give a detailed plan that outline all sources and uses of cash and, furthermore, are applied for control purposes. The cash budget is affected by planned operations and is heavily integrated into the corporate planning process (Morse et al. 1988; Horngren et al. 2002). The capital accounting system provides a cash budget which predicts the cash positions at a given level of operations and helps to control cash-flows with respect to cash idles and unnecessary cash deficiencies (Horngren et al. 2005).

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Chapter 3
Conceptual and Theoretical Framework

Abstract This chapter provides the conceptual and the theoretical basis for this simulation study. In the first section, the concepts of bias and error are elaborated. In a first step, the conceptual understanding of the terms bias and error in various contexts which are relevant to this simulation study are reviewed and finally brought into a concept which is applied in this study. As a second part of the conceptual framework, sources for biasing behavior (from both an intended and an unintended perspective) are discussed. The second section provides the theoretical framework. In particular, this section presents the hidden action problem. Additionally, earnings management and the revelation principle are discussed.

3.1 Conceptual Framework

The terms bias and error have become part of the common vernacular and have a wide variety of meanings. An important element of concept analysis is the etymological origin of the respective words because it offers ideas on their evolution (Hansen 2006). Hence, the etymology and current usage of the words bias and error are analyzed.

According to Onions (1969), Skeat (1968), and Harper (2001) the word bias dates back to approximately 1520 and stems from the old-french and old-provencale *biais* and the latin *biescio*. Bias stands for slant and oblique. Error dates back to 1300 and stems from the old-french *error* and the latin *errorem*. In most languages error means to wander, to go astray. Furthermore error stands for a faults, a mistake and wrongdoing. According to Johnson (1983) and Hornby (2000) in current usage the term bias stands for unfair influence and prejudice, while the word error is a synonym for the word mistake and for involuntary deviations from the truth.

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3.1.1 Bias and Error in Different Contexts

The specified literature of different fields of research provides a large set of definitions for the terms bias and error. This section aims at giving an overview of the different understandings of the words bias and error in disciplines that are relevant to this simulation study. The understanding in research on human error and the usage of the terms bias and error in research on accounting and in research on data quality are analyzed. The final section specifies the concepts of bias and error which are applied in this simulation study.

The following sections frequently use the term accuracy. Harris and Smith (2009) define accuracy as repeated measurements (or estimates) that have low repeatability but the mean of the measurements (or estimates) is very close to the correct value. Precision, on the contrary, Harris and Smith (2009) define as repeated measurements (or estimates) that are close together but all are equally biased from the correct value. Hence, if repeated measurements (or estimates) have high accuracy and high precision, each estimation is very close to the correct value.

3.1.1.1 Research on Human Error

In his elaborations, Diamantopoulos (2006) develops an integrated framework for error management for organizations. He concentrates on (1) errors of decision-making, (2) errors of action, (3) incidences and errors of reaction and (4) errors of investigation as special characterizations of human error. In this framework, Diamantopoulos (2006) also distinguishes sources of errors where especially the distinction into intended and unintended errors appears to be an important feature because in the model of integrated error management it is applied to (2) errors of action as well as (3) incidences (Diamantopoulos 2006). Furthermore, the differentiation in intended and unintended biasing behavior is consistent with a set of other investigations (cf. Fox 1961; Barefield 1970; Dechow et al. 2010; Hennes et al. 2008).

Zhao and Olivera (2006) investigate whether or not individuals in organizations report their errors to the respective manager or supervisor. They distinguish between (1) errors, (2) suboptimal results, (3) failures and (4) violations. They define (1) errors as undesirable gaps between intended and real states that might lead to negative consequences for organizational functioning that could have been avoided and that is due to decisions and actions of individuals. (2) Suboptimal results are actions that turn out to be suboptimal with respect to the fulfillment of a plan. (3) Failures are potential consequences of errors and refer to negative and undesired outcomes. Finally, for (4) violations they refer to Reason (1990) and define them as intended deviations from organizational practice. Hence, in the understanding of Zhao and Olivera (2006), errors do not imply prior intention while violations are intended actions. Furthermore, they refer to Reason (1990) and distinguish three different types of human error. First, the define skill-based mistakes, i.e. slips and actions that are not carried out as planned. Second, rule-based mistakes refer to situations in which actions are executed as planned, but these plans do not conform with the respective objectives. Third, they define knowledge-based errors as situations in which people are not capable of properly analyzing a problem or recognize relations among elements of the problem (cf. also Rasmussen 1983; James 1995). Skill-based mistakes capture errors during activities which take place without conscious control. In particular, skill-based mistakes represent smooth, automated and highly integrated behavioral patterns (Rasmussen 1986; Reason 1990). Hence, skill-based mistakes deal with errors that occur in familiar and non problematic situations (Reason 1990). Rule-based and knowledge-based mistakes, on the contrary, capture situations where the human being is conscious of a problem and an unanticipated internal or external event leads to deviations from a plan. The three-layer model of human error as elaborated by Rasmussen (1983) and Reason (1990) is widely applied in research on human error (cf. inter alia Yang et al. 2006; Hoogendoorn et al. 2009; Lin and Salvendy 1999; Targoutzidis 2010). Lehto (1991) proposes to add a further level to the three layer model of Rasmussen (1983) and Reason (1990). Lehto (1991) adds a judgement-based level. This level refers to different value judgements which have effects on goal prioritization and also affect the knowledge- and rule-based level (cf. Lehto 1991; Lin and Salvendy 1999). In addition to the three-layer model, Reason (1990) distinguishes intentional and non-intentional actions as potential sources for errors.

In their investigation on neural signals associated with different types of human error, Fedota and Parasuaman (2010) argue that there are many definitions for human error but at the same time there is no agreement on the understanding. They differentiate between slips and mistakes. For slips they refer to Norman (1988) who states that slips occur if actions are carried out without conscious deliberation, i.e. due to loss of activation or attention, errors are committed while plans are carried out. At the same time, Fedota and Parasuaman (2010) remark that not all errors that occur during the execution of actions are slips. As for mistakes, Fedota and Parasuaman (2010) argue that they occur during earlier stages of information processing than slips. Mistakes are the incapability to select appropriate responses to stimuli. For the cognitive aspect of mistakes, Fedota and Parasuaman (2010) refer to heuristics as elaborated by Tversky and Kahneman (1974). Fedota and Parasuaman (2010) argue that the selection of inappropriate responses to events due to heuristics might lead to errors. Furthermore, Fedota and Parasuaman (2010) refer to Reason (1990) who points out that mistakes are usually difficult to identify because interactions of cognitive processes in the context of response selection are sometimes subtle.

In their paper, Kim and Bishu (2006) investigate methodologies for human reliability analysis and introduce a fuzzy logic approach for the evaluation of human interacting systems' reliability. They argue that human errors have been defined differently by (1) psychologists and (2) engineers. For the (1) psychological domain, Kim and Bishu (2006) refer to Singleton (1973) and argue that psychologists tend to classify errors on the base of underlying motives and intentions. In contrast to the definition from the psychological perspective, Ahlstrom and Hartman (2001) argue that human errors are more associated with systems' design than with human characteristics. Furthermore, Kim and Bishu (2006) refer to Rasmussen (1982) who points out that quantifying human errors from the psychologists' point of view, i.e. on the base of psychological processes, might be particularly difficult. For a classification from the (2) engineering domain, Kim and Bishu (2006) argue that definitions focus on consequences of human behavior. For the definition of human error from the engineers' perspective they refer to Rigby (1970) who defines human error as a set of actions that diverges from desired actions where the divergence exceeds a limit of acceptability.

Senders and Moray (1991) define human error as a deviation from the original action intended by an operator, from an expectation or desired outcome. The classification of Senders and Moray (1991) includes (1) the selection of action which might lead to deviations due to the decision-makers intentions or beliefs and (2) consequences with respect to outcome. Hence, this definition captures both the psychologists' and the engineers' perspective as elaborated by Kim and Bishu (2006).

In his investigation of the concept of human error, Hansen (2006) systematically groups definitions on the base of their background, i.e. transportation, accident investigation, human factors, nursing and medicine, engineering, educational testing and computer programming. Some of these clusters have already been applied by Kim and Bishu (2006) who group definitions by psychological and engineering background. After an extensive literature review, Hansen (2006) specifies attributes for human errors. These attributes are: (1) the action is performed by a human being, (2) the action occurs at an interface between a human being and another system, (3) the action is voluntary and deliberate and (4) the action exceeds tolerance limits. An important feature of the definition given by Hansen (2006) is the statement that actions which cause human error are deliberate. Hansen (2006) states that actions performed involuntarily are not errors. This perspective on intended errors is different to the one elaborated by the management and accounting literature (cf. Sect. 3.1.1.2). Hansen (2006) refers to forced actions while the accounting literature refers to intended biasing behavior in order to serve one's own ends. Furthermore, Hansen (2006) distinguishes between human errors and human limitations. He states that in contrast to human errors, human limitations are due to limited mental, physical or psychological capabilities of human beings.

3.1.1.2 Research on Accounting

For the context of accounting, Brief (1990) distinguishes between two distinct error concepts. First, errors might result from the application of accounting principles that are not consistent with general accounting principles. This conceptualization is also referred to as error of principle. Second, errors can be defined on the basis of the statistical concept. In this case, an accounting error can be defined as the difference between the estimate of a parameter and its correct value. Hicks (1973) outlines the problem of estimates and states that estimates are relative to a purpose and, consequently, estimates for different purposes might be made in different ways (Brief 1990; Hicks 1973).

Bushman and Indjejikian (1993) investigate benefits of noisy accounting information. They argue that the distortion of accounting numbers is undesirable from the shareholders' point of view and argue that distorted data is characterized as (1) biased in relation to expected firm value or (2) measured with error (or noise). Their understanding of bias concerns the application of accounting principles and a resulting prevention or delay in the recognition of business transactions, while their understanding of error captures noise in estimations required by accounting standards (e.g. useful lives of assets).

In their investigation, Fischer and Verrecchia (2000) analyze managerial reporting bias in the context of external reporting. In their elaborations they define bias as the difference between a manager's actual earnings report and the realization of earnings. They concentrate on intentional biasing behavior. In particular, they map the manager as intentionally biasing his report in order to manipulate the valuation of the firm from the market's point of view.

Fox (1961) also aims at applying statistical error concepts to accounting. On the one hand, Fox (1961) distinguishes between deviations from correct values that arise from unknown and deliberate sources. On the other hand, Fox (1961) differentiates between errors in accounting for measurement and accounting for control. According to the respective elaborations, errors in measurement might be due to (1) input into and (2) the structure of the accounting system and (3) operations. The concept for errors in accounting for control refers to misleading information for decision-making, e.g. a favorable situation might appear as unfavorable, and errors in application, e.g. the accountant might not be familiar with the subject matter.

Copeland et al. (1981) investigate observation errors in accounting. At a general level, they define observation error as measurement inaccuracies made by observers to some attributes or objects. The set of possible observation errors, Copeland et al. (1981) differentiate in accordance to Rosenthal (1976). In particular, observation errors are divided to errors that result from (1) apprehending the relation between the object to be measured and the measurement criterion (cause-effect relations), (2) recording and computing errors and (3) interpretation errors (Rosenthal 1976). Errors in (2) recording and computing might be due to cognitive and motor skill functions while (3) interpretation errors might arise from cognitive dysfunctions (Copeland et al. 1981).

Barefield (1970) investigates forecast biasing behavior and elaborates a model of biasing behavior. Specifically, in accordance with Fox (1961) and Barefield (1970) distinguishes between biases that result from intentional and unintentional sources. Unintentional biases are defined as differences of the forecast of an 'ideal observer' and an agent's forecast, where the 'ideal observer' has the best available knowledge for the estimation and both the agent and the 'ideal observer' have no incentive to distort the forecast based on their estimation. Intentional biases are defined as the difference between the agent's estimation and the actually reported forecast. For these setups, the observer is assumed to intentionally distort his estimation.

Lowe and Shaw (1968) analyze biasing behavior in the context of a company's budgeting process. In their investigation they concentrate on biases that result from intentional manipulation of forecasts. This understanding of bias corresponds to elaborations of Barefield (1970). According to Lowe and Shaw (1968), intentional manipulations are due to the forecasters' personal interests and perceptions. As main sources of bias, Lowe and Shaw (1968) identify (1) the reward system, (2) company practice and norms and (3) insecurity of managers. In addition to the distinction between intended and unintended biases, they distinguish between biasing behavior that causes downward and upward bias.

Dechow et al. (2010) analyze various measures for earnings quality. In this context they also distinguish between intentional and unintentional biasing behavior. This differentiation corresponds to elaborations by Barefield (1970). For intentional biases Dechow et al. (2010) refer to earnings management (cf. Sect. 3.2.2), while unintentional biases are defined as (unintentional) deviation from correct values which might be due to a set of various sources (e.g. misclassification, estimation, . . .) (Dechow et al. 2010). In contrast to Barefield (1970), who uses the term bias for intentional and unintentional sources, Dechow et al. (2010) use the term bias for intentional biasing behavior and the term error for unintentional biasing behavior.

Hennes et al. (2008) analyze errors in the context of restatement research. In their investigation they differentiate between errors and irregularities. For the concept of error they refer to unintended misapplications of accounting principles. Hence, their understanding of error corresponds to the elaboration of 'error of principle' as elaborated by Brief (1990). They define irregularities as intentional misreporting, which corresponds to the elaboration of intentional bias by Barefield (1970) and Dechow et al. (2010).

In their empirical investigation Ham et al. (1985) report error characteristics in accounting populations. Their understanding of the term error corresponds to the elaborations of Harris and Smith (2009) on accuracy and precision. Ham et al. (1985) define errors as deviations from the correct value which is also consistent with a statistical understanding of errors (cf. Fox 1961).

Merchant and Shields (1993) investigate information quality in activity based costing systems. They analyze accuracy of these systems. In order to give a measure for accuracy, Merchant and Shields (1993) apply the ideas of precision and bias. In particular, precision stands for the magnitude of noise in measurement. They conceptualize freedom of error as measures that skewed neither downward nor upward from the correct value. Furthermore, they concentrate on accounting systems in which biases are deliberately introduced in order to induce desirable responses (of information recipients) (Merchant and Shields 1993). By concentrating on intended biasing behavior, they implicitly also apply the differentiation between unintended and intended biases.

In their simulation study, Labro and Vanhoucke (2007) analyze effects of interactions among errors in activity-based-costing systems on accuracy. Their representation of errors corresponds to the statistic error concept which Fox (1961) applied to accounting issues. Furthermore, Labro and Vanhoucke (2007) distinguish between (1) aggregation errors, (2) measurement errors and (3) specification errors. In the model of Labro and Vanhoucke (2007), (1) aggregation errors are considered for activity cost pools as well as for resource cost pools. This type of error occurs if heterogenous actions and resources are pooled. (2) Measurement errors refer to misclassification of resources, incorrect estimates for allocation within the activity-based-costing system and incorrect estimates for activity drivers. For (3) specification errors they refer to Datar and Gupta (1994) who define this type of error as methods used for the allocation of costs to products that do not reflect the demand placed on resources by the respective products.

Bisbe et al. (2007) analyze the risk of conceptual misspecification of management accounting constructs. In order to express errors they apply various measures. First, they use validity in order to express the best available approximation to the truth or falsity of a proposition or conclusion (cf. also Cook and Campbell 1979). Second, they use reliability as a measure for quality and consistent measurement accuracy, i. e. the absence of systematic errors in measurement (cf. also Kerlinger and Lee 2000).

3.1.1.3 Research on Data Quality

In order to express data quality in information systems, Agmon and Ahituv (1987) use the concept of reliability. According to Robertson (1971), reliability can be defined as the ability of a product to function for a specific period. Based on this definition, Agmon and Ahituv (1987) distinguish between three types of reliability, (1) internal reliability, (2) relative reliability and (3) absolute reliability. (1) Internal reliability expresses characteristics of data items within the information system and their conformance to universal criteria, (2) relative reliability captures compliance of data to user requirements, and (3) absolute reliability determines the level of accordance of data in the information system to reality.

In their paper, Kahn et al. (2002) develop a methodology to assess the quality of information produced by organizations and delivered to consumers. In order to define quality they refer to Juran (1974) who defines quality as compliance of a product to consumer demands. Kahn et al. (2002) substantiate the broad definition given by Juran (1974) and apply two perspectives on data quality, i.e. (1) the conforming to specifications and (2) the meeting or exceeding of consumer expectations. They furthermore distinguish between product quality and service quality. For the product quality perspective, (1) conforming to specifications means that information meets standards previously defined for the respective information and (2) the meeting or exceeding of consumer expectations means that the information provided meets the consumer task needs. For the service quality perspective they state that (1) conforming the specifications means that the converting from data to information meets standards and (2) the meeting or exceeding of consumer expectations means the process of converting data to information meets or exceeds consumer expectations.

Wixom and Watson (2001) investigate factors that affect the success of data warehouses. In this context, they argue that the success of information systems is a multi-faceted construct which consists of the dimensions data quality, systems quality and perceived net benefits. In order to define data quality, they refer to Watson and Haley (1997) who argue that providing decision-makers with high-quality data is the main reason for building data warehouses. To give a more specific definition, Wixom and Watson (2001), Shanks and Darke (1998), and Lyon (1998) who define data accuracy, completeness and consistency as critical aspects of data quality. System quality focuses on the information system itself and refers to measures such as response time, flexibility and integration (cf. DeLone and McLean 1992). For perceived net benefits, Wixom and Watson (2001) inter alia refer to Seddon and Kiew (1994) who argue that higher levels of data quality and system quality lead to higher levels of net benefits.

Strong et al. (1997) and Wang et al. (1998) introduce an information product approach and provide a framework for its implementation. In their paper, they define data quality as a multidimensional concept. In particular, they distinguish the dimensions (1) intrinsic information quality (with the elements accuracy, objectivity, believability and reputation), (2) accessibility information quality (with the elements accessibility, ease of operations and security), (3) contextual information quality (with the elements relevancy, value added, timeliness, completeness and amount of information) and (4) representational information quality (with the elements interpretability, ease of understanding, concise representation and consistent representation). For the understanding of bias and error in this simulation study the dimensions accuracy, objectivity, completeness and reliability are of particular interest. The definition of accuracy is consistent with the elaborations by Harris and Smith (2009) as outlined above. Definitions of objectivity and completeness are given by Pipino et al. (2002) who define objectivity as the extent to which data is unbiased, unprejudiced and impartial. Completeness is defined as the extent to which data is present. Reliability as listed by Strong et al. (1997) and Wang et al. (1998) refers to freedom-of-error as elaborated by Pipino et al. (2002) who define freedom-of-error as the extent to which data is correct and reliable. Errors represent deviations from correct values in these dimensions.

Redman (1998) elaborates the impact of poor data quality on the operational, tactical and strategic level of organizations. For a classification of data quality issues he builds four clusters of data quality issues with various: (1) issues related to data views, (2) issues related to data values, (3) issues related to the presentation of data and (4) other issues (cf. also Redman 1992, 1996). The dimensions accuracy and completeness are of particular interest for further elaborations. In accordance to Harris and Smith (2009), accuracy is defined as the proximity of a measurement or an estimate to the correct value. Completeness stands for the extent to which data is present in a data collection (Redman 1992).

3.1.1.4 Summary and Applied Concept of Bias and Error

Table 3.1 summarizes Sects. 3.1.1.1–3.1.1.3 and gives an overview of the understanding of bias and error in the field of research on (1) human error, (2) accounting and (3) data quality. Table 3.1 lists the context of the definition given by the respective authors, an outline of the applied understanding of bias and error and, if authors refer to further sources of literature, the respective references.

For this simulation study, the word bias is used in order to express deviations from correct values. Thus, the applied understanding refers to the statistical concept of error (cf. Fox 1961; Ham et al. 1985; Brief 1990). This is also consistent with elaborations on absolute reliability by Agmon and Ahituv (1987) who define absolute reliability as the extent to which data in the information system corresponds to reality. The understanding of biases as deviations from the correct value also aligns with the understanding of Bushman and Indjejikian (1993), i.e. noisy accounting information, and the work on observation error by Copeland et al. (1981). In their simulation study, Labro and Vanhoucke (2007) also apply the statistical error concept. Furthermore, this simulation study distinguishes between unintentional and intentional biasing behavior. As outlined above, this appears to be a prominent approach for classifying sources for biasing behavior (cf. inter alia Diamantopoulos 2006; Fox 1961; Barefield 1970; Dechow et al. 2010; Hennes et al. 2008; Zhao and Olivera 2006; Lowe and Shaw 1968; Merchant and Shields 1993; Reason 1990; Fischer and Verrecchia 2000). With reference to the work of Kim and Bishu (2006), Singleton (1973), and Senders and Moray (1991), from the psychologists' point of view this simulation study uses opportunism as the source for intended biasing behavior, while, with respect to elaborations of Rasmussen (1983; 1986) and Reason (1990), skill-based mistakes are considered as the source for unintended biasing behavior (for further details on sources for biasing behavior cf. Sect. 3.1.2.1 for intended and Sect. 3.1.2.2 for unintended biases). Both intended and unintended biasing behavior are consistent with the attributes of human error as elaborated by Hansen (2006), i.e. (1) the action is performed by a human being, (2) the bias occurs at an interface between the human being and a system, (3) the action is not forced and (4) exceeds tolerance limits. The exceeding of limits is consistent with biases from the engineering perspective as elaborated by Rigby (1970). Furthermore, the deviation from data quality standards previously defined also corresponds to elaborations of Kahn et al. (2002) on data quality. The data quality literature gives multi-dimensional concepts of data quality where specifically the dimensions accuracy and completeness are relevant to the applied understanding of bias (cf. Redman 1998; Wixom and Watson 2001). This refers to intrinsic information quality as elaborated by Strong et al. (1997). Completeness indicates that no data is missing and accuracy corresponds to elaborations on accuracy and precision as outlined by Harris and Smith (2009), i.e. estimates with high accuracy and high precision are each very close to the correct value (cf. also Sect. 3.1).

3.1.2 Sources for Biasing Behavior

Apart from differences in the definition and usage of the terms bias and error, the literature discusses various sources for biasing behavior. As outlined in Sect. 3.1.1.4,

Table 3.1 Surveyed concepts of bias and error

Author(s)	Context	Understanding	Reference
Research on human error			
Diamantopoulos (2006)	Management of human errors in organizations	Characterizes error types and differentiates between indented and unintended sources	–
Fedota and Parasuaman (2010)	Neural signals associated with errors	Differentiate between slips and mistakes	Norman (1988), Tversky and Kahneman (1974), Reason (1990)
Hansen (2006)	Concept analysis	Elaborates attributes for human errors	
Kim and Bishu (2006)	Human reliability analysis	Differentiate between definitions from the psychological and engineering domain, respectively	Singleton (1973), Rasmussen (1982), Rigby (1970)
Senders and Moray (1991)	Error reduction	Human error is a deviation from a desired action, expectation or outcome	–
Zhao and Olivera (2006)	Error reporting	Elaborate characterizations of human error and differentiate between indented and unintended sources	Reason (1990), Rasmussen (1983; 1986)
Research on accounting			
Barefield (1970)	Forecasting	Differentiates between intended and unintended sources	–
Bisbe et al. (2007)	Misspecification of management accounting constructs	Use validity and reliability in order to express quality of data	Cook and Campbell (1979)
Brief (1990)	Error concepts and accounting	Error of principle and statistical error concept	–
Bushman and Indjejikian (1993)	Noisy accounting information	Differentiate between bias and error	–
Copeland et al. (1981)	Observation error in accounting	Differentiate between sources for errors	Rosenthal (1976)
Dechow et al. (2010)	Earnings quality	Differentiate between intended and unintended error sources	–

Fischer and Verrecchia (2000)	Managerial reporting bias	Focus on intentional biasing behavior	–
Fox (1961)	Statistical error concept and accounting	Differentiates between unknown and deliberate sources; and accounting error for management and accounting error for control	
Hennes et al. (2008)	Restatements	Differentiate between errors and irregularities	–
Labro and Vanhoucke (2007)	Interactions in activity-based-costing systems	Differentiate between aggregation errors, measurement errors and specification errors	Datar and Gupta (1994)
Lowe and Shaw (1968)	Budgeting	Focus on intentional manipulations	–
Merchant and Shields (1993)	Information quality in activity-based-costing systems	Differentiate between precision and bias	–
Research on data quality			
Agmon and Ahituv (1987)	Information systems	Distinguish between internal, relative and external reliability	Robertson (1971)
Kahn et al. (2002)	Assessment of quality provided from organizations to consumers	Distinguish between product and service quality; conforming to specifications and meeting of demands as characterization of data quality	Juran (1974)
Redman (1998)	Impact of poor data quality on organizations	Multi-dimensional concept of data quality	Redman (1992, 1996)
Strong et al. (1997) and Wang et al. (1998)	Information as product	Differentiate between intrinsic, accessibility and contextual information quality	Pipino et al. (2002)
Wixom and Watson (2001)	Success of data warehouses	Data quality as multi-faceted construct	Wixom and Watson (2001) Shanks and Darke (1998), Lyon (1998), and Seddon and Kiew (1994)

this simulation study distinguishes between intentional and unintentional biasing behavior. The following two subsections discuss potential sources for the agents' biasing behavior. In particular, in Sect. 3.1.2.1 opportunistic behavior as a source for intentional biasing behavior is outlined while Sect. 3.1.2.2 elaborates on unintentional biasing behavior which might be subject to a set of psychological, physiological and physical factors, respectively.

3.1.2.1 Intentional Biasing Behavior

There is evidence that individuals (intentionally) misrepresent their private information for even small increases in personal wealth (cf. Baiman and Lewis 1989; Baiman 1990; Harrell and Harrison 1994). A central assumption in order to describe this misrepresentation of information is that these agents act opportunistically, i.e. respective agents are self-interest seeking and aim at maximizing their personal utility by misleading, distorting and disguising information (cf. Williamson 1985; Niesten and Jolink 2012).

The notion of opportunism goes back to transaction cost economics (cf. inter alia Williamson 1993; Wathne and Heide 2000; Crosno and Dahlstrom 2008). Williamson (1975, 1985) defines opportunism as self-interest seeking with guile, whereby guile can be defined as "lying, stealing, cheating, and calculated efforts to mislead, distort, disguise, obfuscate, or otherwise confuse". Wathne and Heide (2000) state that in the definition of Williamson (1975), the notion of guile distinguishes opportunism from self-seeking behavior which is a standard assumption in economics (cf. Simon 1978). This definition of guile, and consequentially the notion of opportunism, builds on human beings that (1) are morally weak and (2) do not follow previously fixed rules of interaction (Wathne and Heide 2000; John 1984; Williamson 1993). Masten (1988) describes this conceptualization of opportunism as blatant or strong opportunism.

Blatant opportunism can be divided into two forms, i.e. (1) ex-ante opportunism which manifests itself in the deliberate misrepresentation of various kinds during the building of contractual relationships, and (2) ex-post opportunism which is conceptualized as violations during the course of the previously build contractual relationship (Williamson 1985; Wathne and Heide 2000). Bridging to agency theory, (1) ex-ante opportunism refers to the problem of adverse selection, while (2) ex-post opportunism covers situations of moral hazard. The concept of adverse selection goes back to Akerlof (1970) who illustrates this concept on the market for used cars. In the context of contracting, adverse selection covers situations of hidden characteristics, i.e. the information asymmetry means that the agent has better (private) information on personal characteristics than the principal. Due to the lack of knowledge of the agent's characteristics and potential misrepresentation of abilities by the agent, the principal runs the risk of adverse selection, i.e. the principal might select agents who are not advantageous with respect to the task to be fulfilled (cf. Eisenhardt 1989; Jost 2001b; Bannier 2005). The problem of moral hazard captures situations of information asymmetry ex-post to the building of the contractual relationship. Early investigations of moral-hazard go back to e.g. Arrow (1963), Pauly (1974), Spence and Zeckhauser (1971), and Holmstrom (1979). The information asymmetry which constitutes the source for situations with moral hazard results from individual agents' actions that cannot be observed or, if actions can be observed, cannot be assessed with respect to task fulfillment. At the same time, these actions affect the probability distribution of the outcome (Holmstrom 1979). These two situations are referred to as (1) hidden action and (2) hidden information (cf. Eisenhardt 1989; Lambert 2001; Jost 2001b). The focus of this investigation is on ex-post opportunism, and in particular on the problem of hidden action (for detailed information on the hidden-action problem cf. Sect. 3.2.1).

In addition to ex-ante and ex-post opportunism, Wathne and Heide (2000) distinguish between (1) active and (2) passive opportunism for situations with existing and new circumstances. Specifically, for situations in which the the fulfillment of the contract (e.g. an exchange of information) takes place without changes in the environment, Wathne and Heide (2000) use the term existing circumstances. Environment which changes due to exogenous influences, Wathne and Heide (2000) refer to as changing circumstances. (1) Active (ex-post) opportunism under existing circumstances comprises situations in which one party of the contractual relationship engages in explicitly or implicitly prohibited behaviors in order to serve their own ends. Situations of active (ex-post) opportunism under new circumstances, Wathne and Heide (2000) also refer to as forced renegotiation where one party of the relationship uses the new circumstances to extract concessions from the other party. (2) Passive (ex-post) opportunism under existing circumstances refers to shirking and evasion of obligations, while passive (ex-post) opportunism under new circumstances takes the forms of inflexibility and refusal to adapt (cf. Wathne and Heide 2000). The division into opportunism under existing and new circumstances corresponds to the forms of uncertainty which opportunism might result from as suggested by Crosno and Dahlstrom (2008). They distinguish between environmental uncertainty, which covers changes in the environment that are not considered at the time of contracting (cf. also Noordewier et al. 1990), and behavioral uncertainty, which refers to performance assessment and contractual compliance of exchange partners (cf. also Rindfleisch and Heide 1997). Hence, situations with existing circumstances in the sense of Wathne and Heide (2000) cover problems that arise from behavioral uncertainty in the sense of Crosno and Dahlstrom (2008), while situations with new circumstances as elaborated by Wathne and Heide (2000) comprise problems that arise from environmental uncertainty as elaborated by Crosno and Dahlstrom (2008). For this simulation study, renegotiation of contracts and adaption in case of changing circumstances are excluded. The focus of the agents' behavioral assumptions is on active and passive ex-post opportunism and on the hidden action problem in particular (for further details on the hidden-action problem cf. Sect. 3.2.1).

3.1.2.2 Unintentional Biasing Behavior

It is a known fact that physiological, psychological and physical factors all influence human reliability (Kolarik et al. 2004). Following Wegner and Erskine (2003), situations in which one feels that "something is happening" rather than "someone is doing it" might happen under a set of conditions. On the one hand, this might occur in situations in which a human being performs complicated, lengthy and goal-oriented actions. Furthermore, dynamic situations and continuously changing conditions contribute to biasing behavior (Kolarik et al. 2004). On the other hand, this involuntariness might happen due to automatisms. Moray (1994) and Reason (1997) argue that biasing behavior typically reflects multiple factors such as poor interface design, insufficient training, lack of maintenance, regulatory policies or organizational pressure. Fedota and Parasuaman (2010) argue that in addition to other perspectives, neuro-ergonomics might help to understand errors and error-types. In the context of neuroergonomics, many factors which influence human performance have been analyzed, these are inter alia mental workload (Wickens 2008), agents' vigilance (Warm et al. 2008), stress (Hancock and Szalma 1997) and the assessment of individual differences so as to develop better selection and training methodologies (Parasuraman 2009).

As outlined in Sects. 3.1.1.1 and 3.1.1.4, skill-based mistakes are considered as a source for unintentional biasing behavior. Following Reason (1990), there are two distinct clusters of behavioral patterns that might lead to mistakes at the skill-based level, i.e. (1) inattention and (2) overattention (cf. also Viller et al. 1999). (1) Inattention refers to the omission to perform attentional checks at critical nodes (e.g. deviation from common practice), while (2) overattention stands for situations in which attentional checks are made at inappropriate time steps during routine actions.

For skill-based mistakes due to (1) inattentions, Reason (1990) lists five potential failure modes, i.e. (1.1) double-capture slips, (1.2) omissions following interruptions, (1.3) reduced intentionality, (1.4) perceptual confusions and (1.5) interference errors. For (1.1) double-capture slips Reason (1990) refers to Norman (1981) and states that they are probably the most common consequences of omitted checks. According to Norman (1981), slips are the performance of actions that are not carried out as intended. Furthermore, Norman (1981) claims that these slips result from conflicting actions or thoughts, intermixing components of an action's sequence or from selecting acts in an inappropriate way. Double capture slips are a special type of action slips and can be defined as unintended activation and, hence, execution of actions that are related to another action, i.e. a human being switches to a related strong action when carrying out another action. The originally intended action is overruled by the related action (Zhang et al. 2004; Targoutzidis 2010). For (1.2) omissions following interruptions, Reason (1990) outlines that failures are due to external events, e.g. interruptions. As a result, certain steps of a routine of actions might be omitted (Targoutzidis 2010). (1.3) Failures that are due to reduced intentionality might result from some delay in the formulation of an intention and the corresponding execution of the respective action. During this delay the originally formulated intention might be overlaid by other demands, e.g. “what-am-I-doing-here” experience (Reason 1990; Targoutzidis 2010; Wegner and Erskine 2003). According to Reason (1990), (1.4) perceptual confusions occur in situations in which one’s own object is recognized as something very similar, i.e. the human being accepts look-likes. This happens due to the fact that in routinized and often repeated tasks the recognition and action schemata become automatized and rough rather than precise approximations to inputs. (1.5) Interference errors occur in situations in which two or more simultaneous plans or actions compete for attention. This might lead to incongruous blends of action or in producing a behavioral spoonerism (Reason 1990; Targoutzidis 2010).

In failures at the skill-based level that are due to (2) overattention, Reason (1990) lists three potential behavioral patterns, i.e. (2.1) omissions, (2.2) repetitions and (2.3) reversals. Reason (1990) argues that mistimed checks in series of largely automatic actions that need to be carried out in the right order (with probable periods of waiting) might lead to (2.1) omission and (2.2) repetition. Both failures occur because of a wrong assessment of the current step in the sequence of actions. In case of omissions, the human being concludes that the process is further along than it actually is. As a consequence, certain actions within the sequence of actions are omitted. In case of repetitions, one decides that the actual point in the sequence of actions has not actually been reached. As a result, certain steps within the sequence of actions are repeated. Rare form are failures at the skill-based level which are due to mistimed checks and are represented by (2.3) reversals, i.e. due to the mistimed check the sequence of actions doubles back on itself. Consequences might be bi-directional, i.e. omissions or repetitions (Reason 1990).

In their investigation, Wei and Salvendy (2006) develop a model for human task performance analysis which is based on human-information processing theory. In order to capture human cognitive performance, they consider an attention module. In particular, they consider six different aspects of attention. These aspects might also contribute to the understanding of human beings making unintentional biases. For (1) attention bottlenecks, Wei and Salvendy (2006) argue that there are limitations in perception, response selection and response production. In the context of (2) attention resources, Wei and Salvendy (2006) differentiate unitary and multiple resource models (cf. also Meyer and Kieras 1997). For unitary resource models they refer to Pashler (1998) who argues that attention is limited, controllable, divisible and varies from moment to moment. The limit depends on the demands of other current activities. In case of multiple resource models, there are a number of resources which are combined for individual tasks. If multiple tasks demand the same attention resource, the available capacity is allocated to the different tasks. As a result, attention capacity might be limited (Pashler 1998; Wei and Salvendy 2006). For (3) attention limitation on memory storage, Wei and Salvendy (2006) argue that attentional (imperfect) filtering mechanisms might prevent human-beings from complete semantic analysis and that parallel mental operations might affect memory storage. For (4) attention limitation on memory retrieval, Wei and Salvendy (2006) refer to Trumbo and Milone (1971), Rohrer et al. (1995), and Pashler (1998) and claim that memory retrieval is subject to capacity limitations. For (5) mental workload, Wei and Salvendy (2006) argue that the amount of mental work necessary to perform a task might be beyond or below human ability requirements. In case of the mental workload being too high, human task performance might decrease while in case of the mental workload being too low, human beings might become passive, i.e. they might ignore or take too much time to recognize and handle abnormal situations. Finally, for (6) arousal and vigilance, Wei and Salvendy (2006) claim that the arousal level affects the available attention resources, while performance in vigilance tasks might be dependent on the intensity of the signal to be observed and the agents' motivation (Pashler 1998).

3.2 Theoretical Framework

The idea that organizations basically rely on two economic principles, i.e. (1) cooperation and (2) distribution of tasks, goes back to Smith (1984) (cf. also Jost 2001b, 2000). While the neoclassical theory was stripped off all institutional content (Alessi 1990; Furubotn and Richter 2000), New Institutional Economics (NIE) focus on the economic analysis of institutions and is sensitive to organizational issues (Furobotn and Richter 1991b; Furubotn and Richter 2008; Wall 2006). The body of literature referred to as NIE extends neoclassical theory by considering how property-rights structure and transaction costs affect incentives and economic behavior (Furobotn and Richter 1991b; Furubotn and Richter 2000). Hence, (1) the property rights approach, (2) transaction cost theory and (3) contracting theory can be said to be the main streams (for the organizational context) within the NIE (Furubotn and Richter 2000, 2008). The (1) property rights approach concentrates on individuals' rights to "possess" and dispose over goods (Furobotn and Richter 1991b; Göbel 2002). The central thesis of this approach is that particular structures of property rights influence the allocation and utilization of limited goods and resources in specific ways (Demsetz 1967; Furubotn and Pejovic 1972), i.e., how do certain setups of property rights affect the behavior of rational and self-interested individuals (Göbel 2002). The (2) transaction cost theory considers the market not to work without incurring costs (as originally assumed by neoclassical theory) (Coase 1937; Göbel 2002). In particular, the transaction cost theory assumes transaction costs to occur in the context of exchanges and affect the design of contracts and the characterization of economic processes. The central idea of the transaction cost theory is to determine governance structures (market, hybrid, hierarchy) for specific types of transactions (Williamson 1991; Göbel 2002; Furubotn and Richter 2000). The (3) contracting theory is closely related to the property rights approach and the transaction cost theory and concentrates on asymmetric information and problems of incentives (Furubotn and Richter 2000; Wall 2006). Within contracting theory two schools of thought can be distinguished, i.e. the theory of relational contracts and agency theory. The theory of relational contracts concentrates mainly on long-term contracts and on information asymmetries *between parties of a contract and a third party*. Agency theory, on the contrary, concentrates on problems *between parties of a contract* which are due to information asymmetries (Furubotn and

Richter 2000; Erlei et al. 1999; Wall 2006). Agency theory can be further subdivided into positive agency theory and normative agency theory (Jensen 1983; Eisenhardt 1989; Furubotn and Richter 2000). Positive agency theory is less mathematical than normative agency theory and focuses on the identification of situations in which a principal and agents have potentially conflicting objectives and *describe* governance mechanisms in order to limit self-serving behavior. The focus is almost exclusively on relationships between owners and managers (Eisenhardt 1989). According to Eisenhardt (1989), positive agency theory is particularly influenced by Jensen and Meckling (1976), Fama (1980), and Fama and Jensen (1983), who all mainly focus on ownership-executive relationships. Normative agency theory, on the contrary, aims at constructing a more general theory that can be applied to various relationships, e.g. employer-employee, buyer-supplier (Harris and Raviv 1978; Eisenhardt 1989). While positive agency theory might enrich economics with its more complex view on organizations, normative agency theory is a more general approach and has a broader focus (Jensen 1983; Eisenhardt 1989). The core of work on normative agency theory (cf. inter alia the work of Demski and Feltham 1978; Holmstrom 1979; Shavell 1979) is the tradeoff between the cost of measuring behavior, the cost of measuring outcomes and transferring risk to agents (Eisenhardt 1989).

Within the NIE, agency theory appears to be the appropriate theoretical framework for the current simulation study. Due to the lack of institutional content, neoclassical theory is not appropriate. For theories that consider institution, the property rights approach and the transaction cost economics also do not appear to be appropriate in order to investigate the research questions. The main focus of the property rights approach is to control individual behavior via the right to possess and dispose goods (Furobotn and Richter 1991b; Göbel 2002). For the context of MAS this does not apply. Due to the focus on exchanges and the determination of optimal governance structures (Williamson 1991; Furubotn and Richter 2000; Göbel 2002), the transaction cost theory does not apply either. (Normative) Agency theory, on the contrary, provides a model that allows mapping these delegation relationships in organizations with potential divergence of interest (Eisenhardt 1989).

Within agency theory, organizations are regarded to be a set of contracting relationships among individuals. One basic assumption of agency theory is that individuals aim at maximizing personal utility. Agents might not always act in the principal's interest (Jensen and Meckling 1976). Furthermore, the assumptions of bounded rationality (cf. inter alia Simon 1955) and opportunism (cf. inter alia Williamson 1975) might also contribute to agents' behavior that deviates from the one desired by the principal. From these behavioral assumptions, two problems result that are of particular interest in the context of agency research, i.e., the problem of adverse selection and the problem of moral hazard (Fama and Jensen 1983; Baiman 1990; Lambert 2001; Jost 2001b; Eisenhardt 1989; Nilakant and Rao 1994; Shapiro 2005). Adverse selection problems refer to situations ex-ante to contracting in which the agent has better private information on personal characteristics than the principal. As a result, the principal might select agents who are not advantageous with respect to the task to be fulfilled (Akerlof 1970;

Eisenhardt 1989; Jost 2001b; Bannier 2005). The problem of moral hazard refers to situations ex-post to contracting. The problem of moral hazard can be divided into the problem of hidden information and the problem of hidden action. In case of hidden information, the principal is able to observe actions selected by the agent in order to fulfill tasks but cannot asses them. Due to a lack of information the principal cannot determine whether or not the chosen action is the most efficient way to fulfill the delegated task. In case of hidden action, the action chosen in oder to fulfill the delegated task cannot be observed without incurring costs (Lambert 2001; Eisenhardt 1989; Jost 2001b; Bannier 2005). But at the same time, the chosen actions affect the probability distribution of the outcome and affect both the agent's and the principals utility (Holmstrom 1979). For this simulation study, the hidden action problem appears to be practicable, while the problems of adverse selection and hidden information remain unconsidered.

3.2.1 The Hidden Action Problem

As outlined above, the hidden action problem is a characterization of moral hazard. This section gives an outline of the basic problem of hidden action which builds the basis for the elaboration of the model of the agents' behavior and the resulting biases (cf. Sect. 4.2). In particular, this section gives the hidden action problem for a delegation relationship between a principal and one agent. It has to be noted that this simulation study does not aim at finding optimal contracts for specific situations as originally intended by agency theory. Rather, this study investigates effects of agents' biasing behavior in case of given contracts. Thus, this section outlines the hidden action problem, but does not focus on finding the optimal contract. For extensive reviews of agency theory cf. inter alia Rees (1985), Eisenhardt (1989), Baiman (1990), Erlei et al. (1999), Furubotn and Richter (2000), Demougin and Jost (2001), Jost (2001b), Lambert (2001), Macho-Stadler and Perez-Castrillo (2001), Göbel (2002), Bannier (2005), Shapiro (2005), and Wall (2006) on which the following outline of the hidden action problem is based.

The hidden action problem captures situations in which the principal contracts the agent. In particular, the principal offers a contract to the agent who decides whether to accept or reject the offer. Inter alia, the contract contains a task that is delegated to the agent, a scheme for the agent's compensation including a performance measure and an effort desired by the principal to be chosen by the agent in order to fulfill the task. If the contract is accepted, the agent chooses an action to exert effort for task fulfillment in exchange for monetary effort. The delegation relationship is characterized by asymmetric information. Both the principal and the agent have information on the production function, the distribution of the random variable which captures a random state of nature (which affects outcome) and both know the utility function of the other party. But besides this symmetric information, the principal is unable to observe the agent's behavior. It cannot be used as a contracting variable. The outcome, on the contrary, is observable at the end of the

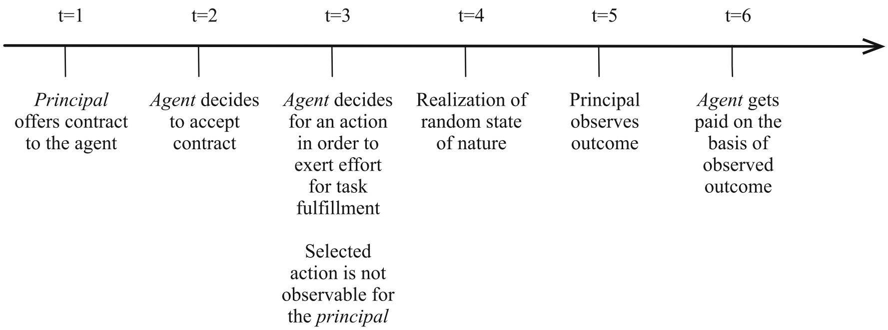

Fig. 3.1 Basic hidden action model: sequence of events

period. Consequently, the result is used as a contracting variable and is the basis for the agent's variable compensation component.

Figure 3.1 summarizes the timeline as outlined in the previous paragraph. The following paragraphs give a formal model of the hidden action problem.

For further elaborations on the basic hidden action problem, the principal and the agent are denoted as P and H, respectively. As outlined above, the principal P delegates a task to the agent H. In order to exert effort for task fulfillment, the agent selects an action $a \in A$. The selected action $a \in A$ and a random state of nature $\theta \in \Theta$ together define the outcome W, i.e.

$$W = f^w(a, \theta). \tag{3.1}$$

During contracting, θ is not observable, neither for the principal nor for the agent. While the selected action a is not observable for the principal, the outcome W is observable without incurring costs. Furthermore, the selected action a is assumed to result in direct disutility for the agent (Holmstrom 1979).

In addition to the delegated task, the contract contains the compensation scheme. For the fact that the selected action a is not observable, but W is observable, the agent's H compensation is based W. The agents compensation function results as

$$f^S(W) = f^S(f^w(a, \theta)). \tag{3.2}$$

Both the principal and the agent are assumed to aim at maximizing their individual utility functions (Jensen and Meckling 1994). The principal's P utility U^P is based on outcome W and the agent's H compensation, i.e.

$$U^P\left(W, f^S(W)\right) = W - f^S(W). \tag{3.3}$$

The agent's H utility is given by the difference between utility of compensation and disutility of exerted effort. Utility of compensation is given by function $f^v\left(f^S(W)\right)$, while disutility of exerted effort is given by function $f^g(a)$, where $f^{v}(\cdot)$ is increasing and convex and $f^{v}(\cdot)$ is increasing and concave, i.e. $f^{v\prime}\left(f^{S}(W)\right) > 0$, $f^{g\prime}(a) > 0$, $f^{v\prime\prime}\left(f^{S}(W)\right) \leq 0$ and $f^{g\prime\prime}(a) \geq 0$. The agent's H utility results as

$$U^{H}\left(f^{S}(W), a)\right) = f^{v}\left(f^{S}(W)\right) - f^{g}(a). \tag{3.4}$$

Both the principal and the agent aim at maximizing their utility functions (cf. Eqs. 3.3 and 3.4). Given the principal's and the agent's utility functions, the principal's target function can be formalized as

$$\max_{a, f^{S}(W)} E_{\theta}\left(f^{w}(a,\theta) - f^{S}\left(f^{w}(a,\theta)\right)\right). \tag{3.5}$$

The principal aims at maximizing outcome which is given by the expected outcome minus the agent's compensation, whereby, as outlined above, the contract defines which task is delegated to the agent, which action a the principal desires the agent to choose in order to fulfill the task and which compensation scheme is applied.

At the same time, there are two constraints, namely (1) participation constraint and (2) the incentive compatibility constraint. The (1) participation constraint considers the fact that the agent can always reject the contract at time step $t = 2$ (cf. Fig. 3.1). The agent's expected utility in case of accepting the contract must be at least equal to what the agent can obtain from alternatives in the market. The participation constraint can be formalized as

$$E_{\theta}\left(f^{v}\left(f^{S}\left(f^{w}(a,\theta)\right)\right)\right) - f^{g}(a) \geq \underline{U}, \tag{3.6}$$

where $\underline{U}$ represents the utility the agent can obtain from alternatives, i.e. $\underline{U}$ represents an outside-option in case of rejection of the contract. In order to assure that the agent does not reject the contract, the incentive scheme has to be designed correspondingly.

The (2) incentive compatibility constraint reflects the moral hazard problem. Since the hidden action model assumes the selected action a not to be verifiable for the principal, after signing the contract the agent will choose an action that maximizes his utility function. The principal can propose an action (that leads to the highest utility from the principal's point of view) but, at the same time, must make sure that the agent wants to choose exactly that action in order to exert effort at time-step $t = 3$ (cf. Fig. 3.1). Obviously, in order to assure that the agent chooses the optimal action from the principal's point of view, the principal must consider the agent's disutility of effort and the utility of compensation. The incentive compatibility constraint can be formalized as

$$a \in \arg\max_{\hat{a}} E_{\theta}\left(f^{v}\left(f^{S}\left(f^{w}(\hat{a},\theta)\right)\right)\right) - f^{g}(\hat{a}). \tag{3.7}$$

The aim is to design an incentive scheme which leads the agent to decide for that action $\hat{a}$ that also solves the maximization problem from the principal's point of view. Thus, the contracting problem from the principal's point of view results as maximization of Eq. 3.5 in consideration of the constraints given in Eqs. 3.6 and 3.7. On the one hand, the agent autonomously decides about the action a she chooses in order to fulfill a delegated task. The principal, on the other hand, provides incentives that lead the agent to chose that action a that (besides the agent's expected utility) also maximizes the principal's expected utility.

3.2.2 Earnings Management and the Revelation Principle

Managerial reporting captures the reporting of managers' private information to upper management. On the one hand, this communication can potentially increase the organizations' welfare (e.g. truthful data is introduced into the costing system and the costing system can provide unbiased information for decision making). On the other hand, managers' potential opportunistic behavior might limit the value of communication (cf. inter alia Evans et al. 2001; Baiman and Evans 1983; Melumad and Reichelstein 1987). In economic literature, judgement (or manipulation) in order to influence contactual outcome is referred to as earnings management (Schipper 1989; Evans and Sridhar 1996; Arya et al. 1998; Healy and Wahlen 1999; Dechow and Skinner 2000). In order to give a definition, Dechow and Skinner (2000) refer to the National Association of Certified Fraud Examiners (1991) and argue that earnings management captures the intentional, deliberate misstatement or omission of material facts of accounting data which is misleading. Furthermore, they argue that the revealed information which is subject to earnings management would cause the recipient to alter the judgement or decision.

In order to cope with earnings management, economic literature provides the revelation principle. This principle states that each mechanism which involves non-truthful reporting by the agent can be beaten by an equilibrium mechanism in which truthful reporting is induced (Myerson 1979; Gjesdal 1982; Arya et al. 1998; Ziv 1998; Lambert 2001; Wagenhofer and Ewert 2002; Ewert and Wagenhofer 2008). For this equilibrium mechanism to hold, a set of conditions have to be fulfilled. These conditions are (1) communication is not blocked, (2) the form of contract is not restricted and (3) the principal is able to commit to use the reported information in any pre-specified manner (Arya et al. 1998; Wall 2006; Wagenhofer and Ewert 2002). (1) Unblocked communication means that the agent can fully report all facets of private information without incurring additional costs. In situations in which the agents' information is multifaceted or multidimensional, this assumption is violated. Furthermore, if aggregated information is subject to communication, the assumption of unblocked information is also violated (Arya et al. 1998; Wagenhofer and Ewert 2002). The assumption that (2) the form of contract is not restricted indicates that the agents' compensation function can take all forms and that reported information is considered in the agents' compensation (Healy and Wahlen 1999; Wagenhofer and Ewert 2002). The third assumption is that (3) the principal commits to using the reported information in any pre-specified manner, i.e. the principal is bound to a certain usage of the provided information, even if (in absence of the commitment) the principal could use the provided information for other purposes (Arya et al. 1998; Wagenhofer and Ewert 2002). For further information on the revelation principle cf. Arya et al. (1998), who systematically group violations of the revelation principle's assumptions and various earnings management stories.

For economic explanations of earnings management, one or more assumptions of the revelation principle need to be violated (Arya et al. 1998). For the present simulation study, the revelation principle's assumptions do not hold from the very start. Costing systems are designed for a certain level of aggregation of data to be introduced. Reporting more detailed information would, consequently, lead to additional costs of communication. As argued by Arya et al. (1998) and Wagenhofer and Ewert (2002), in case of aggregated data the assumption of unblocked communication is violated. Hence, the revelation principle is suspended for the given setup.

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Chapter 4
Research Design and Model Formalization

Abstract In order to give a comprehensive and systematic overview of the simulation model, there are three aspects that have to be discussed in detail. First, the formal model of the costing system has to be specified. On the one hand, this model defines the way in which data is processed by the different components of the costing system; on the other hand, this section focuses on how the different components of the costing system logically interact with each other and how different agents interact with the costing system in order to introduce or manipulate data. As the second component of the simulation model, the behavioral model has to be worked out. The behavioral model is the basis for all biases under investigation. The third section of this chapter discusses how the different types of biases are incorporated into the model of the costing system.

4.1 The Computational Model of the Costing System

At a general level, costing systems can be defined as techniques for collecting cost information, classifying costs and assigning costs to particular cost objects (Horngren et al. 2002; Morse et al. 1988; Cooper and Kaplan 1999). Costing systems are usually designed modularly. According to this modular structure, the representation of the model of the costing system is subdivided into the following sections: (1) determining and classifying costs, (2) allocation of costs to cost centers, (3) internal cost allocation, (4) cost allocation to products and finally (5) the modes of calculation used for different types of information provided by the costing system (for the roles of information cf. also Sect. 2.2.2).

4.1.1 Determining and Classifying Costs

The model considers costs to be collected from business cases. As the first step and as the basis for all further operations, a set of business cases $bc_i \in BC$, whereby $i \in$

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$\{1, \ldots, |BC|\}$, is generated that contains aggregated cost information. The number of business cases $|BC|$ and the uniformly interval $U[\underline{a}_{bc}; \overline{a}_{bc}]$ the respective costs are costs are randomly drawn from, are exogenously given. Agents observe these business cases and introduce the observed cost information into the costing system. With this interaction, the respective agents generate a number of input cost objects $c_{in_i} \in C_{in}$, whereby $i \in \{1, \ldots, |BC|\}$. In the computational model, the step of observing and introducing cost information into the costing system is represented by the function f^c, i.e.,

$$\forall bc_i \in BC : \exists c_{in_i} \in C_{in} : f^c(bc_i) = c_{in_i}. \tag{4.1}$$

Furthermore, costs are categorized according to a given structure of cost categories. Specifically, for each input cost object an agent assigns a cost category $k_j \in K$, whereby $j \in \{1, \ldots, |K|\}$. The agents introduce information into the costing system. In the simulation model, the function f^k f^k represents this interaction, i.e.,

$$\forall c_{in_i} \in C_{in} : \exists k_j \in K : f^k(c_{in_i}) = k_j. \tag{4.2}$$

The set of cost categories can be disjunctively divided into a subset of direct and a subset of indirect cost categories, i.e., $k_j \in K^{dir}$ and $k_j \in K^{indir}$, whereby $j \in \{1, \ldots, |K|\}$, i.e.,

$$\forall k_j \in K^{dir} : k_j \notin K^{indir}; \forall k_j \in K^{indir} : k_j \notin K^{dir}. \tag{4.3}$$

The absolute number of cost categories $|K|$ and the numbers of direct $|K^{dir}|$ and indirect $|K^{indir}|$ cost categories are exogenously given. Agents interact Agents interact with the costing system and introduce information on the categorization of cost categories. In interacting with the costing system the agents determine which cost category is handled as direct or indirect cost category. This interaction is represented by the function $f^{k,cat}$, i.e.

$$\forall k_j \in K : f^{k,cat}\left(k_j\right) = \begin{cases} k_j \in K^{dir} & \text{with } p\left(k_j \in K^{dir}\right) = |K^{dir}|/|K| \\ k_j \in K^{indir} & \text{otherwise,} \end{cases} \tag{4.4}$$

whereby $j \in \{1, \ldots, |K|\}$. Given Eq. 4.4 and the condition of disjunctive subsets (cf. Eq. 4.3), $p\left(k_j \in K^{dir}\right) + p\left(k_j \in K^{indir}\right) = 1$.

With the assignment of cost categories to certain business cases, the agent determines whether incurred costs are categorized as direct or indirect costs. Direct costs can be exclusively identified with a certain cost objective, e.g., cost centers or fabrication stages. In contrast, indirect costs cannot be specifically assigned to a certain cost object in an economic feasible way (Horngren et al. 2002). Hence, in consideration of the assigned cost categories, the set of input cost objects can be subdivided into objects that contain information on direct and indirect costs.

For further elaborations, the set of input cost objects that have been assigned a direct cost category $k_j \in K^{dir}$ are denoted as $c_{in_i} \in C_{in}^{dir}$, while the set of input cost objects that have been assigned an indirect cost category $k_j \in K^{indir}$are given by $c_{in_i} \in C_{in}^{indir}$, whereby $i \in \{1, \ldots, |BC|\}$ and $j \in \{1, \ldots, |K|\}$.

In some cases, cost information used for management accounting purposes differs from the information used for other purposes, e.g., depreciation might be differentially valued for internal and external accounting purposes. The model applied in this simulation study considers these differences in valuation. For each input cost object an agent determines a rate of differences in valuation s_i, where $i \in \{1, \ldots, |BC|\}$. If $s_i \neq 0$, costs of the corresponding business case are differently valued for management accounting purposes. Consequentially, if $s_i = 0$, differences in valuation are not applicable for the respective input cost object. In the simulation model, the frequency of occurrence of differences in valuation is given by the probability p_s. Whenever differences in valuation are applicable, the value for s_i is randomly drawn from a uniform distribution $U[\underline{a}_s; \overline{a}_s]$. The probability p_s and the parameterization of the interval, i.e., $\underline{a}_s$ and $\overline{a}_s$, are exogenously given. In the computational model this interaction of agents with the costing system (i.e., the determination of the rate of differences in valuation and the interaction with the costing system in order to enter the determined percentage rate) is captured by the function f^s, i.e.,

$$\forall c_{in_i} \in C_{in} : f^s\left(c_{in_i}\right) = \begin{cases} s_i & \text{if differences in valuation are applicable} \\ 0 & \text{otherwise.} \end{cases} \tag{4.5}$$

The further processing steps depend on whether input cost objects have assigned cost categories that indicate direct or indirect costs, respectively. While for indirect costs the next step is internal cost allocation (cf. Sects. 4.1.2 and 4.1.3), direct costs are pooled into direct cost pools. After internal cost allocation, these direct cost pools are used as a basis for the calculation of overhead rates (cf. Sect. 4.1.4).

In the model of the costing system, the pooling of direct cost categories $k_j \in K^{dir}$ into clusters $k_n^{dir,group} \in K^{dir,group}$ is captured by the function $f^{k,dir}$, whereby $j \in \{1, \ldots, |K|\}$ and $n \in \{1, \ldots, |K^{dir,group}|\}$, i.e.,

$$\forall k_j \in K^{dir} : \exists k_n^{dir,group} \in K^{dir,group} : f^{k,dir}\left(k_j\right) = k_n^{dir,group}. \tag{4.6}$$

This function represents agents' interactions with the costing in order to define pools of direct costs as an element of the system's structure. This interaction takes place ex-ante to operations. Once structural elements of the costing system are defined, they cannot be changed for the remaining processing steps.

As next calculation step, the total amount of costs per direct cost pool can be calculated by summing up cost information of the respective input cost objects and considering eventual rates of differences in valuation, i.e.

$$cost_n^{dir} = \sum_{\forall i: c_{in_i} \in C_{in}: f^{k,dir}\left(f^k\left(c_{in_i}\right)\right)=k_n^{dir,group}} c_{in_i} \cdot (1 + s_i), \tag{4.7}$$

whereby $i \in \{1, \ldots, |BC|\}$ and $n \in \{1, \ldots, |K^{dir,group}|\}$.

4.1.2 Allocation of Indirect Costs to Cost Centers

In assigning cost categories to cost objects, agents determine whether the cost object is classified as direct or indirect costs. In case of direct costs, costs are grouped to pools of direct costs (cf. Eqs. 4.6) and 4.7. In case of indirect costs, costs are allocated to cost centers, i.e., allocation type 1 (Horngren et al. 2002).

The first step of internal cost allocation is to build a vector $\vec{g}$ that contains cost information of all cost objects that have been assigned an indirect cost category. For each input cost object that has been assigned an indirect cost category, in consideration of the rate of differences in valuation s_i the entries g_j are calculated according to

$$\forall c_{in_i} \in C_{in}^{indir} : \exists g_j \in \vec{g} : f^g\left(c_{in_i}\right) = c_{in_i} \cdot (1 + s_i) = g_j, \tag{4.8}$$

whereby $i \in \{1, \ldots, |BC|\}$ and $j \in \{1, \ldots, |C_{in}^{indir}|\}$.

Allocation from indirect costs to cost centers is usually based on plausible and reliable output measures (Horngren et al. 2002). In this simulation study, for each simulation run cost driver activities for allocation type 1 are generated randomly. For each element of vector $\vec{g}$ the allocation key contains information on which shares of the contained costs are imputable to which cost centers. In the computational model, the allocation keys are denoted as matrices $\mathbf{CD^{ex}}$. Agents observe $\mathbf{CD^{ex}}$ and introduce the observed information into the costing system. Introduced allocation keys are denoted as $\mathbf{CD}$. Elements of vectors $\mathbf{CD^{ex}}$ and $\mathbf{CD}$ are denoted as $cd_{i,j}^{ex}$ and $cd_{i,j}$, respectively, with $i \in \{1, \ldots, |M|\}$ indexing cost centers $m_i \in M$ and $j \in \{1, \ldots, |C_{in}^{indir}|\}$ indexing elements of vector $\vec{g}$. The interaction with the costing system in order to introduce the basis for allocation type 1 is represented by the function $f^{cd^{type:1}}$, i.e.,

$$\forall cd_{i,j}^{ex} \in \mathbf{CD^{ex}} : \exists cd_{i,j} \in \mathbf{CD} : f^{cd^{type:1}}\left(cd_{i,j}^{ex}\right) = cd_{i,j}. \tag{4.9}$$

According to this, element $cd_{i,j}$ of matrix $\mathbf{CD}$ stands for the share of the business case listed as the jth element of vector $\vec{g}$ that can be imputed to cost center m_i. To assure that the respective costs are allocated correctly, for each business case, the sum of the shares allocated to cost centers is 1, i.e., $\sum_{i=1}^{|M|} cd_{i,j} = 1$.

Elements of vector $\vec{g}$ represent indirect costs collected from different business cases that have to be allocated to cost centers. Matrix $\mathbf{CD}$ contains the corresponding allocation keys. In multiplying elements of vector $\vec{g}$ with the corresponding elements of matrix **CD**, allocation type 1 is executed. Costs allocated in allocation type 1 are represented by matrix **Q**, i.e.,

$$\mathbf{Q} = \begin{pmatrix} g_1 cd_{1,1} & \cdots & g_j cd_{1,j} \\ \vdots & \ddots & \vdots \\ g_1 cd_{i,1} & \cdots & g_j cd_{i,j} \end{pmatrix} = \begin{pmatrix} q_{1,1} & \cdots & q_{1,j} \\ \vdots & \ddots & \vdots \\ q_{i,1} & \cdots & q_{i,j} \end{pmatrix}. \tag{4.10}$$

Based on matrix **Q**, costs allocated to cost centers in allocation type 1 can be calculated, i.e.,

$$costs_i^{prim} = \sum_{j=1}^{|C_{in}^{indir}|} q_{i,j}, \tag{4.11}$$

whereby $i \in \{1, \ldots, |M|\}$.

4.1.3 Internal Cost Allocation

In the model of the costing system applied in this study, cost centers are mapped to correspond to organizational units. If organizational units provide other units with services or products, costs incurred at the providing unit have to be reallocated to the receiving units (Horngren et al. 2002; Hansen and Mowen 1994). In internal cost allocation, costs allocated to providing units in allocation type 1 are reallocated to receiving units, i.e., allocation type 2 (Horngren et al. 2002).

The model distinguishes between direct and indirect cost centers, whereby indirect cost centers represent providing units and direct cost centers represent receiving units. The set of direct and indirect cost centers are denoted as M^{dir} and M^{indir}, respectively. M^{dir} and M^{indir} are disjunct subsets of M, i.e.,

$$\forall m_i \in M^{dir} : m_i \notin M^{indir}; \forall m_i \in M^{indir} : m_i \notin M^{dir}, \tag{4.12}$$

whereby $i \in \{1, \ldots, |M|\}$. The present model considers a set of indirect cost centers $m_i \in M^{indir}$ that solely support the direct cost centers $m_i \in M^{dir}$. Cost centers can be classified as direct or indirect cost centers. There is no direct cost center that provides other cost centers with products or services. Consequently, $costs_i^{prim}$ allocated to cost centers $m_i \in M^{indir}$ have to be reallocated to direct cost centers $m_i \in M^{dir}$ in total.

The total numbers of cost centers $|M|$, the number of direct $|M^{dir}|$ and indirect $|M^{indir}|$ cost centers are exogenously given. In order to determine which cost center is handled as direct or indirect cost center, agents interact with the costing system and introduce information on the categorization of cost centers. This interaction is given by the function $f^{m,cat}$, i.e.,

$$\forall m_i \in M : f^{m,cat}(m_i) = \begin{cases} m_i \in M^{dir} & \text{with } p\left(m_i \in M^{dir}\right) \\ & = |M^{dir}|/|M| \\ m_i \in M^{indir} & \text{otherwise,} \end{cases} \tag{4.13}$$

whereby $i \in \{1, \ldots, |M|\}$. According to Eqs. 4.12 and 4.13, $p\left(m_i \in M^{dir}\right) + p\left(m_i \in M^{dir}\right) = 1$.

The reallocation of costs from indirect to direct cost centers is based on cost driver activities. The set of potential cost drivers for allocation type 2 is denoted as R. Cost driver activities for allocation type 2 are generated on the fly, i.e., for each simulation run they are drawn from an exogenously given and uniformly distributed interval $U[\underline{a}_{cd^{type:2}}; \overline{a}_{cd^{type:2}}]$. Agents observe this information and introduce it into the costing system. There is a matrix $\mathbf{R^{ex}}$ that contains information on cost driver activities $r^{ex}_{i,j,n}$, with $i \in \{1, \ldots, |R|\}$ indicating the cost driver and $j, n \in \{1, \ldots, |M|\}$ indicating the cost centers. The providing cost center is denoted as m_j while the receiving unit is given by m_n, whereby $j \neq n$.

As in case of allocation type 1, agents observe this cost driver information and introduce it into the costing system. Matrix $\mathbf{R^{ex}}$ contains information on combinations of each cost driver and each cost centers. Cost driver information introduced into the costing system is denoted as matrix $\mathbf{R}$. According to the denotation of elements of matrix $\mathbf{R^{ex}}$, elements of $\mathbf{R}$ are given by $r_{i,j,n}$. These agents' interaction with the costing system is given by function $f^{cd^{type:2}}$, i.e.,

$$\forall r^{ex}_{i,j,n} \in \mathbf{R^{ex}} : \exists r_{i,j,n} \in \mathbf{R} : f^{cd^{type:2}}\left(r^{ex}_{i,j,n}\right) = r_{i,j,n}, \tag{4.14}$$

whereby $i \in \{1, \ldots, |R|\}$, $j, n \in \{1, \ldots, |M|\}$ and $j \neq n$. Although for each cost center, information on each cost driver is introduced into the costing system, only one specific cost driver per indirect cost center is used as the basis for the reallocation of costs. Which cost driver is applied as the allocation base is determined ex-ante to operations. Once this element of the costing systems' structure is defined, it cannot be changed during the remaining calculation steps. For each indirect cost center, the function f^r defines which cost driver is applicable as the allocation base for reallocating costs and gives the corresponding information on cost driver activities, i.e.,

$$\forall m_j \in M^{indir} : \exists r_{i,j,n} \in R : f^r\left(m_j; m_n\right) = r_{i,j,n}, \tag{4.15}$$

The function $f^r(m_j; m_n)$ defines which cost driver has to be applied in order to allocate $costs^{prim}_j$ (and eventual re-allocated costs) from cost center m_j to cost center m_n and gives the respective cost driver information.

In this simulation study, for the reallocation of $costs^{prim}_j$ incurred at indirect cost centers, a step-down method is applied (cf. Horngren et al. 2002, 2005; Hansen and Mowen 1994). Services rendered from indirect cost centers to other indirect cost centers are partly considered.

Allocation type 2 is subdivided into two calculation steps. In a first step, internal cost allocation among indirect cost centers takes place. As a result of the first step of allocation type 2, for each indirect cost center, secondary costs $costs_{i,j}^{sec}$ are calculated, i.e. costs allocated in allocation type 2 from indirect cost centers $m_j \in M^{indir}$ to indirect cost center $m_i \in M^{indir}$, whereby $i > j$. According to the applied step-down method, secondary costs result as

$$costs_{i,j}^{sec} = \frac{costs_j^{prim} + \sum_{n=1}^{j-1} costs_{j,n}^{sec}}{\sum_{n=j}^{|M|} f^r\left(m_j; m_n\right)} \cdot f^r\left(m_j; m_i\right), \tag{4.16}$$

whereby $i, j \in \{1, \ldots, |M|\}$.

As the second step of allocation type 2, costs are fully reallocated to direct cost centers. As a result of this second allocation step, all costs allocated to indirect cost centers in allocation type 1 and the first step of allocation type 2 are reallocated to direct cost centers, i.e., entire costs $costs_n^{ent}$ per direct cost center $m_n \in M^{dir}$ can be calculated, i.e.

$$costs_n^{ent} = costs_n^{prim} + \sum_{\forall i: m_i \in M^{indir}} \left(\frac{costs_i^{prim} - \sum_{\forall j > i: m_j \in M^{indir}} costs_{j,i}^{sec} + \sum_{\forall j < i: m_j \in M^{indir}} costs_{i,j}^{sec}}{\sum_{\forall j \geq i: m_j \in M} f^r\left(m_i; m_j\right)} \cdot f^r\left(m_i; m_n\right) \right). \tag{4.17}$$

After this step of internal cost allocation, no more costs are assigned to indirect cost centers. In fact, all indirect costs allocated to indirect cost centers in allocation type 1 are reallocated to direct cost centers.

4.1.4 Cost Allocation to Products

In the first step of cost allocation, costs categorized as indirect costs are assigned to cost centers. These assigned costs are reallocated from indirect to direct cost centers in allocation type 2. As a last step of internal cost allocation, costs now assigned to direct cost centers have to be allocated to cost objects, i.e., services, products or activities. The model of the costing system considers overhead rates for the allocation of costs to cost objectives. The final reallocation of costs is referred to as allocation type 3 (Horngren et al. 2002).

This simulation study considers different bases for the calculation of overhead rates. On the one hand, there is a set of cost centers $M^{dir^{dcp}}$ that can be exclusively identified with a direct cost pool (as introduced in Eq. 4.7). Consequently, the corresponding direct cost pools are the basis for the calculation of overhead rates. On the other hand, residual cost centers are denoted as $M^{dir^{mc}}$. For members of $M^{dir^{mc}}$, the manufacturing costs are the basis for allocation type 3. Manufacturing costs include all direct and indirect costs allocated to the set of direct costs centers $M^{dir^{dcp}}$. Hence, in the model applied in this simulation study, the set of direct cost centers can be disjunctively divided into two subsets, i.e.,

$$\forall m_i \in M^{dir^{dcp}} : m_i \notin M^{dir^{mc}}; \forall m_i \in M^{dir^{mc}} : m_i \notin M^{dir^{dcp}}. \tag{4.18}$$

The absolute number of members of $|M^{dir^{dcp}}|$ and $|M^{dir^{mc}}|$ is exogenously given. An agent interacts with the costing system and defines for which cost centers the generated direct cost pools or the manufacturing costs, are the basis for the calculation of overhead rates. This interaction is given by the function $f^{m^{dir},cat}$, i.e.,

$$\forall m_i \in M^{dir} : f^{m^{dir},cat}(m_i) = \begin{cases} m_i \in M^{dir^{dcp}} & \text{with } p\left(m_i \in M^{dir^{dcp}}\right) \\ & = |M^{dir^{dcp}}|/|M^{dir}| \\ m_i \in M^{dir^{mc}} & \text{otherwise.} \end{cases} \tag{4.19}$$

Ex-ante to operations, an agent interacts with the costing system and for each cost center $m_i \in M^{dir^{dcp}}$ introduces information on which direct cost pool it is exclusively identified with. With this interaction, an element of the costing system's structure is defined. This structural element cannot be changed during the remaining calculation steps. This interaction is represented by the function f^{dcp}, i.e.,

$$\forall m_i \in M^{dir^{dcp}} : \exists k_j^{dir,group} \in K^{dir,group} : f^{dcp}(m_i) = k_j^{dir,group}, \tag{4.20}$$

whereby $i \in \{1, \ldots, |M|\}$ and $j \in \{1, \ldots, |K^{dir,group}|\}$. Function f^{subscr} is defined to give the subscript of a function. With reference to Eq. 4.20, $f^{subscr}\left(f^{dcp}(m_i)\right) = j$.

For direct cost centers $m_i \in M^{dir^{dcp}}$ overhead rates can be calculated now. For the calculation of these overhead rates, the direct cost pool that the respective cost center can be exclusively identified with, is the basis. An overhead rate b_i^{dcp}, relative to the direct costs assigned to that cost center, is calculated, i.e.

$$\forall m_i \in M^{dir^{dcp}} : b_i^{dcp} = \frac{costs_i^{ent}}{costs^{dir}_{f^{subscr}\left(f^{dcp}(m_i)\right)}}, \tag{4.21}$$

whereby $i \in \{1, \ldots, |M|\}$.

For direct cost centers $m_i \in M^{dir^{mc}}$, the calculation of overhead rates is based on the manufacturing costs. As outlined above, the manufacturing costs are given by the sum of direct and indirect costs allocated to direct cost centers $m_i \in M^{dir^{dcp}}$. For direct cost centers $m_i \in M^{dir^{mc}}$, overhead rates b_i^{mc} result as

$$\forall m_i \in M^{dir^{mc}} : b_i^{mc} = \frac{costs_i^{ent}}{\sum_{\forall j: m_j \in M^{dir^{dcp}}} costs^{dir}_{f^{subscr}\left(f^{dcp}\left(m_j\right)\right)} \cdot (1 + b_j^{dcp})}, \quad (4.22)$$

whereby $i, j \in \{1, \ldots, |M|\}$.

4.1.5 Calculation of Decision Influencing and Decision Facilitating Information

Costing systems provide different types of information. According to elaborations in Sect. 2.2.2, this simulation study distinguishes between the decision-influencing and decision-facilitating role of accounting information.

Overall costs per cost center are referred to as decision influencing-information. Overall costs per cost center are differentially calculated for cost centers $m_i \in M^{dir^{dcp}}$ and cost centers $m_i \in M^{dir^{mc}}$. In particular, for direct cost centers $m_i \in M^{dir^{dcp}}$ overall costs $costs_i^{prod,di}$ are represented by the sum of all direct costs allocated to the respective cost centers plus the according overheads calculated on the basis of overhead rates b_i^{dcp} (cf. Eq. 4.21). Costs per cost center $m_i \in M^{dir^{dcp}}$ are given by

$$\forall m_i \in M^{dir^{dcp}} : costs_i^{prod,di} = costs^{dir}_{f^{subscr}\left(f^{dcp}(m_i)\right)} \cdot \left(1 + b_i^{dcp}\right). \quad (4.23)$$

As outlined above, for direct cost centers $m_i \in M^{dir^{mc}}$, the manufacturing costs are the basis for the calculation of overheads. This type of cost center does not have any direct costs allocated to it. Consequently, for cost centers $m_i \in M^{dir^{mc}}$, overall costs are only given by the allocated overheads. Overall costs for cost centers $m_i \in M^{dir^{mc}}$ are given by

$$\forall m_i \in M^{dir^{mc}} : costs_i^{prod,di} = \left(\sum_{\forall j: m_j \in M^{dir^{dcp}}} costs^{dir}_{f^{subscr}\left(f^{dcp}\left(m_j\right)\right)} \cdot \left(1 + b_j^{dcp}\right) \right) \cdot b_i^{mc}. \quad (4.24)$$

Decision-facilitating information, on the contrary, is represented by single product calculations. For the calculation of decision-facilitating information provided by costing systems, for each cost center $m_i \in M^{dir^{dcp}}$ a number dc_i is randomly drawn from a uniform distribution $U[\underline{a}_{prod}; \overline{a}_{prod}]$, whereby $i \in \{1, \ldots, |M|\}$. For each cost center $m_i \in M^{dir^{dcp}}$, this number represents the direct costs that can exclusively be related to the respective product. According to this, the costs per product result as sum of direct costs dc_i and corresponding overheads (calculated on the basis of overhead rates b_i^{dcp}, cf. Eq. 4.21) per direct cost center $m_i \in M^{dir^{dcp}}$, plus overheads coming from cost centers $m_i \in M^{dir^{mc}}$ (calculated on the basis of overhead rates b_i^{mc}, cf. Eq. 4.22). Consequently, costs per product $costs^{prod,df}$ are given by

$$\begin{aligned} costs^{prod,df} = & \sum_{\forall i: m_i \in M^{dir^{dcp}}} dc_i \cdot \left(1 + b_i^{dcp}\right) \\ & + \sum_{\forall j: m_j \in M^{dir^{mc}}} \left(\sum_{\forall i: m_i \in M^{dir^{dcp}}} dc_i \cdot \left(1 + b_i^{dcp}\right)\right) \cdot b_j^{mc}. \end{aligned} \tag{4.25}$$

4.1.6 Overview of the Main Processing Steps and Interactions

Table 4.1 summarizes the model of the costing system described in the previous sections, gives a systematic overview of the agents' interactions with the costing system and lists the corresponding denotations and formulas. Furthermore, Table 4.1 brings the different steps into chronological order. Three time frames are considered: (1) Ex-Ante to operations, (2) During operations and (3) Ex-post to operations. In the first timespan, (1) Ex-ante to operations, the structure of the costing system is defined. Once the structure is defined, it cannot be changed for the remaining periods, i.e., time frames (2) and (3) are based on the costing system's structure defined in time frame (1). Time frame (2) covers the steps of operations. During this period, business cases and cost center output are generated in organizations. For this simulation study, this information is generated randomly on the basis of exogenously given parameterization. Time frame (3) is the period ex-post to operations. In this timespan agents observe information generated in timespan (2) and heavily interact with the costing system in order to introduce information. Finally, after cost allocation, decision-influencing and decision-facilitating information provided by costing systems can be calculated.

4.2 The Model of the Agents' Behavior and Resulting Biases

This study covers the simulation of costing systems in hierarchical organizations. One aspect that all simulated organizations have in common is that they incorporate a large number of principal-agent relationships. The organizations consist of headquarters and a number of departments that can either be cost centers or the accounting department. Departments are under the responsibility of cost center managers or the accounting department's manager.

Table 4.1 Overview: computational model of the costing system

No.	Step	Denotation[a]	Function[b]	Equation
Ex-ante to operations: Define the costing system's structure				
1	Define the set of cost centers	M	–	–
	Subset of direct cost centers	M^{dir}	$f^{m,cat}$	4.13
	... with direct cost pools as basis for allocation type 3	$M^{dir^{dcp}}$	$f^{m^{dir},cat}$	4.19
	... with manufacturing costs as basis for allocation type 3	$M^{dir^{mc}}$	$f^{mdir,cat}$	4.19
	Subset of indirect cost centers	M^{indir}	$f^{m,cat}$	4.13
2	Define set of of cost categories	K	–	–
	Subset of direct cost categories	K^{dir}	$f^{k,cat}$	4.4
	Build direct cost pools	$K^{dir,group}$	$f^{k,dir}$	4.6
	Assign direct cost pools to cost centers $M^{dir^{dcp}}$	–	f^{dcp}	4.20
	Subset of indirect cost categories	K^{indir}	$f^{k,cat}$	4.4
3	Define set of cost drivers	R	–	–
	Assign cost drivers to cost centers for allocation type 2	–	f^{r}	4.15
Operations: Production of goods and services				
4	Generate business cases	BC	–	–
5	Generate allocation keys for allocation type 1	$\mathbf{CD^{ex}}$	–	–
6	Generate cost driver activities for allocation type 2	$\mathbf{R^{ex}}$	–	–
Ex-post to operations: Run cost allocation and calculation				
7	Observe business cases and introduce cost information into the costing system (generate cost objects)	C_{in}	f^{c}	4.1
8	Assign cost categories	–	f^{k}	4.2
9	Determine differences in valuation	–	f^{s}	4.5
10	Allocation type 1			
	Observe allocation keys and introduce them into the system	$\mathbf{CD}$	$f^{cd^{type:1}}$	4.9
	Calculate costs per cost center assigned in allocation type 1	$costs_i^{prim}$	–	4.11
11	Allocation type 2	–	–	–
	Observe cost driver activities and introduce them into the system	$\mathbf{R}$	$f^{cd^{type:2}}$	4.14
	Calculate entire costs per direct cost center assigned in allocation type 1 and 2	$costs_i^{ent}$	–	4.16/4.17
12	Allocation type 3			
	Calculate overhead rates	b_i^{dcp} / b_i^{mc}	–	4.21/4.22
13	Calculations			
	Decision-influencing information: Costs per cost center	$costs_i^{prod,di}$	–	4.23/4.24
	Decision-facilitating information: Product calculation	$costs^{prod,df}$	–	4.25

[a] For indices cf. the respective paragraphs and equations in Sect. 4.1,

[b] Agents' interactions are represented by these functions

In order to map the incorporated principal-agent relationships and to represent a model of the agents' behavior, the next section introduces an agency model. There are some aspects that all principal-agent relationships have in common. Thus, as a first step, Sect. 4.2.1 introduces a generalized multi-task principal-agent setup. The level of abstraction of this model allows for describing all incorporated principal-agent relations from a meta-perspective. In Sect. 4.2.2, the previously introduced agency model is applied to the different types of agents that interact with the costing system. In this step, some generalized aspects of the model are put into concrete terms for each principal-agent relationship individually. The end of Sect. 4.2.2 brings the different agents' actions into a sequence of events. Finally, Sect. 4.2.3 summarizes the elaborated biases under investigation.

4.2.1 The Generalized Model of Principal-Agent Relations

In the simulated organizations, there is a number of relationships between headquarters and departments. In the behavioral model, headquarters are represented by the principal and the managers of the different departments are represented by the different agents. In particular, there is one principal P and a number of agents $h \in H$. The principal and the agents are assumed to have dissimilar risk-attitudes. The principal is assumed to be risk-neutral while the agents are assumed to be risk-averse.

At the beginning of the observation period, the principal P offers contracts to the different agents $h \in H$. This investigation does not aim at optimizing contracts for different agency setups. This simulation study rather focuses on analyzing effects of agents' biasing behavior in case of given contracts. Contracts can be considered as exogenously given and constant for the whole observation period. With regards to participation constraints, the applied behavioral model considers reservation utility to be fulfilled in all cases. Due the fact that contract design is not within the scope of this simulation study, all exogenously given contracts are mapped to lead to individual utility that is higher than reservation utility (cf. also reservation utility in Sect. 3.2.1).

The main elements of the contracts between the principal and the different agents are (1) the nature of task(s) delegated to the involved agent, (2) the way to fulfill the task as required by the principal, (3) the reward scheme and (4) a performance measure for task fulfillment which also builds the basis for the variable compensation component.

In the principal-agent setup addressed in this simulation study, the principal has a set of tasks that are delegated to agents (for the specific attributes of the different incorporated principal-agent relations cf. Sect. 4.2.2). The principal delegates at least one task to each agent. The applied agency model also considers setups in which agents are in charge of executing more than one task simultaneously. The set of tasks the principal delegates to the different agents is denoted as $l \in L$. Tasks delegated to agents $h \in H$ are given by $l \in L^h$. The principal decides which task is delegated to which agent. In the model, the process of delegation is represented by the function f^l. In particular, the function f^l captures the assignment of tasks $l \in L$ to agents $h \in H$, i.e.,

$$\forall l \in L : \exists h \in H : f^l(l) := h. \tag{4.26}$$

For this simulation study, the model considers tasks that are linked to the costing system. Considered tasks focus on the input and manipulation of data at different processing steps. Contracts considered in the behavioral model contain information on which task is delegated to which agent. Contracts specify which agent is in charge of introducing or manipulating which data at which processing step of the costing system (for processing steps cf. Table 4.1, for specific delegated tasks cf. Sect. 4.2.2).

After the principal has offered the contract to the agent and the agent has decided to accept the contract, the model assumes the agent to *privately* take an action $a^{h,l} \in A^{h,l}$ where, according to previous elaborations, indices h and l denote the agent and the delegated task. From a set of potential actions $A^{h,l}$ agent $h \in H$ selects action $a^{h,l}$ in order to fulfill task $l \in L^h$. The action finally selected from the set of potential actions is not observable, neither for the principal nor for other agents. Furthermore, side-contracts are excluded from this investigation, i.e. the principal-agent setup used in this simulation study assumes agents not to communicate with each other. In particular, agents do not coordinate selected actions among each other. Each agent rather chooses an action separately.

The contract defines which action the agent should choose in order to fulfill the delegated task. Due to the large number of agents' interactions with the costing system, the quality of data provided by the costing system critically depends on the agents' effort in introducing data. With respect to the quality of provided information, this simulation study considers the principal to desire the agent to introduce non-defective data into the costing system for all principal-agent relationships. The corresponding action is denoted as $a^{h,l,*} \in A^{h,l}$, i.e., for the case that agent $h \in H$ chooses action $a^{h,l,*}$ in order to fulfill task $l \in L^h$, the task is executed as desired by the principal. In the applied agency model, the actions $a^{h,l,*}$ lead to the highest level of data quality, i.e., in selecting actions $a^{h,l}$, agents cannot decide for a higher level of quality of data introduced into the costing system than desired by the principal.

The behavioral model considers each action $a^{h,l}$ chosen in order to fulfill the respective task to be associated with a certain outcome. The outcome of task l delegated to agent h is denoted as $W^{h,l}$. The costing system, as introduced in Sect. 4.1, is characterized by a large number of interactions. On the one hand, the different components of the costing system interact with each other. On the other hand, there is a number of agents that interact with the costing system. Due to these interactions within the costing system, outcomes of different tasks (that are potentially dependent on different agents' actions and, hence, on the quality of data introduced into the costing system by different agents) might be reciprocally interdependent. For each task $l \in L$ these interactions realize with the different processing steps in the costing system (cf. Sect. 4.1). With respect to outcome $W^{h,l}$, for each task $l \in L$ the model considers a state of interactions θ^l. This state of interactions stands for those effects that interactions of agents with the costing system have on tasks, that these agents are not in charge of. In particular, θ^l denotes the effect of actions of agents $k \in H$ on the outcome $W^{h,l}$, where k denotes agents that are not in charge of the respective task and $h \neq k$.

Given the complex interactions within the costing system, the outcome of a task is dependent on the responsible agent's effort in executing the respective task and, due to interactions, probably to other agents' actions. Outcome $W^{h,l}$ of task l delegated to agent h is given by the function $f^{w^{h,l}}$, i.e.,

$$W^{h,l} = f^{w^{h,l}}\left(a^{h,l}; \theta^l\right). \tag{4.27}$$

In the agency model applied in this simulation study, the outcome per task $W^{h,l}$ is used as measure to evaluate the agents' performance and is observable for the principal without incurring costs. In addition to outcome per task, the principal can also observe overall outcome W^{ent} at no cost. Corresponding to the outcome per task, the overall outcome is affected by the selected actions of all involved agents and the respective states of interactions. The function $f^{w^{ent}}$ gives the overall outcome, i.e.,

$$W^{ent} = f^{w^{ent}}\left(a^{i=1,j=1}, \ldots, a^{i=|H|,j=|L|}; \theta^{j=1}, \ldots, \theta^{j=|L|}\right). \tag{4.28}$$

The quality of information provided by the costing system critically depends on the actions the agents select in order to fulfill the delegated tasks. In addition to outcome per task and overall outcome provided by the costing system, the model considers the principal to have information on unbiased overall outcome W^{ent}_{true} from other informational sources.

The applied agency model considers all agents to be rewarded individually. Team compensation is not considered in the principal-agent setup as it is only beneficial to individual compensation when side-contracting behavior is also included in the investigation (cf. Holmstrom and Milgrom 1990). The agents' compensation is given by function f^{S^h}. Agents are rewarded a fixed compensation component. Additionally, agents are rewarded variably on the basis of the outcome of the assigned task(s). The fixed compensation component is denoted as S^h_0 and the variable compensation based on delegated tasks is given by the function $f^{S^h,var}$. Given the outlined reward scheme, for each agent $h \in H$ compensation results as

$$f^{S^h}\left(\sum_{\forall l \in L: f^l(l)=h} W^{h,l}\right) = S^h_0 + f^{S^h,var}\left(\sum_{\forall l \in L: f^l(l)=h} W^{h,l}\right). \tag{4.29}$$

The behavioral model assumes agents to aim at maximizing their individual utility functions and the principal to aim at maximizing overall utility (Jensen and Meckling 1994). For the principal, utility is defined as overall outcome minus the agents' compensation. For overall outcome cf. Eq. 4.28, compensation per agent is given in Eq. 4.29. The principal's utility U^P results as

$$U^P\left(W^{ent}; \sum_{h=1}^{|H|} f^{S^h}\left(\sum_{\forall l \in L: f^l(l)=h} W^{h,l}\right)\right) = \\ -W^{ent} - \sum_{h=1}^{|H|} f^{S^h}\left(\sum_{\forall l \in L: f^l(l)=h} W^{h,l}\right). \tag{4.30}$$

For agents, the model assumes that actions chosen in order to fulfill delegated tasks result in direct disutility (cf. Holmstrom 1979). Correspondingly, the agents' utility is given by the utility that results from compensation and the disutility for effort. The agents' utility from compensation is represented by the function f^{v^h}, while the function for disutility for effort is denoted as function f^{g^h}, where $h \in H$ denotes the respective type of agent (for the various types of agents cf. Sect. 4.2.2). The agents' utility function results as

$$U^{A^h}\left(f^{S^h}\left(\sum_{\forall l \in L: f^l(l)=h} W^{h,l}\right); a^{h,j=1}, \ldots, a^{h,j=|L^h|}\right) \\ = f^{v^h}\left(f^{S^h}\left(\sum_{\forall l \in L: f^l(l)=h} W^{h,l}\right)\right) - f^{g^h}\left(a^{h,j=1}, \ldots, a^{h,j=|L^h|}\right). \tag{4.31}$$

The model assumes the principal and the agents to have conflicting target functions (Holmstrom 1979) and the principal and the agents to seek to maximize their respective utility functions (Jensen and Meckling 1994). For the principal's utility function cf. Eq. 4.30, for the agents' utility function cf. Eq. 4.31. Hence, there is a potential divergence of interests between the principal and the agents. This might result in situations in which the action(s) chosen by the agents in order to fulfill the delegated task(s) do not necessarily correspond to the actions desired by the principal, i.e., action $a^{h,l,*}$ for task $l \in L$ delegated to agent $h \in H$. The fact that for the principal, outcome is observable without incurring costs, but the chosen actions are unobservable, contributes to potential opportunistic behavior. Given the setup outlined above, agents' opportunistic actions might aim at maximizing individual utility in several ways. On the one hand, agents might *intentionally* introduce defective data into the costing system. Two characterizations of intentional biasing behavior are considered in this model. First, agents might try to affect the performance measure that builds the basis for the variable compensation. Second, if the compensation function does not lead to an acceptable level of perceived utility, agents might try to maximize utility by minimizing disutility for effort (Lambert 2001; Luft 1997). On the other hand, agents might *unintentionally* introduce defective data into the costing system (for sources of biasing behavior cf. Sect. 3.1.2).

As outlined above, the principal P can observe outcome per task $W^{h,l}$ and (potentially biased) overall outcome provided by the costing system W^{ent}, but not unbiased outcome per task. Additionally, the principal has information on unbiased overall outcome W^{ent}_{true} from other informational sources. Hence, the principal is capable of calculating effects of biasing behavior on the costing systems' accuracy on the overall outcome level. But due to limited information, the principal cannot calculate effects of biasing behavior on the task level. Because of the complex interactions within the costing system, effects of biasing behavior per task also cannot be derived from overall error. Due to the lack of knowledge of effects of biases per task, the agents' risk-aversion and the principal's risk-neutrality, the principal bears the risk of interactions (cf. Kreps 1990). As a result, agents are rewarded on the basis of (potentially distorted) information provided by the costing system within the simulated organizations.

4.2.2 Specific Characteristics of the Incorporated Principal-Agent Relations and the Agents' Biasing Behavior

Section 4.2.1 gives a generalized agency model in order to describe the commonalities of the delegation relationships within the simulated organizations. As a next step, this section applies the abstract model to the incorporated principal-agent relationships and brings them into concrete terms. In particular, the relations differ in (1) the nature of the delegated task, (2) the agent the respective task is delegated to and (3) the bases for the agents' variable compensation component. Furthermore, at the end of this section, the principal's and the agents' action are brought into a sequence of events.

This simulation study distinguishes between three different types of agents. In consideration of the structure of the costing system, the agents considered are managers of direct cost centers, managers of indirect cost centers and the manager of the accounting department. Managers of direct and indirect cost centers are denoted as $h \in H^{direct}$ and $h \in H^{indirect}$. The accounting department's manager is given by $h \in H^{acc-dep}$. The principal P selects the performance measures that the different agents' variable compensation components are based on (Lambert 2001). For this simulation study, the variable compensation of managers of direct cost centers $h \in H^{direct}$ is based on costs that incurred in their area of responsibility. For managers of indirect cost centers $h \in H^{indirect}$, performance is measured by incurred costs and cost center output of the cost centers that the respective agents are in charge of. The accounting department's manager's variable compensation component, i.e., $h \in H^{acc-dep}$, is based on a measure for quality of information provided by the costing system.

As outlined in Sect. 4.2.1, the principal delegates tasks to the different agents. The present simulation study analyzes tasks in the context of costing systems. The set of tasks result from the agents' interactions with the costing system, as outlined in Sect. 4.1. Table 4.1 brings the interactions with the costing system into a chronological order. In particular, three time-spans are distinguished, i.e., ex-ante to operations, operations and ex-post to operations. The elaboration of the specific characteristics of the incorporated principal-agent relationships is structured according to these time-spans. This simulation study does not analyze effects of interactions during operations. For the time-span of operations, key-parameters are exogenously given and respective data is generated without considering agents' interactions. Figure 4.1 gives an overview of principal-agent relationships and interactions with the costing system. In particular, Fig. 4.1 shows tasks and corresponding interactions with the costing system and the assignment of specific tasks to different types of agents.

4.2.2.1 Principal-Agent Relations Ex-Ante to Operations

Interactions of agents ex-ante to operations concern the structure of the costing system. Agents interact with the costing system in order to set up the structure of the cost centers, cost categories and cost drivers (cf. Fig. 4.1). In the applied model, all tasks regarding the costing systems' structure are delegated to the accounting department. Once the costing systems' structure is defined, it cannot be changed for the remaining time-spans of operations and ex-post operations. The following section gives the detailed characteristics of all principal-agent relationships ex-ante to operations.

Cost Centers

The task of defining the *structure of cost centers* is delegated to the accounting department. In order to fulfill that task, the accounting department's manager $h \in H^{acc-dep}$ interacts with the costing system and specifies which cost centers are handled as direct or indirect cost centers. The total number of cost centers, i.e., the number of members of the set M, the number of direct cost centers M^{dir} and the number of indirect cost centers M^{indir} are exogenously given. In consideration of this exogenously given parameterization, the accounting department's manager categorizes cost centers as direct or indirect (cf. Eq. 4.13).

According to the generalized model of principal-agent relationships (cf. Sect. 4.2.2), the agent selects an action in order to fulfill the delegated task. In case of categorization of cost centers, in selecting an action the agent decides for a level

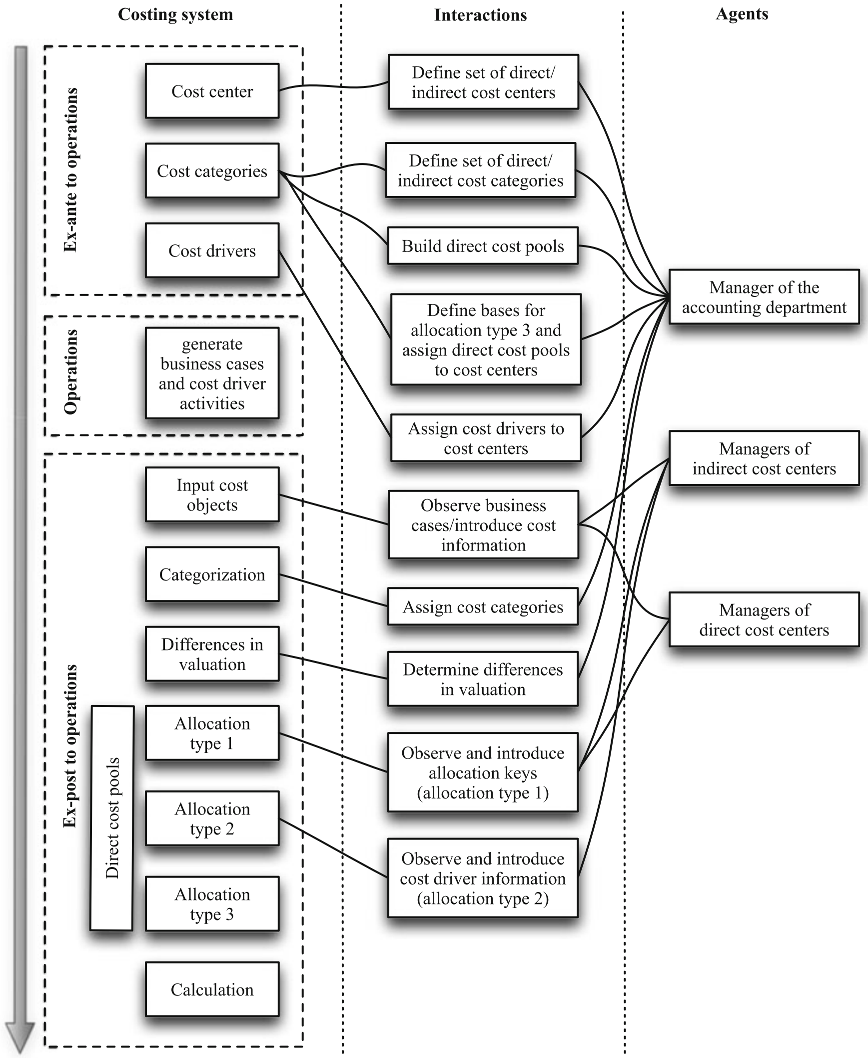

Fig. 4.1 Computational model: structure, interactions and agents

of effort to execute the task with. Selecting the action $a^{h,l,*}$ and fulfilling the task as desired by the principal, in this context means that all cost centers are categorized correctly. Besides the scenario of selecting less effort than desired by the principal, agents might also unintendedly introduce biases in the context of the categorization of cost centers. For both scenarios, a certain number of cost centers is categorized wrongly. It cannot be distinguished whether the bias is introduced intendedly or unintendedly.

For the fact that all further calculation steps are based on this generated structure of costing systems, this miscategorization might have an impact on data quality. This type of biasing behavior is referred to as *input bias in the categorization of cost centers*.

Cost Categories

For the context of cost categories, the principal delegates an overall of three tasks to agents. These tasks are: (1) to define the structure of cost categories, (2) to cluster cost categories into direct cost pools and (3) to assign direct cost pools to cost centers.

In the case of (1) defining the structure of cost categories, the principal P assigns the accounting department's manager $h \in H^{acc-dep}$ the task of determining which cost categories are are categorized as direct or indirect. As in the case of cost centers, the total number of cost categories K and the total numbers direct K^{dir} and direct K^{indir} cost categories are exogenously given. The task is executed according to Eqs. 4.3 and 4.4. According to the generalized agency model, the agent decides for a level of effort to execute the task with. On the one hand, agents might intentionally select an effort unequal to $a^{h,l,*}$. On the other hand, respective biases might also be introduced unintendedly. For both cases, biasing behavior results in miscategorization of cost categories. It cannot be distinguished whether biases are introduced intendedly or unintendedly. For the fact that all further calculation steps are based on this once defined structure, this miscategorization might also affect the quality of the finally provided information. This type of bias is referred to as *input bias on the categorization of cost categories*.

Once the set of cost categories is subdivided into subsets of direct K^{dir} and indirect K^{indir} cost categories, the accounting department's manager is in charge of (2) clustering direct cost categories into direct cost pools. According to Eq. 4.6 the agent interacts with the costing system and defines which direct cost category is assigned to which direct cost pool. The total number of direct cost pools $K^{dir,group}$ is exogenously given. Once the structure of direct cost pools is defined, all steps of the calculation of information provided by costing systems are based on it. If the agents decide to put less effort into the building of direct cost pools, this might affect quality of decision-influencing and decision-facilitating information crucially. Biases in the building of direct cost pools and, as a consequence, distortions in provided information, might also be due to unintentional biasing behavior. For further elaborations, biasing behavior in the building of direct cost pools is referred to as *input bias on the building of direct cost pools* whereby it cannot be distinguished whether this bias is introduced into the costing system intendedly or unintendedly.

In the next step of defining the structure of the costing system, the accounting department's manager interacts with the system according to Eqs. 4.18 and 4.19 and (3) allocates direct cost pools to cost centers (i.e., the bases for allocation type 3 are defined). These can either be direct costs or manufacturing costs. For cost centers with direct costs as the basis for allocation type 3, the accounting department's manager $h \in H^{acc-dep}$ assigns the previously defined direct cost pools $K^{dir,group}$. The agents interact with the costing system and assign a direct cost $k_j^{dir,group} \in K^{dir,group}$ to each cost center $m_i \in M^{dir^{dcp}}$ according to Eq. 4.20, whereby $i \in \{1, \ldots, |M|\}$ and $j \in \{1, \ldots, |K^{dir,group}|\}$. As in previous interactions regarding the costing systems' design, once direct cost pools are assigned all remaining calculation steps are based on this assignment. If the accounting department's manager decides to put less effort into fulfilling this task or task fulfillment is unintendedly biased, quality of information provided by the costing system might be affected. The agents' biasing behavior might be intended or unintended and cannot be explicitly distinguished from each other. For this simulation study, this type of bias is referred to as *input bias on the assignment of direct cost pools*.

Cost Drivers

The final task delegated to the accounting department's manager regarding the structure of the costing system considered in this simulation study is to determine which cost drivers are used for internal cost allocation. In particular, the principal P delegates to agent $h \in H^{acc-dep}$ to interact with the costing system in order to introduce information on which cost drivers are used to reallocate costs from indirect cost centers to direct cost centers in allocation type 2 (cf. also Eq. 4.15). If the accounting department's manager selects an action in order to fulfill this task which differs from the action desired by the principal, i.e., $a^{h,l} \neq a^{h,l,*}$, or the assignment of cost drivers is unintendedly biased, costs in allocation type 2 might be reallocated incorrectly. This might affect information quality. For further elaborations, this type of bias is referred to as *input bias on the assignment of cost drivers for allocation type 2*. No differentiation between intended and unintended behavior is considered in the simulation model.

4.2.2.2 Principal-Agent Relations Ex-Post to Operations

After the costing systems' structure has been defined, i.e., the time-span ex-post to operations, and data for operations have been generated on the basis of exogenously given parameterization, agents heavily interact with the costing system in order to introduce and manipulate data. This subsection gives detailed information on the principal-agent relationships for the time-span ex-post to operations. This section is structured on the basis of the costing systems' main components. The agents' interactions with the respective components are elaborated in detail in the corresponding subsections.

Input Cost Objects

After operations, i.e. goods and services have been produced and provided by different cost centers, the principal delegates the task of introducing cost information into the costing system. Managers $h \in H^{direct}$ of direct cost centers M^{dir} and managers $h \in H^{indir}$ of indirect cost centers M^{indir} are in charge of introducing information on costs into the costing system that incurred in their own area of responsibility. Therefore, these agents observe business cases that have been generated in the time-span of operations and enter the observed data into the costing system (cf. also Eq. 4.1). With this interaction the set of input cost objects is generated. These input cost objects are the basis for further calculation steps.

In selecting an action $a^{h,l}$ in order to fulfill this delegated task, the respective agents decide whether input cost objects are to be generated free of bias or to be defective. If the agents select an action $a^{h,l}$ that is equal to $a^{h,l,*}$, the task is executed as desired by the principal, i.e., all business cases are observed and introduced correctly. If agents select an action that is unequal to the one desired by the principal, they might, on the one hand, intendedly decide to put less effort into task execution than desired by the principal. On the other hand, agents might introduce biased cost information unintendedly. This results in a certain number of business cases observed and introduced incorrectly. It cannot be differentiated whether it is due to decreasing effort or due to unintentional biasing behavior that input cost objects are generated wrongly. As a further characterization of this type of bias, agents might observe business cases correctly and deliberately introduce distorted cost information into the costing system in order to serve their own ends by manipulating the basis for their variable compensation components. In this case the respective agents decide for a magnitude of bias and a number of business cases to be introduced into the costing system incorrectly. All characterizations of this type of biasing behavior are referred to as *input bias on input cost objects*.

Categorization and Differences in Valuation

After managers of direct and indirect cost centers have introduced cost information into the costing system, the accounting department's manager $h \in H^{acc-dep}$ is in charge of assigning cost categories and determining differences in valuation. For each generated input cost object the accounting department's manager assigns one cost category of the set of cost categories defined ex-ante to operations. In the computational model this interaction is represented by function Eq. 4.2.

According to elaborations of the agency model in Sect. 4.2.1, in selecting an action $a^{h,l}$ the agent decides whether to assign cost categories correctly, as desired by the principal, or to put less effort into the assignment of cost categories. The assignment of cost categories might also be distorted due to unintentional biasing behavior. It cannot be distinguished whether the biasing behavior is intended or unintended. In both scenarios, this type of bias results in a certain number of wrongly assigned cost categories. Due to the fact that the remaining calculation steps are based on assigned cost categories, this might affect the quality of information provided by the costing system. This type of bias is referred to as *input bias on the assignment of cost categories*.

Furthermore, the principal P delegates the task of determining the rate of differences in valuation to the accounting department's manager $h \in H^{acc-dep}$. According to elaborations of previous biases, if the agents selects an action $a^{h,l}$ equal to $a^{h,l,*}$, the delegated task is fulfilled as desired by the principal. Biasing behavior, in the context of this task, can have different sources. On the one hand, agents might decide to reduce effort in order to increase their individual utility. On the other hand, agents might unintendedly introduce the respective biases into the costing system. The accounting department's manager is rewarded on the basis of a measure for information quality and, hence, has no incentive to intentionally distort the magnitude of differences in valuation. Consequently, for this type of bias it cannot be distinguished whether the agent intentionally or unintentionally introduces biased data into the costing system.

In all cases, biasing behavior can result in an incorrect magnitude of differences in valuation to be calculated or differences in valuation might not be considered for the respective input cost objects. This type of bias is referred to as *input bias on differences in valuation*.

Allocations Types 1 and 2

As outlined in Sects. 4.1.2 and 4.1.3, allocation of indirect costs to cost centers and the following reallocation of costs from indirect to direct cost centers are based on cost driver activities. For both steps of allocation, the principal P delegates tasks to the respective agents. In case of allocation type 1, the task of observing and introducing information on cost driver activities into the costing system is delegated to managers of direct and indirect cost centers, i.e., $h \in H^{dir}$ and $h \in H^{indir}$. According to Eq. 4.9, the managers transfer the exogenously given information on bases for allocation type 1 into the costing system. In selecting an action $a^{h,l}$ in order to fulfill the delegated task, the agents decide whether to act as desired by the principal or to act opportunistically whereby it cannot be distinguished which source the bias is due to. Furthermore, this type of bias might be unintendedly introduced into the costing system. For all scenarios, a certain number of input cost objects is allocated incorrectly in allocation type 1. This might effect quality of information finally provided by costing systems. This type of bias is referred to as *input bias on the basis for allocation type 1*.

In addition to observing and introducing allocation keys for allocation type 1, managers of indirect cost centers $h \in H^{indir}$ are in charge of introducing cost center output into the costing system. For further calculation steps, this information on output of indirect cost centers is used as the basis for allocation type 2. Output measures are generated in the time-span of operations and, for this simulation study, are exogenously given.

According to Eq. 4.14 agents interact with the costing system and introduce the exogenously given data which they have previously observed. If agents choose an action that does not conform with the one desired by the principal, i.e., $a^{h,l} \neq a^{h,l,*}$, this type of bias can have two different characterizations. On the one hand, agents might intentionally introduce a higher cost center output than originally provided in order to increase the basis for their variable compensation component. On the other hand, agents might reduce disutility for effort or act under the regime of unintended biasing behavior. In all scenarios this type of bias results in the output of indirect cost centers being introduced incorrectly. Consequently, costs might be reallocated incorrectly in allocation type 2. This type of bias is referred to as *input bias on the basis for allocation type 2*.

4.2.3 Sequence of Events and Overview of Biases Under Investigation

Sections 4.2.1 and 4.2.2 introduce an agency model. In particular, the first section gives a generalized model that is applied to different principal-agent relations in the second sections. Figure 4.2 summarizes the actions of the principal and the agents. According to the temporal clustering used in the model of the costing system, the timeline in Fig. 4.2 distinguishes between actions ex-ante to operations, during operations and ex-post to operations.

Apart from the application of the general model to the different principal-agent relations, Sect. 4.2.2 gives information on the agents' possible biasing behavior. For certain actions potential biases that are introduced into the costing system are elaborated. Table 4.2 summarizes these biases and lists the agents that are mapped to potentially introduce the respective types of biases into the costing system. Furthermore, the table gives reference to the sections in which the biasing behavior is elaborated and information on the source of bias. The source of bias refers to elaborations in Sect. 3.1.2.

4.3 Operationalization of the Structure of Biases

In the previous sections the model of the costing system and the model of the agents' behavior have been introduced. Section 4.1 gives the different processing steps within the costing system and the interactions of agents in order to introduce and manipulate data, Sects. 4.2.1 and 4.2.2 introduce a generalized agency model and apply it to the different principal-agent relationships incorporated into the simulated organizations. The model of the agents' behavior develops a set of potential biases. For an overview of the set of biases cf. Table 4.2. Now that the model model of the costing system and the behavioral model have been introduced, this sections discusses how the different types of biases are incorporated into the computational model.

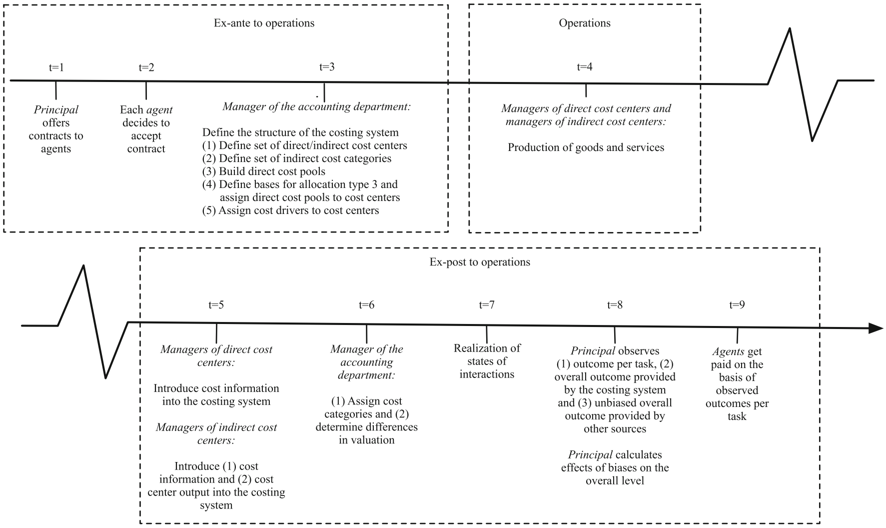

Fig. 4.2 Agency model: sequence of events

Table 4.2 Summary of biases under investigation

Type of input bias	Agent[a]	Source[b]
Ex-ante to operations		
Categorization of cost centers	$H^{acc-dep}$	$+/-$
Categorization of cost categories	$H^{acc-dep}$	$+/-$
Building of direct cost pools	$H^{acc-dep}$	$+/-$
Assignment of direct cost pools	$H^{acc-dep}$	$+/-$
Assignment of cost drivers	$H^{acc-dep}$	$+/-$
Ex-post to operations		
Input cost objects	H^{dir}/H^{indir}	$+/+$
Assignment of cost categories	$H^{acc-dep}$	$+/-$
Differences in valuation	$H^{acc-dep}$	$+/-$
Bases for allocation type 1	H^{dir}/H^{indir}	$+/-$
Bases for allocation type 2	H^{indir}	$+/+$

[a] These agents are mapped to introduce the various types of bias, $H^{acc-dep}$: Manager accounting department, H^{dir}: Manager direct cost center, H^{indir}: Manager indirect cost center;

[b] Potential sources of bias, denotation: intentional biasing behavior / unintentional biasing behavior, characteristics: $+/+$ it can be explicitly distinguished whether this type of bias is introduced unintendedly or intendedly, $+/-$ it cannot be explicitly distinguished whether this type of bias is introduced unintendedly or intendedly

4.3.1 Input Biases Ex-Ante to Operations

According to elaborations in previous section, agents might introduce different types of biases ex-ante to operations. For this time-span, this simulation study considers input biases on (1) the categorization of cost centers, (2) the categorization of cost categories, (3) the building of direct cost pools, (4) the assignment of direct cost pools and (5) the assignment of cost drivers for allocation type 2. For further information on the sources of these types of biases cf. Table 4.2 and Sect. 4.2.2.1. The following sections discuss how these types of biases are incorporated into the simulation model.

4.3.1.1 Categorization of Cost Centers

Input biases on the categorization of cost centers result from interactions of the accounting department's manager with the costing system. The manager categorizes the set of cost centers into direct and indirect cost centers. Input biases on the categorization of cost centers are denoted as $\gamma_{catcenter,i}$, whereby index $i \in \{1, \ldots, |M|\}$ indicates cost centers. The probability of occurrence of input biases on the categorization of cost centers is denoted as $p_{catcenter}$. $\gamma_{catcenter,i}$ can either be true, i.e., cost center m_i is categorized incorrectly, or false, i.e., no categorization error occurred. With exogenously given probability $p_{catcenter}$, $\gamma_{catcenter,i}$ is true. The unbiased interaction is given in Eq. 4.13. In case of biasing behavior, function $f^{m,cat}$ is replaced by function $f^{m,cat}_{biased}$ with probability $p_{catcenter}$, i.e.,

$$f^{m,cat}_{biased}(m_i) = \begin{cases} m_i \in M^{dir} & \text{if } f^{m,cat}(m_i) = m_i \in M^{indir} \\ m_i \in M^{indir} & \text{if } f^{m,cat}(m_i) = m_i \in M^{dir}. \end{cases} \tag{4.32}$$

If $\gamma_{catcenter,i}$ is true the interaction of the accounting department's manager with the costing system in order to categorize cost center m_i is represented by function $f^{m,cat}_{biased}$. As a consequence, cost center m_i is categorized incorrectly. In the case that $\gamma_{catcenter,i}$ is false, the interaction in order to categorize cost center m_i is still represented by the function $f^{m,cat}$. For this case, $f^{m,cat}_{biased}$ is irrelevant.

4.3.1.2 Categorization of Cost Categories

Moreover, input biases on the categorization of cost categories result from interactions of the accounting department's manager with the costing system. The probability of occurrence for input biases on the categorization of cost categories is given by $p_{catcategory}$. This type of bias is denoted as $\gamma_{catcategory,i}$, whereby $i \in \{1, \ldots, |K|\}$ indicates cost categories. $\gamma_{catcategory,i}$ can either be true or false. In case of it being true, input bias on the categorization of cost categories is applicable for cost category k_i, in case of it being false, no input bias occurred. The interaction of the accounting department's manager with the costing system in order to categorize cost categories is formalized in Eq. 4.4. If in this interaction biased data is introduced into the costing system, i.e., $\gamma_{catcategory,i}$ is true and cost category k_i is categorized incorrectly, function $f^{k,cat}$ is replaced by function $f^{k,cat}_{biased}$, i.e.,

$$f_{biased}^{k,cat}(k_i) = \begin{cases} k_i \in K^{dir} & \text{if } f^{k,cat}(k_i) = k_i \in K^{indir} \\ k_i \in K^{indir} & \text{if } f^{k,cat}(k_i) = k_i \in K^{dir}. \end{cases} \tag{4.33}$$

If $\gamma_{catcategory,i}$ is true, the interaction of the accounting department's manager results in cost category k_i being categorized incorrectly. Miscategorization of cost categories occurs with exogenously given probability $p_{catcategory}$. With probability $1 - p_{catcategory}$, $\gamma_{catcategory,i}$ is false, i.e., the interaction is represented by function $f^{k,cat}$ and no bias is introduced into the costing system.

4.3.1.3 Building of Direct Cost Pools

The third type of bias considered for the time-span ex-ante to operations is input bias on the building of direct cost pools. The accounting department's manager interacts with the costing system and clusters cost categories which have previously been categorized as direct cost categories into direct cost pools. This interaction is represented by function $f^{k,dir}$, cf. Eq. 4.6. The probability of occurrence for this type of bias is given by p_{dcp}. The bias is denoted as $\gamma_{dcp,i}$, whereby $i \in \{1, \ldots, |K|\}$ indicates direct cost categories $k_i \in K^{dir}$. As in previous elaborations, $\gamma_{dcp,i}$ can either be true or false. In case of it being true, cost category $k_i \in K^{dir}$ is assigned to the wrong direct cost pool. If $\gamma_{dcp,i}$ is false, no bias is introduced into the costing system. In cases in which $\gamma_{dcp,i}$ is true, function $f^{k,dir}$ (cf. Eq. 4.6) is replaced by function $f_{biased}^{k,dir}$, i.e.,

$$f_{biased}^{k,dir}(k_i) = k_n^{dir,group}. \tag{4.34}$$

Hence, $f^{k,dir}(k_i) = k_j^{dir,group}$ (cf. Eq. 4.6) and $f_{biased}^{k,dir}(k_i) = k_n^{dir,group}$ (cf. Eq. 4.34), whereby $j, n \in \{1, \ldots, |K^{dir,group}|\}$ and $j \neq n$.

To sum up, if indicator $\gamma_{dcp,i}$ for input biases on the building of direct cost pools is true, the interaction of the accounting department's manager with the costing system originally given by Eq. 4.6 is replaced by function $f_{biased}^{k,dir}$. This type of input bias occurs with the exogenously given probability p_{dcp}. As a result, the direct cost category $k_i \in K^{dir}$ is assigned to the wrong direct cost pool. Due to the fact that all further processing steps are based on the costing system's structure in time-span ex-ante to operations, this leads to potential distortions in the bases for the calculation of overhead rates and, hence, might affect information provided by costing systems.

4.3.1.4 Assignment of Direct Cost Pools

Input biases on the assignment of direct cost pools to direct cost centers might result from interactions of the accounting department's manager with the costing system. In the time-span ex-ante to operations the accounting department's manager interacts with the costing system and introduces information on which direct cost pools are assigned to which direct cost center as basis for the calculation of overhead rates. This type of bias is denoted as $\gamma_{asgnm-dcp,i}$, whereby $i \in \{1, \ldots, |M|\}$ and indicates the cost center $m_i \in M^{dir^{dcp}}$ that has been assigned a wrong direct cost pool. $\gamma_{asgnm-dcp,i}$ can either be true or false. If it is true, cost center m_i has been assigned the wrong direct cost pools for calculation of overhead rates. If it is case false, no bias in the assignment of direct cost pools is introduced into the costing system. The corresponding probability of occurrence is exogenously given and denoted as $p_{asgnm-dcp}$. For scenarios in which biased data is introduced into the costing system, the function f^{dcp} given in Eq. 4.20 is replaced by the function f^{dcp}_{biased}, i.e.,

$$f^{dcp}_{biased}(m_i) = k^{dir,group}_{k}. \tag{4.35}$$

Following Eqs. 4.20 and 4.35, $f^{dcp}(m_i) = k^{dir,group}_{j}$ and $f^{dcp}_{biased}(m_i) = k^{dir,group}_{n}$ whereby $i \in \{1, \ldots, |M|\}$, $j, n \in \{1, \ldots, |K^{dir}_{group}|\}$ and $j \neq n$. If $\gamma_{asgnm-dcp,i}$ is set to true, an input bias on the assignment of direct cost pools is introduced into the costing system, i.e., cost center m_i has been assigned direct cost pool $k^{dir,group}_{n}$ instead of direct cost pool $k^{dir,group}_{j}$. As a consequence, overhead rates are calculated on the basis of wrong direct costs. This might affect the quality of information provided by the costing system.

4.3.1.5 Assignment of Cost Drivers for Allocation Type 2

The last interaction in order to define the structure of the costing system considered in the simulation model is to assign cost drivers for allocation type 2. The accounting department's manager introduces information on which cost driver is used to reallocate costs from indirect to direct cost centers, i.e., allocation type 2. Input biases on the assignment of cost drivers for allocation type 2 are denoted as $\gamma_{asgnm-cd^{type:2},j,c}$, whereby $j, c \in \{1, \ldots, |M|\}$. In case of it being true, costs in allocation type 2 are reallocated from cost center $m_j \in M^{indir}$ to cost center $m_i \in M$ on basis of the wrong cost driver. In case of it being false, no bias is introduced. The corresponding probability of occurrence is exogenously given and denoted as $p_{asgnm-cd^{type:2}}$. For unbiased interactions, the interaction is given by Eq. 4.15. For scenarios in which input biases on the assignment of cost drivers for allocation type 2 are introduced into the costing system, function f^r given in Eq. 4.15 is replaced by function f^r_{biased}, i.e.,

$$f^{r}_{biased}\left(m_j; m_c\right) = r_{n,j,c}. \tag{4.36}$$

In consideration of Eqs. 4.15 and 4.36, $f^r\left(m_j; m_c\right) = r_{i,j,c}$ and $f^r_{biased}\left(m_j; m_c\right) = r_{n,j,c}$, whereby $i, n \in \{1, \ldots, |R|\}$, $j, c \in \{1, \ldots, |M|\}$, $m_j \in M^{indir}$, $m_c \in M$, $j \neq c$ and $i \neq n$. As a consequence, if this type of bias is introduced into the costing system, allocation type 2 is based on activities of the wrong cost driver. This might have an impact on the quality of provided information.

4.3.2 Input Biases Ex-Post to Operations

For the time-span ex-post to operations, this simulation study considers five different types of input biases. These biases are input biases (1) on input cost objects, (2) on the assignment of cost categories, (3) on differences in valuation, (4) on the basis for allocation type 1 and (5) on the basis for allocation type 2. For further information on the nature of these types of biases cf. Sect. 4.2.2.2 and Table 4.2. The next sections discuss how these different biases are incorporated into the model of the costing system.

4.3.2.1 Input Cost Objects

After the time-span of operations, i.e. goods and services have been produced, managers of direct and indirect cost centers are in charge of introducing information on occurred costs into the costing system. In particular, each cost center manager introduces this cost information for their own area of responsibility. This simulation study is designed to distinguish between intentional and unintentional behavior in case of input biases on input cost objects. For unintentional biasing behavior and reduced effort in task execution, the direction of bias can either be positive or negative. Given the elaborations in Sect. 4.2, cost center managers are inter alia rewarded on the basis of costs that incurred in their area of responsibility. For setups in which agents intentionally aim at manipulating the basis for their variable compensation component, these agents might introduce less costs than have actually incurred into the costing system, i.e., in the case of intentional biasing behavior the bias goes in a negative direction.

For further elaborations, input biases on input cost objects are denoted as $\gamma_{ico,i}$, whereby $i \in \{1, \ldots, |BC|\}$ indicates input cost objects. $\gamma_{ico,i}$ can either be true or false. In the case of it being true, for input cost object c_{in_i} this type of bias is introduced while in the case of it being false, cost information is introduced into the costing system correctly. In order to operationalize this type of bias, a probability of occurrence p_{ico} and an interval for the magnitude of bias $U[\underline{a}_{ico}; \overline{a}_{ico}]$ are exogenously given. Hence, with probability of p_{ico} this type of bias is introduced into the costing system, i.e., $\gamma_{ico,i}$ is true. The distortion $\delta_{ico,i}$ of input cost object c_{in_i} introduced intro the costing system is drawn from the uniformly distributed interval $U[\underline{a}_{ico}; \overline{a}_{ico}]$.

In the model of the costing system, the interaction of the cost center managers in order to generate input cost objects is represented by function f^c (cf. Eq. 4.1). In cases where input biases on input cost objects are introduced into the costing system, function f^c is replaced by the function f^c_{biased}, i.e.,

$$f^c_{biased}(bc_i) = c_{in_i} \cdot (1 + \delta_{ico,i}). \tag{4.37}$$

Depending on the source of bias, the introduced costs can either be too low or too high. Due to the fact that all further calculation steps are based on the introduced cost information, this might affect the quality of information provided by the costing system.

4.3.2.2 Assignment of Cost Categories

After cost information has been introduced into the costing system, the manager of the accounting department is in charge of assigning cost categories to input cost objects. In the model of the costing system, this interaction is represented by the function f^k (cf. Eq. 4.2). Input biases on the assignment of cost categories are denoted as $\gamma_{acat,i}$, whereby $i \in \{1, \ldots, |BC|\}$ indicates the input cost objects. $\gamma_{acat,i}$ can either be true or false, where true indicates that input cost object c_{in_i} has been assigned a wrong cost category. In case of it being false, the respective input cost object has been assigned the correct cost category. For this simulation study, the probability of occurrence for this type of bias is exogenously given and denoted as p_{acat}.

If $\gamma_{acat,i}$ is true, for input cost object c_{in_i} function f^k (cf. Eq. 4.2) is replaced by function f^k_{biased}, i.e.

$$f^k_{biased}(c_{in_i}) = k_n. \tag{4.38}$$

Following Eqs. 4.2 and 4.38, $f^k(c_{in_i}) = k_j$ and $f^k_{biased}(c_{in_i}) = k_n$, whereby $i \in \{1, \ldots, |BC|\}$, $j, n \in \{1, \ldots, |K|\}$ and $j \neq n$. Consequently, if $\gamma_{acat,i}$ is true input cost object c_{in_i} has been assigned cost category k_n instead of cost category k_j. All further calculation steps within the costing system are based on this assignment. Hence, the quality of information provided by the costing system might be affected if this type of bias is introduced into the costing system.

4.3.2.3 Differences in Valuation

In addition to assigning cost categories, the accounting department's manager is in charge of determining the rate of differences in valuation. In the computational model, this interaction is given by function f^s in Eq. 4.5. This simulation study is organized to distinguish between two characterizations of this type of bias. First, incorrect rates of differences in valuation might be considered for certain input cost objects which might be due to unintentional biasing behavior and reduced task execution effort. Second, certain input cost object differences might not be considered at all.

Cases in which differences in valuation are determined incorrectly, are denoted as $\gamma_{div,i}$, whereby $i \in \{1, \ldots, |BC|\}$ denotes the respective input cost objects. $\gamma_{div,i}$ can either be true or false, whereby true indicates that differences in valuation for input cost object c_{in_i} are determined incorrectly. In case of it being false, no respective bias is introduced into the costing system. The corresponding probability of occurrence is exogenously given and denoted as p_{div}. The magnitude of bias introduced into the costing system for input cost object c_{in_i} is denoted as $\delta_{div,i}$ and is drawn from a uniformly distributed interval $U[\underline{a}_{div}; \overline{a}_{div}]$ that is exogenously given. If $\gamma_{div,i}$ is true, for input cost object c_{in_i} function f^s (cf. Eq. 4.5) is replaced by function $f^{s,div}_{biased}$, i.e.,

$$f^{s,div}_{biased}(c_{in_i}) = s_i \cdot (1 + \delta_{div,i}). \tag{4.39}$$

For cases in which differences in valuation are not considered at all, input biases on differences in valuation are denoted as $\gamma_{divnc,i}$. If $\gamma_{divnc,i}$ is true, differences in valuation for input cost object c_{in_i} are not considered. In this cases the function f^s (cf. Eq. 4.5) is replaced by function $f^{s,divnc}_{biased}$, i.e.,

$$f^{s,divnc}_{biased}(c_{in_i}) = 0. \tag{4.40}$$

In the case of wrong magnitudes of differences in valuation, due to the fact that all further calculations are based on the introduced rates of differences in valuation, the quality of information provided by the costing system might be affected.

4.3.2.4 Basis for Allocation Type 1

Input biases on the basis for allocation type 1 might be caused by managers of direct and indirect cost centers. These agents interact with the costing system in order to introduce bases for the allocation of indirect costs to cost centers. In the case of input biases on the basis for allocation type 1, this information is distorted, which leads to costs being allocated incorrectly in allocation type 1.

Input biases on the basis of allocation type 1 are denoted as $\gamma_{cd^{type:1},i,j}$, whereby $i \in \{1, \ldots, |M|\}$ indicates cost centers and $j \in \{1, \ldots, |C^{indir}_{in}|\}$ indicates input cost objects that are categorized as indirect costs. $\gamma_{cd^{type:1},i,j}$ can either be true or false. In the case of it being true, the share $cd_{i,j}$ of indirect costs g_j (cf. Eq. 4.8) that should originally have been allocated to cost center m_i is allocated to another cost center m_n. In the case of it being false, no respective bias is introduced. The corresponding probability of occurrence for this type of bias is exogenously given and denoted as $p_{cd^{type:1}}$. In the model of the costing system, the interaction of the cost center managers with the system in order to introduce the bases for allocation type 1 is represented by function $f^{cd^{type:1}}$ (cf. Eq. 4.9). In the case that $\gamma_{cd^{type:1},i,j}$ is true, for allocation base $cd^{ex}_{i,j}$ in order to allocate a share indirect costs given by g_j to cost center m_i, function $f^{cd^{type:1}}$ is replaced by function $f^{cd^{type:1}}_{biased}$, i.e.,

$$f^{cd^{type:1}}_{biased}\left(cd^{ex}_{i,j}\right) = cd_{n,j}, \tag{4.41}$$

whereby $i, n \in \{1, \ldots, |M|\}$ indicate cost centers and $i \neq n$. As a consequence, the share $f^{cd^{type:1}}\left(cd^{ex}_{i,j}\right) = cd_{i,j}$ (cf. Eq. 4.9) of indirect costs g_j that should originally have been allocated to cost center m_i is allocated to cost center m_n

(cf. Eq. 4.41). This might have an impact on the quality of information provided by costing systems.

4.3.2.5 Basis for Allocation Type 2

Input biases on the basis for allocation type 2 might result from interactions of managers of indirect cost centers with the costing system. As in the case of input biases on input cost objects, the simulation study is designed to distinguish between intentional biasing behavior on the one hand and unintentional biasing behavior and reduced effort for task execution on the other hand. Depending on the respective source, the direction of bias can either go in both directions or be positive, i.e., for cases in which agents intentionally manipulate the basis for their variable compensation component, they introduce a higher level of goods and services to be provided to other cost centers. In the case of unintentional biasing behavior and reduced effort for task execution, distortions go in both directions, i.e., agents might introduce not only a higher, but also a lower level of goods and services provided.

Input biases on the basis for allocation type 2 are denoted as $\gamma_{cd^{type:2},i,j,n}$, whereby $i \in \{1, \ldots, |R|\}$ indicates the type of cost driver, $j, n \in \{1, \ldots, |M|\}$ indicate cost centers, m_j refers to the cost center that provides goods and services to cost center m_n and $j \neq n$. $\gamma_{cd^{type:2},i,j,n}$ can either be true or false. True indicates that the respective bias is introduced into the costing system while in the case of false, data is introduced correctly.

In order to operationalize input biases on the basis for allocation type 2, the probability of occurrence $p_{cd^{type:2}}$ is exogenously given. Furthermore, the magnitude of input bias $\delta_{cd^{type:2},i,j,n}$ is drawn from a uniformly distributed interval $U[\underline{a}_{cd^{type:2}}; \overline{a}_{cd^{type:2}}]$. Parameterization for the interval, i.e., $\underline{a}_{cd^{type:2}}$ and $\overline{a}_{cd^{type:2}}$, is exogenously given. In the model of the costing system, the interaction of managers of indirect cost centers with the costing system in order to introduce cost driver activities is given by function $f^{cd^{type:2}}$ (cf. Eq. 4.14). In case of biasing behavior, i.e., $\gamma_{cd^{type:2},i,j,n}$ is true, this function is replaced by function $f_{biased}^{cd^{type:2}}$, i.e.,

$$\begin{aligned} f_{biased}^{cd^{type:2}}\left(r_{i,j,n}^{ex}\right) &= f^{cd^{type:2}}\left(r_{i,j,n}^{ex}\right) \cdot \left(1 + \delta_{cd^{type:2},i,j,n}\right) \\ &= r_{i,j,n} \cdot \left(1 + \delta_{cd^{type:2},i,j,n}\right). \end{aligned} \tag{4.42}$$

As a consequence of defective cost driver information being introduced into the costing system, costs are reallocated incorrectly in allocation type 2 which might have an impact on the quality of information provided by the costing system.

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Chapter 5
Costing System Sophistication and Quality of Provided Information

Abstract This chapter analyzes the research question (1) "How does the level of (traditional) costing system sophistication affect the quality of decision-facilitating and decision-influencing information provided by costing systems in case of intended and unintended biases in input data?". Hence, the main focus is on measures for costing system sophistication and how a variation in these measures affects the effects on the input biases under investigation. Parameterization of input biases is kept constant during all simulation runs. The main focus of the analyses is on whether or not the effects of the various types of input biases are sensitive to costing system sophistication. Section 5.1 gives the parameterization applied in order to investigate the research question and elaborates the method of data analysis. Sections 5.2 and 5.3 present the results of the simulation runs. Chapter 8 discusses the presented results.

5.1 Parameterization and Data Analysis

This simulation study is set up in accordance with prior work on accounting and errors (e.g. Babad and Balachandran 1993; Gupta 1993; Datar and Gupta 1994; Homburg 2001; Labro and Vanhoucke 2007, 2008). In order to investigate effects of input biases on the quality of provided information, this study builds on a framework that assumes one unbiased costing benchmark and a large number of experiments where biased data is introduced into the costing systems (i.e., in case of the benchmark scenario all delegated tasks are fulfilled as desired by the principal, no bias is considered in benchmark scenarios).

This chapter investigates effects of (traditional) costing systems' sophistication in case of biased input data. Costing system sophistication is expressed via two measures, i.e. (1) the relation between direct and indirect cost centers, whereby direct cost centers with direct cost pools as the basis for allocation type 3 are considered for variation ($soph^{cent} = |M^{dir^{dcp}}|/|M^{indir}|$), and (2) the relation between direct and indirect cost categories ($soph^{cat} = |K^{dir}|/|K^{indir}|$). Direct cost centers

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with manufacturing costs as basis for allocation type 3 are kept constant throughout all simulations (these might represent cost centers such as administration and sales while other cost centers might represent organizational units in production).

In their investigation, Friedl et al. (2009) found that during recent years the number of indirect cost centers in implemented costing systems has increased. This indicates that the relation between (1) direct and indirect cost centers has changed. In addition, they found that managers perceive to be well supported by costing systems in cost management and that costing systems support them in achieving cost transparency in case of indirect costs. This indicates that also the relation between direct and indirect cost categories changes. In this simulation study relations between (1) direct and indirect cost centers and (2) direct and indirect cost categories that range from 0.5 to 5 are analyzed (whereby a decreasing measure (1) or (2) indicates a higher level of sophistication), i.e. for both measures relations range from 10/20 to 10/2 whereby all possible combinations of measure (1) and (2) are analyzed. Equation 5.1 gives the respective ranges of potential values for the sophistication measures under investigation.

$$soph^{cat}, soph^{cent} \in \{\frac{10}{2}, \frac{10}{4}, \frac{10}{6}, \frac{10}{8}, \frac{10}{10}, \frac{10}{12}, \frac{10}{14}, \frac{10}{16}, \frac{10}{18}, \frac{10}{20}\} \tag{5.1}$$

All other parameters regarding costing system design are kept constant, detailed parameterization for generating the costing systems' structure is given in Table 5.1. Effects are analyzed for the decision-influencing as well as for the decision-facilitating perspective and for both intended and unintended biasing behavior.

The investigated types of biases correspond to elaborations in Sect. 4.2. Correspondingly, the agents' interactions with the costing system are grouped into time-periods ex-ante and ex-post to operations. Biases for the time-period ex-ante to operations are input biases in the categorization of cost centers, the categorization of cost categories, the building of direct cost pools, the assignment of direct cost pools and the assignment of cost drivers for allocation type 2. For the time-period ex-post to operations input biases in input cost objects, the assignment of cost categories, the calculation of differences in valuation and in the bases for allocation type 1 and 2 are considered. According to the outlined operationalization of the structure of biases (cf. Sect. 4.3), for some types of biases in addition to the probability of occurrence, the magnitude of bias is exogenously given. Furthermore, for some types of biases the model distinguishes between intentional and unintentional biasing behavior. For the investigation of the effects of costing system sophistication on the quality of provided information, the probability of occurrence in set to 0.5 for all biases whereby all parameters regarding the magnitude of bias range up to $\pm$ 0.1 (positive or negative, depending on whether the bias in introduced intentionally or unintentionally). In addition, and in order to analyze effects of the level of probability of occurrence and the magnitude of bias separately, for biases which require a magnitude of bias, this investigation considers scenarios where the probability is set to 0.1 and the magnitude of bias ranges up to $\pm$ 0.5.

Table 5.1 Parameterization for generating costing systems (sophistication)

Parameter	Denotation	Parameterization
Cost categories		
Cost categories	K	cf. Eq. 5.1
Direct cost categories	K^{dir}	cf. Eq. 5.1
Indirect cost categories	K^{indir}	cf. Eq. 5.1
Direct cost pools	$K^{dir,group}$	10
Cost centers		
Cost centers	M	cf. Eq. 5.1
Direct cost centers with direct cost pools as basis for allocation type 3	$M^{dir^{dcp}}$	cf. Eq. 5.1
Direct cost centers with manufacturing costs as basis for allocation type 3	$M^{dir^{mc}}$	2
Indirect cost centers	M^{indir}	cf. Eq. 5.1
Cost drivers		
Cost drivers (type 2)	$\mathbf{R}$	Depends on the number of M^{indir}, cf. Eq. 5.1
Interval for cost drivers (type 2)	$U\left[\underline{a}_{cd^{type:2}}; \overline{a}_{cd^{type:2}}\right]$	U [40,000; 80,000]
Business cases		
Business cases	BC	7,000
Interval for input cost objects	$U\left[\underline{a}_{bc}; \overline{a}_{bc}\right]$	U [500; 5,000]
Differences in valuation		
Probability of occurrence	p_s	0.30
Interval for differences in valuation	$U\left[\underline{a}_{s}; \overline{a}_{s}\right]$	U [−0.35; 0.35]
Provided information		
Interval for decision-facilitating information	$U\left[\underline{a}_{prod}; \overline{a}_{prod}\right]$	U [500; 5,000]

Resulting types of biases and the respective parameterization are given in Table 5.2. During simulation experiments, parameterization for input biases is kept constant.

Presented results are based on 100 randomly generated costing system structures for each level of costing system sophistication and 100 simulation runs per costing system structure, i.e., for each possible combination of the sophistication measures given in Eq. 5.1, results are based on 10,000 simulation runs.

In order to analyze the effects of costing systems' structure on the quality of provided information in case of intended and unintended biases in input data, this simulation study uses the mean absolute relative error. This measure is also applied in prior work on errors in MAS (cf. Christensen and Demski 1997). As outlined above, for each simulation run one benchmark scenario is calculated where all delegated tasks are fulfilled as desired by the principal, i.e., all data is introduced into the costing system without distortion, whereby the benchmark for the decision-influencing perspective is calculated according to Eqs. 4.23 and 4.24. For the decision-facilitating perspective, the benchmark is calculated according to Eq. 4.25. Costs that stem from benchmark scenarios are denoted as $costs_{i,j}^{prod,di,bench}$ for the

Table 5.2 Sensitivity of biases to costing system sophistication

Type of input bias	Prob. of occurrence	Interval	Decision-influencing $\underline{e}_n^{mean,di}$ [a]	$\overline{e}_n^{mean,di}$ [b]	δ_n^{di} [c]	Decision-facilitating $\underline{e}_n^{mean,df}$ [a]	$\overline{e}_n^{mean,df}$ [b]	δ_n^{df} [c]
Ex-ante to operations								
Categorization of cost centers	0.50	–	0.0044	0.0206	**0.0162**	0.0007	0.0025	0.0018
Categorization of cost categories	0.50	–	0.0236	0.2608	**0.2373***	0.0177	0.5685	**0.5508****
Building of direct cost pools	0.50	–	0.0202	0.0231	0.0029	0.0024	0.0027	0.0003
Assignment of direct cost pools	0.50	–	0.0186	0.0241	**0.0055**	0.0023	0.0030	0.0007
Assignment of cost drivers for allocation type 2	0.50	–	0.0068	0.0099	0.0031	0.0008	0.0011	0.0003
Ex-post to operations								
Input cost objects								
Intentional (magnitude)	0.10	$U[-0.50; 0.00[$	0.0255	0.0255	0.0000	0.0008	0.0008	0.0000
Unintentional (magnitude)	0.10	$U[-0.50; 0.50]$	0.0027	0.0030	0.0003	0.0008	0.0008	0.0000
Intentional (probability)	0.50	$U[-0.10; 0.00[$	0.0275	0.0275	0.0000	0.0003	0.0003	0.0000
Unintentional (probability)	0.50	$U[-0.50; 0.10]$	0.0012	0.0014	0.0002	0.0004	0.0004	0.0000
Assignment of cost categories	0.50	–	0.0289	0.0883	**0.0594**	0.0161	0.3054	**0.2892*****
Differences in valuation[d]								
Unintentional (magnitude)	0.10	$U[-0.50; 0.50]$	0.0001	0.0002	0.0000	0.0000	0.0000	0.0000
Unintentional (probability)	0.50	$U[-0.50; 0.10]$	0.0003	0.0003	0.0000	0.0001	0.0001	0.0000
Not calculated	0.50	–	0.0021	0.0024	0.0003	0.0006	0.0007	0.0001
Basis for allocation type 1	0.50	–	0.0127	0.0204	**0.0077**	0.0015	0.0023	0.0009
Basis for allocation type 2								
Intentional (magnitude)	0.10	$U[-0.50; 0.00[$	0.0000	0.0038	0.0038	0.0000	0.0005	0.0004

Unintentional (magnitude)	0.10	$U[-0.50; 0.50]$	0.0000	0.0037	0.0036	0.0000	0.0005	0.0005
Intentional (probability)	0.50	$U[-0.10; 0.00[$	0.0000	0.0017	0.0017	0.0000	0.0002	0.0002
Unintentional (probability)	0.50	$U[-0.50; 0.10]$	0.0000	0.0018	0.0018	0.0000	0.0002	0.0002

Bold δ_n^{di} and δ_n^{df} indicate sensitivity to costing system sophistication (i.e. >0.0050), n indicates the different types of bias under investigation

Confidence for relative errors with $\alpha = 0.001$: *[0.0003;0.0012]; **[0.0003;0.0060]; ***[0.0002;0.0006]; for remaining scenarios [0.0000;0.0003]

[a]Minimum mean absolute relative error

[b]Maximum mean absolute relative error

[c]Difference between minimum and maximum mean absolute relative error for the decision-influencing and decision-facilitating perspective

[d]Input biases on differences in valuation are also referred to as unintentional although it cannot be distinguished whether this type of bias is introduced intendedly or unintendedly

decision-influencing perspective and $costs_j^{prod,df,bench}$ for the decision-facilitating perspective, whereby $i \in \{1, \ldots, |M^{dir}|\}$ indicates the cost centers and $j \in \{1, \ldots, |CO_{out}|\}$ indicates the simulation runs.

For the decision-influencing perspective the relative error results as

$$e_{i,j,n}^{di} = \frac{costs_{i,j}^{prod,di,bench} - costs_{i,j,n}^{prod,di}}{costs_{i,j}^{prod,di,bench}}, \tag{5.2}$$

whereby (in addition to denotation in Eqs. 4.23 and 4.24) $n \in B$ indicates the type of bias the provided information is affected by. Hence, measure $e_{i,j,n}^{di}$ gives the relative error from the decision-influencing perspective that is due to input bias n and occurred at cost center m_i at simulation run j. Correspondingly, for the decision-facilitating perspective the relative error is calculated as

$$e_{j,n}^{df} = \frac{costs_j^{prod,df,bench} - costs_{j,n}^{prod,df}}{costs_j^{prod,df,bench}}, \tag{5.3}$$

i.e., $e_{j,n}^{df}$ gives the relative error from the decision-facilitating perspective that occurred at simulation run j and is due to input bias n.

Finally, for the decision-influencing perspective, the mean absolute relative error $e_n^{mean,di}$ results as

$$e_n^{mean,di} = \frac{1}{|M^{dir}| \cdot |CO_{out}|} \sum_{i=1}^{|M^{dir}|} \sum_{j=1}^{|CO_{out}|} |e_{i,j,n}^{di}|, \tag{5.4}$$

while for the decision-facilitating perspective the mean absolute relative error is calculated as

$$e_n^{mean,df} = \frac{1}{|CO_{out}|} \sum_{j=1}^{|CO_{out}|} |e_{j,n}^{df}|. \tag{5.5}$$

With respect to the different levels of costing system sophistication given in Eq. 5.1, for each type of input bias and each level of costing system sophistication a mean absolute relative errors is calculated (i.e., 100 mean absolute relative errors for each type of bias). Out of the set of mean absolute relative errors, for each type of bias n the minimum and the maximum characterization is determined. The minimum mean absolute relative errors are denoted as $\underline{e}_n^{mean,di}$ and $\underline{e}_n^{mean,df}$ for the decision-influencing and the decision-facilitating perspective. Correspondingly, the maximum mean absolute relative errors are denoted as $\overline{e}_n^{mean,di}$ for the decision-influencing and $\overline{e}_n^{mean,df}$ for the decision-facilitating perspective. Additionally, in order to give a range of mean absolute relative errors, for each type of input bias and for both the decision-influencing and the decision-facilitating perspective, the difference between the minimum and the maximum relative errors are calculated.

For the decision-influencing perspective this range is calculated as

$$\delta_n^{di} = \overline{e}_n^{mean,di} - \underline{e}_n^{mean,di}, \tag{5.6}$$

while for the decision-facilitating perspective the range results as

$$\delta_n^{df} = \overline{e}_n^{mean,df} - \underline{e}_n^{mean,df}, \tag{5.7}$$

whereby subscript n denotes the different types of input biases.

5.2 Sensitivity of Biases to Costing System Sophistication

Table 5.2 gives the results of the simulations on the sensitivity information quality to costing system sophistication. For each type of input bias Table 5.2 gives the minimum and the maximum absolute relative error for the decision-influencing as well as for the decision-facilitating perspective. In addition, the corresponding ranges between the minimum and the maximum mean absolute relative errors are given. Biases that can be associated with a range that is higher than 0.0050 are further analyzed in Sect. 5.3. Deltas below 0.0050 are considered to be negligible and, hence, these types of input biases are not analyzed in this chapter.

Results indicate that the effects of some types of biases are not sensitive to costing system sophistication. The higher the delta (i.e., δ_n^{di} for the decision-influencing and δ_n^{df} for the decision-facilitating perspective) is, the more sensitive the respective input bias n appears to be to costing system sophistication. Biases that appear to be sensitive to costing system sophistication are input biases on (1) the categorization of cost centers, (2) the categorization of cost categories, (3) the assignment of direct cost pools, (4) the assignment of cost categories and (5) the basis for allocation type 1 (marked as bold in Table 5.2). These biases are further analyzed in Sect. 5.3. While the effects of all of these biases appear to be sensitive in the decision-influencing perspective, for the decision-facilitating perspective a sensitivity can only be observed in case of biases (2) and (4). For the remaining biases no sensitivity (above the threshold of 0.0050) can be observed. This chapter does not analyze the remaining types of biases any further.

5.3 Biases that Turn Out to be Sensitive to Costing System Sophistication

As outlined in Sect. 5.2, this section analyzes input biases where effects on information quality appear to be sensitive to costing system sophistication. In particular, the following input biases are analyzed in the following subsections: input bias on

(1) the categorization of cost centers, (2) the categorization of cost categories, (3) the assignment of direct cost pools, (4) the assignment of cost categories and (5) the basis for allocation type 1.

5.3.1 Categorization of Cost Centers

Results regarding input biases in the categorization of cost centers indicate that effects of this type of bias are sensitive to costing system sophistication. Specifically for the decision-influencing perspective, the higher the sophistication of cost centers is (i.e., the more indirect cost centers there are within the organization in relation to direct cost centers), the more distorted the provided information appears to be (cf. Fig. 5.1 and Table A.1). For cost category sophistication, no sensitivity in case of the decision-influencing perspective can be observed.

For the decision-facilitating perspective, input biases on the categorization of cost centers do neither appear to be sensitive to cost category nor to cost center sophistication (cf. Table 5.2).

5.3.2 Categorization of Cost Categories

Results regarding input biases on the categorization of cost categories are presented in Fig. 5.2 and Table A.2 for the decision-influencing perspective and in Fig. 5.3 and Table A.3 for the decision-facilitating perspective. It has to be noted that due to the high extent of errors resulting from input biases on the categorization of cost categories, scales of mean absolute relative errors in Figs. 5.2 and 5.3 differ from previously presented figures and range up to 60 %.

The results suggest that in both the decision-influencing and the decision-facilitating perspective, the effects of input biases on the categorization of cost categories are sensitive to the level of sophistication of cost categories (i.e., indirect cost categories relative to direct cost categories, cf. Sect. 5.1). In case of a low level of sophistication, the extent of distortion is higher for the decision-influencing perspective than it is for the decision-facilitating perspective. With increasing sophistication (up to 10/6) the extent of distortion decreases. For levels of sophistication 10/8 and above, the extent of distortion increases again. For highly sophisticated costing systems (with respect to cost categories) the distortion is higher for the decision-facilitating perspective. Hence, results indicate that costing systems with a high level of cost category sophistication appear to lead to a higher extent of distortion than costing systems with a low level of costing category sophistication. In highly sophisticated costing systems, the extent of distortion is higher for the decision-facilitating perspective than it is for the decision-influencing perspective while for lowly sophisticated costing systems input biases on the categorization of cost categories affect the quality of provided decision-influencing information more heavily than the quality of decision-facilitating information.

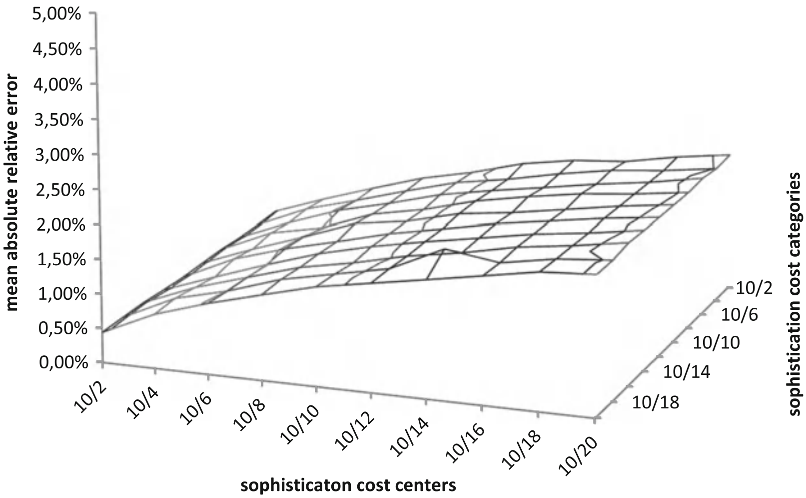

Fig. 5.1 Categorization of cost centers, decision-influencing perspective

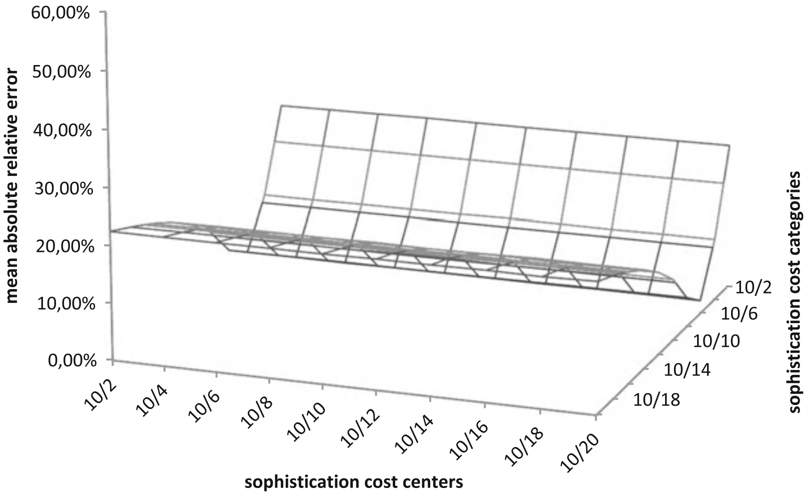

Fig. 5.2 Categorization of cost categories, decision-influencing perspective

For the decision-influencing as well as for the decision-facilitating perspective, the lowest extent of distortion can be observed for the level of sophistication 10/6.

5.3.3 Assignment of Direct Cost Pools

Figure 5.4 and Table A.4 present results on input biases on the assignment of direct cost pools for the decision-influencing perspective.

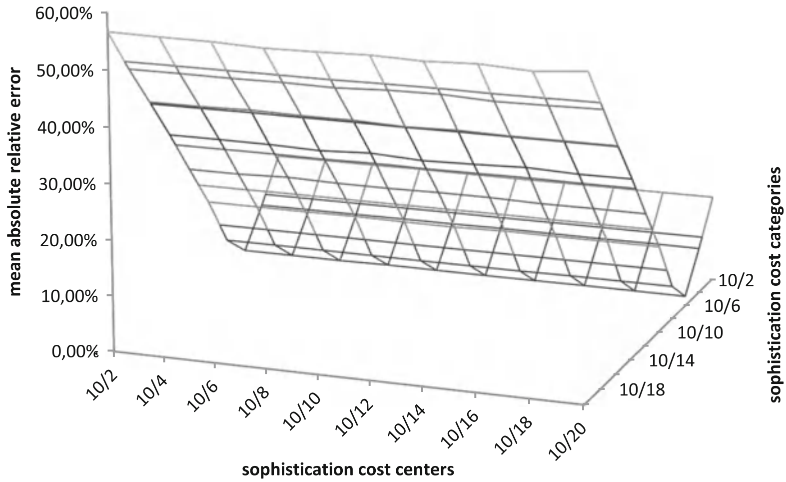

Fig. 5.3 Categorization of cost categories, decision-facilitating perspective

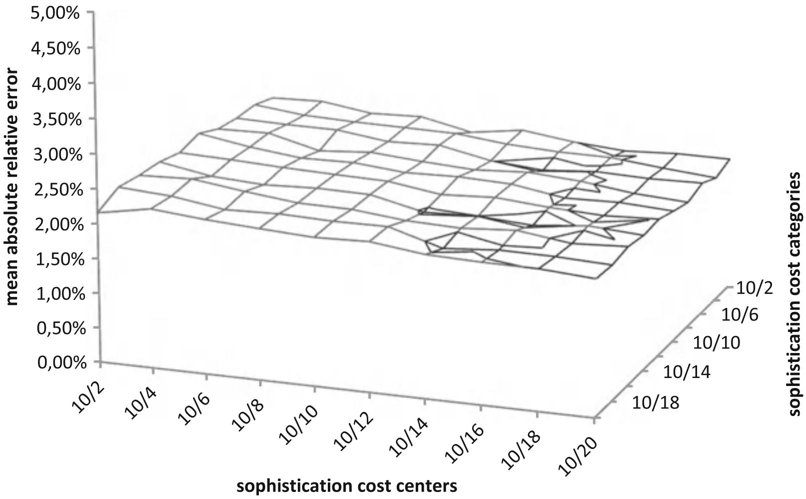

Fig. 5.4 Assignment of direct cost pools, decision-influencing perspective

The results suggest that effects of this type of input bias on the quality of provided information marginally decrease with increasing sophistication of cost centers. For the level of cost category sophistication, no sensitivity of effect of input biases on the assignment of direct cost pools can be observed. For the decision-facilitating perspective, no sensitivity, neither for the level of cost center sophistication nor for the level of cost category sophistication, can be observed (cf. Table 5.2).

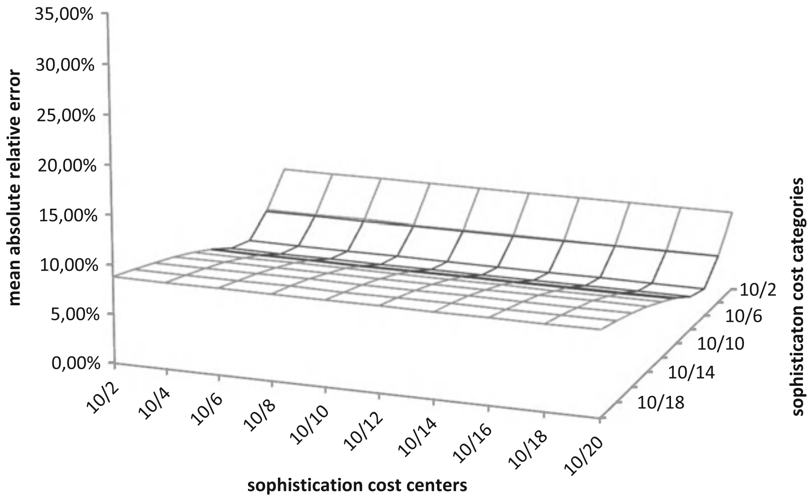

Fig. 5.5 Assignment of cost categories, decision-influencing perspective

5.3.4 Assignment of Cost Categories

Figures 5.5 and 5.6 and Tables A.5 and A.6 present results of input biases on the assignment of cost categories for the decision-influencing and the decision-facilitating perspective. It has to be noted that due to high extents of output errors, in Figs. 5.5 and 5.6 the axis for mean absolute relative error is scaled to 35 %.

For both the decision-influencing and the decision-facilitating perspective, a sensitivity of effects of input biases on cost category sophistication can be observed while output errors do not appear to be sensitive to cost center sophistication. Results suggest the extent of distortion to be higher in the case of decision-facilitating information. For both roles of provided information, from levels of cost category sophistication 10/2 to 10/6, mean absolute relative errors decrease. For levels of cost category sophistication 10/8 and higher, mean absolute relative errors increase again. The lowest extent of mean absolute relative error can be observed at cost category sophistication level 10/6.

5.3.5 Basis for Allocation Type 1

Results regarding input biases on the basis for allocation type 1 are presented in Fig. 5.7 and Table A.7 for the decision-influencing perspective.

Effects of input biases on allocation type 1 appear to be sensitive to cost center sophistication while for cost category sophistication, no sensitivity can be observed. The results indicate that the extent of output errors decreases with increasing cost center sophistication. Effects of input biases on the basis for allocation type 1 do not appear to be sensitive to costing system sophistication from the decision-facilitating perspective (cf. Table 5.2).

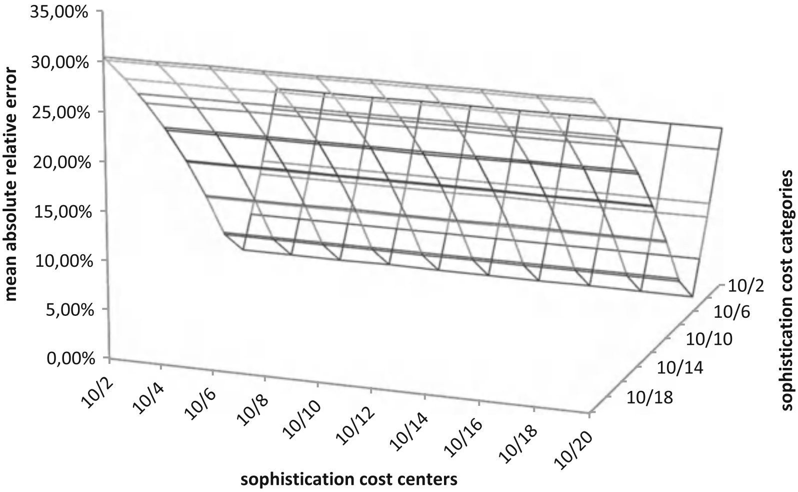

Fig. 5.6 Assignment of cost categories, decision-facilitating perspective

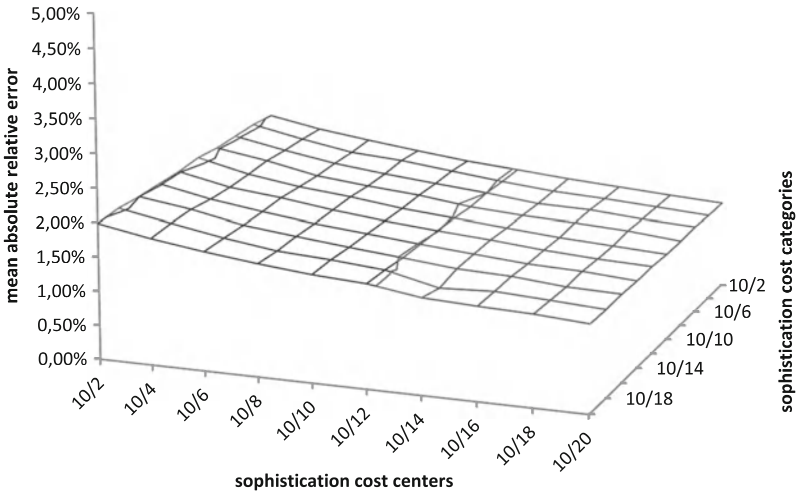

Fig. 5.7 Basis for allocation type 1, decision-influencing perspective

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Chapter 6
Effects of Single Input Biases on the Quality of Provided Information

Abstract This chapter analyzes the research question (2) "What are the effects of intended and unintended single biases in input data on the quality of decision-facilitating and decision-influencing information provided by costing systems?". While Chap. 5 concentrates on different levels of costing system sophistication and keeps parameterization of input biases constant, this chapter keeps the parameterization for the generation of costing systems constant and analyzes different setups for the input biases under investigation whereby each scenario considers one type of input bias. Section 6.1 gives the applied parameterization for generating costing systems and describes the method of data analysis. Sections 6.2 and 6.3 present the results of the simulation runs. Results are discussed in Chap. 8.

6.1 Simulation Experiments and Data Analysis

As in Chap. 5, the analysis of effects of single input biases assumes one unbiased costing benchmark and a set of simulation runs in which biased data is introduced into the costing system. Parameterization for the generation of costing systems is kept constant throughout all simulation runs (for the parameterization cf. Table 6.1). With respect to measures for costing system sophistication introduced in Chap. 5, cost center sophistication $soph^{cent} = 1$ and cost category sophistication $soph^{cat} = 0.833$ (cf. also Sect. 5.1).

This investigation gives multiple measures for the quality of provided information. First, this investigation follows Christensen and Demski (1997) and presents the mean absolute relative error as introduced in Chap. 5, cf. Eq. 5.4 for mean absolute relative errors from the decision-influencing perspective and Eq. 5.5 for the error measure calculated from the decision-facilitating perspective. Second, this investigation follows Babad and Balachandran (1993), Hwang et al. (1993), Homburg (2001) and Labro and Vanhoucke (2007, 2008) and presents the Euclidean Distance as a more condensed measure for information quality. The Euclidean Distance for the decision-influencing perspective is calculated as

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Table 6.1 Parameterization for generating costing systems (single input biases)

Parameter	Denotation	Parameterization
Cost categories		
Cost categories	K	44
Direct cost categories	K^{dir}	20
Indirect cost categories	K^{indir}	24
Direct cost pools	K^{dir}_{group}	10
Cost centers		
Cost centers	M	22
Direct cost centers with direct cost pools as basis for allocation type 3	$M^{dir^{dcp}}$	10
Direct cost centers with manufacturing costs as basis for allocation type 3	$M^{dir^{mc}}$	2
Indirect cost centers	M^{indir}	10
Cost drivers		
Cost drivers (type 2)	$\mathbf{R}$	10
Interval for cost drivers (type 2)	$U\left[\underline{a}_{cd^{type:2}};\overline{a}_{cd^{type:2}}\right]$	U [40,000; 80,000]
Business cases		
Business cases	BC	7,000
Interval for input cost objects	$U\left[\underline{a}_{bc};\overline{a}_{bc}\right]$	U [500; 5,000]
Differences in valuation		
Probability of occurrence	p_s	0.30
Interval for differences in valuation	$U\left[\underline{a}_{s};\overline{a}_{s}\right]$	U [−0.35; 0.35]
Provided information		
Interval for decision-facilitating information	$U\left[\underline{a}_{prod};\overline{a}_{prod}\right]$	U [500; 5,000]

$$EUCD_n^{di} = \sqrt{\sum_{i=1}^{|M^{dir}|}\sum_{j=1}^{|CO_{out}|} {e_{i,j,n}^{di}}^2}\,, \tag{6.1}$$

whereby index n gives the type of input bias from the set of biases B, index i stands for direct cost centers M^{dir} and index j stands for simulation runs CO_{out}. For the relative error measure $e_{i,j,n}^{di}$ cf. Eq. 5.2. For the decision-facilitating perspective, the Euclidean Distance is calculated according to

$$EUCD_n^{df} = \sqrt{\sum_{j=1}^{|CO_{out}|} {e_{j,n}^{df}}^2}\,. \tag{6.2}$$

As in case of the decision-influencing perspective, index n stands for types of input biases B and index j stands for the simulation runs CO_{out}. For the calculation of the relative error measure $e_{j,n}^{df}$ cf. Eq. 5.3.

Third and in addition to the measures for information quality introduced above, this simulation study presents a measure which is similar to the measure applied by Datar and Gupta (1994), i.e. the root of the mean squared error. For the decision-influencing perspective, this measure is calculated as

$$MSE_n^{di} = \sqrt{\frac{1}{|M^{dir}| \cdot |CO_{out}|} \sum_{i=1}^{|M^{dir}|} \sum_{j=1}^{|CO_{out}|} {e_{i,j,n}^{di}}^2}\,. \tag{6.3}$$

For the decision-facilitating perspective, the root of the mean squared error results as

$$MSE_n^{df} = \sqrt{\frac{1}{|CO_{out}|} \sum_{j=1}^{|CO_{out}|} {e_{j,n}^{df}}^2}\,, \tag{6.4}$$

whereby n indicates types of input biases B, index i stands for direct cost centers M^{dir} and index j gives the simulation runs CO_{out}. Relative error measures are introduced in Eqs. 5.2 and 5.3.

As all these measures are symmetric and do not give any information on the economic consequences of the respective types of input biases, this study also presents the probabilities for under- and overcosting. For the decision-influencing perspective the probability for undercosting $p_n^{under,di}$ (i.e. $e_{i,j,n}^{di} < 0$) and the probability for overcosting $p_n^{over,di}$ (i.e. $e_{i,j,n}^{di} > 0$) are based on the relative error measure $e_{i,j,n}^{di}$ (cf. Eq. 5.2). For the decision-facilitating perspective, the probability for undercosting $p_n^{under,df}$ (i.e. $e_{j,n}^{di} < 0$) and the probability of overcosting $p_n^{over,df}$ (i.e. $e_{j,n}^{df} > 0$) are based on the relative error measure $e_{j,n}^{df}$ (cf. Eq. 5.3).

In addition, the extreme values for relative errors are presented, i.e., the maximum negative and the maximum positive relative errors are reported. For the decision-influencing perspective, the maximum negative relative error is denoted as $\underline{e}_n^{di}$ and the maximum positive relative error is given by $\overline{e}_n^{di}$ whereby the determination of the two extreme values is based on relative errors $e_{i,j,n}^{di}$ (cf. Eq. 5.2). Correspondingly, for the decision-facilitating perspective the maximum negative relative error is denoted as $\underline{e}_n^{df}$ and the maximum positive relative error is denoted as $\overline{e}_n^{df}$, whereby the two extreme values are based on relative errors $e_{j,n}^{df}$ (cf. Eq. 5.3).

In the presentation of the results, Sects. 6.2 and 6.3 focus on the mean absolute relative error, the Euclidean Distance and probabilities for under- and overcosting. The remaining measures on effects of single input biases (i.e., root of the mean squared error, maximum negative and maximum positive relative error) are given in Appendix B. Parameterization of input biases is given in the subsequent tables.

6.2 Single Input Biases Ex-Ante to Operations

Results regarding the effects of single input biases that occur ex-ante to operations are presented in Table 6.2 for the decision-influencing perspective and in Table 6.2 for the decision-facilitating perspective.

For the decision-influencing perspective, results indicate that the highest extent of distortion occurs in case of input biases on the categorization of cost categories followed by input biases on the building of direct cost pools, the assignment of direct cost pools and the categorization of cost centers. The lowest extent of distortion can be observed for input biases on the assignment of cost drivers for allocation type 2. Input biases on the categorization of cost categories tend to lead to overcosting while input biases on the categorization of cost categories and input biases on the assignment of cost drivers for allocation type 2 appear to lead to under- and overcosting with almost the same probability. Input biases on the building and the assignment of direct cost appear not to lead to distortions in all cases (i.e., the probability of undercosting $p_n^{under,di}$ plus the probability of overcosting $p_n^{over,di}$ is <1). This is due to the fact that for the decision-influencing perspective, the probabilities for under- and overcosting are calculated on the basis of relative errors per cost-center. Biases in the building of direct cost pools and the assignment of direct cost pools do not affect all existing cost centers but a subset of cost centers. Thus, these two input biases do not lead to distortions in provided information in some cost centers. Consequently, with increasing probability of occurrence for the two types of input bias, the number of cost centers where no bias can be observed decreases. However, input biases on the building and the assignment of direct cost pools tend to lead to under- and overcosting with almost the same probability. Additional information on simulation results from the decision-influencing perspective of biases which occur ex-ante to operations (i.e., root of the mean squared relative error and maximum negative and maximum positive relative error) are given in Appendix B, Table B.1.

For the decision-facilitating perspective, except for input biases on the categorization of cost categories, results suggest the extent of distortion to be lower than in case of decision-influencing information. It has to be noted that due to the different calculation modes, the effects of input biases in the decision-influencing and in the decision-facilitating perspective cannot be compared on the basis of the Euclidean Distance but on the basis of the mean absolute relative error and on the basis of the root of the mean squared error. As in the case of decision-influencing information, input biases on the categorization of cost categories lead to the highest extent of distortion, followed by input biases on the building of direct cost pools, the assignment of cost categories, the categorization of cost centers and the assignment of cost drivers for allocation type 2. As in case of the decision-

Table 6.2 Single input biases ex-ante to operations, decision-influencing perspective

Prob. of occurrence[a]	Interval	Mean abs. rel. error[b]	Euclidean Distance[c]	Prob. of undercosting[d]	Prob. of overcosting[d]
Categorization of cost centers[1]					
0.10	–	0.0049	3.9652	0.5046	0.4954
0.20	–	0.0079	5.6051	0.4980	0.5020
0.30	–	0.0105	6.8284	0.4989	0.5011
Categorization of cost categories[2]					
0.10	–	0.0485	22.2804	0.1559	0.8428
0.20	–	0.0787	31.8948	0.2662	0.7338
0.30	–	0.0981	39.1047	0.3434	0.6566
Building of direct cost pools[3]					
0.10	–	0.0081	6.8043	0.2258	0.2199
0.20	–	0.0138	9.0993	0.3074	0.2983
0.30	–	0.0178	10.5520	0.3551	0.3475
Assignment of direct cost pools[1]					
0.10	–	0.0049	5.6801	0.1581	0.1504
0.20	–	0.0096	7.9430	0.2321	0.2240
0.30	–	0.0143	9.6129	0.3015	0.2947
Assignment of cost drivers for allocation type 2[4]					
0.10	–	0.0047	2.4122	0.4985	0.5015
0.20	–	0.0066	3.3227	0.5004	0.4996
0.30	–	0.0079	3.9268	0.4993	0.5007

In all cases index n stands for types of input biases B

Each number is based on 10,000 simulation runs (100 randomly generated costing system structures each with 100 simulation runs)

Confidence intervals for relative errors with $\alpha = 0.001$:

[1] [0.0001;0.0002]

[2] [0.0003;0.0006]

[3] 0.0002

[4] 0.0001

[a] Probability of occurrence p_n

[b] Mean absolute relative error $e_n^{mean,di}$, cf. also Eq. 5.4

[c] Euclidean Distance $EUCD_n^{di}$, cf. also Eq. 6.1

[d] Probability of undercosting $p_n^{under,di}$

[e] Probability of overcosting $p_n^{over,di}$

influencing perspective, input biases on the categorization of cost categories tend to lead to overcosting while the remaining types of biases appear to lead to under- and overcosting with almost the same probability. The root of the mean squared error and the maximum positive and the maximum negative error are given in Appendix B, Table B.2 (Table 6.3).

Table 6.3 Single input biases ex-ante to operations, decision-facilitating perspective

Prob. of occurrence[a]	Interval	Mean abs. rel. error[b]	Euclidean Distance[c]	Prob. of undercosting[d]	Prob. of overcosting[d]
Categorization of cost centers[1]					
0.10	–	0.0011	0.1832	0.4983	0.5017
0.20	–	0.0018	0.2606	0.4905	0.5095
0.30	–	0.0023	0.3272	0.4999	0.5001
Categorization of cost categories[2]					
0.10	–	0.0637	7.3173	0.0004	0.9984
0.20	–	0.1201	13.1304	0.0000	1.0000
0.30	–	0.1700	18.2563	0.0000	1.0000
Building of direct cost pools[3]					
0.10	–	0.0034	0.5635	0.5047	0.4898
0.20	–	0.0051	0.7524	0.5038	0.4962
0.30	–	0.0063	0.8827	0.5023	0.4977
Assignment of direct cost pools[4]					
0.10	–	0.0016	0.2751	0.4942	0.4921
0.20	–	0.0026	0.3838	0.5042	0.4958
0.30	–	0.0034	0.4696	0.4993	0.5007
Assignment of cost drivers for allocation type 2[5]					
0.10	–	0.0008	0.1121	0.5038	0.4962
0.20	–	0.0012	0.1552	0.5110	0.4890
0.30	–	0.0014	0.1821	0.4966	0.5034

In all cases index n stands for types of input biases B
Each number is based on 10,000 simulation runs (100 randomly generated costing system structures each with 100 simulation runs)
Confidence intervals for relative errors with $\alpha = 0.001$:
[1] 0.0001
[2] [0.0012;0.0022]
[3] [0.0002;0.0003]
[4] [0.0001;0.0002]
[5] $\leq$0.0001
[a] Probability of occurrence p_n
[b] Mean absolute relative error $e_n^{mean,df}$, cf. also Eq. 5.5
[c] Euclidean Distance $EUCD_n^{df}$, cf. also Eq. 6.2
[d] Probability of undercosting $p_n^{under,df}$
[e] Probability of overcosting $p_n^{over,df}$

6.3 Single Input Biases Ex-Post to Operations

Results of the simulation experiments on biases ex-post to operations are given in Table 6.4 for the decision-influencing perspective and in Table 6.5 for the decision-facilitating perspective.

Due to negligible differences in effects in case of some characterizations of input biases, some characterizations are pooled for further elaborations. In particular,

Table 6.4 Single input biases ex-post to operations, decision-influencing perspective

Prob. of occurrence[a]	Interval	Mean abs. rel. error[b]	Euclidean Distance[c]	Prob. of undercosting[d]	Prob. of overcosting[d]
Input cost objects, intentional (probability)[1]					
0.10	$U[-0.10; 0.00[$	0.0055	1.9209	1.0000	0.0000
0.20	$U[-0.10; 0.00[$	0.0110	3.8236	1.0000	0.0000
0.30	$U[-0.10; 0.00[$	0.0165	5.7295	1.0000	0.0000
Input cost objects, intentional (magnitude)[1]					
0.10	$U[-0.10; 0.00[$	0.0055	1.9209	1.0000	0.0000
0.10	$U[-0.20; 0.00[$	0.0105	3.6674	1.0000	0.0000
0.10	$U[-0.30; 0.00[$	0.0155	5.4147	1.0000	0.0000
Input cost objects, unintentional (probability)[1]					
0.10	$U[-0.10; 0.10]$	0.0006	0.2515	0.4985	0.5015
0.20	$U[-0.10; 0.10]$	0.0008	0.3551	0.5011	0.4989
0.30	$U[-0.10; 0.10]$	0.0010	0.4349	0.4981	0.5019
Input cost objects, unintentional (magnitude)[1]					
0.10	$U[-0.10; 0.10]$	0.0006	0.2515	0.4985	0.5015
0.10	$U[-0.20; 0.20]$	0.0011	0.5010	0.5022	0.4978
0.10	$U[-0.30; 0.30]$	0.0017	0.7517	0.4994	0.5006
Assignment of cost categories[2]					
0.10	–	0.0178	8.0539	0.4455	0.5545
0.20	–	0.0303	14.1907	0.4542	0.5458
0.30	–	0.0425	20.3187	0.4579	0.5421
Differences in valuation, unintentional (probability)[1]					
0.10	$U[-0.10; 0.10]$	0.0001	0.0280	0.5009	0.4992
0.20	$U[-0.10; 0.10]$	0.0001	0.0395	0.5005	0.4995
0.30	$U[-0.10; 0.10]$	0.0001	0.0486	0.5001	0.4999
Differences in valuation, unintentional (magnitude)[1]					
0.10	$U[-0.10; 0.10]$	0.0001	0.0280	0.5009	0.4992
0.10	$U[-0.20; 0.20]$	0.0001	0.0395	0.5013	0.4987
0.10	$U[-0.30; 0.30]$	0.0001	0.0482	0.4995	0.5005
Differences in valuation, not calculated[1]					
0.10	–	0.0011	0.4736	0.5380	0.4620
0.20	–	0.0015	0.6558	0.5538	0.4462
0.30	–	0.0018	0.7862	0.5626	0.4374
Basis for allocation type 1[3]					
0.10	–	0.0074	3.6249	0.4998	0.5002
0.20	–	0.0105	5.1181	0.5000	0.5000
0.30	–	0.0128	6.2503	0.4982	0.5018
Basis for allocation type 2, intentional (probability)[1]					
0.10	$U]0.00; 0.10]$	0.0007	0.3555	0.6811	0.3189
0.20	$U]0.00; 0.10]$	0.0010	0.4923	0.5942	0.4058
0.30	$U]0.00; 0.10]$	0.0012	0.5901	0.5699	0.4301
Basis for allocation type 2, intentional (magnitude)[1]					
0.10	$U]0.00; 0.10]$	0.0007	0.3555	0.6811	0.3189

(continued)

Table 6.4 (continued)

Prob. of occurrence[a]	Interval	Mean abs. rel. error[b]	Euclidean Distance[c]	Prob. of undercosting[d]	Prob. of overcosting[d]
0.10	$U]0.00; 0.20]$	0.0013	0.6865	0.6929	0.3071
0.10	$U]0.00; 0.30]$	0.0019	1.0164	0.6936	0.3064
Basis for allocation type 2, unintentional (probability)[1]					
0.10	$U[-0.10; 0.10]$	0.0006	0.3466	0.5018	0.4982
0.20	$U[-0.10; 0.10]$	0.0009	0.4819	0.4990	0.5010
0.30	$U[-0.10; 0.10]$	0.0011	0.5956	0.4978	0.5022
Basis for allocation type 2, unintentional (magnitude)[1]					
0.10	$U[-0.10; 0.10]$	0.0006	0.3466	0.5018	0.4982
0.10	$U[-0.20; 0.20]$	0.0011	0.6863	0.4986	0.5014
0.10	$U[-0.30; 0.30]$	0.0016	1.0384	0.4932	0.5068

In all cases index n stands for types of input biases B

Each number is based on 10,000 simulation runs (100 randomly generated costing system structures each with 100 simulation runs)

Confidence intervals for relative errors with $\alpha = 0.001$:

[1] <0.0001

[2] [0.0001;0.0002]

[3] 0.0001

[a] Probability of occurrence p_n

[b] Mean absolute relative error $e_n^{mean,di}$, cf. also Eq. 5.4

[c] Euclidean Distance $EUCD_n^{di}$, cf. also Eq. 6.1

[d] Probability of undercosting $p_n^{under,di}$

[e] Probability of overcosting $p_n^{over,di}$

for *input biases on input cost objects* from the decision-influencing perspective, results suggest that it does not make a significant difference whether the parameter probability of occurrence of magnitude of bias are varied. Thus, for further elaborations input biases on input cost objects are differentiated into intended and unintended input biases with no further differentiation. With respect to the extent of distortion in decision-influencing information, for *input biases on the basis for allocation type 2* it makes just a slight differences whether the parameter probability of occurrence or magnitude of bias is varied. Slight differences in the probabilities for under- and overcosting between intended and unintended input biases on the basis for allocation type 2 can be observed. Hence, further elaborations do not distinguish between types of biases on the basis of whether the input bias varies in the probability of occurrence or the magnitude of bias but on the basis of whether the bias is introduced intendedly or unintendedly.

For the decision-influencing perspective, results indicate that input biases on the assignment of cost categories lead to the highest extent of distortion followed by input biases on the basis for allocation type 1, on input cost object (intended), on differences in valuation (not calculated), on the basis for allocation type 2, on input cost objects (unintended) and on differences in valuation (unintended). Presented results on directions of biases suggest that input biases on input cost

Table 6.5 Single input biases ex-post to operations, decision-facilitating perspective

Prob. of occurrence[a]	Interval	Mean abs. rel. error[b]	Euclidean Distance[c]	Prob. of undercosting[d]	Prob. of overcosting[d]
Input cost objects, intentional (probability)[1]					
0.10	$U[-0.10; 0.00[$	0.0002	0.0285	0.4983	0.5017
0.20	$U[-0.10; 0.00[$	0.0003	0.0381	0.4830	0.5170
0.30	$U[-0.10; 0.00[$	0.0004	0.0447	0.4946	0.5054
Input cost objects, intentional (magnitude)[1]					
0.10	$U[-0.10; 0.00[$	0.0002	0.0285	0.4983	0.5017
0.10	$U[-0.20; 0.00[$	0.0004	0.0547	0.5044	0.4956
0.10	$U[-0.30; 0.00[$	0.0006	0.0816	0.4935	0.5065
Input cost objects, unintentional (probability)[1]					
0.10	$U[-0.10; 0.10]$	0.0002	0.0275	0.5025	0.4975
0.20	$U[-0.10; 0.10]$	0.0003	0.0389	0.4912	0.5088
0.30	$U[-0.10; 0.10]$	0.0004	0.0485	0.5033	0.4967
Input cost objects, unintentional (magnitude)[1]					
0.10	$U[-0.10; 0.10]$	0.0002	0.0275	0.5025	0.4975
0.10	$U[-0.20; 0.20]$	0.0004	0.0557	0.5052	0.4948
0.10	$U[-0.30; 0.30]$	0.0007	0.0827	0.4978	0.5022
Assignment of cost categories[2]					
0.10	–	0.0299	3.0754	0.0000	1.0000
0.20	–	0.0613	6.2197	0.0000	1.0000
0.30	–	0.0943	9.5378	0.0000	1.0000
Differences in valuation, unintentional (probability)[1]					
0.10	$U[-0.10; 0.10]$	0.0000	0.0031	0.5057	0.4943
0.20	$U[-0.10; 0.10]$	0.0000	0.0043	0.5001	0.4999
0.30	$U[-0.10; 0.10]$	0.0000	0.0054	0.5033	0.4967
Differences in valuation, unintentional (magnitude)[1]					
0.10	$U[-0.10; 0.10]$	0.0000	0.0031	0.5057	0.4943
0.10	$U[-0.20; 0.20]$	0.0000	0.0044	0.4989	0.5011
0.10	$U[-0.30; 0.30]$	0.0000	0.0053	0.4902	0.5098
Differences in valuation, not calculated[1]					
0.10	–	0.0004	0.0520	0.5100	0.4900
0.20	–	0.0006	0.0716	0.4972	0.5028
0.30	–	0.0007	0.0866	0.5056	0.4944
Basis for allocation type 1[3]					
0.10	–	0.0013	0.1736	0.4999	0.5001
0.20	–	0.0019	0.2492	0.5181	0.4819
0.30	–	0.0024	0.3032	0.5121	0.4879
Basis for allocation type 2, intentional (probability)[1]					
0.10	$U]0.00; 0.10]$	0.0001	0.0169	0.5475	0.4525
0.20	$U]0.00; 0.10]$	0.0002	0.0238	0.5343	0.4657
0.30	$U]0.00; 0.10]$	0.0002	0.0276	0.5306	0.4694
Basis for allocation type 2, intentional (magnitude)[1]					
0.10	$U]0.00; 0.10]$	0.0001	0.0169	0.5475	0.4525

(continued)

Table 6.5 (continued)

Prob. of occurrence[a]	Interval	Mean abs. rel. error[b]	Euclidean Distance[c]	Prob. of undercosting[d]	Prob. of overcosting[d]
0.10	$U]0.00; 0.20]$	0.0002	0.0333	0.5484	0.4516
0.10	$U]0.00; 0.30]$	0.0004	0.0491	0.5549	0.4451
Basis for allocation type 2, unintentional (probability)[1]					
0.10	$U[-0.10; 0.10]$	0.0001	0.0167	0.5047	0.4953
0.20	$U[-0.10; 0.10]$	0.0002	0.0236	0.4965	0.5035
0.30	$U[-0.10; 0.10]$	0.0002	0.0289	0.5021	0.4979
Basis for allocation type 2, unintentional (magnitude)[1]					
0.10	$U[-0.10; 0.10]$	0.0001	0.0167	0.5047	0.4953
0.10	$U[-0.20; 0.20]$	0.0002	0.0326	0.5028	0.4972
0.10	$U[-0.30; 0.30]$	0.0004	0.0494	0.4998	0.5002

In all cases index n stands for types of input biases B
Each number is based on 10,000 simulation runs (100 randomly generated costing system structures each with 100 simulation runs)
Confidence intervals for relative errors with $\alpha = 0.001$:
[1] <0.0001
[2] [0.0002;0.0005]
[3] 0.0001
[a] Probability of occurrence p_n
[b] Mean absolute relative error $e_n^{mean,df}$, cf. also Eq. 5.5
[c] Euclidean Distance $EUCD_n^{df}$, cf. also Eq. 6.2
[d] Probability of undercosting $p_n^{under,df}$
[e] Probability of overcosting $p_n^{over,df}$

objects (intended) lead to undercosting in all cases and input biases on the basis for allocation type 2 (intended) tend to lead to undercosting. The remaining types of biases appear to lead to under- and overcosting with almost the same probabilities. Further information on effects of biases ex-post to operations on the quality of decision-influencing information is given in Appendix B, Table B.3.

With the exception of input biases on the assignment of cost categories, for the decision-facilitating perspective results suggest the extent of distortions to be lower than from the decision-influencing perspective. As in the case of decision-influencing information, due to negligible differences in mean absolute relative errors and Euclidean Distances, further elaborations do not distinguish between biases on the basis of variations in probability of occurrence and magnitude of bias in the case of intended and unintended input biases on input cost objects and intended and unintended input biases on the basis for allocation type 2.

As in the case of decision-influencing information, results indicate that input biases on the assignment of cost categories lead to the highest extent of distortion followed by input biases on the basis for allocation type 2. The third-highest extent of distortion can be observed in the case of input biases on differences in valuation (not calculated). For the remaining types of biases the relative errors are so low that observable differences are negligible. Presented probabilities for the direction of bias suggest that input biases on the assignment of cost categories lead to overcosting while for the remaining types of biases, an almost equal probability for under- and overcosting can be observed. Additional information on effects of biases ex-post to operations on the quality of decision-facilitating information is given in Appendix B, Table B.4.

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Chapter 7
Effects of Multiple Input Biases on the Quality of Provided Information

Abstract This chapter analyzes the research question (3) "What are the effects of interactions among multiple intended and unintended biases in input data on the quality of decision-facilitating and decision-influencing information provided by costing systems?". As in Chap. 6, this chapter analyzes different levels of distortion in input data whereby, in contrast to Chap. 6, results on multiple input biases are presented. For this chapter, the parameterization for generating costing systems is kept constant during the simulation runs. Section 7.1 gives the parameterization and the method of data analysis. Section 7.2 presents results regarding interactions among biases and Sect. 7.3 focuses on potential compensations among biases in costing systems. Results are discussed in Chap. 8.

7.1 Simulation Experiments and Data Analysis

As in Chaps. 5 and 6, the analysis of results on multiple input biases assumes one unbiased costing benchmark (i.e., all data is introduced into the costing system without distortion). Parameterization for generating costing systems corresponds to Chap. 6 (cf. Table 6.1). Referring to measures for costing system sophistication introduced in Chap. 5, cost center sophistication $soph^{cent} = 1$ and cost category sophistication $soph^{cat} = 0.833$ (cf. also Sect. 5.1).

In the following, the denotation introduced in Chaps. 5 and 6 is expanded by subscript q which, in addition to subscript n, indicates input biases, where $n \neq q$. In the case of input biases n and q, relative errors introduced in Eqs. 5.2 and 5.3 result as

$$e^{di}_{i,j,n,q} = \frac{costs^{prod,di,bench}_{i,j} - costs^{prod,di}_{i,j,n,q}}{costs^{prod,di,bench}_{i,j}}\ , \tag{7.1}$$

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for the decision-influencing perspective and as

$$e^{df}_{j,n,q} = \frac{costs^{prod,df,bench}_{j} - costs^{prod,df}_{j,n,q}}{costs^{prod,df,bench}_{j}} \tag{7.2}$$

for the decision-facilitating perspective. Costs that stem from benchmark scenarios are denoted as $costs^{prod,di,bench}_{i,j}$ for the decision-influencing perspective and $costs^{prod,df,bench}_{j}$ for the decision-facilitating perspective. Index $i \in \{1, \ldots, |M^{dir}|\}$ indicates the cost centers and $j \in \{1, \ldots, |CO_{out}|\}$ indicates the simulation runs. In addition to elements of the set of errors under investigation B, 0 is also a potential characterization for subscripts n and q which denotes that there is no bias n or q introduced. Consequently, $e^{di}_{i,j,n,q=0}$ stands for the relative error from a decision-influencing perspective that is due to input bias n and occurred at cost center m_i at simulation run j. Measure $e^{di}_{i,j,n=0,q}$ denotes the corresponding relative error in the case of input bias q and $e^{di}_{i,j,n,q}$ stands for the corresponding relative error in the case of input bias n and q. Relative errors for the decision-facilitating perspective are denoted correspondingly.

The analysis applied in this chapter is primarily based on the Euclidean Distance introduced in Eqs. 6.1 and 6.2. In case of multiple input biases, the Euclidean Distance results as

$$EUCD^{di}_{n,q} = \sqrt{\sum_{i=1}^{|M^{dir}|} \sum_{j=1}^{|CO_{out}|} {e^{di}_{i,j,n,q}}^{2}}. \tag{7.3}$$

for the decision-influencing perspective. For the decision-facilitating perspective the Euclidean Distance is calculated as

$$EUCD^{df}_{n,q} = \sqrt{\sum_{j=1}^{|CO_{out}|} {e^{df}_{j,n,q}}^{2}}. \tag{7.4}$$

In order to express interactions among biases, this chapter introduces two measures that are based on the Euclidean Distance introduced in Eqs. 7.3 and 7.4, i.e., measures for (1) interaction among biases and (2) potential compensation among biases. The (1) measure for interaction among biases results as

$$\rho^{di}_{n,q} = \frac{EUCD^{di}_{n,q}}{EUCD^{di}_{n,q=0} + EUCD^{di}_{n=0,q}}, \tag{7.5}$$

for the decision-influencing perspective and as

$$\rho^{df}_{n,q} = \frac{EUCD^{df}_{n,q}}{EUCD^{df}_{n,q=0} + EUCD^{df}_{n=0,q}}, \tag{7.6}$$

for the decision-facilitating perspective. Consequently, if the measures for interaction $\rho^{di}_{n,q}$ or $\rho^{df}_{n,q}$ are >1, biases n and q reinforce each other regarding their effects on information quality from a decision-influencing or a decision-facilitating perspective. If the measures for interaction $\rho^{di}_{n,q}$ or $\rho^{df}_{n,q}$ are <1, biases n and q mitigate each other, i.e., the Euclidean Distance in the case of input bias n and q is lower than a notional Euclidean Distance with assumed linear interactions among biases n and q.

In order to illustrate a potential compensation among biases, this chapter introduces a (2) measure for compensation. For the decision-influencing perspective, this measure results as

$$\nu^{di}_{n,q} = \frac{EUCD^{di}_{n,q} - EUCD^{di}_{n,q=0}}{EUCD^{di}_{n,q=0}} . \tag{7.7}$$

Correspondingly, the measure for compensation among biases for the decision-facilitating perspective is calculated as

$$\nu^{df}_{n,q} = \frac{EUCD^{df}_{n,q} - EUCD^{df}_{n,q=0}}{EUCD^{df}_{n,q=0}} . \tag{7.8}$$

If the measures for compensation $\nu^{di}_{n,q}$ or $\nu^{df}_{n,q}$ are ≤ 0, effects of input bias n on information quality are compensated by interactions among biases n and q in the decision-influencing or in the decision-facilitating perspective. Consequently, if the measures for compensation $\nu^{di}_{n,q}$ or $\nu^{df}_{n,q}$ are >0, no compensation can be observed.

In addition to the measures for information quality and interactions among biases outlined above, this simulation study presents the mean absolute relative errors, the root of the mean squared error, probabilities for under- and overcosting as well as the maximum negative and the maximum positive error also for the case of multiple input biases. The following paragraphs elaborate the corresponding denotation for the case of multiple input biases.

The mean absolute relative errors are introduced in Chap. 5 for single input bias scenarios in order to analyze sensitivity of effects of input biases to costing system sophistication. With reference to Eqs. 5.4 and 5.5, for the case of multiple input biases the mean absolute relative errors are calculated as

$$e^{mean,di}_{n,q} = \frac{1}{|M^{dir}| \cdot |CO_{out}|} \sum_{i=1}^{|M^{dir}|} \sum_{j=1}^{|CO_{out}|} |e^{di}_{i,j,n,q}| \tag{7.9}$$

for the decision-influencing perspective and as

$$e^{mean,df}_{n,q} = \frac{1}{|CO_{out}|} \sum_{j=1}^{|CO_{out}|} |e^{df}_{j,n,q}| \tag{7.10}$$

for the decision-facilitating perspective.

The root of the mean squared errors is introduced in Chap. 6 for scenarios where one type of input bias is introduced into the costing systems (cf. Eqs. 6.3 and 6.4).

For cases where two biases are introduced into the costing system simultaneously, the root of the mean squared error for the decision-influencing perspective results as

$$MSE^{di}_{n,q} = \sqrt{\frac{1}{|M^{dir}| \cdot |CO_{out}|} \sum_{i=1}^{|M^{dir}|} \sum_{j=1}^{|CO_{out}|} e^{di}_{i,j,n,q}{}^{2}}\,. \tag{7.11}$$

For the decision-facilitating perspective the root of the mean squared error is calculated as

$$MSE^{df}_{n,q} = \sqrt{\frac{1}{|CO_{out}|} \sum_{j=1}^{|CO_{out}|} e^{df}_{j,n,q}{}^{2}}\,. \tag{7.12}$$

With reference to elaborations in Sect. 6.1, probabilities for under- and overcosting are presented. For the decision-influencing perspective, the probability of undercosting $p^{under,df}_{n,q}$ (i.e., $e^{di}_{i,j,n,q} < 0$) and the probability of overcosting $p^{over,di}_{n,q}$ (i.e., $e^{di}_{i,j,n,q} > 0$) are based on relative errors introduced in Eq. 7.1. For the decision-facilitating perspective, corresponding probabilities $p^{under,df}_{n,q}$ and $p^{over,df}_{n,q}$ are based on relative errors as introduced in Eq. 7.2.

In addition, maximum negative and maximum positive relative errors in case of input biases n and q are presented. For the decision-influencing perspective, the maximum negative relative error $\underline{e}^{di}_{n,q}$ and the maximum positive relative error $\overline{e}^{di}_{n,q}$ are based on relative errors as introduced in Eq. 7.1. For the decision-facilitating perspective, the determination of the extreme values is based on relative errors as introduced in Eq. 7.2. The corresponding maximum negative relative error is denoted as $\underline{e}^{df}_{n,q}$ and the corresponding maximum positive relative error is denoted as $\overline{e}^{df}_{n,q}$.

In the presentation of the results, Sects. 7.2 and 7.3 focus on the measures for interaction and compensation among biases. Additional information on the effects of multiple input biases on information quality (i.e., Euclidean Distance, mean absolute relative error, root of the mean squared error, probabilities for under- and overcosting and maximum negative and maximum positive error) are given in Appendix C. The parameterization of the various types of input biases is given in the respective tables.

7.2 Interactions Among Biases

This section presents results regarding interactions among biases. The following sections discuss effects of interactions among biases that occur ex-ante (Sect. 7.2.1) and ex-post to operations (Sect. 7.2.2) interacting with the other types of biases. An overview of interactions is given in Table 7.1 for the decision-influencing perspective and in Table 7.2 for the decision-facilitating perspective. The two tables present the measures for interactions among biases which are introduced in Eq. 7.5 for the decision-influencing perspective and in Eq. 7.6 for the decision-facilitating perspective.

According to elaborations in Sect. 6.3, some types of biases are pooled. In particular, for input biases on input cost objects it does not make a difference whether the parameter probability of occurrence or magnitude of bias is varied. Therefore, the presented results are based on input biases on input cost objects with variation in probability whereby a differentiation is made between intendedly and unintendedly introduced biases. Similarly, the following results are presented also for input biases on the basis for allocation type 2 for the cases of variation in probability whereby intended and unintended biasing behavior is differentiated.

7.2.1 Ex-Ante to Operations

This section outlines the effects of interactions of input biases that occur ex-ante to operations with other biases under investigation. The following elaborations are based on the measures for interaction given in Table 7.1 for the decision-influencing perspective and in Table 7.2 for the decision-facilitating perspective.

The results regarding the effects of multiple input biases on the accuracy of decision-influencing information suggest that *input biases on the categorization of cost centers* overproportionally interact with input biases on differences in valuation, i.e., interactions of these types of biases lead to a distortion of provided decision-influencing information that is higher than in the case of a fictional distortion with assumed linear interaction among biases. A (nearly) linear interaction can be observed for the combination with input biases on input cost objects (unintended). For the remaining combinations of input biases on the categorization of cost categories with other types of biases, a mitigation can be observed from the decision-influencing perspective. For the decision-facilitating perspective, results suggest a mitigation for all combinations of input biases on the categorization of cost centers with other types of biases.

For *input biases on the categorization of cost categories* in interaction with other types of biases under investigation, no overproportional interaction can be observed in the case of decision-influencing as well as in the case of decision-facilitating information. From the decision-influencing perspective, results suggest an (almost) linear interaction for the combination with unintended input biases on input cost objects, input biases on differences in valuation and intended and unintended input biases on the basis for allocation type 2. For the remaining combinations, a mitigation in case of decision-influencing information can be observed. In the case of decision-facilitating information, for the combination with input biases on differences in valuation and intended and unintended input biases on the basis for allocation type 2 a (nearly) linear interaction can be observed. With increasing probabilities of occurrence of the respective input biases, the measure for interaction increases towards 1. For the remaining scenarios, the results suggest a mitigation among biases even though in the majority of cases, the extent of mitigation is very low, i.e., the measure for interaction is >0.90.

For the decision-influencing perspective, results regarding interactions of *input biases on the building of direct cost pools* interacting with other biases suggest an almost linear interaction for the combination with input biases on differences in valuation. For the remaining scenarios, the results indicate a mitigation whereby in the cases of a combination with intended and unintended input biases on the basis for allocation type 2 and unintended input biases on input cost object only a slight mitigation can be observed. Similarly, for the decision-facilitating perspective, the results suggest a (nearly) linear interaction for the combination with input biases on differences in valuation and input biases on the basis for allocation type 2. With increasing probabilities of occurrence of the respective biases, in case of combination with input biases on differences in valuation, the measure for interaction increases and finally even indicates an overproportional interaction among biases. The results on the remaining scenarios indicate a mitigation among biases.

Simulation experiments on *input biases on the assignment of direct cost pools* interacting with other types of biases, indicate an overproportional interaction for the combination with input biases on differences in valuation from the decision-influencing perspective. The results on the remaining scenarios suggest a mitigation among biases for the decision-influencing as well as for the decision-facilitating perspective

Interactions of *input biases on the basis for allocation type 2* from the decision-influencing as well as in the decision-facilitating perspective appear to lead to a mitigation in all scenarios. A low extent of distortion can be observed for the combination with input biases on differences in valuation. With increasing probability of occurrence, interactions among input biases on the basis for allocation type 2 with input biases on differences in valuation appear to be closer to linear interactions, i.e., the measures for interactions increase towards 1.

7.2.2 Ex-Post to Operations

This section outlines interactions among biases that occur ex-post to operations with other types of biases. The measures for interaction, which build the basis for the following elaborations, are listed in Table 7.1 for the decision-influencing perspective and in Table 7.2 for the decision-facilitating perspective.

For the decision-influencing perspective, results suggest that *intended input biases on input cost objects* lead to (nearly) linear interactions in combination with input biases on differences in valuation. The simulation experiments on the remaining scenarios suggest a mitigation among biases in the case of decision-influencing information. For the decision-facilitating perspective, an almost linear interaction can be observed for the combination with input biases on the assignment of cost categories. Interactions with input biases on the categorization of cost categories

Table 7.1 Interactions among biases in costing systems, decision-influencing perspective

	Cat. of cost categories	Building of direct cost pools	Assignm. of direct cost pools	Assignm. cost drivers all. type 2	Input cost obj., intended[d]	Input cost obj., unintended[e]	Assignm. cost categories	Diff. in val. unintended[e]	Diff. in val., not calculated	Basis all. type 1	Basis all. type 2, intended[f]	Basis all. type 2, unintended[e]
Ex-ante to operations												
	0.8612[a]	0.7439	0.7034	0.7542	0.7581	1.0160	0.7592	1.0514	0.9349	0.6956	0.9525	0.9429
Cat. of cost centers	0.8635[b]	0.7355	0.6794	0.7545	0.7141	1.0085	0.7769	1.0044	0.9169	0.6824	0.9439	0.9448
	0.8662[c]	0.7222	0.6508	0.7423	0.7062	0.9873	0.7985	1.0422	0.9269	0.6659	0.9430	0.9414
		0.7975	0.8223	0.9064	0.9055	0.9871	0.7988	0.9955	0.9772	0.8634	0.9801	0.9809
Cat. of cost categories		0.7998	0.8263	0.9070	0.8652	0.9856	0.7591	0.9942	0.9803	0.8670	0.9816	0.9762
		0.8023	0.8317	0.9117	0.8338	0.9824	0.7208	1.0009	0.9823	0.8710	0.9817	0.9809
			0.7083	0.7892	0.8054	0.9675	0.7046	0.9985	0.9236	0.7461	0.9638	0.9726
Building of direct cost pools			0.7128	0.7890	0.7525	0.9547	0.7129	1.0378	0.9456	0.7393	0.9554	0.9595
			0.7161	0.7567	0.7258	0.9681	0.7227	1.0182	0.9442	0.7166	0.9208	0.9205
				0.8082	0.7896	0.9930	0.7363	1.0186	0.9191	0.7035	0.9445	0.9477
Assignm. of direct cost pools				0.7913	0.7371	0.9686	0.7439	1.0245	0.9427	0.6811	0.9599	0.9545
				0.8014	0.7169	0.9784	0.7630	1.0040	0.9392	0.6601	0.9595	0.9542

(continued)

Table 7.1 (continued)

	Cat. of cost categories	Building of direct cost pools	Assignm. of direct cost pools	Assignm. cost drivers all. type 2	Input cost obj., intended[d]	Input cost obj., unintended[e]	Assignm. cost categories	Diff. in val. unintended[e]	Diff. in val., not calculated	Basis all. type 1	Basis all. type 2, intended[f]	Basis all. type 2, unintended[e]
Assign. cost drivers all. type 2					0.7023	0.9018	0.8065	0.9754	0.8369	0.7173	0.8696	0.8823
					0.7052	0.9024	0.8433	0.9734	0.8433	0.7311	0.8780	0.8826
					0.7163	0.8983	0.8652	0.9888	0.8505	0.7364	0.8816	0.8822
Ex-post to operations												
Input cost obj., intended[d]							0.7737	0.9861	0.8437	0.7384	0.8583	0.8605
							0.7510	0.9904	0.8814	0.7057	0.8933	0.8954
							0.7375	0.9914	0.9027	0.6980	0.9108	0.9107
Input cost obj., unintended[e]							0.9634	0.9036	0.7414	0.9385	0.7114	0.7108
							0.9752	0.9052	0.7392	0.9395	0.7167	0.7232
							0.9750	0.9059	0.7367	0.9428	0.7109	0.7151
Assignm. cost categories								0.9911	0.9410	0.7558	0.9613	0.9648
								1.0002	0.9642	0.7862	0.9736	0.9760
								0.9986	0.9723	0.8035	0.9776	0.9815

Diff.in val., unintended[e]	0.9910	0.9311	0.9222
	0.9879	0.9248	0.9335
	0.9983	0.9235	0.9328
Diff. in val., not calculated	0.8903	0.7165	0.7194
	0.8906	0.7116	0.7199
	0.8964	0.7150	0.7146
Basis all. type 1		0.9185	0.9145
		0.9158	0.9208
		0.9227	0.9208

Probabilities of occurrence for input biases (applies to the whole table):

[a] 0.10 for both biases
[b] 0.20 for both biases
[c] 0.30 for both biases; interval for biases
[d] $U[-0.10; 0.00[$
[e] $U[-0.10; 0.10]$
[f] $U]0; 0.10]$

Each number is based on 10.000 simulation runs (100 randomly generated costing system structures each with 100 simulation runs)

For more detailed results and confidence intervals for relative errors with $\alpha = 0.001$: cf. Tables C.1–C.13

Table 7.2 Interactions among biases in costing systems, decision-facilitating perspective

	Cat. of cost categories	Building of direct cost pools	Assignm. of direct cost pools	Assignm. cost drivers all. type 2	Input cost obj., intended[d]	Input cost obj., unintended[e]	Assignm. cost categories	Diff. in val. unintended[e]	Diff. in val., not calculated	Basis all. type 1	Basis all. type 2, intended[f]	Basis all. type 2, unintended[e]
Ex-ante to operations												
Cat. of cost centers	0.9548[a]	0.8149	0.6772	0.7305	0.8939	0.8388	0.9421	0.9675	0.7783	0.7034	0.9088	0.9138
	0.9753[b]	0.7872	0.6628	0.7393	0.8354	0.8299	0.9676	0.9641	0.7661	0.6693	0.9205	0.9094
	0.9772[c]	0.7554	0.6359	0.7085	0.8198	0.8201	0.9755	0.9279	0.7562	0.6372	0.9039	0.8960
Cat. of cost categories		0.9214	0.9388	0.9734	0.9787	0.9806	0.9120	0.9775	0.9787	0.9580	0.9841	0.9769
		0.9351	0.9658	0.9789	0.9801	0.9861	0.8666	0.9823	0.9695	0.9666	0.9913	0.9869
		0.9461	0.9678	0.9821	0.9765	0.9708	0.8159	1.0029	0.9775	0.9750	0.9913	0.9967
Building of direct cost pools			0.7580	0.8788	0.9637	0.9312	0.8518	0.9293	0.8962	0.8030	1.0003	0.9921
			0.7441	0.8886	0.9082	0.9274	0.9038	1.0244	0.9043	0.8071	1.0006	0.9983
			0.7217	0.8171	0.9119	0.9151	0.9220	1.0176	0.8938	0.7664	0.9110	0.9290
Assignm. of direct cost pools				0.7432	0.9249	0.8353	0.9166	0.9261	0.7945	0.6639	0.8965	0.8791
				0.7723	0.8774	0.8328	0.9482	0.9576	0.7940	0.6618	0.8915	0.8913
				0.7848	0.8753	0.8486	0.9654	0.9182	0.8013	0.6450	0.9266	0.9059
Assign. cost drivers all. type 2					0.8474	0.8264	0.9617	0.9448	0.7611	0.7259	0.8988	0.8962
					0.8422	0.8222	0.9834	0.9929	0.7548	0.7187	0.8982	0.8950
					0.8482	0.7989	0.9878	1.0157	0.7655	0.7315	0.9109	0.9077

Ex-post to operations						
Input cost obj., intended[d]	0.9942	0.8958	0.7354	0.8680	0.7204	0.7347
	0.9934	0.9026	0.7531	0.8756	0.7242	0.7277
	0.9989	0.9077	0.7465	0.8796	0.7319	0.7203
Input cost obj., unintended[e]	0.9886	0.9104	0.7478	0.8791	0.7283	0.7262
	0.9951	0.9161	0.7489	0.8630	0.7241	0.7309
	0.9973	0.9036	0.7359	0.8690	0.7255	0.7207
Assignm. cost categories		0.9915	0.9764	0.9427	0.9916	0.9950
		0.9996	0.9874	0.9670	1.0024	1.0023
		1.0085	0.9917	0.9751	1.0042	1.0079
Diff.in val., unintended[e]				0.9682	0.8628	0.8471
				0.9608	0.8574	0.8475
				0.9732	0.8555	0.8549
Diff. in val., not calculated				0.7872	0.7967	0.7902
				0.7878	0.7972	0.7856
				0.7952	0.7893	0.7876
Basis all. type 1					0.9122	0.9195
					0.8857	0.8894
					0.8991	0.9044

Probabilities of occurrence for input biases (applies to the whole table):

[a] 0.10 for both biases
[b] 0.20 for both biases
[c] 0.30 for both biases; interval for biases
[d] $U[-0.10; 0.00[$
[e] $U[-0.10; 0.10]$
[f] $U]0; 0.10]$

Each number is based on 10.000 simulation runs (100 randomly generated costing system structures each with 100 simulation runs)
For more detailed results and confidence intervals for relative errors with $\alpha = 0.001$: cf. Tables C.1–C.13

appear to lead to a slight extent of mitigation. As in the case of decision-influencing information, the results on the remaining cases suggest a mitigation among biases.

For *unintended input biases on input cost objects* interacting with other types of biases, from the decision-influencing perspective, results indicate a (nearly) linear interaction for the combination with input biases on the categorization of cost centers and the categorization of cost categories. For the remaining scenarios, a mitigation can be observed for interactions in the case of decision-influencing information even though the extent of mitigation is very low in some cases. From the decision-facilitating perspective, for interactions with input biases on the assignment of cost categories, the results almost suggest linearity. For the remaining scenarios, the results indicate a mitigation among biases whereby, as from the decision-influencing perspective, some scenarios only lead to a slight extent of mitigation.

From the decision-influencing perspective, the results on *input biases on the assignment of cost categories* interacting with input biases on differences in valuation suggest (nearly) linear interactions. For the remaining scenarios, the results suggest a mitigation among biases for the decision-influencing perspective, whereby the results regarding the case of combination with input biases on differences in valuation (not calculated) suggest that increasing the probabilities of occurrence of the respective input biases leads to the measure of interaction increasing towards 1, i.e., the interactions become more like a linear interaction with increasing probabilities of occurrence. In the case of decision-facilitating information, for more combinations of biases (nearly) linear interactions can be observed. For the cases of combination with intended and unintended input biases on input cost objects, all variations of input biases on differences in valuation and intended and unintended input biases on the basis for allocation type 2, the results suggest a linear interaction. The results on the remaining scenarios suggest a mitigation among biases.

From the decision-influencing perspective, for *input biases on differences in valuation* for the majority of cases a (nearly) linear interaction can be observed. For the combinations with input biases on the categorization of cost categories, the building of direct cost pools, intended input biases on input cost objects, input biases on the assignment of cost categories and input biases on the basis for allocation type 1, the results suggest a (nearly) linear interaction. For combinations with input biases on the assignment of direct cost pools and input biases on the categorization of cost centers, the results suggest an overproportional interaction. For the remaining scenarios a mitigation among biases can be observed. From the decision-facilitating perspective, linear interactions can be observed for the combinations with input biases on the categorization of cost centers, the building of direct cost pools and the assignment of cost categories. The remaining scenarios indicate a mitigation among biases.

From the decision-influencing perspective, *input biases on differences in valuation (not calculated)*, except for the case of combination with input biases on the categorization of cost categories, appear to interact underproportionally with other biases. The results regarding the combination with input biases on the categorization of cost categories suggest a (nearly) linear interaction. From the decision-facilitating perspective, the combination with input biases on the assignment of cost categories appear to lead to (nearly) linear interactions. Also from the decision-facilitating perspective, a mitigation among biases can be observed for the remaining scenarios.

For *input biases on the basis for allocation type 1*, from the decision-influencing as well as from the decision-facilitating perspective, the results indicate a mitigation among biases for all scenarios.

In the case of decision-influencing information, interactions of *intended and unintended input biases on the basis for allocation type 2* with other biases appear to lead to mitigation in the majority of cases. Only for the combination with input biases on the categorization of cost categories a (nearly) linear interaction can be observed. For the decision-facilitating perspective, in case of the combination with input biases on the categorization of cost categories, the building of direct cost pools and the assignment of cost categories, the results indicate a (nearly) linear interaction. For the remaining scenarios, the results suggest a mitigation among biases.

7.3 Compensation Among Biases

This section focuses on potential compensation among biases in costing systems. Section 7.3.1 focuses on whether or not interactions among biases which occur ex-ante to operations with other types lead to compensation with respect to their effects on information-quality. Section 7.3.2 presents results on potential compensation of biases which occur ex-post to operations. On overview of the presented results is given in Table 7.3 for the decision-influencing perspective and in Table 7.4 for the decision-facilitating perspective. The two tables present the measures for compensation among biases as introduced in Eqs. 7.7 and 7.8.

As in Sect. 7.2, some types of biases are pooled for the presentation of results on compensation among biases due to negligible differences in their effects on information quality (input biases on input cost objects and input biases on the basis for allocation type 2, cf. also Sect. 6.3).

7.3.1 Ex-Ante to Operations

From the decision-influencing perspective, a compensation for all levels of probability of occurrence can be observed for input biases on the categorization of cost categories and input biases on the assignment of cost drivers for allocation type 2. *Input biases on the categorization of cost categories* appear to be compensated by adding input biases on input cost objects, input biases differences in valuation and

Table 7.3 Compensation among biases in costing systems, decision-influencing perspective

	Cat. of cost centers	Cat. of cost categories	Building of direct cost pools	Assignm. of direct cost pools	Assignm. cost drivers all. type 2	Input cost obj., intended[d]	Input cost obj., unintended[e]	Assignm. cost categories	Diff. in val. unintended[e]	Diff. in val., not calculated	Basis all. type 1	Basis all. type 2, intended[f]	Basis all. type 2, unintended[e]
Ex-ante to operations													
Cat. of cost centers		4.7005[a]	1.0203	0.7109	0.2130	0.1254	0.0805	1.3012	0.0588	0.0465	0.3315	0.0379	0.0253
		4.7773[b]	0.9294	0.6422	0.2017	0.2012	0.0724	1.7437	0.0114	0.0242	0.3056	0.0268	0.0260
		4.8271[c]	0.8381	0.5669	0.1692	0.2987	0.0502	2.1744	0.0496	0.0336	0.2755	0.0245	0.0235
Cat. of cost categories	0.0145		0.0410	0.0320	0.0046	−0.0165	−0.0017	0.0876	−0.0032	−0.0020	0.0039	−0.0042	−0.0039
	0.0153		0.0280	0.0321	0.0015	−0.0311	−0.0034	0.0968	−0.0046	0.0005	0.0061	−0.0033	−0.0091
	0.0175		0.0189	0.0362	0.0033	−0.0441	−0.0067	0.0953	0.0022	0.0020	0.0102	−0.0035	−0.0041
Building of direct cost pools	0.1774	2.4087		0.2996	0.0690	0.0328	0.0032	0.5387	0.0026	−0.0121	0.1436	0.0141	0.0221
	0.1885	2.6032		0.3351	0.0771	0.0687	−0.0080	0.8247	0.0423	0.0137	0.1552	0.0071	0.0103
	0.1895	2.7758		0.3685	0.0383	0.1199	0.0080	1.1144	0.0228	0.0145	0.1411	−0.0277	−0.0276
Assignm. of direct cost pools	0.1944	3.0479	0.5568		0.1514	0.0566	0.0369	0.7804	0.0236	−0.0042	0.1525	0.0037	0.0056
	0.1588	3.1442	0.5294		0.1223	0.0920	0.0119	1.0730	0.0296	0.0206	0.1200	0.0194	0.0124
	0.1130	3.2152	0.5022		0.1288	0.1442	0.0226	1.3759	0.0091	0.0161	0.0892	0.0184	0.0133
Assign. cost drivers all. type 2	0.9939	8.2787	2.0154	1.7113		0.2615	−0.0042	2.4994	−0.0133	0.0012	0.7952	−0.0022	0.0091
	1.0272	8.6131	1.9497	1.6829		0.5168	−0.0012	3.4449	−0.0151	0.0097	0.8573	0.0081	0.0105
	1.0331	8.9908	1.7902	1.7633		0.7614	−0.0023	4.3420	0.0011	0.0208	0.9086	0.0140	0.0160

Ex-post to operations													
Input cost obj., intended[d]	1.3232	10.4080	2.6585	2.1244	0.5842			3.0178	0.0004	0.0517	1.1320	0.0172	0.0158
	0.7608	7.0823	1.5431	1.2684	0.3181			2.5380	0.0007	0.0326	0.6504	0.0083	0.0083
	0.5478	5.5243	1.0625	0.9198	0.2072			2.3531	−0.0002	0.0265	0.4594	0.0046	0.0053
Input cost obj., unintended[e]	16.0330	87.4245	26.1390	22.4166	8.5497			30.8098	0.0041	1.1374	13.4630	0.7168	0.6902
	15.9299	88.5269	24.4229	21.6372	8.3475			38.9502	0.0060	1.1047	13.4820	0.7103	0.7046
	15.4904	88.3192	23.4583	21.6051	8.0094			45.5322	0.0072	1.0686	13.4932	0.6754	0.6944
Assignm. cost categories	0.1330	2.0087	0.2999	0.2556	0.0481	−0.0418	−0.0066		−0.0055	−0.0036	0.0960	0.0037	0.0063
	0.0837	1.4651	0.1700	0.1603	0.0408	−0.0467	−0.0004		0.0030	0.0088	0.0698	0.0074	0.0091
	0.0668	1.1080	0.0980	0.1240	0.0324	−0.0545	−0.0041		0.0010	0.0100	0.0507	0.0060	0.0103
Diff.in val., unintended[e]	149.1140	793.0679	242.9068	206.8797	84.1009	67.7096	8.0303	285.3876			128.4295	11.7657	11.3502
	142.4963	802.6086	239.0639	205.9991	81.8375	95.8462	8.0406	359.2698			127.9619	11.4472	11.3193
	146.4302	805.1059	221.0099	198.5247	79.8596	116.8321	8.0095	417.3505			128.3491	11.1326	11.3600
Diff. in val., not calculated	7.7619	45.9497	13.1930	10.9424	4.0993	3.2653	0.1352	15.9434			6.7047	0.2543	0.2458
	7.7537	47.6578	13.0651	11.3605	4.1157	5.0201	0.1394	20.8280			6.8407	0.2458	0.2489
	7.9774	48.8394	12.6165	11.4232	4.0983	6.4807	0.1442	25.1016			7.0226	0.2517	0.2559

(continued)

Table 7.3 (continued)

	Cat. of cost centers	Cat. of cost categories	Building of direct cost pools	Assignm. of direct cost pools	Assignm. cost drivers all. type 2	Input cost obj., intended[d]	Input cost obj., unintended[e]	Assignm. cost categories	Diff. in val. unintended[e]	Diff. in val., not calculated	Basis all. type 1	Basis all. type 2, intended[f]	Basis all. type 2, unintended[e]
	0.4564	5.1704	1.1466	0.8060	0.1946	0.1297	0.0036	1.4352	−0.0014	0.0067		0.0085	0.0019
Basis all. type 1	0.4298	5.2698	1.0538	0.7382	0.2058	0.2330	0.0047	1.9662	−0.0045	0.0047		0.0039	0.0075
	0.3935	5.3205	0.9265	0.6752	0.1991	0.3378	0.0084	2.4156	0.0061	0.0091		0.0098	0.0086
Basis all. type 2, intended[f]	10.5775	61.4120	18.4114	15.0370	5.7707	4.4962	0.2148	21.7407	0.0044	0.6711	9.2843		
	10.6921	63.5792	17.6165	15.4481	5.8049	6.8323	0.2336	28.0415	−0.0010	0.6597	9.4377		
	10.8556	65.0424	16.3882	15.5911	5.7482	8.7549	0.2348	33.6402	−0.0004	0.6678	9.6959		
Basis all. type 2, unintended[e]	10.7313	63.0385	19.0676	15.4806	6.0234	4.6298	0.2267	22.3850	−0.0033	0.7025	9.4791		
	10.9354	64.5904	18.0781	15.6881	5.9685	7.0011	0.2561	28.7188	0.0101	0.6998	9.7012		
	10.7344	64.3887	16.2287	15.3552	5.6987	8.6715	0.2372	33.4666	0.0089	0.6579	9.5849		

Probabilities of occurrence for input biases (applies to the whole table):
[a] 0.10 for both biases
[b] 0.20 for both biases
[c] 0.30 for both biases; interval for biases
[d] $U[-0.10; 0.00[$
[e] $U[-0.10; 0.10]$
[f] $U]0; 0.10]$
Each number is based on 10.000 simulation runs (100 randomly generated costing system structures each with 100 simulation runs)
For more detailed results and confidence intervals for relative errors with $\alpha = 0.001$: cf. Tables C.1–C.13

Table 7.4 Compensation among biases in costing systems, decision-facilitating perspective

	Cat. of cost centers	Cat. of cost categories	Building of direct cost pools	Assignm. of direct cost pools	Assignm. cost drivers all. type 2	Input cost obj., intended[d]	Input cost obj., unintended[e]	Assignm. cost categories	Diff. in val. unintended[e]	Diff. in val., not calculated	Basis all. type 1	Basis all. type 2, intended[f]	Basis all. type 2, unintended[e]
Ex-ante to operations													
Cat. of cost centers		38.0908[a]	2.3215	0.6941	0.1773	0.0329	−0.0355	15.7579	−0.0161	−0.0009	0.3701	−0.0072	−0.0030
		49.1072[b]	2.0596	0.6387	0.1796	−0.0426	−0.0463	23.0561	−0.0199	−0.0235	0.3091	0.0044	−0.0083
		54.4955[c]	1.7931	0.5486	0.1028	−0.0683	−0.0583	28.4101	−0.0570	−0.0435	0.2276	−0.0197	−0.0249
Cat. of cost categories	−0.0213		−0.0077	−0.0259	−0.0117	−0.0175	−0.0157	0.2954	−0.0221	−0.0143	−0.0193	−0.0136	−0.0208
	−0.0053		−0.0114	−0.0059	−0.0096	−0.0171	−0.0110	0.2770	−0.0174	−0.0252	−0.0151	−0.0069	−0.0113
	−0.0053		−0.0081	−0.0073	−0.0081	−0.0211	−0.0266	0.2421	0.0032	−0.0179	−0.0088	−0.0072	−0.0017
Building of direct cost pools	0.0799	11.8861		0.1280	0.0536	0.0124	−0.0234	4.5006	−0.0656	−0.0212	0.0504	0.0304	0.0214
	0.0599	16.2525		0.1237	0.0719	−0.0459	−0.0247	7.3748	0.0303	−0.0097	0.0743	0.0322	0.0296
	0.0354	19.5136		0.1056	−0.0143	−0.0419	−0.0345	9.8838	0.0238	−0.0184	0.0297	−0.0605	−0.0406
Assignm. of direct cost pools	0.1281	24.9070	1.3104		0.0459	0.0206	−0.0813	10.1635	−0.0635	−0.0554	0.0828	−0.0483	−0.0677
	0.1130	33.0111	1.2031		0.0847	−0.0356	−0.0829	15.3162	−0.0316	−0.0579	0.0915	−0.0533	−0.0539
	0.0791	37.5937	1.0782		0.0891	−0.0415	−0.0637	19.5734	−0.0714	−0.0508	0.0615	−0.0189	−0.0383
Assign. cost drivers all. type 2	0.9247	63.5353	4.2982	1.5679		0.0628	0.0289	26.3553	−0.0291	0.1141	0.8506	0.0347	0.0296
	0.9805	82.7704	4.1955	1.6814		0.0487	0.0282	39.3816	0.0207	0.1028	0.8721	0.0357	0.0310
	0.9816	98.4357	3.7780	1.8085		0.0562	0.0119	51.7257	0.0455	0.1297	0.9495	0.0491	0.0517

(continued)

Table 7.4 (continued)

	Cat. of cost centers	Cat. of cost categories	Building of direct cost pools	Assignm. of direct cost pools	Assignm. cost drivers all. type 2	Input cost obj., intended[d]	Input cost obj., unintended[e]	Assignm. cost categories	Diff. in val. unintended[e]	Diff. in val., not calculated	Basis all. type 1	Basis all. type 2, intended[f]	Basis all. type 2, unintended[e]
Ex-post to operations													
Input cost obj., intended[d]	5.6435	251.4142	19.0307	8.8587	3.1816			107.3485	−0.0067	1.0776	5.1588	0.1489	0.1649
	5.5559	338.0619	17.8607	8.7235	3.2772			162.3123	0.0055	1.1689	5.6069	0.1765	0.1788
	5.8258	399.1210	17.9342	9.0775	3.3064			213.3059	0.0165	1.1945	5.8506	0.1848	0.1861
Input cost obj., unintended[e]	5.4352	261.2914	19.0404	8.2050	3.1988			110.7207	0.0132	1.1636	5.4370	0.1776	0.1673
	5.3925	332.9441	17.8706	8.0511	3.1046			159.1581	0.0183	1.1271	5.3920	0.1668	0.1745
	5.3482	365.1109	16.5570	8.0578	2.7963			195.9546	0.0032	1.0495	5.2976	0.1386	0.1497
Assignm. cost categories	−0.0018	2.0820	0.0078	−0.0014	−0.0033	0.0034	−0.0025		−0.0075	−0.0071	−0.0041	−0.0030	0.0004
	0.0081	1.6959	0.0131	0.0067	0.0079	−0.0005	0.0014		0.0003	−0.0012	0.0057	0.0063	0.0061
	0.0090	1.3775	0.0073	0.0129	0.0067	0.0036	0.0023		0.0090	0.0007	0.0061	0.0071	0.0110
Diff.in val., unintended[e]	57.1423	230, 7.1956	168.8509	82.1105	34.0958	8.1258	7.9747	983.5749			54.1898	4.5770	4.4049
	57.8592	297, 1.5854	177.6203	84.6272	35.5069	7.8186	8.1237	143, 2.4765			55.1155	4.5536	4.4559
	56.6507	342, 0.6407	167.8395	80.4708	34.5713	7.4825	8.0978	179, 7.0359			55.1044	4.2734	4.4688
Diff. in val., not calculated	2.5210	137.7538	9.6107	3.9995	1.4017	0.1383	0.1429	57.7438			2.4162	0.0563	0.0438
	2.5565	177.8525	9.4124	4.0519	1.3922	0.1536	0.1558	85.8070			2.5306	0.0621	0.0446
	2.6124	205.9435	9.0007	4.1447	1.3746	0.1313	0.1482	109.1613			2.5781	0.0411	0.0502

	0.4457	40.3358	2.4095	0.7159	0.1945	0.0104	0.0181	16.6418	−0.0145	0.0229		0.0012	0.0078
Basis all. type 1	0.3695	50.9039	2.2444	0.6813	0.1665	0.0094	−0.0024	24.1056	−0.0225	0.0141		−0.0297	−0.0263
	0.3248	58.6766	1.9976	0.6440	0.1708	0.0091	0.0081	30.6461	−0.0096	0.0224		−0.0189	−0.0094
Basis all. type 2, intended[f]	9.7372	425.1178	33.2765	14.4574	5.8447	0.9318	0.9089	180.0266	0.0207	2.2415	9.2614		
	10.0118	547.4828	31.6686	14.2815	5.7631	0.8836	0.9086	262.2520	0.0139	2.1969	9.1682		
	10.6054	654.7780	29.0046	15.6697	5.9122	0.9146	0.9995	346.5163	0.0212	2.2636	9.7631		
Basis all. type 2, unintended[e]	9.9506	428.5558	33.5079	14.3785	5.9174	0.9892	0.9216	183.4534	0.0046	2.2530	9.4900		
	9.9521	549.0345	31.8240	14.3835	5.7816	0.9012	0.9352	264.1237	0.0033	2.1674	9.2786		
	10.0455	629.8640	28.3146	14.6326	5.6299	0.8339	0.9317	332.7792	0.0133	2.1497	9.3977		

Probabilities of occurrence for input biases (applies to the whole table):

[a] 0.10 for both biases
[b] 0.20 for both biases
[c] 0.30 for both biases; interval for biases
[d] $U[-0.10; 0.00[$
[e] $U[-0.10; 0.10]$
[f] $U]0; 0.10]$

Each number is based on 10.000 simulation runs (100 randomly generated costing system structures each with 100 simulation runs)

For more detailed results and confidence intervals for relative errors with $\alpha = 0.001$: cf. Tables C.1–C.13

input biases on the basis for allocation type 2 (if applicable, intended and unintended). In the case of a combination with input biases on input cost objects (intended), the highest extent of compensation can be observed whereby increasing the probabilities of occurrence also appears to increase the extent of compensation. For the remaining combinations, the observed extent of compensation is <0.01.

For *input biases on the assignment of cost drivers for allocation type 2*, a compensation can be observed for the combination with input biases on input cost objects (unintended) and input biases on differences in valuation whereby results suggest a higher extent of compensation for the latter combination. For the remaining combinations, for some scenarios it can be observed that whether or not there is a compensation among biases changes with the respective probabilities of occurrence. In particular, for input biases on the building of direct cost pools in combination with input biases on the basis for allocation type 2 (unintended) no compensation can be observed for low probabilities of occurrence, while for higher levels of probabilities of occurrence, the results indicate a compensation. Similar results can be observed for some other scenarios whereby in most cases, the extent of compensation – due to the respective (low) level of compensation – is negligible (cf. Table 7.3).

From the decision-facilitating perspective, a compensation can be observed for more combinations of biases. *Input biases on the categorization of cost centers* appear to be compensated by adding all variations of input biases on input cost objects, input biases on differences in valuation and input biases on the basis for allocation type 2. For the majority of cases, the results indicate that increasing the probabilities of occurrence also leads to an increasing extent of compensation (cf. Table 7.4)

For *input biases on the categorization of cost categories*, a compensation can be observed for all combinations (except for input biases on the assignment of cost categories) whereby the highest extents of compensation can be observed for the combinations with input biases on input cost objects (intended) and input biases on differences in valuation (not calculated). For some scenarios, the results suggest minor compensations (i.e., the compensation is <0.01).

For *input biases on the building of direct cost pools*, a compensation can be observed for the combination with input biases in input cost objects (unintended) and input biases on differences in valuation (not calculated) at all levels of probabilities of occurrence. For the combinations with input biases on the basis for allocation type 2 and input biases on the assignment of cost drivers for allocation type 2, the results suggest a compensation only in the case of high levels of probabilities of occurrence of the respective biases. On the contrary, the results indicate a compensation at low levels of probability of occurrence for the combination with input biases on differences in valuation.

For *input biases on the assignment of direct cost pools*, the results suggest a compensation for the combinations with input biases on input cost objects (unintended), input biases on differences in valuation and input biases on the basis for allocation type 2 (intended and unintended). For the combination of input biases on the assignment of direct cost pools with input biases on input cost objects (intended), a compensation can be observed for the majority of scenarios whereby the extent of compensation appears to increase with increasing probabilities of occurrence.

For *input biases on the assignment of cost drivers for allocation type 2*, the results suggest a compensation for the combination with input biases on differences in valuation at the lower levels of probabilities of occurrence. Increasing probabilities, for these cases, appear to lead to increasing the measure for compensation among biases. For the remaining combinations, results partly suggest a minor compensation (cf. Table 7.4).

7.3.2 Ex-Post to Operations

From the decision-influencing perspective, a compensation among biases can be observed for *input biases on the assignment of cost categories* in combination with input biases on input cost objects whereby for the combination with unintended input biases on input cost objects, the extent of compensation is significantly lower. For the combination with input biases on differences in valuation, the results suggest a minor compensation at low levels of probability of occurrence.

At low levels of probabilities of occurrence, the results indicate *input biases on the basis for allocation type 1* to be compensated by input biases on differences in valuation. Furthermore, for *input biases on the basis for allocation type 2 (intended)* in combination with input biases on differences in valuation, a compensation can be observed whereby the compensation is quite low. For the combination of input biases on the basis for allocation type 2 (intended) with input biases on differences in valuation, a compensation can only be observed for the cases with low probabilities of occurrence.

For the decision-facilitating perspective, minor compensations can be observed for *input biases on the assignment of cost categories* in combination with the majority of other types of biases. Due to the low extent of compensation, these compensations might be negligible. For *input biases on the basis for allocation type 1* in combination with input biases on differences in valuation, the results also indicate a slight compensation for all levels of probability of occurrence. For the remaining scenarios, in some cases the results suggest minor compensations (cf. Table 7.4).

Chapter 8
Discussion

Abstract This simulation study analyzes three research questions. The first research question focuses on how the level of (traditional) costing system sophistication affects the quality of the provided decision-influencing and decision-facilitating information. The aim of the second research question is to analyze the effects of intended and unintended biases in raw accounting data on the quality of the provided decision-influencing and decision-facilitating information from a single input bias perspective. The third research question aims at analyzing interactions among multiple input biases and the respective effects of interactions on the quality of decision-influencing and decision-facilitating information. The results concerning these three research targets are presented in Chaps. 5–7. The following chapter is organized correspondingly. In particular, Sect. 8.1 discusses results concerning the sensitivity of information quality to the sophistication of costing systems, Sect. 8.2 discusses the results regarding the effects of single and multiple input biases on the quality of provided information and, finally, Sect. 8.3 discusses limitations and elaborates avenues for future research.

8.1 Costing System Sophistication and Quality of Provided Information

In the results of the sensitivity of the effects of input biases to costing systems sophistication for some types of biases a sensitivity can be observed (cf. Table 5.2). For the decision-influencing perspective, the results suggest a sensitivity to cost center sophistication for input biases on the categorization of cost centers, input biases on the building of direct cost pools and input biases on the basis for allocation type 2. For input biases on the categorization of cost categories and input biases on the assignment of cost categories, the results indicate a sensitivity to cost category sophistication for the decision-influencing as well as for the decision-facilitating perspective. A stronger impact on information quality can be observed for biases

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which are sensitive to cost category sophistication, whereby the results indicate the lowest extent of distortion for the level of sophistication 10/6 (cf. also Chap. 5 and Eq. 5.1), i.e., a lower or a higher cost category sophistication leads to a decrease in information quality (with respect to the types of input biases listed above). For biases which are sensitive to cost center sophistication, no such definite trend can be observed. For input biases on the categorization of cost centers, an increase in the extent of distortion with an increasing level of sophistication can be observed while for the remaining types of biases (as listed above), increasing the level of sophistication improves the information quality.

The results suggest that more types of biases are sensitive to costing system sophistication from a decision-influencing perspective than from a decision-facilitating perspective. From the latter perspective, there are only two types of biases for which a sensitivity can be observed. For the costing system design this indicates that if the information provided by the costing system is exclusively used for decision-facilitating purposes, only cost category sophistication needs to be considered with respect to information quality and error propagation. If the information provided by the costing system (in addition) is used for decision-influencing purposes, there are more types of biases for which a sensitivity can be observed whereby, as outlined above, the higher extent of distortion can be observed in cases of biases that involve cost categories. Thus, one implication might be that the primary focus should be put on cost category sophistication for decision-influencing purposes, too.

Abernethy et al. (2001) argue that there is considerable effort to design more sophisticated costing systems due to an increased need to improve accuracy. With respect to error propagation in costing systems, results presented above indicate that increased sophistication does not necessarily increase the accuracy of information provided by costing systems. Rather, the presented results suggest a higher robustness of costing systems to errors for lower levels of sophistication.

Brierley (2008) found that decision makers are not satisfied with the accuracy of information provided by costing systems if there is a lack of sophistication of overhead assignment. This finding might indicate that organizations tend to increase the number of (indirect) cost categories in order to give more detailed classification for indirect costs. This can be proved by the investigation of Friedl et al. (2009) who state that during the last decade the number of cost categories and the number of indirect cost centers have increased. For cost categories, Friedl et al. (2009) do not further specify whether the number of direct or indirect cost categories increased. Moreover, Friedl et al. (2009) found that transparency in indirect costs will gain importance within organizations. Thus, it might be assumed that the number of indirect cost categories will (further) increase in the future. According to the presented results, an increase in indirect cost categories would, with respect to some types of input biases, decrease information quality from the decision-influencing as well as from the decision-facilitating perspective.

According to Friedl et al. (2009), the two most important functions of costing systems within organizations are efficiency in cost-control and (short-term) decision-support. Increasing the number of indirect cost categories and increasing the number of indirect cost centers might significantly affect the fulfillment of these functions because of the above outlined potential negative impact on information quality. Considering the presented results concerning the sensitivity of biases to the costing system sophistication in designing costing systems appears to be crucial.

8.2 Effects of Single and Multiple Input Biases on the Quality of Provided Information

The results on the effects of different levels of input biases for the cases of single and multiple input biases are presented in Chaps. 6 and 7. The results presented in Chap. 6 indicate which types of biases lead to high distortions in provided information and which types of biases lead to an extent of distortion that is negligible for the decision-influencing as well as for the decision-facilitating perspective. On the basis of these results it can be determined whether or not to invest resources in order to eliminate the respective bias. Of course, the threshold of distortion that indicates whether or not to invest resources depends on the organizations' expectations with respect to information quality. It cannot be generalized when to eliminate biases and when to accept them. But the results can be applied as a basis for this decision.

Labro and Vanhoucke (2007) found that it is more beneficial to reduce errors at later steps in the allocation process in activity based costing-systems. This cannot be proved for traditional costing systems and single input bias scenarios. For the decision-influencing as well as for the decision-facilitating perspective, input biases on the basis for allocation type 2 appear to lead to a lower extent of distortion than input biases on the basis for allocation type 1. This implies a focus on earlier steps in the allocation process for traditional costing systems. Furthermore, for both the decision-influencing and the decision-facilitating perspective (for the majority of cases), the results indicate that input biases which occur ex-ante to operations affect information quality more negatively than input biases which occur ex-post to operations. Thus, investing resources in the setup of unbiased costing systems' structures appears to be more beneficial than focussing on biases ex-post to operations.

In the case of multiple input biases, the results indicate that it is necessary to consider also interactions among biases in making data quality policies. These results are presented in Table 7.1 for the decision-influencing perspective and in Table 7.2 for the decision-facilitating perspective. The results suggest that mitigation and potential compensation among biases are crucially affected by the respective probabilities for under- and overcosting and the magnitude of the respective biases in a single-input bias scenario. Three scenarios can be identified for interactions among biases: (1) Biases interact linearly, (2) biases interact overproportionally or (3) biases interact underproportionally.

For the case of a (1) linear interaction, the decision of where to tolerate biases and where to invest resources in order to eliminate biases can be made on the basis of the results presented in Chap. 6. The type of bias that leads to the higher extent of distortion in information quality should be eliminated with the higher priority. From a decision-influencing perspective, a linear interaction can be observed for input biases on the categorization of cost centers and input biases on input cost objects (unintended) (cf. Table 7.1). The results on single input biases indicate that input biases on the categorization of cost centers lead to a higher extent of distortion than input biases on input cost objects (unintended) (cf. Tables 6.2 and 6.3). Thus, eliminating input biases on the categorization of cost centers would lead to a better quality of information than eliminating the latter type of bias. If the extent of distortion exceeds the organization-specific threshold for distortions in information provided by costing systems, resources should be invested in order to eliminate input biases on the categorization of cost centers at first hand. Similarly, organizational data quality policies can be derived from the presented results for all cases in which a linear interaction among biases can be observed.

For the case of an (2) overproportional interaction, the procedure does not differ from the case of a linear interaction among biases. In particular, in the case of multiple input biases and an overproportional interaction among the respective biases, on the basis of the results presented in Chap. 6 the effects in the case of single input bias scenarios can be determined. With this information, a prioritization for eliminating biases can be made. First, resources should be invested in order to eliminate the bias that leads to the higher extent of distortion and the bias where results indicate the lower extent of distortion in provided information should be tolerated at least temporarily. For example, from a decision-influencing perspective in the case of input biases on the categorization of cost centers in combination with input biases on differences in valuation (unintended), an overproportional interaction can be observed (cf. Table 7.1). The results on single input biases indicate that input biases on differences in valuation lead to a lower extent of distortion (cf. Tables 6.2 and 6.3). Thus, resources should be invested into eliminating input biases on the categorization of cost centers first. Whether to invest further resources into eliminating input biases on differences in valuation can be handled as in the case of a single input bias (as listed above). Of course, this policy requires effects with respect to information quality in the case of the two input biases to exceed the organization specific threshold for distortions in information provided by costing systems. Such as in these scenarios, policies for further combinations of input biases for which overproportional interactions can be observed, can be derived. For (1) linear as well as for (2) overproportional interactions among biases, eliminating one type of bias leads to an increase quality of information. Based on the presented results, data quality policies can be derived in which those biases that lead to the higher increases in information quality are eliminated first.

For the case of (3) underproportional interactions among biases, it has to be considered whether or not there is a compensation among biases. If there is no compensation, the data quality policy can be derived as in the case of a linear or an overproportional interaction. If there is a compensation among biases, contrary to linear and overproportional interactions among biases, eliminating the wrong type of bias might lead to a decrease in information quality. For example, from the decision-influencing perspective for input biases on the categorization of cost categories in combination with input biases on input cost objects (intended), a compensation can be observed (cf. Table 7.3). Eliminating the wrong type of bias (i.e., eliminating input biases on input cost objects (intended)) would lead to a decrease in information quality, i.e., the mean absolute relative error is higher for the single bias scenario with input biases on the categorization of cost categories than it is in combination with input biases on input cost objects (intended). In the case of compensation among biases, eliminating the wrong type of bias with a higher priority does not just lead to suboptimal data quality policies (with respect to the best possible way to improve data quality). Rather, it leads to a decrease in data quality. On the basis of the presented results, prioritization of resource investment in data quality issues in the case of compensation can be derived. As just illustrated for the combination with input biases on the categorization of cost categories in combination with input biases on input cost objects (intended), data quality policies can be derived from the presented results for all other combinations where a compensation among biases can be observed.

For the design of costing systems, knowledge about the interactions among biases in costing systems might support management in decisions regarding the investment of resources in order to increase accuracy. The presented results give insights into the impact of specific types of errors on accuracy and interactions among them. On the one hand, this knowledge and the policies suggested above for the three scenarios in the case of multiple input biases might support management in building more efficient data quality policies. On the other hand, implications for the design of costing systems might be derived. As inter alia suggested by Merchant and Shields (1993) and Banker and Potter (1993) in the design of costing systems, some types of biases might be (intendedly) considered in order to increase accuracy.

On the one hand, on the basis of the presented results some situations can be defined in which (partial) improvement with respect to one type of bias might decrease the overall accuracy. For the remaining scenarios with multiple input biases, the results provide guidance in finding the best possible way to increase accuracy, i.e., to achieve more rapid progresses in the improvement of information quality at first hand. On the other hand, results also indicate that these three scenarios (linear, overproportional and underproportional interaction) are not stable for all combinations of biases along probabilities of occurrence. Rather, it can be observed that the impact on data quality changes with increasing/decreasing probability in some scenarios. This is consistent with prior work on interactions among biases in activity based costing-systems by Labro and Vanhoucke (2007) who define *some* situations in which (partial) improvement of biases in raw accounting data increases overall accuracy.

Of course, each organization has to define a threshold for distortions in the quality of accounting information itself. On the basis of this threshold and the presented results, it can be derived whether or not biases (also in consideration of interactions among biases) have a negligible impact on data quality or biases need to be considered in organizational data quality policies. Thus, the results can be the basis for individual prioritization of actions or for evaluating efforts for improving data quality in costing systems from a cost-benefit perspective.

8.3 Limitations and Future Research

The benefits of this large scale simulation study are twofold. First, this study gives guidance for the design of costing systems Second, it supports organizations in generating organizational data quality policies. However, at the same time, there are some limitations.

The set of simulated costing systems covers only full-cost accounting systems. Marginal costing systems remain unconsidered. Furthermore, this simulation study focuses on single-product setups. Setups in which organizations produce multiple products might not only affect the impact of various input biases on information quality, but multiple product setups might also lead to other biases being investigated. Of course, the set of biases under investigation is by no means exhaustive. There might be a certain number of other types of input biases which have a stronger effect on information quality than the biases investigated. Thus, one avenue for future research might be to test the robustness of the presented results with respect to other characterizations of (traditional) costing systems.

While the results concerning sensitivity of output errors to several levels of costing system sophistication consider various levels of sophistication, the level of sophistication is constant for the results on the effects of single and multiple input biases on information quality. Due to the observed sensitivity for some types of biases, the results are limited by the fixed level of sophistication for setups which involve these biases. For these scenarios, changes in the level of costing system sophistication would probably change measures for interaction and compensation among biases. The results concerning the sensitivity of biases to costing system sophistication, on the contrary, are limited by the fixed probabilities of occurrence/magnitudes of biases. Other probabilities of occurrence/magnitudes of biases should be considered in future simulations.

The model considers a set of agents interacting with the costing system. These agents are not considered to communicate with each other. This might be another limitation. Communicating agents might co-operate for mutual benefits. This is a feature that is not considered in this simulation model.

The simulation model is designed so that the distribution of variables and the boundaries of intervals are exogenously given. This might also limit the presented results. Future research might consider other distributions for input biases and design the intervals being endogenized, i.e., one option for future research might be to have agents set the boundaries for input biases. Furthermore, in future research some more variables could be endogenized into the simulation model. For example, the decision which bias to introduce under which circumstances could be made by the agent herself. Summing up, an option for future research might be to design the dynamics of the simulation study in a more agent-driven way.

Future research should address these limitations. In particular, biases and interactions among them in marginal costing systems and multiple product systems should be investigated. It should be checked whether the derived findings presented in this simulation study hold for other types of costing systems too. Furthermore, the set of biases should be extended and interactions among more than two types of biases at a time should be investigated. Effects of biases and interactions among them at different levels of costing system sophistication should be investigated in order to determine the impact of costing system sophistication on interaction and compensation among biases. In addition, communicating agents should be considered in future research.

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Chapter 9
Summary and Conclusion

Abstract This section summarizes and concludes the results that are presented in the previous chapters.

One of the main aims of management accounting is to provide managers with accurate information in order to provide a good basis for decision making (cf. inter alia Crossman 1958; Singer 1961; Feltham 1968; Bruns and McKinnon 1993). There is evidence that data provided by MAS is distorted (Madnick and Wang 1992; Orr 1998; Banham 2002; Redman 1996, 1998) and the occurrence of biases in accounting information is widely accepted among users of MAS (Labro and Vanhoucke 2007). At the same time, the intensity and the frequency of use of management accounting systems in order to retrieve information as the basis for managerial decision making increase (Paradice and Fürst 1991; Chong 1996). Consequently, the quality of the provided information is critical. The effects of biases in the provided accounting information might range from disruptions in operations to organizational extinction (cf. inter alia Fox 1961; Cooper and Kaplan 1988; Wang and Strong 1996). In order to react appropriately to biases in the provided accounting information, knowledge of the impact of distortions in raw accounting data on the quality of provided information is indubitably necessary. This emphasizes the need of research on biases in MAS and interactions among them and the respective impact on the quality of the provided information.

This simulation study investigates the impact of a set of input biases in raw accounting data on the quality of the provided information in the case of traditional costing systems. Although there is evidence that traditional costing systems show a higher application rate than newer conceptions of costing systems (Drury and Tayles 1998; Garg et al. 2003), prior research has mainly focused on biases in activity based costing systems. The focus of this simulation study is twofold. On the one hand, the impact of traditional costing system sophistication on error propagation in the case of a set of input biases is investigated. On the other hand, the impact of single and multiple input biases on the quality of information provided by traditional costing

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systems is the second research focus of this simulation study. In order to investigate the research questions, a simulation approach is applied.

The presentation of the results is organized in three chapters. Chapter 5 presents results on the effects of costing system sophistication on error propagation in case of the investigated biases and Chaps. 6 and 7 present results on the impact of single and multiple input biases on the quality of the provided information. In Chap. 5, some types of biases can be identified for which a sensitivity to costing system sophistication can be observed. Furthermore, the results indicate that from the decision-influencing perspective, more types of biases appear to be sensitive to the level of sophistication than from the decision-facilitating perspective. In the case of decision-influencing as well as in the case of decision-facilitating information, cost category sophistication has a stronger impact on error propagation and, hence, on the quality of provided information than cost center sophistication. With regards to information quality this implies that in the design of costing systems, cost category sophistication should be considered above all.

In the cases of single and multiple input biases, the results suggest that input biases do not lead to a decisive extent of distortion in all cases. Rather, some types of biases lead to a negligible extent of output error. Furthermore, the presented results indicate that interactions among biases lead to mitigation or even compensation among biases in some cases. These findings bring along challenges for the building of organizational data quality policies. First, in some scenarios the elimination of the wrong type of bias increases performance but does not increase the quality of the provided information in the best possible way. Second, for some other scenarios, eliminating the wrong type of bias first might lead to a decrease in information quality (cf. also Chap. 8). The presented results can support management in finding efficient ways to improve the quality of the provided information in the best possible way. In particular, for the results concerning the impact of single and multiple input biases on the quality of provided information, three scenarios are defined in the discussion, i.e., (1) biases interact linearly, (2) biases interact underproportionally and (3) biases interact overproportionally. For the scenarios (1) and (2), the way of improving the quality of the provided information can be optimized on the basis of the presented results whereby there is no risk of a decrease in information quality in case of a wrong course of actions. For the case (3), presented results give guidance on how to create data quality policies whereby in case of imperfectly designed policies, there is the threat of a decrease in information quality.

Of course, whether or not to invest resources in data quality policies depends on the organization-specific expectations of the quality of information provided by costing systems, i.e., each organization should set a threshold for the extent of accepted distortion. Thus, there is no general statement on when to tolerate biases in costing systems and when to eliminate them. This decision critically depends on the organization-specific threshold. On the basis of the presented results and the fixed threshold, situation-specific decisions on whether or not to invest resources can be made.

At the same time, there are some limitations which might be addressed in future research (cf. also Sect. 8.3). The main limitations of the presented simulation study are that this investigation covers full-cost accounting systems and single product setups. Future research should also investigate biases in the case of (traditional) marginal costing systems and multi product setups. On the one hand, this would allow for testing the robustness of the derived findings to other conceptualizations of costing systems. On the other hand, this would allow for new types of biases to be investigated. Furthermore, there are some parameters and distributions which are exogenously given. In further research, the decision concerning these parameters might be endogenized, i.e., future research on biases in costing systems might be conducted in a more agent-driven way. In particular, decisions concerning the type and the magnitude of input bias as well as the combination with other types of biases might be made by agents themselves which might increase the dynamics of the simulation model. However, the present simulation study might be considered as the basis for some research questions which could be investigated in future research.

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Appendix A

Table A.1 Mean absolute relative error, categorization of cost centers, decision-influencing perspective

		Soph. cost centers[a]									
		10/2	10/4	10/6	10/8	10/10	10/12	10/14	10/16	10/18	10/20
Soph. cost cat.[b]	10/2	0.0049	0.0076	0.0100	0.0123	0.0140	0.0161	0.0173	0.0179	0.0193	0.0203
	10/4	0.0047	0.0079	0.0100	0.0122	0.0143	0.0155	0.0171	0.0183	0.0190	0.0201
	10/6	0.0046	0.0077	0.0103	0.0122	0.0142	0.0156	0.0168	0.0181	0.0191	0.0204
	10/8	0.0047	0.0080	0.0095	0.0124	0.0139	0.0159	0.0173	0.0185	0.0192	0.0202
	10/10	0.0046	0.0075	0.0101	0.0129	0.0140	0.0159	0.0168	0.0180	0.0193	0.0203
	10/12	0.0044	0.0080	0.0103	0.0121	0.0141	0.0156	0.0171	0.0183	0.0194	0.0203
	10/14	0.0045	0.0072	0.0099	0.0123	0.0142	0.0156	0.0170	0.0183	0.0192	0.0204
	10/16	0.0046	0.0077	0.0100	0.0123	0.0137	0.0155	0.0168	0.0184	0.0194	0.0206
	10/18	0.0045	0.0081	0.0100	0.0125	0.0141	0.0157	0.0193	0.0181	0.0195	0.0201
	10/20	0.0044	0.0079	0.0103	0.0123	0.0143	0.0156	0.0169	0.0183	0.0197	0.0201

Each number is based on 10.000 simulation runs (100 randomly generated costing system structures each with 100 simulation runs);
Confidence intervals for relative errors with $\alpha = 0.001$: [0.0001;0.0002]

[a] Sophistication cost centers $soph^{cent}$, cf. also Eq. 5.1

[b] Sophistication cost categories $soph^{cat}$, cf. also Eq. 5.1

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Table A.2 Mean absolute relative error, categorization of cost categories, decision-influencing perspective

		Soph. cost centers[a]									
		10/2	10/4	10/6	10/8	10/10	10/12	10/14	10/16	10/18	10/20
Soph. cost cat.[b]	10/2	0.2596	0.2601	0.2601	0.2608	0.2602	0.2598	0.2599	0.2602	0.2601	0.2603
	10/4	0.1117	0.1114	0.1118	0.1117	0.1117	0.1128	0.1121	0.1113	0.1119	0.1115
	10/6	0.0268	0.0266	0.0257	0.0260	0.0256	0.0250	0.0244	0.0249	0.0244	0.0236
	10/8	0.0539	0.0539	0.0539	0.0534	0.0530	0.0528	0.0527	0.0533	0.0531	0.0531
	10/10	0.1103	0.1100	0.1098	0.1097	0.1096	0.1095	0.1101	0.1100	0.1099	0.1096
	10/12	0.1465	0.1461	0.1473	0.1467	0.1462	0.1467	0.1470	0.1455	0.1458	0.1455
	10/14	0.1735	0.1744	0.1738	0.1733	0.1742	0.1727	0.1735	0.1750	0.1739	0.1737
	10/16	0.1940	0.1942	0.1951	0.1949	0.1947	0.1939	0.1948	0.1938	0.1939	0.1939
	10/18	0.2104	0.2106	0.2105	0.2110	0.2099	0.2118	0.2119	0.2105	0.2108	0.2117
	10/20	0.2256	0.2249	0.2246	0.2246	0.2241	0.2249	0.2243	0.2249	0.2236	0.2253

cf. legend of Table A.1

Confidence intervals for relative errors with $\alpha = 0.001$: [0.0003;0.0012]

Table A.3 Mean absolute relative error, categorization of cost categories, decision-facilitating perspective

		Soph. cost centers[a]									
		10/2	10/4	10/6	10/8	10/10	10/12	10/14	10/16	10/18	10/20
Soph. cost cat.[b]	10/2	0.1579	0.1579	0.1579	0.1584	0.1579	0.1576	0.1579	0.1579	0.1578	0.1579
	10/4	0.0839	0.0839	0.0840	0.0841	0.0840	0.0848	0.0843	0.0839	0.0843	0.0837
	10/6	0.0185	0.0185	0.0180	0.0190	0.0184	0.0181	0.0181	0.0184	0.0181	0.0177
	10/8	0.0615	0.0615	0.0611	0.0606	0.0601	0.0602	0.0599	0.0607	0.0604	0.0604
	10/10	0.1567	0.1567	0.1564	0.1570	0.1559	0.1554	0.1573	0.1567	0.1567	0.1565
	10/12	0.2397	0.2397	0.2425	0.2404	0.2400	0.2412	0.2411	0.2390	0.2393	0.2388
	10/14	0.3242	0.3242	0.3236	0.3211	0.3252	0.3205	0.3225	0.3255	0.3223	0.3227
	10/16	0.4042	0.4042	0.4062	0.4043	0.4045	0.4013	0.4035	0.4018	0.4018	0.4017
	10/18	0.4825	0.4826	0.4821	0.4828	0.4815	0.4855	0.4864	0.4822	0.4833	0.4849
	10/20	0.5670	0.5655	0.5650	0.5616	0.5628	0.5651	0.5625	0.5658	0.5613	0.5685

cf. legend of Table A.1

Confidence intervals for relative errors with $\alpha = 0.001$: [0.0003;0.0060]

Table A.4 Mean absolute relative error, assignment of direct cost pools, decision-influencing perspective

	Soph. cost centers[a]									
Soph. cost cat.[b]	10/2	10/4	10/6	10/8	10/10	10/12	10/14	10/16	10/18	10/20
10/2	0.0227	0.0228	0.0217	0.0218	0.0201	0.0212	0.0201	0.0194	0.0197	0.0196
10/4	0.0233	0.0224	0.0221	0.0219	0.0217	0.0208	0.0203	0.0202	0.0193	0.0186
10/6	0.0230	0.0227	0.0226	0.0215	0.0217	0.0200	0.0193	0.0199	0.0196	0.0196
10/8	0.0231	0.0231	0.0212	0.0217	0.0210	0.0205	0.0209	0.0203	0.0192	0.0187
10/10	0.0241	0.0228	0.0219	0.0219	0.0212	0.0213	0.0209	0.0196	0.0198	0.0193
10/12	0.0230	0.0227	0.0223	0.0220	0.0217	0.0205	0.0208	0.0201	0.0197	0.0200
10/14	0.0234	0.0220	0.0215	0.0218	0.0216	0.0198	0.0200	0.0194	0.0202	0.0196
10/16	0.0233	0.0235	0.0224	0.0215	0.0213	0.0205	0.0202	0.0207	0.0196	0.0199
10/18	0.0234	0.0228	0.0217	0.0218	0.0215	0.0216	0.0192	0.0198	0.0197	0.0193
10/20	0.0216	0.0229	0.0222	0.0216	0.0212	0.0214	0.0204	0.0201	0.0200	0.0194

cf. legend of Table A.1
Confidence intervals for relative errors with $\alpha = 0.001$: [0.0002;0.0003]

Table A.5 Mean absolute relative error, assignment of cost categories, decision-influencing perspective

	Soph. cost centers[a]									
Soph. cost cat.[b]	10/2	10/4	10/6	10/8	10/10	10/12	10/14	10/16	10/18	10/20
10/2	0.0832	0.0829	0.0832	0.0830	0.0827	0.0826	0.0827	0.0827	0.0826	0.0826
10/4	0.0511	0.0508	0.0514	0.0505	0.0507	0.0507	0.0505	0.0501	0.0504	0.0501
10/6	0.0313	0.0307	0.0304	0.0306	0.0301	0.0298	0.0295	0.0297	0.0292	0.0289
10/8	0.0363	0.0354	0.0357	0.0352	0.0353	0.0351	0.0350	0.0350	0.0350	0.0347
10/10	0.0488	0.0481	0.0480	0.0475	0.0476	0.0477	0.0473	0.0475	0.0473	0.0477
10/12	0.0589	0.0584	0.0589	0.0587	0.0582	0.0580	0.0582	0.0574	0.0577	0.0577
10/14	0.0675	0.0677	0.0674	0.0671	0.0669	0.0669	0.0668	0.0672	0.0673	0.0670
10/16	0.0748	0.0749	0.0750	0.0753	0.0746	0.0746	0.0749	0.0745	0.0743	0.0747
10/18	0.0819	0.0815	0.0814	0.0818	0.0809	0.0812	0.0814	0.0810	0.0811	0.0813
10/20	0.0883	0.0877	0.0879	0.0875	0.0874	0.0875	0.0870	0.0871	0.0868	0.0871

cf. legend of Table A.1
Confidence intervals for relative errors with $\alpha = 0.001$: [0.0002;0.0003]

Table A.6 Mean absolute relative error, assignment of cost categories, decision-facilitating perspective

		Soph. cost centers[a]									
		10/2	10/4	10/6	10/8	10/10	10/12	10/14	10/16	10/18	10/20
Soph. cost cat.[b]	10/2	0.1697	0.1697	0.1694	0.1701	0.1697	0.1694	0.1696	0.1698	0.1697	0.1697
	10/4	0.0875	0.0875	0.0875	0.0873	0.0871	0.0880	0.0874	0.0868	0.0871	0.0876
	10/6	0.0168	0.0168	0.0165	0.0173	0.0166	0.0165	0.0163	0.0166	0.0163	0.0161
	10/8	0.0470	0.0470	0.0468	0.0469	0.0465	0.0469	0.0465	0.0468	0.0467	0.0464
	10/10	0.1021	0.1021	0.1023	0.1030	0.1022	0.1021	0.1030	0.1026	0.1023	0.1021
	10/12	0.1519	0.1519	0.1523	0.1517	0.1518	0.1519	0.1520	0.1513	0.1518	0.1514
	10/14	0.1960	0.1960	0.1964	0.1961	0.1965	0.1957	0.1962	0.1969	0.1961	0.1961
	10/16	0.2357	0.2357	0.2363	0.2362	0.2356	0.2357	0.2365	0.2357	0.2357	0.2357
	10/18	0.2719	0.2719	0.2711	0.2723	0.2717	0.2722	0.2727	0.2718	0.2717	0.2727
	10/20	0.3050	0.3047	0.3053	0.3047	0.3046	0.3053	0.3050	0.3054	0.3046	0.3054

cf. legend of Table A.1
Confidence intervals for relative errors with $\alpha = 0.001$: [0.0002;0.0006]

Table A.7 Mean absolute relative error, basis for allocation type 1, decision-influencing perspective

		Soph. cost centers[a]									
		10/2	10/4	10/6	10/8	10/10	10/12	10/14	10/16	10/18	10/20
Soph. cost cat.[b]	10/2	0.0199	0.0185	0.0174	0.0165	0.0156	0.0149	0.0142	0.0137	0.0132	0.0127
	10/4	0.0202	0.0186	0.0173	0.0167	0.0158	0.0149	0.0142	0.0138	0.0133	0.0127
	10/6	0.0201	0.0187	0.0173	0.0164	0.0157	0.0150	0.0141	0.0140	0.0133	0.0129
	10/8	0.0201	0.0188	0.0172	0.0164	0.0158	0.0148	0.0142	0.0139	0.0135	0.0127
	10/10	0.0204	0.0186	0.0174	0.0166	0.0156	0.0150	0.0143	0.0136	0.0132	0.0127
	10/12	0.0201	0.0184	0.0176	0.0165	0.0157	0.0150	0.0144	0.0137	0.0132	0.0129
	10/14	0.0201	0.0185	0.0174	0.0164	0.0157	0.0150	0.0143	0.0137	0.0134	0.0128
	10/16	0.0200	0.0189	0.0173	0.0165	0.0157	0.0149	0.0142	0.0139	0.0132	0.0129
	10/18	0.0202	0.0188	0.0174	0.0163	0.0158	0.0152	0.0134	0.0137	0.0133	0.0128
	10/20	0.0199	0.0185	0.0174	0.0165	0.0157	0.0152	0.0140	0.0136	0.0134	0.0128

cf. legend of Table A.1
Confidence intervals for relative errors with $\alpha = 0.001$: [0.0001;0.0002]

Appendix B

Table B.1 Single input biases ex-ante to operations, decision-influencing perspective

Prob. of occurrence[a]	Interval	Root of mean squared error[b]	Max. neg. rel. error[c]	Max. pos. rel. error[c]
Categorization of cost centers[1]				
0.10	–	0.0114	−0.1969	0.2294
0.20	–	0.0162	−0.1909	0.2411
0.30	–	0.0197	−0.2088	0.2578
Categorization of cost categories[2]				
0.10	–	0.0643	−0.3710	0.1739
0.20	–	0.0921	−0.3570	0.2685
0.30	–	0.1129	−0.3588	0.3683
Building of direct cost pools[3]				
0.10	–	0.0196	−0.1690	0.2127
0.20	–	0.0263	−0.1834	0.2127
0.30	–	0.0305	−0.1834	0.2127
Assignment of direct cost pools[1]				
0.10	–	0.0164	−0.1553	0.2393
0.20	–	0.0229	−0.1690	0.2393
0.30	–	0.0277	−0.1725	0.2393

(continued)

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Table B.1 (continued)

Prob. of occurrence[a]	Interval	Root of mean squared error[b]	Max. neg. rel. error[c]	Max. pos. rel. error[c]
Assignment of cost drivers for allocation type 2[4]				
0.10	–	0.0070	−0.0533	0.0570
0.20	–	0.0096	−0.0780	0.0823
0.30	–	0.0113	−0.0803	0.0886

In all cases index n stands for types of input biases B

Each number is based on 10.000 simulation runs (100 randomly generated costing system structures each with 100 simulation runs);

Confidence intervals for relative errors with $\alpha = 0.001$:

[1] [0.0001;0.0002]

[2] [0.0003;0.0006]

[3] 0.0002

[4] 0.0001

[a] Probability of occurrence p_n

[b] Root of the mean squared error MSE_n^{di}, cf. also Eq. 6.3

[c] Maximum negative error $\underline{e}_n^{di}$ and maximum positive error $\overline{e}_n^{di}$, cf. Sect. 6.1

Table B.2 Single input biases ex-ante to operations, decision-facilitating perspective

Prob. of occurrence[a]	Interval	Root of mean squared error[b]	Max. neg. rel. error[c]	Max. pos. rel. error[c]
Categorization of cost centers[1]				
0.10	–	0.0018	−0.0148	0.0171
0.20	–	0.0026	−0.0171	0.0279
0.30	–	0.0033	−0.0185	0.0248
Categorization of cost categories[2]				
0.10	–	0.0732	−0.0035	0.2948
0.20	–	0.1313	0.0000	0.3799
0.30	–	0.1826	0.0000	0.5310
Building of direct cost pools[3]				
0.10	–	0.0056	−0.0451	0.0472
0.20	–	0.0075	−0.0532	0.0441
0.30	–	0.0088	−0.0532	0.0508
Assignment of direct cost pools[4]				
0.10	–	0.0028	−0.0281	0.0216
0.20	–	0.0038	−0.0384	0.0198
0.30	–	0.0047	−0.0217	0.0264

(continued)

Table B.2 (continued)

Prob. of occurrence[a]	Interval	Root of mean squared error[b]	Max. neg. rel. error[c]	Max. pos. rel. error[c]
Assignment of cost drivers for allocation type 2[5]				
0.10	–	0.0011	−0.0061	0.0077
0.20	–	0.0016	−0.0112	0.0083
0.30	–	0.0018	−0.0091	0.0086

In all cases index n stands for types of input biases B

Each number is based on 10.000 simulation runs (100 randomly generated costing system structures each with 100 simulation runs)

Confidence intervals for relative errors with $\alpha = 0.001$:

[1] 0.0001

[2] [0.0012;0.0022]

[3] [0.0002;0.0003]

[4] [0.0001;0.0002]

[5] $\leq$0.0001

[a] Probability of occurrence p_n

[b] Root of the mean squared error MSE_n^{df}, cf. also Eq. 6.4

[c] Maximum negative error $\underline{e}_n^{df}$ and maximum positive error $\overline{e}_n^{df}$, cf. Sect. 6.1

Table B.3 Single input biases ex-post to operations, decision-influencing perspective

Prob. of occurrence[a]	Interval	Root of mean squared error[b]	Max. neg. rel. error[c]	Max. pos. rel. error[c]
Input cost objects, intentional (probability)[1]				
0.10	$U[-0.10; 0.00[$	0.0055	−0.0098	0.0000
0.20	$U[-0.10; 0.00[$	0.0110	−0.0162	0.0000
0.30	$U[-0.10; 0.00[$	0.0165	−0.0217	0.0000
Input cost objects, intentional (magnitude)[1]				
0.10	$U[-0.10; 0.00[$	0.0055	−0.0098	0.0000
0.10	$U[-0.20; 0.00[$	0.0106	−0.0186	0.0000
0.10	$U[-0.30; 0.00[$	0.0156	−0.0276	0.0000
Input cost objects, unintentional (probability)[1]				
0.10	$U[-0.10; 0.10]$	0.0007	−0.0037	0.0034
0.20	$U[-0.10; 0.10]$	0.0010	−0.0051	0.0051
0.30	$U[-0.10; 0.10]$	0.0013	−0.0055	0.0061
Input cost objects, unintentional (magnitude)[1]				
0.10	$U[-0.10; 0.10]$	0.0007	−0.0037	0.0034
0.10	$U[-0.20; 0.20]$	0.0014	−0.0067	0.0073
0.10	$U[-0.30; 0.30]$	0.0022	−0.0098	0.0106
Assignment of cost categories[2]				
0.10	–	0.0232	−0.0727	0.1017
0.20	–	0.0410	−0.0942	0.1778
0.30	–	0.0587	−0.1114	0.2364

(continued)

Table B.3 (continued)

Prob. of occurrence[a]	Interval	Root of mean squared error[b]	Max. neg. rel. error[c]	Max. pos. rel. error[c]
Differences in valuation, unintentional (probability)[1]				
0.10	$U[-0.10; 0.10]$	0.0001	−0.0005	0.0005
0.20	$U[-0.10; 0.10]$	0.0001	−0.0007	0.0007
0.30	$U[-0.10; 0.10]$	0.0001	−0.0008	0.0007
Differences in valuation, unintentional (magnitude)[1]				
0.10	$U[-0.10; 0.10]$	0.0001	−0.0005	0.0005
0.10	$U[-0.20; 0.20]$	0.0001	−0.0006	0.0006
0.10	$U[-0.30; 0.30]$	0.0001	−0.0006	0.0009
Differences in valuation, not calculated[1]				
0.10	–	0.0014	−0.0085	0.0101
0.20	–	0.0019	−0.0114	0.0099
0.30	–	0.0023	−0.0119	0.0110
Basis for allocation type 1[3]				
0.10	–	0.0105	−0.0811	0.0741
0.20	–	0.0148	−0.1037	0.1088
0.30	–	0.0180	−0.1444	0.1288
Basis for allocation type 2, intentional (probability)[1]				
0.10	$U]0.00; 0.10]$	0.0010	−0.0038	0.0140
0.20	$U]0.00; 0.10]$	0.0014	−0.0049	0.0161
0.30	$U]0.00; 0.10]$	0.0017	−0.0068	0.0191
Basis for allocation type 2, intentional (magnitude)[1]				
0.10	$U]0.00; 0.10]$	0.0010	−0.0038	0.0140
0.10	$U]0.00; 0.20]$	0.0020	−0.0061	0.0254
0.10	$U]0.00; 0.30]$	0.0029	−0.0091	0.0415
Basis for allocation type 2, unintentional (probability)[1]				
0.10	$U[-0.10; 0.10]$	0.0010	−0.0129	0.0126
0.20	$U[-0.10; 0.10]$	0.0014	−0.0144	0.0132
0.30	$U[-0.10; 0.10]$	0.0017	−0.0154	0.0137
Basis for allocation type 2, unintentional (magnitude)[1]				
0.10	$U[-0.10; 0.10]$	0.0010	−0.0129	0.0126
0.10	$U[-0.20; 0.20]$	0.0020	−0.0251	0.0287
0.10	$U[-0.30; 0.30]$	0.0030	−0.0357	0.0365

In all cases index n stands for types of input biases B

Each number is based on 10.000 simulation runs (100 randomly generated costing system structures each with 100 simulation runs)

Confidence intervals for relative errors with $\alpha = 0.001$:

[1] <0.0001

[2] [0.0001;0.0002]

[3] 0.0001

[a] Probability of occurrence p_n

[b] Root of the mean squared error MSE_n^{di}, cf. also Eq. 6.3

[c] Maximum negative error $\underline{e}_n^{di}$ and maximum positive error $\overline{e}_n^{di}$, cf. Sect. 6.1

Table B.4 Single input biases ex-post to operations, decision-facilitating perspective

Prob. of occurrence[a]	Interval	Root of mean squared error[b]	Max. neg. rel. error[c]	Max. pos. rel. error[c]
Input cost objects, intentional (probability)[1]				
0.10	$U[-0.10; 0.00[$	0.0003	−0.0011	0.0012
0.20	$U[-0.10; 0.00[$	0.0004	−0.0013	0.0017
0.30	$U[-0.10; 0.00[$	0.0004	−0.0017	0.0017
Input cost objects, intentional (magnitude)[1]				
0.10	$U[-0.10; 0.00[$	0.0003	−0.0011	0.0012
0.10	$U[-0.20; 0.00[$	0.0005	−0.0024	0.0023
0.10	$U[-0.30; 0.00[$	0.0008	−0.0030	0.0035
Input cost objects, unintentional (probability)[1]				
0.10	$U[-0.10; 0.10]$	0.0003	−0.0011	0.0010
0.20	$U[-0.10; 0.10]$	0.0004	−0.0019	0.0017
0.30	$U[-0.10; 0.10]$	0.0005	−0.0021	0.0019
Input cost objects, unintentional (magnitude)[1]				
0.10	$U[-0.10; 0.10]$	0.0003	−0.0011	0.0010
0.10	$U[-0.20; 0.20]$	0.0006	−0.0019	0.0021
0.10	$U[-0.30; 0.30]$	0.0008	−0.0037	0.0035
Assignment of cost categories[2]				
0.10	–	0.0308	0.0000	0.0632
0.20	–	0.0622	0.0000	0.1107
0.30	–	0.0954	0.0000	0.1583
Differences in valuation, unintentional (probability)[1]				
0.10	$U[-0.10; 0.10]$	0.0000	−0.0001	0.0001
0.20	$U[-0.10; 0.10]$	0.0000	−0.0001	0.0002
0.30	$U[-0.10; 0.10]$	0.0001	−0.0002	0.0002
Differences in valuation, unintentional (magnitude)[1]				
0.10	$U[-0.10; 0.10]$	0.0000	−0.0001	0.0001
0.10	$U[-0.20; 0.20]$	0.0000	−0.0002	0.0002
0.10	$U[-0.30; 0.30]$	0.0001	−0.0002	0.0002
Differences in valuation, not calculated)[1]				
0.10	–	0.0005	−0.0021	0.0021
0.20	–	0.0007	−0.0031	0.0028
0.30	–	0.0009	−0.0037	0.0043
Basis for allocation type 1[3]				
0.10	–	0.0017	−0.0088	0.0074
0.20	–	0.0025	−0.0131	0.0120
0.30	–	0.0030	−0.0141	0.0140
Basis for allocation type 2, intentional (probability)[1]				
0.10	$U]0.00; 0.10]$	0.0002	−0.0006	0.0009
0.20	$U]0.00; 0.10]$	0.0002	−0.0010	0.0015
0.30	$U]0.00; 0.10]$	0.0003	−0.0012	0.0015

(continued)

Table B.4 (continued)

Prob. of occurrence[a]	Interval	Root of mean squared error[b]	Max. neg. rel. error[c]	Max. pos. rel. error[c]
Basis for allocation type 2, intentional (magnitude)[1]				
0.10	$U]0.00; 0.10]$	0.0002	−0.0006	0.0009
0.10	$U]0.00; 0.20]$	0.0003	−0.0014	0.0029
0.10	$U]0.00; 0.30]$	0.0005	−0.0016	0.0034
Basis for allocation type 2, unintentional (probability)[1]				
0.10	$U[-0.10; 0.10]$	0.0002	−0.0009	0.0009
0.20	$U[-0.10; 0.10]$	0.0002	−0.0013	0.0014
0.30	$U[-0.10; 0.10]$	0.0003	−0.0014	0.0014
Basis for allocation type 2, unintentional (magnitude)[1]				
0.10	$U[-0.10; 0.10]$	0.0002	−0.0009	0.0009
0.10	$U[-0.20; 0.20]$	0.0003	−0.0019	0.0017
0.10	$U[-0.30; 0.30]$	0.0005	−0.0028	0.0029

In all cases index n stands for types of input biases B

Each number is based on 10.000 simulation runs (100 randomly generated costing system structures each with 100 simulation runs)

Confidence intervals for relative errors with $\alpha = 0.001$:

[1] <0.0001

[2] [0.0002;0.0005]

[3] 0.0001

[a] Probability of occurrence p_n

[b] Root of the mean squared error MSE_n^{df}, cf. also Eq. 6.4

[c] Maximum negative error $\underline{e}_n^{df}$ and maximum positive error $\overline{e}_n^{df}$, cf. Sect. 6.1

Appendix C

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Table C.1 Input biases on the categorization of cost centers interacting with other biases

		Decision-influencing							Decision-facilitating						
p_n[1]	p_q[1]	$EUCD^{di}_{n,q}$[2]	$MSE^{di}_{n,q}$[3]	$e^{mean,di}_{n,q}$[4]	$p^{under,di}_{n,q}$[5]	$p^{over,di}_{n,q}$[5]	$\underline{e}^{di}_{n,q}$[6]	$\overline{e}^{di}_{n,q}$[6]	$EUCD^{df}_{n,q}$[2]	$MSE^{df}_{n,q}$[3]	$e^{mean,df}_{n,q}$[4]	$p^{under,df}_{n,q}$[5]	$p^{over,df}_{n,q}$[5]	$\underline{e}^{df}_{n,q}$[6]	$\overline{e}^{df}_{n,q}$[6]
Ex-ante to operations															
Categorization of cost categories															
0.10	0.10	22.6036	0.0653	0.0486	0.1683	0.8317	−0.3590	0.3012	7.1613	0.0716	0.0623	0.0012	0.9988	−0.0023	0.2753
0.20	0.20	32.3824	0.0935	0.0784	0.2711	0.7289	−0.3503	0.3910	13.0601	0.1306	0.1193	0.0000	1.0000	0.0000	0.4627
0.30	0.30	39.7895	0.1149	0.0980	0.3461	0.6540	−0.3821	0.4733	18.1591	0.1816	0.1688	0.0000	1.0000	0.0000	0.5509
Building of direct cost pools															
0.10	0.10	8.0111	0.0231	0.0122	0.4968	0.5032	−0.2114	0.2329	0.6085	0.0061	0.0039	0.4864	0.5136	−0.0472	0.0476
0.20	0.20	10.8147	0.0312	0.0196	0.4970	0.5030	−0.2119	0.2384	0.7975	0.0080	0.0056	0.4716	0.5284	−0.0428	0.0503
0.30	0.30	12.5514	0.0362	0.0244	0.5016	0.4984	−0.2156	0.3181	0.9140	0.0091	0.0066	0.5228	0.4772	−0.0495	0.0563
Assignment of direct cost pools															
0.10	0.10	6.7843	0.0196	0.0088	0.4998	0.5002	−0.1861	0.3065	0.3104	0.0031	0.0021	0.4919	0.5081	−0.0160	0.0230
0.20	0.20	9.2045	0.0266	0.0147	0.4981	0.5019	−0.2085	0.3068	0.4271	0.0043	0.0031	0.4890	0.5110	−0.0207	0.0286
0.30	0.30	10.6995	0.0309	0.0191	0.4971	0.5029	−0.2253	0.3282	0.5067	0.0051	0.0038	0.4869	0.5131	−0.0222	0.0270
Assignment of cost drivers for allocation type 2															
0.10	0.10	4.8098	0.0139	0.0074	0.4970	0.5030	−0.1778	0.2556	0.2157	0.0022	0.0015	0.5093	0.4907	−0.0169	0.0130
0.20	0.20	6.7358	0.0194	0.0112	0.5006	0.4994	−0.2191	0.2950	0.3075	0.0031	0.0022	0.5179	0.4821	−0.0172	0.0180
0.30	0.30	7.9836	0.0230	0.0140	0.5015	0.4985	−0.2189	0.2814	0.3609	0.0036	0.0027	0.5206	0.4794	−0.0210	0.0206
Ex-post to operations															
Input cost objects, intentional (probability)[a]															
0.10	0.10	4.4625	0.0129	0.0078	0.9002	0.0998	−0.2006	0.2206	0.1892	0.0019	0.0012	0.4925	0.5075	−0.0160	0.0169
0.20	0.20	6.7327	0.0194	0.0141	0.9170	0.0831	−0.1912	0.3370	0.2495	0.0025	0.0017	0.5005	0.4995	−0.0178	0.0173
0.30	0.30	8.8680	0.0256	0.0201	0.9173	0.0827	−0.2017	0.3706	0.3049	0.0030	0.0022	0.4965	0.5035	−0.0215	0.0195

Input cost objects, unitentional (probability)[b]															
0.10	0.10	4.2843	0.0124	0.0050	0.5064	0.4936	−0.2210	0.2300	0.1767	0.0018	0.0011	0.5019	0.4981	−0.0158	0.0141
0.20	0.20	6.0110	0.0174	0.0081	0.5027	0.4973	−0.2242	0.2412	0.2486	0.0025	0.0017	0.4997	0.5003	−0.0140	0.0141
0.30	0.30	7.1712	0.0207	0.0108	0.4925	0.5075	−0.2030	0.2412	0.3081	0.0031	0.0022	0.4997	0.5003	−0.0158	0.0180
Assignment of cost categories															
0.10	0.10	9.1249	0.0263	0.0192	0.4511	0.5489	−0.1721	0.2769	3.0700	0.0307	0.0298	0.0001	0.9999	−0.0014	0.0600
0.20	0.20	15.3790	0.0444	0.0322	0.4523	0.5477	−0.1359	0.3289	6.2701	0.0627	0.0617	0.0000	1.0000	0.0000	0.1249
0.30	0.30	21.6763	0.0626	0.0448	0.4551	0.5449	−0.1373	0.4000	9.6235	0.0962	0.0951	0.0000	1.0000	0.0000	0.1654
Differences in valuation, unintentional (probability)[b]															
0.10	0.10	4.1985	0.0121	0.0049	0.4983	0.5017	−0.2062	0.2251	0.1802	0.0018	0.0011	0.4987	0.5013	−0.0140	0.0147
0.20	0.20	5.6692	0.0164	0.0078	0.4946	0.5054	−0.2050	0.2125	0.2555	0.0026	0.0018	0.4977	0.5023	−0.0180	0.0159
0.30	0.30	7.1674	0.0207	0.0107	0.4968	0.5032	−0.2255	0.2805	0.3086	0.0031	0.0022	0.4870	0.5130	−0.0278	0.0206
Differences in valuation (not calculated)															
0.10	0.10	4.1497	0.0120	0.0051	0.5209	0.4791	−0.1846	0.2160	0.1830	0.0018	0.0012	0.5124	0.4876	−0.0133	0.0151
0.20	0.20	5.7409	0.0166	0.0080	0.4955	0.5045	−0.2060	0.2313	0.2545	0.0025	0.0018	0.5186	0.4814	−0.0189	0.0176
0.30	0.30	7.0581	0.0204	0.0107	0.4978	0.5022	−0.2172	0.2542	0.3130	0.0031	0.0023	0.5184	0.4816	−0.0185	0.0189
Basis for allocation type 1															
0.10	0.10	5.2795	5.2795	0.0095	5.2795	0.4990	−0.1775	0.2177	0.2510	0.0025	0.0018	0.4914	0.5086	−0.0203	0.0180
0.20	0.20	7.3178	7.3178	0.0138	7.3178	0.5009	−0.1999	0.2734	0.3412	0.0034	0.0026	0.4826	0.5174	−0.0216	0.0183
0.30	0.30	8.7096	8.7096	0.0168	8.7096	0.5019	−0.2264	0.2518	0.4017	0.0040	0.0031	0.4901	0.5099	−0.0194	0.0227

(continued)

Table C.1 (continued)

		Decision-influencing							Decision-facilitating						
p_n [1]	p_q [1]	$EUCD_{n,q}^{di}$ [2]	$MSE_{n,q}^{di}$ [3]	$e_{n,q}^{mean,di}$ [4]	$p_{n,q}^{under,di}$ [5]	$p_{n,q}^{over,di}$ [5]	$\underline{e}_{n,q}^{di}$ [6]	$\overline{e}_{n,q}^{di}$ [6]	$EUCD_{n,q}^{df}$ [2]	$MSE_{n,q}^{df}$ [3]	$e_{n,q}^{mean,df}$ [4]	$p_{n,q}^{under,df}$ [5]	$p_{n,q}^{over,df}$ [5]	$\underline{e}_{n,q}^{df}$ [6]	$\overline{e}_{n,q}^{df}$ [6]
Basis for allocation type 2, intentional (probability)[c]															
0.10	0.10	4.1156	0.0119	0.0050	0.5017	0.4983	−0.1778	0.2304	0.1819	0.0018	0.0011	0.4929	0.5071	−0.0166	0.0152
0.20	0.20	5.7556	0.0166	0.0081	0.4959	0.5042	−0.1832	0.2346	0.2618	0.0026	0.0018	0.4925	0.5075	−0.0186	0.0168
0.30	0.30	6.9956	0.0202	0.0107	0.4964	0.5036	−0.1851	0.2455	0.3208	0.0032	0.0023	0.4900	0.5100	−0.0180	0.0184
Basis for allocation type 2, unintentional (probability)[b]															
0.10	0.10	4.0657	0.0117	0.0049	0.4992	0.5008	−0.1813	0.2254	0.1826	0.0018	0.0011	0.4911	0.5089	−0.0131	0.0134
0.20	0.20	5.7511	0.0166	0.0080	0.4942	0.5058	−0.1893	0.2377	0.2585	0.0026	0.0018	0.4902	0.5098	−0.0176	0.0188
0.30	0.30	6.9886	0.0202	0.0107	0.4968	0.5032	−0.1974	0.2274	0.3191	0.0032	0.0023	0.4859	0.5141	−0.0178	0.0191

Subscript n indicates input biases on the categorization of cost centers
Subscript q indicates the remaining types of biases as listed in the table
[1] Probabilities of occurrence
[2] Euclidean Distance (cf. Eqs. 7.3 and 7.4)
[3] Root of the mean squared error (cf. Eqs. 7.11 and 7.12)
[4] Mean absolute relative error (cf. Eqs. 7.9 and 7.10)
[5] Probabilities for under- and overcosting (cf. Sect. 7.1)
[6] Maximum negative and maximum positive error (cf. Sect. 7.1)
Interval for biases:
[a] $U[-0.10; 0.00[$
[b] $U[-0.10; 0.10]$
[c] $U]0.00; 0.10]$
Each number is based on 10.000 simulation runs (100 randomly generated costing system structures each with 100 simulation runs)
Confidence intervals for relative errors with $\alpha = 0.001$: ex-ante to operations [0.0001; 0.0022]; ex-post to operations [0.0001; 0.0005]

Table C.2 Input biases on the categorization of cost categories interacting with other biases

		Decision-influencing							Decision-facilitating						
p_n [1]	p_q [1]	$EUCD^{di}_{n,q}$ [2]	$MSE^{di}_{n,q}$ [3]	$e^{mean,di}_{n,q}$ [4]	$p^{under,di}_{n,q}$ [5]	$p^{over,di}_{n,q}$ [5]	$\underline{e}^{di}_{n,q}$ [6]	$\overline{e}^{di}_{n,q}$ [6]	$EUCD^{df}_{n,q}$ [2]	$MSE^{df}_{n,q}$ [3]	$e^{mean,df}_{n,q}$ [4]	$p^{under,df}_{n,q}$ [5]	$p^{over,df}_{n,q}$ [5]	$\underline{e}^{df}_{n,q}$ [6]	$\overline{e}^{df}_{n,q}$ [6]
Ex-ante to operations															
Categorization of cost centers															
0.10	0.10	22.6036	0.0653	0.0486	0.1683	0.8317	−0.3590	0.3012	7.1613	0.0716	0.0623	0.0012	0.9988	−0.0023	0.2753
0.20	0.20	32.3824	0.0935	0.0784	0.2711	0.7289	−0.3503	0.3910	13.0601	0.1306	0.1193	0.0000	1.0000	0.0000	0.4627
0.30	0.30	39.7895	0.1149	0.0980	0.3461	0.6540	−0.3821	0.4733	18.1591	0.1816	0.1688	0.0000	1.0000	0.0000	0.5509
Building of direct cost pools															
0.10	0.10	23.1936	0.0670	0.0510	0.2142	0.7844	−0.3627	0.2618	7.2612	0.0726	0.0631	0.0017	0.9983	−0.0150	0.2797
0.20	0.20	32.7867	0.0946	0.0799	0.3037	0.6963	−0.3535	0.3309	12.9812	0.1298	0.1185	0.0002	0.9998	−0.0029	0.4576
0.30	0.30	39.8419	0.1150	0.0984	0.3632	0.6368	−0.3640	0.3692	18.1076	0.1811	0.1684	0.0000	1.0000	0.0000	0.4750
Assignment of direct cost pools															
0.10	0.10	22.9925	0.0664	0.0494	0.1824	0.8160	−0.3565	0.3584	7.1274	0.0713	0.0621	0.0009	0.9991	−0.0055	0.2852
0.20	0.20	32.9177	0.0950	0.0789	0.2804	0.7195	−0.3821	0.4564	13.0524	0.1305	0.1192	0.0001	0.9999	−0.0041	0.4452
0.30	0.30	40.5199	0.1170	0.0986	0.3477	0.6523	−0.3722	0.4704	18.1234	0.1812	0.1687	0.0000	1.0000	0.0000	0.5162
Assignment of cost drivers for allocation type 2															
0.10	0.10	22.3825	0.0646	0.0482	0.1605	0.8395	−0.3522	0.1687	7.2316	0.0723	0.0629	0.0009	0.9991	−0.0029	0.2993
0.20	0.20	31.9420	0.0922	0.0780	0.2646	0.7354	−0.3634	0.3014	13.0047	0.1300	0.1187	0.0000	1.0000	0.0000	0.4372
0.30	0.30	39.2321	0.1133	0.0977	0.3437	0.6563	−0.3842	0.4238	18.1078	0.1811	0.1686	0.0000	1.0000	0.0000	0.5006
Ex-post to operations															
Input cost objects, intentional (probability)[a]															
0.10	0.10	21.9131	0.0633	0.0444	0.1661	0.8339	−0.3607	0.1631	7.1891	0.0719	0.0627	0.0012	0.9988	−0.0007	0.2959
0.20	0.20	30.9036	0.0892	0.0724	0.2704	0.7296	−0.3686	0.2632	12.9061	0.1291	0.1182	0.0001	0.9999	−0.0079	0.4350
0.30	0.30	37.3809	0.1079	0.0908	0.3496	0.6504	−0.3836	0.3301	17.8714	0.1787	0.1667	0.0000	1.0000	0.0000	0.4994

(continued)

Table C.2 (continued)

		Decision-influencing							Decision-facilitating						
p_n [1]	p_q [1]	$EUCD^{di}_{n,q}$ [2]	$MSE^{di}_{n,q}$ [3]	$e^{mean,di}_{n,q}$ [4]	$p^{under,di}_{n,q}$ [5]	$p^{over,di}_{n,q}$ [5]	$\underline{e}^{di}_{n,q}$ [6]	$\overline{e}^{di}_{n,q}$ [6]	$EUCD^{df}_{n,q}$ [2]	$MSE^{df}_{n,q}$ [3]	$e^{mean,df}_{n,q}$ [4]	$p^{under,df}_{n,q}$ [5]	$p^{over,df}_{n,q}$ [5]	$\underline{e}^{df}_{n,q}$ [6]	$\overline{e}^{df}_{n,q}$ [6]
Input cost objects, unintentional (probability)[b]															
0.10	0.10	22.2415	0.0642	0.0483	0.1567	0.8433	−0.3650	0.1684	7.2021	0.0720	0.0629	0.0010	0.9990	−0.0004	0.3272
0.20	0.20	31.7868	0.0918	0.0782	0.2648	0.7352	−0.3749	0.2674	12.9862	0.1299	0.1190	0.0000	1.0000	0.0000	0.4081
0.30	0.30	38.8422	0.1121	0.0972	0.3421	0.6579	−0.3650	0.3884	17.7710	0.1777	0.1656	0.0000	1.0000	0.0000	0.5201
Assignment of cost categories															
0.10	0.10	24.2316	0.0700	0.0526	0.2498	0.7502	−0.3431	0.2276	9.4785	0.0948	0.0886	0.0000	1.0000	0.0000	0.3197
0.20	0.20	34.9818	0.1010	0.0804	0.3347	0.6654	−0.3252	0.3594	16.7678	0.1677	0.1614	0.0000	1.0000	0.0000	0.4105
0.30	0.30	42.8314	0.1236	0.0961	0.3990	0.6010	−0.3246	0.4268	22.6762	0.2268	0.2209	0.0000	1.0000	0.0000	0.4897
Differences in valuation, unintentional (probability)[b]															
0.10	0.10	22.2089	0.0641	0.0481	0.1558	0.8442	−0.3597	0.1679	7.1555	0.0716	0.0622	0.0011	0.9989	−0.0047	0.3016
0.20	0.20	31.7488	0.0917	0.0782	0.2652	0.7348	−0.3685	0.2861	12.9018	0.1290	0.1181	0.0000	1.0000	0.0000	0.4031
0.30	0.30	39.1891	0.1131	0.0982	0.3445	0.6555	−0.3870	0.3663	18.3144	0.1831	0.1706	0.0000	1.0000	0.0000	0.5965
Differences in valuation (not calculated)															
0.10	0.10	22.2361	0.0642	0.0481	0.1571	0.8429	−0.3401	0.1650	7.2126	0.0721	0.0627	0.0018	0.9982	−0.0088	0.2809
0.20	0.20	31.9109	0.0921	0.0784	0.2647	0.7353	−0.3749	0.2823	12.7992	0.1280	0.1176	0.0000	1.0000	0.0000	0.4054
0.30	0.30	39.1842	0.1131	0.0981	0.3437	0.6563	−0.3728	0.3620	17.9293	0.1793	0.1674	0.0000	1.0000	0.0000	0.5437
Basis for allocation type 1															
0.10	0.10	22.3673	0.0646	0.0480	0.1644	0.8356	−0.3616	0.1946	7.1762	0.0718	0.0620	0.0020	0.9980	−0.0128	0.3154
0.20	0.20	32.0891	0.0926	0.0781	0.2657	0.7344	−0.3496	0.2979	12.9320	0.1293	0.1183	0.0001	0.9999	−0.0026	0.4465
0.30	0.30	39.5052	0.1140	0.0981	0.3443	0.6557	−0.3752	0.4217	18.0951	0.1810	0.1685	0.0000	1.0000	0.0000	0.5347

Basis for allocation type 2, intentional (probability)[c]															
0.10	0.10	22.1863	0.0640	0.0481	0.1565	0.8435	−0.3577	0.1612	7.2179	0.0722	0.0626	0.0015	0.9985	−0.0003	0.3493
0.20	0.20	31.7898	0.0918	0.0782	0.2647	0.7353	−0.3539	0.2945	13.0397	0.1304	0.1192	0.0001	0.9999	−0.0002	0.3976
0.30	0.30	38.9695	0.1125	0.0977	0.3441	0.6559	−0.3687	0.3569	18.1253	0.1813	0.1688	0.0000	1.0000	0.0000	0.5036
Basis for allocation type 2, unintentional (probability)[b]															
0.10	0.10	22.1940	0.0641	0.0481	0.1564	0.8436	−0.3474	0.2384	7.1647	0.0716	0.0623	0.0014	0.9986	−0.0025	0.2687
0.20	0.20	31.6049	0.0912	0.0777	0.2645	0.7356	−0.3708	0.2710	12.9818	0.1298	0.1185	0.0002	0.9998	−0.0015	0.3828
0.30	0.30	38.9433	0.1124	0.0976	0.3446	0.6554	−0.3617	0.3586	18.2244	0.1822	0.1695	0.0000	1.0000	0.0000	0.5526

cf. the agenda of Table C.1

Subscript n indicates input biases on the categorization of cost categories

Confidence intervals for relative errors with $\alpha = 0.001$: ex-ante and ex-post to operations [0.0003; 0.0022]

Table C.3 Input biases on the building of direct cost pools interacting with other biases

		Decision-influencing							Decision-facilitating						
p_n[1]	p_q[1]	$EUCD^{di}_{n,q}$[2]	$MSE^{di}_{n,q}$[3]	$e^{mean,di}_{n,q}$[4]	$p^{under,di}_{n,q}$[5]	$p^{over,di}_{n,q}$[5]	$\underline{e}^{di}_{n,q}$[6]	$\overline{e}^{di}_{n,q}$[6]	$EUCD^{df}_{n,q}$[2]	$MSE^{df}_{n,q}$[3]	$e^{mean,df}_{n,q}$[4]	$p^{under,df}_{n,q}$[5]	$p^{over,df}_{n,q}$[5]	$\underline{e}^{df}_{n,q}$[6]	$\overline{e}^{df}_{n,q}$[6]
Ex-ante to operations															
Categorization of cost centers															
0.10	0.10	8.0111	0.0231	0.0122	0.4968	0.5032	−0.2114	0.2329	0.6085	0.0061	0.0039	0.4864	0.5136	−0.0472	0.0476
0.20	0.20	10.8147	0.0312	0.0196	0.4970	0.5030	−0.2119	0.2384	0.7975	0.0080	0.0056	0.4716	0.5284	−0.0428	0.0503
0.30	0.30	12.5514	0.0362	0.0244	0.5016	0.4984	−0.2156	0.3181	0.9140	0.0091	0.0066	0.5228	0.4772	−0.0495	0.0563
Categorization of cost categories															
0.10	0.10	23.1936	0.0670	0.0510	0.2142	0.7844	−0.3627	0.2618	7.2612	0.0726	0.0631	0.0017	0.9983	−0.0150	0.2797
0.20	0.20	32.7867	0.0946	0.0799	0.3037	0.6963	−0.3535	0.3309	12.9812	0.1298	0.1185	0.0002	0.9998	−0.0029	0.4576
0.30	0.30	39.8419	0.1150	0.0984	0.3632	0.6368	−0.3640	0.3692	18.1076	0.1811	0.1684	0.0000	1.0000	0.0000	0.4750
Assignment of direct cost pools															
0.10	0.10	8.8429	0.0255	0.0122	0.2788	0.2760	−0.2166	0.2715	0.6356	0.0064	0.0041	0.4879	0.5121	−0.0530	0.0409
0.20	0.20	12.1481	0.0351	0.0212	0.3737	0.3722	−0.2387	0.2963	0.8455	0.0085	0.0061	0.4726	0.5274	−0.0498	0.0511
0.30	0.30	14.4402	0.0417	0.0277	0.4236	0.4266	−0.2413	0.3788	0.9759	0.0098	0.0072	0.5298	0.4702	−0.0487	0.0579
Assignment of cost drivers for allocation type 2															
0.10	0.10	7.2738	0.0210	0.0120	0.4995	0.5005	−0.1779	0.2377	0.5937	0.0059	0.0037	0.4790	0.5210	−0.0395	0.0477
0.20	0.20	9.8010	0.0283	0.0184	0.4998	0.5003	−0.2214	0.2261	0.8066	0.0081	0.0055	0.4662	0.5338	−0.0428	0.0532
0.30	0.30	10.9565	0.0316	0.0220	0.4985	0.5015	−0.1744	0.2230	0.8701	0.0087	0.0062	0.5135	0.4865	−0.0446	0.0760
Ex-post to operations															
Input cost objects, intentional (probability)[a]															
0.10	0.10	7.0274	0.0203	0.0121	0.8741	0.1259	−0.1883	0.1953	0.5705	0.0057	0.0035	0.5067	0.4933	−0.0435	0.0387
0.20	0.20	9.7240	0.0281	0.0202	0.8239	0.1761	−0.1863	0.2063	0.7179	0.0072	0.0049	0.5359	0.4641	−0.0450	0.0431
0.30	0.30	11.8173	0.0341	0.0263	0.8089	0.1911	−0.1931	0.2141	0.8457	0.0085	0.0060	0.5376	0.4624	−0.0438	0.0471
Input cost objects, unitentional (probability)[b]															
0.10	0.10	6.8263	0.0197	0.0085	0.5036	0.4964	−0.1870	0.2010	0.5503	0.0055	0.0034	0.4988	0.5012	−0.0361	0.0450
0.20	0.20	9.0265	0.0261	0.0141	0.5012	0.4988	−0.1899	0.2006	0.7338	0.0073	0.0050	0.4970	0.5030	−0.0397	0.0392
0.30	0.30	10.6362	0.0307	0.0184	0.5012	0.4988	−0.1952	0.2371	0.8522	0.0085	0.0060	0.5030	0.4970	−0.0505	0.0531

Assignment of cost categories															
0.10	0.10	10.4696	0.0302	0.0229	0.4311	0.5689	−0.1424	0.2096	3.0995	0.0310	0.0296	0.0027	0.9973	−0.0136	0.0787
0.20	0.20	16.6035	0.0479	0.0370	0.4339	0.5661	−0.2722	0.2507	6.3014	0.0630	0.0615	0.0031	0.9969	−0.1681	0.1339
0.30	0.30	22.3107	0.0644	0.0492	0.4380	0.5621	−0.1733	0.2372	9.6073	0.0961	0.0946	0.0000	1.0000	0.0000	0.1789
Differences in valuation, unintentional (probability)[b]															
0.10	0.10	6.8217	0.0197	0.0082	0.4990	0.5010	−0.1549	0.2139	0.5265	0.0053	0.0032	0.5158	0.4842	−0.0376	0.0440
0.20	0.20	9.4844	0.0274	0.0143	0.4991	0.5009	−0.1731	0.2328	0.7753	0.0078	0.0053	0.5164	0.4836	−0.0492	0.0424
0.30	0.30	10.7931	0.0312	0.0183	0.5026	0.4975	−0.1758	0.2096	0.9037	0.0090	0.0065	0.4800	0.5200	−0.0499	0.0476
Differences in valuation (not calculated)															
0.10	0.10	6.7220	0.0194	0.0088	0.5389	0.4611	−0.1601	0.1992	0.5516	0.0055	0.0034	0.5256	0.4744	−0.0425	0.0413
0.20	0.20	9.2242	0.0266	0.0148	0.5335	0.4665	−0.1518	0.2032	0.7451	0.0075	0.0051	0.5301	0.4699	−0.0423	0.0362
0.30	0.30	10.7054	0.0309	0.0189	0.5336	0.4664	−0.1654	0.2071	0.8664	0.0087	0.0062	0.5316	0.4684	−0.0478	0.0388
Basis for allocation type 1															
0.10	0.10	7.7813	0.0225	0.0142	0.4996	0.5004	−0.2087	0.2336	0.5919	0.0059	0.0039	0.4792	0.5208	−0.0420	0.0359
0.20	0.20	10.5113	0.0303	0.0212	0.4997	0.5004	−0.2164	0.2568	0.8083	0.0081	0.0057	0.4726	0.5274	−0.0450	0.0655
0.30	0.30	12.0411	0.0348	0.0255	0.4998	0.5003	−0.1787	0.2136	0.9089	0.0091	0.0066	0.5249	0.4751	−0.0467	0.0523
Basis for allocation type 2, intentional (probability)[c]															
0.10	0.10	6.9004	0.0199	0.0087	0.6304	0.3696	−0.2126	0.2329	0.5806	0.0058	0.0035	0.4819	0.5181	−0.0446	0.0349
0.20	0.20	9.1642	0.0265	0.0144	0.5521	0.4479	−0.2143	0.2338	0.7767	0.0078	0.0053	0.4835	0.5165	−0.0449	0.0617
0.30	0.30	10.2602	0.0296	0.0177	0.5339	0.4661	−0.1710	0.2261	0.8293	0.0083	0.0059	0.5174	0.4826	−0.0497	0.0547
Basis for allocation type 2, unintentional (probability)[b]															
0.10	0.10	6.9549	0.0201	0.0086	0.4994	0.5006	−0.2128	0.2343	0.5756	0.0058	0.0035	0.4747	0.5253	−0.0384	0.0417
0.20	0.20	9.1928	0.0265	0.0144	0.4983	0.5017	−0.2154	0.2333	0.7747	0.0077	0.0052	0.4731	0.5269	−0.0471	0.0505
0.30	0.30	10.2608	0.0296	0.0176	0.4996	0.5004	−0.1582	0.2076	0.8468	0.0085	0.0060	0.5176	0.4824	−0.0427	0.0555

cf. the agenda of Table C.1

Subscript n indicates input biases on the building of direct cost pools

Confidence intervals for relative errors with $\alpha = 0.001$: ex-ante to operations [0.0002; 0.0022]; ex-post to operations [0.0002; 0.0006]

Table C.4 Input biases on the assignment of direct cost pools interacting with other biases

		Decision-influencing							Decision-facilitating						
p_n [1]	p_q [1]	$EUCD^{di}_{n,q}$ [2]	$MSE^{di}_{n,q}$ [3]	$e^{mean,di}_{n,q}$ [4]	$p^{under,di}_{n,q}$ [5]	$p^{over,di}_{n,q}$ [5]	$\underline{e}^{di}_{n,q}$ [6]	$\overline{e}^{di}_{n,q}$ [6]	$EUCD^{df}_{n,q}$ [2]	$MSE^{df}_{n,q}$ [3]	$e^{mean,df}_{n,q}$ [4]	$p^{under,df}_{n,q}$ [5]	$p^{over,df}_{n,q}$ [5]	$\underline{e}^{df}_{n,q}$ [6]	$\overline{e}^{df}_{n,q}$ [6]
Ex-ante to operations															
Categorization of cost centers															
0.10	0.10	6.7843	0.0196	0.0088	0.4998	0.5002	−0.1861	0.3065	0.3104	0.0031	0.0021	0.4919	0.5081	−0.0160	0.0230
0.20	0.20	9.2045	0.0266	0.0147	0.4981	0.5019	−0.2085	0.3068	0.4271	0.0043	0.0031	0.4890	0.5110	−0.0207	0.0286
0.30	0.30	10.6995	0.0309	0.0191	0.4971	0.5029	−0.2253	0.3282	0.5067	0.0051	0.0038	0.4869	0.5131	−0.0222	0.0270
Categorization of cost categories															
0.10	0.10	22.9925	0.0664	0.0494	0.1824	0.8160	−0.3565	0.3584	7.1274	0.0713	0.0621	0.0009	0.9991	−0.0055	0.2852
0.20	0.20	32.9177	0.0950	0.0789	0.2804	0.7195	−0.3821	0.4564	13.0524	0.1305	0.1192	0.0001	0.9999	−0.0041	0.4452
0.30	0.30	40.5199	0.1170	0.0986	0.3477	0.6523	−0.3722	0.4704	18.1234	0.1812	0.1687	0.0000	1.0000	0.0000	0.5162
Building of direct cost pools															
0.10	0.10	8.8429	0.0255	0.0122	0.2788	0.2760	−0.2166	0.2715	0.6356	0.0064	0.0041	0.4879	0.5121	−0.0530	0.0409
0.20	0.20	12.1481	0.0351	0.0212	0.3737	0.3722	−0.2387	0.2963	0.8455	0.0085	0.0061	0.4726	0.5274	−0.0498	0.0511
0.30	0.30	14.4402	0.0417	0.0277	0.4236	0.4266	−0.2413	0.3788	0.9759	0.0098	0.0072	0.5298	0.4702	−0.0487	0.0579
Assignment of cost drivers for allocation type 2															
0.10	0.10	6.5402	0.0189	0.0090	0.5006	0.4994	−0.2573	0.3941	0.2878	0.0029	0.0019	0.5229	0.4771	−0.0236	0.0217
0.20	0.20	8.9145	0.0257	0.0144	0.4989	0.5012	−0.2508	0.3999	0.4163	0.0042	0.0029	0.5155	0.4845	−0.0294	0.0249
0.30	0.30	10.8509	0.0313	0.0190	0.5001	0.4999	−0.2707	0.4132	0.5115	0.0051	0.0037	0.5257	0.4743	−0.0330	0.0232
Ex-post to operations															
Input cost objects, intentional (probability)[a]															
0.10	0.10	6.0015	0.0173	0.0095	0.9268	0.0733	−0.1742	0.2338	0.2808	0.0028	0.0017	0.5043	0.4957	−0.0172	0.0249
0.20	0.20	8.6737	0.0250	0.0172	0.8823	0.1177	−0.1959	0.2331	0.3701	0.0037	0.0026	0.5043	0.4957	−0.0255	0.0242
0.30	0.30	10.9995	0.0318	0.0239	0.8597	0.1403	−0.1989	0.2293	0.4501	0.0045	0.0033	0.5080	0.4920	−0.0223	0.0219
Input cost objects, unitentional (probability)[b]															
0.10	0.10	5.8900	0.0170	0.0054	0.5035	0.4965	−0.1967	0.2536	0.2528	0.0025	0.0015	0.5028	0.4972	−0.0205	0.0185
0.20	0.20	8.0374	0.0232	0.0099	0.4996	0.5004	−0.1965	0.2510	0.3520	0.0035	0.0024	0.5005	0.4995	−0.0223	0.0189
0.30	0.30	9.8303	0.0284	0.0145	0.4996	0.5004	−0.2035	0.2849	0.4397	0.0044	0.0031	0.5033	0.4967	−0.0270	0.0280

Assignment of cost categories															
0.10	0.10	10.1129	0.0292	0.0205	0.4545	0.5455	−0.1859	0.3438	3.0713	0.0307	0.0297	0.0001	0.9999	−0.0017	0.0667
0.20	0.20	16.4659	0.0475	0.0338	0.4586	0.5414	−0.1398	0.3567	6.2617	0.0626	0.0615	0.0000	1.0000	0.0000	0.1229
0.30	0.30	22.8390	0.0659	0.0465	0.4597	0.5403	−0.4249	0.4821	9.6612	0.0966	0.0953	0.0021	0.9979	−0.2176	0.1704
Differences in valuation, unintentional (probability)[b]															
0.10	0.10	5.8141	0.0168	0.0049	0.5007	0.4993	−0.2023	0.2820	0.2576	0.0026	0.0015	0.5044	0.4956	−0.0240	0.0211
0.20	0.20	8.1781	0.0236	0.0097	0.5010	0.4990	−0.2202	0.2343	0.3716	0.0037	0.0025	0.4937	0.5063	−0.0192	0.0225
0.30	0.30	9.7000	0.0280	0.0140	0.5008	0.4992	−0.2173	0.3205	0.4361	0.0044	0.0032	0.4872	0.5128	−0.0291	0.0304
Differences in valuation (not calculated)															
0.10	0.10	5.6561	0.0163	0.0057	0.5476	0.4525	−0.2178	0.2483	0.2599	0.0026	0.0016	0.5065	0.4935	−0.0218	0.0199
0.20	0.20	8.1063	0.0234	0.0106	0.5417	0.4583	−0.2306	0.2868	0.3615	0.0036	0.0025	0.5293	0.4707	−0.0209	0.0275
0.30	0.30	9.7672	0.0282	0.0150	0.5360	0.4640	−0.2317	0.2890	0.4457	0.0045	0.0033	0.5346	0.4654	−0.0262	0.0263
Basis for allocation type 1															
0.10	0.10	6.5466	0.0189	0.0108	0.4988	0.5012	−0.2150	0.2988	0.2979	0.0030	0.0021	0.4963	0.5037	−0.0171	0.0183
0.20	0.20	8.8961	0.0257	0.0163	0.4999	0.5001	−0.2070	0.3304	0.4189	0.0042	0.0031	0.4810	0.5190	−0.0299	0.0255
0.30	0.30	10.4706	0.0302	0.0201	0.4999	0.5001	−0.2137	0.3053	0.4985	0.0050	0.0038	0.4873	0.5127	−0.0244	0.0311
Basis for allocation type 2, intentional (probability)[c]															
0.10	0.10	5.7009	0.0165	0.0054	0.6504	0.3496	−0.1877	0.3099	0.2618	0.0026	0.0016	0.4999	0.5001	−0.0185	0.0238
0.20	0.20	8.0967	0.0234	0.0103	0.5637	0.4363	−0.2108	0.3105	0.3633	0.0036	0.0025	0.4983	0.5017	−0.0177	0.0231
0.30	0.30	9.7899	0.0283	0.0148	0.5333	0.4667	−0.2097	0.3195	0.4607	0.0046	0.0033	0.4869	0.5131	−0.0231	0.0302
Basis for allocation type 2, unintentional (probability)[b]															
0.10	0.10	5.7117	0.0165	0.0053	0.4994	0.5007	−0.1910	0.3109	0.2565	0.0026	0.0016	0.4829	0.5171	−0.0163	0.0231
0.20	0.20	8.0412	0.0232	0.0101	0.4976	0.5024	−0.1892	0.3126	0.3631	0.0036	0.0025	0.4847	0.5153	−0.0258	0.0333
0.30	0.30	9.7406	0.0281	0.0147	0.4983	0.5017	−0.2127	0.3147	0.4516	0.0045	0.0033	0.4854	0.5146	−0.0242	0.0355

cf. the agenda of Table C.1

Subscript n indicates input biases on the assignment of direct cost pools

Confidence intervals for relative errors with $\alpha = 0.001$: ex-ante to operations [0.0001; 0.0022]; ex-post to operations [0.0001; 0.0006]

Table C.5 Input biases on the assignment of direct cost drivers for allocation type 2 interacting with other biases

		Decision-influencing							Decision-facilitating						
p_n [1]	p_q [1]	$EUCD^{di}_{n,q}$ [2]	$MSE^{di}_{n,q}$ [3]	$e^{mean,di}_{n,q}$ [4]	$p^{under,di}_{n,q}$ [5]	$p^{over,di}_{n,q}$ [5]	$\underline{e}^{di}_{n,q}$ [6]	$\overline{e}^{di}_{n,q}$ [6]	$EUCD^{df}_{n,q}$ [2]	$MSE^{df}_{n,q}$ [3]	$e^{mean,df}_{n,q}$ [4]	$p^{under,df}_{n,q}$ [5]	$p^{over,df}_{n,q}$ [5]	$\underline{e}^{df}_{n,q}$ [6]	$\overline{e}^{df}_{n,q}$ [6]
Ex-ante to operations															
Categorization of cost centers															
0.10	0.10	4.8098	0.0139	0.0074	0.4970	0.5030	−0.1778	0.2556	0.2157	0.0022	0.0015	0.5093	0.4907	−0.0169	0.0130
0.20	0.20	6.7358	0.0194	0.0112	0.5006	0.4994	−0.2191	0.2950	0.3075	0.0031	0.0022	0.5179	0.4821	−0.0172	0.0180
0.30	0.30	7.9836	0.0230	0.0140	0.5015	0.4985	−0.2189	0.2814	0.3609	0.0036	0.0027	0.5206	0.4794	−0.0210	0.0206
Categorization of cost categories															
0.10	0.10	22.3825	0.0646	0.0482	0.1605	0.8395	−0.3522	0.1687	7.2316	0.0723	0.0629	0.0009	0.9991	−0.0029	0.2993
0.20	0.20	31.9420	0.0922	0.0780	0.2646	0.7354	−0.3634	0.3014	13.0047	0.1300	0.1187	0.0000	1.0000	0.0000	0.4372
0.30	0.30	39.2321	0.1133	0.0977	0.3437	0.6563	−0.3842	0.4238	18.1078	0.1811	0.1686	0.0000	1.0000	0.0000	0.5006
Building of direct cost pools															
0.10	0.10	7.2738	0.0210	0.0120	0.4995	0.5005	−0.1779	0.2377	0.5937	0.0059	0.0037	0.4790	0.5210	−0.0395	0.0477
0.20	0.20	9.8010	0.0283	0.0184	0.4998	0.5003	−0.2214	0.2261	0.8066	0.0081	0.0055	0.4662	0.5338	−0.0428	0.0532
0.30	0.30	10.9565	0.0316	0.0220	0.4985	0.5015	−0.1744	0.2230	0.8701	0.0087	0.0062	0.5135	0.4865	−0.0446	0.0760
Assignment of direct cost pools															
0.10	0.10	6.5402	0.0189	0.0090	0.5006	0.4994	−0.2573	0.3941	0.2878	0.0029	0.0019	0.5229	0.4771	−0.0236	0.0217
0.20	0.20	8.9145	0.0257	0.0144	0.4989	0.5012	−0.2508	0.3999	0.4163	0.0042	0.0029	0.5155	0.4845	−0.0294	0.0249
0.30	0.30	10.8509	0.0313	0.0190	0.5001	0.4999	−0.2707	0.4132	0.5115	0.0051	0.0037	0.5257	0.4743	−0.0330	0.0232
Ex-post to operations															
Input cost objects, intentional (probability)[a]															
0.10	0.10	3.0430	0.0088	0.0070	0.8526	0.1475	−0.0568	0.0451	0.1191	0.0012	0.0009	0.5035	0.4965	−0.0068	0.0062
0.20	0.20	5.0399	0.0145	0.0123	0.9137	0.0863	−0.0817	0.0703	0.1628	0.0016	0.0012	0.4953	0.5047	−0.0085	0.0113
0.30	0.30	6.9168	0.0200	0.0175	0.9440	0.0560	−0.1117	0.0756	0.1923	0.0019	0.0015	0.4928	0.5072	−0.0093	0.0099
Input cost objects, unitentional (probability)[b]															
0.10	0.10	2.4021	0.0069	0.0048	0.5009	0.4991	−0.0549	0.0582	0.1153	0.0012	0.0009	0.5003	0.4997	−0.0060	0.0058
0.20	0.20	3.3189	0.0096	0.0067	0.5013	0.4987	−0.0763	0.0752	0.1596	0.0016	0.0012	0.5006	0.4994	−0.0093	0.0090
0.30	0.30	3.9179	0.0113	0.0079	0.4991	0.5009	−0.0830	0.1084	0.1843	0.0018	0.0014	0.5001	0.4999	−0.0087	0.0101

Assignment of cost categories															
0.10	0.10	8.4414	0.0244	0.0184	0.4485	0.5515	−0.0671	0.1316	3.0653	0.0307	0.0298	0.0000	1.0000	0.0000	0.0648
0.20	0.20	14.7694	0.0426	0.0314	0.4513	0.5487	−0.0939	0.2092	6.2689	0.0627	0.0617	0.0000	1.0000	0.0000	0.1139
0.30	0.30	20.9771	0.0606	0.0439	0.4537	0.5464	−0.1168	0.2678	9.6016	0.0960	0.0949	0.0000	1.0000	0.0000	0.1568
Differences in valuation, unintentional (probability)[b]															
0.10	0.10	2.3801	0.0069	0.0047	0.4992	0.5008	−0.0556	0.0574	0.1088	0.0011	0.0008	0.5112	0.4888	−0.0055	0.0053
0.20	0.20	3.2727	0.0094	0.0065	0.5007	0.4993	−0.0686	0.0816	0.1584	0.0016	0.0012	0.5039	0.4961	−0.0077	0.0091
0.30	0.30	3.9310	0.0113	0.0079	0.4994	0.5006	−0.0851	0.0975	0.1904	0.0019	0.0014	0.5004	0.4996	−0.0113	0.0106
Differences in valuation (not calculated)															
0.10	0.10	2.4151	0.0070	0.0048	0.5150	0.4850	−0.0547	0.0582	0.1248	0.0012	0.0010	0.5076	0.4924	−0.0067	0.0070
0.20	0.20	3.3550	0.0097	0.0068	0.5159	0.4841	−0.0741	0.0848	0.1712	0.0017	0.0013	0.5048	0.4952	−0.0088	0.0087
0.30	0.30	4.0084	0.0116	0.0081	0.5182	0.4818	−0.0881	0.0858	0.2057	0.0021	0.0016	0.5077	0.4923	−0.0090	0.0112
Basis for allocation type 1															
0.10	0.10	4.3305	0.0125	0.0088	0.4984	0.5016	−0.1017	0.0992	0.2074	0.0021	0.0016	0.5148	0.4852	−0.0122	0.0101
0.20	0.20	6.1714	0.0178	0.0126	0.4992	0.5008	−0.1217	0.1461	0.2906	0.0029	0.0022	0.5155	0.4845	−0.0131	0.0136
0.30	0.30	7.4949	0.0216	0.0153	0.4980	0.5020	−0.1632	0.2187	0.3550	0.0036	0.0028	0.5165	0.4835	−0.0172	0.0183
Basis for allocation type 2, intentional (probability)[c]															
0.10	0.10	2.4069	0.0069	0.0047	0.5016	0.4984	−0.0540	0.0588	0.1159	0.0012	0.0008	0.4982	0.5018	−0.0065	0.0082
0.20	0.20	3.3498	0.0097	0.0067	0.5012	0.4988	−0.0714	0.0855	0.1608	0.0016	0.0012	0.5037	0.4963	−0.0083	0.0092
0.30	0.30	3.9819	0.0115	0.0080	0.5010	0.4990	−0.0921	0.1006	0.1910	0.0019	0.0014	0.5024	0.4976	−0.0100	0.0094
Basis for allocation type 2, unintentional (probability)[b]															
0.10	0.10	2.4341	0.0070	0.0048	0.4998	0.5002	−0.0541	0.0556	0.1154	0.0012	0.0009	0.5110	0.4890	−0.0082	0.0067
0.20	0.20	3.3578	0.0097	0.0067	0.5011	0.4989	−0.0759	0.0906	0.1601	0.0016	0.0012	0.4950	0.5050	−0.0066	0.0129
0.30	0.30	3.9895	0.0115	0.0080	0.5033	0.4967	−0.0886	0.0941	0.1915	0.0019	0.0014	0.5047	0.4953	−0.0105	0.0084

cf. the agenda of Table C.1
Subscript n indicates input biases on the assignment of cost drivers for allocation type 2
Confidence intervals for relative errors with $\alpha = 0.001$: ex-ante to operations [0.0001; 0.0022]; ex-post to operations]0.0000; 0.0005]

Table C.6 Input biases on input cost objects, intentional (probability) interacting with other biases

		Decision-influencing							Decision-facilitating						
p_n [1]	p_q [1]	$EUCD^{di}_{n,q}$ [2]	$MSE^{di}_{n,q}$ [3]	$e^{mean,di}_{n,q}$ [4]	$p^{under,di}_{n,q}$ [5]	$p^{over,di}_{n,q}$ [5]	$\underline{e}^{di}_{n,q}$ [6]	$\overline{e}^{di}_{n,q}$ [6]	$EUCD^{df}_{n,q}$ [2]	$MSE^{df}_{n,q}$ [3]	$e^{mean,df}_{n,q}$ [4]	$p^{under,df}_{n,q}$ [5]	$p^{over,df}_{n,q}$ [5]	$\underline{e}^{df}_{n,q}$ [6]	$\overline{e}^{df}_{n,q}$ [6]
Ex-ante to operations															
Categorization of cost centers															
0.10	0.10	4.4625	0.0129	0.0078	0.9002	0.0998	−0.2006	0.2206	0.1892	0.0019	0.0012	0.4925	0.5075	−0.0160	0.0169
0.20	0.20	6.7327	0.0194	0.0141	0.9170	0.0831	−0.1912	0.3370	0.2495	0.0025	0.0017	0.5005	0.4995	−0.0178	0.0173
0.30	0.30	8.8680	0.0256	0.0201	0.9173	0.0827	−0.2017	0.3706	0.3049	0.0030	0.0022	0.4965	0.5035	−0.0215	0.0195
Categorization of cost categories															
0.10	0.10	21.9131	0.0633	0.0444	0.1661	0.8339	−0.3607	0.1631	7.1891	0.0719	0.0627	0.0012	0.9988	−0.0007	0.2959
0.20	0.20	30.9036	0.0892	0.0724	0.2704	0.7296	−0.3686	0.2632	12.9061	0.1291	0.1182	0.0001	0.9999	−0.0079	0.4350
0.30	0.30	37.3809	0.1079	0.0908	0.3496	0.6504	−0.3836	0.3301	17.8714	0.1787	0.1667	0.0000	1.0000	0.0000	0.4994
Building of direct cost pools															
0.10	0.10	7.0274	0.0203	0.0121	0.8741	0.1259	−0.1883	0.1953	0.5705	0.0057	0.0035	0.5067	0.4933	−0.0435	0.0387
0.20	0.20	9.7240	0.0281	0.0202	0.8239	0.1761	−0.1863	0.2063	0.7179	0.0072	0.0049	0.5359	0.4641	−0.0450	0.0431
0.30	0.30	11.8173	0.0341	0.0263	0.8089	0.1911	−0.1931	0.2141	0.8457	0.0085	0.0060	0.5376	0.4624	−0.0438	0.0471
Assignment of direct cost pools															
0.10	0.10	6.0015	0.0173	0.0095	0.9268	0.0733	−0.1742	0.2338	0.2808	0.0028	0.0017	0.5043	0.4957	−0.0172	0.0249
0.20	0.20	8.6737	0.0250	0.0172	0.8823	0.1177	−0.1959	0.2331	0.3701	0.0037	0.0026	0.5043	0.4957	−0.0255	0.0242
0.30	0.30	10.9995	0.0318	0.0239	0.8597	0.1403	−0.1989	0.2293	0.4501	0.0045	0.0033	0.5080	0.4920	−0.0223	0.0219
Assignment of cost drivers for allocation type 2															
0.10	0.10	3.0430	0.0088	0.0070	0.8526	0.1475	−0.0568	0.0451	0.1191	0.0012	0.0009	0.5035	0.4965	−0.0068	0.0062
0.20	0.20	5.0399	0.0145	0.0123	0.9137	0.0863	−0.0817	0.0703	0.1628	0.0016	0.0012	0.4953	0.5047	−0.0085	0.0113
0.30	0.30	6.9168	0.0200	0.0175	0.9440	0.0560	−0.1117	0.0756	0.1923	0.0019	0.0015	0.4928	0.5072	−0.0093	0.0099

Ex-post to operations															
Assignment of cost categories															
0.10	0.10	7.7176	0.0223	0.0176	0.5497	0.4503	−0.0685	0.1023	3.0859	0.0309	0.0300	0.0000	1.0000	0.0000	0.0609
0.20	0.20	13.5280	0.0391	0.0307	0.5757	0.4243	−0.1021	0.1751	6.2163	0.0622	0.0612	0.0000	1.0000	0.0000	0.1040
0.30	0.30	19.2112	0.0555	0.0433	0.5942	0.4058	−0.1317	0.2364	9.5720	0.0957	0.0946	0.0000	1.0000	0.0000	0.1578
Differences in valuation, unintentional (probability)[b]															
0.10	0.10	1.9217	0.0055	0.0055	1.0000	0.0000	−0.0091	0.0000	0.0283	0.0003	0.0002	0.5090	0.4910	−0.0010	0.0012
0.20	0.20	3.8262	0.0110	0.0110	1.0000	0.0000	−0.0163	0.0000	0.0383	0.0004	0.0003	0.5030	0.4970	−0.0015	0.0015
0.30	0.30	5.7284	0.0165	0.0165	1.0000	0.0000	−0.0219	0.0000	0.0454	0.0005	0.0004	0.5014	0.4986	−0.0018	0.0018
Differences in valuation (not calculated)															
0.10	0.10	2.0201	0.0058	0.0056	0.9996	0.0004	−0.0135	0.0030	0.0592	0.0006	0.0005	0.5043	0.4957	−0.0025	0.0023
0.20	0.20	3.9481	0.0114	0.0112	1.0000	0.0000	−0.0230	0.0000	0.0826	0.0008	0.0007	0.4845	0.5155	−0.0034	0.0036
0.30	0.30	5.8814	0.0170	0.0168	1.0000	0.0000	−0.0282	0.0000	0.0980	0.0010	0.0008	0.4928	0.5072	−0.0037	0.0051
Basis for allocation type 1															
0.10	0.10	4.0952	0.0118	0.0089	0.7583	0.2417	−0.0796	0.0723	0.1754	0.0018	0.0014	0.5053	0.4947	−0.0072	0.0086
0.20	0.20	6.3104	0.0182	0.0144	0.8272	0.1728	−0.1104	0.1199	0.2515	0.0025	0.0020	0.5015	0.4985	−0.0151	0.0143
0.30	0.30	8.3615	0.0241	0.0197	0.8680	0.1320	−0.1311	0.1532	0.3060	0.0031	0.0024	0.5054	0.4946	−0.0138	0.0132
Basis for allocation type 2, intentional (probability)[c]															
0.10	0.10	1.9538	0.0056	0.0055	0.9963	0.0037	−0.0103	0.0086	0.0327	0.0003	0.0003	0.5116	0.4884	−0.0015	0.0015
0.20	0.20	3.8555	0.0111	0.0110	0.9996	0.0004	−0.0179	0.0051	0.0448	0.0004	0.0004	0.4997	0.5003	−0.0020	0.0018
0.30	0.30	5.7560	0.0166	0.0165	1.0000	0.0000	−0.0247	0.0037	0.0529	0.0005	0.0004	0.4893	0.5107	−0.0020	0.0022
Basis for allocation type 2, unintentional (probability)[b]															
0.10	0.10	1.9511	0.0056	0.0055	0.9980	0.0020	−0.0173	0.0081	0.0332	0.0003	0.0003	0.5109	0.4891	−0.0013	0.0022
0.20	0.20	3.8553	0.0111	0.0110	0.9998	0.0002	−0.0255	0.0020	0.0449	0.0004	0.0004	0.5013	0.4987	−0.0021	0.0018
0.30	0.30	5.7600	0.0166	0.0165	1.0000	0.0000	−0.0326	0.0009	0.0530	0.0005	0.0004	0.4993	0.5007	−0.0020	0.0026

cf. the agenda of Table C.1

Subscript n indicates input biases on input cost objects, intended (probability) with interval for biases $U[-0.10; 0.00[$

Confidence intervals for relative errors with $\alpha = 0.001$: ex-ante to operations $]0.0000; 0.0021]$; ex-post to operations $]0.0000; 0.0005]$

Table C.7 Input biases on input cost objects, unintentional (probability) interacting with other biases

		Decision-influencing							Decision-facilitating						
p_n [1]	p_q [1]	$EUCD^{di}_{n,q}$ [2]	$MSE^{di}_{n,q}$ [3]	$e^{mean,di}_{n,q}$ [4]	$p^{under,di}_{n,q}$ [5]	$p^{over,di}_{n,q}$ [5]	$\underline{e}^{di}_{n,q}$ [6]	$\overline{e}^{di}_{n,q}$ [6]	$EUCD^{df}_{n,q}$ [2]	$MSE^{df}_{n,q}$ [3]	$e^{mean,df}_{n,q}$ [4]	$p^{under,df}_{n,q}$ [5]	$p^{over,df}_{n,q}$ [5]	$\underline{e}^{df}_{n,q}$ [6]	$\overline{e}^{df}_{n,q}$ [6]
Ex-ante to operations															
Categorization of cost centers															
0.10	0.10	4.2843	0.0124	0.0050	0.5064	0.4936	−0.2210	0.2300	0.1767	0.0018	0.0011	0.5019	0.4981	−0.0158	0.0141
0.20	0.20	6.0110	0.0174	0.0081	0.5027	0.4973	−0.2242	0.2412	0.2486	0.0025	0.0017	0.4997	0.5003	−0.0140	0.0141
0.30	0.30	7.1712	0.0207	0.0108	0.4925	0.5075	−0.2030	0.2412	0.3081	0.0031	0.0022	0.4997	0.5003	−0.0158	0.0180
Categorization of cost categories															
0.10	0.10	22.2415	0.0642	0.0483	0.1567	0.8433	−0.3650	0.1684	7.2021	0.0720	0.0629	0.0010	0.9990	−0.0004	0.3272
0.20	0.20	31.7868	0.0918	0.0782	0.2648	0.7352	−0.3749	0.2674	12.9862	0.1299	0.1190	0.0000	1.0000	0.0000	0.4081
0.30	0.30	38.8422	0.1121	0.0972	0.3421	0.6579	−0.3650	0.3884	17.7710	0.1777	0.1656	0.0000	1.0000	0.0000	0.5201
Building of direct cost pools															
0.10	0.10	6.8263	0.0197	0.0085	0.5036	0.4964	−0.1870	0.2010	0.5503	0.0055	0.0034	0.4988	0.5012	−0.0361	0.0450
0.20	0.20	9.0265	0.0261	0.0141	0.5012	0.4988	−0.1899	0.2006	0.7338	0.0073	0.0050	0.4970	0.5030	−0.0397	0.0392
0.30	0.30	10.6362	0.0307	0.0184	0.5012	0.4988	−0.1952	0.2371	0.8522	0.0085	0.0060	0.5030	0.4970	−0.0505	0.0531
Assignment of direct cost pools															
0.10	0.10	5.8900	0.0170	0.0054	0.5035	0.4965	−0.1967	0.2536	0.2528	0.0025	0.0015	0.5028	0.4972	−0.0205	0.0185
0.20	0.20	8.0374	0.0232	0.0099	0.4996	0.5004	−0.1965	0.2510	0.3520	0.0035	0.0024	0.5005	0.4995	−0.0223	0.0189
0.30	0.30	9.8303	0.0284	0.0145	0.4996	0.5004	−0.2035	0.2849	0.4397	0.0044	0.0031	0.5033	0.4967	−0.0270	0.0280
Assignment of cost drivers for allocation type 2															
0.10	0.10	2.4021	0.0069	0.0048	0.5009	0.4991	−0.0549	0.0582	0.1153	0.0012	0.0009	0.5003	0.4997	−0.0060	0.0058
0.20	0.20	3.3189	0.0096	0.0067	0.5013	0.4987	−0.0763	0.0752	0.1596	0.0016	0.0012	0.5006	0.4994	−0.0093	0.0090
0.30	0.30	3.9179	0.0113	0.0079	0.4991	0.5009	−0.0830	0.1084	0.1843	0.0018	0.0014	0.5001	0.4999	−0.0087	0.0101

Ex-post to operations															
Assignment of cost categories															
0.10	0.10	8.0011	0.0231	0.0177	0.4451	0.5549	−0.0799	0.1165	3.0677	0.0307	0.0298	0.0000	1.0000	0.0000	0.0571
0.20	0.20	14.1845	0.0409	0.0303	0.4518	0.5482	−0.1040	0.1866	6.2281	0.0623	0.0613	0.0000	1.0000	0.0000	0.1091
0.30	0.30	20.2355	0.0584	0.0425	0.4559	0.5441	−0.1241	0.2580	9.5602	0.0956	0.0945	0.0000	1.0000	0.0000	0.1569
Differences in valuation, unintentional (probability)[b]															
0.10	0.10	0.2526	0.0007	0.0006	0.4972	0.5028	−0.0036	0.0033	0.0278	0.0003	0.0002	0.4986	0.5014	−0.0012	0.0012
0.20	0.20	0.3572	0.0010	0.0008	0.4990	0.5010	−0.0046	0.0046	0.0396	0.0004	0.0003	0.5057	0.4943	−0.0018	0.0014
0.30	0.30	0.4380	0.0013	0.0010	0.4979	0.5021	−0.0066	0.0069	0.0487	0.0005	0.0004	0.4927	0.5073	−0.0021	0.0019
Differences in valuation (not calculated)															
0.10	0.10	0.5376	0.0016	0.0012	0.5366	0.4634	−0.0076	0.0083	0.0594	0.0006	0.0005	0.5032	0.4968	−0.0028	0.0024
0.20	0.20	0.7473	0.0022	0.0017	0.5470	0.4530	−0.0104	0.0127	0.0827	0.0008	0.0007	0.5146	0.4854	−0.0036	0.0037
0.30	0.30	0.8996	0.0026	0.0021	0.5588	0.4412	−0.0138	0.0138	0.0995	0.0010	0.0008	0.5152	0.4848	−0.0046	0.0039
Basis for allocation type 1															
0.10	0.10	3.6379	0.0105	0.0074	0.5006	0.4994	−0.0774	0.0774	0.1768	0.0018	0.0014	0.5009	0.4991	−0.0083	0.0107
0.20	0.20	5.1419	0.0148	0.0105	0.5008	0.4992	−0.0954	0.1228	0.2486	0.0025	0.0019	0.5125	0.4875	−0.0118	0.0115
0.30	0.30	6.3027	0.0182	0.0129	0.5002	0.4998	−0.1288	0.1267	0.3057	0.0031	0.0024	0.5107	0.4893	−0.0150	0.0120
Basis for allocation type 2, intentional (probability)[c]															
0.10	0.10	0.4318	0.0012	0.0009	0.5550	0.4450	−0.0046	0.0167	0.0323	0.0003	0.0003	0.5062	0.4938	−0.0012	0.0012
0.20	0.20	0.6072	0.0018	0.0013	0.5370	0.4630	−0.0069	0.0165	0.0454	0.0005	0.0004	0.4946	0.5054	−0.0018	0.0022
0.30	0.30	0.7286	0.0021	0.0016	0.5288	0.4712	−0.0090	0.0183	0.0553	0.0006	0.0004	0.5025	0.4975	−0.0022	0.0028
Basis for allocation type 2, unintentional (probability)[b]															
0.10	0.10	0.4251	0.0012	0.0009	0.4988	0.5013	−0.0133	0.0167	0.0321	0.0003	0.0003	0.5031	0.4969	−0.0015	0.0014
0.20	0.20	0.6052	0.0017	0.0013	0.4986	0.5015	−0.0165	0.0141	0.0457	0.0005	0.0004	0.5033	0.4967	−0.0019	0.0018
0.30	0.30	0.7368	0.0021	0.0016	0.5004	0.4996	−0.0180	0.0175	0.0558	0.0006	0.0004	0.5033	0.4967	−0.0021	0.0026

cf. the agenda of Table C.1

Subscript n indicates input biases on input cost objects, unintended (probability) with interval for biases $U[-0.10; 0.10]$

Confidence intervals for relative errors with $\alpha = 0.001$: ex-ante to operations]0.0000; 0.0021]; ex-post to operations]0.0000; 0.0005]

Table C.8 Input biases on the assignment of cost categories interacting with other biases

		Decision-influencing							Decision-facilitating						
p_n [1]	p_q [1]	$EUCD^{di}_{n,q}$ [2]	$MSE^{di}_{n,q}$ [3]	$e^{mean,di}_{n,q}$ [4]	$p^{under,di}_{n,q}$ [5]	$p^{over,di}_{n,q}$ [5]	$\underline{e}^{di}_{n,q}$ [6]	$\overline{e}^{di}_{n,q}$ [6]	$EUCD^{df}_{n,q}$ [2]	$MSE^{df}_{n,q}$ [3]	$e^{mean,df}_{n,q}$ [4]	$p^{under,df}_{n,q}$ [5]	$p^{over,df}_{n,q}$ [5]	$\underline{e}^{df}_{n,q}$ [6]	$\overline{e}^{df}_{n,q}$ [6]
Ex-ante to operations															
Categorization of cost centers															
0.10	0.10	9.1249	0.0263	0.0192	0.4511	0.5489	−0.1721	0.2769	3.0700	0.0307	0.0298	0.0001	0.9999	−0.0014	0.0600
0.20	0.20	15.3790	0.0444	0.0322	0.4523	0.5477	−0.1359	0.3289	6.2701	0.0627	0.0617	0.0000	1.0000	0.0000	0.1249
0.30	0.30	21.6763	0.0626	0.0448	0.4551	0.5449	−0.1373	0.4000	9.6235	0.0962	0.0951	0.0000	1.0000	0.0000	0.1654
Categorization of cost categories															
0.10	0.10	24.2316	0.0700	0.0526	0.2498	0.7502	−0.3431	0.2276	9.4785	0.0948	0.0886	0.0000	1.0000	0.0000	0.3197
0.20	0.20	34.9818	0.1010	0.0804	0.3347	0.6654	−0.3252	0.3594	16.7678	0.1677	0.1614	0.0000	1.0000	0.0000	0.4105
0.30	0.30	42.8314	0.1236	0.0961	0.3990	0.6010	−0.3246	0.4268	22.6762	0.2268	0.2209	0.0000	1.0000	0.0000	0.4897
Building of direct cost pools															
0.10	0.10	10.4696	0.0302	0.0229	0.4311	0.5689	−0.1424	0.2096	3.0995	0.0310	0.0296	0.0027	0.9973	−0.0136	0.0787
0.20	0.20	16.6035	0.0479	0.0370	0.4339	0.5661	−0.2722	0.2507	6.3014	0.0630	0.0615	0.0031	0.9969	−0.1681	0.1339
0.30	0.30	22.3107	0.0644	0.0492	0.4380	0.5621	−0.1733	0.2372	9.6073	0.0961	0.0946	0.0000	1.0000	0.0000	0.1789
Assignment of direct cost pools															
0.10	0.10	10.1129	0.0292	0.0205	0.4545	0.5455	−0.1859	0.3438	3.0713	0.0307	0.0297	0.0001	0.9999	−0.0017	0.0667
0.20	0.20	16.4659	0.0475	0.0338	0.4586	0.5414	−0.1398	0.3567	6.2617	0.0626	0.0615	0.0000	1.0000	0.0000	0.1229
0.30	0.30	22.8390	0.0659	0.0465	0.4597	0.5403	−0.4249	0.4821	9.6612	0.0966	0.0953	0.0021	0.9979	−0.2176	0.1704
Assignment of cost drivers for allocation type 2															
0.10	0.10	8.4414	0.0244	0.0184	0.4485	0.5515	−0.0671	0.1316	3.0653	0.0307	0.0298	0.0000	1.0000	0.0000	0.0648
0.20	0.20	14.7694	0.0426	0.0314	0.4513	0.5487	−0.0939	0.2092	6.2689	0.0627	0.0617	0.0000	1.0000	0.0000	0.1139
0.30	0.30	20.9771	0.0606	0.0439	0.4537	0.5464	−0.1168	0.2678	9.6016	0.0960	0.0949	0.0000	1.0000	0.0000	0.1568
Ex-post to operations															
Input cost objects, intentional (probability)[a]															
0.10	0.10	7.7176	0.0223	0.0176	0.5497	0.4503	−0.0685	0.1023	3.0859	0.0309	0.0300	0.0000	1.0000	0.0000	0.0609
0.20	0.20	13.5280	0.0391	0.0307	0.5757	0.4243	−0.1021	0.1751	6.2163	0.0622	0.0612	0.0000	1.0000	0.0000	0.1040
0.30	0.30	19.2112	0.0555	0.0433	0.5942	0.4058	−0.1317	0.2364	9.5720	0.0957	0.0946	0.0000	1.0000	0.0000	0.1578

Input cost objects, unintentional (probability)															
0.10	0.10	8.0011	0.0231	0.0177	0.4451	0.5549	−0.0799	0.1165	3.0677	0.0307	0.0298	0.0000	1.0000	0.0000	0.0571
0.20	0.20	14.1845	0.0409	0.0303	0.4518	0.5482	−0.1040	0.1866	6.2281	0.0623	0.0613	0.0000	1.0000	0.0000	0.1091
0.30	0.30	20.2355	0.0584	0.0425	0.4559	0.5441	−0.1241	0.2580	9.5602	0.0956	0.0945	0.0000	1.0000	0.0000	0.1569
Differences in valuation, unintentional (probability)[b]															
0.10	0.10	8.0098	0.0231	0.0177	0.4472	0.5528	−0.0654	0.1175	3.0522	0.0305	0.0297	0.0000	1.0000	0.0000	0.0608
0.20	0.20	14.2335	0.0411	0.0306	0.4507	0.5493	−0.1051	0.1658	6.2217	0.0622	0.0612	0.0000	1.0000	0.0000	0.1171
0.30	0.30	20.3382	0.0587	0.0427	0.4559	0.5441	−0.1127	0.2416	9.6240	0.0962	0.0952	0.0000	1.0000	0.0000	0.1573
Differences in valuation (not calculated)															
0.10	0.10	8.0246	0.0232	0.0177	0.4492	0.5508	−0.0648	0.1108	3.0536	0.0305	0.0297	0.0000	1.0000	0.0000	0.0607
0.20	0.20	14.3153	0.0413	0.0307	0.4542	0.5458	−0.1009	0.1983	6.2122	0.0621	0.0612	0.0000	1.0000	0.0000	0.1261
0.30	0.30	20.5213	0.0592	0.0431	0.4604	0.5396	−0.1184	0.2479	9.5442	0.0954	0.0944	0.0000	1.0000	0.0000	0.1721
Basis for allocation type 1															
0.10	0.10	8.8274	0.0255	0.0190	0.4551	0.5450	−0.0712	0.1474	3.0627	0.0306	0.0298	0.0000	1.0000	0.0000	0.0583
0.20	0.20	15.1813	0.0438	0.0320	0.4530	0.5471	−0.0964	0.2231	6.2552	0.0626	0.0616	0.0000	1.0000	0.0000	0.1088
0.30	0.30	21.3484	0.0616	0.0443	0.4561	0.5439	−0.1152	0.3003	9.5957	0.0960	0.0949	0.0000	1.0000	0.0000	0.1729
Basis for allocation type 2, intentional (probability)[c]															
0.10	0.10	8.0839	0.0233	0.0178	0.4449	0.5551	−0.0620	0.1118	3.0664	0.0307	0.0298	0.0000	1.0000	0.0000	0.0597
0.20	0.20	14.2960	0.0413	0.0306	0.4490	0.5510	−0.0867	0.1662	6.2586	0.0626	0.0616	0.0000	1.0000	0.0000	0.1208
0.30	0.30	20.4401	0.0590	0.0430	0.4518	0.5482	−0.1176	0.2410	9.6051	0.0961	0.0950	0.0000	1.0000	0.0000	0.1620
Basis for allocation type 2, unintentional (probability)[b]															
0.10	0.10	8.1046	0.0234	0.0179	0.4463	0.5537	−0.0618	0.1215	3.0766	0.0308	0.0299	0.0001	0.9999	−0.0013	0.0642
0.20	0.20	14.3201	0.0413	0.0307	0.4484	0.5516	−0.0980	0.1784	6.2574	0.0626	0.0616	0.0000	1.0000	0.0000	0.1065
0.30	0.30	20.5271	0.0593	0.0431	0.4525	0.5475	−0.1119	0.2467	9.6422	0.0964	0.0954	0.0000	1.0000	0.0000	0.1586

cf. the agenda of Table C.1

Subscript n indicates input biases on input the assignment of cost categories

Confidence intervals for relative errors with $\alpha = 0.001$: ex-ante to operations [0.0001; 0.0017]; ex-post to operations [0.0001; 0.0005]

Table C.9 Input biases on differences in valuation, unintentional (probability) interacting with other biases

		Decision-influencing							Decision-facilitating						
p_n [1]	p_q [1]	$EUCD^{di}_{n,q}$ [2]	$MSE^{di}_{n,q}$ [3]	$e^{mean,di}_{n,q}$ [4]	$p^{under,di}_{n,q}$ [5]	$p^{over,di}_{n,q}$ [5]	$\underline{e}^{di}_{n,q}$ [6]	$\overline{e}^{di}_{n,q}$ [6]	$EUCD^{df}_{n,q}$ [2]	$MSE^{df}_{n,q}$ [3]	$e^{mean,df}_{n,q}$ [4]	$p^{under,df}_{n,q}$ [5]	$p^{over,df}_{n,q}$ [5]	$\underline{e}^{df}_{n,q}$ [6]	$\overline{e}^{df}_{n,q}$ [6]
Ex-ante to operations															
Categorization of cost centers															
0.10	0.10	4.1985	0.0121	0.0049	0.4983	0.5017	−0.2062	0.2251	0.1802	0.0018	0.0011	0.4987	0.5013	−0.0140	0.0147
0.20	0.20	5.6692	0.0164	0.0078	0.4946	0.5054	−0.2050	0.2125	0.2555	0.0026	0.0018	0.4977	0.5023	−0.0180	0.0159
0.30	0.30	7.1674	0.0207	0.0107	0.4968	0.5032	−0.2255	0.2805	0.3086	0.0031	0.0022	0.4870	0.5130	−0.0278	0.0206
Categorization of cost categories															
0.10	0.10	22.2089	0.0641	0.0481	0.1558	0.8442	−0.3597	0.1679	7.1555	0.0716	0.0622	0.0011	0.9989	−0.0047	0.3016
0.20	0.20	31.7488	0.0917	0.0782	0.2652	0.7348	−0.3685	0.2861	12.9018	0.1290	0.1181	0.0000	1.0000	0.0000	0.4031
0.30	0.30	39.1891	0.1131	0.0982	0.3445	0.6555	−0.3870	0.3663	18.3144	0.1831	0.1706	0.0000	1.0000	0.0000	0.5965
Building of direct cost pools															
0.10	0.10	6.8217	0.0197	0.0082	0.4990	0.5010	−0.1549	0.2139	0.5265	0.0053	0.0032	0.5158	0.4842	−0.0376	0.0440
0.20	0.20	9.4844	0.0274	0.0143	0.4991	0.5009	−0.1731	0.2328	0.7753	0.0078	0.0053	0.5164	0.4836	−0.0492	0.0424
0.30	0.30	10.7931	0.0312	0.0183	0.5026	0.4975	−0.1758	0.2096	0.9037	0.0090	0.0065	0.4800	0.5200	−0.0499	0.0476
Assignment of direct cost pools															
0.10	0.10	5.8141	0.0168	0.0049	0.5007	0.4993	−0.2023	0.2820	0.2576	0.0026	0.0015	0.5044	0.4956	−0.0240	0.0211
0.20	0.20	8.1781	0.0236	0.0097	0.5010	0.4990	−0.2202	0.2343	0.3716	0.0037	0.0025	0.4937	0.5063	−0.0192	0.0225
0.30	0.30	9.7000	0.0280	0.0140	0.5008	0.4992	−0.2173	0.3205	0.4361	0.0044	0.0032	0.4872	0.5128	−0.0291	0.0304
Assignment of cost drivers for allocation type 2															
0.10	0.10	2.3801	0.0069	0.0047	0.4992	0.5008	−0.0556	0.0574	0.1088	0.0011	0.0008	0.5112	0.4888	−0.0055	0.0053
0.20	0.20	3.2727	0.0094	0.0065	0.5007	0.4993	−0.0686	0.0816	0.1584	0.0016	0.0012	0.5039	0.4961	−0.0077	0.0091
0.30	0.30	3.9310	0.0113	0.0079	0.4994	0.5006	−0.0851	0.0975	0.1904	0.0019	0.0014	0.5004	0.4996	−0.0113	0.0106

Ex-post to operations															
Input cost objects, intentional (probability)[a]															
0.10	0.10	1.9217	0.0055	0.0055	1.0000	0.0000	−0.0091	0.0000	0.0283	0.0003	0.0002	0.5090	0.4910	−0.0010	0.0012
0.20	0.20	3.8262	0.0110	0.0110	1.0000	0.0000	−0.0163	0.0000	0.0383	0.0004	0.0003	0.5030	0.4970	−0.0015	0.0015
0.30	0.30	5.7284	0.0165	0.0165	1.0000	0.0000	−0.0219	0.0000	0.0454	0.0005	0.0004	0.5014	0.4986	−0.0018	0.0018
Input cost objects, unintentional (probability)															
0.10	0.10	0.2526	0.0007	0.0006	0.4972	0.5028	−0.0036	0.0033	0.0278	0.0003	0.0002	0.4986	0.5014	−0.0012	0.0012
0.20	0.20	0.3572	0.0010	0.0008	0.4990	0.5010	−0.0046	0.0046	0.0396	0.0004	0.0003	0.5057	0.4943	−0.0018	0.0014
0.30	0.30	0.4380	0.0013	0.0010	0.4979	0.5021	−0.0066	0.0069	0.0487	0.0005	0.0004	0.4927	0.5073	−0.0021	0.0019
Assignment of cost categories															
0.10	0.10	8.0098	0.0231	0.0177	0.4472	0.5528	−0.0654	0.1175	3.0522	0.0305	0.0297	0.0000	1.0000	0.0000	0.0608
0.20	0.20	14.2335	0.0411	0.0306	0.4507	0.5493	−0.1051	0.1658	6.2217	0.0622	0.0612	0.0000	1.0000	0.0000	0.1171
0.30	0.30	20.3382	0.0587	0.0427	0.4559	0.5441	−0.1127	0.2416	9.6240	0.0962	0.0952	0.0000	1.0000	0.0000	0.1573
Basis for allocation type 1															
0.10	0.10	3.6200	0.0104	0.0073	0.5020	0.4980	−0.0745	0.0856	0.1711	0.0017	0.0013	0.5054	0.4946	−0.0089	0.0082
0.20	0.20	5.0950	0.0147	0.0104	0.5012	0.4988	−0.1002	0.1056	0.2436	0.0024	0.0019	0.4959	0.5041	−0.0110	0.0112
0.30	0.30	6.2883	0.0182	0.0128	0.4996	0.5004	−0.1349	0.1512	0.3003	0.0030	0.0023	0.4931	0.5069	−0.0137	0.0132
Basis for allocation type 2, intentional (probability)[c]															
0.10	0.10	0.3570	0.0010	0.0007	0.6801	0.3199	−0.0034	0.0154	0.0173	0.0002	0.0001	0.5383	0.4617	−0.0007	0.0012
0.20	0.20	0.4918	0.0014	0.0010	0.5966	0.4034	−0.0051	0.0162	0.0241	0.0002	0.0002	0.5327	0.4673	−0.0009	0.0015
0.30	0.30	0.5898	0.0017	0.0012	0.5697	0.4303	−0.0065	0.0189	0.0282	0.0003	0.0002	0.5193	0.4807	−0.0011	0.0015
Basis for allocation type 2, unintentional (probability)[b]															
0.10	0.10	0.3454	0.0010	0.0006	0.4987	0.5013	−0.0123	0.0111	0.0168	0.0002	0.0001	0.4976	0.5024	−0.0010	0.0010
0.20	0.20	0.4867	0.0014	0.0009	0.4968	0.5032	−0.0152	0.0139	0.0237	0.0002	0.0002	0.5011	0.4989	−0.0014	0.0014
0.30	0.30	0.6009	0.0017	0.0011	0.4984	0.5016	−0.0153	0.0158	0.0293	0.0003	0.0002	0.4973	0.5027	−0.0015	0.0014

cf. the agenda of Table C.1

Subscript n indicates input biases on differences in valuation, unintended (probability) with interval for biases $U[-0.10; 0.10]$

Confidence intervals for relative errors with $\alpha = 0.001$: ex-ante to operations $]0.0000; 0.0022]$; ex-post to operations $]0.0000; 0.0005]$

Table C.10 Input biases on differences in valuation (not calculated) interacting with other biases

		Decision-influencing							Decision-facilitating						
p_n [1]	p_q [1]	$EUCD^{di}_{n,q}$ [2]	$MSE^{di}_{n,q}$ [3]	$e^{mean,di}_{n,q}$ [4]	$p^{under,di}_{n,q}$ [5]	$p^{over,di}_{n,q}$ [5]	$\underline{e}^{di}_{n,q}$ [6]	$\overline{e}^{di}_{n,q}$ [6]	$EUCD^{df}_{n,q}$ [2]	$MSE^{df}_{n,q}$ [3]	$e^{mean,df}_{n,q}$ [4]	$p^{under,df}_{n,q}$ [5]	$p^{over,df}_{n,q}$ [5]	$\underline{e}^{df}_{n,q}$ [6]	$\overline{e}^{df}_{n,q}$ [6]
Ex-ante to operations															
Categorization of cost centers															
0.10	0.10	4.1497	0.0120	0.0051	0.5209	0.4791	−0.1846	0.2160	0.1830	0.0018	0.0012	0.5124	0.4876	−0.0133	0.0151
0.20	0.20	5.7409	0.0166	0.0080	0.4955	0.5045	−0.2060	0.2313	0.2545	0.0025	0.0018	0.5186	0.4814	−0.0189	0.0176
0.30	0.30	7.0581	0.0204	0.0107	0.4978	0.5022	−0.2172	0.2542	0.3130	0.0031	0.0023	0.5184	0.4816	−0.0185	0.0189
Categorization of cost categories															
0.10	0.10	22.2361	0.0642	0.0481	0.1571	0.8429	−0.3401	0.1650	7.2126	0.0721	0.0627	0.0018	0.9982	−0.0088	0.2809
0.20	0.20	31.9109	0.0921	0.0784	0.2647	0.7353	−0.3749	0.2823	12.7992	0.1280	0.1176	0.0000	1.0000	0.0000	0.4054
0.30	0.30	39.1842	0.1131	0.0981	0.3437	0.6563	−0.3728	0.3620	17.9293	0.1793	0.1674	0.0000	1.0000	0.0000	0.5437
Building of direct cost pools															
0.10	0.10	6.7220	0.0194	0.0088	0.5389	0.4611	−0.1601	0.1992	0.5516	0.0055	0.0034	0.5256	0.4744	−0.0425	0.0413
0.20	0.20	9.2242	0.0266	0.0148	0.5335	0.4665	−0.1518	0.2032	0.7451	0.0075	0.0051	0.5301	0.4699	−0.0423	0.0362
0.30	0.30	10.7054	0.0309	0.0189	0.5336	0.4664	−0.1654	0.2071	0.8664	0.0087	0.0062	0.5316	0.4684	−0.0478	0.0388
Assignment of direct cost pools															
0.10	0.10	5.6561	0.0163	0.0057	0.5476	0.4525	−0.2178	0.2483	0.2599	0.0026	0.0016	0.5065	0.4935	−0.0218	0.0199
0.20	0.20	8.1063	0.0234	0.0106	0.5417	0.4583	−0.2306	0.2868	0.3615	0.0036	0.0025	0.5293	0.4707	−0.0209	0.0275
0.30	0.30	9.7672	0.0282	0.0150	0.5360	0.4640	−0.2317	0.2890	0.4457	0.0045	0.0033	0.5346	0.4654	−0.0262	0.0263
Assignment of cost drivers for allocation type 2															
0.10	0.10	2.4151	0.0070	0.0048	0.5150	0.4850	−0.0547	0.0582	0.1248	0.0012	0.0010	0.5076	0.4924	−0.0067	0.0070
0.20	0.20	3.3550	0.0097	0.0068	0.5159	0.4841	−0.0741	0.0848	0.1712	0.0017	0.0013	0.5048	0.4952	−0.0088	0.0087
0.30	0.30	4.0084	0.0116	0.0081	0.5182	0.4818	−0.0881	0.0858	0.2057	0.0021	0.0016	0.5077	0.4923	−0.0090	0.0112

Ex-post to operations															
Input cost objects, intentional (probability)[a]															
0.10	0.10	2.0201	0.0058	0.0056	0.9996	0.0004	−0.0135	0.0030	0.0592	0.0006	0.0005	0.5043	0.4957	−0.0025	0.0023
0.20	0.20	3.9481	0.0114	0.0112	1.0000	0.0000	−0.0230	0.0000	0.0826	0.0008	0.0007	0.4845	0.5155	−0.0034	0.0036
0.30	0.30	5.8814	0.0170	0.0168	1.0000	0.0000	−0.0282	0.0000	0.0980	0.0010	0.0008	0.4928	0.5072	−0.0037	0.0051
Input cost objects, unintentional (probability)															
0.10	0.10	0.5376	0.0016	0.0012	0.5366	0.4634	−0.0076	0.0083	0.0594	0.0006	0.0005	0.5032	0.4968	−0.0028	0.0024
0.20	0.20	0.7473	0.0022	0.0017	0.5470	0.4530	−0.0104	0.0127	0.0827	0.0008	0.0007	0.5146	0.4854	−0.0036	0.0037
0.30	0.30	0.8996	0.0026	0.0021	0.5588	0.4412	−0.0138	0.0138	0.0995	0.0010	0.0008	0.5152	0.4848	−0.0046	0.0039
Assignment of cost categories															
0.10	0.10	8.0246	0.0232	0.0177	0.4492	0.5508	−0.0648	0.1108	3.0536	0.0305	0.0297	0.0000	1.0000	0.0000	0.0607
0.20	0.20	14.3153	0.0413	0.0307	0.4542	0.5458	−0.1009	0.1983	6.2122	0.0621	0.0612	0.0000	1.0000	0.0000	0.1261
0.30	0.30	20.5213	0.0592	0.0431	0.4604	0.5396	−0.1184	0.2479	9.5442	0.0954	0.0944	0.0000	1.0000	0.0000	0.1721
Basis for allocation type 1															
0.10	0.10	3.6490	0.0105	0.0075	0.5100	0.4900	−0.0792	0.0827	0.1776	0.0018	0.0014	0.5012	0.4988	−0.0079	0.0094
0.20	0.20	5.1421	0.0148	0.0105	0.5104	0.4896	−0.0982	0.1189	0.2527	0.0025	0.0020	0.5161	0.4839	−0.0176	0.0143
0.30	0.30	6.3075	0.0182	0.0129	0.5114	0.4886	−0.1375	0.1707	0.3100	0.0031	0.0024	0.5369	0.4631	−0.0163	0.0164
Basis for allocation type 2, intentional (probability)[c]															
0.10	0.10	0.5941	0.0017	0.0013	0.5698	0.4302	−0.0092	0.0126	0.0549	0.0005	0.0004	0.5257	0.4743	−0.0022	0.0020
0.20	0.20	0.8170	0.0024	0.0018	0.5644	0.4356	−0.0115	0.0170	0.0760	0.0008	0.0006	0.5165	0.4835	−0.0030	0.0031
0.30	0.30	0.9841	0.0028	0.0022	0.5702	0.4298	−0.0136	0.0184	0.0902	0.0009	0.0007	0.5247	0.4753	−0.0041	0.0040
Basis for allocation type 2, unintentional (probability)[b]															
0.10	0.10	0.5900	0.0017	0.0013	0.5454	0.4546	−0.0131	0.0118	0.0543	0.0005	0.0004	0.5191	0.4809	−0.0024	0.0026
0.20	0.20	0.8190	0.0024	0.0018	0.5533	0.4467	−0.0167	0.0160	0.0748	0.0007	0.0006	0.5317	0.4683	−0.0030	0.0035
0.30	0.30	0.9874	0.0029	0.0022	0.5583	0.4417	−0.0177	0.0173	0.0910	0.0009	0.0007	0.5285	0.4715	−0.0039	0.0037

cf. the agenda of Table C.1

Subscript n indicates input biases on differences in valuation (not calculated)

Confidence intervals for relative errors with $\alpha = 0.001$: ex-ante to operations]0.0000; 0.0021]; ex-post to operations]0.0000; 0.0005]

Table C.11 Input biases on the basis for allocation type 1 interacting with other biases

		Decision-influencing							Decision-facilitating						
p_n [1]	p_q [1]	$EUCD^{di}_{n,q}$ [2]	$MSE^{di}_{n,q}$ [3]	$e^{mean,di}_{n,q}$ [4]	$p^{under,di}_{n,q}$ [5]	$p^{over,di}_{n,q}$ [5]	$\underline{e}^{di}_{n,q}$ [6]	$\overline{e}^{di}_{n,q}$ [6]	$EUCD^{df}_{n,q}$ [2]	$MSE^{df}_{n,q}$ [3]	$e^{mean,df}_{n,q}$ [4]	$p^{under,df}_{n,q}$ [5]	$p^{over,df}_{n,q}$ [5]	$\underline{e}^{df}_{n,q}$ [6]	$\overline{e}^{df}_{n,q}$ [6]
Ex-ante to operations															
Categorization of cost centers															
0.10	0.10	5.2795	5.2795	0.0095	5.2795	0.4990	−0.1775	0.2177	0.2510	0.0025	0.0018	0.4914	0.5086	−0.0203	0.0180
0.20	0.20	7.3178	7.3178	0.0138	7.3178	0.5009	−0.1999	0.2734	0.3412	0.0034	0.0026	0.4826	0.5174	−0.0216	0.0183
0.30	0.30	8.7096	8.7096	0.0168	8.7096	0.5019	−0.2264	0.2518	0.4017	0.0040	0.0031	0.4901	0.5099	−0.0194	0.0227
Categorization of cost categories															
0.10	0.10	22.3673	0.0646	0.0480	0.1644	0.8356	−0.3616	0.1946	7.1762	0.0718	0.0620	0.0020	0.9980	−0.0128	0.3154
0.20	0.20	32.0891	0.0926	0.0781	0.2657	0.7344	−0.3496	0.2979	12.9320	0.1293	0.1183	0.0001	0.9999	−0.0026	0.4465
0.30	0.30	39.5052	0.1140	0.0981	0.3443	0.6557	−0.3752	0.4217	18.0951	0.1810	0.1685	0.0000	1.0000	0.0000	0.5347
Building of direct cost pools															
0.10	0.10	7.7813	0.0225	0.0142	0.4996	0.5004	−0.2087	0.2336	0.5919	0.0059	0.0039	0.4792	0.5208	−0.0420	0.0359
0.20	0.20	10.5113	0.0303	0.0212	0.4997	0.5004	−0.2164	0.2568	0.8083	0.0081	0.0057	0.4726	0.5274	−0.0450	0.0655
0.30	0.30	12.0411	0.0348	0.0255	0.4998	0.5003	−0.1787	0.2136	0.9089	0.0091	0.0066	0.5249	0.4751	−0.0467	0.0523
Assignment of direct cost pools															
0.10	0.10	6.5466	0.0189	0.0108	0.4988	0.5012	−0.2150	0.2988	0.2979	0.0030	0.0021	0.4963	0.5037	−0.0171	0.0183
0.20	0.20	8.8961	0.0257	0.0163	0.4999	0.5001	−0.2070	0.3304	0.4189	0.0042	0.0031	0.4810	0.5190	−0.0299	0.0255
0.30	0.30	10.4706	0.0302	0.0201	0.4999	0.5001	−0.2137	0.3053	0.4985	0.0050	0.0038	0.4873	0.5127	−0.0244	0.0311
Assignment of cost drivers for allocation type 2															
0.10	0.10	4.3305	0.0125	0.0088	0.4984	0.5016	−0.1017	0.0992	0.2074	0.0021	0.0016	0.5148	0.4852	−0.0122	0.0101
0.20	0.20	6.1714	0.0178	0.0126	0.4992	0.5008	−0.1217	0.1461	0.2906	0.0029	0.0022	0.5155	0.4845	−0.0131	0.0136
0.30	0.30	7.4949	0.0216	0.0153	0.4980	0.5020	−0.1632	0.2187	0.3550	0.0036	0.0028	0.5165	0.4835	−0.0172	0.0183

Input cost objects, unintentional (probability)															
0.10	0.10	3.6379	0.0105	0.0074	0.5006	0.4994	−0.0774	0.0774	0.1768	0.0018	0.0014	0.5009	0.4991	−0.0083	0.0107
0.20	0.20	5.1419	0.0148	0.0105	0.5008	0.4992	−0.0954	0.1228	0.2486	0.0025	0.0019	0.5125	0.4875	−0.0118	0.0115
0.30	0.30	6.3027	0.0182	0.0129	0.5002	0.4998	−0.1288	0.1267	0.3057	0.0031	0.0024	0.5107	0.4893	−0.0150	0.0120
Assignment of cost categories															
0.10	0.10	8.8274	0.0255	0.0190	0.4551	0.5450	−0.0712	0.1474	3.0627	0.0306	0.0298	0.0000	1.0000	0.0000	0.0583
0.20	0.20	15.1813	0.0438	0.0320	0.4530	0.5471	−0.0964	0.2231	6.2552	0.0626	0.0616	0.0000	1.0000	0.0000	0.1088
0.30	0.30	21.3484	0.0616	0.0443	0.4561	0.5439	−0.1152	0.3003	9.5957	0.0960	0.0949	0.0000	1.0000	0.0000	0.1729
Differences in valuation, unintentional (probability)[b]															
0.10	0.10	3.6200	0.0104	0.0073	0.5020	0.4980	−0.0745	0.0856	0.1711	0.0017	0.0013	0.5054	0.4946	−0.0089	0.0082
0.20	0.20	5.0950	0.0147	0.0104	0.5012	0.4988	−0.1002	0.1056	0.2436	0.0024	0.0019	0.4959	0.5041	−0.0110	0.0112
0.30	0.30	6.2883	0.0182	0.0128	0.4996	0.5004	−0.1349	0.1512	0.3003	0.0030	0.0023	0.4931	0.5069	−0.0137	0.0132
Differences in valuation (not calculated)															
0.10	0.10	3.6490	0.0105	0.0075	0.5100	0.4900	−0.0792	0.0827	0.1776	0.0018	0.0014	0.5012	0.4988	−0.0079	0.0094
0.20	0.20	5.1421	0.0148	0.0105	0.5104	0.4896	−0.0982	0.1189	0.2527	0.0025	0.0020	0.5161	0.4839	−0.0176	0.0143
0.30	0.30	6.3075	0.0182	0.0129	0.5114	0.4886	−0.1375	0.1707	0.3100	0.0031	0.0024	0.5369	0.4631	−0.0163	0.0164
Basis for allocation type 2, intentional (probability)[c]															
0.10	0.10	3.6559	0.0106	0.0074	0.5010	0.4990	−0.0774	0.0765	0.1738	0.0017	0.0013	0.4878	0.5122	−0.0082	0.0079
0.20	0.20	5.1381	0.0148	0.0105	0.5000	0.5000	−0.1016	0.1153	0.2417	0.0024	0.0019	0.4954	0.5046	−0.0106	0.0114
0.30	0.30	6.3113	0.0182	0.0129	0.4988	0.5012	−0.1311	0.1419	0.2975	0.0030	0.0023	0.4776	0.5224	−0.0143	0.0127
Basis for allocation type 2, unintentional (probability)[b]															
0.10	0.10	3.6318	0.0105	0.0074	0.5005	0.4995	−0.0819	0.0801	0.1750	0.0017	0.0014	0.4869	0.5131	−0.0085	0.0083
0.20	0.20	5.1564	0.0149	0.0105	0.4996	0.5004	−0.1122	0.1057	0.2426	0.0024	0.0019	0.4898	0.5102	−0.0106	0.0116
0.30	0.30	6.3040	0.0182	0.0129	0.4996	0.5004	−0.1316	0.1530	0.3004	0.0030	0.0023	0.4826	0.5174	−0.0141	0.0146

cf. the agenda of Table C.1

Subscript n indicates input biases on the basis for allocation type 1

Confidence intervals for relative errors with $\alpha = 0.001$: ex-ante to operations [0.0001; 0.0022]; ex-post to operations [0.0001; 0.0005]

Table C.12 Input biases on the basis for allocation type 2, intentional (probability) interacting with other biases

		Decision-influencing							Decision-facilitating						
p_n [1]	p_q [1]	$EUCD^{di}_{n,q}$ [2]	$MSE^{di}_{n,q}$ [3]	$e^{mean,di}_{n,q}$ [4]	$p^{under,di}_{n,q}$ [5]	$p^{over,di}_{n,q}$ [5]	$\underline{e}^{di}_{n,q}$ [6]	$\overline{e}^{di}_{n,q}$ [6]	$EUCD^{df}_{n,q}$ [2]	$MSE^{df}_{n,q}$ [3]	$e^{mean,df}_{n,q}$ [4]	$p^{under,df}_{n,q}$ [5]	$p^{over,df}_{n,q}$ [5]	$\underline{e}^{df}_{n,q}$ [6]	$\overline{e}^{df}_{n,q}$ [6]
Ex-ante to operations															
Categorization of cost centers															
0.10	0.10	4.1156	0.0119	0.0050	0.5017	0.4983	−0.1778	0.2304	0.1819	0.0018	0.0011	0.4929	0.5071	−0.0166	0.0152
0.20	0.20	5.7556	0.0166	0.0081	0.4959	0.5042	−0.1832	0.2346	0.2618	0.0026	0.0018	0.4925	0.5075	−0.0186	0.0168
0.30	0.30	6.9956	0.0202	0.0107	0.4964	0.5036	−0.1851	0.2455	0.3208	0.0032	0.0023	0.4900	0.5100	−0.0180	0.0184
Categorization of cost categories															
0.10	0.10	22.1863	0.0640	0.0481	0.1565	0.8435	−0.3577	0.1612	7.2179	0.0722	0.0626	0.0015	0.9985	−0.0003	0.3493
0.20	0.20	31.7898	0.0918	0.0782	0.2647	0.7353	−0.3539	0.2945	13.0397	0.1304	0.1192	0.0001	0.9999	−0.0002	0.3976
0.30	0.30	38.9695	0.1125	0.0977	0.3441	0.6559	−0.3687	0.3569	18.1253	0.1813	0.1688	0.0000	1.0000	0.0000	0.5036
Building of direct cost pools															
0.10	0.10	6.9004	0.0199	0.0087	0.6304	0.3696	−0.2126	0.2329	0.5806	0.0058	0.0035	0.4819	0.5181	−0.0446	0.0349
0.20	0.20	9.1642	0.0265	0.0144	0.5521	0.4479	−0.2143	0.2338	0.7767	0.0078	0.0053	0.4835	0.5165	−0.0449	0.0617
0.30	0.30	10.2602	0.0296	0.0177	0.5339	0.4661	−0.1710	0.2261	0.8293	0.0083	0.0059	0.5174	0.4826	−0.0497	0.0547
Assignment of direct cost pools															
0.10	0.10	5.7009	0.0165	0.0054	0.6504	0.3496	−0.1877	0.3099	0.2618	0.0026	0.0016	0.4999	0.5001	−0.0185	0.0238
0.20	0.20	8.0967	0.0234	0.0103	0.5637	0.4363	−0.2108	0.3105	0.3633	0.0036	0.0025	0.4983	0.5017	−0.0177	0.0231
0.30	0.30	9.7899	0.0283	0.0148	0.5333	0.4667	−0.2097	0.3195	0.4607	0.0046	0.0033	0.4869	0.5131	−0.0231	0.0302
Assignment of cost drivers for allocation type 2															
0.10	0.10	2.4069	0.0069	0.0047	0.5016	0.4984	−0.0540	0.0588	0.1159	0.0012	0.0008	0.4982	0.5018	−0.0065	0.0082
0.20	0.20	3.3498	0.0097	0.0067	0.5012	0.4988	−0.0714	0.0855	0.1608	0.0016	0.0012	0.5037	0.4963	−0.0083	0.0092
0.30	0.30	3.9819	0.0115	0.0080	0.5010	0.4990	−0.0921	0.1006	0.1910	0.0019	0.0014	0.5024	0.4976	−0.0100	0.0094

Ex-post to operations															
Input cost objects, intentional (probability)[a]															
0.10	0.10	1.9538	0.0056	0.0055	0.9963	0.0037	−0.0103	0.0086	0.0327	0.0003	0.0003	0.5116	0.4884	−0.0015	0.0015
0.20	0.20	3.8555	0.0111	0.0110	0.9996	0.0004	−0.0179	0.0051	0.0448	0.0004	0.0004	0.4997	0.5003	−0.0020	0.0018
0.30	0.30	5.7560	0.0166	0.0165	1.0000	0.0000	−0.0247	0.0037	0.0529	0.0005	0.0004	0.4893	0.5107	−0.0020	0.0022
Input cost objects, unintentional (probability)															
0.10	0.10	0.4318	0.0012	0.0009	0.5550	0.4450	−0.0046	0.0167	0.0323	0.0003	0.0003	0.5062	0.4938	−0.0012	0.0012
0.20	0.20	0.6072	0.0018	0.0013	0.5370	0.4630	−0.0069	0.0165	0.0454	0.0005	0.0004	0.4946	0.5054	−0.0018	0.0022
0.30	0.30	0.7286	0.0021	0.0016	0.5288	0.4712	−0.0090	0.0183	0.0553	0.0006	0.0004	0.5025	0.4975	−0.0022	0.0028
Assignment of cost categories															
0.10	0.10	8.0839	0.0233	0.0178	0.4449	0.5551	−0.0620	0.1118	3.0664	0.0307	0.0298	0.0000	1.0000	0.0000	0.0597
0.20	0.20	14.2960	0.0413	0.0306	0.4490	0.5510	−0.0867	0.1662	6.2586	0.0626	0.0616	0.0000	1.0000	0.0000	0.1208
0.30	0.30	20.4401	0.0590	0.0430	0.4518	0.5482	−0.1176	0.2410	9.6051	0.0961	0.0950	0.0000	1.0000	0.0000	0.1620
Differences in valuation, unintentional (probability)[b]															
0.10	0.10	0.3570	0.0010	0.0007	0.6801	0.3199	−0.0034	0.0154	0.0173	0.0002	0.0001	0.5383	0.4617	−0.0007	0.0012
0.20	0.20	0.4918	0.0014	0.0010	0.5966	0.4034	−0.0051	0.0162	0.0241	0.0002	0.0002	0.5327	0.4673	−0.0009	0.0015
0.30	0.30	0.5898	0.0017	0.0012	0.5697	0.4303	−0.0065	0.0189	0.0282	0.0003	0.0002	0.5193	0.4807	−0.0011	0.0015
Differences in valuation (not calculated)															
0.10	0.10	0.5941	0.0017	0.0013	0.5698	0.4302	−0.0092	0.0126	0.0549	0.0005	0.0004	0.5257	0.4743	−0.0022	0.0020
0.20	0.20	0.8170	0.0024	0.0018	0.5644	0.4356	−0.0115	0.0170	0.0760	0.0008	0.0006	0.5165	0.4835	−0.0030	0.0031
0.30	0.30	0.9841	0.0028	0.0022	0.5702	0.4298	−0.0136	0.0184	0.0902	0.0009	0.0007	0.5247	0.4753	−0.0041	0.0040
Basis for allocation type 1															
0.10	0.10	3.6559	0.0106	0.0074	0.5010	0.4990	−0.0774	0.0765	0.1738	0.0017	0.0013	0.4878	0.5122	−0.0082	0.0079
0.20	0.20	5.1381	0.0148	0.0105	0.5000	0.5000	−0.1016	0.1153	0.2417	0.0024	0.0019	0.4954	0.5046	−0.0106	0.0114
0.30	0.30	6.3113	0.0182	0.0129	0.4988	0.5012	−0.1311	0.1419	0.2975	0.0030	0.0023	0.4776	0.5224	−0.0143	0.0127

cf. the agenda of Table C.1

Subscript n indicates input biases on the basis for allocation type 2, intended (probability) with interval for biases $U\,]0.00; 0.10]$

Confidence intervals for relative errors with $\alpha = 0.001$: ex-ante to operations]0.0000; 0.0022]; ex-post to operations]0.0000; 0.0005]

Table C.13 Input biases on the basis for allocation type 2, unintentional (probability) interacting with other biases

		Decision-influencing							Decision-facilitating						
p_n[1]	p_q[1]	$EUCD^{di}_{n,q}$[2]	$MSE^{di}_{n,q}$[3]	$e^{mean,di}_{n,q}$[4]	$p^{under,di}_{n,q}$[5]	$p^{over,di}_{n,q}$[5]	$\underline{e}^{di}_{n,q}$[6]	$\overline{e}^{di}_{n,q}$[6]	$EUCD^{df}_{n,q}$[2]	$MSE^{df}_{n,q}$[3]	$e^{mean,df}_{n,q}$[4]	$p^{under,df}_{n,q}$[5]	$p^{over,df}_{n,q}$[5]	$\underline{e}^{df}_{n,q}$[6]	$\overline{e}^{df}_{n,q}$[6]
Ex-ante to operations															
Categorization of cost centers															
0.10	0.10	4.0657	0.0117	0.0049	0.4992	0.5008	−0.1813	0.2254	0.1826	0.0018	0.0011	0.4911	0.5089	−0.0131	0.0134
0.20	0.20	5.7511	0.0166	0.0080	0.4942	0.5058	−0.1893	0.2377	0.2585	0.0026	0.0018	0.4902	0.5098	−0.0176	0.0188
0.30	0.30	6.9886	0.0202	0.0107	0.4968	0.5032	−0.1974	0.2274	0.3191	0.0032	0.0023	0.4859	0.5141	−0.0178	0.0191
Categorization of cost categories															
0.10	0.10	22.1940	0.0641	0.0481	0.1564	0.8436	−0.3474	0.2384	7.1647	0.0716	0.0623	0.0014	0.9986	−0.0025	0.2687
0.20	0.20	31.6049	0.0912	0.0777	0.2645	0.7356	−0.3708	0.2710	12.9818	0.1298	0.1185	0.0002	0.9998	−0.0015	0.3828
0.30	0.30	38.9433	0.1124	0.0976	0.3446	0.6554	−0.3617	0.3586	18.2244	0.1822	0.1695	0.0000	1.0000	0.0000	0.5526
Building of direct cost pools															
0.10	0.10	6.9549	0.0201	0.0086	0.4994	0.5006	−0.2128	0.2343	0.5756	0.0058	0.0035	0.4747	0.5253	−0.0384	0.0417
0.20	0.20	9.1928	0.0265	0.0144	0.4983	0.5017	−0.2154	0.2333	0.7747	0.0077	0.0052	0.4731	0.5269	−0.0471	0.0505
0.30	0.30	10.2608	0.0296	0.0176	0.4996	0.5004	−0.1582	0.2076	0.8468	0.0085	0.0060	0.5176	0.4824	−0.0427	0.0555
Assignment of direct cost pools															
0.10	0.10	5.7117	0.0165	0.0053	0.4994	0.5007	−0.1910	0.3109	0.2565	0.0026	0.0016	0.4829	0.5171	−0.0163	0.0231
0.20	0.20	8.0412	0.0232	0.0101	0.4976	0.5024	−0.1892	0.3126	0.3631	0.0036	0.0025	0.4847	0.5153	−0.0258	0.0333
0.30	0.30	9.7406	0.0281	0.0147	0.4983	0.5017	−0.2127	0.3147	0.4516	0.0045	0.0033	0.4854	0.5146	−0.0242	0.0355
Assignment of cost drivers for allocation type 2															
0.10	0.10	2.4341	0.0070	0.0048	0.4998	0.5002	−0.0541	0.0556	0.1154	0.0012	0.0009	0.5110	0.4890	−0.0082	0.0067
0.20	0.20	3.3578	0.0097	0.0067	0.5011	0.4989	−0.0759	0.0906	0.1601	0.0016	0.0012	0.4950	0.5050	−0.0066	0.0129
0.30	0.30	3.9895	0.0115	0.0080	0.5033	0.4967	−0.0886	0.0941	0.1915	0.0019	0.0014	0.5047	0.4953	−0.0105	0.0084

Ex-post to operations															
Input cost objects, intentional (probability)[a]															
0.10	0.10	1.9511	0.0056	0.0055	0.9980	0.0020	−0.0173	0.0081	0.0332	0.0003	0.0003	0.5109	0.4891	−0.0013	0.0022
0.20	0.20	3.8553	0.0111	0.0110	0.9998	0.0002	−0.0255	0.0020	0.0449	0.0004	0.0004	0.5013	0.4987	−0.0021	0.0018
0.30	0.30	5.7600	0.0166	0.0165	1.0000	0.0000	−0.0326	0.0009	0.0530	0.0005	0.0004	0.4993	0.5007	−0.0020	0.0026
Input cost objects, unintentional (probability)															
0.10	0.10	0.4251	0.0012	0.0009	0.4988	0.5013	−0.0133	0.0167	0.0321	0.0003	0.0003	0.5031	0.4969	−0.0015	0.0014
0.20	0.20	0.6052	0.0017	0.0013	0.4986	0.5015	−0.0165	0.0141	0.0457	0.0005	0.0004	0.5033	0.4967	−0.0019	0.0018
0.30	0.30	0.7368	0.0021	0.0016	0.5004	0.4996	−0.0180	0.0175	0.0558	0.0006	0.0004	0.5033	0.4967	−0.0021	0.0026
Assignment of cost categories															
0.10	0.10	8.1046	0.0234	0.0179	0.4463	0.5537	−0.0618	0.1215	3.0766	0.0308	0.0299	0.0001	0.9999	−0.0013	0.0642
0.20	0.20	14.3201	0.0413	0.0307	0.4484	0.5516	−0.0980	0.1784	6.2574	0.0626	0.0616	0.0000	1.0000	0.0000	0.1065
0.30	0.30	20.5271	0.0593	0.0431	0.4525	0.5475	−0.1119	0.2467	9.6422	0.0964	0.0954	0.0000	1.0000	0.0000	0.1586
Differences in valuation, unintentional (probability)[b]															
0.10	0.10	0.3454	0.0010	0.0006	0.4987	0.5013	−0.0123	0.0111	0.0168	0.0002	0.0001	0.4976	0.5024	−0.0010	0.0010
0.20	0.20	0.4867	0.0014	0.0009	0.4968	0.5032	−0.0152	0.0139	0.0237	0.0002	0.0002	0.5011	0.4989	−0.0014	0.0014
0.30	0.30	0.6009	0.0017	0.0011	0.4984	0.5016	−0.0153	0.0158	0.0293	0.0003	0.0002	0.4973	0.5027	−0.0015	0.0014
Differences in valuation (not calculated)															
0.10	0.10	0.5900	0.0017	0.0013	0.5454	0.4546	−0.0131	0.0118	0.0543	0.0005	0.0004	0.5191	0.4809	−0.0024	0.0026
0.20	0.20	0.8190	0.0024	0.0018	0.5533	0.4467	−0.0167	0.0160	0.0748	0.0007	0.0006	0.5317	0.4683	−0.0030	0.0035
0.30	0.30	0.9874	0.0029	0.0022	0.5583	0.4417	−0.0177	0.0173	0.0910	0.0009	0.0007	0.5285	0.4715	−0.0039	0.0037
Basis for allocation type 1															
0.10	0.10	3.6318	0.0105	0.0074	0.5005	0.4995	−0.0819	0.0801	0.1750	0.0017	0.0014	0.4869	0.5131	−0.0085	0.0083
0.20	0.20	5.1564	0.0149	0.0105	0.4996	0.5004	−0.1122	0.1057	0.2426	0.0024	0.0019	0.4898	0.5102	−0.0106	0.0116
0.30	0.30	6.3040	0.0182	0.0129	0.4996	0.5004	−0.1316	0.1530	0.3004	0.0030	0.0023	0.4826	0.5174	−0.0141	0.0146

cf. the agenda of Table C.1

Subscript n indicates input biases on the basis for allocation type 2, unintended (probability) with interval for biases $U[-0.10; 0.10]$

Confidence intervals for relative errors with $\alpha = 0.001$: ex-ante to operations $]0.0000; 0.0022]$; ex-post to operations $]0.0000; 0.0005]$